A Location Estimation Method using BLE Tags Distributed Among Participants of a Large-Scale Exhibition

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ABSTRACT

Indoor location estimation is essential technology when we analyse the participants' activities in large-scale exhibition. There are some problems with existing methods such as PDR, ultrasound and laser range finder: installation location of measurement equipment at large site, cost for measurement equipment, and necessity of smartphone application. We focus on Bluetooth Low Energy(BLE). Currently, BLE technology is used as proximity notification for smartphones and cannot detect the exact distance between two BLE devices. This is because BLE radiowave is unstable and signal strength changes every time at the same distance. In this paper, we propose a location estimation method which utilizes BLE beacon tags and single board computers. In contrast to conventional ways using location-fixed BLE beacons, BLE beacon tags are distributed to participants at the event. Signal strengths of BLE advertising packets captured by multiple location-fixed scanners are used for location estimation. The method requires less cost for equipment and labor of installing an application. It can be used without complex initial setting. We had a data collection experiment at real large-scale exhibition. We estimate locations of participants by applying the proposed method to the collected data, then evaluate accuracy of estimation and analyse the activities such as the time of longer stay booths based on participants' occupation. As a result, we could track the movement of the participants to some meters error and find the characteristic booths based on longer-stay booths per occupations.

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CCS Concepts

•**Information systems → Location based services;**

Keywords

BLE; Large-Scale Exhibition; Large-Scale Event; Location Estimation

1. INTRODUCTION

It is important to analyse participants' activities when we make large-scale exhibitions or conferences more attractive. In this context, "participants' activities" means the time duration of stay at each booth or the visiting order of the booths. Combining participants' activities with their properties such as age and occupation, we can analyse the popular booth based on age or deviation of visit booth based on occupation. To carry out this analysis, we have to know the locations of participants.

At a large-scale exhibition which is held indoors, it is required to detect the participants' locations without GPS because GPS signal hardly reach inside a building. There are many solutions for indoor location estimation. Pedestrian Dead Reckoning(PDR)[1] detects walking steps from internal acceleration sensor and gyro sensor in smartphone. Another example utilizes Wireless LAN signal strength detected by smartphone[2][3]. There are also solutions which are independent of smartphone: a method with laser range finder(LRF) and high accuracy method with ultrasonic[4].

When using smartphone as the device for location estimation, specific application must be installed. It is not easy for all participants to install such application just for temporary use. Moreover, data amount which is collected by smartphones application depends on the number of devices which run the application.

When not using smartphone, measurement equipment has to be put in the site. This means larger site requires higher cost and harder labor for installing the equipment to cover everywhere in the site. Another problem is that such methods often cannot identify and track a participant.

BLE, latest Bluetooth technology has utility value for indoor localization. BLE beacon is now used for proximity-based location services. When a smartphone approaches a BLE beacon, a proximity event happens and it triggers off a notification from an application corresponds to the beacon. By using proximity, we can develop a room-level location tracking system with a smartphone application, which cannot avoid bothersome installation. However proximity is abstract due to instability of BLE signal strength.

In this paper, we propose a method for indoor localization, which utilizes BLE tags, for analysis of participants' activities in large-scale exhibition. We use BLE tags distributed to the participants and scanners in the event site. Advertising packets from BLE tags are captured by multiple scanners and signal strength data of advertising packets are used to detect the locations. Proposed method has some advantages. No necessity of smartphone: BLE tags which are distributed among participants are used for location estimation. Identifiability: A person can be tracked with BLE tag's own identifier. Cheaper cost for measurement equipment: as using BLE, simple single board computers(such as Raspberry Pi) with Bluetooth dongles can be used for scanner and one scanner covers wide area.

There are also challenging factors. Moving BLE tags: while BLE beacons/tags are usually fixed to the space and devices carried by people detect them, people carry BLE tags and location-fixed scanners detect BLE tags in our method. This means simple proximity method cannot be used, which requires close distance of a device and BLE tag and estimates abstract location. Large-scale: we havce to estimate locations of dozens of people without complex prior setting which is not suitable for large-scale exhibition.

This paper is organized as follows. In the next section, related work is discussed. In Section 4, we describe the overview of data collection experiment and the detail of location estimation method. Accuracy of location estimation and the analysis of participants' activities based on their occupation is discussed in Section 4, followed by conclusions.

2. RELATED WORK

Depending on equipment and algorithm, many indoor location estimation methods are proposed. RFID(Radio Frequency IDentify), Wi-Fi and UWB(Ultra-Wide Band) are typical methods using wireless communication[5][6]. Other methods utilize laser range finder, ultrasonic or PDR with IMU(Inertial Measurement Unit)[1][7]. Moreover, some methods are combinations of these methods to reach high accuracy.

Ultrasonic method[4] is high accuracy with some ten centimeters error. However it requires ultrasonic transmitter located in every some meters. This requirement is disadvantageous for large site. In case of using laser range finder[8], it is needed to locate laser range finders where obstacles are few. This method is also not suitable for large site because of

Figure 1: Wearing a BLE tag

expensive laser range finders. Instead of locating many laser range finders, combination method with Wi-Fi is proposed.

In contrast to these methods, PDR does not requires special on-site equipment. However accumulated error affects the accuracy. Smartphone internal sensors tend to be low accuracy, error correction is essential. To estimate location on smartphone, the application for location estimation must be installed.

Data collection at a large-scale event with Bluetooth was done by Arkadiusz[9]. They have developed smartphone applications for outdoor rock festival and collected the data of Bluetooth devices combined with GPS based location. However the amount of data were dependent on the number of the devices running the applications. Komai[10] estimates subject's location based on the fact that detecting a tag with one scanner indicates the tag is in proximity of the scanner.

From above, existing methods have following weaknesses.

1. difficulty on placement of measuring equipment
2. cost for special measurement equipment
3. necessity of smartphone application

These weaknesses can be solved by our method. Less concern is needed for location of measurement equipment because BLE uses 2.4GHz radiowave. Measurement equipment is reasonable because BLE scanning can be performed by cheap single board computer. As BLE tags are independent of smartphone, there is no need for smartphone application.

3. LOCATION ESTIMATION

3.1 Data Collection Experiment at Geo-Spatial EXPO

To perform location estimation, we had an experiment at a real site. The experiment was held in Geo-spatial EXPO(G-EXPO) 2015 at National Museum of Emerging Science and Innovation. G-EXPO was 3-days exhibition and cumulative total number of people was over 18,000.

We asked participants to join the experiment, and distributed BLE tags to who accept joining the experiment. In addition, we lent Android devices to collect sensor data. The participants carried BLE tags and Android devices like shown in Figure 1. Android devices were near from BLE tags, to compare sensor data from Android devices and sensor-equipped BLE tags. We did not impose any limitation on the participants' time of stay and move, except returning BLE tags and Android devices when they left the exhibition. We asked them to answer questionnaires about age,

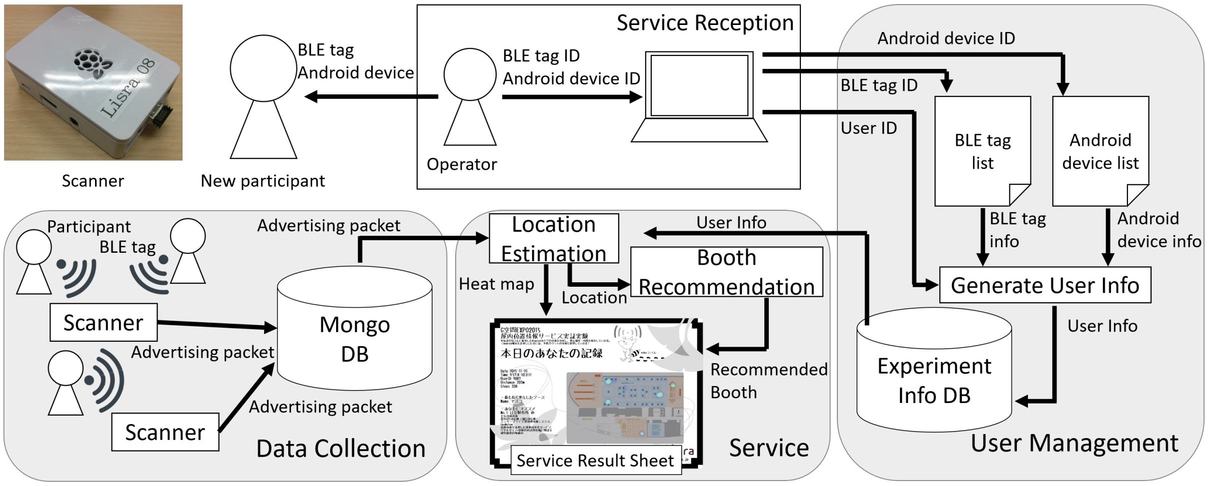

Figure 2: System configuration

occupation and purpose of visit. There were another question on the questionnaires: longer stay booths, estimated by location estimation service, are right or not.

Cumulative total number of people joined this experiment was 185. Log amount of advertising packets of BLE tags is 2,631,357 records.

3.1.1 *Equipment*

Equipment for data collection experiment are shown in Table 1. BLE tag is ultra-thin type beacon device with sensor AZ001[11] made by FDK Corporation. This tag sends an advertising packet once a second which includes sensor values from internal triaxial accelerometer and geomagnetic sensor.

Raspberry Pi(Model B), which is popular single board computer, is used as BLE scanner for advertising packets from BLE tags. Since no onboard Bluetooth device is available, Bluetooth dongle(ELECOM LBT-UAN05C2 or IO-DATA USB-BT40LE) is attached to Raspberry Pi. It extracts UUID, majorID, minorID, MAC Address and sensor values from received advertising packet, then adds meta information such as receive time, RSSI and its hostname. This advertising packet with meta information is sent to server. For the experiment, 30 scanners were put in the site. Locations of scanners are shown as green circles in Figure 3. Blue colored area is the main exhibition area and scanners are put high density at this area.

Android device runs an application named HASC Logger[12] which collects sensor values from device internal sensors. Data collected by Android device is used as correct location data.

3.1.2 *Experiment Management System*

To carry out the experiment smoothly, we developed a management system. The system consists of three parts as shown in Figure 2.User management part links user ID, BLE tag ID and Android device ID, operator can easily control individual experiment status such as start time or end time.Data collection part records advertising packets received by scanners. Scanners send received advertising packets to Mongo DB server via log forward tool fluentd[13]. We

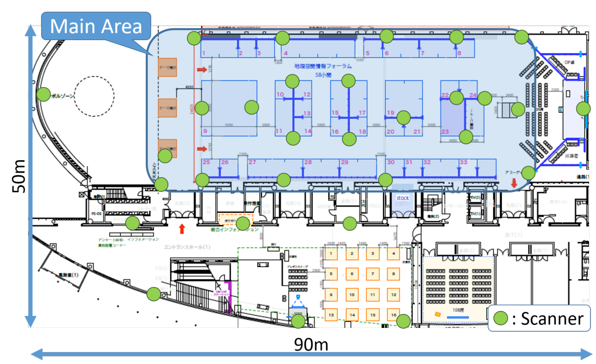

Figure 3: Scanners in the site

Table 1: Equipment used at experiment

Equipment	Amount	Target data
BLE tag	120	Acceleration, geomagnetism
Raspberry Pi	30	Advertising packets from BLE tags
Android device	40	Acceleration, gyro, geomagnetism, walk steps, Wi-Fi, BLE

can extract collected advertising packets simply by accessing Mongo DB server.Service part is developed to provide a practice service for participants. When a participant leaves the exhibition, we print a service result sheet. The sheet contains a heat map generated from longer stay booths and recommended booths.

3.2 Location Estimation using RSSI

3.2.1 *Algorithm*

Our method uses particle filter to express probabilistic location of a participant. Location estimation is executed as following steps.

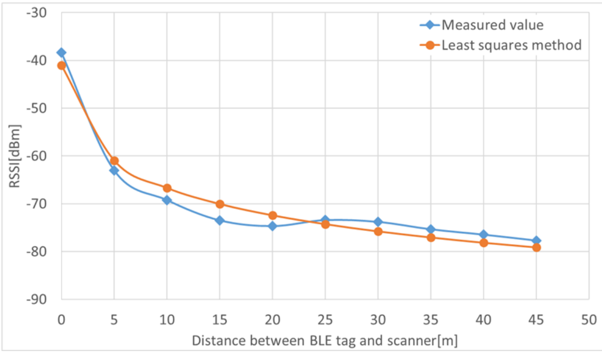

Figure 4: Attenuation of RSSI: real value and least squares method

1. Initialization of particles with start position.
2. Move of particles
3. Generation of likelihood map from advertising packets
4. Decision of weight for particles
5. Resample of particles based on the weight

At step 1, start position is service reception because all participants start moving from there. At step 2, speed of move is assumed to be maximum 1.2 m/s according to average walking speed of adult. We describe about step 3 in detail later. At step 5, particles which weight is lower than pre-determined threshold are deleted.

3.2.2 *Parameters of RSSI-Distance Function*

We need the distance between a BLE tag and a scanner to estimate location. This distance d is calculated from RSSI with equation 1. This equation contains two parameters: Tx and n.

$$RSSI = Tx - 10n \log_{10} d(\text{dBm}) \tag{1}$$

Parameter Tx is called transmission power. This is the RSSI measured at one meter from BLE tag. Another parameter n is attenuation constant, which changes on space where radiowave propagates. We decided these two parameters from measured values.

We measured RSSI to determine parameters at the open space in front of university auditorium, where obstructive other wireless communication radiowave seemed to be less. In measurement, BLE tag was put in the same way as Figure 1. Then standing in front of scanner's Bluetooth dongle, from 0 meter to 45 meter with increments of 5 meters, advertising packets were recorded 60 seconds for each distance. After the measurement, Tx and n were determined by least squares method using average RSSI for each distance. Figure 4 shows the comparison of measured values and least squares method. Tx was -47.62(dBm) and n was 1.906. These values were used at location estimation.

3.2.3 *Generation of Likelihood Map*

Likelihood of a particles is determined from likelihood map generated from measured RSSIs of a BLE tag at time

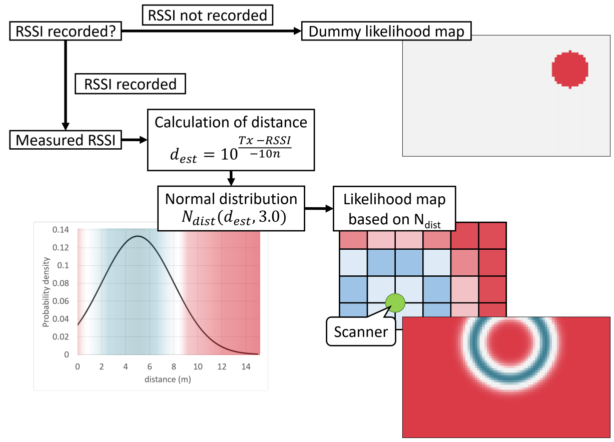

Figure 5: Generation of one likelihood map

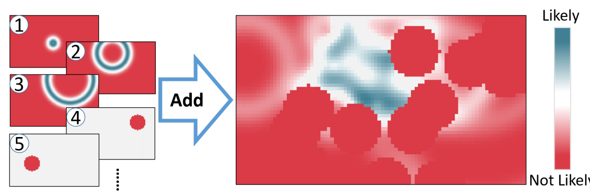

Figure 6: Addition of likelihood maps

t. Likelihood map is expressed in 1 meter mesh with likelihood. At first, one likelihood map is generated for each scanner. Generation flow is shown in Figure 5.

First step is confirmation of RSSI record from scanner $s_i (i = 1, 2, ..., 30)$ at time t. RSSI record at time t is the average RSSI from time t-10 to time t. If RSSI record from scanner s_i does not exist, target BLE tag is estimated not to be in 7.5 meters from scanner s_i. Then likelihood is set to zero for meshes in 7.5 meters(empirically determined) from scanner s_i.

If RSSI record is available, distance d_{est} between scanner s_i and target BLE tag is calculated from equation 2 which is deformation of equation 1.

$$d_{est} = 10^{\frac{RSSI-Tx}{-10n}}(\text{m}) \tag{2}$$

Then normal distribution N_{dist} is generated with mean d_{est} and variance 3.0. Likelihood for meshes is set depending on N_{dist} value. Iterate this operation for all scanners, finally addition of likelihood maps of each scanners is used as likelihood map for time t. Sample likelihood map is shown in Figure 6. When setting likelihood for a particle, likelihood for the mesh corresponds to the particle's location is used.

4. EVALUATION AND ANALYSIS

This section describes evaluation of location estimation accuracy to the data collected in the experiment at subsection 3.1. Location estimation is performed to all 185 experiment subjects. Reference location data for evaluation is generated from sensor data of Android device carried by

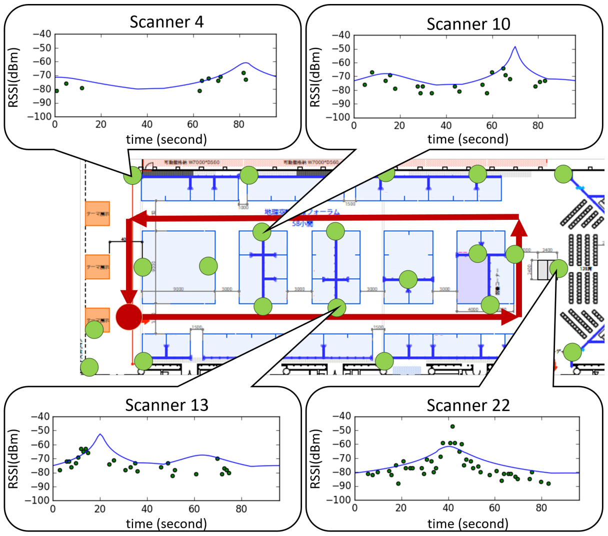

Figure 7: Calculated ideal RSSI and measured RSSI

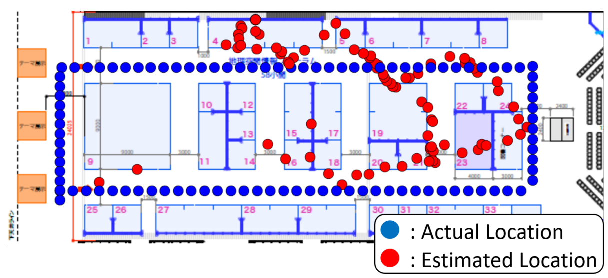

Figure 8: Plotting of actual and estimated locations

some experiment participants.

4.1 RSSI Comparison

Because we did not impose a limit on participants' movement, there is no accurate location data. For that reason, this part describes about evaluation for two pieces of data which is recorded as test data with particular path. The path is counter-clockwise from service reception to service reception again through main area without stop.

Tester's actual locations per second are calculated from sensor data collected by Android device. Then ideal RSSI for each second can be calculated. Comparison of calculated ideal RSSI with measured RSSI for some scanners is shown in Figure 7. On the graph in Figure 7, blue line indicates calculated ideal RSSI and green dots show measured RSSI.

From Figure 7, scanner 22 worked well with many measured RSSI dots and some measured RSSIs are stronger than calculated values. Scanner 10 and 13 recorded moderate amount while no record around maximum value of calculated ideal RSSI curve. Scanner 4 hardly received advertising packets.

4.2 Error of Location Estimation

To evaluate the accuracy of location estimation, we compared estimated location data with actual location data used

Table 2: Location estimation error

Tester	Max(m)	Min(m)	Average(m)	Variance
A	27.60	1.04	12.51	53.70
B	48.25	0.41	27.75	176.4

Table 3: Location estimation error for right-half area

Tester	Max(m)	Min(m)	Average(m)	Variance
A	19.78	1.04	8.44	19.79
B	48.25	7.27	28.96	143.0

in previous subsection. Average error and variance are calculated from Euclidean distance every second between estimated location and actual location. Result is shown in Table 2. Plotting of actual locations and estimated locations for Tester A is shown in Figure 8 with blue dots for actual locations and red dots for estimated locations. It is clear that variances are huge from Table 2.

Estimation for right-half area of the site is relatively good from Figure 8. Table 3 is the result of evaluation only for right-half area of the site. Compared to Table 2, average error and variance are decreased for Tester A. For Tester B, there is no improvement. It is assumed that particles could not move to the right-half of the site.

Some factors can be considered causes. One is, as already discussed, ideal RSSIs and measured RSSIs are different. When making likelihood map, distance between a BLE tag and a scanner is calculated from RSSI. If RSSI is weaker than that should be measured, distance goes longer than real.

Another considerable cause is location estimation algorithm itself. In proposed algorithm, if RSSI record from scanner s_i does not exist, target BLE tag is estimated not to be in 7.5 meters from scanner s_i. As shown in Figure 7, advertising packets are often not received by scanners. This means algorithm often judges target BLE tag does not exist near a scanner although the BLE tag is near the scanner.

These problems should be solved to achieve booth-level –numerically, about 1m– accuracy.

4.3 Analysis Based on One's Occupation

We performed an analysis based on occupation. We summarized longer stay booths by participants' occupation from the result of location estimation. Top 5 booths for 5 occupation field and overall are shown in Table 4. The numbers of people for each occupation field are as follows: 37 for telecommunication, 7 for survey, 6 for geographical information, 9 for technical service and 6 for manufacturing. Booth IDs written in bold are characteristic for corresponding occupation fields and do not appear in other occupation fields.

For example, booth 17 appeared third position in geographical survey displayed the next generation tools for geographical survey. Booth 32 appeared third position in geographical information was about the application which utilizes geographical information and head mount display. Booth 28, first place in technical service was about practical use of open data. Booth 25, first place in manufacturing was the exhibition of positioning equipment which can re-

Table 4: Longer stay booths(number indicates booth ID)

	Occupation field				
Rank	Telecommunication	Geographical survey	Geographical information	Technical service	Manufacturing
1	9	9	19	**28**	**25**
2	19	36	36	36	36
3	11	**17**	**32**	9	9
4	36	11	3	19	19
5	3	19	**20**	**105**	**35**

ceive signal from quasi-zenith satellite system. From these examples, booths correspond to each occupation fields seem to be in higher rank.

However, some booths appeared regardless of occupation filed: Booth 9, 19 and 36. Booth 9 an 19 have wider area than other standard booths; as a result, these two booths appeared more when deciding the staying booth. Booth 36 is standard-sized booth positioned at the corner of the site. Further investigation is needed because there is no considerable reason for higher rank.

5. CONCLUSIONS

In this paper, we proposed a location estimation method using BLE tags at large-scale exhibitions. BLE tags distributed to the participants and scanners in the event site are the equipment for location estimation. Advertising packets from BLE tags are captured by multiple scanners and signal strength data of advertising packets are used to detect the locations. The proposed method does not need smartphone application or high-cost equipment.

We collected the data at a large-scale exhibition Geospatial EXPO 2015. In inspection of the data, we noticed some important issues. Low packet receive rate and gap between ideal RSSI and measured RSSI. These affects the accuracy of estimation, we have to deal with these issues by adjusting the locations of scanners or performing calibration of RSSI. Location estimation algorithm in this paper is simple. Accuracy of location estimation is found uneven in comparison of estimated locations with actual locations. However, the analysis of the participants' longer stay booths based on their occupation led to an interesting result. Booths corresponding the occupations appeared at higher rank in the summary.

There are some tasks found. The algorithm has to be revised. For example, number of scanners which received same advertising packet or time series information can be included. Although it limits type of usable BLE tag, sensor values included in advertising packets can also be used.

6. ACKNOWLEDGMENTS

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