Indoor Positioning Estimation Using BLE Beacons

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***Abstract*—In this paper, we propose four unsupervised position estimation strategies from very noisy observations. Moreover, we discuss their performance, applying them to data gathered under a sensor system constructed with common devices. An observed RSSI, which denotes radio wave intensity, is distorted by noises because of multipath fading and obstacles to prevent radio wave communication and nobody knows correct RSSI. Hence, a position estimation strategy should be an unsupervised method and we must introduce some assumptions to an observation generation process. The position estimation strategies have the following assumptions; (1)receivers with too low RSSI are not reliable and (2)human move is enough slow. Using the assumption, we proposed four position estimation strategies with an unsupervised method. We gathered RSSI logs in an international academic conference to discuss the performance of the four strategies. Moreover, we applied the strategies to the logs and estimated positions are discussed from the viewpoint of stability of estimated positions.**

***Keywords*—Indoor detection, human moves, proximity-based detection**

I. Introduction

Indoor positioning estimation[1] is a basic technology to understand human moves in a real environment. GPS-based system[2] is used outside but for indoor positioning estimation, other technologies are needed to detect human position because GPS signal does not reach inside a building generally. For indoor positioning estimation, Wi-Fi, Bluetooth or Radio Frequency Identification (RFID)[3] technology is used to detect a human position. The structure inside a building is more complicated than outside a building because there are many walls and many persons coming and going inside a building. The walls and the persons are obstacles to interrupt communications between equipments. Hence, indoor position estimation needs different estimation algorithm.

Indoor positioning estimation technologies are basically four approaches; proximity[4], lateration[5], angulation[6], [7], [8], and fingerprinting[9], [10]. In this paper, we employ proximity to estimate a human position.

Proximity regards a human position as a location of a device (a receiver) you set previously. Hence, it is impossible to estimate a correct human position and a detected position is approximate. Theoretically, radio wave intensity is proportional to a distance between a transmitter and a receiver. The nearest receiver is selected as a human position according to radio wave intensity in proximity.

It is difficult to estimate a human position with indoor positioning estimation in a real environment because radio wave intensity does not match a theoretical model. Multipath fading and obstacles change theoretical intensity and the intensity is not proportional to a distance directly. Hence, it is not favorable to select the nearest receiver based on the observed radio wave intensity. A approach to reduces the noise is an alignment of radio wave sensitivity according to sensor characteristics and building design. The alignment needs some pairs of radio wave intensity and correct position gathering data in a controlled environment. In this paper, we do not use such the alignment and have to estimate a human position with observations including many noises.

We introduce two assumptions into a position estimation algorithm to estimate a correct position regardless of the noises. The assumptions are (1) receivers with too low RSSI are not reliable and (2) human moves are slow. Using assumption (1), we neglect some receivers with low RSSI. Using assumption (2), we neglect some receivers changing rapidly. Hence, we propose four position estimation strategies and compare them each other.

“Position estimation strategy 1” selects a receiver with the biggest RSSI strength as the nearest receiver simply. This strategy is a simple implementation of proximity.

“Position estimation strategy 2” selects a receiver with the biggest RSSI strength and over -90 RSSI scores as the nearest receiver. A small RSSI score denotes a large distance between a transmitter and a receiver or existing some obstacles between a transmitter and a receiver. However, we cannot separate a reason why a receiver measures a low RSSI score because there is less information on an observation environment. Hence, in this strategy, we neglect a receiver with a small RSSI score and use only reliable receivers.

“Position estimation strategy 3” determine the nearest receiver which appears during some intervals the most frequently. An observed RSSI score includes much noise and it is difficult to remove the noise from observations. Hence, we employ an assumption that human moves do not change rapidly and in the nearest receiver selection, A receiver is selected, which is near the preceding receivers and the following receivers

“Position estimation strategy 4” is improved “Position estimation strategy 3” adding a restriction which denotes we use receivers with over -90 RSSI score. We can determine the nearest receiver using only reliable receivers.

Comparing them and discussing the performances from the viewpoint of computational cost and estimation characteristics, we employ “Position estimation strategy 4”.

This paper is constructed below. In Section 2 related works are introduced, which are indoor positioning systems with wireless sensors. In Section 3 we introduced our sensoring system and explain four position estimation strategies. In Section 4 some experiments are executed with Low Energy Bluetooth (BLE) based indoor positioning data of academic conference participants. We compare the strategies and explain why we select "Position estimation strategy 4". In Section 5 we describe conclusions and future works.

II. Related Works

An indoor positioning system is classified into four approaches: proximity, lateration, angulation, fingerprinting.

In proximity, we assume that we know where a receiver, which is an access point of Wi-Fi, Bluetooth, and RFID, is located. On the other hand, we do not know where a transmitter, which is a beacon with a person, is located. We estimate the nearest receiver based on radio wave intensity, for example, RSSI (Received Signal Strength Indication). Proximity is a very simple approach but has some drawbacks. RSSI-based proximity is difficult to find a line of sight path between a transmitter and a receiver because there are many obstacles in the environment. Moreover, because radio propagation in indoor environment suffers from multipath fading, it is very difficult to estimate a correct RSSI.

Lateration, which is called triangulation, estimates a location based on distances between receivers and transmitters. Distance is calculated with propagation time from a transmitter to a receiver and RSSI decay from a transmitter, which is proportional to the distance. If we know three and more distances between receivers and a transmitter, we can estimate location[5]. Generally, it is so sensitive to distance estimation and suffers from obstacles in a real environment.

Angulation is an algorithm to estimate location based on angles between a receiver and transmitters. Angulation needs information on two angles to derive the 2D location[6], [7], [8]. However, because usual receivers, which are Wi-Fi routers, does not have a directivity of radio wave, we have to prepare special devices to use angulation. Hence, it is difficult to construct an indoor positioning system with commodity electric devices.

Fingerprinting is employed in the environment where you do not know where transmitters which do not move. Moreover, it can be applied to an environment where multipath fading happens and other persons prevent radio wave communication. In fingerprinting, you have to measure RSSI at some points previously and you construct an RSSI strength map, which is called a fingerprint. When you estimate a human position, you predict a position with the fingerprint. In fingerprinting, various machine learning methods are used, which are probabilistic methods, k-nearest neighbor, neural networks, support vector machines, smallest M-vertex polygon. [9] and [10] use support vector machines to estimate location. Fingerprinting assumes that there is a similar situation in both in constructing a fingerprint and in predicting a human position. When an environment changes dynamically, you can prepare some fingerprints previously and change the fingerprints according to an estimation environment.

TABLE I. Devices employed in experiments

Devices	Chipsets	Functions
Beacons	CC2650STK	The device is attached with a person and emits advertisement packets. It includes some other sensors; Accelerometers, Gyroscope, Ambient temperature, and so on.
Scanners	mbed TY51822r3	The deice receives packets from wireless tags and send information; RSSIs to a database server.

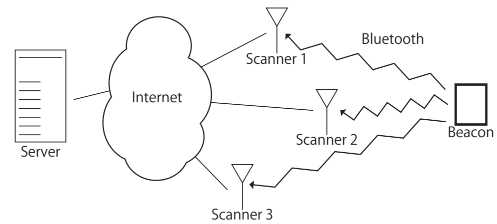

Fig. 1. Sensoring system for international conference participant behavior analysis

III. Indoor Position Estimation Based on BLE Beacons RSSI

We construct a sensoring system to gather BLE beacons RSSI and propose position estimation algorithms. We describe methodologies to detect indoor position using BLE beacon RSSIs.

A. *Human behavior sensoring system*

We explain a human behavior sensoring system to estimate indoor human position with common electric devices. We assume the sensoring system works inside a building and during some days and the system is designed.

We use two devices, a beacon and a scanner, to measure human behaviors. The beacons are attached with persons and emit advertisement packets at regular intervals. Because they are moves with a person, it is difficult to supply electrical power to them constantly. We have to make a beacon that executes with a small battery and consume less electrical power. The scanners receive the advertisement packets from beacons and are able to measure RSSI. We can set many scanners inside a building and they do not move at all. Hence, it is not important to make a scanner be small and be less power consumption because we can supply them with electric power from outlets or a big battery.

In Table I, we explain beacons and scanners. BLE technology is employed to construct beacons and beacons continue to run during a few years with a coin cell battery. A beacon emits advertisement packets with Bluetooth technology. Scanners are constructed with mbed, which is a kind of onboard computer, to receive the advertisement packets via Bluetooth.

Scanners send information on advertise packets to a server via the Internet. In the server the information is stored as log files and the logs are analyzed to estimate human behavior. Figure 1 shows our sensoring system.

A Beacon emits an advertising packet every 10 seconds with the same strength. On the other hand, some scanners receive the packet every 10 seconds and store RSSI of the packet. Hence, we obtain logs including beacon ID, scanner

ID, and RSSI and estimate human behavior form the log data. In this paper, we would like to determine indoor position based on RSSI because a distance between a beacon and a scanner makes RSSI be weak theoretically. However, it is difficult to determine a correct position in a real world although we combine many measurements. Hence, we regard the nearest scanner as an estimated position of a person with a beacon. This approach is called “proximity”. Because RSSI is proportional to the distance between a beacon and a scanner theoretically, we can a scanner with the largest RSSI as the nearest scanner.

B. The strongest RSSI Based Estimation

We select a scanner with the maximum RSSI as the nearest scanner from a person and regard the scanner position as user' s position. This approach based on a very simple criterion and is called “Position Estimation Strategy 1”.

$$\arg\max_x \mathrm{RSSI}(t,x) \qquad (x \in \mathrm{ID}) \tag{1}$$

where ID denotes a set of scanners and $\mathrm{RSSI}(x)$ denotes RSSI strength of a scanner x at t.

The idea does not consider dynamic environment changes. RSSI is proportional to a distance between a beacon and a scanner without any obstacles theoretically. However, there are many other persons in an experimental situation and they are regarded as obstacles making RSSI be weak. Moreover, when we measure RSSI in a room, reflected radio wave disturbs RSSI. Hence, the idea is too naive to choose a correct scanner in many cases.

C. The strongest RSSI based Estimation Considering Threshold

We select a scanner with the maximum RSSI that achieves over -90 and regard the scanner position as user ' s position. This approach is an approach modifying “Position Estimation Strategy 1” and is called “Position Estimation Strategy 2”.

$$\arg\max_x \mathrm{RSSI}(t,x) \qquad (x \in \{y|y \in \mathrm{ID}, \mathrm{RSSI}(t,y) > z\}) \tag{2}$$

where z denotes a threshold which controls reliability of a scanner.

RSSI is proportional to a distance between a beacon and a scanner theoretically but in a real environment, we have to consider obstacles, which are other persons and building facilities. Moreover, because multipath fading makes RSSI increase or decrease, we do not measure RSSI under the theoretical condition. Hence, RSSI is not enough clue to estimate person position. Moreover, when there is no scad scanner with over -90 RSSI, this strategy generates some missing values. Selected scanners are very reliable but a prediction is incomplete because of a lack of position estimation.

We can assume that a person does not move too fast and selected scanners do not change during a small interval dynamically. We can predict a better scanner to approximate the person with the assumption than with RSSI. Speaking concretely, we obtain a sequence estimated based on scanners with the maximum RSSI at first. Next, we determine a scanner based on scanners that appear during a predefined interval (we call an observational window.). Using this strategy, we can reduce changes in scanners within a small interval.

TABLE II. EXAMPLES OF SCANNER LOGS

No.	Timestamp	Scanner ID	Beacon ID	RSSI
1	”2017-07-09 14:42:50”	“ scanner 1”	” beacon 1”	-110
3	”2017-07-09 14:42:51”	“ scanner 2”	“ beacon 1”	-101
4	”2017-07-09 14:42:51”	“ scanner 3”	“ beacon 1”	-92
5	”2017-07-09 14:42:51”	“ scanner 4”	“ beacon 1”	-83
19	”2017-07-09 14:42:52”	“ scanner 5”	“ beacon 1”	-100
82	”2017-07-09 14:42:53”	“ scanner 6”	”beacon 1”	-99
90	”2017-07-09 14:42:53”	“ scanner 7”	“ beacon 1”	-93

D. Voting Based Estimation with observational window

Based on the previous assumption, we determine a scanner that is near by a person. We choose a scanner that is observed the most frequently during some intervals. At each time a scanner is selected, which measures the strongest RSSI from person's beacon. This approach is called “Position Estimation Strategy 3”. It avoids missing values and rapid change of the strongest RSSI scanners.

$$\arg\max_x \mathrm{RSSI}(t,x) \qquad (x \in \mathrm{ID}, t \in [t-w, t+w]) \tag{3}$$

where w denotes a window size.

This approach does not consider the reliability of estimation because we employ all scanners regardless of RSSI strength. For more improvement, we can consider the reliability of estimation like “Position Estimation Strategy 2”. Speaking concretely, we select a scanner that appears most frequently within a window and is over an RSSI strength. This approach combines Position Estimation Strategy 2 with a majority rule within an observational window and solves missing values and rapid changes of selected scanners.

E. Voting based estimation considering threshold

We combine “Position Estimation Strategy 3” with the reliability of estimation based on RSSI strength and solve missing values and violent transition of the strongest scanners. We call this approach “Position Estimation Strategy 4”.

$$\arg\max_x \mathrm{RSSI}(t,x) \qquad (x \in \{y|y \in \mathrm{ID}, \mathrm{RSSI}(t,y) > z\}, \; t \in [t-w, t+w]) \tag{4}$$

Measurement of RSSI depends on observation environment strongly. Hence, we use only two simple assumptions: (a) the nearest scanner measures the strongest RSSI strength, and (b) a sequence of scanners with the strongest RSSI changes smoothly because a person does not move rapidly. Of course, we can introduce more assumptions but such assumptions need a strong restriction of the observation environment. In this paper, we do not need strong assumptions for person movement and observation environment.

IV. EXPERIMENTS

A. Datasets

We use dataset, which is gathered in an international academic conference, to evaluate the proposed strategies. The dataset consists of logs during three days, which includes a timestamp, beacon ID, scanner ID, RSSI, and so on. In Table II we show an example of logs obtained by our experiment. We gathered the logs from almost all participants in the international conference and beacons information was stored

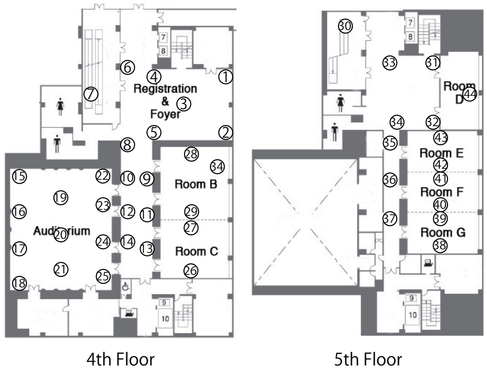

Fig. 2. Scanner location in a conference venue

in the logs simultaneously. In Table II, some logs, which denote one participant; "beacon 1" at a time, are picked up. The RSSI scores in Table II are measured in each scanner and is proportional to a distance between a beacon and the scanner theoretically. The sensoring system is constructed with common electric devices and a beacon and a scanner have unique characteristics. If we can use some data including correct positions and RSSI strength, we can revise the device characteristics with the data. However, in this experiments, we do not know any correct participants positions and we cannot execute alignments of devices.

A beacon sends an advertising packet every 10 seconds and scanners receiving the packet record RSSI scores. The RSSI scores are sent from a scanner to a log server via the Internet. Because the server has to process much information which arrives there simultaneously and at some times a transfer rate of the Internet is very low, some delays happen. In estimating a participant position, we neglect a small delay and logs within some durations are regarded as a packet that is sent from the same position.

The conference uses two floors in a conference venue center and scanners are allocated in two floors. Figure 2 shows where scanners are on the 4th floor and the 5th floor. In this experiments, scanners are distributed in a place uniformly but we have to discuss more appropriate allocation of scanners. This is one of the future works.

In this experiments 320 participants have beacons are their behavior are observed via the beacons for 4 days. We choose only logs within a poster session and we estimate participant indoor position with the logs. In this experiments, we do not record the correct participant position and it is impossible to evaluate our proposed method from the viewpoint of estimation accuracy. Moreover, it is impossible to adjust position estimation algorithms using observations. We need to make ground truth data and evaluate the proposed strategies from the viewpoint of estimation error but it is one of the future works. Estimated positions from logs do not match the correct participant position perfectly but we can understand the abstract of participant behaviors. Based on the assumption we discussed participant similarity based on their behavior[11]. In this case, we regarded the estimated position as data with missing values and much noise.

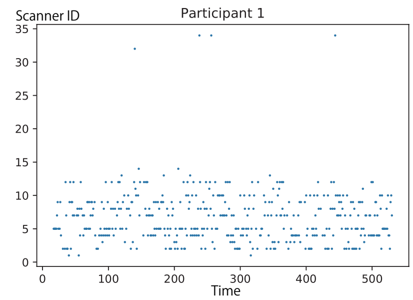

Fig. 3. Position Estimation Strategy 1: A BLE beacon exits in the scanner receiving the strongest RSSI

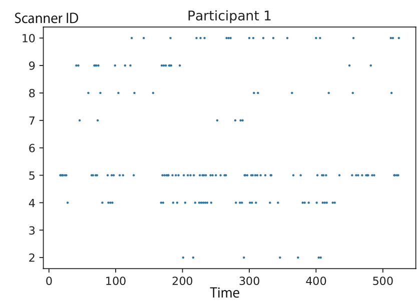

Fig. 4. Position Estimation Strategy 2: A BLE beacon exits in the scanner receiving the strongest RSSI and RSSI is over -90

B. Results

We estimate an indoor position of conference participants with the previous position estimation strategies. Especially, we discuss how much noise the algorithms can reduce under our assumptions.

Figure 3 shows scanners selected with position estimation strategy 1 during an hour. In position estimation strategy 1, all log data is used to choose the nearest scanner and we can estimate the most positions of participants. However, many conference participants move freely and are regarded as obstacles in sending advertise packets. Hence, selected scanners are changed rapidly and the result is not appropriate to estimate participants' positions. At some times scanners with over 30 ID appear suddenly and should be regarded as wrong estimations because the change denotes rapid movements from the 4th floor to the 5th floor. Because an advertising packet can reach at scanners through wall and floor, scanners on a different floor receive the packets. Except such detections almost all position estimations denote participant stay around "Registration & Foyer". The poster session holds at "Registration & Foyer" and we think the estimation is appropriate. A simple proximity-based algorithm is very sensitive to noises and estimated positions are not stable. We introduce some assumption into a position estimation algorithm.

Figure 4 shows scanners selected with position estimation strategy 2 during an hour. In the strategy, we neglect scanners with less than -90 RSSI because such the scanners are not reliable. "Position estimation strategy 1" determines the nearest scanner regardless of its RSSI strength. When many participants exist in a room, the participants are obstacles to prevent

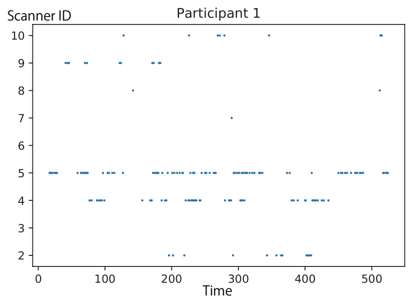

Fig. 5. Position Estimation Strategy 3: A BLE beacon exits in the scanner selected from the maximum RSSI scanners during 40 seconds

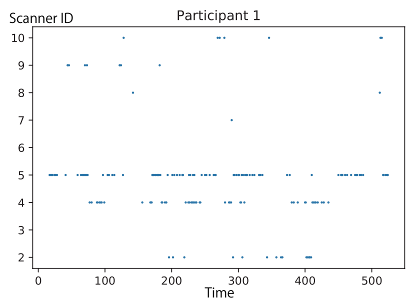

Fig. 6. Position Estimation Strategy 4: A BLE beacon exit in the scanner that selected from the maximum RSSI scanners during 40 seconds and RSSI is over -90

radio wave from beacons. In this case, a far scanner obtains the strongest RSSI and it is selected as the nearest scanner. In Figure 4 some scanners with over 30 ID are deleted because wall and floor make RSSI be weak. Moreover, many position estimates are deleted because participants stay at “Registration & Foyer” but each participant is acted as an obstacle to make RSSI be weak. We think estimation is more reliable but the estimation result includes many missing values. When you develop an application based on the estimation, you have to consider missing values more carefully. Totally, ”position estimation strategy 2” can estimate a more correct position than ”position estimation strategy 1”.

Figure 5 and Figure 6 show results of position estimation strategy 3 and position estimation strategy 4 respectively. The strategies assume that participants do not move rapidly and the next position is near the previous position. Hence, the strategies regard estimations that are different from neighbor estimations as noises and estimates more neighbor positions. In a voting algorithm, we can estimate participant’s position as a scanner which frequently appears within some evaluation duration. We can determine positions when there is no candidate scanner because of low RSSI and advertise packet loss. In this case, we employ a voting algorithm to neglect delays within 20 seconds. We select scanners that appears the most frequently for 40 seconds, which include the preceding data within 20 seconds and the following data within 20 seconds.

Comparing Figure 5 with Figure 6, the result is very similar regardless of a threshold. Smooth movement assumption can reduce noises and complement missing values. On the other hand, comparing Figure 4 with Figure 5, in Figure 5 many sensors which are far from “Registration & Foyer” are deleted. It means that position estimation strategy 3 and position estimation strategy 4 tends to estimate near “Registration & Foyer” because the strategies consider the participant stays there.

From these results, we think position estimation strategy 4 is superior to other strategies from the viewpoint of computational cost and estimation precision. In position estimation strategy 4 we can decrease log data to analyze using a threshold. Moreover, a voting algorithm can complement missing values appropriately. Hence, we think position estimation strategy 4 utilize log data including many noises efficiently.

V. Conclusions

In this paper, we develop an indoor position system with commodity electric devices and gather information on beacon devices at an international academic conference. We proposed 4 position estimation strategies to estimate the nearest scanner based on RSSI from the gathered data. The RSSI strength is proportional to a distance between a beacon and a scanner theoretically but in a real environment, many obstacles and multipath fading make an RSSI change regardless of the distance. Hence, we estimate position by only reliable scanners with over -90 RSSI score and complement missing observation with a voting algorithm.

Many tasks remain as future works. In this experiment, we set scanners in a conference venue as they distribute uniformly. Hence, we did not determine a distribution of scanners based on sensors’ sensitivity. To measure more correct RSSI we have to discuss a scanner setting strategy considering sensor characteristics and venue design. Moreover, in this experiment, we were not able to know where a participant is correct. Hence, we can not discuss the performance of a position estimation strategy from the viewpoint of estimation error. Discussing the performance more strictly, we have to gather ground truth data. Finally, because there are many noises in a sensoring system with commodity electric devices, we have to develop a new analysis method which is robust for noises and missing values.

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