Regular Paper

BLE Beacon's Defect Detection Method Based on Room Model of BLE and Wi-Fi

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Abstract - In this research, we propose a defect-detection method for a Bluetooth Low Energy (BLE) beacon. The types of defect are breakdown, battery exhaustion, removal and relocation. To detect such defects, we create a BLE model and Wi-Fi model for each room. The BLE model and Wi-Fi model consist of probabilities of observation of each beacon's radio information. By comparing the newly acquired BLE radio information and Wi-Fi radio information with the BLE/Wi-Fi room model, it is possible to detect the problem occurring in the beacon. As a proposed method, we compare the room model with the radio-wave information of the acquired BLE and Wi-Fi, and detect the beacon defect automatically. We conducted indoor experiments and beacon defect-detection experiments using the proposed method. In the room estimation experiment, the accuracy of estimation at BLE with the optimal boundary value was 86%, and the estimation accuracy at Wi-Fi was 95%. In beacon defect-detection experiments, the correct answer rate for defect detection was 94%. However, when the beacon disappeared from a room, the detection accuracy was 35%, which was less than half.

Keywords: BLE beacon, fingerprint, room estimation, defect detection, Wi-Fi

1 INTRODUCTION

BLE beacons (from here on, simply 'beacons') are increasingly used for services in public facilities such as indoor location estimation, room estimation, attendance management, distribution of coupons, mountaineer distress prevention, and checkpoints of electronic stamp rallies [1]–[4]. To estimate the position of a room in room estimation, one to several beacons are installed in each room. Also, there are many methods of installing beacons at a fixed distance, and they are used for indoor management and recording of walking routes [5], [6]. They are used to distribute coupons to the smartphones of people who pass in front of a store [7]. For mountaineering safety, climbers can bring beacons that sound an alert if anyone strays too far from the group. In electronic stamp rallies, beacons are installed at checkpoints. When a smartphone is close to the checkpoint's beacon, the user can press the stamp on the smartphone application [8], [9].

Because beacons are small and easy to carry, it is difficult to manage many beacons simultaneously. Beacons run on batteries whose lifetime is from about six months to two years. Thus, when dealing with many beacons, we have to check every one to figure out which has run out of batteries. Also, beacons are small, have the same shape, and are easy to carry. Therefore, someone can move them accidentally, or they can be miss installed.

When the target environment is small, usually the administrator of the environment can easily manage the small number of beacons because it is easy to grasp what kind of defect is occurring in which beacon and respond quickly.

In a large-scale environment with many beacons such as a university or electronic stamp rally at a large park, the administrator must collectively manage the system, and it is unrealistic to check beacons for failure one by one.

In this research, we generate a BLE/Wi-Fi-based room model to estimate defects such as battery outage, malfunction, removal, and relocation. The BLE model and the Wi-Fi model consist of probabilities of observation of signal information for each room. When a new BLE/Wi-Fi radio wave observation is acquired, the system compares the obtained radio wave information with each room model, and estimates the room from which the radio waves were acquired. After that, the system compares the estimated room model with the acquired radio wave information and finds the beacon defect.

Battery-powered beacons are mostly used, so the batteries run out during long-term operation. Also, since beacons are small and have a shape that is difficult to fix to a wall, there is the possibility of them being moved. Additionally, in order to manage many beacons, there are cases where beacons are mistakenly installed in the wrong room. Because beacons only transmit BLE radio waves, they cannot communicate with each other. Therefore, it is impossible to confirm problems between beacons.

Using the proposed method, the administrator does not have to undertake the impractical task of checking each beacon individually.

The rest of this paper is structured as follows. In Section 2, we explain related research. Section 3 describes our beacon defect detection method. Section 4 describes experiments using the proposed method. Section 5 summarizes and discusses future issues.

2 RELATED RESEARCH

Wireless LAN, beacons, built-in sensors of smart phones, etc. are often used for indoor position estimation and room estimation research. However, there are few studies on detecting activity or defects of beacons for terminal management.

There is research on the behavior monitoring of BLE beacons using participatory sensing. In Asahi's method [8], the beacon is used as a check point of an electronic stamp rally. When the smartphone terminal that introduced the application receives radio waves, beacon information and time data are sent to the server. When monitoring the information transmitted to the server, the data continuously transmitted may be interrupted in some cases. Since the transmission of data suddenly stops, it is a method that grasps the activity state of the beacon. This method is considered to be effective as beacon management during service operation. However, if the beacon installed as a checkpoint is moved, or if it is installed at a place where people do not always go, it cannot be determined whether the beacon is running or not. Also, there is a possibility that some time lag may occur between a beacon sending information, and that information being confirmed. Additionally, even if a beacon is moved to an unexpected place, when someone brings a smartphone within range of that beacon, the method confirms that the beacon is normal.

When estimating position using campus LAN, it is necessary to measure the radio wave intensity of Wi-Fi for each position. When using the wireless access point to estimate the position as in Dhruv's method [10], it is necessary to determine the observation position of the radio wave intensity considering the base station. In contrast, our method creates Wi-Fi and BLE fingerprints. Instead of a fingerprint for each location, it creates a fingerprint for each room based on the measured data. When you create a fingerprint for each room, you cannot figure out where you are in the room. However, it becomes easy to grasp whether or not you are in the room. When indoor position estimation using radio field strength of a BLE device is carried out, radio waves of BLE are weaker than Wi-Fi.

Kajioka's method involving indoor positioning using BLE radio intensity [11] targets small classrooms. Therefore, only one beacon is placed for each room. Even though radio waves may be weak, the beacon's radio waves could be received everywhere in small rooms. It is considered that the possibility of a radio wave not reaching an estimation device is low. However, we also assume a lecture room and a large lecture room compared to Kajioka's research. Therefore, there is a possibility that some places cannot be reached depending on location. Therefore, we should install multiple beacons if a room is so large.

3 BEACON DEFECT DETECTION METHOD USING WI-FI AND BLE OBSERVATION

In this research, we generate a Wi-Fi model and BLE model for each room, and detect defects such as battery outage or breakdown or relocation of a beacon. An outline of this method is shown in Fig. 1. In scene 1, when comparing the observed data with the room model of each room, it can be estimated that the user is at room α from the Wi-Fi model. However, the BLE signal is not received from beacon A. Therefore, beacon A is thought to have experienced a defect such as battery exhaustion or relocation. In scene 2, when comparing the model of room α with the observed data, the existence of beacon B can be confirmed. Since there is no beacon B in the room

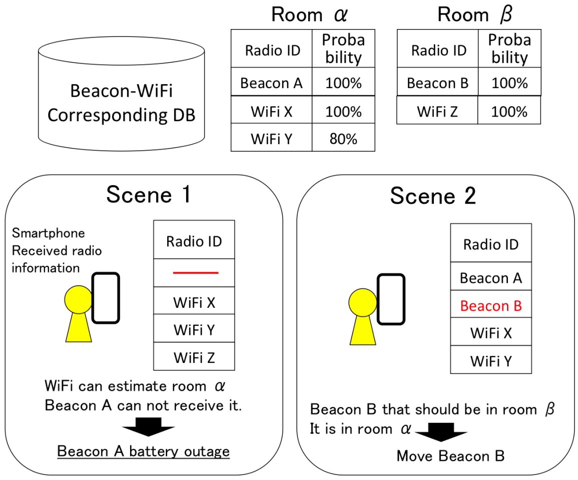

Figure 1: Outline of proposed method

model of room α, there is a high possibility that beacon B was moved from room β to room α.

By using this method, operation check of a beacon can be done automatically. It is not necessary to periodically check the operation of each beacon. It is also considered that defects such as in Fig. 1 can be detected during operation. By doing this, it is possible to deal with the beacons which the defects have occurred.

3.1 System Overview

An overview of the system is shown in Fig. 2. This method is introduced together with room estimation-based applications such as attendance-management applications and coupon-delivery applications. BLE/Wi-Fi observation data is acquired for users who frequently use these applications. The timing to acquire the data is when the BLE is received. Also, the user here is not a system manager, but general users who use the application on a daily basis. In the normal state, when it receives BLE radio waves, it communicates with the room estimation server and receives room information. There is a room recognition library as the foundation of location information service. Normally, in the library, room recognition is performed using only BLE in order to judge the occupancy situation necessary for location information service. BLE models of all rooms are synchronized from maintenance server to room estimation server, and regular room estimation is done by using BLE model. Sometimes, when receiving BLE, it also receives Wi-Fi and sends two pieces of observed information to the maintenance server. Please note that the BLE/Wi-Fi observation task is not explicit. Observed BLE/Wi-Fi can be uploaded to the management database without the user ' s awareness. When observation information is uploaded, the maintenance server estimates the beacon defect based on the received radio wave information. The server detects a problem with the BLE beacon using both the BLE model and the Wi-Fi model. When a problem is found in the beacon, information on the room and the beacon in which the problem occurred is presented to the manager. Then, the

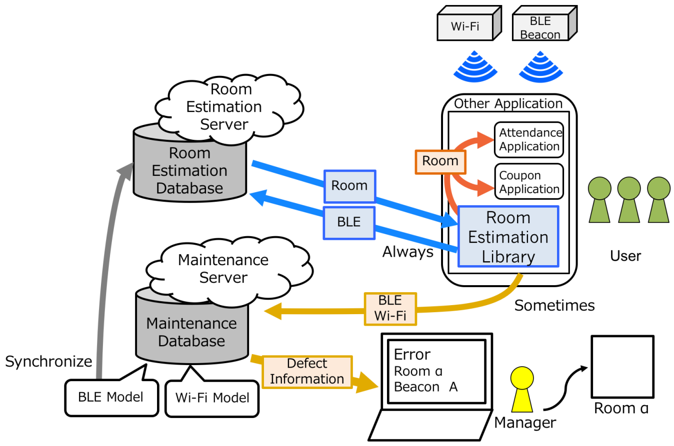

Figure 2: System overview

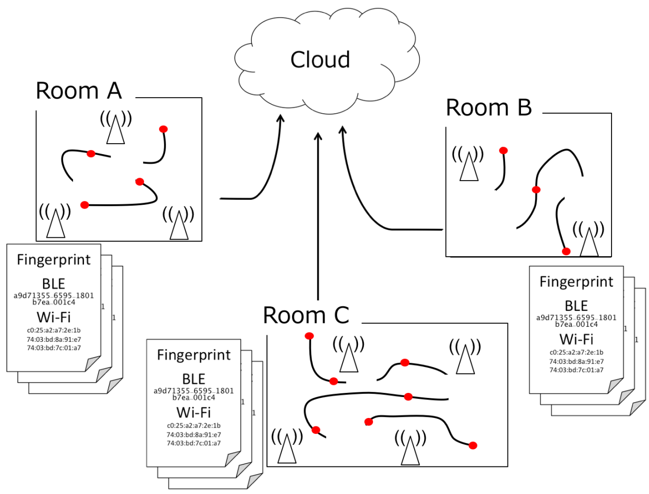

Figure 3: Collecting fingerprint

Table 1: Characteristics of beacon and Wi-Fi router

	BLE beacon	Wi-Fi router
Installation cost	○	△
Installation place	○	△
Driving time	△	○
Detection range	△	○
Power consumption	○	△

manager can see the defect information and go to the place to correct the problem.

In fact, you can estimate a room without using beacons if you use Wi-Fi. A comparison of the characteristics of Wi-Fi routers and beacons is shown in Table 1. We decided to utilize beacons instead of Wi-Fi routers based on that. Beacons are inexpensive to install and many can be placed in the same location. Also, since they are mostly battery-powered, installation is possible without being restricted by electrical access. Because beacons use BLE, they operate with power saving, and the transmission range of radio waves is narrow. However, the lifespan is as short as one to two years. Wi-Fi routers are expensive to install and not suitable for installation in many rooms. Since they need a power supply to operate, installation locations are limited. However, since the possibility of interrupting operation is low, reliability is high and radio waves can be transmitted over a wide range.

In this study, we are targeting all the rooms of one building or one campus such as a university, so it is considered that beacons are suitable for installing in each room because they are cheap and easy to install. Basically, Wi-Fi routers are used to access the Internet, so it is not realistic to install them in a room that is not used much. If we estimate the narrow range of a room, it is considered that a narrower range is better than transmitting a radio wave over a wide range. As such, beacons are considered suitable.

3.2 Features of This Method

In this method, we generate a fingerprint for each room rather than a fingerprint for each measured position [12]–[15], which is being done in many position estimation studies. For each room, not for each location, no matter the detailed location of the observation point. Observe each room rather than location. Then, it is estimated as that room which is regardless of where in the room. Therefore, room estimation is easy. Also, compared to the method that requires observation of detailed positions, the number of observations of radio-wave fingerprints for information can be reduced. This leads to cost reduction. Furthermore, there is no need to clearly decide when to measure radio information. There is the advantage that it is sufficient to observe data everywhere in the room.

The reason for combining Wi-Fi and BLE is to use Wi-Fi to detect a beacon defect when it occurs. It also plays the role of room estimation. When estimating a room by installing a single beacon in a small room such as a small classroom or a laboratory, it is impossible to estimate a room if a beacon fails or a beacon is taken out. Also, in the case of breakdown, the beacon will be repaired if replaced. However, when it is taken out, it is necessary to search for a beacon terminal.

Data collection and modeling of this method are shown in Fig. 3 and Fig. 4. In this method, the system knows all beacon ID's and their room placements. In the case of a small room, beacon radio waves can be acquired anywhere in the room. In the case of a large room, radio waves of the arranged beacon may not be acquired in some cases. If data cannot be acquired continuously, it could be erroneously detected that a defect has occurred in the beacon. Therefore, in our assumption, several beacons are placed in a large room to avoid this problem. The system collects Wi-Fi and BLE radio wave information to estimate a room, and integrates the collected Wi-Fi and data for each BLE. We create a Wi-Fi model and a BLE model for each room as in Fig. 4.

During operation, we gather BLE/Wi-Fi observation data from various people that use room estimation-based applications such as automatic attendance systems and stamp rally games. Basically, BLE data is observed when entering a room as in Fig. 3. The system also observes Wi-Fi data at regular intervals and compares the observed BLE list with the BLE

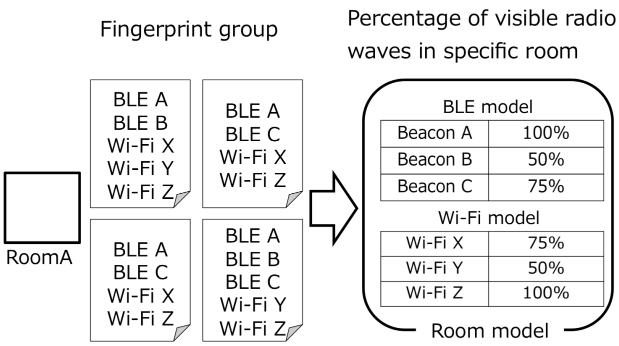

Figure 4: Model creation method

model in every room and estimates the room. Room information is sent after room estimation is done. The system compares the Wi-Fi list observed every fixed period with the Wi-Fi model of every room and estimates the room. The system then compares the observed Wi-Fi list with the Wi-Fi model of the room.

Basically, room estimation for room estimation-based applications is performed using BLE data, but room estimation is performed simultaneously with BLE using Wi-Fi data at regular intervals for detecting beacon defects. We believe that estimation of beacon movement, malfunction, battery exhaustion, etc. will be possible. In addition, when room estimation is performed normally, each model is updated using the observed Wi-Fi and BLE data.

In this method, the system only knows the initial placement room of the beacons. We do not consider it to be a defect situation if a beacon is slightly moved in the same room because the beacon is still in the correct room. However, the BLE signal model for the room should be updated in such a situation. We assume that participatory sensing is a suitable method to update the BLE/Wi-Fi signal model for each room. In operation of room-estimation applications, a user's smartphone uploads BLE/Wi-Fi observation information automatically. By using the collected observation information, the BLE/Wi-Fi model can be updated.

3.3 Data Collection and Assumption

In the proposed method, the fingerprint for Wi-Fi and BLE is collected in advance to generate the BLE/Wi-Fi model for each room. As a premise, smartphones are used to collect data. Observation data at the time of preliminary collection are gathered with the correct room name known. In data collection, we walk around in each room, and record radio observation information of BLE and Wi-Fi at 10-second intervals. In a general Wi-Fi fingerprint collecting method, radio waves obtained while stationary for several seconds are regarded as the fingerprint at that position. On the other hand, in the proposed method, we model the radio-wave environment of each room. Therefore, radio-wave information of the whole room is necessary. BLE and Wi-Fi radio waves are affected by people and objects, and they decay as distance increases. Therefore, it is insufficient to observe only one point in the room, especially in a large room. We walk around the room and collect fingerprints in various places in the room.

At the time of data collection, we assume that beacons have already been installed in each room. In addition, many kinds of BLE devices have been released in recent years. To avoid confusion, only beacons with a specific UUID (ID that can be set in the beacon) are targets for data collection. The transmission interval of the beacon device used was 300 ms, and the transmission strength was set to -4 dBm.

Data collection is conducted by participatory sensing, and when a user with a smartphone enters a room, observation is assumed simultaneously with room estimation. Basically, the smartphone collects BLE data, but also collects Wi-Fi data at regular intervals. We integrate the collected Wi-Fi of the room and data of each BLE, create a Wi-Fi model and BLE model for each room, and make a room model.

3.4 BLE/Wi-Fi Modeling For Each Room

We create Wi-Fi and BLE models for each room based on the data observed as in Fig. 4 for room estimation. In the proposed method, for the radio waves observed in the room, the probability of observing the radio waves is calculated, and the Wi-Fi model and BLE model are generated. However, for Wi-Fi, radio wave broadcast distance is greater than that of BLE. Therefore, it is limited to those observed above a certain received signal strength. The main reason for using such a simple model is to ease implementation and reduce calculation cost.

Also, for both the Wi-Fi model and BLE model, radio waves with observation probability of less than 50% are not included in the model. Room estimation is performed based on the observation probability of each radio wave. However, if extremely low radio-wave information is included at that time, the probability of room estimation is considered to be low. This is because radio-wave information, which is not frequently observed, is used for room estimation.

3.5 Room Estimation

Room estimation during operation is explained here. We compare the data observed at a certain timing, the list of Wi-Fi and BLE in each room built in advance, the BLE model and the Wi-Fi model, and estimate the room. We focus on room estimation by the BLE model, but that using the Wi-Fi model is done in the same way.

We use only the BLE model for room estimation for location-based services such as attendance management systems. We use the BLE model and the Wi-Fi model for maintenance as to whether the BLE beacon is installed properly.

Let O_b be the set of BLE radio waves contained in observational data O. At this time, the probability $p(r)$ existing in a room r is calculated as follows. Here, we denote the observed probability of radio wave a in room r as $p(a|r)$ and the set of radio waves contained in the BLE model of room r as M_b^r. First, we obtain the set of radio waves common to O_b and

M_b^r as $O_b \cap M_b^r$. Also, we obtain a set of radio waves that are included in M_b^r and not included in O_b as $M_b^r - (O_b \cap M_b^r)$. Next, we obtain the probability that the radio waves of the set element can be observed in room r as follows.

$$p(r) = \prod p(a|r) \times \prod (1 - p(b|r))$$

where

$$a \in O_b \cap M_b^r, b \in M_b^r - (O_b \cap M_b^r).$$

Next, we will explain room estimation with the Wi-Fi model. It is the same as room estimation using the BLE model just by changing the sign of the calculation.

Let O_w be the set of Wi-Fi radio waves contained in observational data O. At this time, the probability $p(r)$ existing in a room r is calculated as follows. Here, we denote the observed probability of radio wave a in room r as $p(a|r)$ and the set of radio waves contained in the Wi-Fi model of room r as M_w^r. First, we obtain the set of radio waves common to O_w and M_w^r as $O_w \cap M_w^r$. Also, we obtain a set of radio waves that are included in M_w^r and not included in O_w as $M_w^r - (O_w \cap M_w^r)$. Next, we obtain the probability that the radio waves of the set element can be observed in room r as follows.

$$p(r) = \prod p(a|r) \times \prod (1 - p(b|r))$$

where

$$a \in O_w \cap M_w^r, w \in M_w^r - (O_w \cap M_w^r).$$

Comparing the observation data with any room model as described above, the probability of being a specific room is required. Let the room with the highest probability be the room where the smartphone is currently.

3.6 Beacon Defect Detection

Based on the results of BLE room estimation and Wi-Fi room estimation, we compare BLE radio wave list O_b with the BLE model of the estimated room and detect the defect of a BLE beacon. The malfunction of a BLE beacon is such that radio waves are not transmitted due to battery exhaustion or breakdown, or it has been taken out of the room. For these defects, we will discover two types of inconsistencies: "Should not be observable" and "Observable but are not". Then, we perform defect analysis.

As a precondition, R_b is the room estimated by the BLE model. R_w is the room estimated by the Wi-Fi model. O_b is the set of BLE beacons received at a given observation. M_b^R is the set of BLE beacons included in the BLE model in room R.

First, we will show the algorithm for finding the beacon set Emh (mh means "move here" from somewhere), which is supposed to be unobservable. What can be found with this pattern is that the beacon was moved to a room observed from some room.

Suppose the room estimate R_b based on the BLE model is correct. The beacon set that is supposed to be impossible to observe can be obtained as follows.

$$E_b^{mh} = O_b - (M_b^{R_b} \cap O_b)$$

On the other hand, suppose that the room estimate R_w based on the Wi-Fi model is correct. The beacon set that is supposed to be impossible to observe can be obtained as follows.

$$E_w^{mh} = O_b - (M_b^{R_w} \cap O_b)$$

Here, if R_b and R_w are different, elements of E_b^{mh} and E_w^{mh} are also different. In that case, their union is regarded as a candidate for a problem.

$$E^{mh} = E_b^{mh} \cup E_w^{mh}$$

Next, we show an algorithm to examine the beacon set E^{mt}(mt means "move to somewhere"), which is supposed to be observed but is not observed. What we can discover with this pattern is a malfunction, a battery exhaustion, or that the beacon has been moved out of the observed room.

Suppose the room estimate R_b based on the BLE model is correct. A beacon set that is supposed to be observed but is not observed is obtained as follows.

$$E_b^{mt} = M_b - (M_b^{R_b} \cap O_b)$$

On the other hand, suppose that the room estimate R_w based on the Wi-Fi model is correct. A beacon set that is supposed to be observed but is not observed is obtained as follows.

$$E_w^{mt} = M_b - (M_b^{R_w} \cap O_b)$$

Here, if R_b and R_w are different, elements of E_b^{mt} and E_w^{mt} are also different. In that case, their union is regarded as a candidate for a problem.

$$E^{mt} = E_b^{mt} \cup E_w^{mt}$$

3.7 Comparison With Other Methods

As related research, compare Asahi's method, described in Section 2, with our method. Table 2 compares attributes of the two methods. In Asahi's method, a beacon is arranged as a checkpoint of a stamp rally. Therefore, it is necessary to transmit data at every checkpoint. Since it is sufficient to transmit only the BLE data, it is considered that the power consumption does not increase very much. However, with this method, it is necessary to transmit Wi-Fi and BLE data when entering the room. Since entrance/exit is repeatedly performed, it is thought that power consumption will increase.

With regard to estimation of defects, Asahi's method does not transmit data unless a person passes near a beacon. Furthermore, we cannot observe data. Also, defect cannot be detected if data cannot be observed. However, in our method, data observation is done at entry. Except for rooms that are not used much, we believe that we can respond quickly to a problem with beacons.

Regarding the type of defect, Asahi's method can only detect defects such as a beacon's battery outage. Also, if a beacon is taken out, you do not know where it has gone. In our

Table 2: Comparison of methods

	Asahi's method [8]	This method
Power consumption	○	△
Immediate nature of defect detection	△	○
Types of defects	△	○

method, a room model is created, and observed data are compared. As a result, in addition to a defect of the beacon, movement such as replacement can be detected.

4 ROOM ESTIMATION AND BEACON DEFECT DETECTION EXPERIMENT

By examining the room-estimation method conducted in Section 3, we can verify the accuracy of room estimation. We also conducted experiments as to whether beacon defects could be detected. If the accuracy of room estimation obtained by experiment is low, there is a possibility that estimation of beacon defects may be affected.

As the first experiment, after creating the BLE/Wi-Fi model, we observe the Wi-Fi and BLE data in each room and obtain the accuracy of room estimation. Since beacon radio waves are weaker than Wi-Fi, it can be considered observable in the room and still not be observed. Therefore, we observe data at various places in the room. It is considered that room estimation is possible with a high probability if the room is isolated. However, it is considered difficult if it is possible to observe radio waves of the same Wi-Fi or beacon, such as in a room next door. In addition, it is thought that the probability of room estimation will be low if all the beacons with low radio field intensity are used. Then, estimation of a beacon defect is affected. Therefore, the boundary value of the radio field intensity is also found.

As a second experiment, we will detect malfunctions assuming beacon movement, defect, etc. We anticipate the following kinds of defect: one cannot observe the beacon in the room; the beacon in the room has malfunctioned; a beacon that should not be observable originally is detected; and a beacon installed in one room has been moved to another room. As a result, we believe that by comparison with BLE/Wi-Fi observation and the BLE/Wi-Fi model of each room, beacon movement and malfunction can be detected.

The factors that affect detection accuracy are considered to be the size of the room, location of the room, and number of beacons.

These factors, along with multiple potential defects, may combine variously to affect detection accuracy.

4.1 Experiment Setting

As the experimental setting, data collection is done in each room using a smartphone as in Section 3. The room used in the experiment is shown in Fig. 5. One Wi-Fi access point is installed in each room. Data collection takes place everywhere in the room.

The beacon arrangements for each room are shown in Fig. 6. Everywhere in the room at least one beacon's signal can be

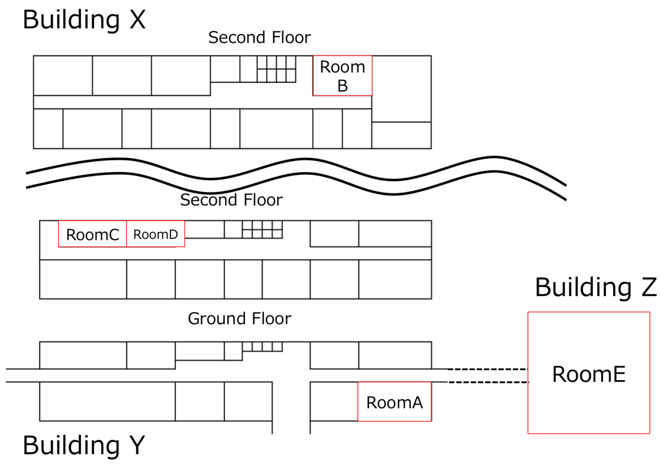

Figure 5: Floor map

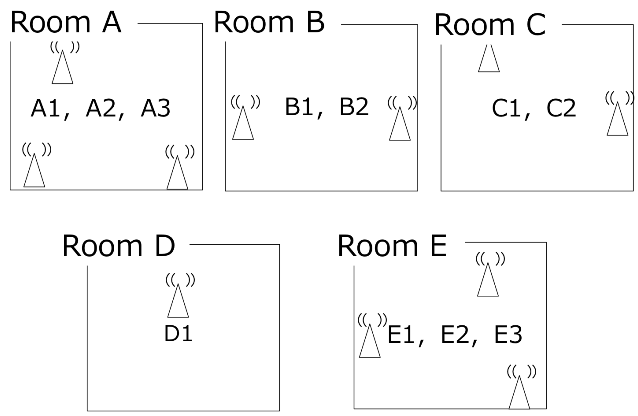

Figure 6: Beacon arrangement diagram

received. All UUIDs are unified. In room A, three beacons are installed in different corners of the room, three in total, and it is apart from the other rooms. In room B, two beacons are installed on opposite walls; and room B is in a different building from the other rooms and thus furthest away. In room C, two beacons are installed, and it is next to room D. In room D, one beacon is installed in the center. Room E is a large lecture room and has beacons installed in three places: entrance 1, entrance 2, and next to the central pillar. Observe BLE and Wi-Fi while walking through the room. Also BLE and Wi-Fi data are acquired 10 times in each room, 50 times in total. The quality of room model will be better when observation time becomes long. Also, the accuracy of room estimation will be approved. However, we decided the number of observation per room is 10 times, because the purpose of the experiment is to confirm the ability of defect detection in the experiment. Actually, the setting of the number of observation per room is rigid condition.

Table 3: Room estimation result

	-50dBm		-75dBm		-90dBm	
Room estimation	BLE	Wi-Fi	BLE	Wi-Fi	BLE	Wi-Fi
RoomA	100%	100%	100%	100%	100%	100%
RoomB	100%	100%	100%	100%	100%	100%
RoomC	100%	70%	100%	80%	100%	100%
RoomD	30%	100%	40%	100%	30%	80%
RoomE	100%	100%	100%	100%	100%	100%
Overall probability	86%	94%	88%	96%	86%	96%

4.2 Room Estimation Experiment

In the room-estimation experiment, we used the Wi-Fi and BLE observation data and experimented on how accurately room estimation could be estimated. We compared the observed data with the model created in Section 3. If the accuracy of room estimation is low, it is thought that estimation of beacon defects will be affected. Also, if all the base-station information is used, there is a possibility that the probability of room estimation will be low. Since there is a possibility that the experiments to be performed next may be affected, the boundary value is also examined. Boundary values of -50 dBm, -75 dBm, and -90 dBm were used for room estimation. Experimental results are shown in Table 3.

For room A, the room estimate for BLE was 100% at any boundary value of the radio field strength. Room B was 100% different at any boundary value because it is in a different building from the other rooms. For room C, the estimate for BLE was 100%, but for Wi-Fi the estimate at -50 dBm was 70% and the estimate at -75 dBm was 80%. For room D, BLE estimates were less than 40% at any boundary value; estimate for Wi-Fi at -90 dBm was 80% and others were 100%. Room E was 100% in BLE and Wi-Fi estimates.

From the experimental results, we could estimate a room with high probability except for ones with a room next door. However, in rooms next to each other, we could observe the BLE and Wi-Fi radio waves from either room. Therefore, it is considered difficult to estimate only by whether the base station can be observed. Moreover, accuracy is high when room estimation is performed at -75 dBm from the experimental result. Therefore, the boundary value considered to be suitable for defect detection is -75 dBm.

As a result, the influence of the number of beacons and the size of the room is small. However, when the position of the room is close, the beacon radio waves can be acquired, so the detection accuracy is low.

4.3 Beacon Defect Detection Experiment

In the defect-detection experiment, a beacon defect was detected, assuming a malfunction such as battery exhaustion, defect or movement of a beacon. The verified defect situation is shown in Fig. 7. In defect 1, one of three beacons in room A is unusable due to battery outage or malfunction. In defect 2, the beacons of room B and room C were arranged mistakenly, or moved. In defect 3, it is assumed that the beacon of room E has been moved to room D. In fact, in simple situations with only one beacon defect, our method can detect the defect easily. Therefore, we set these more complex situations for the experiment.

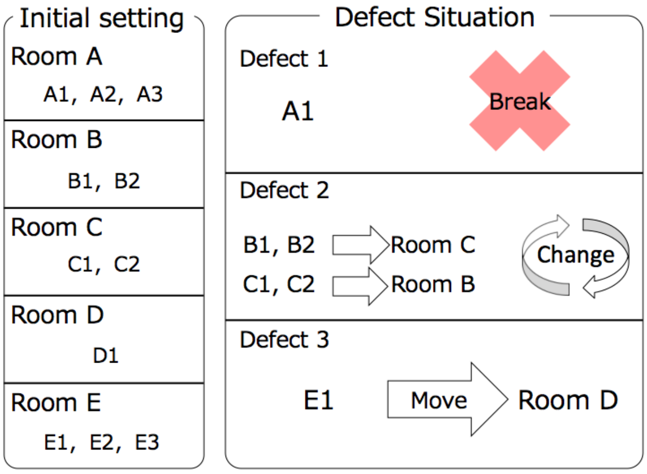

Figure 7: Assumed defect situation

Table 4: Defects that expected to be detected

Room name	Should not be observable	Observable but are not
RoomA	None	A1
RoomB	C1, C2	B1, B2
RoomC	B1, B2	C1, C2
RoomD	E1	None
RoomE	None	E1

Figure 4 represents the details of defect situations. As Defect 1, Beacon A1 is broken, so that A1 cannot be observed in Room A. Therefore, the defect situation named "Observable but are not" should be detected in Room A. Also, there are no beacons to be moved to Room A, so that the defect situation named "Should not be observed" should not be detected in Room A. We set Defect 2 in Room B and C. The defect suppose misplacement by the system operator. Beacon B1 and B2, they should be placed in Room B, are misplaced in Room C. Also, Beacon C1 and C2, they should be placed in Room C, are misplaced in Room B. Therefore, both of the defect situations named "Observable but are not" and "Should not be observed" should be detected in Room B and C. Defect 3 is mischief situation. One of the beacon named E1 in Room E is moved to Room D by someone. Therefore, "Observable but are not" should be detected in Room E1, also "Should not be observed" should be detected in Room D. The result of detection is presented in Fig.6

Table 5 shows the detailed result of room estimation and defect detection. At first, the method estimates existing room. If observed room and estimated room are same, room estimation result is correct. Then, each defect is checked on the condition of the user observed in estimated room.

In defect 1, existing room is estimated as room A, and the estimation is correct. On the condition that the user observed

Table 5: Detailed result of defect detection

	Observed room	Room estimation result	Estimated room	Defect detection result	Estimated number of defects	
					Should not be observable	Observable but are not
Defect1	RoomA	Correct	RoomA	Correct	None	A1:10
				Wrong	None	None
Defect2	RoomB	Correct	RoomB	Correct	C1:10, C2:10	B1:10, B2:10
				Wrong	None	None
	RoomC	Wrong	RoomB	Correct	None	None
				Wrong	D1:7. E1:5	None
		Correct	RoomC	Correct	B1:4, B2:4	C1:4, C2:4
				Wrong	E1:1	None
		Wrong	RoomD	Correct	None	None
				Wrong	B1:6, B2:6, E1:4	D1:3
Defect3	RoomD	Wrong	RoomB	Correct	None	None
				Wrong	D1:10, E1:10	None
		Correct	RoomD	Correct	E1:10	None
				Wrong	B1:10, B2:10	None
	RoomE	Correct	RoomE	Correct	None	E1:10
				Wrong	None	None

Table 6: Accuracy of defect detection

	Should not be observable	Observable but are not
Total number of defect detections	107	51
Number of correct answers for defect detection	38	48
Incorrect number of defects detected	69	3
Correct answer rate	35%	94%

BLE/Wi-Fi signals in room A, BLE A1 was estimated 10 times as "Observable but are not". The defect detection is correct, so that "A1:10" is appeared in a cell of "Defect detection result - Correct" and "Observable but are not". Also, the defect "Should not be observable" should not be observed in room A, so that "None" is set in a cell of "Defect detection result - Wrong" and "Should not be observed". There are no estimation error in terms of defect 1. Therefore, "None" is set both of the cells of "Defect detection result - Wrong. "

In defect 2, room estimation was succeeded when the user exists in room B. On the condition that the user observed BLE/Wi-Fi signals in room B, BLE C1, C2 were estimated 10 times as "Should not be observed". Also, BLE B1, B2 were estimated 10 times as "Observable but are not". The defect detections are all correct, so that "C1:10, C2:10" appears in "Defect detection result - Correct" and "Should not be observable" and "B1:10, B2:10" are appears in "Defect detection result - Correct" and "Should not be observable". The number after colon means the number of defect detection times. On the other hand, in room C, room estimations contain errors as room B and room D, so that they are shown as "Wrong". If room estimation failed, the method tends to derive wrong defects. For example, when the room is wrongly estimated as room B, wrong defects of "D1:7. E1:5" appears in "Defect detection result - Wrong" and "Should not be observable". When the room is wrongly estimated as room D, wrong defects of "B1:6, B2:6, E1:4" appears in "Defect detection result - Wrong" and "Should not be observable". Also, wrong defects of "D1:3" appears in "Defect detection result - Wrong" and "Observable but are not". Even if the room estimation is correct, defect detection may contain errors. When the room is correctly estimated as room C, wrong defects of "E1:1" appears in "Defect detection result - Wrong" and "Should not be observable".

In defect 3, as same as defect 2, there are several defect detection failures even the room estimation is correct. The corresponding cell is, "Defect 3 - Room D - Correct - Room D - Wrong" and "Should not be observable", and the concrete defect detections are "B1:10, B2:10".

From Table 6, the number of defect detections is larger than the number of observations. In this research, we estimate rooms using BLE and Wi-Fi and detect defects of BLE. Therefore, the result will come up two estimating of the rooms for BLE and Wi-Fi. If the room estimation results using BLE and Wi-Fi are different, defects are detected for each estimated room. When the estimation of BLE is room A and the room estimation in Wi-Fi is room B, the result of defect detection in room A and defect detection in room B are obtained. Also, even if it is in the same room, there are cases where multiple defects such as "BLE A1 can not be observed" and "BLE A2 can not be observed". In the situation, the number of defect is counted for each defect. Therefore, the total number of defect detection will be larger than 50 observations. For example, BLE C1 and BLE C2, which do not exist in room B, were observed. The total number of defect detections is represented by the sum of correct and incorrect detections of "Should not be observable" and "Observable but are not" in Table 5, respectively. The number of correct answers for defect detection is expressed by the sum of “Correct” each defect detection. The incorrect number of defects detected is expressed by the sum of “Wrong” each defect detection. The correct answer rate is represented by “total number of defects estimated / correct defect detections”.

The first “Observable but are not” targets are rooms A, B, C and E from Table 6. The number of observations and the number of defects detected are not much different. In addition, the number of correct answers for defect detection is large, and the correct answer rate is 94%. For defect detection, rooms A, B, D and E are accurately detected. However, room B has detected a different BLE than expected. The next deficiency is “Should not be observed”. Detectable estimation results are for rooms B, C, and D. The number of estimated defects is almost twice the number of observations. About one third of the correct answers are correct, and the correct answer rate is 35%.

As a consideration of defect detection, as shown in Table 5, in rooms A and E, the BLE of the other room cannot be seen. Therefore, “Should not be observable” and “Observable but are not” defects are detected correctly. It is thought that this is because the rooms are far away from each other, so their BLEs do not interfere with each other. Room B is separate from other rooms. Therefore, it is considered that it is not influenced by other beacons, and defects can be accurately detected. Rooms C and D are next to each other. Therefore, they are considered to be more affected by BLE compared to other rooms. As a result, as shown in Table 5, unexpected BLE is detected, and erroneous detection becomes a problem. From these results, it can be considered that it is possible to detect malfunction accurately when the room is separated and not affected by other beacons. However, if the room to be observed is close to another, the estimates of the room by BLE and Wi-Fi may be different. Therefore, it is considered that the number of detected defects increases and the number of correct answers for defects decreases. In this hypothesized defect experiment, it was executed assuming that all BLEs located in rooms B and C were replaced. Therefore, it is considered that a significant estimation error occurred between BLE and Wi-Fi.

5 CONCLUSION

In this paper, we proposed a BLE beacon defect detection method. The method is based on WiFi and BLE fingerprints for each room. We modeled the observed Wi-Fi and BLE data for each room. Basically, we compared the BLE model with the observed BLE list and estimated the room. We also compared Wi-Fi models and Wi-Fi lists at regular intervals.

A room-estimation experiment was conducted. We calculated the probability that room estimation would succeed. Also, we obtained the boundary value of the signal strength that does not affect beacon-defect estimation. We experimented with three boundary values: -50 dBm, -75 dBm, and -90 dBm. The best result was -75 dBm. Therefore, Wi-Fi signal that is under -75 dBm is removed for our method.

We conducted a beacon defect detection experiment, and it was possible to detect a beacon in which a malfunction had occurred. However, it was difficult to estimate a defect in a room with a neighboring room or a room with a small space. The reason for this is that beacons are confused because they are more vulnerable to nearby BLE radio waves. Isolated rooms could be detected with 100% accuracy. However, adjacent rooms could only be detected with 35% accuracy.

In this experiment, we observed data only in rooms. We did not observe BLE/Wi-Fi information in hallways. Therefore, there is a possibility that room estimation could be done even from a hallway. If you are in a room, you may mistake some room estimation if tracking for several tens of seconds. However, if the number of times estimated in the same room is large, you can presume that you are in the room.Also, in the case of a hallway, room estimation is considered to change one after another. Therefore, it can be presumed that you are walking in the hallway.

As future work, we should modify the BLE/Wi-Fi room model and improve room estimation accuracy. One idea is to introduce a Gaussian distribution model to express possible signal strength. By modeling with Gaussian distribution, we can understand the range of the radio-wave intensity seen in a specific room and consider that the room can be accurately estimated even with an adjacent room. If the room can be estimated accurately, it can be expected that the accuracy of estimation of beacon defects should be improved.

At the time of operation, it is possible to automatically update the room model by using the uploaded BLE/Wi-Fi observation data. If we keep the model we created first, we may not be able to estimate rooms, such as when a beacon is changed out or there are many people or things in the rooms. Therefore, we should update the model in operation. We believe that data of various situations can be observed and changed according to the situation and changes in the environment.

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(Received November 18th, 2017)
(Revised April 18th, 2018)

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