RSSI-based Localization of BLE-attached HVACs by Utilizing Peak Detection

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Abstract: Nowadays, there is a concern about how to use energy efficiently. Energy management is one of the technologies which play an important role to reduce energy consumption in buildings. For building energy management, there are several technologies which make the resident feel comfortable by controlling HVAC and lighting through IoT. The critical information, which enables such management in a building, is the location of IoT devices. However, the manual location identification manner requires a significant labor effort for a large number of IoT devices deployed in the building. Although the wired network has reliable, low-delay and secured characteristics, it has no property to be used for the localization technique in the physical environment. Hence, Bluetooth Low Energy (BLE) is one of the most popular wireless network modules for IoT devices because it can provide a cost-effective and easy-deployment network. As a signal strength of wireless technology is related to the distance between receiver and transmitter, the BLE modules can be used to generate the signal fingerprint to estimate their locations. In this paper, it is assumed to attach a BLE module to each HVAC individually, and then the location of HVACs can be estimated by observing the signal strength of BLE. We propose a survey mechanism to collect signal propagation. We provide a method to estimate the location of BLE without visiting every place by analyzing the change in signal strength of every BLE. Our method requires the floorplan and physical location of HVAC. We request one tester to carry the smartphone and walk around the building for collecting the signal strength of every BLE. After that our method generates the candidate list of the BLEs to each physical location. We evaluate our algorithm by deploying 26 BLEs in an office building. The results show that the average number of matching BLE candidates for each location is 2.17, which is useful to identify BLEs which cannot be identified by network-based localization.

1. Introduction

Since smart building technologies are becoming more innovative, they are expected to provide energy efficiency and resident comfort simultaneously using information and communication technologies. Such technologies commonly install HVAC (Heating, Ventilation and Air Conditioning) system in buildings. Some system emphasizes the environmental features such as temperature indoor and outdoor, the wind flows to control the temperature and energy usage in each area in the building individually [1], [2], [3], [4]. Although control strategy based on the environment provide a good result in energy saving, there are some rooms such as meeting rooms which are not used for the whole day. For example, there is some research that shows the benefit of localization of human to power management systems, in which, energy management systems can manage both energy consumption and comfort of occupant simultaneously depending on the presence of humans, for example, POEM [5], Smart Thermostat [6], HitoNavi [7] and the occupancy-based HVAC system [8].

In order to provide such services, HVAC units and sensors have wired network modules for connecting themselves to Network for more efficient management and control. However, we have to map their network addresses (IDs) with the physical locations in order to control the HVAC system precisely, which needs considerable labour cost. Currently, we perform the mapping procedure manually. For instance, workers turn on HVAC units one by one at a time, and the physical address of HVAC unit which is turned on is shown on the controller screen, then the workers can map the physical address onto the layout map. In particular, there will be tens of thousands of HVAC in a large building, thus this procedure is unrealistic as it is too time-consuming, and it incurs high labour cost for both configuration and validation effort. Let us assume the situation in a hotel and an office building, where they are currently operating, which contain a numerous number of small rooms where each room has one or more HVAC units inside. Unfortunately, some rooms may not be allowed to access due to privacy and administrative reasons (privileged access policy and/or confidential space), and the workers may just be allowed to move on only pub-

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lic hallways. Consequently, the workers cannot enter those privileged areas to identify the location of HVAC units.

In this paper, we propose a semi-automatic position estimation that links network IDs and their physical positions, which contributes greatly to the reduction of management cost. We attach the wireless modules, especially BLE, to be used to the location estimation technology based on radio field intensity to identify the location of HVAC units. We assume that we can get the floor plan of building with the location of HVAC units from the owner or construction manager, and it has already been analyzed. We send only one tester carrying a smartphone to collect RSSI (Received Signal Strength Indicator) of BLEs. In this approach, we mention on finding the list of BLE IDs which are possible to be located at each physical location before we apply another technique to find the best matching between each BLE ID and physical location. We let the tester walk along given routes that are calculated from that floor plan information. Our method emphasizes the RSSI peak of BLE ID during walking in two directions to estimate the potential list of HVAC locations which contain a set of the BLE IDs that are possible to be located on those HVAC locations individually. We evaluate our method by deploying BLEs in the actual office building.

2. Related work

2.1 Radio Signal Strength and Its Benefits

Received signal strength indicator (RSSI) is one of the noticeable characteristics of wireless technologies as they broadcast the radio signal to communicate with each other through the air. As the RSSI can show the distance between the radio transmitter and radio receiver [9], [10], [11], [12], [13], there are several benefits of RSSI such as RSSI-based indoor localization. RSSI-based indoor localization leverages the RSSI to estimate the trajectory of Wi-Fi devices (*e.g.* smartphones) in the indoor environment by calculating the distance between Wi-Fi devices and anchor [9], [10], [11]. The basic method to estimate the location of the Wi-Fi device is the multilateration mathematical method which relies on the estimated distance between the Wi-Fi device holder and at least 3 surrounding APs based on signal propagation model [9]. However, the RSSI based indoor localization requires a calibration effort such as configuring the location of each well-known anchor in the building to pursue good accuracy. Hence, there are some research teams who propose an RSSI survey method to estimate the location of anchors. They propose that if we collect the RSSI on the known locations, the anchor locations are able to be identified [10], [11].

specifically, the literature [10] proposes that the relative location can be obtained by estimating the distance between anchors to Wi-Fi devices at many locations. They apply an optimization technique to find the estimated location of a human without information about the localization of anchors. In order to estimate the actual trajectory of human, they leverage the GPS-fixed locations which are obtained when a tester walks close to the windows during the calibration phase.

Since the fluctuation in RSSI of BLE will increase if the receiver is far from transmitter and receiver [12], [14], we have to collect the RSSI close to the transmitter for better accuracy. However, there are possibilities that a tester may not have permission to enter some rooms in the case of reconstruction. Consequently, the existing techniques in localization of anchors will be unable to apply in this case.

2.2 Pedestrian Dead Reckoning (PDR)

Another popular technique for indoor localization is Pedestrian Dead Reckoning (PDR), which estimates the trajectory of human by analyzing the number of steps and the head direction of human who holds the smartphone from its embedded sensors [15], [16]. However, the location error of PDR is accumulated because most types of sensors embedded in the smartphone has much noise [15], [16]. Therefore, a research team proposes a technique to reset a location error by identifying a landmark in the building [15].

In our proposed method, we avoid the location error by providing the walking paths to the tester, thus the location error will be reset every time we give the path to the tester. Moreover, our approach does not require the fine-grained localization of human. Hence we will calculate only the number of steps which is enough information to roughly estimate the location of the tester on the given path.

3. Methodology

In the building, HVAC has been used to manage indoor temperature and indoor air quality for improving living quality. To accomplish HVAC management, most techniques need primary information, which is the location of HVAC components. Currently, HVAC units are equipped with Ethernet module for connecting to the central network. The general location identification method requires a worker to go to HVAC location where that the worker needs to configure, and then to turn on that HVAC unit. After that, the HVAC unit will connect to the central server, and the worker can see the network ID. Consequently, the worker can match that HVAC unit to the location where that worker turned on the HVAC unit. Next, the worker goes to another location to turn on another HVAC unit and matches that unit to the location. The worker repeats the matching procedure until every HVAC unit is identified.

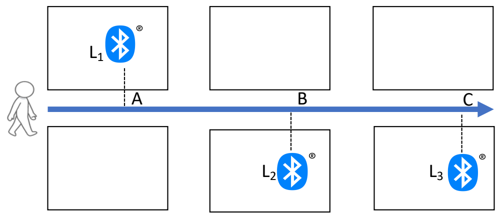
The performance of this manual manner is ineffective when a large number of HVAC units are deployed in a large building due to time-consuming, heavy workload. Thus, we leverage the advantage of radio signal to perform localization of HVAC automatically. We will attach a wireless module such as Bluetooth Low-Energy (BLE) to each HVAC device. Hence, we can estimate the location of HVAC by analyzing the wireless information.

3.1 Problem Definition

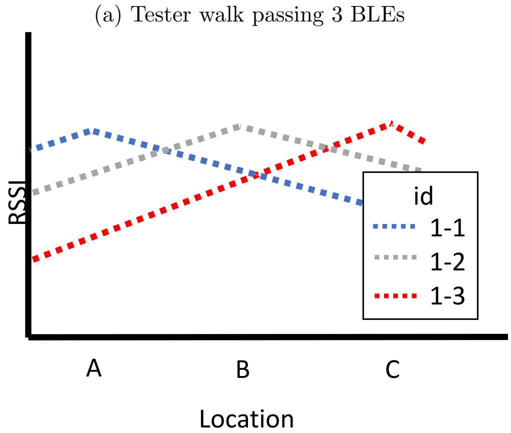
The localization techniques of radio transmitter have been proposed so far [10], [11]. Those researches require a worker carrying a radio receiver to collect the signal strength around the building. Those methods require the worker to visit many spots in a building for improving accuracy. Then they apply the signal propagation model to estimate the distance between receiver and transmitter.

However, the RSSI of BLE is more fluctuated when the BLE receiver is far from the transmitter. As a result, the worker needs to collect the RSSI at closer location to the BLE transmitter to improve the performance of BLE localization. For such cases, the HVAC system is deployed in the reconstruction site or the building which has already been operated. There are some areas where the tester is prohibited. Consequently, the location of BLEs in those rooms are inaccurate.

In this paper, we identify the location of HVAC units by detecting the strongest RSSI location of every BLE on the walking paths. We assume that the floorplan has already been identified before performing localization of BLE. As a result, we know rooms, walkable area, HVAC locations and prohibited area from the floorplan. According to literature [17], we match the BLE device IDs to the physical locations by means of RSSI peak measurement. For such an example, when a tester walks passing 3 BLEs as in Fig1a, the application in the smartphone will perceive the RSSI as Fig 1b. Consequently, we can match the BLE ID “1-1” to location L_1, “1-2” to location L_2 and “1-3” to location L_3, respectively.



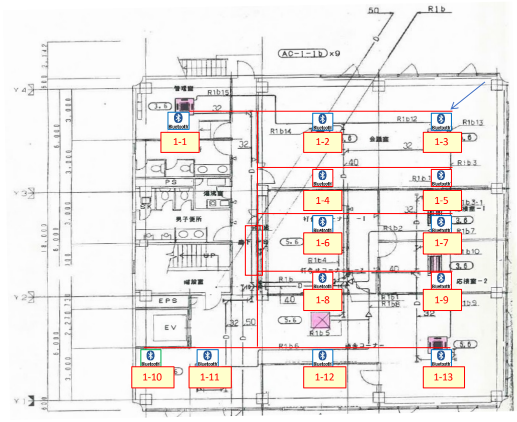
(a) Tester walk passing 3 BLEs



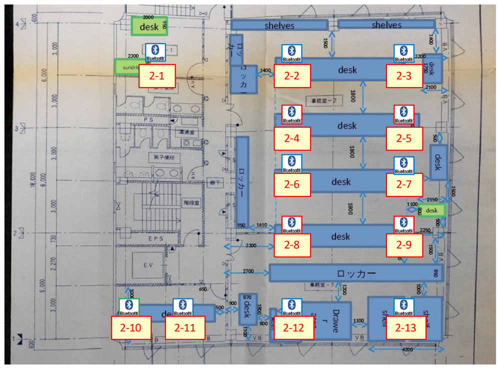
(b) RSSI of 3 BLEs

Fig. 1: Location estimation by the order of rssi’s peak

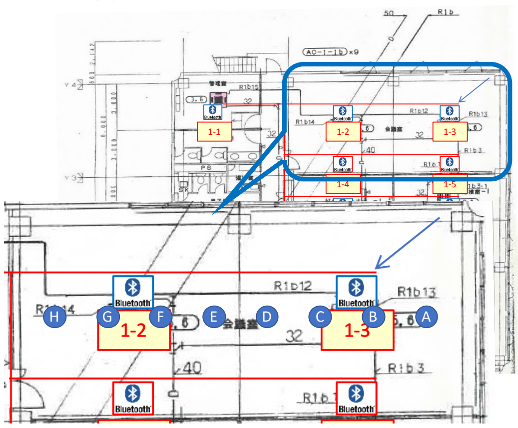
According to Fig2b, we hardly generate the suitable walking path for every HVAC location because the walkable paths in the real environment are limited due to furniture etc. Therefore, we will discuss how we can design a survey method such as walking path design and a method to collect RSSI to clearly see the peak order of every BLE in general buildings.



(a) Location of BLEs on 1st floor.



(b) Location of BLEs on 2nd floor.

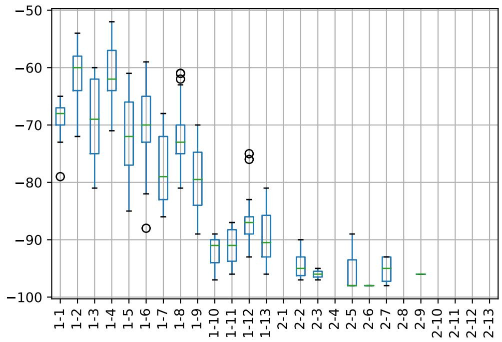


(c) Smartphones are placed on 8 locations.

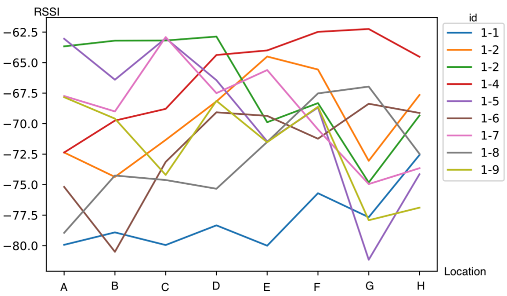
Fig. 2: Location of BLEs Deployeed in This Project.

3.2 Algorithm Design

In order to design an algorithm, we have to know some behaviour of RSSI when we observe it on the walking path. We, therefore, placed smartphones on 8 locations as in Fig 2c and had collected the RSSI for 30 seconds. We found that the RSSI of BLE is not stable, and that the RSSI of BLE cannot represent the distance between transmitter and receiver. Specifically, the RSSI of BLE ID “1-2” seems to be similar to RSSI of BLE ID “1-4” where a smartphone is placed under BLE ID “1-2” as Fig 3a. Consequently, we think that the techniques leveraging the RSSI to estimate the distance between the transmitter and receiver cannot be applied directly. Additionally, when we calculate the average of RSSI on 8 locations, we found that the average RSSI of BLE located in the same perpendicular alignment of collecting direction have a similar trend as Fig 3b.



(a) The RSSI of 26 BLEs at Location **G** in Fig2c



(b) Average RSSI on 8 locations in Fig2c

Fig. 3: RSSI

Since the shape of most buildings is rectangle and the walkable paths usually belong to both sides of the building, we suppose when we walk on one side of the building, we can see the peak of BLE representing on the orthogonal projection location of BLE location onto the walking path that belong to that side. Accordingly, if we consider the peak location in both sides of the building as in Fig 4, we can estimate the location of HVAC and we will discuss this topic in the "2-dimensional localization" section.

In order to acquire RSSI, our method requests the tester to survey the RSSI of each BLE around the building by carrying a smartphone with our application. Our application collects the RSSI values in the format $< l_i, rssi_{1,i}, rssi_{2,i}, ..., rssi_{n,i} >$ where l_i is the place the data are collected using the PDR technique, and $rssi_{n,i}$ is the RSSI from BLE ID n at location l_i. For estimating the location where RSSI data is collected, we apply a *Roughly-Controlled PDR* from literature [17]. Especially, we give the walking path including the start and stop positions to a tester, and thus we can estimate the walking size (meters per step) and the location of tester for each step of the tester.

Nevertheless, we found the insufficient sample when we walk continuously on the walking path. Specifically, we deploy 26 BLEs in the first and second floors of the office building whose size is 18x18 square-meters and set the BLEs

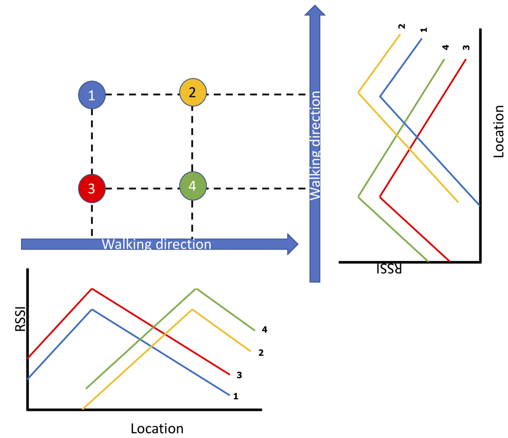


Fig. 4: Concept of 2 dimensional peak order for BLE localization

to broadcast the advertising beacon every 1 second. Our application cannot receive the beacon every second due to shadowing and collision problem. Moreover, the RSSI data for one location will not be reliable due to fluctuation as in Fig 3a. Therefore, we will ask the tester to stop walking for collecting RSSI at designed locations. We will describe the detail in the "Stand and walk Scheme" section.

3.3 Stand and Walk Scheme

Even though we would like to ask the tester to collect RSSI around the building by walking continuously, the beacons which are received by walking continuously seem to be inadequate. We guess the number of beacon collision will increase when we densely deploy more BLE in the building. Consequently, we consider the average value of RSSI in each location which is able to represent more stable and reliable than a single value. Hence, the tester needs to stop walking at designed locations for some time to collect more beacon packages for calculating the average RSSI then he/she resumes walking again. It is almost impossible for the tester to stand on the correct locations when we give numerous locations for measuring RSSI on the map due to no accurate indoor localization deployment. For instance, we need to collect the RSSI for every one meter for seeing the change of RSSI clearly when the gap between HVACs are close with each other (about 2-3 meters). After the application gives the locations for collecting data on the map, the tester has to go to the exact location and push the location where he/she is to the application before collecting data. The tester may misunderstand and make a problem easily, so we apply the *Roughly-Controlled PDR* [17] to address this problem.

To apply *Roughly-Controlled PDR* to the data collection, we give walking path p_j to a tester with start point $p_{j,start}$ and stop point $p_{j,stop}$ on the smartphone application as in Fig 5. The tester goes to the start point and pushes the start button, and our application starts increasing step count $p_{j,count}$. After the tester walks p_{step} steps and stops walking p_{stand} second for collecting rssi, the tester repeats "Stand and Walk Scheme" until he/she reaches the end point. When the tester reaches the end point, he/she presses the stop button to finish recording the RSSI on the walking path p_j. After that the application estimates the step side $w_{stepsize} = p_j.length/p_{j,totalcount}$ where $p_j.length$ and $p_{j,totalcount}$ are the total distance of walking path p_j and the number of total steps, respectively. To record the location where the tester stands to collect RSSI, we define the location $l_i = (p_j, l_{r,i})$ as a set of walking path and the relative distance from start point $l_{r,i} = p_{j,count} * w_{stepsize}$ at location l_i.

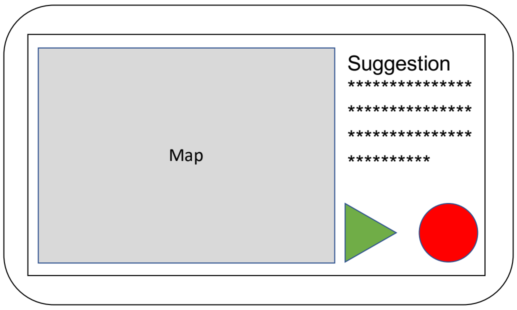


Fig. 5: Smartphone application.

In reality, the time where the tester spends on our survey method is depended on how often we need to stand for collecting data and how long we collect the RSSI. Specifically, the tester may spend more time if tester stands for a long time to collect the RSSI for every step. However, the RSSI data will be inefficient if we collect for a short time and we cannot see the trend of RSSI if we walk more step before standing to collect the RSSI in the case that HVACs are installed close with each other. Hence the number of steps before collecting the RSSI p_{step} and then the time for collecting RSSI p_{stand} should be varied and we will show the effect of them in the experimental section.

3.4 2 Dimensional Localization

In this work, we observe the locations of RSSI peak from every BLE belonging to the 2 sides of the building. For easily explaining, we define the side of the building which is longer is the "horizontal side" and another side is the "vertical side". Because our method needs to show the floor plan and the given walking path, we assume the floorplan information and the device locations on the floorplan are already identified. We believe every large building has the floorplan information. Another fundamental information is the walkable paths, and we assume the floorplan information also provides that information. If the floorplan information does not provide the walkable paths, it can be generated by some indoor floorplans construction methods [18], [19]. Then we can pick up the possible walking paths $p_i \in P_{walk}$ with attribute $p_i.detection \in \{“horizon'', “vertical''\}$ from the walkable path.

For the large building, the tester may not finish a survey within one day if the tester performs the “Stand and Walk Scheme” on every walking path. Therefore we will calculate the capability to estimate the BLE localization for each

Algorithm 1 *PathSelection*(P_{walk})

Require: The possible walking paths P_{walk}.
for $\forall p_i \in P_{walk}$ **do**
  for $\forall s_{ble} \in S_{ble}$ **do**
    if $F_{appro}(s_{ble}, p_i)$ **then**
      $p_i.list_{ble} < -p_i.list_{ble} \cup s_{ble}$
    end if
  end for
end for
$C_{discover,h} \leftarrow \varnothing$
$C_{discover,v} \leftarrow \varnothing$
while *isReliable*$(\forall id_i in ID_{ble})$ **do**
  for $\forall p_i \in P_{walk}$ **do**
    if $p_i.direction$ = 'horizontal' **then**
      select pi where $|C_{discover,h} \cup p_i.list_{ble}|$ is max
      $C_{discover,h} \leftarrow C_{discover,h} \cup p_i.list_{ble}$
      give p_i to tester
    end if
  end for
  for $\forall p_i \in P_{walk}$ **do**
    if $p_i.direction$ = 'vertical' **then**
      select pi where $|C_{discover,v} \cup p_i.list_{ble}|$ is max
      $C_{discover,h} \leftarrow C_{discover,v} \cup p_i.list_{ble}$
      give p_i to tester
    end if
  end for
end while

walking path and ranking them. After that, we will give the best set of walking paths to the tester, which cover all the BLE location. To reduce the number of walking paths that our method gives to the tester, we calculate the peak of every BLE ID and we verify which BLE ID we can trust after the tester stops at the end point of every given path. Our method will give the walking path until the peak location of all BLE IDs is reliable as in algorithm 1.

The algorithm starts from calculating a capable list $p_{i,ble_{reliable}}$ of BLE of walking path p_i where we can perceive reliable RSSI from those BLEs if we collect RSSI for every path. Specifically, we consider that the RSSI of BLE is reliable on 2 conditions as in Table 1. In order to assess walking path p_i is appropriate to see the correct peak location of RSSI from BLE s_{ble}, we assume we obtain the perpendicular distance $F_{dist}(s_{ble}, p_i)$ between BLE s_{ble} and the walking path p_i from the floorplan information. Note that, there are short walking paths where we cannot draw the perpendicular line from every BLE to those walking paths as in Fig 6. We also know the number $F_{obst}(sble, p_i)$ of obstacles such as walls and doors between BLE s_{ble} and the walking path p_i.

Table 1: The rule to estimate the RSSI of BLE s_{ble} which is collected on the walking path p_i is reliable or not

$F_{dist}(s_{ble}, p_i)$	$F_{obst}(s_{ble}, p_i)$	$F_{appro}(s_{ble}, p_i)$
$\leq \beta_a$	0	True
$\leq \beta_b$	1	True
*	≥ 2	False

In Equation 1, we have 3 conditions to consider which

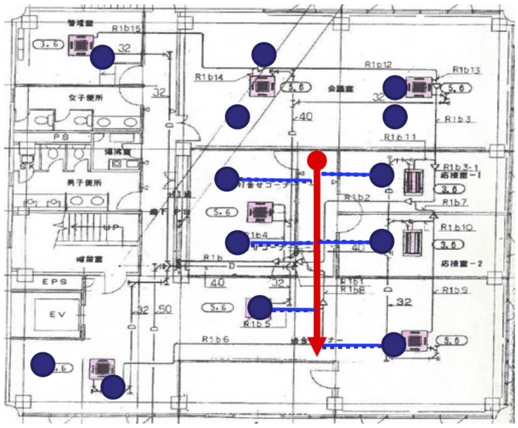


Fig. 6: Dot lines from BLE locations (dark blue circle) to walking path (red line) are Perpendicular distance

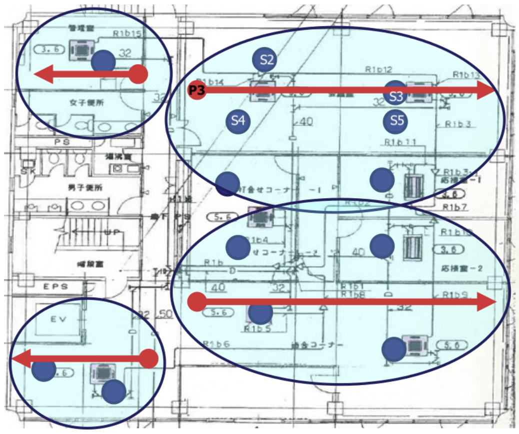
BLE can be collected reliably. The first condition is that the perpendicular distance $F_{dist}(s_{ble}, p_i)$ from BLE s_{ble} to the walking path p_i should be lower than β_a (we use $\beta_a = 12$ maters in this paper). The second condition is that the perpendicular distance $F_{dist}(s_{ble}, p_i)$ from BLE s_{ble} to the walking path p_i should be lower than β_b (we use 6 maters in this paper) and the number $F_{obst}(s_{ble}, p_i)$ of obstacles between BLE s_{ble} and walking path p_i should not be greater than two obstacles. Otherwise, the RSSI of that BLE location is regarded unreliable.

When the capability list for every walking paths has already been estimated, we give the walking path which has the highest number of capable BLE to the tester for walking on the given path. We will repeat to give the walking path until we see reliable RSSI data for covering every physical location of BLE as in Fig 7.

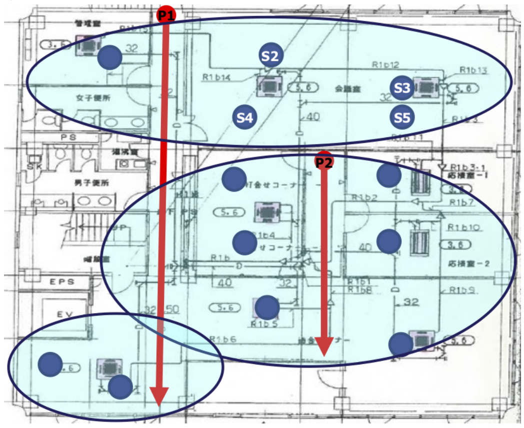
Fig 7a and Fig 7b show the walking paths where we request the tester to collect the RSSI data. Specifically, the blue circles are locations of BLE, the red arrow lines are walking paths and the light blue areas are the coverage area where the RSSI data from every BLE inside this area will be reliable if the tester walks on the walking path inside this area. For example, the tester walks on path $P3$ as in Fig 7a, we expect the order of RSSI peaks from BLE $S4$, $S2$, $S3$ and $S5$ respectively. However, the receiver can widely receive the beacon from surrounding BLE transmitters. Specifically, we will see the peak of BLEs $S2, S3, S4$ and $S5$ at the beginning of walking path $P2$ in Fig 7b when the tester walks on that walking path. As a result, we will involve some invalid RSSI peak location to the calculation process.

To tackle this problem, we should use the knowledge from the path selection method. Especially, we use the capable list $p_{i,ble_{reliable}}$ of BLE of path p_i in our location estimation method. Especially, we will be able to see the RSSI peak location of BLEs $S2, S3, S4$ and $S5$ correctly if the tester walks on path $P3$ in Fig 7a and path $P1$ in Fig 7b. Therefore, we have to use the RSSI data in those paths to identify which BLE IDs are located on BLE locations $S2, S3, S4$ and $S5$.

Accordingly, we pick up BLE location s_l if BLE location



(a) 4 paths for covering all BLE in horizontal direction



(b) 3 paths for covering all BLE in vertical direction

Fig. 7: Walking path after apply path selection algorithm.

s_l is in a capable list of RSSI of horizontal walking path p_i and vertical walking path p_j. We analyze the RSSI data from each BLE ID id_k when the tester walks on horizontal walking path p_i and vertical walking path p_j to find a RSSI peak from every BLE ID. We define the 2 dimension peak location $l_{id_k,p_i,p_j} = \{x_{id_k,p_i}, y_{id_k,p_j}\}$ of BLE ID id_k on the horizontal direction x_{id_k,p_i} when walking on horizontal walking path p_i and the vertical direction y_{id_k,p_j} when walking on vertical walking path p_j. We ignore RSSI data from some BLE IDs when the average RSSI data from those BLE IDs are weaker than a threshold δ_1 (we use -85dB in this paper). Then we calculate the distance error $d_{l_{id_k,p_i,p_j},s_l}$ between the 2 dimension peak location l_{id_k,p_i,p_j} and the BLE location s_l. Then, we apply the threshold δ_2 to generate the potential list $id_k \in P_{s_l}$ of BLE location s_l which is BLE ID id_k that will be located at BLE locationn s_l. Specifically, the 2 dimension peak location of BLE ID id_k, whose distance error to BLE location is less than δ_2, is possible to be located at BLE location s_l. Finally, we will estimate the potential list for the rest BLE locations.

4. Experiment

The experiment is conducted in an office building whose size is 18 x 18 square meters, and we deploy 13 BLEs over the ceiling on the first floor and another 13 BLEs over the ceiling on the second floor (26 BLEs as a total). These BLEs

(a) Plastic box in which a BLE module is deployed (b) BLE module inside plastic box

Fig. 8: Experiment setup

are laid in the plastic boxes individually. We, thus, provided 26 plastic boxes and deployed them close to HVAC units as in Fig 2a and Fig 2b. In each plastic box, we provided a power supply for the BLE module.

In order to perform an experiment in "Stand and Walk scheme", we have developed an android application to collect the RSSI of BLE. Accomplishing the RSSI collection, we requested the tester to carry the NEXUS6P and walk on the given walking path. Note that, the experiment was conducted in an uncontrolled environment, i.e. other members also did their normal activities during collection.

4.1 Evaluation

In this experiment, we measured the performance of our algorithm by *"precision"* and *"recall"*. Specifically, after we created the candidate list which was a set of BLE IDs for each BLE location, we could calculate the true positive TP which was 1 if there was a true answer in the candidate list, and 0 otherwise. We also calculated the *false positive* FP and the false negative FN. Finally, we calculated the *"precision"* and *"recall"* as in Equation 1.

$$Precision = \frac{TP}{TP + FP} \tag{1}$$

$$Recall = \frac{TP}{TP + FN} \tag{2}$$

4.2 Walking Path Selection

In this section, we discuss the effect of path selection. First of all, we assume the walking paths have been identified from the floorplan. There are 20 walking paths on the first floor and 15 walking paths on the second floor as in the Figure. After that we applied our path selection method. we can reduce the number of walking paths which need to be given to the tester as in Table 2.

Table 2: Walking Distance for Collecting RSSI Before and After Applying Path Selection

floor	wo Path selection		w Path selection	
	# paths	distance(m)	# paths	distance(m)
1	20	157.5	6	64.5
2	15	137.5	5	48.5

4.3 Performance of Candidate estimation Using 2D Peak Localization

In this section, we discuss the performance of our 2 dimension localization. We give the selected walking paths to the tester through our smartphone application. The tester performs the "Stand and Walk Scheme" following the instruction on the smartphone application. In this experiment, the tester stopped for 20, 15 and 10 seconds for collecting RSSI after walking 1 steps, and we measured *"precision"* and *"recall"* as in Table 3.

Table 3: Performance of Our Algorithm to Generate Candidate List by Varying Time to Collect RSSI

parameter δ_2	p_{stand}=10		p_{stand}=15		p_{stand}=20	
	Precision	*Recall*	*Precision*	*Recall*	*Precision*	*Recall*
1	0.5	0.15	0.29	0.23	0.29	0.23
2	0.36	0.38	0.42	0.42	0.46	0.46
3	0.51	0.77	0.58	0.81	0.53	0.77
4	0.44	0.88	0.5	0.92	0.5	0.92
5	0.34	0.92	0.46	1.0	0.45	0.96
6	0.34	1.0	0.44	1.0	0.35	1.0
7	0.32	1.0	0.32	1.0	0.32	1.0

We found the results from the data collected in 10, 15 and 20 seconds seem to be similar as in Table 3. Although the data should be reliable if we receive enough beacons, the results when we collect RSSI for 15 seconds look better than the data collected in 20 seconds. The reason is the average value is sensitive to the noise. However, we tried other methods such as median and mode and the results were the same. The reason is that the RSSI of BLE was unstable and we carried one device and stood p_{stand} seconds to collect RSSI. When we can use median and mode to remove outlier, we need to collect sufficient data at the same time. For example, we need to carry many phones to collect the data and this method will create burden on the tester.

In our algorithm, there is another parameter such as the distance interval between collecting location where we need to adjust. To measure the effect of distance between collecting location, we set the time to stand for collecting RSSI to 20 seconds. Then, we make the three scenarios in which the tester walks 1,2 and 3 steps before stop to collect RSSI, and we measure *"precision"* and *"recall"* as in Table 4.

Table 4: Performance of Our Algorithm to Generate Candidate List by Varying the Number of Steps Before Standing to Collect RSSI

parameter δ_2	p_{step}=1		p_{step}=2		p_{step}=3	
	Precision	*Recall*	*Precision*	*Recall*	*Precision*	*Recall*
1	0.29	0.23	0.31	0.35	0.22	0.38
2	0.46	0.46	0.31	0.62	0.18	0.65
3	0.53	0.77	0.32	0.88	0.21	0.92
4	0.50	0.92	0.26	0.96	0.20	1.0
5	0.45	0.96	0.16	0.96	0.12	1.0
6	0.35	1.0	0.15	1.0	0.10	1.0
7	0.32	1.0	0.13	1.0	0.10	1.0

In this experiment, the tester spent around 40,20 and 13 minutes for collecting the RSSI on the first floor, and spent around 30, 15 and 10 minutes for collecting the RSSI on the second floor when the tester stopped 20 seconds after walked 1,2 and 3 steps respectively. We can see that the *recalls* in Table 4 are very low when we increase a gap between collecting location as increasing the walking step p_{step}. The reason is when the tester increases walking step p_{step}, that tester will miss collecting RSSI at the peak location. Consequently, it makes the error of estimated peak location longer than the collected data by using $p_{step} = 1$. As a result, the peak location of many BLE IDs will be projected to be at the same location.

In summary, when we increase parameter δ_2, the *recalls* increase while the *precisions* decrease as in Table 3 and Table 4. According to Table 3, if we consider every true answer is contained in candidate lists, the best *false negative* is 0.46. It means if our algorithm returns the candidate lists all of which contain the true answers, the average size of candidate list will be 2.17.

5. Conclusion

In this paper, we have presented the semi-automatic BLE localization. Our algorithm can reduce the walking area and can estimate the location of every BLE without entering every location in the building. The result of our algorithm is a set of BLEs which are suitable to be located on each BLE location. We evaluate our algorithm by deploying BLE in the office building.

In the future, We will design a one-to-one matching procedure, and we also need to apply our algorithm to another building. In particular, we will collect the data on another setting such as sparse deployment to prove our approach can be performed in any environment.

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