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Localization of IoT devices for Energy Management System

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Abstract: IoT-based energy management is an important technology to reduce energy consumption in the building by controlling HVAC and lighting through IoT by providing network functions to those equipment. In order to enable such IoT device management in a building, the location of IoT devices is fundamental information. However, the manual location identification effort for a number of IoT devices in a whole building consume labour-intensive and time-consuming. Bluetooth Low Energy (BLE) is one of most popular network modules for IoT devices because it can provide the cost-effective and easy-deployment network. Fortunately, the signal propagation of BLE can be used to generate the signal fingerprint to estimate their locations. In this paper, the IoT devices are equipped the BLE module individually and we can estimate the location of BLEs instead of the location of IoT devices directly. We propose a survey mechanism to collect the signal propagation and consider the change in signal strength of every BLE for localization of BLE modules. Our method requires the floorplan and physical location of IoT devices. We request one tester to carry the smartphone and walk around the building for collecting the signal strength of every BLEs. After that our method matches the BLEs to the physical locations. We conducted the experiment in the real world environment and our matching method acquired 80% accuracy.

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 emphasize the environmental features such as temperature indoor and outdoor, the wind flows to control the temperature in each area in the building individually. To improve energy-efficiency, some researchers apply data prediction in control strategy. For example, Oldewurtel et.al deal uncertain weather forecast data with the Stochastic Model Predictive Control (SMPC) [1]. Moreover, Harle and Hopper investigate the benefit of localization of human to power management systems [2] thus Energy management systems can manage both energy consumption and comfort of occupant simultaneously depending on the presence of humans [3].

In order to provide such services, HVACs have network modules for easier and more efficient management and control, and wireless technologies have a certain advantage over wired networks. Among a considerable number of wireless technologies, BLE-based wireless technology is one of the most appropriate solutions to connect HVAC to networks because of its cost-effective and easy-to-deploy characteristics.

However, regardless of wired/wireless, in order to control HVACs, we have to map their network addresses (IDs) with the physical locations, which needs ignorable labour cost. In particular, there will be tens of thousands of HVAC in a large building, and manual mapping work is almost impossible and unrealistic as construction-site administrators might spend a huge amount of time to make such mapping records and verify each of them. Let us assume the situation in a hotel and an office building which contain a numerous number of small rooms where each room has one or more HVACs 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 configurator may just be allowed to move on only public hallways. Consequently, the configurator spends a long time but cannot identify the HVACs in the privileged areas.

In this paper, we propose semi-automatic position estimation that links BLE IDs and their physical positions, which contributes greatly to the reduction of management cost. We assume only one tester having a smartphone to collect RSSI and let him/her walk along a route calculated from a given building plan with HVAC location information. Our method leverages the trend (increasing/steady/decreasing) of RSSI change during walking to estimate the relative positions between the tester and each HVAC. As collecting more

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samples on different routes, more information about relative locations between each HVAC is obtained. Consequently, the estimation accuracy increases. We conducted an experiment where BLE devices were deployed on the ceiling of our laboratory room, and their locations were estimated on the given floorplan with BLE locations without BLE IDs. The result shows that our method can match more than 80% of BLE devices with their correct locations.

Our main contributions can be summarized as follows:

- Our method can match the BLE equipped IoT devices to the 80% correct locations even when they are placed near each other, i.e. the minimum distance between BLEs is about 2 meters.
- Our method does not require the tester to stop for collecting data. Thus the tester can finish his/her job even in a large building within one day survey.
- Our method can match the BLEs to their locations without need of labeled data and supervised techniques.
- We validated our method in real-world experiment.

2. Related work

2.1 Anchor Localization in Indoor Environment

RSSI-based Wi-Fi localization is one of most popular techniques to track Wi-Fi devices (*e.g.* smartphones) in indoor environment. The multilateration mathematical method relies on the estimated distance between the Wi-Fi device holder and surrounding APs based on signal propagation model [4]. However, this technique requires well-known points as anchor nodes in the building to pursue good accuracy. The manual calibration effort to find the anchor locations for indoor localization system is a major problem for deploying and relocating the system in the large building due to its time-consuming aspect. Hence, some researchers leverage the signal propagation to find the location of anchors by calculating the distance between Wi-Fi devices with known positions and each anchor [5], [6]. More concretely, the authors of [5] propose the zero-calibration localization system which can estimate the location of anchors, but they do not provide accuracy in the localization of anchors. Thus our method can compare to the work in [6] as shown in Table 1. However, in indoor environment, RSSI values fluctuate even

Table 1: Comparison of Localization of AP/BLE

	Floor plan	Walking path	Device location	Location Error	Accuracy
proposed method	given	given	given	–	80–90%
ZHUANG et. al [6]	given	given	not given	4.91-9.77m	–

without obstacle between sender and receiver [7], and the location estimation error in the method [6] is greater than the shortest distance between two HVACs. Consequently, we cannot apply the location estimation of WiFi devices to estimate the location of BLE devices directly.

2.2 Pedestrian Dead Reckoning (PDR)

An alternative technique for Indoor Localization is Pedestrian Dead Reckoning (PDR), which estimates the trajectory of human by using the sensors embedded in smartphones [8], [9]. However, the data from those sensors have much noise, which causes accumulating errors in localization [8], [9]. In order to reduce the effect of noise, some researchers estimate the trajectory of human by using a step counter and a head direction as the proposed works in [8], [9], but the accumulating error still exists. In our proposed method, the fine-grained localization of human is not necessary because we assume that the tester understands the given walking path based on the floorplan, and follows the instructed walking path correctly. Hence the step counter is enough to roughly estimate the location on the given path. Turn detection can also be used to correct errors if the given path has turns.

3. Methodology

Since we attempt to match the BLE device IDs to the physical locations, we need floorplan information and the device locations on the floorplan. We assume every large building has its floorplan information. When the building's owner has a plan to install HVACs, they must design the location of HVACs before installation. Thus, our system knows the places of BLE equipped HVACs. 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 [10], [11].

Our method requests the tester to survey the RSSI of each BLE around the building to generate the matching likelihood of each pair of BLE device and physical location. We leverage the approximate point in triangulation test [12] for generating that likelihood. In order to accomplish it, we firstly generate the smallest non-overlapped triangles from all physical locations. After that, we generate the walking path that is a part of the walkable paths to pass as many triangles as possible. Note that, the walking path is composed of a path segment, and each path segment is used for a single triangle. In this paper, we focus on a method to match each BLE ID to one of the physical locations. Therefore the automatic calculation of walking path is out of scope, but we are now studying on this issue.

When the tester walks, a carried smartphone with 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 location of the tester identified by our PDR method explained later, and $rssi_{n,i}$ is the RSSI from BLE ID n at location l_i. Finally, we propose the reverse of APIT test to match the BLE IDs to BLE device physical locations in the floorplan. There are two problems with collecting the RSSI in our experiment. The first problem is fluctuation of RSSI values in each BLE device. The second problem is the accumulation of PDR errors. To overcome those two problems, we propose a *Roughly-Controlled PDR* which works as follows.

3.1 Roughly-Controlled Pedestrian Dead Reckoning

In order to help the walk easily, the walking path should be the path which is frequently used and such a path that reaches some locations such as alcove and corner should be excluded. Our method divides the walking path into many short paths and our application on the smartphone gives the start and end points for each of them to the tester. The tester has to walk following our instruction until she/he reaches the end of the last short path.

When the tester reaches and stops at the end point of each short path, our application calculates the linear regression model using the measured RSSI values during walking on the path by Equations (1) – (3) below. We define the linear regression formula $r\hat{s}si_{j,i} = a_{j,1} * x_i + a_{j,0}$ where $r\hat{s}si_{j,i}$ is an expected RSSI of BLE ID j at location l_i, x_i is the walking distance between the start point and location l_i, $a_{j,1}$ is the slope of the linear regression model and $a_{j,0}$ is the offset of the linear regression model. $\bar{x}$ is the average of x_i from the start point to end point, and $\overline{rssi_{j,*}}$ is the average RSSI from BLE ID j during walking from the starting point to l_i.

$$a_{j,1} = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(rssi_{j,i} - \overline{rssi_{j,*}})}{\sum_{i=1}^{n}(x_i - \bar{x})^2} \tag{1}$$

$$a_{j,0} = \overline{rssi_{j,*}} - a_{j,1} * \bar{x} \tag{2}$$

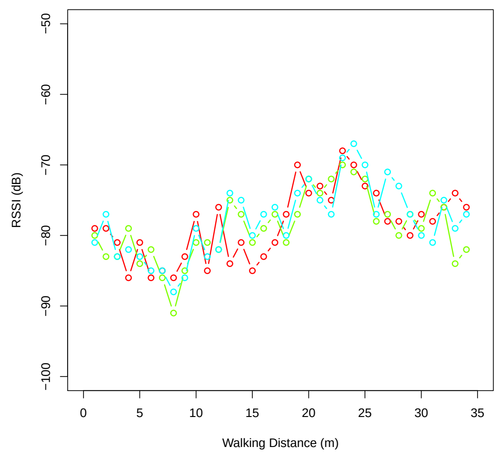
$$MSE_j = \frac{\sum_{i=1}^{n}(rssi_{j,i} - r\hat{s}si_{j,i})^2}{n} \tag{3}$$

In case that the signal strength propagated from BLE devices is insufficient and unreliable, *i.e.*, the mean square error of the calculated linear regression model (MSE_j) is greater than a given threshold β_0, our application requests the tester to walk on the same path again. The walking procedure can be summarized as below:

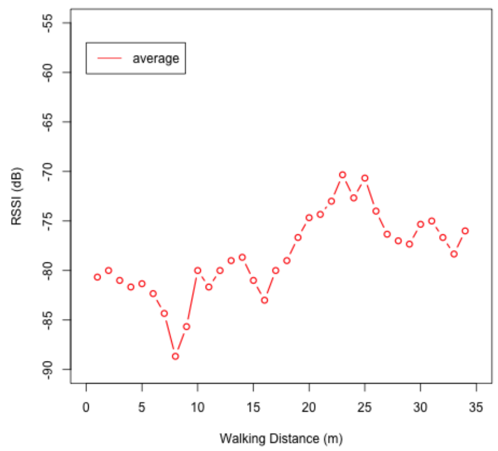
(1) Application gives Tester a short path with start and stop points in the floor map on smartphone screen.
(2) Tester touches the start button in Application, and then walks until he/she reaches the stop point.
(3) Tester touches the stop button, and then Application calculates the 3 equations (1)–(3).
  (a) If MSE is greater than an acceptable error, Application requests Tester to go back to the start point.
  (b) If MSE is lower than an acceptable error, Application gives Tester a new short path with new start and stop points.
(4) Tester performs Steps 1)-3) until finishing every short path in the walking path.

In Figure 1a, there are fluctuations in RSSI while the tester walks to collect data, but the patterns are similar. After we collect more data where the tester walks multiple times on the same short path, the average RSSI becomes smooth as shown in Figure 1b.

Because our application gives the short path to the tester, we know the total walking distance for each given path, thus we can estimate the location of the tester by counting the walking steps of the tester. Furthermore, the variables in step size and walking speed will be solved by this mechanism.



(a) Signal strength of one device during walking 3 times.



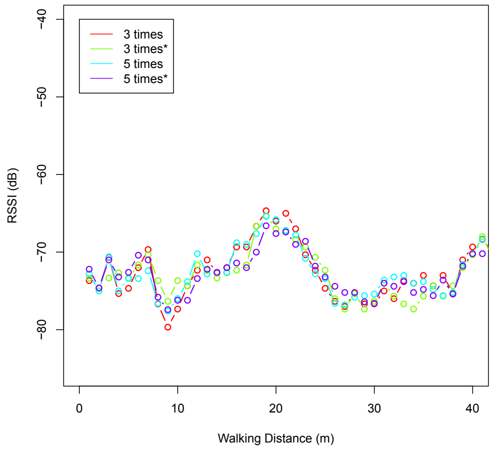
(b) Average of RSSI of one device.

Fig. 1: Signal strength collected during walking.

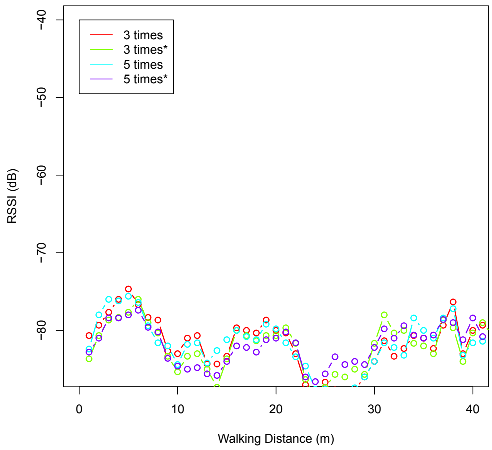
3.2 Reverse of Approximate Point in Triangulation

In the APIT test, the location of a wireless device can be estimated to be in the triangle of 3 closest anchors by using 3 strongest RSSIs. When the device moves, a moving direction can also be estimated by detecting an upward trend and downward trend of RSSI from surrounding anchors [12]. Hence, we can compare the trend of collected RSSIs with the estimated trend of RSSIs for each tuple of three stationary BLE devices that compose a triangle where the tester walks to pass.

To deal with a large building case where there are many rooms, the triangles may contain the BLE placed in different rooms. This situation may make it difficult to estimate the node is in the triangle containing the BLE place in a different room due to signal reduction by walls. Hence, we



(a) RSSI of BLE placed in the experimental room.



(b) RSSI of BLE placed outside the experimental room.

Fig. 2: RSSI collected data of BLE placed in the experimental room and outside

investigated the signal propagation from the BLE placed in an adjacent room. According to Fig. 2, the signal strength from BLE placed in the adjacent room as in Fig. 2b is weaker than the signal strength from BLE placed in the same room as in Fig. 2a even though we walk close to the wall or the door. Therefore, we will create the triangles that contain only same room locations and we match the BLE IDs and BLE locations for each room individually.

According to the RSSI collection method in Section 3.1, the tester may walk on the same path many times to make data smooth. Fortunately, the tester can collect the RSSI data while he/she walks back to the start point to reduce the number of times to walk for collecting data. For example, the data collected by walking the same direction as in the line "3 times" and "5 times" of Fig. 2 are similar to the data collected by walking in the mixed direction as in the line "3 times*" and "5 times*" of Fig. 2.

Although we do not mention the walking path generation, this paper gives some idea to generate the suitable path segment for our algorithm. Note that the given short paths are not the path segments. Since we have to generate the path segments which fit to each triangle individually, the path segment can overlap with or separate from each other. In order to select start and stop points of a path segment for triangle individually, we consider the path segment, firstly, should pass inside the smallest triangle and far from another triangle because we can identify which triangle the tester walks through easily. We define $P = \{p_1, p_2, ..., p_n\}, S = \{s_1, s_2, ..., s_m\}$ and $\delta \in \Delta$ be the set of n path segment, the set of m BLE locations and the set of triangle, respectively. Each triangle δ is consists of the 3 BLE locations, $\delta = \{s_a, s_b, s_c\}$, and each path segment p_i contains the path element $p_{i,j}$ where $j = \{1, 2, .., z\}$. We also define $d_{s_k,p_{i,j}}$ be the distance from BLE locations s_k to the path element $p_{i,j}$. We consider a path segment p_i is suitable for the triangle δ if the path segment satisfies the condition in Equation 4 where $S' = S - \delta$ is a set of BLE outside triangle δ.

$$\max_{\forall s_k \in \delta} \frac{\sum_{i=1}^{n} d_{s_k,p_{i,j}}}{n} < \min_{\forall s_k \in S'} \frac{\sum_{i=1}^{n} d_{s_k,p_{i,j}}}{n} \quad (4)$$

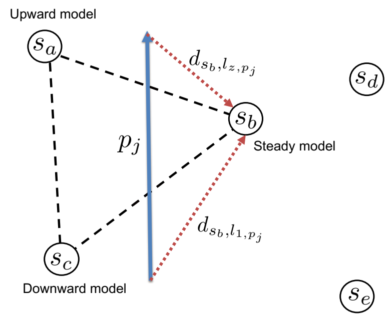


Fig. 3: Path segment

By looking at Figure 3, we mention on the path segment that passes the smallest triangle as $\delta = (s_a, s_b, s_c)$, therefore we assume when the tester walk passing the triangle δ the smartphone may perceive the top 3 strongest signals from s_a, s_b and s_c while the signal strength from s_d and s_e may not be strong enough to affect our estimation method. Our method also mentions on the expectation in the trend of the signal strength of BLE in triangle. We leverage the phenomenon of signal that becomes stronger when the receiver comes closer to the transmitter and becomes weaker when the receiver leaves the transmitter. In this approach, we create the path segments to classify the trend of RSSI from 3 BLE in triangle into 3 classes. The slope of RSSI from Equation 1 is supposed to be steady when tester walks close to the BLE then walks far away from that BLE, be rising when tester walks close to the BLE, and be dropping when tester leaves the BLE. Since it is difficult to distinguish the locations of BLEs with the same trend of RSSIs, the trend of RSSIs from the top 3 strongest BLEs should contain the steady trend, the upward trend and the downward trend for classification. In particular, we can expect the trend of RSSI from BLE by considering the change of distance between path segment and the BLE location. Hence, the trend of RSSI from BLE $s \in \delta$ will be steady when the path segment p_i satisfies the condition in Equation 5, be upward when the path segment p_i satisfies the condition in Equation 6, downward when the path segment p_i satisfies the condition in Equation 7.

$$\sum_{i=2}^{n}(d_{s\in\delta,l_{i,p_j}} - d_{s_a,l_{i-1,p_j}}) \approx 0 \qquad (5)$$

$$\sum_{i=2}^{n}(d_{s\in\delta,l_{i,p_j}} - d_{s_a,l_{i-1,p_j}}) < 0 \qquad (6)$$

$$\sum_{i=2}^{n}(d_{s\in\delta,l_{i,p_j}} - d_{s_a,l_{i-1,p_j}}) > 0 \qquad (7)$$

Aside from the path segment creation, we should mention which triangles we consider. In particular, some BLEs are members in many triangle as in Fig. 4. Thus, we need to select some triangle to be used in our method, and every BLE is in the selected triangle. For example in Fig. 4, we can estimate the location of every BLE unless we use only the triangles δ_1 and δ_4. A simple approach is to count the number of the triangle containing a BLE for each BLE individually. After that, we remove the triangle in which two or more BLEs have the highest counters while maintaining every BLE to has the counter over 0. We repeat this removing step until we cannot remove the triangle.

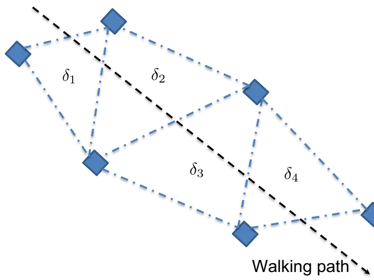


Fig. 4: Triangulation selection

Our method considers the similarity between the expectation models and the real measurements on the same path segment. For each path segment, we identify which BLEs forming triangle by selecting top-k strongest RSSIs. Hence, we calculate the average of collected RSSIs for each BLE device, then we select the k BLE devices whose average RSSI values are highest. For example, the average signal strength from the BLEs in the triangle (BLE id: 3,5 and 9) are higher than the average signal strength of BLE id:7 placed near the considered triangle as in Fig. 5.

After that, we calculate the likelihood of the BLE locations of triangle and the selected k BLE devices. The likelihood function $LH(s_j, l_i)$, which means the probability that BLE device s_j is placed in BLE location l_i, is supposed to be a function as that of Fig. 6(a) when the BLE location satisfies Equation 6, be a function as that of Fig. 6(b) when the BLE location satisfies Equation 5, be a function as that

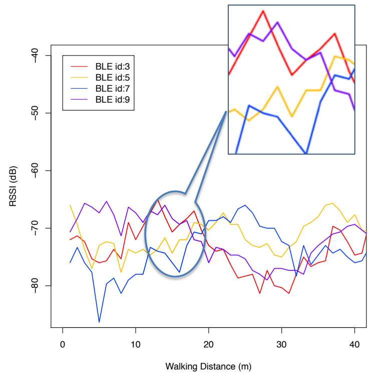


Fig. 5: Triangulation selection

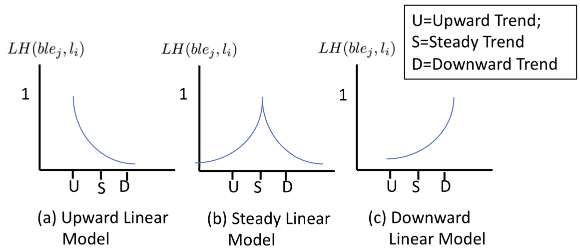


Fig. 6: Signal strength collected during walking

of Fig. 6(c) when the BLE location satisfies Equation 7.

For each likelihood function, the x-axis is the slope classification which identifies it to the upward trend when $a_{j,1} > \alpha_1$, to the steady trend when $-\alpha_1 < a_{j,1} < \alpha_1$, and to the downward trend when $a_{j,1} < -\alpha_1$ as in the Fig. 7.

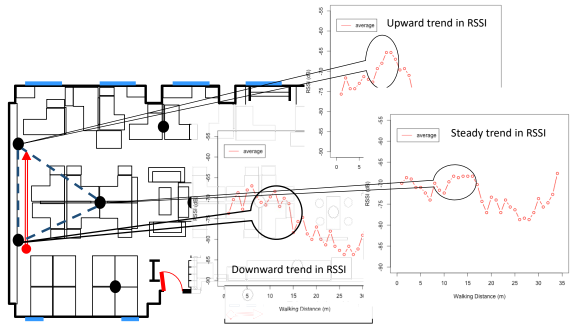


Fig. 7: Signal strength collected during walking

After calculating the likelihood for all path segment completely, we estimate the BLE ID j to be placed in location l_i by finding the largest value of likelihood as equation (8).

$$\arg\max_{i} \quad LH(s_j, l_i) \qquad (8)$$

In summary, the whole method can be summarized in the following steps:

(1) We received the floor plans with the interior design and device locations from the building manager, and analyze that floor plan to create the walking path and the triangle.

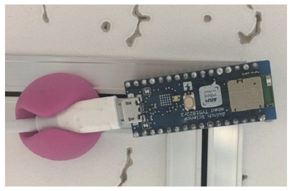
(2) We generate the path segments and the expectation trend of RSSI change by equation (4)–(7).

(3) We separate the path segment and give it to the tester for collecting the RSSI data. Note that, the tester may walk over one time depending on the result of equation 3 for each of the short paths individually.
(4) We calculate the linear model of the measured data from Equation 1 and 2 for each path segment.
(5) We compares the expected trend of RSSI change in step 2 and the slope of measured RSSI in step 4 to calculate the likelihood between BLE id and BLE location by likelihood function as in Fig. 6.
(6) Finally, we match the BLE id to the BLE locations using equation 8.

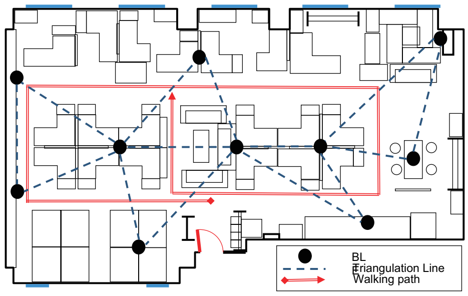
4. Experiment

The experiment is conducted in a laboratory room whose size is 10.6 x 17.79 square meters, and we manually generate the walking path and path segments whose distance are 45 meters and 4 meters respectively. We deploy 10 BLE BT 4.1 devices as in Fig. 8c, and deploy 9 BLE BT 4.1 devices as in Fig. 8d. We develop an android application to collect the signal strength of BLE using RSSI data. Accomplishing the RSSI collection, we request the tester to carry the NEXUS6P and walk on the walking path 5 times in clockwise direction and 5 times in counterclockwise direction. Note that, the experiment was conducted in an uncontrolled environment, i.e. other members also did their normal activities during collection. In addition, the floor plan, BLE location with triangle and walking path in this experiment are shown in Figure 8c. We assume the antenna will be on the surface of the devices such as lightning and HVAC, i.e. ceiling air vent as in Fig. 8a. Consequently, we place BLE on the ceiling(Fig. 8b) to simulate the situation as our assumption.

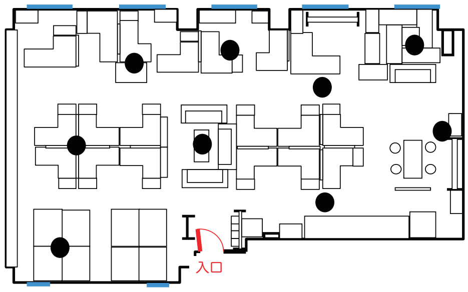
(a) Air vent where the antenna can be attached on the surface



(b) BLE module is placed on the ceiling



(c) The experimental floor plan with 10 BLE locations and walking path.



(d) The experimental floor plan with 9 BLE locations.

Fig. 8: Experiment setup

4.1 Parameter Selection

In order to perform our algorithm, parameters k and α_1 are necessary. For parameter k, we consider the BLEs which are suitable to be located in the triangle for each path segment. Since RSSI of BLE is unstable, we may be unable to apply $k = 3$ and get the accurate result. Therefore, we use the RSSI collection from the experiment as in the Fig. 8c and vary parameter k to investigate the effect of k to the matching accuracy. In the experiment, we measure the percentage of selected BLEs that are correct as "coverage".

Table 2: The experiment to find the parameter k

Round	$\overline{MSE}$	Coverage	
		$k = 3$	$k = 4$
1	1.71	85%	100%
2	0.83	85%	100%
3	0.62	90%	100%
4	0.46	90%	100%
5	0.35	90%	100%

The result in Table 2 demonstrates the coverage is 100% when $k = 4$. This means all of the correct BLE devices are selected. However, one invalid BLE device is also involved in the likelihood calculation, which may make the accuracy lower. Consequently, we use $k = 3$ where the coverages are at least 85%, and less invalid BLEs are involved in the likelihood calculation.

α_1 is the threshold for classifying slope of the linear model of RSSI. We apply two types of techniques to set threshold α_1; one is called *dynamic* that uses standard deviations (std) and another is called *fixed* that uses predefined values that are independent of the measurement.

Table 3: The experiment to find the threshold α_1

Method	α_1	correct
Dynamic	std	52%
	0.5*std	73%
Fixed	0.05	71.6%
	0.1	71.6%
	0.15	73%
	0.2	73%

Table 3 shows the percentage of correct classification. It shows that using half of the standard deviation as α_1 achieves better result than the normal std. Although some fixed values also achieved similar values, we need more investigation to choose the best values.

4.2 Matching Result

Based on the results in the previous section, we experiment on the matching accuracy with variables $k = 3$ and $\alpha_1 = 0.5 * std$. We compare the accuracy, the ratio of correct matching places to the total number of locations. In Table 4, accuracy when walking 1 to 5 rounds is shown.

Table 4: Matching Accuracy

Round	Accuracy(Fig. 8c)	Accuracy(Fig. 8d)
1	70%	78%
2	70%	78%
3	80%	89%
4	80%	89%
5	80%	89%

Our method captures 80% accuracy. According to Table 2, the performance of BLE selection affected the accuracy of matching. When the tester walked to collect the RSSI 3 times, 90% of correct BLE devices are selected, and the accuracy of localization was improved. Unfortunately, the accuracies cannot be 100% even when we walk more than 5 times because the average RSSI data become smooth after the tester walk 3 times.

4.3 Robustness

The result where BLEs are installed in the same room is satisfiable. However, the signal can propagate through the wall. Therefore we conduct the experiment to confirm our approach can match the BLE IDs to the BLE locations for each room individually. Specifically, we deploy 7 BLEs inside the experiment room and 3 BLEs close to the wall outside the experiment room as in Fig. 9.

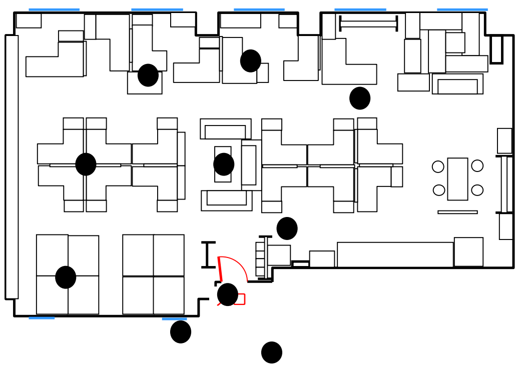


Fig. 9: The experimental floor plan with 7 BLE locations inside and 3 BLE locations outside.

We found our method can match the BLE IDs to BLE locations with the same accuracy as the experiment in Fig. 8d. Moreover, our method did not select the BLE located outside experiment room when the tester walks on the path segment which is close to those BLEs.

5. Discussion

We found the walking path affected the accuracy of our method. The reason is the path segment must pass inside the triangle as long as possible because we can spend more time on that triangle and can select the 3 BLEs by top-3 strongest RSSI method correctly. Particularly, when we walk close to one side of triangle, we may pick up some invalid BLE devices to be located in the triangle. For example, the BLE at the top right of Figure 8c, is located a little bit far from the walking path, and there are partitions located between that BLE and the walking path. In this situation, when the tester walks on the path segment which passes the triangular where that BLE is involved, the RSSI of that BLE is not high enough to be selected, and accordingly, the result becomes wrong in that location.

6. Conclusion

In this paper, we have presented the semi-automatic BLE localization. The experimental result in a single room has shown our method captured an acceptable result. We are now tailoring our method to work for larger areas. In particular, we will collect the data on the floor-level experiment to observe the patterns and behaviour of RSSI from the BLE in different ceiling pattern such as an open ceiling. will also consider the interior design which hinders the signal propagation to generate the walking path and path segments. Especially, there will be a material of the wall used to separate two rooms that does not reduce the signal strength too much (maybe glass and acrylic), and we can apply our algorithms as those rooms are the same room. Moreover, the automatic route generation is significant in our method because the manual route generation causes the burden on the prerequisite task, and the routes where the tester can pass most BLE devices are crucial.

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