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RSSI-based Bluetooth Indoor Localization

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***Abstract*-The Global Positioning System (GPS) has been widely used to determine the location for a variety of different applications. However, it doesn't work well in indoor environments because it requires the line of sight to the satellites and therefore stops working when the line of sight is not available. High-precision indoor localization is critical to many personal and business applications. After Bluetooth Low Energy (BLE), an energy-efficient version of Bluetooth, is widely deployed, Bluetooth-based indoor localization turns out to be a practical method to locate Bluetooth-enabled devices due to its low battery cost. In this paper, we present two novel BLE-based localization schemes, Low-precision Indoor Localization (LIL) and High-precision Indoor Localization (HIL). Different than most of the existing localization methods that attempt to find the specific location of the object under investigation, LIL and HIL utilize the collected RSSI measurements to generate a small region in which the object is guaranteed to be found. Compared with LIL, HIL leads to smaller localization regions. However, HIL requires an extra data-training phase.**

Keywords-Indoor Localization, Bluetooth-based Localization, Bluetooth LE

I. INTRODUCTION

People across the world have benefitted much from the Global Position System (GPS) over the past decades. The navigation capability enabled by GPS has been critical to many outdoor activities, such as hiking, flying, sailing, cross-country skiing, etc. However, GPS doesn't work well in indoor environments because it requires the line of sight to the satellites and therefore stops working when the line of sight is not available [1]. Over the past years, indoor localization has grown into an important research topic, attracting much attention in the networking research community.

GPS has significantly changed the manner in which outdoor activities are carried out. Indoor localization is expected to lead to a similar impact on our life. On the personal level, one important application of indoor localization is indoor navigation. With accurate indoor navigation, museum visitors or mall customers will not be lost any more. Another key application is object localization. With the localization capability, an object can be localized precisely. As a result, personal properties can be securely protected. And if they are lost, their locations can be easily pinpointed. On the business level, indoor localization can also be used in many different applications. One example application is to use indoor localization to study consumer interest and behaviour. With a deep understanding of consumer behaviour, a retail store can modify its layout and product type to satisfy its customers.

Many communication technologies, such as Wi-Fi, can be used for indoor localization. In our research, we chose to use Bluetooth Low Energy (BLE) because of its low energy and wide adoption features. The low energy feature guarantees that a Bluetooth tag attached to an object to be localized has a long lifetime. The wide adoption feature signifies that our proposed localization schemes can be used in many different applications and platforms [2].

In this paper, we present two novel BLE-based localization schemes, Low-precision Indoor Localization (LIL) and High-precision Indoor Localization (HIL). Different than the existing localization methods that provide the specific location of the object under investigation, LIL and HIL use the collected RSSI measurements to generate a small region in which the object is guaranteed to be found. In many applications, a precise region that covers the ground truth location is more important than a rough estimation of the real position. Compared with LIL, HIL leads to smaller localization regions. However, HIL requires an extra data-training phase.

The rest of this report is organized as follows. Section 2 discusses the related work of this project. Section 3 presents the design and implementation of LIL and HIL. The detailed experimental results on LIL and HIL are summarized in Section 4. Finally, Section 5 includes our conclusions.

II. RELATED WORK

Over the past two decades, many studies have been dedicated to indoor localization. Most of them can be divided into three categories: proximity detection, triangulation, and scene analysis. Proximity detection is a very simple method that determines the location of an object when it is close to a cell tower or access point [3]. Triangulation utilizes the geometric property of a triangle to locate the target [3]. Scene analysis is a pattern recognition method that finds the best matching pattern using scene characteristics [4]. In detail, the triangulation method can be further divided into two sub-categories: direction-based and distance-based. And there have been two types of distance-

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based schemes: time-based and signal property based methods. Since the proposed schemes are related to distance-based methods, we only focus on the distance-based methods: time-based and signal property based methods.

Time-based methods are normally used to measure range, we need to receive the precise ranges between target and beacons, and then utilize Triangulation method to calculate target location. Acoustic signal is the most commonly used in Time-based methods because of its low transmission speed and no additional hardware. It only requires the basic hardware such as speaker, microphone, and some inter-devices communication to achieve high accuracy ranging. Typically, high accuracy ranging is achieved through measuring time-of-arrival (TOA) information of acoustic signal because of its relatively slow speed. In practice, on both sides, TOA measurement takes a timestamp of their respective local clock at the moment that the signal is emitted or received [5]. Using TOA measurement, device A transmits a sound pulse at time t_A and says device B receives the sound pulse at t_B. The time difference is $\Delta t_{AB} = t_B - t_A$ and the distance d_{AB} between the devices is then $c*\Delta t_{AB}$. Then we can use triangulation method to determine the target location. From TOA method, we can understand that there are three keys implementation challenges, which are acoustic detection, software delays, and precise time synchronization. If the time is not precisely synchronized, it will cause very serious consequence. For example, each 0.01s error will result in about 3m error. Thus, we introduce Time Difference of Arrival (TDOA) method that will overcome this defect. TDOA requires relative time measurement instead of absolute time measurement. The possible target location is specified by the intersection of multiple hyperbolic curves, which are produced by multiple differences of arrival time measurements.

Signal Property based methods rely on measuring the strength of signals from proximate Radio Frequency source such as Wi-Fi access point (AP) or cell towers. In this section, we talk about the most popular Signal Property based method, which is Wi-Fi based indoor localization, because it does not require additional software or hardware. Moreover, in the previous section, we mentioned TOA and TDOA, which can provide high precision ranging. However, it requires line of sight acoustic signal. In contrast, Wi-Fi based Localization is not required. Wi-Fi based localization usually has two phases. First is training phase. We introduce a Fingerprinting approach that determines the location and constructs the radio map. The main theme is tantamount to collect the RSS (receive signal strength) characteristics of the various APs in the target (indoor) environment and then build a fingerprint database. In the second phase, the location of the object is later determined by matching online measurement with the closed location against the database [6]. However, this method can have lower accuracy and the previous studies investigated root cause [7]. In essence, two physically distant locations happen to share similar Wi-Fi signal strength measurements, thus a testing sample can be erroneously located to a physically faraway location with short Euclidean distance in the signal fingerprinting database [7]. There are also certain Wi-Fi limitations: signal attenuation of the static environment like wall, movement of furniture and doors [3], or some environmental factors such as temperatures, humidity and air flow rate.

Bluetooth technology is similar to Wi-Fi, but requires less power consumption, especially after BLE technology came out. BLE is a part of Bluetooth 4.0 specification, which was released in 2010 [8], and it uses the same radio frequencies and antenna as Bluetooth classic. The reason why BLE technology became so interesting compared to many other wireless protocols for engineers or product designers is that BLE uses an efficient design that can talk to any modern mobile platform such as iOS, Android, Windows phone and etc [2]. The most attractive feature for BLE is its low power consumption and we will talk about it from three aspects [9]: Lower Standby Time, faster Connections, lower Peak Power.

III. LIL and HIL: Two Indoor Localization Schemes

In this section, we present the details of LIL and HIL, two novel indoor localization schemes used to find a small region in which a Bluetooth-enabled device is guaranteed to be found.

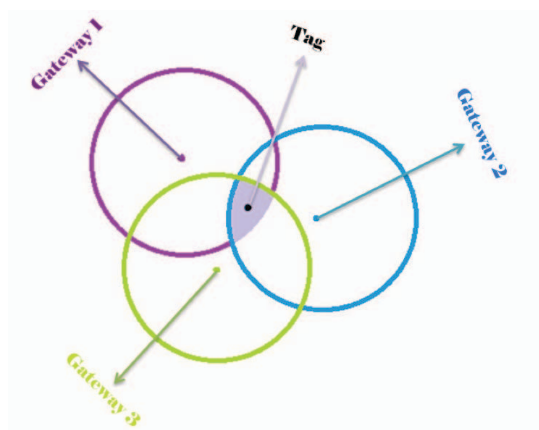

Figure 1. Tag within the Transmission Range of Multiple Gateways

A. LIL: Low-precision Indoor Localization

Due to the fluctuation about Received Signal Strength Indicator (RSSI), a Low-precision Indoor Localization (LIL) method was proposed to use different power levels to achieve compromised localization precision. The advantage of LIL is that the RSSI value does not affect our final result. Our only concern is whether our gateways receive RSSI signals or not. In concept, each transmission power of the tag will have a maximum transmission range limit. Beyond that limit, our gateways cannot get the RSSI signal anymore. As a consequence, we can draw a circle for each gateway, and the radius of the circle is the transmission range limit. Once one of our gateways gets RSSI signal, we will highlight that circle. If more than one gateway get signal, we will highlight the overlapping region which is the most possible location of the tag, and then we developed a Matrix-based determination method that will return the coordinates of the overlapping region. Figure 1 illustrates the scenario where the tag is within the transmission range of multiple gateways.

The idea of matrix-based determination comes from pixel-based graphics. The experimental field is transforming to a matrix, and each entry of matrix will represent a small region of whole experimental field. We can determine the resolution of matrix, which means changing the edge of each matrix cell. Clearly, the smaller the edge we set, the higher resolution we get.

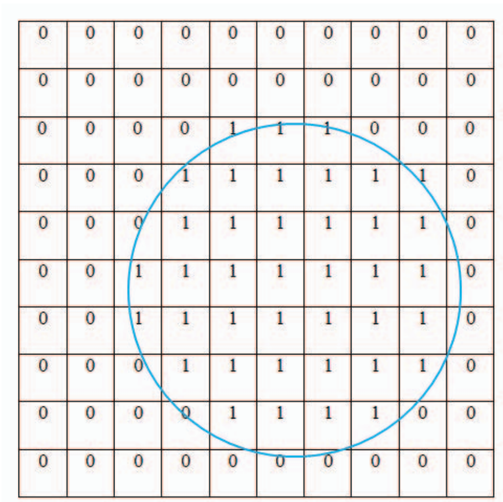

Figure 2. 10x10 Matrix-based Determination

For each matrix cell, at first, we initialize cell content to one, which means the tag can be in anywhere. Once a gateway obtains signals, any cells that outside the transmission range limit (radius) will be set to zero. It is very useful that no matter what floor maps look like, we just need a virtual rectangle to cover the whole region and return related coordinated range based on gateway locations, as we know the coordinates of every matrix cells. Figure 2 illustrates the case in which a 10x10 matrix is used to determine the coverage of a gateway.

We assume that the experimental field is a 7m x 7m region. The origin is located at top left corner. There are four gateways located at the 4 corners of the 7m by 7m region. The coordinates of the 4 gateways are (0, 0), (0, 7), (7, 7), and (7, 0), respectively. We set up two power levels. The tag's transmission range of low power level is 2m, and high power level is 5m. For each power level of each gateway, we created a matrix using Matrix-based determination. In this simulator, we had eight matrixes (4 gateways x 2 power level). In order to simulate a tag on the experimental region, we generate a random location of the tag. Due to different degrees of radio irregularity (DoI), although the tag is inside a gateway transmission range limit, we cannot guarantee the gateway can receive the signal. Figure 3 shows radio signal patterns for different DoIs.

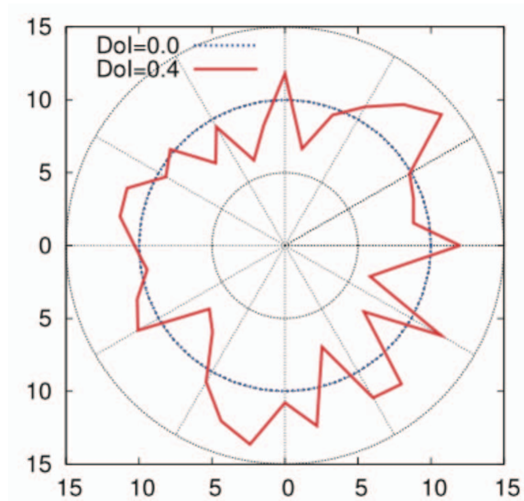

Figure 3. Radio Signal Transmission Pattern: Two Different Degrees of Radio Irregularity (DoI) [10]

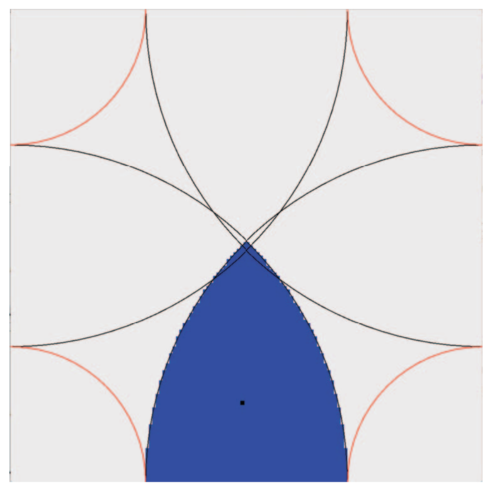

Figure 4. A 7m x 7m Simulation Field with Two Power Levels

Because of that, we have four possibilities for one gateway:

1. The gateway of high power level does not get a signal and low power level does not get a signal either. Clearly, we cannot determine the tag location.
2. The gateway of high power level does not get a signal and the low power level gets a signal. We can conclude that the tag is inside the low power level range.
3. The gateway of high power level gets a signal and the low power level does not get a signal. We can

only conclude that the tag is inside the high power level range.

4. For each gateway's power levels get a signal. We conclude that the tag is inside an overlapping region of both power levels.

At last, we used a logic AND operation on all the experimental matrixes to get final location region. In Figure 4, black line represents high power level, and red line represents low power level. In this case, we set the matrix resolution to 0.05m and realize bottom left gateway's high power level got a signal, and the bottom right gateway's high power also got a signal. As a result, we highlight the overlapping region.

B. HIL: High-precision Indoor Localization

In previous sections, we talked about LIL, which gave us a rough location range. However, the transmission range limit can be very large for high power levels. Consequently, the location of the tag will be in a large region. To solve this problem, we came up with a High-precision Indoor Localization (HIL) scheme based on LIL. HIL requires a RSSI data-training phase, which is used to split different power ranges into smaller bands in order to enhance precision.

At beginning, we are trying to create a training set to discover a potentially predictive relationship between RSSI value and distance. Firstly, we collect a bunch of RSSI samples every meter, and use 68-95-99.7 Rule [11] to filter non-normal sample data. Those samples will be our training set. Secondly, from 0m to transmission range limit, we are doing a cluster analysis that we partition our training set into different groups based on data similarity. Thirdly, in each group, every sample will be calculated the probability of occurrence. At last, there could be some overlapping samples with varying probabilities of occurrence among different groups. The solution is quite simple that we only choose the highest probability of occurrence for the RSSI sample.

Once a fresh RSSI sample is coming, the working process is presented as follows:

Fresh RSSI → Find the same RSSI sample value among different groups → Compare, choose RSSI sample with highest probability of occurrence → Return corresponding distance

To get close with real application, we are using a Bluegiga USB dongle as a gateway, and RadBeacon Tag as our tag. RadBeacon Tag is a fully standalone Bluetooth Smart™ proximity beacon using iBeacon™ technology, implemented in a lightweight package that is powered by a battery [12]. We downloaded and installed their RadBeacon app, which we can set transmission power, transmission frequency, UUID and etc. There are seven transmission power levels from -20db to 4db inside tag, but we only use the lowest two power levels: -20db and -16db, due to the limitation of testing region. As we found in our experiments, the transmission range limit of -20db is around 2m, and -16db is around 5m.

In order to read RSSI from USB dongle, we use Bluegiga's Bluetooth Smart SDK, which provides a complete development framework. There are two architecture modes supported by Bluetooth Smart SDK: Standalone and Hosted architectures. In this project, we used Hosted architecture that allows end user application runs on a separate host, which is our PC. The Bluetooth Smart SDK is made of several components including Binary based communication protocol (BGAPI) and a C library (BGLib) that implements the BGAPI protocol for the host.

There are three message types in BGLib, which are command, response and event. Obviously, command is from the host to the USB dongle stack, while response and event are from the USB dongle stack to the host.

In our ANSI C application, we sent multiple commands to configure the dongle, check connection status, and switch to the scan model. After that, we also needed to implemented corresponding callback function in order to handle a coming event or response. Finally, we read data including RSSI values, MAC address and other information through serial port.

As we discussed before, we used -20db and -16db power levels to provide RSSI samples. For each power level, from 0m to its transmission range limit (-20db: 2m, -16db: 5m), we collected 110 RSSI samples every 0.5m. The first 100 samples were used on data training and the last 10 samples were simulated as new coming input. In data training, we utilize cluster analysis to partition 2m (-20db) into two bands: 0m-0.5m and 0.5m-2m. Just like with the -16db, we partitioned 5m into two bands: 0m-1.5m and 1.5m-5m. Based on these two power levels, the simulator region was constructed by 7m by 7m. We also proposed four gateways located in each corner and a random location tag. The whole procedure shows below:

1. Generate a random location of a tag, and calculate distances to all gateways (D1, D2, D3, D4).
2. For each distance (D1 as the example), use binary search algorithm to find the closest distance in the training data (For instance, if the distance is 4.9m, then the closest distance in the training data is 5m; if the distance is 4.6m, then the closest distance in the training data is 4.5m). Let us call the closest distance D1_c.
3. After finding D1_c (e.g. 5m), randomly choose a RSSI from the last 10 RSSI measurements corresponding to D1_c. The chosen RSSI is used as the simulated RSSI for D1. If D1_c is covered by both the low power and high power range, then two simulated RSSI measurements will be chosen.
4. For D2 to D4, use the same method to generate the simulated RSSI measurements.

5. For each simulated RSSI value, apply data training to find corresponding distance band and use Matrix-based determination to locate the band.
6. Use logic AND operation on all experimental matrixes, and find the ultimate band.

If HIL failed (tag is outside ultimate band), LIL will be applied.

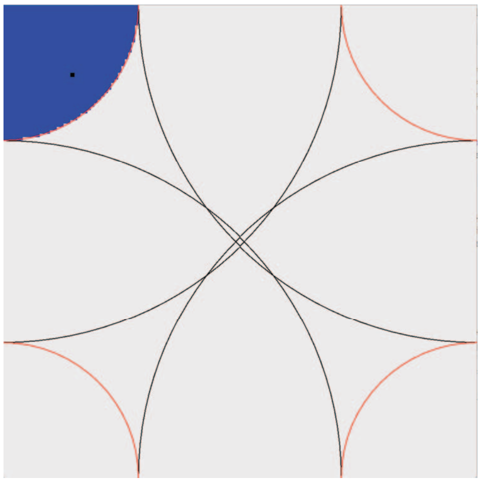

Figure 5. Matrix Resolution = 0.05m

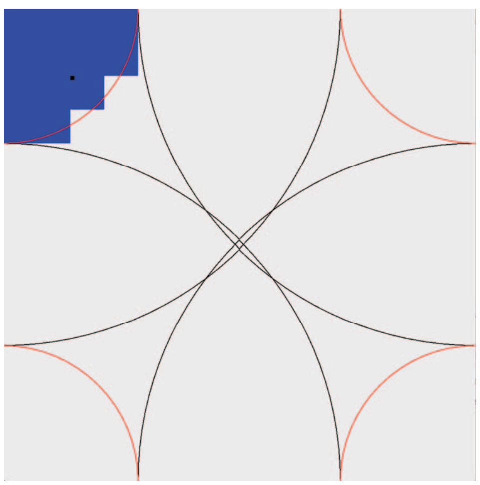

Figure 6. Matrix Resolution = 0.5m

IV. EXPERIMENTAL RESULTS

We carried out extensive simulation-based experiments to study the performance of LIL and HIL. The experimental results are presented from three aspects: resolution and complexity, LIL and HIL region, and localization accuracy. In our simulations, we used a 7m x 7m experimental field. Other detailed settings of the simulations are described in the following sections.

A. Resolution and Computation Complexity

Using the proposed matrix-based region determination method, the higher the resulting resolution, the higher the computation complexity of the localization algorithm. In Figure 5 and 6, the resulting regions of two matrix resolutions are illustrated. In Figure 5, the resolution is set to 0.05m. Consequently, 1256 small matrix cells are used to cover the corresponding area.

However, in Figure 6, only 13 larger rectangles are used because the resolution is set to 0.5m. Clearly, Figure 5 is more accurate than Figure 6 at the cost of higher computation complexity.

B. LIL and HIL Region

LIL and HIL use the RSSI measurement to determine that region in which a Bluetooth tag is located. Figure 7 and 8 illustrate the resulting regions in an example scenario where that the tag location is (1,1) and the matrix setting is 0.05m. Figure 7 shows that the ultimate distance band, which is determined by LIL method, is 0m-2m.

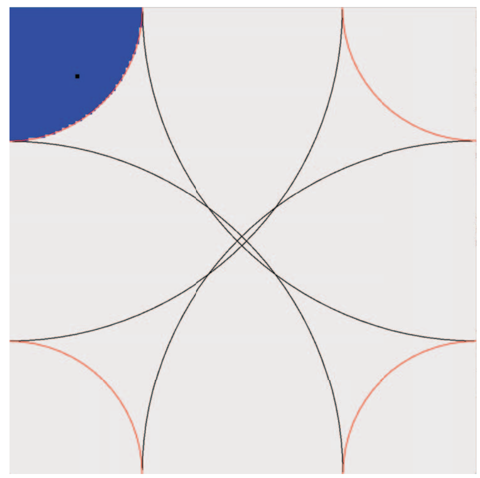

Figure 7. LIL Region

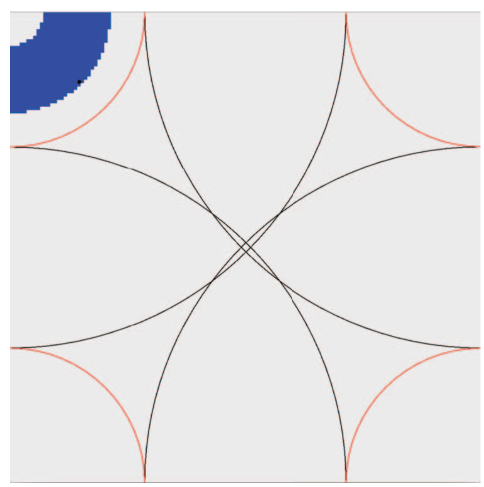

Figure 8. HIL Region

In Figure 8, as the tag location is (1,1). We know the distance from the tag and top left gateway is about 1.414m. So we randomly choose two RSSI values from the nearest distance (1.5m). The low power RSSI value got from top left gateway is -87db, which possibility we know from training data is 57%. Similarly, the high power RSSI value is -84db and its possibility is 77%. As a consequence, the low power level of the top left gateway located 0.5m-2m distance band, and the high power level of top left gateway located 0m-1.5m distance band. Finally, we got the ultimate distance band is 1.5m-2m, which covered by both. Obviously, this result is much smaller than LIL result (0m-2m).

C. Localization Accuracy

In Figure 9, we used our simulator to generate 100 random locations and showed a cumulative distribution function (CDF) curve. In probability theory and statistics, for every value x of statistical distribution, CDF displays the probability that less than the x value. For example, in our case, we used traditional LIL and HIL methods to collected results not Disc-based method. From CDF graph, the Y-axis is the probability and X-axis is ultimate covered region, in which the unit is the square meter. As we mentioned previously, our test field is 7m x 7m and the resolution of the matrix is 0.05m, which means there are 19600 $(7m / 0.05m)^2$ matrix cells in the region and each matrix cell is $0.0025m^2$. As we can see in our CDF graph, the curve is not smooth but stepwise. The reason is that we build our simulator in a symmetrical way. For instance, overlapping region of two high power levels that can have four possibilities in test field represents the specific area that equals 7.395 m^2.

Comparing two CDF graphs below, from $0m^2$ to $2m^2$ in X-axis, obviously, the ultimate covered location region in HIL has more probability than LIL's, which means in 100 samples, about 25 percent of samples are smaller than $2m^2$. However, LIL only has 2 percent. Thus, it proves HIL will provide more accuracy.

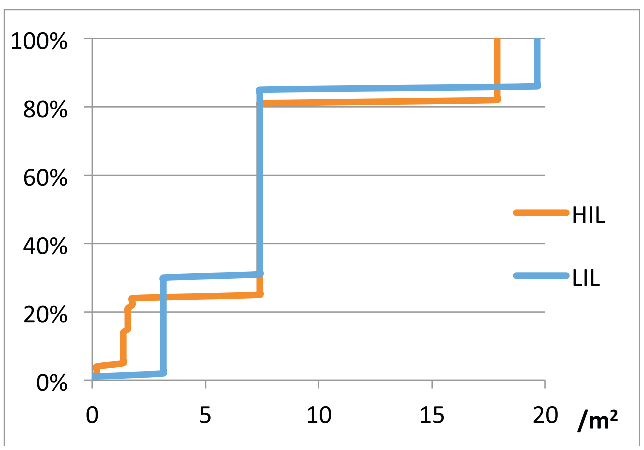

Figure 9. CDF Graph of LIL and HIL

Because HIL utilized data training as a prediction to determine distance band, next we will show a histogram that compares the percentage that the tag is within the region based on LIL and HIL. From Figure 10, based on our 100 experiments on LIL and HIL, we see that HIL is still capable to achieve 93% successful rate.

Figure 10. Successful Rates of HIL and LIL

V. CONCLUSIONS

In this paper, we present two novel Bluetooth-based indoor localization methods, LIL and HIL. Both of them utilize the RSSI measurements to generate a small region in which the Bluetooth-enabled device is guaranteed to be found. Our experimental results indicate that HIL is more accurate than LIL in most scenarios because of its extra phase of data training. Furthermore, HIL leads to a satisfactory successful rate. Overall, if a data training phase is feasible, HIL is a more appropriate scheme than LIL.

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