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Energy-Efficient Indoor Localization of Smart Hand-Held Devices Using Bluetooth

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ABSTRACT Indoor localization of smart hand-held devices is essential for location-based services of pervasive applications. The previous research mainly focuses on exploring wireless signal fingerprints for this purpose, and several shortcomings need to be addressed first before real-world usage, e.g., demanding a large number of access points or labor-intensive site survey. In this paper, through a systematic empirical study, we first gain in-depth understandings of Bluetooth characteristics, i.e., the impact of various factors, such as distance, orientation, and obstacles on the Bluetooth received signal strength indicator (RSSI). Then, by mining from historical data, a novel localization model is built to describe the relationship between the RSSI and the device location. On this basis, we present an energy-efficient indoor localization scheme that leverages user motions to iteratively shrink the search space to locate the target device. An Motion-assisted Device Tracking Algorithm has been prototyped and evaluated in several real-world scenarios. Extensive experiments show that our algorithm is efficient in terms of localization accuracy, searching time and energy consumption.

INDEX TERMS Energy efficiency, indoor localization, data mining, bluetooth, IoT.

I. INTRODUCTION

With Internet of Things (IoT) fast approaching, nowadays people in their daily lives are surrounded by more and more smart devices such as laptops, phones and tablets that are capable of sensing the environment and communicating with each other [1]. While enjoying the numerous benefits of IoT, new problems are also emerging. Among them, indoor localization of smart devices plays a critical role in various pervasive applications such as medicare [2], smart home [3], and social networks [4].

During the last few decades, tremendous research efforts have been dedicated to resolving this localization issue. A majority of previous solutions rely on the wireless signal fingerprints as an efficient way for location determination. In general, wireless fingerprint-based localization consists of two phases: training and serving. In the training phase, it leverages existing wireless access points (APs) and uses off-the-shelf equipments to collect signals from different APs to form the training database, i.e., the location-related fingerprints. In the serving phase, when it receives from a user a query message including unknown wireless fingerprints, it will launch the localization algorithm to obtain the matched record within the database and return the corresponding locations to the user.

For one location, one AP leaves one single entry in the corresponding fingerprint. Thus, the root cause of the localization error for fingerprint-based approaches is that different locations may exhibit similar signatures [5]. More APs naturally lead to more abundant fingerprint information, and thus to more accurate localization results. Chandrasekaran *et al.* reported that high accuracy (e.g., sub-meter median and 2m maximum) can be achieved under hundreds of APs [6].

The localization accuracy also depends on the site survey in the training phase, which is time-consuming and labor intensive. The significantly raised cost caused by APs and site survey poses a great challenge for these fingerprint-based solutions and calls for in-depth studies.

To this end, by exploring Bluetooth RSSI and user motions, we present Motion-assisted Device Tracking Algorithm (MADT), a novel algorithm to fast localize target devices without any APs or the laborious site survey process. Instead of using signature entries from APs, MADT utilizes the fundamental rules of RSSI and environmental factors such as distance and direction, so as to guide a user with a device receiving Bluetooth signal from the target to gradually approach them.

More specifically, we first conduct a systematic experimental study to gain in-depth understandings of

Bluetooth characteristics, .e.g., the impact of various factors such as distance, orientation, obstacles and time of the day on the Bluetooth RSSI. With the empirical experiences, a novel localization model is built to describe the relationship between RSSI and these factors.

In order to fast track down the target device, we explore user motions where a user carrying another device moves around and searches for the Bluetooth signal source, i.e., the target device. We present a RSSI-based localization scheme to online schedule the user movement based on the localization model, which iteratively adjusts the search directions according to RSSI changes.

We have prototyped and evaluated our scheme in several real-world scenarios in our university campus. Experiments confirm that the proposed scheme is efficient in terms of localization accuracy, searching time as well as energy consumption. Note that Bluetooth is chosen due to its low energy consumption. Our proposed system is adaptive to other wireless sources such as WiFi and ZigBee.

In summary, our work makes the following contributions,

- We present an extensive empirical study in real-world scenarios, so as to understand the impact of various factors such as distance, orientation, and obstacles on the Bluetooth signals.
- We build a novel localization model that characterizes the relationship between changes of RSSI values and the target location.
- We propose MADT, a logarithmic complexity algorithm that can quickly approach the target device by iteratively shrinking the search space.
- We prototype our system and conduct extensive real-world experiments. Results confirmed that the proposed scheme is efficient in terms of localization accuracy, searching time and energy consumption. Moreover, important insights have been obtained and valuable hand-on experiences are also provided.

The rest of the paper is organized as follows. We analyze the issue in the next section. Then, we present an empirical study of various factors on bluetooth RSSI in Section III. Section IV gives the details of our localization algorithm. Then, we prototype the design and present real-world experimental results in Section V. Related issues are introduced in Section VI. Finally, Section VII concludes the paper.

II. RESEARCH OVERVIEW

A. OBJECTIVES AND THEORETICAL ANALYSIS

Consider the following scenarios that may happen in our daily lives,

Scenario 1: Bob, living in a single-room apartment, has one iPhone and one iPad. One morning when he is about to work, he can not find his iPhone. He tries to call it on the wired phone but there is no response due to the poor 3G/4G signal indoor. Or simply the phone is set to the silent mode. How can Bob quickly locate his iPhone using iPad?

Scenario 2: Alice, wondering in an exhibition, brings one tablet to record the exhibits. When she is about to leave, she finds her tablet left somewhere within the exhibition room. She has a smart phone, but she could not call the tablet because it is not equipped with any phone module. How can Alice quickly find her tablet using her phone?

The above scenarios have one simple objective:

- **How to localize a smart device (target device) quickly using another smart device (holding device) only?**

Theoretically, the issue is easy to address under the ideal case. The ideal case is defined as a scenario where a perfect signal propagation model exists with parameters precisely given. For instance, a simple propagation model for the free space is presented in [7] as follows,

$$\begin{aligned} RSSI &= P_{TX} + G + 20\log(\frac{c}{4\pi f}) - 10n\log(d) \\ &= P - 10n\log(d) \end{aligned} \tag{1}$$

where P_{TX} is the transmit power (in dBm) of the target device, G is the combined antenna gain (in dBi) of both transmitter and receiver (holding device); c is the speed of light ($3.0 \times 10^8 m/s$) and f is the central frequency (2.44 GHz); n is the attenuation factor (ranging from 2 to 4; 2 in free space) and d is the distance between transmitter and receiver (in m). Therefore, d can be calculated as follows,

$$d = 10^{\frac{P-RSSI}{10n}} \tag{2}$$

However, the deduction of d in the real-world case is much more complicated. On one hand, hardware-related parameters such as P_{TX} and G are usually unknown. On the other hand, there exist various factors that are ignored in the model but could impact the RSSI, such as walls and furniture. Plus, even if d is known, without an accurate direction of the target device, it still takes time and efforts to find it. Therefore, due to unexpected elements in realistic applications, it may not be a good idea to count on the theoretical model to determine the locations of target devices.

The **distance** and **direction** are the most fundamental factors for localizing a target device. Between them, direction is more important because once the user has the right direction it is much easier to find the target using bare-eyes. Therefore accurate distance measurements become less significant.

In the next part, we analyze the unique challenges as well as the countermeasures of this localization issue.

B. CHALLENGES AND COUNTERMEASURES

The theoretical method encounters near-insuperable obstacles in real-world applications, since it demands accurate information about both the propagation model and the environmental factors. Thus it is nearly impossible to present a pervasive model that is adaptive to all scenarios.

However, some general rules between RSSI and the location of the target device may exist and help us design the localization algorithm that locates the target under very limited information.

To this end, let us revisit and analyze the issue,

- *What We Have:* Wireless modules of the target device are turned on (e.g., WiFi or Bluetooth) and the ID is known.

A user is holding another device which is also embedded with the wireless modules.

- *What We Don't Have:* The target location information including the direction and distance from the user. The hardware related parameters such as transmit power, antenna gain of both transmitter and receiver, etc. Environmental factors such as the floor plan, and APs.

In summary, the simple objective involves many challenges from both design and implementation aspects:

- The suitable signal source. In short, Bluetooth or WiFi?
- The general rules between RSSI and location of the signal source, i.e., the target device.
- A light-weight localization algorithm based on these rules that can track down the signal source quickly.

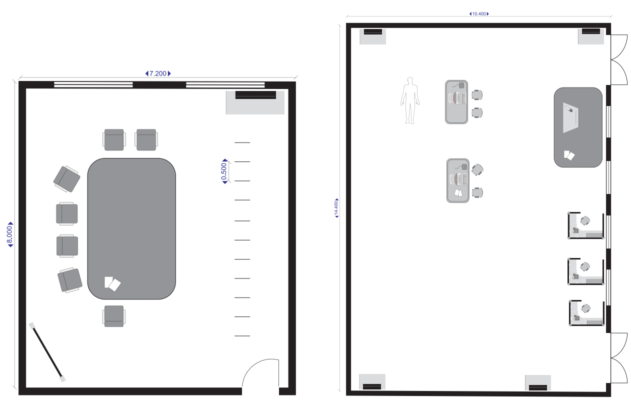
Therefore, to address the challenges, we conduct extensive real-world experiments in the next section to specifically answer the following questions,

- Which source to use in terms of energy efficiency? WiFi or Bluetooth?
- How to set experimental parameters such as sampling rate, number of samples per measurement, and the time of day when the experiments take place?
- What is the relationship between location and RSSI in real-world scenarios?
- How does environmental factors such as obstacles between two devices affect the RSSI?

In the next section, we present details about the empirical study as well as several derived investigations.

III. EMPIRICAL STUDY

To gain in-depth understandings on the Bluetooth characteristics, we conduct an empirical study on some selected factors (e.g., distance, orientation, number of samples, sampling rate, time of the day, obstacles, etc.) in two typical indoor environments, i.e. a conference room and an exhibition room with furniture, as shown in Fig. 1.



(a) (b)

FIGURE 1. The layouts of experimental scenarios. (a) Conference room. (b) Exhibition room.

A. EXPERIMENTAL SETUP

Two experimental sites at Hefei University of Technology are selected to carry out the experiments, namely,

[Conference room, CR]: Room 205 in our facility. Its floor plan is shown in Fig. 1(a). The floor size is $7.2m \times 8m$.

[Exhibition room, ER]: Room 206 in our facility. Its floor plan is shown in Fig. 1(b). The floor size is $10m \times 14m$. It is much bigger than the conference room. Except for several robots placed inside, it is basically empty and therefore is the closest environment similar to the free-space scenario.

We use two tablets as the test hand-held devices: one is Samsung SM-P601 as the target device (Android 4.3); the other one is Samsung GT-N5110 as the holding device (Android 4.1). The Android system is selected due to its customization capabilities. The defaults of factors are highlighted in Table 1.

B. WiFi OR BLUETOOTH

WiFi and Bluetooth are two essential modules in modern hand-held devices to enhance the ability of interacting with others.

On one hand, in indoor scenarios, the distance between two devices are often limited to a few meters. Therefore, both WiFi and Bluetooth are adequate in coverage. On the other hand, energy becomes one of the most critical considerations for the smart devices since people want the battery to hold as long as possible. Therefore, we compare them in terms of energy efficiency. We write an app to record time and battery level every 30 minutes while performing the following actions with screen on:

- Turn the tablet into flight mode.
- Turn only WiFi on and set the sampling rate to 1 sample per second.
- Turn only Bluetooth on and set the sampling rate to 1 sample per second.

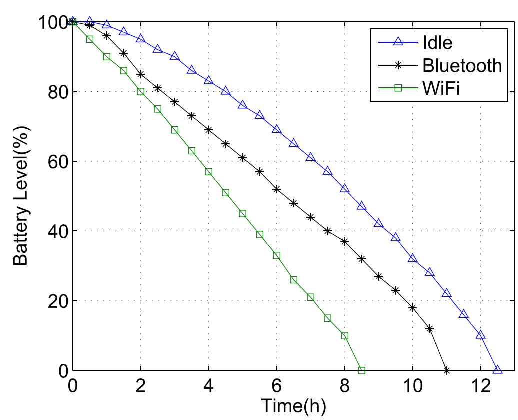


FIGURE 2. Energy consumption comparison of Bluetooth and WiFi over N5110.

Both tablets show the same phenomenon and thus we only discuss N5110 as an example. The results are shown in Fig. 2. The battery can hold over 13 hours under the flight model,.

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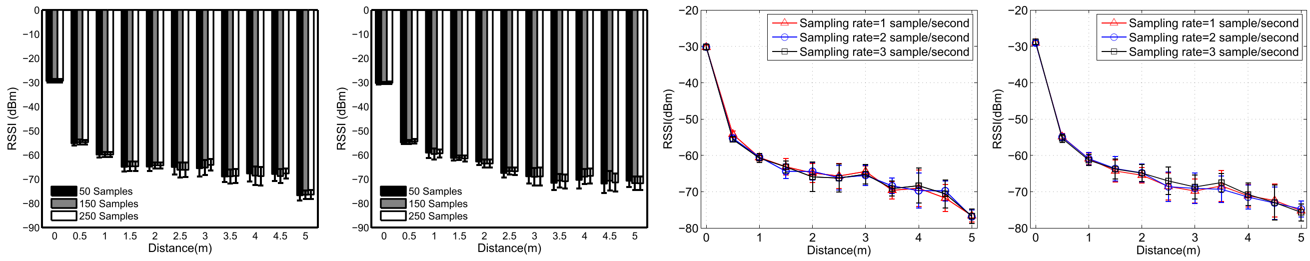
TABLE 1. Factors under study (defaults are highlighted).

Factors	Descriptions	Value
Sampling rate	The number of samples taken per second	{1,2,**3**}
Number of samples	The number of samples taken per measurement	{**50**,150,250}
Time of the day	Different times the measures are taken	{**morning**, afternoon and night}
Distance	The distance between two devices	{0m,0.5m,1m,1.5m,2m,2.5m,**3m**,3.5m,4m,4.5m,5m}
Orientation	The relative direction to which Device A is facing	{**West**, North, East, South}
Obstacles	Different types of obstacles on the target device	{**None**, Book, Cloth, bag}



(a) (b) (c) (d)

FIGURE 3. Bluetooth RSSI versus sampling rate and number of samples. (a) Number of samples, CR. (b) Number of samples, ER. (c) Sampling rate, CR. (d) Sampling rate, ER.

Bluetooth will consume some energy and the lifetime drops slightly (11.5 hours). While the number drops to 9 hours for WiFi. Clearly, Bluetooth consumes much less energy than WiFi (37.5%) and thus should be a better choice.

C. EXPERIMENTAL PARAMETERS

Before we conduct experiments to figure out the relationship between RSSI and physical locations, we should determine suitable experiment parameters such as number of samples per measurement and time of the day.

[Number of Samples VS RSSI]: For each measurement, more samples naturally lead to more accurate measurements, but at the cost of higher energy and time overheads. Therefore, to achieve a tradeoff between accuracy and overheads, we conduct experiments with number of samples ranging from 50 to 150. The results in terms of mean RSSI values as well as the corresponding error bars (the error bar represents the standard error in the mean here and afterwards) are presented in Fig. 3. It turns out that the number of samples has little impact on the RSSI data (the biggest RSSI difference is within 1.1%), implying that accurate measurement does not depend on the sampling intervals (corresponding to the number of samples). Thus we choose 50 samples as default to reduce overheads while maintaining accuracy.

[Sampling Rate VS RSSI]: We vary sampling rate from 1 sample per second to 3 samples per second and record the mean RSSI over distance with error bars in Fig. 3. Two investigations are obtained. First, for both scenarios, the differences between different sampling rates are quite limited: the biggest difference for both cases are within 1%. Therefore, we choose 3 samples per second as default in the following experiments, since it will accelerate the localization process.

The other investigation is that the measurements turn unstable with the increment of distance, suggested by the error bars. The phenomenon has been spotted frequently in the other experiments. The reason is straightforward: initially, the signal is strong within the close range. When the distance increases, the signal grows weak and is easily affected.

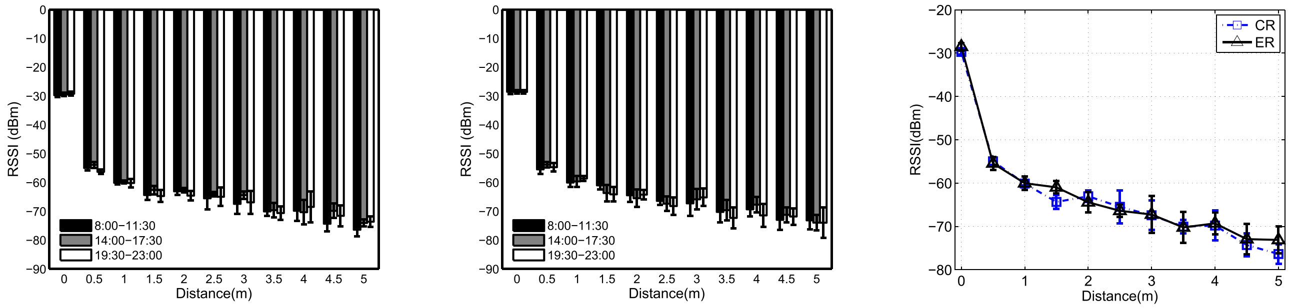
[Time of the Day VS RSSI]: We now study the impact of time of the day on the Bluetooth RSSI. The measurements are taken at three different time periods of a day, i.e. morning (8:00-11:30), afternoon (14:00-17:00), and evening (19:30-23:00). Fig. 4(b) presents the results in terms of mean RSSI values with the corresponding error bars. One interesting observation is that the time when samples are taken only has insignificant affect the RSSI values, i.e., within 1%. In other words, we should not pay much attention to this time factor.

We also compare the measurements taken at both rooms using the afternoon data, as shown in Fig. 4(c). Both curves are very close to each other, but there still exists measurements that exhibit differences to some extent at certain distance, e.g., 1.5m. The phenomenon indicates that sometimes the experimental sites may have limited influences on the RSSI.

D. RELATIONSHIP BETWEEN LOCATION AND RSSI

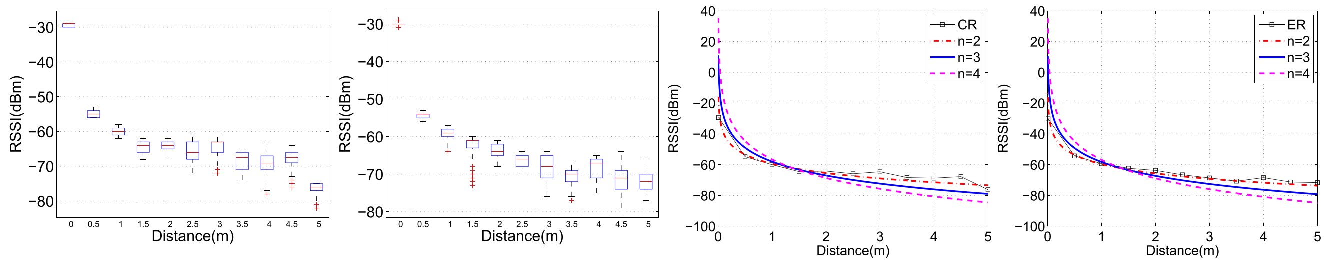
As stated above, there are two essential elements about locating the target device: distance and orientation. Therefore, in this part, we conduct experiments to gain the empirical understandings about the two elements and Bluetooth RSSI.

[Distance VS RSSI]: Experiments are conducted in both CR and ER. The location of AP is fixed while the laptop is moved gradually away from the AP (0.5 meters per step).



(a) (b) (c)

FIGURE 4. WiFi RSSI versus time of the day. (a) CR. (b) ER. (c) Room comparison, Time: afternoon.



(a) (b) (c) (d)

FIGURE 5. WiFi RSSI versus distance-CR and ER. (a) Boxplot, CR. (b) Boxplot, ER. (c) Fitted curves, CR. (d) Fitted curves, ER.

We use the boxplot to summarize the results in Fig. 5(a) and Fig. 5(b), which contains five quantities: lower quartile 25%, median, upper quartile (75%), and the two extreme observations [8].

Eqn.1 theoretically characterizes the relationship between RSSI and distance. To very this equation, we use Matlab 2012 to generate fitted curves with different attenuation factors (ranging from 2 to 4) for both scenarios. The results are shown in Fig. 5(c) and Fig. 5(d).

TABLE 2. Coefficients for the CR and ER.

n	P	95% Confidence Bounds	R-square
		CR	
2	-59.66 dBm	(-62.11, -57.21) dBm	**0.9078**
3	-58.25 dBm	(-65.8, -50.69) dBm	0.1242
4	-56.84 dBm	(-69.56, -44.12) dBm	-1.4844
		ER	
2	-59.41 dBm	(-62.16, -56.67) dBm	**0.8872**
3	-58 dBm	(-65.66, -50.35) dBm	0.1230
4	-56.6 dBm	(-69.37, -43.82) dBm	-1.4462

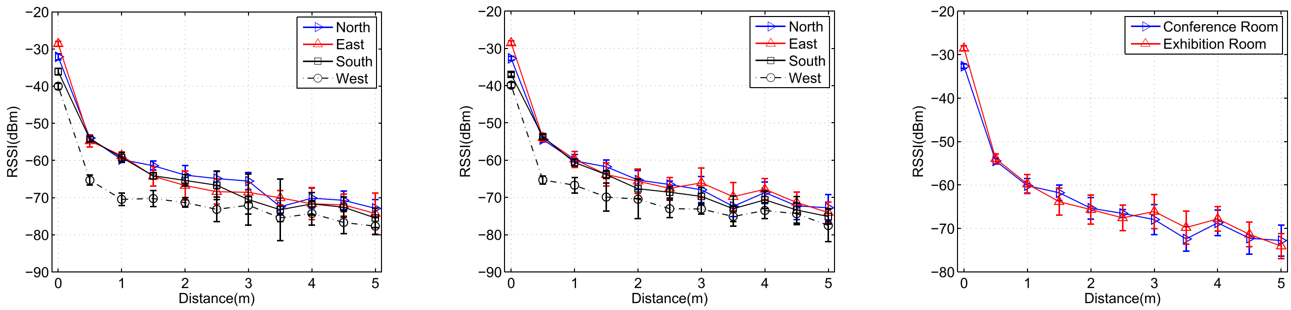
Table 2 shows the details about the fitting curves, where R-square stands for the coefficients of multiple determinations. This statistic measures how successful the fit is in explaining the variation of the data. A value closer to 1 indicates a better fit. For both cases, the highest value is achieved at $n = 2$, as we highlight in the table. Also, we notice that the fitted values of the hardware related parameter P for both scenarios are very close: the difference is about 0.42%, verifying that indeed the same hardware is used for both cases.

In summary, two interesting observations can be derived via experiments from both scenarios. First, Bluetooth RSSI fades with distance. The relationship between them can be briefly described by Eqn.1. Second, we notice that as the distance increases, measurements at one location becomes unstable. This phenomenon can be captured by the SD (Standard Deviation, σ) of the data group at the location. The reason lies in that when the distance increases the signal interferences caused by the shadow fading and multi-path fading become more significant.

[Orientation VS RSSI]: With the stationary target device whose antenna points to the west, we change the orientation of the holding device and take measurements. As shown in Fig. 6, RSSI differences among different orientations are quite notable for both CR and ER. In all cases, when the receiver antenna points to the west, i.e., **the same direction of the transmitter**, RSSI readings are the weakest. The average differences between west and other orientations are listed in Table 3.

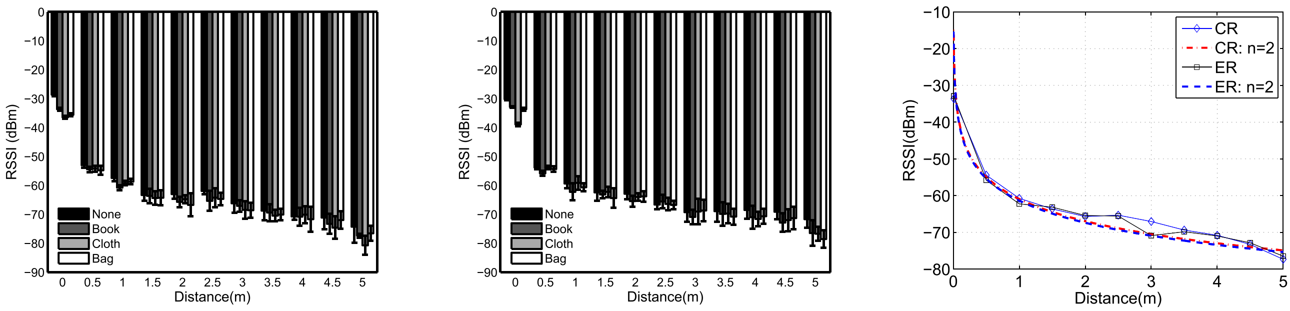
TABLE 3. RSSI differences between west and other orientations.

Orientation	average difference: CR	average difference: ER
North	6.24 dBm	6.41 dBm
East	7.17 dBm	6.81 dBm
South	5.22 dBm	4.14 dBm



(a) (b) (c)

FIGURE 6. **WiFi RSSI versus orientation. (a) CR. (b) ER. (c) Room comparison, Orientation: cm.**



(a) (b) (c)

FIGURE 7. **Bluetooth RSSI VS Obstacles. (a) Conference room. (b) Exhibition room. (c) Room comparison: books.**

For other three orientations, due to signal reflections caused by multi-path or shadow fading, the differences among them are not so obvious. The relationship is hard to be characterized by simple rules. But in general, when the transmitter points to the east, **i.e., the opposite direction of the transmitter**, the signal is the strongest. The reasons are two-folders. First, when the receiver antenna points to the same direction of the transmitter, signal needs to penetrate the device to reach the receiver antenna. Second, the length of the device needs to be considered since signal has to travel an extra distance to reach the antenna.

E. OTHER FACTORS THAT MAY AFFECT LOCALIZATION

The most typical and common factor that may affect the fast localization is the obstacles covering the target device, such as books, clothes and bags.

[RSSI VS Obstacles]: The experimental results are shown in Fig. 7. For both CR and ER, the signal is stronger if there exists no obstacles. That means that obstacles do block the signal.

However, the influences of different kinds of obstacles are different. In general, books degenerate the signal more significantly than others, since it is much harder to penetrate.

Another interesting observation is that though the signal has been affected the fading pattern remains, i.e., RSSI always decreases with distance. To confirm the observation, Fig. 7(c) shows the fitted curves for both scenarios where the book is selected as the obstacle since it has the most severe interferences on the signal. We set $n = 2$ since it is still the most suitable parameter.

As shown in the Table 4, P slightly decreases compared to the none obstacle case, i.e. 1.61 dBm on average. That means the obstacle, i.e., the book, blocks the signal and leads to a reduced the antenna gain. We also notice that judging by the R-square values both curves fit well with measurements.

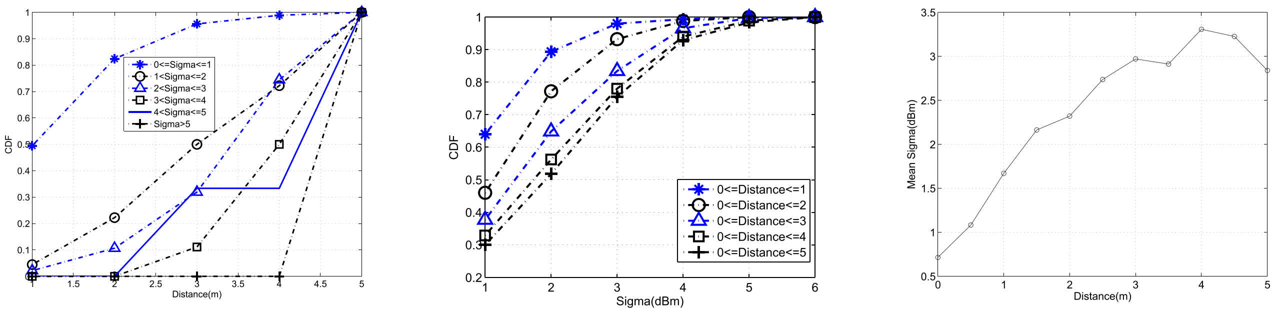
TABLE 4. **Coefficients for both CR and ER when the book is the obstacle.**

n	P	95% Confidence Bounds	R-square
		CR	
2	-60.93 dBm	(-63.97, -57.88) dBm	**0.8506**
		ER	
2	-61.36 dBm	(-64.14, -58.59) dBm	**0.8788**

F. SUMMARIES AND DISCUSSIONS

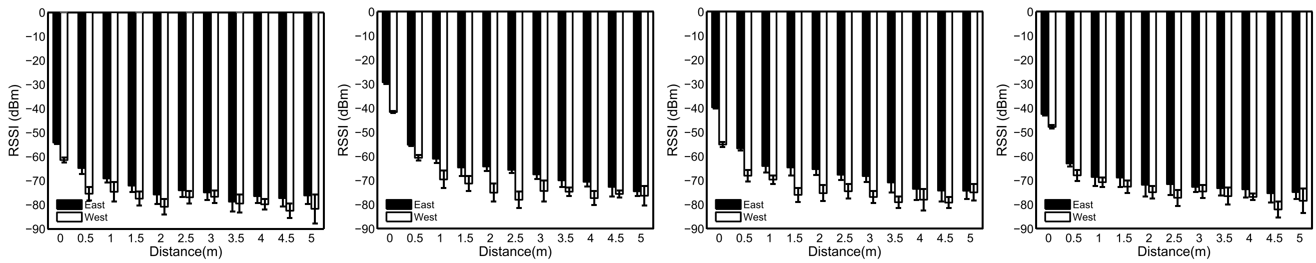
Via the above empirical studies, following fundamental rules are derived, namely,

- *Rule 1:* Bluetooth RSSI fades with the distance and the fading pattern can be characterized by Eqn.1 to some extent. The SD of measurements taken at one location can be explored to determine the range of distance.
- *Rule 2:* At a fixed location, set the average RSSI readings to $RSSI_t$ and $RSSI_b$ when the receiver antennas is aligned towards and backwards to the transmitter, respectively.



(a) (b) (c)

FIGURE 8. **Statistic results of the SD over all measurements. (a) Distance interval: 0.5m. (b) CDF of σ. (c) Overall statistics.**



(a) (b) (c) (d)

FIGURE 9. **Experiments to confirm Rule 2. (a) Transmitter antenna orientation: East. (b) Transmitter antenna orientation: West. (c) Transmitter antenna orientation: South. (d) Transmitter antenna orientation: North.**

Then, $RSSI_t > RSSI_b$ no matter where the transmitter antenna points to.

- *Rule 3:* Other factors such as obstacles may impact RSSI values but have limited influences.

The relationship between SD and distance should be further studied. To this end, the statistical results of the SD over all the measurements (1892 groups of data in total) are shown in Fig. 8. Fig. 8(a) shows the CDF (Cumulated Distribution Function) of distance over different ranges of the SD. Fig. 8(b) describes the CDF of SD over different ranges of distance. Both figures have clearly confirmed the connections between distance and SD: a smaller SD leads to a shorter distance.

To fasciate the following experiments, we record the mean σ of all measurements in Fig. 8(c), which provides empirical values to quickly map SDs to the distances.

For Rule 2, we conduct a new experiment in the ER to make a further confirmation, where the transmitter and receiver are placed in the east and west, respectively. Then, the receiver antenna only has two orientation choices: east (towards the transmitter) and west (backwards to the transmitter) while changing the orientation of the transmitter antenna in four directions, i.e.,. east, west, south and north.

Fig. 9 shows the experimental results. No matter which direction the transmitter antenna points to, we see that signal is always stronger when receiver antenna is aligned towards the transmitter: 4.87, 7.21, 7.94, and 3.96 dBm differences on average for east, west, south and north, respectively.

Considering that under normal circumstances we have no control of the target device, **Rule 2** seems to be particularly useful for determining the search direction.

Based on these rules derived from the empirical study, we will introduce the MADT algorithm in the next section.

IV. MADT ALGORITHM

In this section, first we will give a brief overview of the MADT algorithm. Then, details are given for a better understanding. Lastly, the complexity of MADT will be analyzed.

A. BASIC IDEA

The intuition underlying the MADT algorithm is to treat the target device as a signal source, which emits signals and draws the user to approach it iteratively. The user movements obey certain patterns by the rules derived in the empirical study.

The basic idea is to cut the floor plain into smaller ones until the target has been located. To do so, two essential factors need to be considered: direction and distance during the localization. We use **Rule 2** to determine the search direction and use **Rule 1** to decide whether the target is at close range.

The MADT algorithm works as follows: when a user holding the receiver tries to locate the target device, it searches for the Bluetooth signal emitted from the receiver by cutting the floor plan into smaller pieces iteratively until approaching the target. To do so, the user first manually chooses a start point within the room, e.g., the centrepoint of the room, and constructs a logical coordinate plan where the start point serves as the origin and the floor is divided into four quadrants by X and Y axes. Then the user collects RSSI readings by pointing the receiver antenna to four directions: north(Y^{+}), south(Y^{-}), west(X^{+}) and east(X^{-}). Based on **Rule 2**, these readings will show us the most possible quadrant where the target lies in. Then, **Rule 1** is used to determine whether the target is at close range. If so, the user stops and searches for the target manually. Otherwise, the process continues until the target is located.

In general, MADT iteratively narrows the search area by exploring both **Rule 1 and 2** to determine the potential quadrant where the target may resident. By this cutting plain idea, we gradually eliminate areas that the target is not likely to present, leading to the final position of the target.

In the next part, we will present more details about the MADT algorithm.

B. ALGORITHM DETAILS

The Pseudocode of MADT is shown in Algorithm 1. It consists of four main parts: (a) choose the start point: manually choose the origin of the current search area. A good start point will accelerate the search process. (b) take the RSSI readings: point the receiver to four directions and take measurements. (c) outline the search direction: choose the right quadrant by the average RSSI values of the measurements taken at different directions. (d) judge whether the target is at close range by the SDs of the measurements.

Step 1 (Choose the Start Point): Since the floor plain remains unknown, it is quite difficult and time-consuming to construct a logic one instead. Therefore, here we let the user to choose the start point manually and only give some advice on how to select a suitable start point. Note that though a good start point certainly will accelerate the search process, MADT does not depend on it, i.e, it will eventually locate the target regardless of the start point.

Step 2 (Take RSSI Readings): We could use the embedded compass to determine the directions and take 50 samples per measurement. We could achieve the input data: $\vec{\mu}$ (mean RSSI) and $\vec{\sigma}$ (S.D.) by performing simple calculations on the samples as follows,

$$\mu = \frac{\sum_{1}^{50} RSSI_i}{50} \tag{3}$$

$$\sigma = \sqrt{\frac{\sum_{i=1}^{50}(RSSI_i - \mu)^2}{50}}. \tag{4}$$

Step 3 (Find the Target Orientation): With $\vec{\sigma}$, we could choose the potential quadrant as follows,

Case 1: If $\mu_{X^+} \geq \mu_{X^-}$ and $\mu_{Y^+} > \mu_{Y^-}$, Rule 2 indicates that target is in the **FIRST** quadrant;

Case 2: If $\mu_{X^+} < \mu_{X^-}$ and $\mu_{Y^+} \geq \mu_{Y^-}$, target is in the **SECOND** quadrant;

Case 3: If $\mu_{X^+} \leq \mu_{X^-}$ and $\mu_{Y^+} < \mu_{Y^-}$, target is in the **THIRD** quadrant;

Algorithm 1 Pseudocode for the MADT Algorithm

Input: $\vec{\mu} = \{\mu_{X^+}, \mu_{X^-}, \mu_{Y^+}, \mu_{Y^-}\}$;
$\vec{\sigma} = \{\sigma_{X^+}, \sigma_{X^-}, \sigma_{Y^+}, \sigma_{Y^-}\}$; σ_{TH};
Output: Location of the target device: (X, Y)
begin
    while *TRUE* **do**
        Choose_Start_Point();
        Take_RSSI_Readings($\vec{\mu}$, $\vec{\sigma}$);
        Find_Target_Orientation($\vec{\mu}$);
        if *Is_Close_Range($\vec{\sigma}$)==TRUE* **then**
            Target is in the close area;
            return;

Function *Choose_Start_Point()*
    Scan the target terrain;
    Select the centrepoint manually;
Function *Take_RSSI_Readings($\vec{\mu}$, $\vec{\sigma}$)*
    Point the receiver antenna to the NORTH (X^{+}) and take 50 RSSI samples;
    Point the receiver antenna to the South (X^{-}) and take 50 RSSI samples;
    Point the receiver antenna to the EAST (Y^{+}) and take 50 RSSI samples;
    Point the receiver antenna to the WEST (Y^{-}) and take 50 RSSI samples;
    Calculate μ and σ for each data group;
    Update $\vec{\mu}$, $\vec{\sigma}$;
Function *Find_Target_Orientation($\vec{\mu}$)*
    if $\mu_{X^+} \geq \mu_{X^-}$ ***and*** $\mu_{Y^+} > \mu_{Y^-}$ **then**
        Target is in the **FIRST** quadrant;
        return;
    if $\mu_{X^+} < \mu_{X^-}$ ***and*** $\mu_{Y^+} \geq \mu_{Y^-}$ **then**
        Target is in the **SECOND** quadrant;
        return;
    if $\mu_{X^+} \leq \mu_{X^-}$ ***and*** $\mu_{Y^+} < \mu_{Y^-}$ **then**
        Target is in the **THIRD** quadrant;
        return;
    else
        Target is in the **Fourth** quadrant;
        return;
Function *Is_Close_Range($\vec{\sigma}$)*
    L=Length($\vec{\sigma}$);
    $\sigma_m = \frac{\sum_{1}^{L} \sigma_i}{L}$;
    if $\sigma_m \leq \sigma_{TH}$ **then**
        return **TRUE**;
    else
        return **FALSE**;

Otherwise: Target is in the **Fourth** quadrant;

Step 4 (Range Estimation): Calculate average S.D. of data sampled from four directions: L = Length($\vec{\sigma}$) and

$\sigma_m = \frac{\sum_1^L \sigma_i}{L}$. If $\sigma_m \leq \sigma_{TH}$, the target is at close range and should be identified easily. Otherwise, jump back to Step 1 and start the process again. σ_{TH} is the threshold and can be obtained via Fig. 8(c).

Extensive real-world experiments show that MADT could iteratively narrow down the search space and gradually approach the target. Moreover, only under rare cases, our Rules will fail and lead to a detour, e.g., the distance range is misjudged or the search direction is misinterpreted. However, even under these cases, MADT will quickly adjust to the right course and locate the target eventually.

C. ALGORITHM ANALYSIS

For MADT, we have the following conclusion,

Theorem 1: Assuming the area of the room is D, MADT can locate the target in $O(\log_4 D)$ *steps.*

Proof: MADT terminates until the target is found, i.e., very close to the user (within $1m$). At each step MADT shrinks the search area to one-quarter of the current area. Assuming that at the last step, the target area is a square. So the longest distance between the target and the user is the diagonal. If the length of that diagonal is $1m$, the area of the square is $\frac{1}{2}m^2$. Therefore, at nth step, we have,

$$\frac{D}{4^n} \leq \frac{1}{2} \Rightarrow n \simeq O(\log_4 D) \tag{5}$$

Therefore, the target is located in $O(\log_4 D)$ steps. $\diamond$*End*$\diamond$

We now compare the search time between MADT and manual search. We assume that it takes t_1 and t_2 seconds to search $1m^2$ manually for the uncovered and covered target, respectively. Fig. 10 gives such a comparison where t_1 and t_2 are set to 5 and 10 seconds. For MADT, we take 200 samples in total, corresponding to $66.7s$. We see that for a small room, e.g. $D < 50m^2$, it will cost almost the same time for both MADT and the manual search to find the target. However, since MADT is a logarithmic algorithm, it significantly outperforms the manual search for a bigger room. The superiority grows even larger with the increment of D.

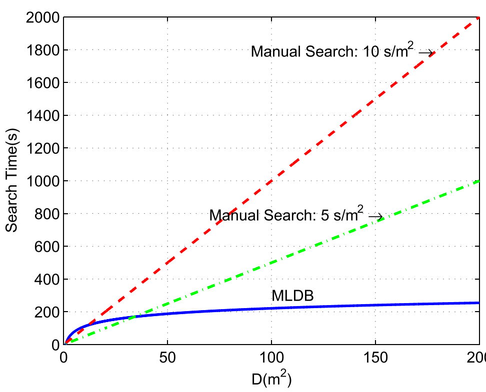


FIGURE 10. Search time comparison: an illustration.

V. PERFORMANCE EVALUATION

A. EXPERIMENTAL SETUP

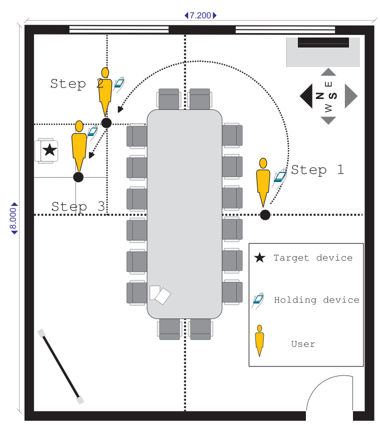
MADT has been prototyped and evaluated via real-world experiments. We use the same experimental setup as in Section III-A. Three metrics are used to evaluate MADT, namely,

- *Accuracy:* Once MADT makes a judgement that the target is at close range R, we will manually measure the physical distance between the target and the user, i.e., r. If the $r \leq R$, there exists no localization error. Otherwise, we take $r - R$ as the localization error.
- *Search Time:* It is the time MADT needs to find the target.
- *Energy Consumption:* Since measuring the energy consumption is difficult, we use the same idea in Section III-B and record the drop of the battery level as the energy consumption.

Two subjects are involved in the experiments. Subject A is responsible for hiding the target device in the CR and ER. He can choose to cover the target device with books or not. While subject B will localize the target using the holding device. If MADT reports the target is at very close range, subject B can manually select the most possible place where the target device may reside (Note that if the target is not covered by books, it would be much easier to be identified). σ_{TH} is set to 2dBm, corresponding to $2m$.

B. CASE STUDY

A case study is conducted in the CR to demonstrate the procedure of the MADT algorthm. Subject A places the target device on a chair located at the top-left corner and covers it with books. Subject B chooses a start point close to the center of the room, which is occupied by a big conference table. It takes three steps for MADT to locate the target device. Fig. 11 shows the user trace as well as the corresponding RSSI data.



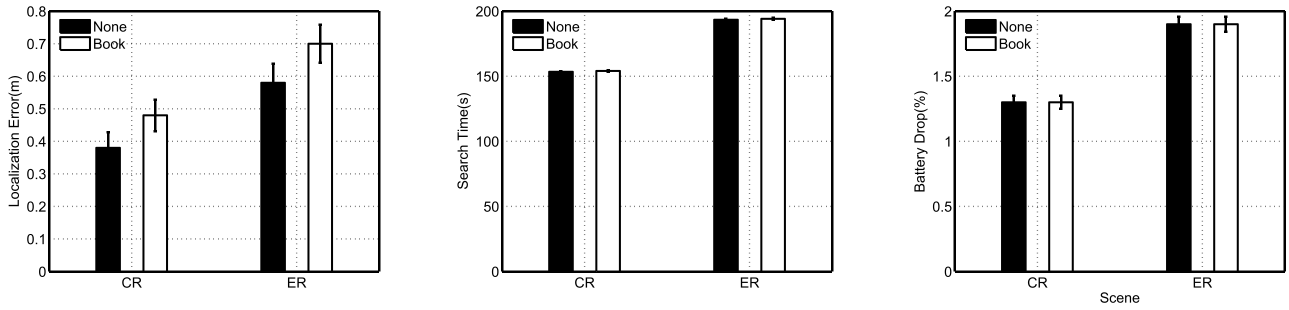
Step 1	Mean RSSI(dBm)	RSSI Sigma(dBm)
East	-73.51	1.81
South	-80.97	2.81
West	-73.82	1.65
North	-75.67	4.17

Step 2	Mean RSSI(dBm)	RSSI Sigma(dBm)
East	-69.79	1.60
South	-67.85	1.51
West	-63.97	1.69
North	-61.62	1.67

Step 3	Mean RSSI(dBm)	RSSI Sigma(dBm)
East	-62.54	0.98
South	-70.18	1.93
West	-66.64	1.0
North	-59.18	0.71

FIGURE 11. Case study: trace along the measurements.

At the first step, based on RSSI readings: $\overrightarrow{\mu} = \{-75.67, -80.97, -73.51, -73.82\}$, MADT points out that the target may resident in the first quadrant, i.e., the



(a) (b) (c)

FIGURE 12. Performance evaluation on the prototype system. (a) Localization accuracy. (b) Search time. (c) Energy consumption.

north-east direction. According to $\vec{\sigma} = \{4.17, 2.81, 1.81, 2.81\}$ and $\sigma_m = 2.9 > 2$, the target is not at close range (the actual distance is 4.2m). So the localization goes on. At the second step, the user chooses the new start point and collects the data again: $\vec{\mu} = \{-61.62, -67.85, -69.79, -63.97\}$, indicating that the target should be in the third quadrant. Moreover, considering $\vec{\sigma} = \{1.67, 1.51, 1.6, 1.69\}$ and $\sigma_m = 1.62 < 2$, the target is close, i.e., within 2m (the actual distance is 1.9m). Actually, at this stage the user is almost certain about the target location since there is nothing within that quadrant but the chair. However, to make sure, an extra step is taken to get closer to the target. At the third step, $\vec{\mu} = \{-59.18, -70.18, -62.54, -66.64\}$, indicating that the target is within the first quadrant while $\sigma_m = 1.15 < 1.62 < 2$ suggests that the target is very close, i.e., within 1m (based on Fig. 8(c)). The actual distance we measured is exactly 1m.

We evaluate the case study via the three metrics as follows,

- *Accuracy:* As stated above, MADT accurately estimated the distance range for all three steps. So for the case study, the mean localization error is 0m.
- *Search Time:* It takes three steps to find the target. Each step needs 200 samples, corresponding to 66.7s. So the overall search time is 200s.
- *Energy Consumption:* The battery level drops from 51% to 50% during the localization. So the overall batter consumption is only 1%.

In the next part, we will conduct extensive real-world experiments to systematically evaluate the proposed scheme.

C. PROTOTYPE PERFORMANCE

The experiment has been repeated 20 times in both CR and ER. Subject A is required to cover the target with books for half of the experiments.

Fig. 12 shows the experimental results. We still use error bars to show the standard errors in the mean. We now analyze the prototype system via the three metrics,

[Accuracy]: As shown in Fig. 12(a), the average localization errors in CR and ER are 0.38m and 0.57m, respectively. The result indicates that our range estimation method works very well in both scenarios.

However, we notice that once the target is covered by books the overall localization error will be slightly increased, i.e., less than 0.2m for both CR and ER. The reason is simple: books will absorb signals and decrease the signal strength, leading to an unstable propagation environment. Meanwhile, our range estimation method uses SD as a metric to evaluate the distance. Therefore, the localization accuracy decreases.

We also notice that the localization error in the ER is larger than the CR. Since ER is much bigger and has less furniture, it provides a stable environment for the Bluetooth signal. Thus, the group of samples collected at the same distance in ER tends to be more stable than the CR. For the same reason illustrated above, the localization accuracy decreases.

[Search Time]: Fig. 12(b) describes the average search time. On average, it takes 153s for subject B to locate the target in the CR. While the number increases to 194s for the ER. This result seems to natural and predictable, since ER is much larger than the CR, i.e. 149.8m^2 versus 57.6m^2. We also notice that the obstacles on the target leaves trivial impact on the search time, confirming the efficiency of the proposed scheme again.

[Energy Consumption]: The energy consumption is closely related to the search time, since we have to keep the screen and Bluetooth on during the localization. As shown in Fig. 12(c), MADT is energy efficient since it only consumes 1.3% and 1.9% of the battery for CR and ER, respectively. Another interesting observation is that obstacles on the target have insignificant impact on the energy consumption. It is consistent with Fig. 12(b).

In summary, MADT manages to quickly localize the target device no matter whether it is covered by obstacles or not. Also, it is efficient in terms of the localization accuracy, search time and energy consumption.

VI. RELATED WORKS

With the rapid development of IoT, the location-based service (LBS) [9] becomes an essential part for various pervasive applications to promote user experiences, such as google maps [10] and Where To Eat [11].

Over the years, tremendous research efforts have been devoted to this specific topic. On one hand, techniques of outdoor localization is well-developed since they benefit a lot from exiting mature positioning techniques such as GPS [12]. On the other hand, indoor localization remains a great challenge due to unique features such as the inoperative GPS, irregular signal propagation and complex environments [13].

In general, current research on indoor localization can be roughly divided into two categories by their localization methods: model-based and fingerprint-based [14]. The model-based approaches use sophisticated geometrical models to estimate the physical locations of target devices. While the fingerprint-based ones explores data mining techniques to recover locations from the historical data.

Eqn.1 is the simplest version of the well-known log-distance path loss model (LDPL). It can be used to estimate the propagation distance using RSS values. However, Eqn.1 itself is only suitable for the free space propagation. To be of practical usage, modifications concerning real-world environments are demanded. For instance, Stoyanova *et al.* proposed a model, which takes free-space path loss, ground reflection path loss, RSS uncertainty and antenna pattern irregularity into consideration, specifically for wireless sensor networks [15]. Lim *et al.* designed a complex model for WLAN, considering factors such as RF multi-path fading, temperature and humidity variations, opening and closing of doors, furniture relocation, and human mobility [16]. There is a recent trend to develop more sophisticated models for a better characterization of physical environments, e.g., the ray-tracing models [17]–[19], Bayesian hierarchical model [20], [21], and Hidden Markov models [22].

Though the model-based solutions inherit various advantages such as low cost on the site survey and training data, there exists one major concern: the ever-changing indoor environment poses a heavy burden on both geometrical models and computing powers, leading to unstable performance, e.g., large localization errors.

The fingerprint-based approaches leverage site survey and data mining techniques to estimate locations from known reference data. The basic idea is to manually gather RF RSSI values (signals could be from WLAN [23], ZigBee [24], Bluetooth [25], FM [26], etc.) as the signatures (fingerprints) at every location within the area of interest, i.e, site survey. The collected fingerprint form the training database and stored in the server. When a user wants to know its current locations, it first samples the surrounding signatures and then sends the test data back to server, which will use data mining techniques to figure out possible locations with similar fingerprints. Such examples include RADAR [27], ActiveCampus [28], UbiSpot [29], FIFS [30], and SSD [31], etc.

Later, researchers realized that site survey not only is time-consuming but also significantly raises cost. Therefore, different methods are proposed to reduce the cost on the labor-intensive site survey and data training. For instance, EZ combines the propagation model with the fingerprint-based approach for a configuration-free indoor localization scheme [32]. However, it involves complex computation and large localization errors caused by inaccurate physical constraints. WiGEM adopted the Expectation Maximization (EM) method to estimate the model parameters instead of site survey [33].

Very recently, motions are explored as a new way. WILL explores user motions and RF signal characteristics to construct the floor plan [14]. Abrupt signal changes is used for discovering different rooms and thus constituting the floor map. Though site survey is avoided, it is still a fingerprint-based technique, and thus needs massive training processes.

Besides indoor localization, Bluetooth has also been explored for the proximity estimation. Recently, Liu *et al.* proposed a proximity estimation technique that sets empirical Bluetooth RSSI values as multiple thresholds for classifying different distance ranges [7].

Inspired by [7] and [14], our work pushes the research one-step further by exploring not only empirical RSSI values but also fundamental rules between locations and RSSI readings, leading to more accurate and stable localization solutions. Unlike previous research, our scheme is light-weight by relieving the dependence on the data training and site survey.

VII. CONCLUSION

This paper introduces a novel localization algorithm named MADT to fast track down a target device in the indoor environment via Bluetooth signals. Unlike previous wireless fingerprint-based research, MADT has some unique features. For instance, it needs neither APs nor detailed site survey that are time-consuming and labor intensive.

To obtain the features, we explore Bluetooth characteristics, .e.g., the impact of various factors such as distance, orientation, and obstacles on the Bluetooth RSSI, via a systematic experimental study. Several basic rules about the relationship between the target location and the RSSI readings are derived to guides the user movement. More specifically, by interpreting RSSI readings using the rules, MADT iteratively shrinks the search space by highlighting the area where the target likely resides. To evaluate the proposed scheme, we prototype and test our system in real-world environments. Experimental results confirm that the proposed scheme is efficient in terms of localization accuracy, searching time and energy consumption.

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