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Accurate Distance Estimation between Things: A Self-correcting Approach

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ABSTRACT

This paper suggests a method to measure the physical distance between an IoT device (a Thing) and a mobile device (also a Thing) using BLE (Bluetooth Low-Energy profile) interfaces with smaller distance errors. BLE is a well-known technology for the low-power connectivity and suitable for IoT devices as well as for the proximity with the range of several meters. Apple has already adopted the technique and enhanced it to provide subdivided proximity range levels. However, as it is also a variation of RSS-based distance estimation, Apple's iBeacon could only provide immediate, near or far status but not a real and accurate distance. To provide more accurate distance using BLE, this paper introduces additional self-correcting beacon to calibrate the reference distance and mitigate errors from environmental factors. By adopting self-correcting beacon for measuring the distance, the average distance error shows less than 10% within the range of 1.5 meters. Some considerations are presented to extend the range to be able to get more accurate distances.

TYPE OF PAPER AND KEYWORDS

Sort Communication: *accurate distance, RSS-based estimation, distance error mitigation, IoT, Bluetooth Low-Energy, BLE, beacon*

1 INTRODUCTION

We are already surrounded by lots of *things* connected to the Internet at our home, offices, and streets. Internet of Things (IoT) is no longer a future technology but a present one being enhanced and evolving every day. Some of them are mobile (smart phones, wearable devices, sensors in a car etc.), while others are fixed (environmental sensors, appliances, smart TV, etc.). Things might have one or more network interfaces to make connections among themselves and to the world. Bluetooth Low-Energy (BLE) might be one of the most popular technologies due to its simplicity, robust radio property, and, above all, low-power operation. The low-power consumption of the BLE makes it as a very attractive connectivity technology for the IoT devices.

Compare to the Bluetooth, BLE uses much smaller transmission power, and thus could be an ideal technology for continuous proximity measurements between the transmitter and receiver [3]. Apple's iBeacon [6] is the commercialized specification based on BLE, and it enhanced the BLE protocol to include the *txPower* field when a BLE client broadcasts signals for the BLE server to scan for discovery and connection. The server can compare the received signal strength and *txPower* value from the client to estimate a rough distance between the client and itself as the *txPower* value is an expected received signal strength at one meter distance.

Currently, the iBeacon specification provides three levels of proximity from the estimated distance, which are immediate, near and far status. Normally, the *txPower* is determined and set by the vendors, but the received signal strength fluctuates over time and also under changing circumstances such as position of walls and people around the devices. Therefore, it is challenging to provide accurate physical distance. In this paper, we present a new and improved method, which is robust for dynamically changing environmental settings, for estimating distance between two devices emitting and receiving signals.

This work is an extension of the paper entitled "Measuring a distance between things with improved accuracy" and it was already presented at the 5th International Symposium on Internet of Ubiquitous and Pervasive Things (IUPT) [7]. In the extensions, several indoor positioning mechanisms are presented. By comparing them in terms of pros and cons we conclude that a received signal strength based approach is feasible to the environment of IoT. This is because the distances between the Things are mostly short and thus they should be operated in low-power consumptions without any local infrastructures. And several considerable application scenarios are presented and discussed. It is feasible to apply the solution suggested in this paper to these scenarios as they need accurate distances in short ranges.

In Section 2, we describe the related works. For completeness, we state general RSS (Returned Signal Strength) based distance measuring methodologies in Section 3. A newly proposed system for accurate distance measurement by adopting the self-correcting beacons will be explained in Section 4. In Section 5, we show the evaluation results of the proposed system. Some possible application scenarios using accurate distance are described in Section 6. Finally, in Section 7, we conclude the paper with further work that can potentially extend the range of accurate distance measurement.

2 RELATED WORK

Many indoor positioning systems (IPSs) have been introduced until now and they also want to know exact global or relative positions of devices or users in the indoor environments. The indoor positioning systems can be classified by the different positioning principles and by the different connectivity and beaconing technologies. The positioning principles contain identity (ID), geometric and fingerprint positioning. The connectivity and beaconing technologies include Wi-Fi, Zigbee, Radio Frequency Identification (RFID), Bluetooth, Ultra-Wideband (UWB), pseudolite, cellular network and laser.

Identity positioning technology detects a user's position through the location of a node which is severing to the user. The node can be a base station (BS), RFID reader, or Access Point (AP) by the underlying connectivity technologies. The accuracy of ID positioning depends on the density of serving nodes with already known location. ID positioning technique is often used in a base station positioning system and RFID positioning system with low cost and low accuracy.

Geometric positioning technology calculates a user's position through measuring the geometric relations between the user and positioning nodes. The classic examples of this technique are Time of Arrive (TOA), Time Difference of Arrival (TDOA), Arrival of Angle (AOA) and the integrations of these. Geometric positioning technique is widely applied in positioning systems with Base Stations, UWB, pseudolite, lasers and ultrasound. This technology is easy to popularize, but the error will increase under non-line-of-sight (NLOS) conditions. For example, in Base Station positioning systems adopting geometric approach, the positioning error could be up to hundreds of meters. Researchers have done a lot of work to mitigate the NLOS error [13], and the error can be reduced by 60-90% in specific environments. But these contributions still cannot fulfill the demand of meter level accuracy for the indoor location based services.

Fingerprint positioning technology is based on fingerprint databases. The positioning area is divided into grids, and the fingerprints in different grids are acquired before positioning. The fingerprints can be acquired through various methods like TOA, TDOA, RSS and AOA. Fingerprint matching would be performed on measured signals at a specific location with fingerprint databases. The typical fingerprint matching algorithms are k-Nearest Neighbor (KNN) algorithm [14], neural network [5], Support Vector Regression (SVR) [20], Support Vector Machine (SVM) [4]. Fingerprint positioning technology can mitigate NLOS error effectively. However, this technology is limited by the heavy workload of fingerprint acquisition and the large amount of fingerprint database. Those limitations make the fingerprint positioning to be applied only to popular regions and to be hard to be popularized.

The following gives detailed descriptions about several well-known technologies of measuring distances.

- **Time of arrival (TOA)**: TOA [2] finds the distance between a transmitter and a receiver using one way propagation delay by exploiting the relationship between the light speed and the carrier frequency of the signal. However, TOA positioning requires an accurately synchronized clock as 1.0 μs error in time equals to 300 meters in terms of distance [12]. TOA will not be used for low cost devices because the high accuracy clock costs quite a lot. It is difficult to say that TOA will be widely applied to solve the accurate positioning problem.

- **Angle of arrival (AOA)**: AOA [11] is usually employed as prior-knowledge for the triangulation method. In 3-dimensional spaces, AOA requires 3 to 4 signal emitters to obtain position of a Bluetooth Low-Energy device, which are also not practical cases.
- **Ultrasound**: A mobile node with an ultrasonic sensor measures the distance by exploiting the signal propagation time. However, the transmission range of an ultrasound signal is small as it cannot propagate further than radio frequency wave [16]. Normally, the size, cost, and energy consumption are not attractive. Although the ultrasound based localization approach demonstrates better accuracy, it is also not suitable for IoT environments.
- **WIFI**: Wi-Fi is a short-range radio transmission technology based on IEEE 802.11, and it can support internet access in a range of tens of meters in indoor environments. Currently, Wi-Fi AP has been massively deployed in most buildings and expanding gradually. But due to the unknown effect of environments, like we cannot know if we have enough APs in IoT environments, it is hard to measure the distances between user and AP by Received Signal Strength Indication (RSSI). The positioning error of this type is about 10 to 20 meters [18].

3 Background and Motivation

Proliferation of smart devices and connected things make the user's context to be understood with a greater accuracy. Examples of a user's context include mobility of the user, different circumstances (e.g. at work, at shopping, at lunch etc.) in which the user is situated, and different things (e.g. conversation, reading a book, watching a TV, exercising etc.) to which they pay attention. We can state that accurate understanding of users' context largely depend on their geographical and semantic locations.

For example, if a person with a smartphone is moving along the trail at walking speed, it is highly likely that user may be exercising. If a user, with a similar device, is found at the corner of the block where a sandwich shop is located, the user may be eating a meal or picking up a bag of sandwich. If smart device is not moving but detecting different people speaking at different times, the owner who holds the device might be in a meeting. If the location of the device happens to be identified as the coordinate where the user's office is located, then he/she might be in a work meeting.

As we discussed in the previous paragraph location information is an important part of the contextual information. If a user is in a building with a lot of IoT devices communicating among themselves and with their smartphone, the data and information sensed from his/her environment is rich enough to know what the user might be up to. In the condition of indoor situation, the accuracy of physical location becomes more important since rooms are located right next to each other. The system may determine different contexts if the location information is not accurate. For instance, if a user is erroneously located within 1 meter from a coffee machine, the system may state that he/she is having a coffee break, but in reality he/she is 2 meters away from the coffee machine in a conference room. If a home automation system was programed to turn on the light when a user gets near the corner of the corridor, it is also desirable to find his/her location with high accuracy. In other words, if the smart devices are able to obtain a user's exact position, the intelligence level of the system would improve greatly.

Received Signal Strength (RSS) based distance estimation is a popular method in wireless sensor networks [15], [10]. RSS value can easily be measured by the devices like cellular phones. It means that we do not need extra devices or apparatus to implement the system in real life situation. Usually the wireless sensor network nodes follow IEEE 802.11 or IEEE 802.15.4

Table 1: Comparison of IEEE 802.11 and 802.15 wireless standard protocol specifications [17]

IEEE Wireless Standard	Radio Frequency	Data Rate	Modulation & Coding
802.11a	5 GHz	54 Mbps	PSK, QAM, OFDM
802.11b	2.4 GHz	11 Mbps	PSK, CCK, DSSS
802.11g	2.4 GHz	54 Mbps	PSK, QAM, OFDM
802.15.1	2.4 GHz	3 Mbps	PSK, FSK, AFH
802.15.4	868/915 MHz, 2.4 GHz	40 Kbps, 250 Kbps	PSK, ASK, DSSS, PSSS

standards, and thus research results from those studies could be applied to BLE [13]. Table 1 shows the comparison of IEEE 802.11/802.15 series of wireless standards.

A radio signal transmitted from an antenna would be propagated through a space experiencing path losses. In this paper, we assume that the signal would follow the log-distance path loss model [19]. The log-distance path loss model is a radio propagation model and it predicts the path loss that a signal encounters inside a building or densely populated areas over distance. Log-distance path loss model is formally expressed as:

$$PL = P_{Tx} - P_{Rx} = PL_0 + 10 \times \gamma \times \log(\frac{d}{d_0}) + X_e \quad (1)$$

Where, PL is the signal strength after total path loss at the distance d measured in Decibel. P_{Tx} and P_{Rx} are the transmitted power and the received power respectively. PL_0 is the signal strength after path loss at the reference distance d_0 measured in Decibel, d is the length of the path, γ is the path loss constant or exponent. X_g is a normal random variable with a zero mean reflecting the attenuation caused by flat fading.

In the iBeacon specification [6], the manufacturer should add *txPower* value to existing BLE protocols. The *txPower* value is the received power at the distance of 1 meter. Then, we can replace some variables with the value of *txPower*. When a receiver received a signal with *txPower* field, the receiver can set

d_0 to 1 meter,

PL_0 to P_{Tx} – *txPower*.

Then, the expression could be

$$\begin{aligned} PL &= P_{Tx} - P_{Rx} \\ &= P_{Tx} - txPower + 10 \times \gamma \times \log(d) + X_e \quad (2) \end{aligned}$$

$$P_{Rx} = txPower - 10 \times \gamma \times \log(d) - X_e \quad (3)$$

The value γ and X_g could be found by empirical measurements. Android beacon library uses following coefficients to calculate distances in indoor environments [1] and we also adopted the same equation:

$$d = (0.89976) \times \left(\frac{P_{Rx}}{txPower}\right)^{7.7095} + 0.111 \quad (4)$$

Now, the number of variables is reduced to just two: P_{Rx} and *txPower*. Because the value of *txPower* is fixed by the manufacturer, the fluctuation in received signal strength directly affects the calculated distance. Even if we adopt some filtering algorithms, it is also difficult to determine the exact distances.

4 SYSTEM DESIGN

To calibrate the system and mitigate the errors, we proposed a self-correcting mechanism by adding an extra *Thing* and place it at a pre-determined distance from the Target Beacon. The extra thing would be a common BLE beacon but tightly coupled with the target beacon. So we call it self-correcting beacon. The system is then equipped with a target beacon, a measuring device, and a self-correcting beacon. We want to calculate the accurate distance between the target beacon and the measuring device by installing the target beacon and self-correcting beacon at positions apart from each other with a fixed distance. Figure 1 shows the installation of the self-correcting system.

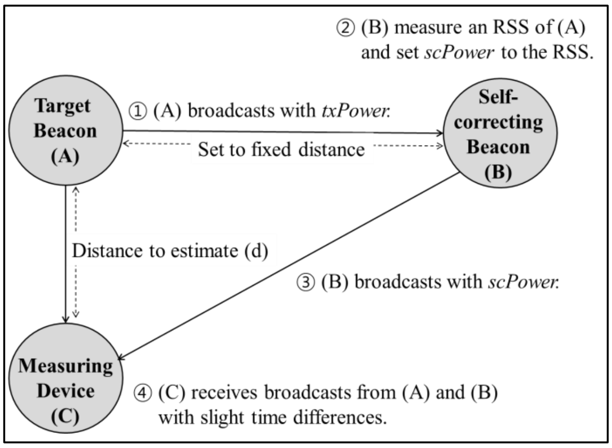

Figure 1: The installation of the self-correcting system. The measuring device can get the RSS from the target beacon and the *scPower* from the self-correcting beacon with slight time differences.

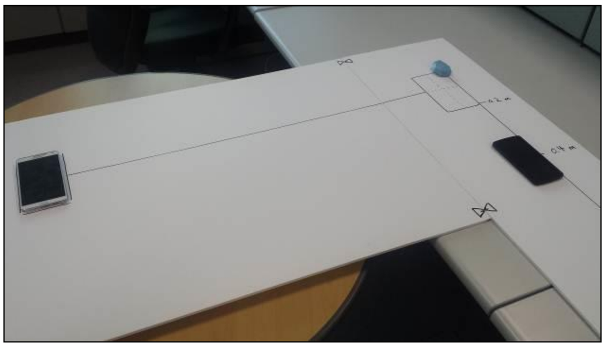

Figure 2: The system test environment. The test was performed in the office with soft partitions. The target beacon and the self-correcting beacon were fixed with one meter distance.

In this self-correcting system, the self-correcting beacon is an extra device to calculate more accurate distance through RSS from the measuring device. The self-correcting beacon receives the signal from the target beacon, and advertises the received signal strength of the target beacon (*scPower*). In the system, the measuring device utilizes the signal strength from the target beacon, *txPower* from the target beacon, and *scPower* from the self-correcting beacon. In the conclusion of Section 3, the main problem is the fixed *txPower*, which could not reflect the user's environment. By replacing the *txPower* with the *scPower*, the distance can be calculated with more stability and accuracy.

Figure 2 shows a picture of the test environments. We used an iBeacon-compatible BLE tag as target beacon, a smart phone as measuring device and another smartphone as emulated self-correcting beacon. We set the advertising time interval of the target beacon to 10ms so as to catch up the fluctuation of the received signal strength as close as possible. Then, we could calculate the accurate distance in very short time by setting the self-correcting beacon manually to know the MAC address of the target beacon.

5 EVALUATIONS

Based on the previous description to calculate the accurate distance between the measuring device and target beacon, we should get the accurate *scPower* (the real RSS of the target beacon at distance of 1 meter, received by the self-correcting beacon) and RSS of the target beacon, which is received by the measuring device. We all know that the RSS of beacon is always fluctuating because of Gaussian white noise and impact of the environment. So the issue is that the *scPower* and RSS of target beacons are both fluctuating, and this will make the error of distance increases.

However, if they have the similar trend simultaneously, we can get more accurate result based on Equation (3). To prove this concept we did the following experiment: placing the measuring device 1.5m away from the target beacon and the correcting beacon 1m away from the target beacon. Then we collected the RSS of the target beacon from the measuring device and the correcting beacon separately for one minute. Figure 3 shows the variation trend of *(RSS of target beacon in 1.5m, time)* and *(scPower, time)*, in which the horizontal axis is time, the vertical axis is RSS, the blue line is RSS of target beacon and the red line is *scPower*. From the figure we can see that:

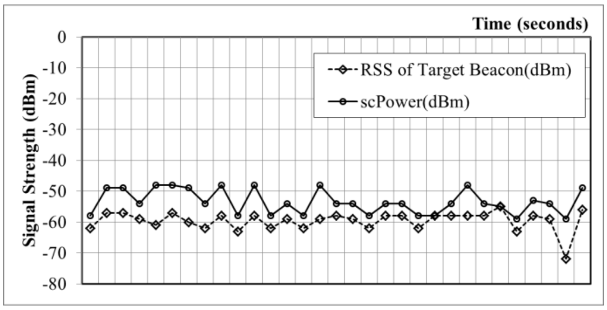

Figure 3: Comparison of RSS from the target beacon, which is located in 1.5 meters away, and scPower value from the self-correcting beacon, which is located in 1 meter away from the target beacon. The two values show the similar trend simultaneously according the time goes.

(1) The RSS of target beacon is fluctuating;

(2) The scPower is also fluctuating;

(3) They do have the similar trend simultaneously, which means when the scPower becomes bigger the RSS of target beacon becomes bigger too.

But there are slight time lags between the RSS and the *scPower* as the self-correcting beacon will receive the RSS firstly from the target beacon and then send the value as *scPower*. As synchronizing the time between the two beacons is uneasy without any precise time module, we used the average value of RSS and *scPower* in 5 seconds instead of using the real time synchronization. As described previously, we set the broadcasting interval of the beacons to 10 meters, and this means that the measuring device can collect 500 RSS values and 500 *scPower* values in 5 seconds. The averaged values of RSS and *scPower* also show the similar trend.

Then we evaluated the accuracy of measuring the distances from the proposed self-correcting system. Table 2 and Figure 4 show the resultant comparison of with and without the self-correcting beacon while measuring distance at each reference distance (0.4m, 0.6m, 0.8m, 1.0m, 1.2m and 1.4m). Without the self-correcting beacon, the distance error shows up to 60.3%, and in average 46.3%. With the self-correcting beacon, the distance error shows up to 8.1%, and in average 4.7%. All the distance errors are the average of the gap between the real distances and the estimated distances.

Table 2: Distance errors comparison of with and without the self-correcting beacon on several reference distances.

Actual distance (meter)	Distance errors with the self-correcting beacon (%)	Distance errors without the self-correcting beacon (%)
0.4	8.1	41.7
0.6	2.7	45.6
0.8	5.0	46.7
1.0	5.3	60.3
1.2	3.1	42.0
1.4	3.7	47.4
Average	4.7	46.3

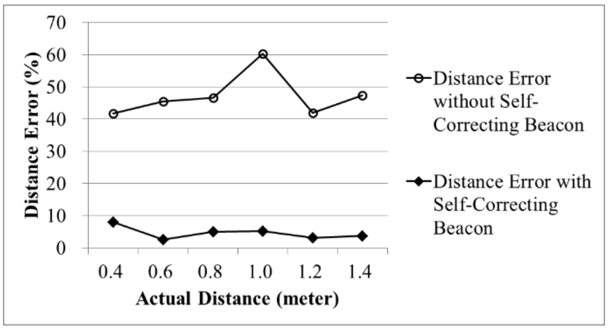

Figure 4: Distance errors comparison of with and without the self-correcting beacon on several reference distances. It is possible to achieve accurate distances with under 10% distance error when we adopt the self-correcting beacon within 1.5 meters range.

6 Applications

Using the self-correcting beacon, the proposed system could estimate the distance between the target beacon and the device at much improved accuracy than the existing techniques. Accurate distance measurement technology enables more interesting usage scenarios.

Childcare mode on Smart TV: Watching TV screen by sitting closely to the TV may cause eyestrain or more seriously weakened eyesight. Parents constantly nag their children about sitting too close to the TV. These days, TVs with 40 to 50 inches screen size is a norm, thus enough to install the self-correcting beacons on the one edge of the TV screen. In this case, the measuring device would be a TV, the target device could be a small attachable beacon on the clothes of the children, and the self-correcting beacon can be located a fixed distance from the measuring device. Then, as the measuring device calculates the distance between the TV and the child, the TV may control the brightness of the screen or volume of the speaker according to the estimated distances.

Find my remote controller: "Where is my remote?" might be a general question with long history. In the proposed system, we separated the function of the target beacon and the self-correcting beacon for better understanding. However, a target beacon could also be used as a self-correcting beacon. If we install a pair of target/self-correcting beacons with fixed distance apart, the measuring device could estimate the distances from the two beacons. As we already know the distance between the beacons, and the measuring device could perform trilateration to determine its relative location from the two beacons. If we install the two beacons on the left and right edges of the TV screen and implement the measuring capability for the remote controller, the remote controller would be able to measure its location and direction from the TV screen. Then, the area where the remote controller could be found would be limited to a certain range. Figure 5 is an illustration of the concept.

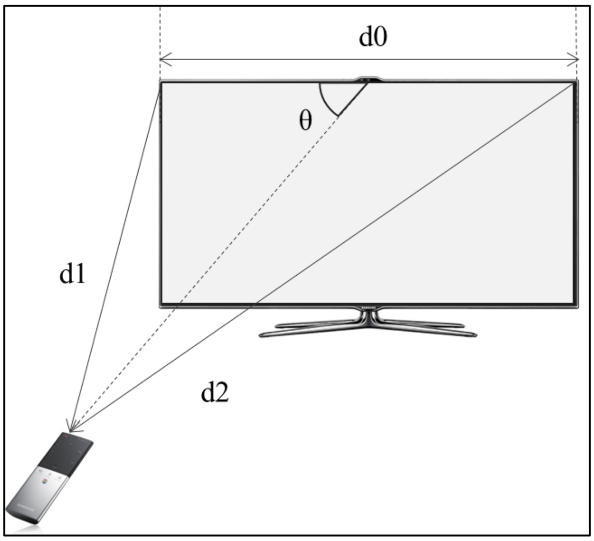

Figure 5: A TV equipped two target and self-correcting beacons each side. A remote controller as measuring device could calculate relative direction and distance from the center of the TV screen.

Driver or Passenger: In many countries, operating smartphones while driving is legally restricted. However, in a moving car, it is not easy to determine whether the ringing smartphone belongs to the driver or the passenger. In this scenario, a target beacon and the self-correcting beacon could be installed on the dashboard. Then, a mobile phone as a measuring device could identify the seat position including driver's seat, passenger seat, and back seats with high accuracy. An accurate contextual identifying of whether a particular person in the car is driving or sitting in the passenger seat is important. Some smartphones in the market already support the car function that enables the driving-safety mode, but it should be activated manually by the driver [9]. If the location of the device is determined with high accuracy in the car, it can be started automatically.

7 CONCLUSION

In this paper, we propose an accurate distance measurement system between the Things having BLE interfaces by adopting a self-correcting beacon. As the system adjusts the white noises and the environmental factors in real time, it can estimate the distances with the relative error of under 10% of the actual distance where the devices are within 1.5 meters range of the coverage. We also conducted an experimental evaluation for the targets located farther than 1.5 meters, but as the distance increases, the errors also increased super linearly. In indoor environments, there exists additional signal attenuation error caused by the multipath signals. Such errors would appear more for longer distances than shorter distances. To extend the coverage of the proposed measurement technique, we can apply multiple model filtering algorithms [8] to track a single target in wireless sensor networks. We expect multi-model filtering method could help to mitigate the additional errors for longer distance cases to obtain the similar accuracy. Addition to the sample scenarios stated in Section 6, there might other possible applications and scenarios that can benefit from the presented measurement method.

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