Design and Implementation of Beacon-Based Positioning

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The Global Positioning System enables mobile device users to achieve rapid positioning. However, its indoor positioning performance is still unsatisfactory. In recent years, numerous scholars have investigated Wi-Fi indoor positioning technologies. However, the distance error of such techniques can be higher than 5 m. Some scholars have proposed new approaches of beacon-based indoor positioning to provide easier installation and decrease the distance error to 2.5 m. For both better positioning performance and being economical, this paper proposes an approach of beacon-based positioning method, using cost-effective Estimote Proximity Beacons and Android smart phones for implementation. The result reveals that the mean distance errors of our method are 0.398 m in stasis and 1.97 m in motion.

Keywords: Positioning, indoor positioning, beacon, Bluetooth low energy

1. INTRODUCTION

Indoor venues such as shopping malls and large indoor recreation centers are frequently crowded. Therefore, the demand for indoor positioning increasingly receives attention. However, the Global Positioning System (GPS) cannot be applied to position items in indoor settings. Therefore, Numerous scholars have researched multiple indoor positioning technologies without GPS [1-3, 22-24].

Indoor Positioning: In 2014, Zhu *et al.* [1] surveyed most existing indoor positioning technologies, and analyzed their positioning accuracy and compared their advantages and disadvantages in various application environments. Basiri *et al.* [2] indicated that no existing indoor positioning technologies could be applied in all situations. Hence, users must select the most appropriate positioning technology according to their requirements. In 2015, Kim and Sung [3] noted that we need high accuracy and precision in emergency situations than common situations. They then proposed an architecture which utilizes various information and big data to measure an exact indoor position and operates with various IoT devices.

Beacon-based Positioning: Beacons use Bluetooth as their communication technology, and its short-distance positioning accuracy is higher than GPS. However, numerous obstacles in indoor settings can severely impede Bluetooth signal transmission and reception. Hence, many scholars have investigated methods and algorithms of beacon-based positioning suitable for indoors. In 2016, Zhuang *et al.* [4] proposed an algorithm that uses the combination of channel-separate polynomial regression model (PRM), channel-separate fingerprinting (FP), two-level outlier detection, and extended

Kalman filtering (EKF) for smartphone-based indoor localization with BLE beacons. Their scheme achieves the accuracy of <2.56 m at 90% of the time with dense deployment of BLE beacons (1 beacon per 9 m), and of <3.88m at 90% of the time with sparse deployment (1 beacon per 18 m). In 2015, Li *et al.* [5] proposed two schemes for indoor positioning by fusing Bluetooth beacons and a pedestrian dead reckoning (PDR) technique to provide 2-meter-precision positioning without additional infrastructure. PDR technique uses effective multi-threshold step detection algorithm to improve positioning accuracy. Yun and So [6] introduced a Bluetooth-beacon-based indoor location and navigation system. Martin *et al.* [7] suggested using iBeacon advertisements for indoor positioning, and the average error measured is 0.53 m. However, the density of beacons in their implementation is not mentioned, each server and some wireless WiFi routers are required in each single place, and the places of advertised-beacons and the often-altered advertisement contents are not easy to control in the real world. Rida *et al.* [8] used CC2450 nodes on the ceiling and conducted positioning with the three nodes closest to the target item, and their average error determined is 0.5-1.0 m. Ji *et al.* [9] analyzed practical path loss model of BLE signals and Wi-Fi signals, and indicated that it requires much more beacons to achieve comparable positioning accuracy because BLE signal, compared to Wi-Fi APs, has relatively lower tx power. They showed that the numbers of deployed beacons from 10 to 100 in a 100m x 100m area obtain estimated errors from about 24 to 8 meters, and the deployed beacon intervals from 5 to 50 meters can achieve estimated errors from about 6 to 33 meters. Kajioka *et al.* [10] experimented on the installation of 22 Bluetooth LE beacon devices inside and outside rooms and attached on the top of the walls. One portable device was placed as observation point for one desk in one room, and each portable device collects 50 beacon data at one observation trial. Over 5800 beacon messages have been gathered and stored on the estimation server, and each message contains 50 beacon data. By template matching, a portable device can make a decision whether it is in the room or not, and the correct estimation rate is 96.6%.

Palumbo *et al.* [11] used beacon RSSI and modified-Min-Max method [25,26] to range distance and used stigmergy to establish an on-line probability map which identifies user position, where the stigmergic process is applied in order to overcome the deep multipath fades typical of the BLE beaconing technology. They deployed 8 RadBeacon X2 devices in a 6m x 6m office, measured the RSSI from a reference beacon at predefined distances with steps of ~25 cm, and collected 100 samples for each step in 44 reference points. Distance is first estimated via the nominal distance-power loss law $RSSI = -(10n\log_{10} d - A)$, and Min-Max-like algorithm and the stigmergic process is then applied, where d, n, A represents the distance, the slope and the intersection with the RSSI axes, and A and n are computed in the off-line phase. Their results show that the localization error is lower than 1.80m in 75% of the cases and 2.01m error is obtained from using a third quartile in the Min-Max-like manner.

Lin *et al.* [12] used RSS-based localization method to estimate the patients' locations. Patients use their mobile devices to get RSS signals, and a system server maps the estimated nearest beacons sent from patient side with the locations of the correspondent subareas according to the mapping table of beacons and locations. They experimented on the installation of 12 beacons deployed on the center of the ceiling of 12 subareas in a building. They used HTC One M8 as a mobile device to obtain current locations such as "Reception desk" or "Door", and achieves 97.22% accuracy of

classification with localization error between 3 and 5 meters.

In 2016, Deepesh *et al.* [13] noted that iBeacon are more suitable for applications around proximity rather than positioning. They experimented on the installation of 4 beacons placed in the 4 corners in a 920 m$\times$340 m office space, which was divided into $6\times3=18$ zones. The zoons were estimated by two algorithms: (1) the k Nearest Neighbors (kNN) algorithm and (2) a decision tree based approach (i.e. Random Forest Algorithm), and it was able to guess the correct zone 62.7% and 53% of the time, respectively. Neburka *et al.* [14] tested the performances and the variation of BLE's RSSI, and their experimental results showed than BLE technology in ideal (no signal reflection) and real (multipath propagation) transmission environments has similar behavior. Lee *et al.* [15] proposed applying a Gaussian filter twice to RSSI values from BLE Beacons to reduce noise and improve location accuracy. It shows that difference between the maximum and the minimum of the filtered values is smaller than that of raw values and the mode of the filtered values are closer to the average. DGF algorithm was used in their scheme to get more accurate and reliable localization result, and the result showed the computed distance is more accurate and achieved the accuracy 11.04m error. Kriz *et al.* [16] used iBeacon to improve the positioning accuracy of a WiFi-based indoor localization. A Weighted *k*-Nearest Neighbors in Signal Space algorithm was used for estimation of the position. The median accuracy improved from 1m (when using WiFi) to 0.77m (when combining both technologies (WiFi + 17 BLE beacons)).

Zhao *et al.* [17] proposed a network-based positioning based on proximity reports from a mobile device (either a proximity indicator, or a vector of RSS from observed nodes), and combine filtering and Gaussian process regression (GPR) to improve the positioning accuracy. Their results show that GP provides 0.5 meter improvement in accuracy for event triggered proximity reports, and the median estimation error decreases by 1.8 meters for event triggered proximity reports by optimizing a set of different thresholds for each different beacons. Arisaka *et al.* [18] developed applications for hospital real-time location systems and communications using BLE. In their system, Peripheral device tags (iPhone 5) communicated with a Central using BLE and communicated with a Monitor using sockets on TCP/IP via a WLAN. They experienced on well patient tracking messaging in indoor environments. Onofre *et al.* [19] used Fuzzy Logic to improve BLE indoor positioning system to determine the robot's location. The Adafruit bluefruit LE Sniffer nRF51822 was connected to a computer (robot) as a BLE signal receptor to receive the RSSI from beacons, allowing to process the input values and implement algorithms to build the desired cyber-physical systems. In real distance from 0.5 m to 3 m, their experienced average error is from 0.101 m to 0.194 m for direct reading, and from 0.028 m to 0.193 m for using Fuzzy Logic, which prove the error reductions.

Sung *et al.* [20] proposed a method to measure the distance between a single beacon and a single AP in an indoor ubiquitous computing environment for Unmanned Aerial Vehicles (UAVs), where the beacon is attached to the bottom of a UAV. They experienced that the accumulated difference from an AP and a beacon was reduced from 112,485 to 35,000 cm via the measured distances range from 49.5 to 386.0 cm, and the accumulated difference was reduced by 31.1 %. Zou *et al.* [21] proposed a positioning method which combines beacons, Wi-Fi, and GPS for the three environment types: outdoor, semi-ourdoor, and indoor. When users are coming from indoors to outdoors, an

IO detection scheme can turn on GPS and turn off WiFi AP searching smartly to save power after it confirms the outdoor status. It provides 96.2% IO detection accuracy and 2.18 m accuracy on average in semi-outdoor areas. Their distance error distribution is mainly within 10 m with the 90th percentile of 7.94 m.

Overview of Results: From our measurement, the distance parameters obtained from Estimote Proximity Beacons have contained too many errors. Even in the situation that one beacon and one mobile phone are positioned statically and closely with no obstacles between them, the measured distance parameters still changed constantly. Environmental factors such as crowding, walls, or topography also affect the Bluetooth signals. This study analyzes the characteristics of distance parameters obtained from beacons positioned at various distances from the target. We also develop the primary and secondary determination criteria to correct distances acquired by the beacons, adopt trilateration to calculate coordinates, and implement our method on Android mobile phones.

Paper Contribution: This article focuses on the method and implementation experience on beacon-based positioning using Estimote Proximity beacons via BLE communication, where the Proximity beacon is the economical type from many kinds of Estimote beacons. Without GPS positioning system, people may misdirect themselves in a large indoor environment. In such instances, the proposed system uses smart phones to obtain indoor locations. The results revealed that the mean errors of this method were 0.398m in stasis and 1.97m in motion, along with being cost effective.

Paper Structure: This paper is divided into six sections. Section one reviews existing studies and the research motivation of the present study. Section two reviews literature relevant to the present study. Section three details the content and structure of the proposed positioning algorithm. Section four addresses analysis on the functions and efficacy of the proposed method for comparison with those of other studies. Section five describes an actual implementation using Android phone and section six provides a conclusion.

2. RELATED WORKS

This section reviews three BLE-based position systems including Zhuang *et al.*'s [4], Martin *et al.*'s [7], and Rida *et al.*'s [8] schemes and analyzes their weaknesses.

2.1. Zhuang *et al.*'s scheme

Zhuang *et al.*'s scheme [4] used the combination of channel-separate polynomial regression model (PRM), channel-separate fingerprinting (FP), two-level outlier detection, and extended Kalman filtering (EKF) for smartphone-based indoor localization with BLE beacons, where PRM are used to estimate the distances between the target and BLE beacons, FP are used to estimate the target's location, the first outlier detection can generate "improved distance estimates" for the EKF and the second outlier detection algorithm based on statistical testing is further performed to remove the outliers after the EKF process. Generally, the PRM is divided into separate PRM (for three advertisement channels) and aggregate PRM (generated through the combination of information from all

channels), and separate PRM (separate strategy) can provide higher accuracy in their scheme. Their scheme achieves the accuracy of <2.56 m at 90% of the time with dense deployment of BLE beacons (1 beacon per 9 m), and of <3.88m at 90% of the time with sparse deployment (1 beacon per 18 m). Their system considers the follow circumstances.

(1) Multichannel model

The BLE protocol uses the 2.4-GHz band, which is divided into 40 channels by using a 2-MHz bandwidth. Channels 37, 38, and 39 are broadcasting channels that can be used to measure RSS. Most related studies have consolidated the measurements of these three channels and discussed them as a whole; however, these three channels feature different bands and characteristics; hence, Zhuang *et al.* discussed them separately and conducted polynomial regression and FP on them individually.

(2) PRM

Using RSS and signal attenuation models to calculate the distance between a target and positioning devices is a common practice. However, in indoor settings, numerous obstacles can disrupt signals and render the actual states of signal attenuation markedly different from theoretical conditions. Hence, Zhuang *et al.* [4] employed the following PRM to convert RSS to distance:

$$\hat{d}_{PRM} = \sum_{i=0}^{n} c_i \cdot RSS^i \ ,$$

where c_i are the coefficients of the *n*th-degree polynomial, RSS is the RSS value, and $\hat{d}_{PRM}$ is the estimated distance.

(3) Multichannel FP

FP involves establishing a radio map database to save signals previously measured on all coordinates. When a new set of signals is detected, these signals can be compared to data in the database to identify or calculate the coordinates of a target location. Zhuang *et al.* [4] measured the noises in a planar space and used the resultant noise data to draw an oval in the coordinate plane of the database. The data enclosed by the oval were extracted and the average position was then calculated based on weighted distance parameters. This average position derived from the obtained coordinates was the target location obtained using FP, where all RSS data were converted to coordinates.

(4) Outlier detection level 1

After separately obtaining the location coordinates of the aforementioned three channels, the distance between each coordinate and the original beacon was calculated. Therefore, FP can be used to separately calculate the distances between each of the three channels and the beacon; these distances can also be calculated using the PRM. Six items of distance data were obtained. After outliers that had fallen outside of the confidence interval had been eliminated, the remaining distance data were averaged.

(5) EKF

EKF was used because it enables an actual state to be considered a combination of predicted and observed states. A state can be expressed as the following matrix:

$$x = \begin{bmatrix} r_e & r_n & v_e & v_n \end{bmatrix}^T,$$
$$x_{k|k+1} = \Phi_{k,k+1} x_{k|k} + \omega_k$$

where x represents a state matrix, e is the east direction, n is the north direction, ω_k is the predicted noise, and $\Phi_{k,k+1}$ is the state transition matrix that transits from the kth state to the (k+1)th state. Therefore, the next state could be predicted using the state transition matrix. $x_{k|k}$ is the state matrix observed at the kth state. Through the aforementioned equations, predictions can be made based on the distance data observed at a previous time point and those observed at the current time point. New distance data can be generated based on the predicted and observed distances.

(6) Outlier detection level 2

EKF incorporates observed and predicted results; a new distance is eventually obtained through the integration of these results using Kalman parameter. However, if the observed results deviate considerably from the predicted results, the final result is unlikely to be credible.

Although Zhuang *et al.* claimed that their algorithm is useful to improve the localization accuracy in environments with sparse beacon deployment, their algorithm is too complex to implement.

2.2. Martin *et al.*'s protocol

Martin *et al.* [7] suggested using iBeacon advertisements for indoor positioning. There system contains a Server, some wireless WiFi routers, several beacons, and some mobile phone, where beacons broadcast advertisements at fixed intervals. Their protocol is shown as follows.

(1) A mobile phone estimate distance

A mobile phone listens to BLE advertisements and estimates distance values $\hat{d} = \exp[a \cdot (P_{RX} - P_{TX})]$ from received signal strengths P_{RX} and calibrated signal strength at a 1-meter distance P_{TX}, where $\hat{d}$ is the estimated distance between the phone and the transmitter and a is a pre-calibrated exponential decay term. The mobile phone then relays $\hat{d}$ and aggregated flying information to a central server.

(2) The server searches for position estimate

After receiving receives these estimated beacon distances $\hat{d}$, the server searches for an instantaneous position estimate $\hat{x} \in R^2$ by solving the equation $\hat{x} = \arg\min_x \sum_{b \in B} w(\hat{d}_b) \| d_b - \hat{d}_b \|^2$, where $d_b = \| x - x_b \|$, B is the set of overheard

beacons, and $w(\hat{d})$ is a certain weight assigned to each such that larger distance estimates have less bearing on the final position estimate.

Martin *et al.* [7] claim that they obtain an average error of 0.53 meters with proper post-processing filtering in a $9\times10\ \mathrm{m}^2$ laboratory. However, in their protocol, the density of beacons in their implementation is not mentioned. In real world, the places of advertised-beacons and the often-altered advertisement contents are not easy to control. Moreover, the pre-calibrated exponential decay term a must be calculated explicitly for each received packet for each device such as an Android tablet, and a certain weight $w(\hat{d})$ must be evaluated and assigned for each estimated distance. In addition, each server and some wireless WiFi routers are required in each single place, and the processes of post-processing filtering are needed to obtain better performance in each advertised-beacon environment.

2.3 Rida *et al.*'s protocol

Rida *et al.* [8] deployed nine CC2450 nodes, as transmission units, on the ceiling and conducted positioning with the three nodes closest to the target item, where each node provides coverage of about 15 m and the distance between each node is six meters. The nodes broadcast a short periodic beacon RF signal frame and will change to sleep mode in every 400ms, where the RF signal carries important information such as RSSI and spaces id. A smart device (Android 4.1 (Samsung)), as a receiver unit, then collects RSSI of the three nearest connected adjacent nodes through RSSI measurement, and calculate the distance between itself and the three nodes by using Trilateration algorithm.

They recorded the maximum, minimum and mean value of RSSI respectively to evaluate the performance of the estimated model and establish a lookup table for any real-time calculations, and obtained the experiment location error between 0.22-0.89 miters. During their real experiment in their lab at a university, more than 30 tests were chosen randomly and the estimated location error in their designated area is 85cm.

Rida *et al.* [8] claim that their accuracy (85cm estimated location error) is acceptable by using CC2540 nodes. However, their nodes are setup on the ceiling, which will generate Bluetooth signal interference upstairs if a similar BLE location system is running at upstairs. Moreover, although CC2540 is a cost-effective, low-power, and system-on-chip (SoC) application, it needs a BLE communication module set up. On the other hand, the stability of CC2540 Bluetooth signals seems acceptable. However, for the signals of many beacons (such as Estimote Proximity Beacon), the signal data distributions (obtained as various distances) are overlapped and the error values are extremely large. Therefore, their simple algorithm is not suitable for these kinds of beacon.

3. PROPOSED SCHEME

This section explains the proposed scheme, comprising two parts. Part 1 focuses on preparatory tasks and positioning algorithms to address the effect of beacon height on positioning performance, and also details the designed algorithm for beacon-based

positioning. Part 2 emphasizes the ranging algorithm, specifically discussing the decision of the beacons' signal transmission power and period to achieve optimal performance, as well as the formulation of the primary ranging criterion RC_P and secondary ranging criterion RC_S based on signal characteristics.

3.1. Preparatory tasks and positioning algorithms

Before the test was conducted, the effect of the installed height of the beacons on signal reception was evaluated so that improvement measures could be proposed. A program supporting trilateration was designed and the input prioritization of various beacon data in the algorithm was determined to ensure rigorous and smooth testing.

(1) Effects of the height of beacon and handheld devices on positioning performance

Depending on the environment, beacons may need to be installed on multiple-height planes. In addition, because beacons use Bluetooth as their communication medium, a setting with no obstacles between the mobile phones and beacons is optimal. Hence, the beacons should be installed in high positions such as on walls or the ceiling. The installation height of the beacons can be determined in advance. The height of mobile devices is set referred to the average height of the adults holding the handheld devices. Therefore, height differences can be resolved through the algorithm operation shown in Fig. 1.

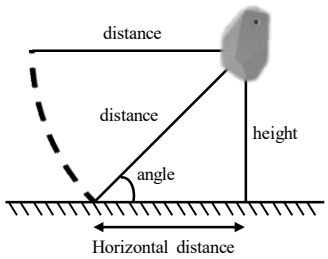


Fig. 1. Schematic of the conversion between the measured distance and horizontal distance

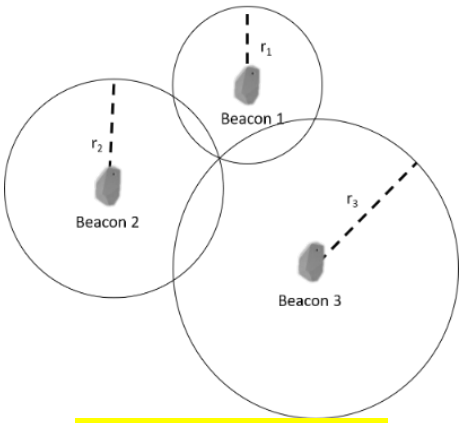
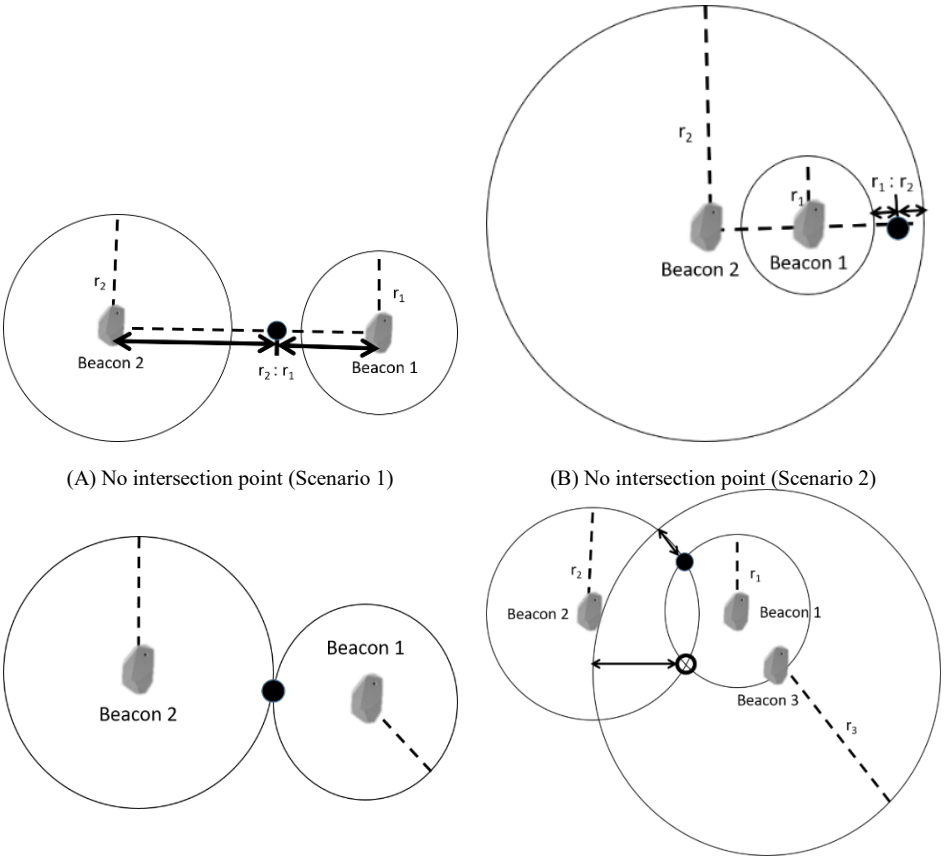


Fig. 2. Schematic of trilateration

(2) Positioning algorithm

In trilateration, three fixed coordinates are expressed as circle centers and a distance is assigned to each center as the radius. Three circles can then be drawn on a plane; the intersection point of these three circles indicates the output coordinates of the positioning algorithm (Fig. 2). However, three circles intersecting at a single point is only one potential scenario. In reality, the three circles may not intersect. Our algorithm employ in the present study: two circles with high credibility are considered first and the remaining circle serves to aid determination. Potential scenarios involving the intersecting of two circles are discussed as follows (i.e., no intersection point, one intersection point, and two intersection points).

A. No intersection point: The lack of an intersection point between two circles can be attributed to two scenarios. In the first scenario, the sum of the radiuses of the two circles is smaller than the length of the line between circle centers (Fig. 3(A)). We assume that the user is located on the line between two centers and that the user's coordinates can be obtained using the proportion of the two circles' radiuses. The



(A) No intersection point (Scenario 1)

(B) No intersection point (Scenario 2)

(C) One intersection point

(D) Two intersection points

Fig. 3. Schematic of the intersection points of two circles

second scenario involves a smaller circle within a larger circle (Fig. 3(B)). Similarly, we assume that the user is located on the line between centers and between the two circles and that the user's coordinates can be obtained using the proportion of the two circles' radiuses.

B. One intersection point: If the two circles have only one intersection point (Fig. 3(C)), this point is directly adopted as the user's coordinates.

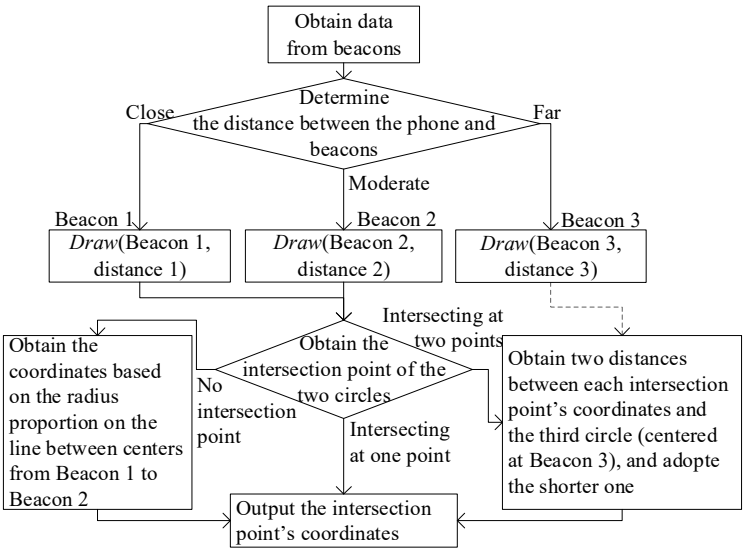
C. Two intersection points: If the two circles have two intersection points (Beacons 1 and 2 in Fig. 3(D)), both intersection points can indicate the location of the mobile phone holder. The third circle (i.e., Beacon 3) is then adopted to assist with determination. The distances between both intersections and the center of the third circle are calculated separately and the intersection point with the shorter distance is finally adopted as the user's coordinates.

(3) Determination of beacon credibility

Because signal transmission between beacons is powered by Bluetooth, the signal is stronger when the distance is shorter. Hence, we can infer that data obtained at shorter distances from the beacons exhibit higher credibility. We initially selected two items of data with shorter distances and used the item with the third shorter distances for reference (Fig. 4).

3.2. Ranging algorithm

This section explains the proposed ranging algorithm, including the determination of transmission period 4 dBm and transmission power 100 ms, the primary ranging criterion RC_P, and the secondary ranging criterion RC_S.



* *Draw*(Beacon i, distance i): Draw a circle whose center is indicated by Beacon i coordinate and whose radius is determined based on the obtained distance i

Fig. 4. Flow chart of positioning algorithm

3.2.1. Determination of the most stable transmission power and transmission period

For adopting the most stable transmission power and transmission period, we first measure variances from 500-distance-item in 450 various parameter settings (i.e. totaling 500 * 450 = 225,000 items). We adopt 4 dBm as the transmission power and 100 ms as the transmission period, because it's number of items with "a variance less than 0.3" is the largest (Fig. 5(F)), which means it is the most stable parameter.

3.2.2. Primary ranging criterion

In this subsection, we proposed a primary ranging criterion. After the transmission power 4 dBm and transmission period 100 ms had been determined, the ranging criterions are then considered from the fixed parameters. By analyzing the statistics of ten 500-distance-item data measured at intervals between the actual distances of 1 to 10 m, we found that the error values are extremely large and the data distributions obtained at various distances are overlapped (Fig. 6). For example, the measured distance is 1 m, whereas the actual distance is 10 m. Therefore, to determine the accuracy of the measured data, differences between multiple datasets are analyzed before a decision is made regarding whether these data were usable. From our observation from the distribution and the statistics in Fig. 6, we proposed two considerations as our primary ranging criterion.

(1) First consideration

As shown in Fig. 7, ten 500-distance-item data measured at various actual distances (i.e., 1–10 m) were separately obtained for each distance. However, various actual distances (1–10 m) were difficult to distinguish because data items excessively overlapped with one another.

Fortunately, from these data, we observed that overlapping was less prominent among the "minimum" data measured at 1-4 m, and this observation entailed relatively high distinguishability. Therefore, the minimum per 10 items of data ($D_{\min}$) was adopted as the reference value for the first consideration of the positioning algorithm. We then set each beacon as the center of a circle with a radius 4 m to attain the most satisfactory positioning result.

Although $D_{\min}$ measured at 1 to 4 m exhibited high distinguishability, it had the following two problems (Fig. 7(A)): (1) The $D_{\min}$ values obtained at 2 and 4 m are overlapped, and (2) the $D_{\min}$ value obtained at 9 m interfered with the 2-m and 4-m data. Therefore, we propose the second consideration as follows.

(2) Second consideration

The second consideration is proposed for solving two problems: (A) the overlapping of 2 and 4 m, and (B) the interference of 9 m with 2-m and 4-m data.

A. Distinguishing between 2-m and 4-m data

We conducted further statistical analysis on the 2-m and 4-m data. Of all the statistical categories, we found that in the third quartile, second largest value, and largest

values (maximum), 2-m and 4-m data could be distinguished when the boundary was set to 1.2 (Fig. 8). Furthermore, the data for the maximum exhibited a minimal error rate (i.e., only 93 items were incorrectly distinguished from 982 distinguished items). Thus, we use the maximum of per-10-item of data ($D_{\max}$) to distinguish between 2- and 4-m data.

B. Elimination of interruptions due to 9-m data

We observed the results of various statistical categories based on 10-item datasets obtained at actual distances of 2, 4, and 9 m and found that 9-m data is the most distinguishable based on the mean and variance (Fig. 9). Although the statistical data for variance has a low error rate, it is relatively volatile. Therefore, we use the mean per 10 items of data (D_{avg}) to eliminate interruptions due to 9-m data.

(3) Primary ranging criterion integrated from two considerations

By using $D_{\min}$ values (Fig. 7(A)), we obtained the following functions to estimate real distances:

$$dist(D_{\min}) = \begin{cases} 1\text{m, if } D_{\min} < 0.24 \\ 3\text{m, if } 0.24 \le D_{\min} < 0.4 \\ 2\text{m, 4m or 9m, if } 0.4 \le D_{\min} < 0.8 \\ \text{discard, others} \end{cases}.$$

Because the data obtained to estimate a distance longer than 4 m do not exhibit distinguishability, we decide to discard these data. Subsequently, by using the value D_{avg} (Fig. 9(A)), we obtained

$$dist(D_{\text{avg}} \mid 0.4 \le D_{\min} < 0.8) = \begin{cases} 2\text{m or 4m, if } 0.5 \le D_3 < 1.2 \\ \text{discard, others} \end{cases}$$

Finally, by using the values $D_{\max}$ (Fig. 8(C)), we obtained

$$dist(D_{\max} \mid 0.4 \le D_{\min} < 0.8, 0.5 \le D_{\text{avg}} < 1.2) = \begin{cases} 2\text{m, if } 0.5 \le D_2 < 1.43 \\ 4\text{m, if } D_2 \ge 1.43 \\ \text{discard, others} \end{cases}.$$

Therefore, the primary ranging criterion RC_P was finalized as

$$dist(D_{\min}, D_{\text{avg}}, D_{\max}) = \begin{cases} 1\text{m, if } D_{\min} < 0.24 \\ 3\text{m, if } 0.24 \le D_{\min} < 0.4 \\ 2\text{m, if } 0.4 \le D_{\min} < 0.8,\ 0.5 \le D_{\text{avg}} < 1.2,\ 0.5 \le D_{\max} < 1.43 \\ 4\text{m, if } 0.4 \le D_{\min} < 0.8,\ 0.5 \le D_{\text{avg}} < 1.2,\ D_{\max} \ge 1.43 \\ \text{discard, others} \end{cases}.$$

3.2.3. Secondary ranging criterion

Through analyzing RC_P, we found that although some statistical analysis results based on per-10-item data exhibited relatively high error rates (Fig. 7), these rates remained within an acceptable range. Therefore, we further analyzed these data and formulated a secondary ranging criterion RC_S, which is similar to Min-Max-like algorithm [25,26].

Dstc. \ Prd.	100	206	306	403	512	614	715	807	911
1	0.01	2.08	0.54	0.01	0.00	0.00	0.27	0.38	0.00
2	0.08	2.17	0.22	0.13	1.13	1.19	0.06	0.21	0.05
3	0.03	4.05	0.10	0.35	0.04	1.18	8.77	1.29	2.44
4	0.02	13.58	26.91	0.24	1.65	5.18	0.39	3.03	0.92
5	0.18	0.39	0.84	0.12	0.11	0.10	1.32	1.81	0.08
6	0.18	0.65	0.43	12.22	0.74	0.32	0.17	0.37	0.03
7	3.00	1.44	1.70	0.78	1.71	1.97	3.25	0.10	0.21
8	0.04	9.06	6.75	0.29	1.51	0.10	0.03	0.16	0.06
9	1.53	1.92	0.24	0.15	0.55	0.78	0.94	1.31	0.06
10	0.27	0.16	5.07	0.58	0.32	0.45	0.47	3.12	0.41

(A) Variances with transmission powers 4dBm

Dstc. \ Prd.	100	206	306	403	512	614	715	807	911
1	0.44	0.25	0.05	0.06	0.01	0.12	0.07	0.03	0.01
2	0.41	0.17	0.03	0.43	0.66	1.87	0.65	0.81	2.95
3	0.88	2.20	4.31	0.57	1.07	0.98	6.51	0.56	0.05
4	2.25	3.79	3.57	0.76	2.28	1.27	0.14	10.15	0.16
5	0.90	0.13	0.26	0.57	2.00	0.84	5.07	7.84	0.23
6	0.61	0.43	2.02	0.16	0.34	0.73	0.17	0.56	0.12
7	0.31	1.60	1.75	0.39	0.91	3.22	0.06	0.64	0.23
8	1.17	0.08	1.51	1.17	23.23	0.50	8.32	0.36	0.45
9	4.18	0.68	0.38	2.13	0.19	0.50	6.49	0.12	3.54
10	0.44	0.60	0.03	5.70	2.71	0.32	5.11	0.74	15.7

(B) Variances with transmission powers 0dBm

Dstc. \ Prd.	100	206	306	403	512	614	715	807	911
1	0.17	0.02	0.22	0.00	0.18	0.30	0.03	0.23	0.01
2	0.99	0.82	4.49	0.18	0.19	3.03	0.09	0.05	0.48
3	3.45	0.29	0.34	0.06	0.14	0.11	0.15	0.04	0.38
4	1.64	1.14	0.30	0.06	0.25	0.23	0.91	0.86	3.18
5	1.59	2.93	1.57	0.51	1.82	1.48	4.70	0.28	0.06
6	1.93	3.70	0.28	1.11	1.20	8.39	0.43	0.51	3.87
7	2.01	0.39	1.32	3.80	0.06	0.83	0.27	0.33	0.31
8	12.98	1.05	1.96	2.00	0.32	0.98	0.51	0.71	0.58
9	1.41	0.47	0.26	0.22	1.76	33.50	0.78	3.71	1.21
10	0.44	0.60	0.03	5.70	2.71	0.32	5.11	0.74	15.7

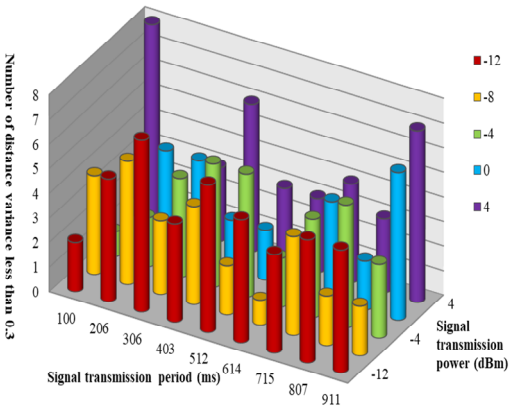
(C) Variances with transmission powers -4dBm

Dstc. \ Prd.	100	206	306	403	512	614	715	807	911
1	0.09	0.01	0.04	0.69	0.31	0.03	5.55	0.08	0.01
2	0.19	0.07	3.70	0.17	0.25	25.12	0.13	0.96	0.43
3	0.07	0.23	0.35	0.36	0.37	0.65	0.24	0.35	0.46
4	0.13	0.54	3.02	4.61	0.76	1.02	5.56	1.11	0.06
5	13.27	0.14	0.29	0.08	0.16	1.32	0.25	1.98	1.74
6	0.38	0.98	0.25	3.00	3.20	1.81	0.50	1.65	0.55
7	0.45	0.07	0.60	0.08	3.39	0.97	0.28	0.78	3.68
8	0.42	0.53	1.61	2.33	0.37	2.31	0.67	0.39	0.99
9	3.81	3.45	10.27	0.40	0.60	0.96	8.72	0.10	1.53
10	0.44	1.58	1.31	0.04	0.39	1.07	0.51	2.27	0.61

(D) Variances with transmission powers -8dBm

Dstc. \ Prd.	100	206	306	403	512	614	715	807	911
1	3.66	1.61	0.11	1.42	0.02	0.02	3.62	0.11	0.06
2	0.32	0.15	0.04	1.44	0.17	0.05	0.35	0.61	0.13
3	0.13	0.26	0.13	0.07	0.27	0.28	3.79	0.40	0.06
4	1.16	0.74	5.48	1.04	0.17	2.82	0.14	0.26	1.38
5	1.67	0.33	0.49	0.12	0.60	1.05	0.14	0.23	3.64
6	0.46	0.22	0.09	0.35	0.14	0.75	0.10	0.78	5.82
7	0.44	0.06	0.09	0.14	0.68	6.62	0.04	0.08	0.39
8	0.18	0.81	0.30	0.11	0.42	0.15	0.68	0.30	0.18
9	0.85	0.53	1.50	5.49	0.31	3.65	1.03	0.38	0.81
10	1.31	0.22	0.05	1.60	0.09	0.14	2.07	0.75	0.27

(E) Variances with transmission powers -8dBm



(F) Number of 500-distance-item variances which are less than 0.3 in 450 various parameters

Fig. 5. Variables and distribution of 500-measured data for 450 items (five transmission powers, nine transmission periods, and ten real distances)

Based on 13 statistical categories (Fig. 10), we can determine the possible ranges of actual distances (e.g., 2–6 m). We compared the error rates of various statistical methods (Table 1). Despite the highest value (maximum) and third highest value exhibiting low error rates, the statistical categories of the first to tenth largest values were relatively disorganized, and thus were of lower reference value. Thus, the median (whose mean error rate was 0.76 m) was adopted as the secondary ranging criterion RC_S.

4. EXPERIMENTS

4.1 Distribution of Variables of each data in 450 various parameter settings

For looking for the most stable transmission power and transmission period, we measure variances from 500-distance-item in 450 various parameter settings (i.e. totaling 500 * 450 = 225,000 items from five transmission powers (-12 dBm to 4 dBm), nine transmission periods (100 ms to 911 ms), and ten real distances (1 m to 10 m)). For each 500-distance-item, the *sliding window partition method* is applied to partition them into 491 ten-item sets, and 491 variances are then calculated from each set. From the mean of 491-variances (Fig. 5(A)-(E)), we adopt 4 dBm as the transmission power and 100 ms as the transmission period, because it's number of items with "a variance less than 0.3" is the largest (Fig. 5(F)).

4.2 Distribution and statistics of measured distances from ten real distances

After the transmission power 4 dBm and transmission period 100 ms had been determined and fixed, we then measure the RSSI signals from ten real distances (1m to 10m) to observe their distribution. 500 distance data are obtained from each real distance (Fig. 6). The error values are extremely large and the data distributions obtained at various distances are overlapped.

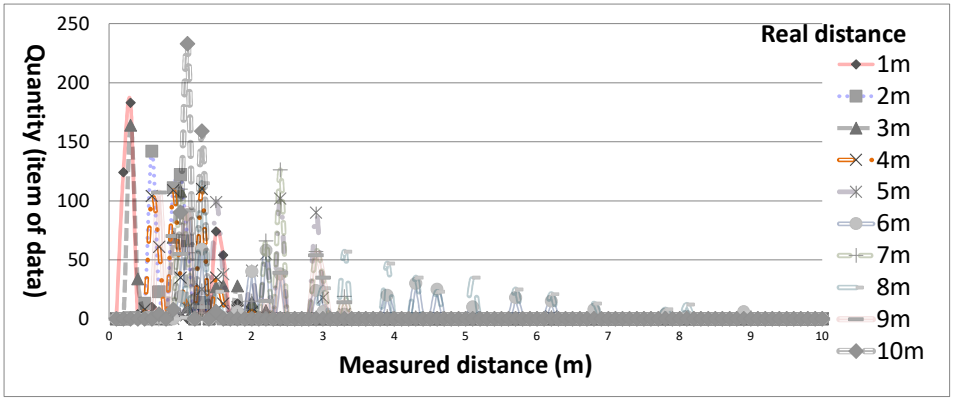
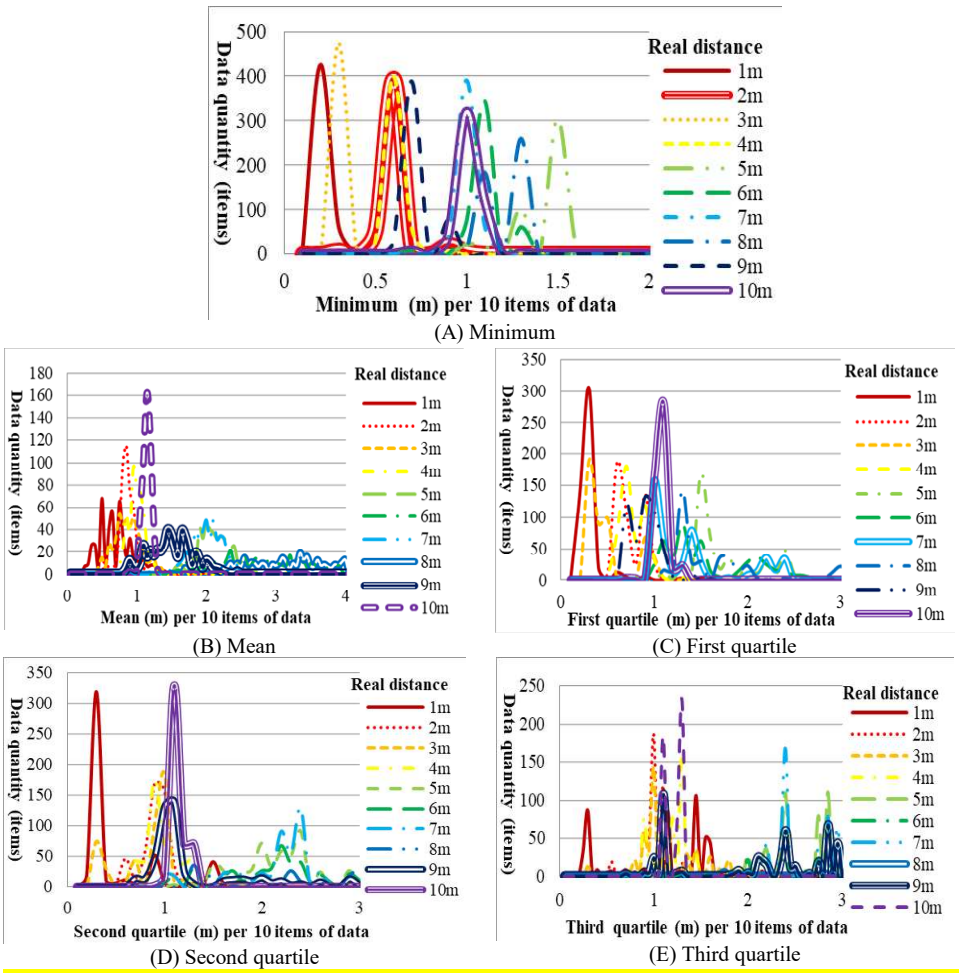


Fig. 6. Distribution of measured distances from ten real distances (with transmission powers 4dBm and transmission periods 100m)

Therefore, to determine their relationship, we further study various statistics of these data, including minimum, mean, first quartile, second quartile and third quartile, etc (Fig. 7). For each 500-distance-item, the *sliding window partition method* is applied to partition them into 491 ten-item sets, and each 491 statistical values (e.g., minimum, mean, quartiles) are then calculated from each set (Fig. 7).

Although various actual distances (1–10 m) were difficult to distinguish because data items excessively overlapped with one another, we observed that overlapping was less prominent among the "minimum" data measured at 1-4 m, and this observation entailed relatively high distinguishability. Therefore, we adopt the minimum per 10 items of data ($D_{\min}$) as the reference value for the first consideration of the positioning algorithm.



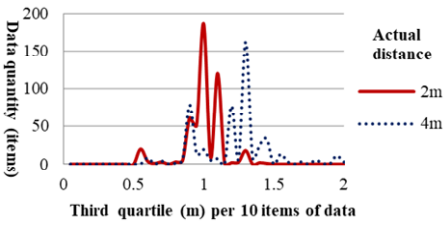
(A) Minimum (B) Mean (C) First quartile (D) Second quartile (E) Third quartile

Fig. 7. Various statistics for data measured at various actual distances (1–10 m) obtained from every 10 items of continuous data

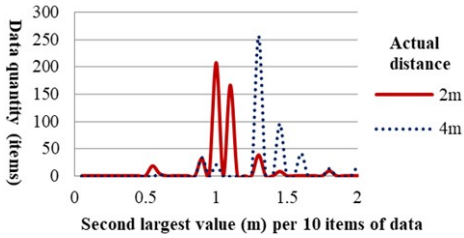
4.3 Distribution and statistics of measured distances from 2 m, 4 m and 9m

Although D_{min} measured at 1 to 4 m exhibited high distinguishability, the D_{min} values obtained at 2 and 4 m are still overlapped. Therefore, to determine the relationship between 2 m and 4 m, we further study other statistics of the two data, and found they could be distinguished in the third quartile, second largest value, and largest values (maximum) (Fig. 8). Finally, we use the maximum of per-10-item of data (D_{max}) to distinguish between 2- and 4-m data because the data for the maximum exhibited a minimal error rate (i.e., only 93 items were incorrectly distinguished from 982 distinguished items).

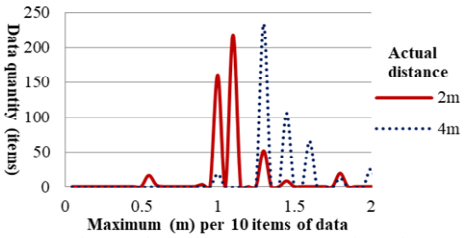
On the other hand, we found 9 m interfered with the 2-m and 4-m data in the D_{min} value. Therefore, to distinguish 9-m data from 2 m and 4 m data, we further study other statistics on the three data, and found they could be distinguished in the mean and variance (Fig. 9). Eventually, we use the mean of per-10-item of data (D_{avg}) to eliminate interruptions due to 9-m data because the statistical data for variance is relatively volatile.



(A) Third quartile (boundary set to 1.2, error rate = 0.169)

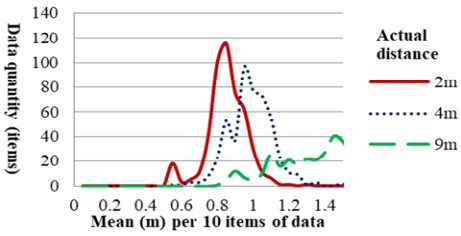


(B) Second largest value (boundary set to approximately 1.2, error rate = 0.115)

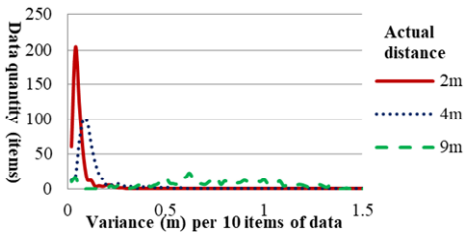


(C) Maximum (boundary set to approximately 1.2, error rate = 0.095)

Fig. 8. Statistical results based on 10-item datasets obtained at actual distances of 2 and 4 m



(A) Mean (boundary set to 1, error rate = 0.119)



(B) Variance (boundary set to 0.3, error rate = 0.070)

Fig. 9. Statistical results based on 10-item datasets obtained at actual distances of 2, 4, and 9 m

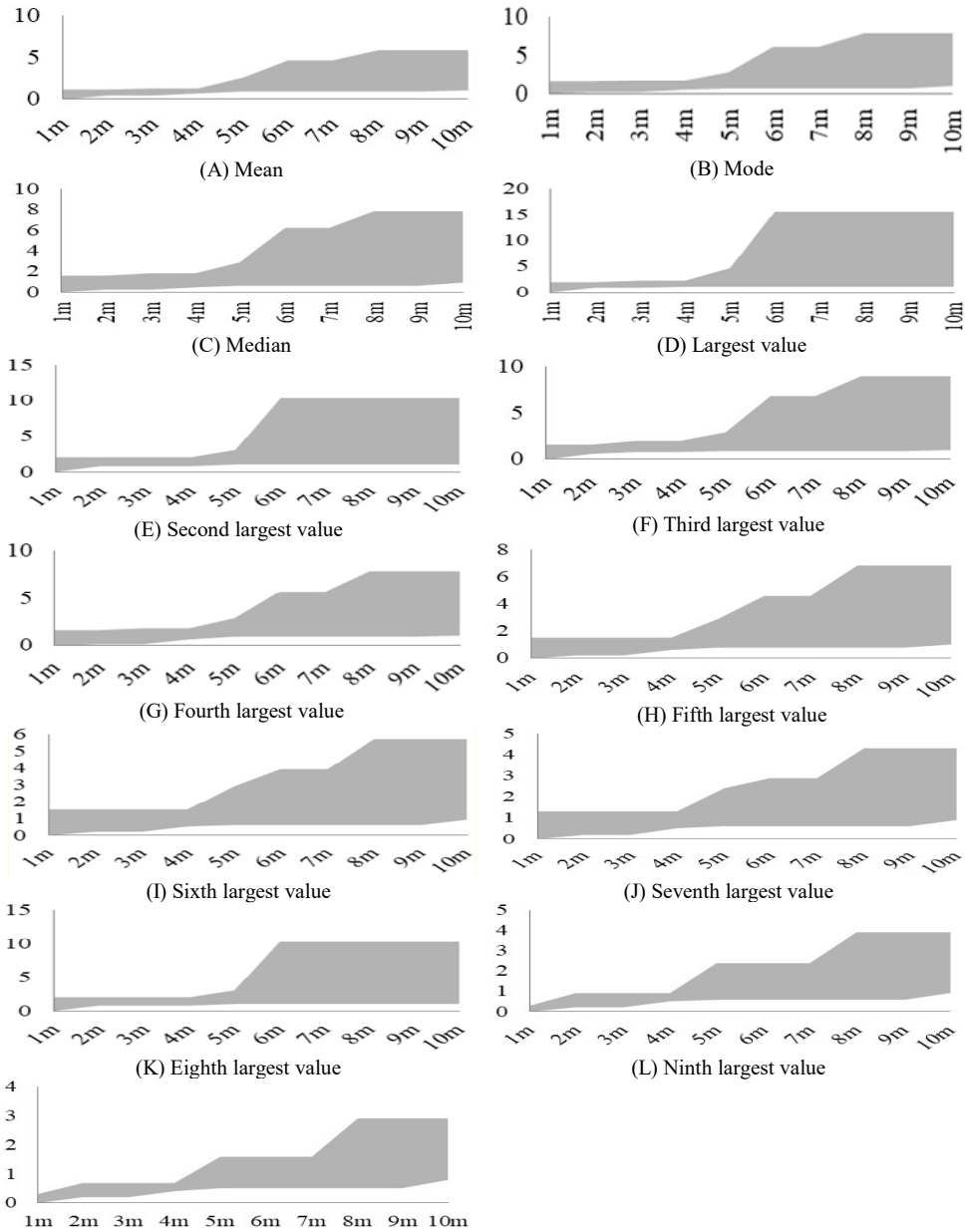


Fig. 10. Ranges of various statistical categories at various actual distances (X-axis) versus measured distance (m) (Y-axis)

4.4 Min-Max-Like model

In addition, we have down many statistical categories (such as the 13 categories shown in Fig. 10), and found the Min-Max method [25,26] can be modified and

integrated into our method. For deciding the most suitable statistical category, we then use three smart phones to measure 500 items of data in each four distances (1 to 4m) (i.e. totaling 500 * 4 * 3 = 6,000 items) to calculate the average error of each 13 statistical categories in Fig. 10 (as shown in Table 1). Finally, we chose the median to be the content of the modified Min-Max and integrated it into our method (as the secondary ranging criterion RC_S)

4.5 Performance of the proposed method for Distance Estimation

The performance for location estimation is described in this subsection. To evaluate the performance of the proposed method RC_P and RC_S, we conducted experiments in a laboratory environment. We use Estimote Proximity Beacons to offer the distance information, and HTC Desire 816 android phones, based on Android 5.0 and Qualcomm S400 1.6GHz, to receive the information. We used three mobile phones to measure three sets of distance data, adopting RC_P and RC_S to analyze the distance error and mean error as follows:

$$e_{mean} = \frac{\sum_{i=1}^{n} | d_t^{(i)} - d_m^{(i)} |}{n},$$

where d_t is the actual distance and d_m is the measured distance when RC_P or RC_S is applied. Table 2 displays the analysis results.

From Table 1 and 2, we can observe that the smart phone #1 always performed the best, probably because most parameters are chosen and criterions are decided via the performance of smart phone #1.

Table 1. Mean errors obtained using various statistical categories as RC_P (m)

	Mean	Mode	Median	LV	Tenth LV	Second LV	Third LV
Phone 1	0.51	0.92	0.40	0.65	0.50	0.01	0.50
Phone 2	1.31	0.99	1.06	0.07	1.40	1.08	0.49
Phone 3	1.20	1.05	0.81	1.01	0.58	1.40	1.23
Average	1.01	0.98	**0.76**	**0.58**	0.83	0.83	**0.74**
	Fourth LV	Fifth LV	Sixth LV	Seventh LV	Eighth LV	Ninth LV	
Phone 1	0.97	1.03	0.92	0.81	0.67	1.01	
Phone 2	0.92	1.07	1.22	0.70	1.05	1.29	
Phone 3	1.18	0.72	1.09	1.13	0.78	1.10	
Average	1.02	0.94	1.08	0.88	0.83	1.13	

LV: Largest value

Table 2. Comparison of errors between phones and criterions (m)

Criterion	Phone 1	Phone 2	Phone 3	Average
RC_P	0.326	0.410	0.459	0.398
RC_S	0.398	1.061	0.810	0.756

4.6 Performance of the proposed method for Location Estimation

This subsection presents the performance for location estimation of our proposed method (Fig. 11) in the laboratory environment (approximate 10 m × 10 m). In the lab, numerous obstacles such as tables and chairs were positioned (Fig. 12). Beacons were installed approximately 4 m apart from one another. The users moved within the space while holding mobile phones that were positioned by beacon signals. Three beacons with the strongest signals were selected, and the distance data of these three beacons were then converted to measured distances by using the ranging algorithm. The measured distances were subsequently input into the positioning algorithm to obtain current coordinates. We found that movement and multiple obstacles in an indoor setting rendered the signals highly unstable. The mean errors from the implementation obtained using two ranging algorithms, namely RC_P and $RC_P + RC_S$, were 2.4 and 1.97 m, respectively.

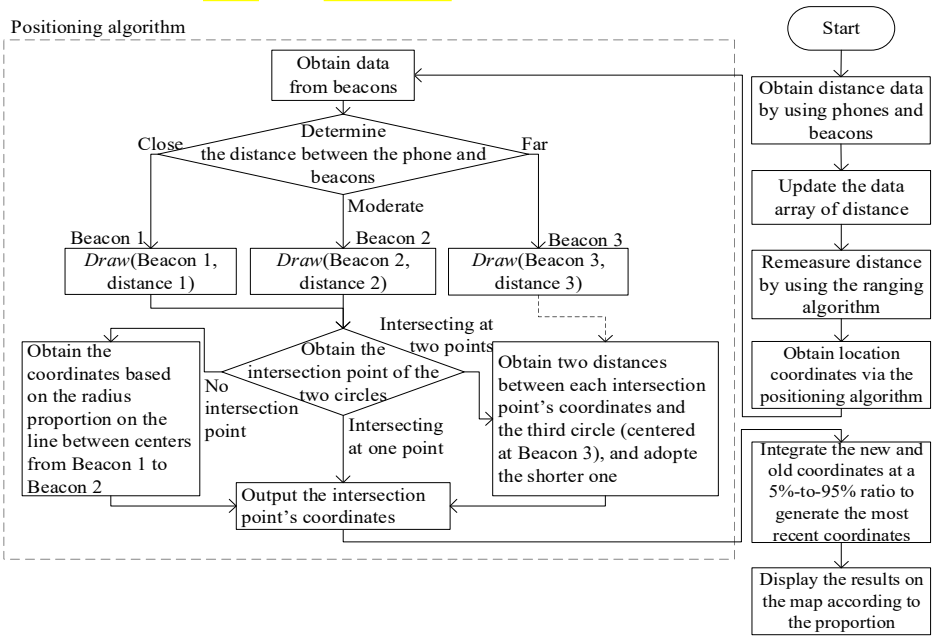


Fig. 11. Program flow framework

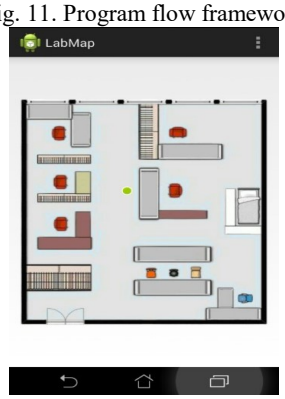


Fig. 12. User interface

4.7 Comparison

Table 3 lists the comparison of the mean errors attained through the schemes proposed by Zhung *et al.* [4], Martin *et al.* [7], and Rida *et al.* [8]. In addition, we compare the scheme features in Table 4.

Table 3. Comparison or mean errors (m)

Scheme	Mean Error
Zhung *et al.*'s scheme [4]	2.56
Martin *et al.*'s scheme [7]	0.53
Rida *et al.*'s scheme [8]	1.0
Proposed scheme (RC_P)	0.398
Proposed scheme (RC_S)	0.756

Table 4. Comparison of features

Features	[4]	[7]	[8]	Our scheme
BLE-based signal	V	V	V	V
Transmission unit	CC2540 (TI)	Beacon *1 (Estimote)	CC2540 (TI)	Proximity Beacon (Estimote)
Receiver unit	iPhone 4S (iOS 8)	Nexus 7 (Android 4.3)	Samsung *2 (Android 4.1)	HTC desire 816 (Android 5.0)
Needless Transmission channel control		V	V	V
Needless Server	V		V	V
Needless WiFi routers	V		V	V
Needless Internet	V	V	V	V
Needless advertised beacons			V	V
Needless post-processing filtering			V	V
Cost effective consideration	V		V	V
Easy to implement			V	V
Low Computation loading			V	V

*1: Unknown type of Estimote Beacon; *2: Unknown type of Samsung smart phone

5. CONCLUSION

Because people in the contemporary world often stay indoors for extended periods of time, the demand for accurate positioning continues to increase, and the consideration of both better positioning performance and being economical is a significant research topic. This study adopts cost-effective Estimote Proximity beacons for positioning and proposes a positioning algorithm for them. The characteristics of their Bluetooth signals are analyzed to design a ranging algorithm. Integrating the results of positioning and ranging algorithms reveals a mean error of 0.398 m when the mobile phones are in stasis. Moreover, the implementation results obtained using Android mobile phones reveal that the mean error is 1.97 m when the mobile phones are in motion. Future work will focus on different and advanced fixed beacons (such as Location UWB Beacon, Location

Beacon, or THLight USBeacon B402X), mobile and wearable beacon (such THLight USBeacon B3029T and Apple smartphones) or different receivers (such iPhone, Android smart phone, or Bluetooth-gateway Receiver) to enhance applications in indoor-positioning environments and improve long-term care conditions.

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