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Design and Implementation of Beacon-Based Positioning

SHIN-YAN CHIOU[1,2] AND ZHEN-YUAN LIAO[1]
[1]*Department of Electrical Engineering*
College of Engineering
Chang Gung University
Taoyuan, 333 Taiwan
[2]*Department of Nuclear Medicine*
Linkou Chang Gung Memorial Hospital
Taoyuan, 333 Taiwan
E-mail: ansel@mail.cgu.edu.tw

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 5m. Some scholars have proposed new approaches of beacon-based indoor positioning to provide easier installation and decrease the distance error to 2.5m. For both better positioning performance and being economical, this paper proposes an approach of beacon-based positioning method, using cost-effective Estimate Proximity Beacons and Android smart phones for implementation. The result reveals that the mean distance errors of our method are 0.398m in stasis and 1.97m in motion.

Keywords: positioning, indoor positioning, beacon, bluetooth low energy, mobile

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].

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.

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 < 2.56m at 90% of the time with dense deployment of BLE beacons (1 beacon per 9m), and of <

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3.88m at 90% of the time with sparse deployment (1 beacon per 18m). 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 0.53m in a $9 \times 10\text{m}^2$ laboratory. 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 0.5-1.0m. 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 $100\text{m} \times 100\text{m}$ 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 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 $6\text{m} \times 6\text{m}$ 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 920m × 340m office space, which was divided into 6 × 3 = 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 beacon. 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 0.5m to 3m, their experienced average error is from 0.101m to 0.194m for direct reading, and from 0.028m to 0.193m 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-outdoor, 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 2.18m accuracy on average in semi-outdoor areas. Their distance error distribution is mainly within 10m with the 90th percentile of 7.94m.

From our measurement, the distance parameters obtained from Estimate 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.

This article focuses on the method and implementation experience on beacon-based positioning using Estimate Proximity beacons via BLE communication, where the Proximity beacon is the economical type from many kinds of Estimate 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.

This paper is divided into six sections. Section 1 reviews existing studies and the research motivation of the present study. Section 2 reviews literature relevant to the present study. Section 3 details the content and structure of the proposed positioning algorithm. Section 4 addresses analysis on the functions and efficacy of the proposed method for comparison with those of other studies. Section 5 describes an actual implementation using Android phone and Section 6 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 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 used to be broadcasted channels and measure RSS that features different characteristics, are discussed separately, and are conducted polynomial regression and FP on individually.

(2) PRM: $\hat{d}_{PRM} = \sum_{i=0}^{n} c_i \cdot RSS^i$ is employed to convert RSS to distance, where c_i are the coefficients of the nth-degree polynomial, RSS is the RSS value, and $\hat{d}_{PRM}$ is the estimated distance.

(3) Multichannel FP: The noises in a planar space are measured and the resultant noise data are used to draw an oval in the coordinate plane of the database, and the average position derived from the obtained coordinates was the target location obtained using FP.

(4) Outlier detection level 1: The estimated distance data were averaged from the six items of distance data obtained from FP and PRM from 3 channels after distrusted-data outliers.

(5) EKF: The next distance can be predicted from an actual state $x_{k|k+1} = \Phi_{k,k+1}x_{k|k} + \omega_k$ which is combined of predicted and observed states, where x represents a state matrix, 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.

(6) Outlier detection level 2: If the difference between the EKF observation result and the prediction result is too large, it will not be adopted.

Although this algorithm is claimed to be useful to improve the localization accuracy in sparse-beacon-deployment environments, it 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. In their protocol, 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. Afterward, the server searches for an instantaneous position estimate $\hat{d} \in R^2$ by solving the equation $\hat{x} = \arg\min_x \sum_{b \in B} w(\hat{d}_b)$ $||b_b - \hat{d}_b||^2$, 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.

However, 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. 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 15m 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.

Although Rida *et al.* [8] claim that their accuracy (85cm estimated location error) is acceptable by using CC2540 nodes, 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 Estimate 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

The proposed scheme comprises two parts, where part 1 focuses on the designed positioning algorithms (including the beacon-height effect and the beacon-credibility determination) and part 2 emphasizes the ranging algorithm (including the primary and secondary criterions).

3.1 Positioning Algorithm

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 shown in Fig. 1.

Moreover, in our algorithm, two circles with high credibility (*i.e.* stronger signals or shorter distances) are considered first and the remaining circle serves to aid determination in Fig. 9 (a). Potential scenarios involving the intersecting of two circles are discussed as follows (*i.e.*, no intersection point, one intersection point, and two intersection points) in Fig. 2.

(1) No intersection point: This situation includes two scenarios: (a) the sum of the radiuses of the two circles is smaller than the length of the line between circle centers in Fig. 2 (a); and (b) a smaller circle is within a larger circle in Fig. 2 (b). The user's coordinates can be obtained using the proportion of the two circles' radiuses.
(2) One intersection point: If the two circles have only one intersection point in Fig. 2 (c), this point is directly adopted as the user's coordinates.

(3) Two intersection points: In this situation (Beacons 1 and 2 in Fig. 2 (d)), between both intersection points, the one with the shorter distance to the third circle is adopted.

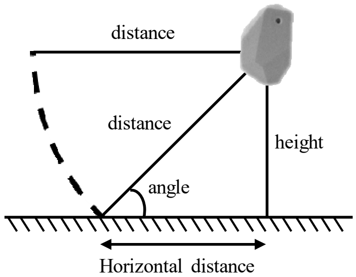
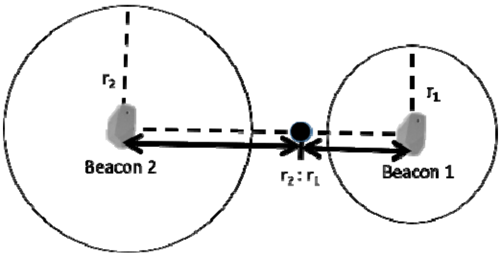
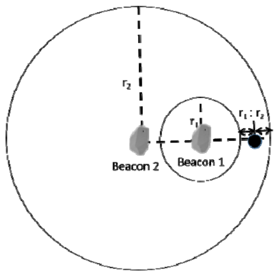


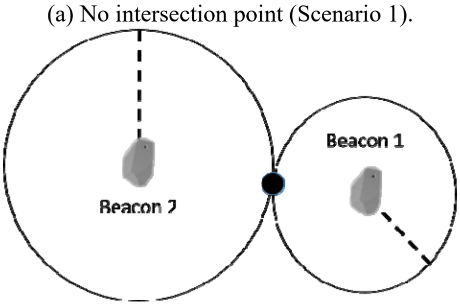
Fig. 1. The conversion between the measured distance and horizontal distance.



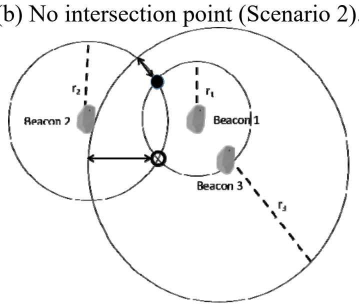
(a) No intersection point (Scenario 1).



(b) No intersection point (Scenario 2).



(c) One intersection point.



(d) Two intersection points.

Fig. 2. Schematic of the intersection points of two circles.

3.2 Ranging Algorithm

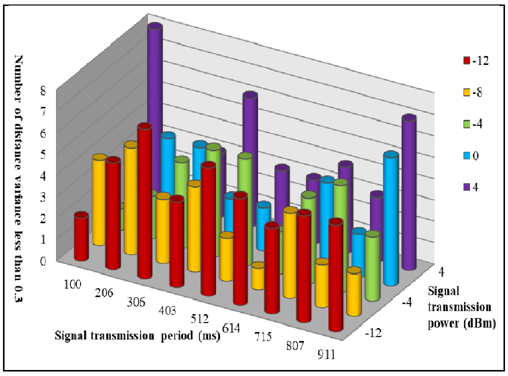
This section explains the proposed ranging algorithm, including the determination of transmission period 4 dBm and transmission power 100 ms, the primary ranging criterion RC_P, and the secondary ranging criterion RC_S.

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 in Fig. 3 (b), which means it is the most stable parameter.

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.



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

Fig. 3. Variables and distribution of 500-measured data for 450 items (five transmission powers, nine transmission periods, and ten real distances).

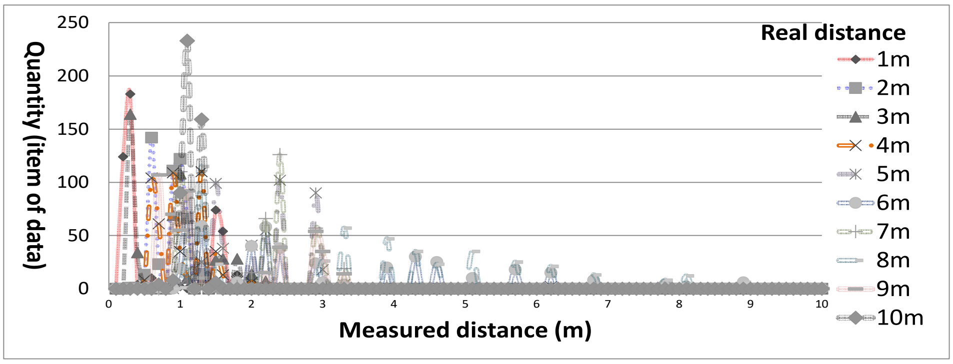


Fig. 4. Distribution of measured distances from ten real distances (with transmission powers 4dBm and transmission periods 100m).

3.2.2 Primary ranging criterion

By analyzing the statistics of ten 500-distance-item data measured at intervals between the actual distances of 1 to 10m, we found that the error values are extremely large and the data distributions obtained at various distances are overlapped in Fig. 4, and then proposed two considerations as our primary ranging criterion.

(1) First consideration

As shown in Fig. 5, various statistics (minimum, mean, first, second, third quartiles) of ten 500-distance-item data measured at various actual distances (*i.e.*, 1-10m) were separately obtained for each distance. However, various actual distances (1-10m) were

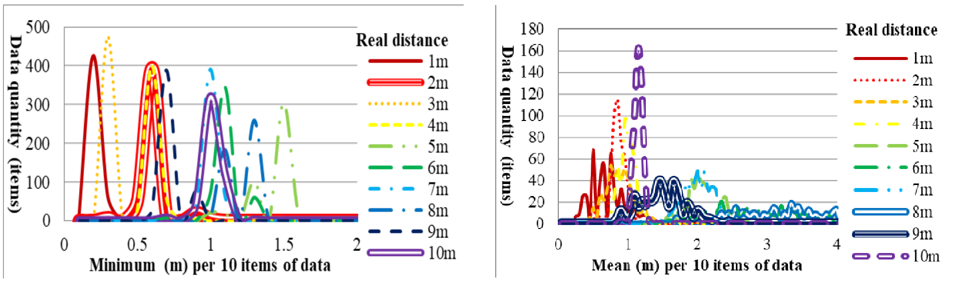


Fig. 5. Various statistics for data measured at various actual distances (1–10 m) obtained from every 10 items of continuous data.

difficult to distinguish because data items excessively overlapped with one another. Fortunately, we observed that overlapping was less prominent among the "minimum" data measured at 1-4m, 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:

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

We then set each beacon as the center of a circle with a radius 4m to attain the most satisfactory positioning result.

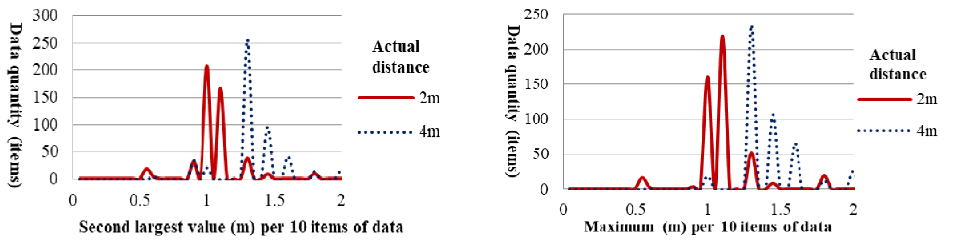
Although $D_{\min}$ measured at 1 to 4m exhibited high distinguishability, it has two problems in Fig. 5 (a): (1) the $D_{\min}$ values obtained at 2 and 4m are overlapped, and (2) the $D_{\min}$ value obtained at 9m interfered with the 2m and 4m data. Therefore, we propose the second consideration as follows.

(2) Second consideration

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

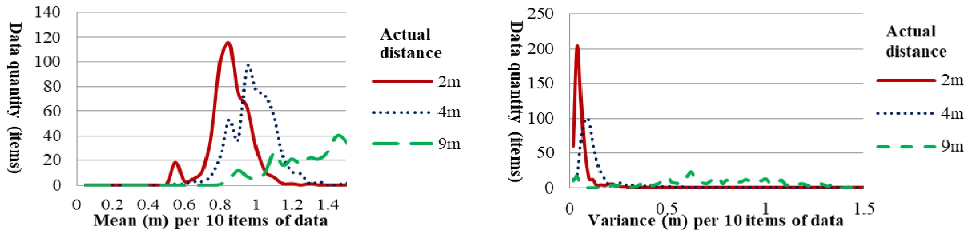
A. Distinguishing between 2m and 4m data: We found that in the third quartile, second largest value, and largest values (maximum), 2m and 4m data could be distinguished when the boundary was set to 1.2 in Fig. 6. Furthermore, the data for the maximum exhibited a minimal error rate (*i.e.*, only 93 items 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 4m data.

B. Elimination of interruptions due to 9m data: We observed the results of various statistical categories based on 10-item datasets obtained at actual distances of 2, 4, and 9m and found that 9m data is the most distinguishable based on the mean and variance in Fig. 7. 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 9m data:



(a) Second largest value (boundary set to approximately 1.2, error rate = 0.115). (b) Maximum (boundary set to approximately 1.2, error rate = 0.095).

Fig. 6. Statistical results based on 10-item datasets obtained at actual distances of 2 and 4m.



(a) Mean (boundary set to 1, error rate = 0.119). (b) Variance (boundary set to 0.3, error rate = 0.070).

Fig. 7. Statistical results based on 10-item datasets obtained at actual distances of 2, 4, and 9m.

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

Therefore, by using the values $D_{\max}$ in Fig. 6 (b), we obtained

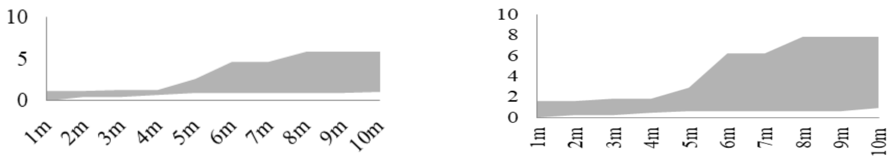
$$dist(D_{\max} \mid 0.4 \le D_{\min} < 0.8, 0.5 \le D_{\text{avg}} < 1.2) = \begin{cases} \text{2m, if } 0.5 \le D_2 < 1.43 \\ \text{4m, if } D_2 \ge 1.43 \\ \text{discard, others} \end{cases},$$

and the primary ranging criterion RC_P was finalized as

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

3.2.3 Secondary ranging criterion

Although some statistical analysis results based on per-10-item data exhibited relatively high error rates in Fig. 5, 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]. Based on 13 statistical categories in Fig. 8, we can determine the possible ranges of actual distances (*e.g.*, 2-6m). We com-



(a) Mean (b) Median

Fig. 8. Ranges of various statistical categories at various actual distances (X-axis) versus measured distance (m) (Y-axis).

pared the error rates of various statistical methods in Table 1. Despite the highest value (maximum) and third highest value exhibiting low error rates, they are relatively disorganized. Thus, the median was adopted as the secondary ranging criterion RC_S.

4. EXPERIMENTS

We measure 225,000 items (500-distance-item in 450 various parameter settings) from five transmission powers (−12 dBm to 4 dBm), nine transmission periods (100 ms to 911 ms), and ten real distances (1m to 10m). 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, we adopt 4 dBm & 100 ms in Fig. 3 (a), because of the largest number of items with of "a variance less than 0.3".

Afterword, we measure the RSSI signals from ten real distances (1-10m) to observe their distribution, and obtain 500 distance data from each real distance in Fig. 4. We further study various statistics of these data, including minimum, mean, and from first to third quartiles in Fig. 5. 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 are calculated from each set. Although various actual distances (1-10m) were difficult to distinguish, we observed that overlapping was less prominent among the "minimum" data measured at 1-4m. Therefore, we adopt the minimum per 10 items of data ($D_{\min}$) as the reference value for the first consideration of the positioning algorithm.

However, the $D_{\min}$ values obtained at 2 and 4m are still overlapped. Fortunately, they could be distinguished in the statistics of third quartile, second largest value, and largest values (maximum) in Fig. 6. Finally, we use the maximum of per-10-item of data ($D_{\max}$) to distinguish between 2 and 4m data because the data for the maximum exhibited a minimal error rate. On the other hand, we found 9m interfered with the 2m and 4m data in the $D_{\min}$ value. Therefore, we found they could be distinguished in the mean and variance in Fig. 7. Eventually, we use the mean of per-10-item of data (D_{avg}) to eliminate interruptions due to 9m data.

In addition, we have down 13 statistical categories (mean, mode, median, and from first to tenth largest values) (such as the two shown in Fig. 8), and found the Min-Max method [25, 26] can be modified and integrated into our method. 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 statistical categories (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)

To evaluate the performance of the proposed method RC_P and RC_S, we conducted experiments in a laboratory environment. We used Estimate 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, and 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 in Table 2. From Tables 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).

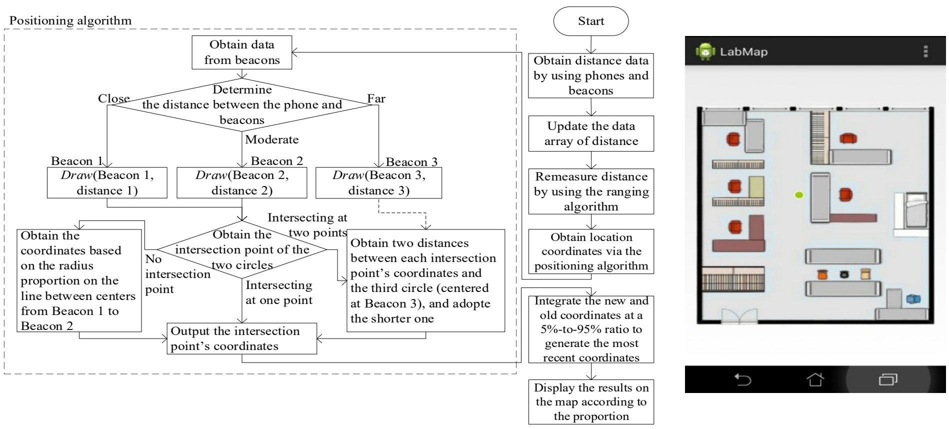
	Mean	Mode	Median	First LV	Second LV	Third LV	Tenth LV
Phone 1	0.51	0.92	0.40	0.65	0.01	0.50	0.50
Phone 2	1.31	0.99	1.06	0.07	1.08	0.49	1.40
Phone 3	1.20	1.05	0.81	1.01	1.40	1.23	0.58
Average	1.01	0.98	**0.76**	**0.58**	0.83	**0.74**	0.83

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

Our proposed method in Fig. 9 (a) is applied in a laboratory environment (approximate $10 \times 10\text{m}^2$), where numerous obstacles such as tables and chairs were positioned in



(a) Program flow framework. (b) User interface.

[*] *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. 9. Program flow framework and user interface.

Fig. 9 (b), and beacons were installed approximately 4m 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 1.97m, respectively. Table 3 lists the comparison of the mean errors the features of Zhung *et al.* [4], Martin *et al.* [7], and Rida *et al.* [8].

Table 3. Comparison of mean errors (m) and features.

	Zhung [4]	Martin [7]	Rida [8]	Proposed RC_P	Proposed RC_S
Mean errors	2.56	0.53	1.0	0.398	0.756
Transmission unit	CC2540 (TI)	Beacon*1 (Estimate)	CC2540 (TI)	Proximity Beacon (Estimate)	
Receiver unit	iPhone 4S (iOS 8)	Nexus 7 (Android 4.3)	Samsung*2 (Android 4.1)	HTC desire 816 (Android 5.0)	
BLE-based signal	V	V	V	V	V
Needless transm. channel control		V	V	V	V
Needless server	V		V	V	V
Needless WiFi routers	V		V	V	V
Needless Internet	V	V	V	V	V
Needless advertised beacons			V	V	V
Needless filters of post processing			V	V	V
Cost effective	V		V	V	V
Easy to implement			V	V	V
Low comput. loading			V	V	V

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

5. CONCLUSION

This study adopts cost-effective Estimate 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 0.398m when the mobile phones are in stasis. Moreover, the implementation results obtained using Android mobile phones reveal that the mean error is 1.97m 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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Shin-Yan Chiou (邱錫彥) received the PhD degree in Electrical Engineering from National Cheng Kung University, Taiwan, in 2004. From 2004 to 2009, he worked at Industrial Technology Research Institute as an RD Engineer. Since 2009, he joined the faculty of the Department of Electrical Engineering, Chang Gung University, Taoyuan, Taiwan, where he is currently a Professor. He also joined the teams of the Division of Nuclear Medicine and the Division of Neurosurgery, Chang Gung Memorial Hospital, Linkou, Taiwan in 2018, and is currently a Researcher at the hospital. He has published a number of journals and conference papers in the areas of information security, social network security, mobile security, smart scheduling, and surgical navigation. His research interests include information security, cryptography, social network security, surgical navigation, mixed reality, and applications between mobile devices.

Zhen-Yuan Liao (廖振淵) received the BS degree and the MS degree in the Department of Electrical Engineering from Chang Gung University in 2016 and 2017. Since 2018, he joined the faculty of the Department of Neurosurgey in Linkou Chang Gung Memorial Hospital, where he is currently an Assistant Engineer. His research interests include information security and secure applications between mobile devices and augmented reality.