Beacon Based Indoor Positioning System Using Weighted Centroid Localization Approach

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***Abstract*— There has been an upward trend in the requirement of indoor positioning systems using bluetooth low energy (BLE), Wi-Fi, and visible light communication. In order to realize the indoor positioning with these communication systems, techniques such as fingerprinting, trilateration, and triangulation have been widely studied. Even though fingerprinting has been chosen as a representative approach in many literatures, it is known as tedious and time consuming method due to the long-time location learning phase. Therefore, the fingerprinting is expected to be integrated with other methods to enhance the location accuracy and reduce the location estimation procedures. In this work, we discuss one of these methods used for indoor positioning, i.e., weighted centroid localization (WCL) using received signal strength indicator (RSSI) observed from neighboring BLE beacons. The WCL is evaluated in our testbed building and analyzed to configure its parameters for indoor positioning.**

***Keywords*— BLE, indoor positioning, fingerprinting, and centroid localization.**

I. INTRODUCTION

Global positioning system (GPS) has been dominating technology in the field of location based system. However, GPS is not practical in indoor positioning because it needs undisturbed reception of signals from at least four satellites with line of sight. Meanwhile, indoor positioning system (IPS) has come to light as an alternative to GPS in indoor locations. Bluetooth low energy (BLE) can be useful in IPS which is designed for a short range wireless transmission while maintaining low energy consumption, small size, and low cost [1].

One of the IPS examples based on BLE beacon is introduced in [2] where gaussian filter is used to pre-process the receiving signals. This BLE technology is used for fingerprinting method consisting of two phases; offline training and online locating phases. In [3], authors proposed a hybrid approach for IPS which is an integration of fingerprinting and trilateration techniques. They used gradient filter for RSSI estimation. Also, another fingerprinting example with BLE has been demonstrated in [4] using various beacons densities. Fingerprinting, trilateration, and triangulation are known as well-established methods with BLE beacons. However, these methods are either tedious or require precise distance estimation through the proper analysis of beacon signals. In our work, we show weighted centroid localization (WCL) derived from a centroid determination method where weights are used to estimate position [5]. The weight is inversely proportional to distance between the reference beacon location and an unknown position. For any environment condition, the distance is raised to a power of degree (g) for the calculation of weight.

For example, the WCL method using Zigbee-based sensor network in outdoor environment is presented in [5]. Here, link quality indicator (LQI) of the Zigbee-based devices is converted to distance by using Friis' free space transmission equation. [6] quotes WCL as coarse grained localization approach and presents adaptive WCL (AWCL) as an improvement of former method. This AWCL is used in wireless sensor networks where measured LQI values of each beacon in range are reduced by a part of the lowest LQI value. Another work for WCL method is [7], where proprietary radio modules are used for tracking a person in a longwall mining application. Here, WCL localization with degree (g) of 2.6 is used further to implement 2D inertial navigation system. The WCL method with BLE is also presented in [8]. However, this work does not have proper RSSI filtration and focuses only on beacon deployment configurations. Also it does not consider weight variation according to environment conditions.

In this paper, we show how a proper value of 'g' is determined for our testing environment. Also, we demonstrate the performance result of the proposed positioning system using Kalman filter and moving average filter, calibrating path loss exponent, and estimating distance from RSSI.

The remainder of the paper is organized as follows. Section II provides brief information on RSSI filtration technique. The WCL method is explained in Section III. Section IV and V presents the experimental results and conclusion, respectively.

II. RSSI FILTERATION WITH KALMAN FILTER AND DISTANCE ESTIMATION

The RSSI value at a mobile device fluctuates over time due to attenuation and several noise factors. Kalman filter is used to produce estimates of current RSSIs that tend to be more precise than those based on a single measurement alone on the top of moving average filter. Then, the estimated RSSIs are converted to distances. In moving average filtration, each of the last ten samples of received RSSIs are averaged and stored. These averages are the inputs to the Kalman filter. A simplified Kalman filter equation [9] is shown as:

- Time update equations

$$\hat{x}_k^- = \hat{x}_{k-1} \quad (1)$$
$$P_k^- = P_{k-1} + Q \quad (2)$$

- Measurement update equations

$$K_k = \frac{P_k^-}{P_k^- + R} \quad (3)$$
$$\hat{x}_k = \hat{x}_k^- \; K_k(z_k - \hat{x}_k^-) \quad (4)$$
$$P_k = (1 - K_k)P_k^-. \quad (5)$$

Here, $\hat{x}_k^-$ and $\hat{x}_{k-1}$ are priori and posteriori state estimate respectively. Similarly, R is the measurement variance, Q is process variance, and P_k^- and P_k are priori and posteriori error variance. z_k is output from the moving average filter. K_k is Kalman gain where k is time instant. By hit and trial method, we determined values of R, Q, and P in our working environment and their values are 0.1, 0.000001 and 0.001 respectively. The estimated RSSIs (400 measurements at a measurement place) at different distances of corridor and computer lab (partitioned into 12 cubicles) in our testbed building are shown in Fig.1.

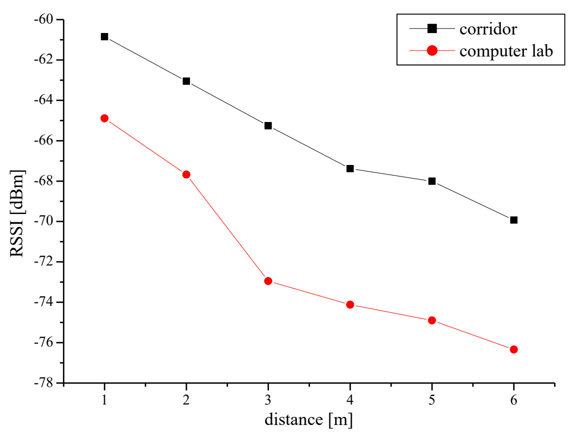

Fig.1: Distribution of estimated RSSIs inside the computer lab and at corridor.

The conversion from RSSI to distance is realized by using relation between distance and received power as presented in [10].

$$P_r(d)[dBm] = A - 10n * log_{10}(d), \quad (6)$$

where, $P_r(d)$ is the received RSSI in dBm at distance d, A is the received RSSI at one meter and n is the path loss exponent. For an example of RSSI conversion to the distance, we placed an Estimote beacon [11] at the center of the corridor and measured RSSIs at distance of 1 meter encircling the beacon, then got average RSSI, $A = -60.85\ dBm$. By using this obtained A, the estimated distance with various n is obtained as shown in Fig.2.

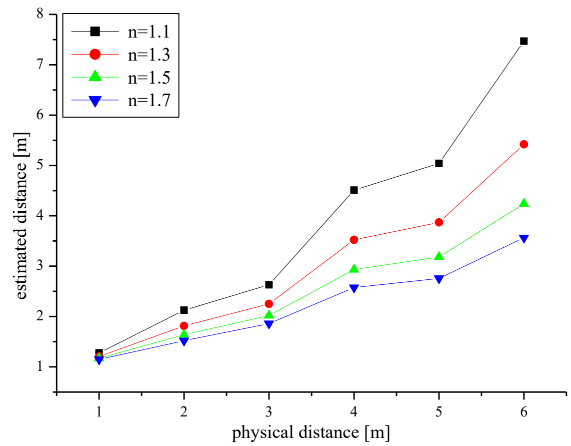

Fig.2: Estimated distance with various path loss exponents against the actual physical distance at the corridor.

III. POSITION ESTIMATION USING WEIGHTED CENTROID LOCALIZATION METHOD

The WCL is a location estimation technique assigning weight (w_i) to each beacon, based on distance to beacon and degree(g). This algorithm confines location estimation inside the region surrounded by beacons. Since any beacon near to tag device will have highest weight, the final location estimation is pulled towards this beacon. The location estimation algorithm is given as follows:

$$x_w = \sum_{i=1}^{m} x_i w_i \,/\, \sum_{i=1}^{m} w_i \quad (7)$$
$$y_w = \sum_{i=1}^{m} y_i w_i \,/\, \sum_{i=1}^{m} w_i \quad (8)$$
$$w_i = \frac{1}{d_i^g}, \quad (9)$$

where, (x_w, y_w) is the estimated location, (x_i, y_i) is the location coordinate of i^{th} beacon, d_i is distance between tag and beacon i, and g is the degree of weight. Total number of beacons considered at any time for position estimation is denoted by m.

The WCL positioning system is depicted in Fig.3.

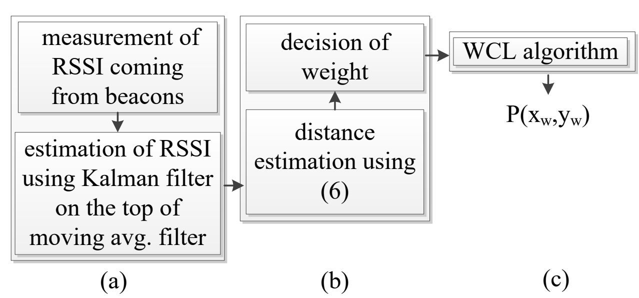

Fig.3: Operation procedure of WCL based positioning system, (a) data acquisition, (b) data processing, (c) location estimation.

Since RSSI fluctuates over time due to attenuation and several noise factors, Kalman filter is used on the top of moving average filter. The estimated RSSI is then converted to distance using (6). Finally, the selected beacons' locations and their respective estimated distances are used in WCL for position estimation. Here, beacons are selected on basis of their current RSSI values.

IV. EXPERIMENTAL RESULT AND DISCUSSIONS

TABLE I. EXPERIMENT CONDITION FOR THE EVALUATION OF WCL

Parameters	***Value***
Total number of beacons	14
Space between two adjacent beacons	4.5 meters
Breadth of corridor	2.5 meters
Height of beacon deployment	2.5 meters
Beacon transmission power	+4dBm
Advertisement interval	300 milliseconds
Tx-Rx devices	Estimote beacons,iPhone-4S
A[dBm]	-60.85
n	1.3

We used Estimote devices as BLE beacons transmitting advertisement packets periodecally and an iOS device receiving those advertisement packets. We developed an iOS application to display the estimated mobile user location according to WCL method. The beacons are deployed in rectangular fashion with orientation towards their opposite wall. At any place of measurement, four closest beacons were selected with respect to their RSSI values. Measurements were taken at two different regions of the corridor- at border of the rectangular polygon formed by beacons and central region of the polygon.

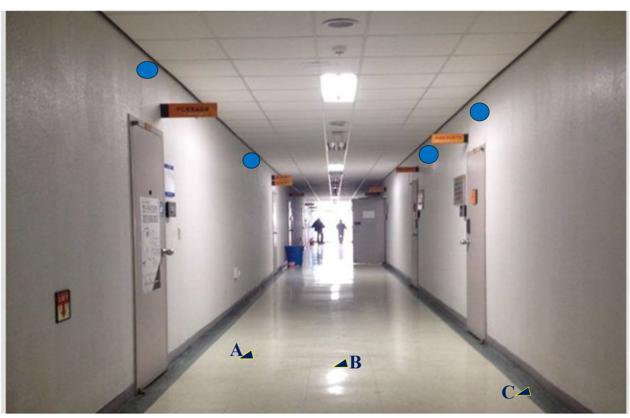

Fig.4: Experimental environment: beacons deployed corridor where blue circular dots along the wall of corridor represent beacon deployment position and measurement places are marked on the floor as A, B, and C.

As shown in Fig.4, in any region, measurements are taken at three different places – near the wall (C), away from the wall, (A) and midway of the corridor (B). We took 100 measurements at each place and location estimation error is averaged as shown in Fig. 5 and 6.

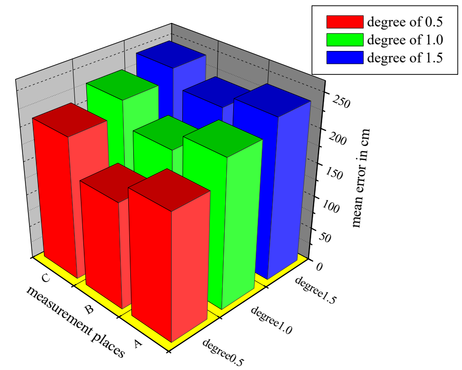

Fig.5: Avg. location error at different measurement places (A,B, and C) in the central region of two rectangualr polygons with respective degree of weight.

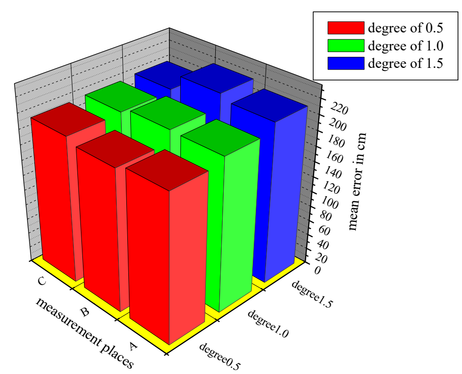

Fig.6: Avg. location error at different measurement places (A,B, and C) in border region of a rectangular polygon with respective degree of weight.

In Fig.5, location error at center place (B) in central region is shown lowest and it increases as we move towards edge of wall (A and C). However, in border region, there is only a small change of location error at three measurement places (A, B, and C) as shown in Fig.6. Specifically, error at border region is slightly increased than that at center regions. Besides, among all the measurements, location error is lowest when degree of 0.5 is used while calculating weight of beacons. The lowest and highest avgerage errors obtained in each region are 1.58 m and 2.45 m, respectively.

V. CONCLUSION AND FUTURE WORK

This paper presents demonstration of WCL method which can be used in IPS with the use of wireless technology called BLE.

We measured the performance of WCL method under the various degrees of weight and obtained that degree of 0.5 is most reliable at our testing environment. This WCL can be joined with fingerprinting to enhance the estimation of the current tag location. This work will be our next step in our BLE based real time IPS application.

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