Implementation of Android Application for Indoor Positioning System with Estimote BLE Beacons

Wook Song[1], HwaMin Lee[2], Seung-Hyun Lee[3], Min-Hyung Choi[4], Min Hong[2]

[1] Department of Computer Science, Soonchunhyang University, South Korea
[2] Department of Computer Software Engineering, Soonchunhyang University, South Korea
[3] School of Architectural Engineering, Hongik University, South Korea
[4] Department of Computer Science and Engineering, University of Colorado Denver, United States
wook2735@sch.ac.kr, leehm@sch.ac.kr, shlee413@hongik.ac.kr, Min.Choi@ucdenver.edu, mhong@sch.ac.kr

Abstract

Due to recent advances in IoT (Internet of Things) related technology, demands of highly accurate indoor positioning system and services have been remarkably increased. The proposed indoor positioning system utilizes 4 Estimote BLE (Bluetooth Low Energy) beacons to measure the user position with a smartphone. Each beacon broadcasts radio signal and a smartphone can receive these signals to estimate the distance by measuring RSSI (Received Signal Strength Indicator) values. In this paper, we proposed a new estimation algorithm to robustly calculate a user's position based on the strength of received signals. The proposed algorithm collects signals at a pre-processing stage to improve the quality of RSSI values, calculates the distance according to the signal strength from each beacon, and then estimates the user position with the triangulation of overlapped regions. The experimental result of our proposed indoor positioning system shows approximately 80% of accuracy within 2m error bound for three types of room. The proposed indoor position tracking is simple and well-suited with low-cost BLE beacons.

Keywords: Indoor positioning system, BLE beacon, Smartphone, RSSI, Triangulation

1 Introduction

Recently, sensor and network related hardware and software technologies have been drastically improved and many sensors are applied for the various devices in IoT fields. One of the recent active research topics is the estimation of a user's position with energy efficient sensors for monitoring behaviors of users or for providing necessary information to audiences or customers. In order to provide helpful guidance to users, the accurate measurement of a user's position and orientation is essential. Unlike suceessful outdoor positioning systems such as GPS (Global Positioning System) that can provide reliable information with satellites, an indoor positioning system should work with different near-field instruments such as wireless access points or Bluetooth beacons [1].

When the indoor positioning system is combined with IoT technology, our daily life can be more comfortable and safe. Since BLE can provide a wireless communication with efficient power management compared with traditional Bluetooth classic service, various researches have been extensively progressed for indoor positioning system using BLE 4.0. beacon. It can be used for more than 6 months with a single CR2477 battery and the price is also very affordable.

BLE beacon transmits signals by communicating data between master and slave or by advertising data to devices. In advertising method, BLE beacon transmits the signals according to advertising interval, so any circumjacent smartphones can receive RSSI values [2]. Generally, BLE beacon is a small transmitter developed by Apple and other companies and it can be applied in various fields, not only for finding the indoor user position, but also for analyzing the life patterns or the consumption patterns of users. In this paper, we designed and implemented the indoor positioning system for estimating a user's position with BLE beacons and smartphone.

The remainder of this paper is organized as follows. Previous related works are summarized and analyzed in Section 2. The proposed indoor positioning system is introduced in Section 3. Section 4 shows the experimental results of proposed indoor positioning system. Finally, Section 5 includes the conclusion and possible future directions.

2 Related Works

There are some possible techniques for estimating the indoor position depending on the purposes. In this section, we have introduced these methods and analyze

*Corresponding Author: Min Hong; E-mail: mhong@sch.ac.kr
DOI: 10.3966/160792642018051903022

them. Typical methods for measuring the indoor position are Wi-Fi, PDR (Pedestrian Dead Reckoning), Geomagnetic, and BLE beacon based method.

2.1 Wi-Fi based Indoor Positioning System

Wi-Fi based indoor positioning system is the most widely known system as the indoor position measurement method. This system uses the RSSI values from each AP (Access Point) [3-5] and doesn't require any additional resources when AP is already installed. In addition, we can apply various possible approaches such as Cell-ID method, AoA (Angle of Arrival) method, ToA (Time of Arrival) method, TDoA (Time Difference of Arrival) method, and fingerprint method [6-7]. However, this system can produce large error in RSSI values by external obstacle factors and can cause the cost burden when Wi-Fi network is not already installed.

2.2 PDR based Indoor Positioning System

PDR based indoor positioning system is widely used in the car navigation. This system estimates the next position from the previous position by the measuring of speed and direction using sensors. This system corrects and estimates indoor user position from the absolute location by number of steps, stride length, and direction of pedestrian using smartphone and other sensors [8]. It is well suited for estimating the movement of sensors for measuring the moving speed of a user. However, it is not easy to implement and it may include errors for the estimation of movements from the initial location and for various user variables such as a step length, and uncounted movement.

2.3 Geo-Magnetic Field based Indoor Positioning System

Unlike traditional radio wave based methods, the geomagnetic field based positioning system uses the earth's magnetic field, thus it doesn't require any pre-deployed infrastructure [9]. This system utilizes the subtle difference of strength or direction of magnetic field according to the location of place and can maintain 1-2 meters accuracy.

This system uses the unique magnetic fingerprint based on the materials affects in structure and geo-magnetic sensor in smartphone is used to figure out the indoor user position. However, this system normally requires a difficult calibration process, can provide geomagnetic disturbances in a particular location, and requires the periodic updates because geomagnetic field can be altered due to various external factors.

2.4 BLE Beacon based Indoor Positioning System

Mori et al. [10] applied template matching method with 22 BLE beacons and successfully figure out the location of Nexus 7 device whether it is inside or outside of room with 2.4m average error. Ji et al. [11] investigated the BLE signal attenuation according to the distance and introduced practical path loss model with Estimote and pebble beacons. They analyzed the relationship not only between the number of beacons and accuracy, but also between the intervals of each beacons and accuracy as well. To figure out the current floor of user position in multi-floor buildings [12], BLE signals was analyzed with path loss model and the result showed that a simple weighted centroid approach provided low distance error and a floor-loss parameter significantly improved the floor detection probability.

Most smartphones with Bluetooth 4.1 or later version can receive RSSI values. BLE beacon based positioning system uses the measured RSSI value with the distance formula and calculates the distance between beacons and smartphone. Then user position is estimated through triangulation [13-15]. One beacon can transmit the RSSI value to multiple smartphones by advertising function.

Usually, beacon can be attached anywhere at low cost and requires low-power by the BLE. When we use the beacon with strong signal or with increased numbers of transmission time, the lifetime of beacon will be reduced accordingly. In addition, BLE beacon has RSSI related errors similar to Wi-Fi based approach. In this paper, the proposed indoor positioning system reduces the noise of RSSI at the pre-processing stage, and user position is estimated with the relative distances between smartphone and 4 beacons.

3 The Proposed Indoor Positioning System with BLE Beacon

Although WLAN (Wireless Local Area Network) has been installed in most spots and provides strong signal of RSSI from AP, we need at least 3 APs to robustly estimate the user position using triangulation approach. In this study, we utilize BLE beacons which are relatively cheaper, lighter and easy to deploy everywhere.

3.1 Estimote BLE Beacon and Samsung Galaxy Note 4

In this paper, the proposed system is implemented with Estimote beacons developed by Estimote Inc. and Samsung Galaxy Note 4 smartphone. The specification of Estimote BLE beacon is shown in Table 1 and it has a small volume which is 3.0×4.3 [16].

Estimote Inc. provides a beacon manager web site which allows users to modify the UUID, MAC Address, Major, and Minor value of beacon, and the modified information of beacon can be updated in the cloud server of Estimote. To improve the accuarcy of location measurement, we set up the beacon with high power (4dBm) and a short interval (100ms) in this

Table 1. Specification of Estimote beacon

Feature	Value
Identification	Estimote model REV.D3.4
Frequency range	2,400 MHz to 2,483.5 MHz
Tx-Rx channel separation	2 MHz
Frequency stability	< 20 ppm
Bandwidth of emission	500 KHz
Power output	-30 dBm ~ 4 dBm
Sensitivity	-93 dBm
CPU	32-bit ARM Cortex M0
Flash memory	256 kB

research, thus the implemented smartphone application can recieve as many numbers of RSSI values as possible in a short period time.

The red box in Figure 1 shows the location of Bluetooth antenna in Samsung Galaxy Note 4. Unlike iPhone, the location of Bluetooth antenna in Android smartphones is different from each manufacturer. Since the performance of RSSI reception performance is deeply dependent to the location of Bluetooth antenna, the reception rate of Android smartphones is different for each device. Therefore, the indoor positioning system should consider the location of Bluetooth antenna to guarantee the reliable performance [17]. The proposed indoor positioning system is implemented on the Samsung Galaxy Note 4 which receives Bluetooth signals on a one-way direction, thus the RSSI reception rate is largely affected by the orientation of smartphone. To alleviate this problem, the proposed algorithm strictly forces the back of smartphone to face the ground during estimation.

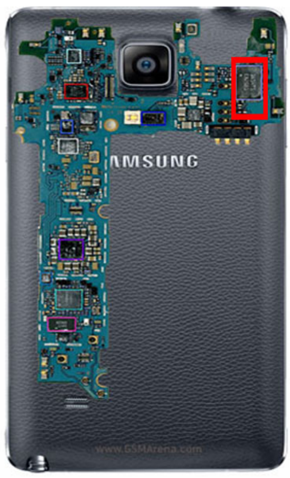


Figure 1. Bluetooth antenna in Samsung Galaxy Note 4

3.2 Algorithm of the Proposed Indoor Positioning System

Figure 2 shows a flowchart of the entire process for proposed indoor positioning system. Firstly, this system checks the status of Bluetooth service in smart phones. When the Bluetooth service turned off, it requests to turn on the Bluetooth service on the implemented application. The implemented application is waiting for receiving the 100 RSSI values from 4 beacons. When all of received RSSI values are stored in application, the proposed system corrects these RSSI values using Kalman filter to accurately estimate user position. When the calculated standard deviation of corrected RSSI values is less than 4 that guarantee minimizing the noise of data, 20% of top and bottom values are removed from the corrected RSSI values using normal distribution. In this moment, the back of smartphone should face the ground during the estimation. Then the proposed algorithm calculates the average of 80 RSSI values for each beacon. Next, the system computes 3 interaction points from 3 influential beacons for user position estimation. When the correct 3 points are determined, the proposed system estimates a user position which is the midpoint of 3 intersection points with triangulation. Otherwise, the proposed system is enforced going back to RSSI re-receiving process.

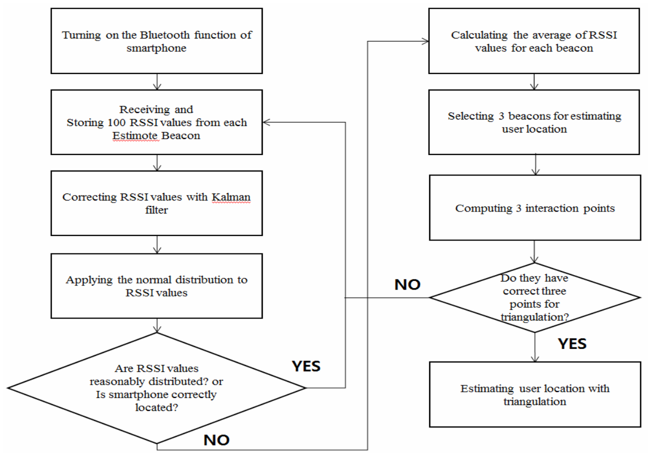


Figure 2. Flowchart of the proposed indoor positioning system

3.3 RSSI Value Collection

The implemented application is waiting for receiving the RSSI values using runOnUiThread. The RSSI values which are received from the different beacons can be classified based on the MAC address of beacons, and then these received RSSI values are stored in the smartphone application using ArrayList respectively. When the smartphone is in ideal noise-free environments, we can receive the constant RSSI value. Unfortunately, due to the noise, interference, and obstructions, the received RSSI values can have various perturbations for the same position in the complex real environments.

Figure 3 shows a collected result of 30 RSSI values, when 4 beacons are located at 3m apart. Although these beacons are on the same position during the experiment, the differences of RSSI values for each beacon are more than 10dBm. In addition, the difference of 30 RSSI values for same beacon also has more than 10dBm. The RSSI values from beacon are largely affected by noise factors in internal environments. Therefore, the proposed indoor positioning system adopts the pre-processing stage to alleviate this noise problem using Kalman filter.

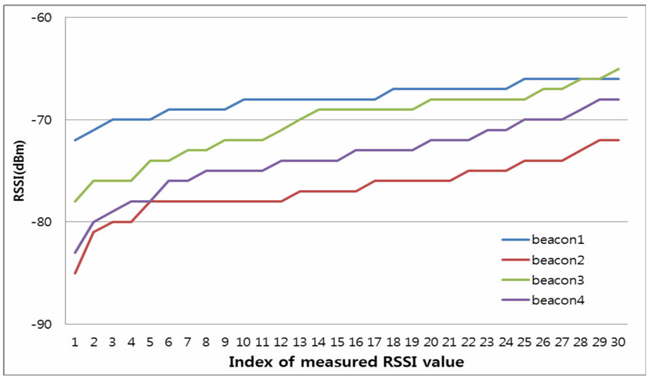


Figure 3. Measured RSSI values from 4 beacons at 3m

3.4 Pre-processing Stage for RSSI Value Tuning

The collected RSSI values in 4 ArrayLists are corrected by a Kalman filter. Kalman filter is usually applied in a pre-treatment process to estimate more precise data in many areas such as vehicle positioning, navigation, image processing, and so on. When sensors detect related data, it may include some errors by noise and these errors can be corrected with Kalman filter by estimating the internal state of a linear dynamic system from a series of noisy input data [18].

$$\begin{aligned} Q &= 0.00001 \\ R &= 0.001 \\ P &= 1 \\ X &= InitRSSI \end{aligned} \quad \textbf{(1)}$$

To apply the Kalman filter to the received RSSI values, the proposed system calculates the corrected RSSI values using Equation (3) while Q, R, P, and X variables are initialized with pre-set values shown in (1). Q is a process noise covariance constant, R is a measurement noise covariance constant, and P is an estimate error covariance constant. X is the estimated RSSI value and is initialized with first RSSI value.

$$\begin{aligned} K &= \frac{P+Q}{P+Q+R} \\ P &= R * \frac{P+Q}{P+Q+R} \end{aligned} \quad \textbf{(2)}$$

$$X = X + (RSSI - X) * K \quad \textbf{(3)}$$

K is a Kalman gain value and P is an updated estimate error covariance value in Equation (2). The estimated RSSI value is calculated by Equation (3). Before calculation of Equation (3), the P and K variables are updated by Equation (2). The Kalman filter reduces the deviation of received RSSI values by correcting excessively big or small values.

The proposed indoor positioning system collects 100 RSSI values for each of 4 beacons to maximize the chance to receive accurate RSSI values. Then the proposed algorithm applies the Kalman filter to these RSSI values. Since the filtered RSSI values still have some noisy values, we apply the normal distribution with 80% confidence interval. Thus 20% of top and bottom values are removed from the original values.

Since the standard deviation shows the variation of collected RSSI values, the proposed algorithm dumps RSSI values and repeats re-receiving RSSI values from specific beacon, when the calculated standard deviation is bigger than 4. We decide this specific threshold by our experimental tests.

3.5 Distance Estimation with RSSI

As we mentioned in previous section, RSSI values can readily include the error caused by noise or interference in the real space. Instead of one collection of RSSI value from a beacon, the proposed algorithm collects 100 RSSI values and then selects 80 RSSI values which are closely clustered from the median value for one beacon in a spot to estimate the distance between beacon and smartphone. The distance between two locations can be calculated using a path loss which is the decreased strength of signal during the transmission. The signal strength reduction is inversely proportional to the square of distance and the transmitted distance can be estimated with the path loss [19].

There are several formulas to calculate the distance with RSSI value. Android iBeacon library provides the RSSI rate based distance calculation method [20]. The reference based method can estimate the distance by 1m. This reference based method can freely modify the reference and is suitable for Android device because the locations of Bluetooth antenna are different for each device. In this paper, we applied the reference based method with 1m for Android device.

$$PL = Tx - Rx \quad \textbf{(4)}$$

$$PL = 20\log(\frac{d_1}{d_2}) \quad \textbf{(5)}$$

$$d_2 = 10^{\frac{(-61.0 - Rx)}{20}} \quad \textbf{(6)}$$

Equation (4) shows that the path loss is the difference of signal strength between transmission and reception. In Equation (5), d1 is the distance between the transmission point and the first point and d2 is the distance between the transmission point and the second point [21]. We set up the d1 variable, the reference value, as 1m and the Tx variable as -61.0dBM from the average of experimental test values in Figure 4. By substituting Equation (5) into Equation (4), the distance between beacon and smartphone can be estimated by Equation (6) from RSSI value. Table 2 shows the experimental results between distance and RSSI value by Equation (6) without the pre-processing stage, when the distance is increased. RSSI value is exponentially changed according to the distance thus the smaller RSSI value can dramatically increase the estimated distance as shown in Table 2.

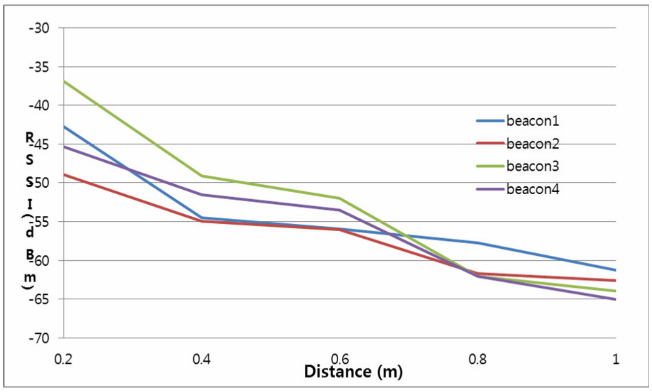


Figure 4. Graph of average value for 80 RSSI values according to the distance change

Table 2. Estimated distance according to RSSI

RSSI (dBm)	-55	-60	-65	-70	-75	-80	-85
Distance (m)	0.50	0.89	1.58	2.81	5.01	8.1	15.84

In this research, 4 beacons are located in the center of each wall in the room such as top, down, left, and right. In the initial stage, the proposed system requires to input the approximated width and height of room size in the implemented application. Figure 5 depicts the 80 RSSI values at 1m after pre-processing stage. Since the received RSSI values are not exactly same with one constant value, the proposed algorithm calculates the average of these values.

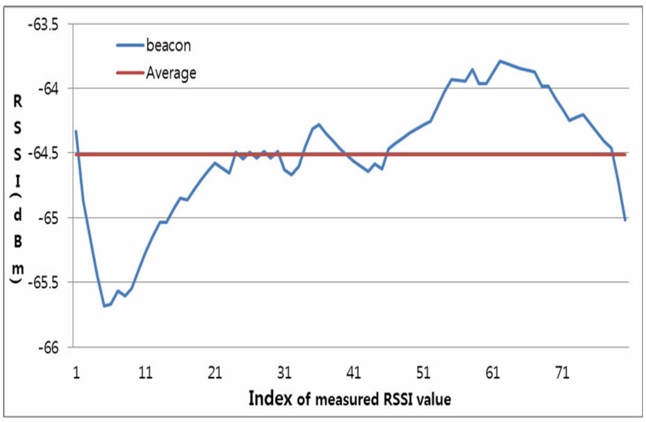


Figure 5. Measured RSSI values at 1m

Although the graph of average for 80 RSSI values from pre-processing stage is not perfectly linear, the average values of RSSI for 4 beacons are decreased according to the distance increment from 0 to 1m as shown in Figure 4.

3.6 Estimation of User Position with the Triangulation

The proposed algorithm utilizes the triangulation to estimate the location of smartphone with the strength of RSSI value from each beacon [22]. Firstly, we calculate the distances between each beacon and smartphone. Since the smallest distance means the strongest signal from all beacons and it is most critical information for distance estimation, the proposed algorithm discards the signal from opposite side of beacon and selects the remaining signals from the other beacons.

Then 3 circles are created using a radius which is the estimated distance from each selected beacon to smartphone as shown in Figure 6. To estimate the user position, the proposed algorithm chooses the nearest 3 intersection points between 3 circles from the center of room. Finally, the user position which is the midpoint of these 3 intersection points is estimated by triangulation. The estimated user position is shown with blue spot in Figure 6. The bottom beacon has the strongest signal, thus the left and right beacons are selected as 3 circles in Figure 6. There are 6 intersection points in this case and a green triangle is created by the nearest 3 intersection points from the center of room.

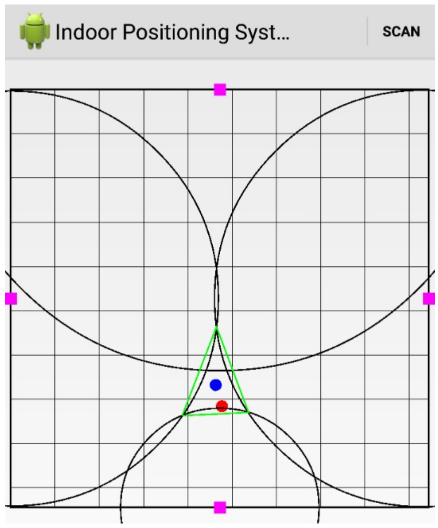


Figure 6. Result of estimated user position using triangulation

The whole process for the estimation of user position with triangulation is shown in Figure 7. To increase the accuracy of proposed system, when the intersection points do not exist between smallest circle and the other circles or when the intersection point between 2 circles except the smallest circle does not exist, the proposed estimation of user position algorithm goes back to RSSI re-receiving stage.

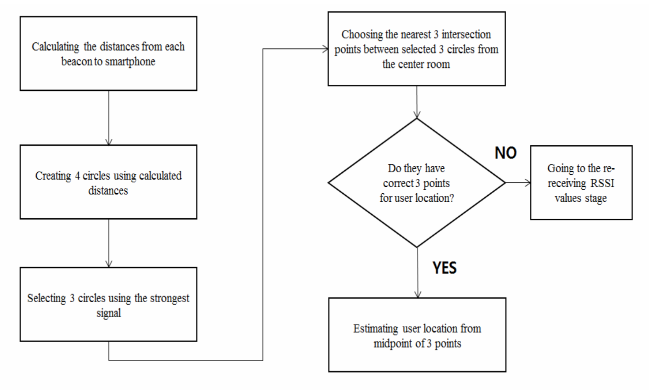


Figure 7. Estimation of user location using triangulation

Figure 8 shows the successful estimation results of user position. 4 pink rectangles represent the location of beacons in the test rooms and they are located in the center of each wall. Each square depicts 1m X 1m size and a green circle shows a targeted error boundary. 2m is defined as the targeted error boundary in this research. A small red spot is the actual position where the user is stand with smartphone and a small blue spot is the estimated user position with the proposed indoor positioning application in the room. Figure 9 shows the failed estimation results for user position. In most cases, the estimated user position is little bit outside of the defined targeted error boundary due to low signal reception.

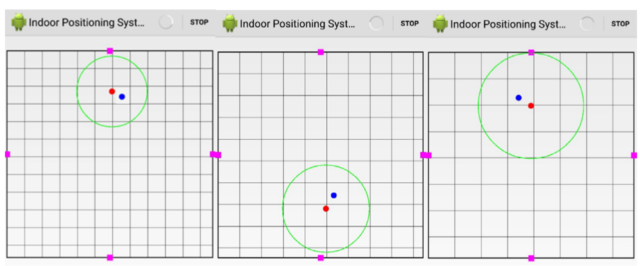


Figure 8. Examples of successful estimation of user position

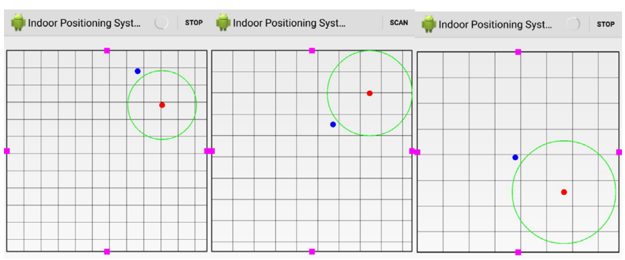


Figure 9. Examples of failed estimation of user position

4 Result of Experimental Tests

To test the performance of proposed indoor positioning system, we applied the implemented smartphone application in the three types of room. A room type is 11.70m X 9.45m in width and height. B room type is 9.45m X 8.55m and C room type is 7.80m X 7.20m. Since the received RSSI values are not accurate to be precisely estimated the user position by noise, interference, and obstructions, we tested the proposed algorithm based on the 2m targeted error boundary to roughly estimate the user position.

For experimental tests, we tested 200 times at random position for each room. We compared the results between the estimated user position with proposed algorithm and the actual user position. Table 3 shows the accuracy of proposed indoor positioning system for 3 rooms with the average of distance error in cm unit.

Table 3. Results of experimental test

Room tpye	True/False	Accuracy	Average of distance error (cm)
A	164/36	82%	116.16
B	168/32	84%	161.22
C	179/21	89.5%	156.32

Room type	Average time for one estimation of user position (sec)	Avearge number of re-measuring
A	31.58	2.24
B	33.02	2.39
C	38.26	2.67

The experimental results show that the accuracy of proposed indoor positioning system depends on the size of room. When the size of room is smaller, the accuracy is much higher than a larger room case. Since A room type is the largest space, it had the lower accuracy in experimental test. Because the signal should be propagated to a long distance in a large room, the strength of signal is not enough to be clearly received on smartphone for distance estimation and not easy to estimate the distance due to the exponential incensement relationship between RSSI and distance. The strongest beacon is very critical to estimate the user position in the proposed algorithm. When these signals are involved with any noise or interference by obstacles, the accuracy of proposed algorithm is significantly dropped.

The experimental results show that the proposed algorithm provides a correct user position with 85% accuracy in 2m targeted error boundary and the average of error is 144.57cm between the estimated user position and the actual user position for 600 times of experimental tests. The proposed algorithm takes 32.297 second for estimating the user position on average. The re-measuring stage is performed averagely 2.43 times for user position estimation.

5 Conclusions

This paper proposed a new indoor positioning system using relatively low-cost BLE beacon and Android smartphone. The proposed algorithm improves the quality of signal accuracy from each beacon at the pre-processing stage by Kalman filter and normal distribution of 80% confidence. The average of RSSI values from each beacon is calculated and the user position is estimated from intersection points which are achieved from 3 beacons using triangulation.

The proposed indoor positioning system has the limitation by the number of variables such as the direction of the Bluetooth antenna of smartphones, the interference of radio signals, and the presence of obstacles. When the beacon is standardized, higher energy with low power becomes possible, and the signal reception with Bluetooth antenna of smartphones is getting better, the proposed system using low-cost beacon can be further improved. In addition, we believe that it is also possible to develop the system for finding exact user position with beacons in the near future.

Acknowledgement

A preliminary version of this paper was presented at ICONI 2015, and was selected as an outstanding paper. This research was supported by the MSIP (Ministry of Science, ICT and Future Planning), Korea, under the ITRC (Information Technology Research Center) support program (IITP-2016-H8601-16-1009) supervised by the IITP (Institute for Information & communications Technology Promotion) and was supported by the Soonchunhyang University Research Fund.

References

[1] H. Huang, J. Zhou, W. Li, J. Zhang, X. Zhang, G. Hou, Wearable Indoor Localisation Approach in Internet of Things, *IET Networks*, Vol. 5, No. 5, pp. 122-126, September, 2016.

[2] J. Decuir, *Bluetooth 4.0: Low Energy*, https://californiaconsultants.org/wp-content/uploads/2014/05/CNSV-1205-Decuir.pdf

[3] S. Woo, S. Jeong, E. Mok, L. Xia, C. Changsu, M. W. Pyeon, J. Heo, Application of WiFi-based Indoor Positioning System for Labor Tracking at Construction Sites: A Case Study in Guangzhou MTR, *Automation in Construction*, Vol. 20, No. 1, pp. 3-13, January, 2011.

[4] P. Bahl, V. N. Padmanabhan, RADAR: An In-Building RF-based User Location and Tracking System, *Proc. Nineteenth Annual Joint Conference of the IEEE Computer and Communications Societies*, Vol. 2, Tel Aviv, Israel, 2000, pp. 775-784.

[5] H. Y. Sun, L.-J. Bi, X. Lu, Y. J. Guo, N. Xiong, Wi-Fi Network-Based Fingerprinting Algorithm for Localization in Coal Mine Tunnel, *Journal of Internet Technology*, Vol. 18, No. 4, pp. 731-741, July, 2017.

[6] W. Zhao, S. Han, W. Meng, D. Zou, A Testbed of Performance Evaluation for Fingerprint Based WLAN Positioning System, *KSII Transactions on Internet and Information Systems*, Vol. 10, No. 6, pp. 2583-2605, June, 2016.

[7] Y. -S. Lu, C.-F. Lai, C.-C. Hu, Y.-M. Huang, X.-H. Ge, Path Loss Exponent Estimation for Indoor Wireless Sensor Positioning, *KSII Transactions on Internet and Information Systems*, Vol. 4, No. 3, pp. 243-257, June, 2010.

[8] S. Beauregard, H. Haas, Pedestrian Dead Reckoning: A Basis for Personal Positioning, *Proc. of the 3rd Workshop on Positioning, Navigation and Communication (WPNC'06)*, Hannover, Germany, 2006, pp. 27-35.

[9] S. Hur, J. Song, Y. Park, Indoor Position Technology in Geo-Magnetic Field, *The Journal of Korean Institute of Communications and Information Sciences*, Vol. 38C, No. 1, pp. 131-140, January, 2013.

[10] T. Mori, S. Kajioka, T. Uchiya, I. Takumi, H. Matsuo, Experiments of Position Estimation by BLE Beacons on Actual Situations, *2015 IEEE 4th Global Conference on Consumer Electronics*, Osaka, Japan, 2015, pp. 683-684.

[11] M. G. Ji, J. Y. Kim, J. I. Jeon, Y. Cho, Analysis of Positioning Accuracy Corresponding to the Number of BLE Beacons in Indoor Positioning System, *17th International Conference on Advanced Communication Technology (ICACT)*, Seoul, South Korea, *2015*, pp. 92-95.

[12] E. S. Lohan, J. Talvitie, P. F. e Silva, H. Nurminen, S. Ali-Löytty, R. Piché, Received Signal Strength Models for WLAN and BLE-based Indoor Positioning in Multi-floor Buildings, *2015 International Conference on Localization and GNSS (ICL-GNSS)*, Gothenburg, Sweden, 2015, pp. 1-6.

[13] D.-H. Ryu, Development of BLE Sensor Module based on Open Source for IoT Applications, *The Journal of the Korea Institute of Electronic Communication Sciences*, Vol. 10, No. 3, pp. 419-424, March, 2015.

[14] C. Gomez, J. Oller, J. Paradells, Overview and Evaluation of Bluetooth Low Energy: An Emerging Low-power Wireless Technology, *Sensors*, Vol. 12, No. 9, pp. 11734-11753, September, 2012.

[15] M. Collotta, G. Pau, A Power Management Solution for Bluetooth Low Energy in Smart Homes of Internet of Things, *International Journal of Internet Protocol Technology*, Vol. 9, No. 2-3, pp. 53-61, 2016.

[16] R. Pierdicca, D. Liciotti, M. Contigiani, E. Frontoni, A. Mancini, P. Zingaretti, Low Cost Embedded System for Increasing Retail Environment Intelligence, *Proc. of Multimedia & Expo Workshops (ICMEW)*, Turin, Italy, 2015, pp. 1-6.

[17] S. S. Jeng, C. W. Tsung, F. P. Chang, WLAN Smart Antenna with Bluetooth Interference Reduction, *IET Communications*, Vol. 2, No. 8, pp. 1098-1107, September, 2008.

[18] B. Ristic, S. Arulampalam, N. Gordon, *Beyond the Kalman Filter: Particle Filters for Tracking Applications*, Artech House, 2004.

[19] V. Erceg, L. J. Greenstein, S. Y. Tjandra, S. R. Parkoff, A. Gupta, B. Kulic, A. A. Julius, R. Bianchi, An Empirically Based Path Loss Model for Wireless Channels in Suburban Environments, *IEEE Journal on Selected Areas in*

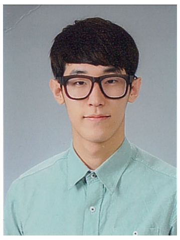
Communications, Vol. 17, No. 7, pp. 1205-1211, July, 1999.

[20] AltBeacon, *Android-beacon-library*, https://github.com/AltBeacon/android-beacon-library

[21] S. S. Ghassemzadeh, R. Jana, C. W. Rice, W. Turin, V. Tarokh, A Statistical Path Loss Model for In-home UWB Channels, *2002 IEEE Conference on Ultra Wideband Systems and Technologies*, Baltimore, MD, 2002, pp. 59-64.

[22] T.-W. Sung, C.-S. Yang, Localised Sensor Direction Adjustments with Geometric Structures of Voronoi Diagram and Delaunay Triangulation for Directional Sensor Networks, *International Journal of Ad Hoc and Ubiquitous Computing*, Vol. 20, No. 2, pp. 91-106, September, 2015.

Biographies



Wook Song received the B.S. degrees in Computer Software Engineering from Soonchunhyaung University in 2016. Now he is undertaking a master degree of computer engineering courses as a member of the computer graphics lab at Soonchunhyang University. His research interests are game development, computer graphics, VR (Virtual Reality) and virtual rehabilitation.

HwaMin Lee is a professor in the Department of Computer Software Engineering at Soonchunhyang University. She received her B.S., the M.S. and the Ph.D. degrees in Computer Science Education from Korea University in Seoul, Korea in 2000, 2002, and 2006, respectively. Her research interests include IoT, Cloud computing, Mobile computing, Grid computing, Wellness and resource management and fault tolerant system for large-scale distributed systems.

Seung-Hyun Lee is an Associate Professor, School of Architectural Engineering, Hongik University. He received his B.S. 1996 Inha University, and his M.S 1999 University of Colorado at Boulder, Ph.D. 2003 University of Florida at Gainesville 2004~2008: Korea Institute of Construction Engineering, Senior Researcher. 2008~Current: Hongik University, Associate Professor. Interesting Research Area: Process Simulation, Productivity, Construction Information Technology, Image Processing, Automatic Data Acquisition.

Min-Hyung Choi is an Associate Professor at the Department of Computer Science and Engineering at University of Colorado Denver. He received his MS and Ph.D. from University of Iowa in 1996 and 1999, respectively. His research interests are in Computer Graphics, Scientific Visualization and Human Computer Interaction with an emphasis on physically-based modeling and simulation for Neuroscience and Bioinformatics applications. Currently he is the Director of Computer Graphics and Virtual Environments Laboratory. In 2003, he received the NSF CAREER Award from National Science Foundation.

Min Hong is a Professor at the Department of Computer Software and Engineering, Soonchunhyang University in Asan, Korea. He received B.S. in Computer Science from Soonchunhyang University in 1995. He also received MS in Computer Science and Ph.D. in Bioinformatics from the University of Colorado in 2001 and 2005, respectively. His research interests are in Computer Graphics, Mobile Computing, Physically-based Modeling and Simulation, Bioinformatics Applications, and u-Healthcare Applications. In present, he is a Director of Computer Graphics Laboratory at Soonchunhyang University.