Journal of Electrical Engineering & Technology Vol. 6, No. 6, pp. 883~887, 2011 **883**
http://dx.doi.org/10.5370/JEET.2011.6.6.883

Adaptive Parameter Estimation Method for Wireless Localization Using RSSI Measurements

Hyun-Hun Cho*, Rak-Hee Lee* and Joon-Goo Park†

Abstract – Location-based service (LBS) is becoming an important part of the information technology (IT) business. Localization is a core technology for LBS because LBS is based on the position of each device or user. In case of outdoor, GPS – which is used to determine the position of a moving user – is the dominant technology. As satellite signal cannot reach indoor, GPS cannot be used in indoor environment. Therefore, research and study about indoor localization technology, which has the same accuracy as an outdoor GPS, is needed for "seamless LBS". For indoor localization, we consider the IEEE802.11 WLAN environment. Generally, received signal strength indicator (RSSI) is used to obtain a specific position of the user under the WLAN environment. RSSI has a characteristic that is decreased over distance. To use RSSI at indoor localization, a mathematical model of RSSI, which reflects its characteristic, is used. However, this RSSI of the mathematical model is different from a real RSSI, which, in reality, has a sensitive parameter that is much affected by the propagation environment. This difference causes the occurrence of localization error. Thus, it is necessary to set a proper RSSI model in order to obtain an accurate localization result. We propose a method in which the parameters of the propagation environment are determined using only RSSI measurements obtained during localization.

Keywords: Received signal strength indicator, Attenuation log model, Adaptive parameter estimation

1. Introduction

With the rapid development of wireless communication technology and internet, users can now easily access the networks where they want to get information and services. To supply information and services to the user, it is important to determine the precise position of the user.

In case of outdoor, GPS is used widely to determine the position of the user with high accuracy. However, it cannot be used in indoor environment because of the restriction of visible satellite as well as signal weakness [1]. Hence, indoor localization technology, which has similar accuracy as GPS, is required for "seamless LBS".

Many studies about indoor localization have been developing. For these purpose, new localization methods using signal strength of RF, ultrasonic wave, RFID, and ultra wide band (UWB) are proposed. But most of these methods require infrastructure which costs high and takes long time for setup. IEEE 802.11 WLAN has recently been used for indoor localization [2]. The WLAN is installed in various places such as universities, hospitals, and airports according to the increase in demand for wireless communication. It does not require additional equipment for positioning. In addition, it also has the benefits of accessibility, mobility, and simplicity.

Many localization methods that use WLAN signal were proposed. Angle of arrival (AOA) uses the information on the angle between the transmitter and the receiver. Meanwhile, the time of arrival (TOA) and the time difference of arrival (TDOA) need information on the difference of arrival time.

In this study, we use the RF signal attenuation to determine the position of the user [3, 4]. However, when using the location estimation method based on a received signal strength indicator (RSSI), it is necessary to investigate the indoor propagation environments prior to localization [2, 4]. If this method is adopted in a large space, this requirement of prior investigation is likely to become a hindrance to localization because of the large amount of labor needed. To make up for this weakness of the RSSI method, we propose a method that does not require prior investigation.

In chapter 2, we introduce the attenuation log model for ranging. In chapter 3, we propose an adaptive parameter estimation method for ranging. Experimental results of the proposed method are then analyzed in chapter 4. Finally, concluding remarks are given in chapter 5.

In this study, the proposed method was evaluated experimentally, and we demonstrated that localization can be successfully implemented even when the preliminary parameter measurements are omitted.

† Corresponding Author: Department of Electrical and Electronic Engineering, Kyungpook National University, Korea (jgpark@knu.ac.kr)
* Department of Electrical and Electronic Engineering, Kyungpook National University, Korea (hhcho,jihyun38317@ee.knu.ac.kr)
Received: April 29, 2011; Accepted: July 25, 2011

2. Attenuation Log Model for Ranging

The attenuation log model was used in this study. This model assumes that the ideal propagation condition is a line-of-sight path between the transmitter and the receiver. It does not consider any effect of multipath fading and other path loss. As such, this model is not precise in an indoor space. However, if there are many sensor nodes in the space, it is still appropriate to determine the distance.

In this model, it is assumed that the received signal power P follows a log-normal distribution; thus, the random variable $P\ [dBm] = 10log_{10}P$ is Gaussian. In this model, the relationship between the RSSI and distance is described as follows:

$$P[dBm] \sim N(\bar{P}[dBm], \sigma^2)$$
$$\bar{P}[dBm] = P_0[dBm] - 20\log_{10}(\frac{4\pi d}{\lambda}) \qquad (1)$$

where

$$\bar{P}[dBm] = \textit{the mean power in decibel milliwatts}$$
$$\sigma^2 = \textit{the variance of the shadowing}$$
$$P_0[dBm] = \textit{offset}$$
$$\lambda = \frac{c}{f} = \frac{3\times 10^8[m/s]}{2.4[GHz]}$$

The RSSI method is a way of measuring the distance between nodes using the RSSI. In general, the RSSI attenuates in proportion to the distance between nodes. If the offset P_0 is known when the node measures the RSSI, the distance between nodes can be determined

It is then assumed that three fixed nodes positions are first known, as shown in Fig. 1, and these nodes are named *node* a, *node* b, and *node* c. When the signal is sent from each fixed node to the target node with unknown position, the target node measures the received signal strength from each node. The value of the received signal strength obtained from each fixed node – named P_a , P_b , and P_c respectively – is converted into the distance between the target node and each fixed node, and denoted as d_a, d_b, and d_c.

To estimate the position of the target node, we draw three circles centered on each of the fixed node. The radii of the circles denote the distances between each fixed node and the target node, which are determined ahead.

We then determine the position of the intersection, which in turn helps estimate the position of the target node.

However, in this method, it is necessary to know the value of the offset P_0 first in order to estimate the position of the target node; unfortunately, this value can have a different value in each measured environment

The following is an example explaining the relationship between the offset P_0 in different environments and distances, where the P_0 of the two measured environments are P_{0_1}, P_{0_2}, respectively, as shown in Fig. 1.

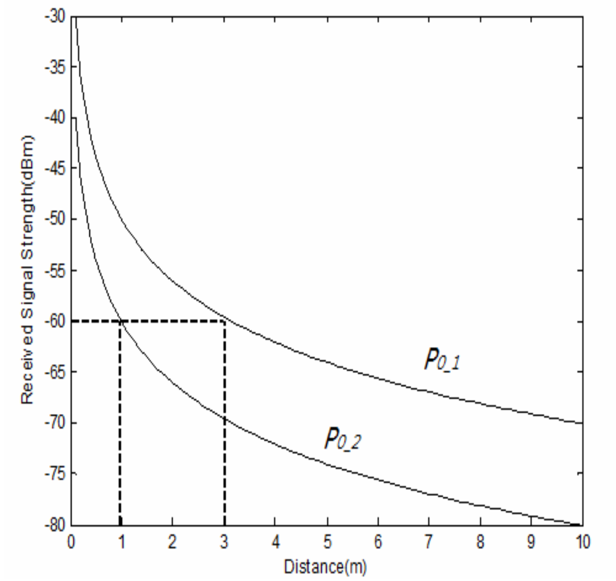

Fig. 1. Ranging on offset P_0

Even if the values of the RSSI obtained by a target node are same, the estimated distances between the target node and the fixed node can be different value depending on the environment. Therefore, a suitable value of the offset P_0 in each environment must be used to estimate the accurate position of the target node.

In the past, knowing the suitable value of the offset P_0 in each measured environment requires that prior measurement is conducted and the obtained large amount of sample data is averaged in order for the propagation characteristic to be determined. However, conducting this prior measurement on all the measured environments is difficult because it is time consuming and troublesome.

In the next section, as a solution to the problem, the proposed method that can determine the value of the offset P_0 without first investigating the measured environment is explained.

3. Adaptive Parameter Estimation for Ranging

In case of the localization procedure using RSSI measurements, information on the position of the mobile unit can be estimated or calculated without prior information. In this section, we propose an enhanced ranging algorithm, with optimized parameters adapting to the radio propagation environments. This algorithm can be implemented with low computation burden.

3.1 The estimation model of the offset constant

First, the N access point (AP) nodes are considered in the testbed. A mobile unit (MU) at position θ (x, y, z) receives a signal from the APs and measures the RSSI. The RSSI measurement obtained by AP_i is given by the following:

$$P_{ri}[dBm] = P_0[dBm] - 20\log_{10}(\frac{4\pi d_i}{\lambda}) + X_\sigma$$
$$d_i = \sqrt{(x-x_i)^2 + (y-y_i)^2 + (z-z_i)^2} \quad (2)$$

where X_σ is the Gaussian noise with a zero mean and a variance of σ^2, and d_i is the distance between AP_i and the MU.

Here, N values of (1) were added to both sides of (2). The offset P_0 is then calculated as follows:

$$P_0 = \frac{20(N\log_{10}\frac{4\pi}{\lambda} + D) + \sum_{i=1}^{N} P_{ri}}{N}[dBm]$$
$$D(x,y,z) = \sum_{i=1}^{N} \log_{10} d_i \quad (3)$$

$D(x, y, z)$ is a distance function between APs, representing the summation of the logarithm of the distance from each AP to the MU [5].

The received power P_{ri} of AP_i is a value measured during localization, and N is the total number of APs. Therefore, the offset P_0 is inferred from the distance function between APs, $D(x, y, z)$.

However, during localization, the coordinates of the MU are unknown; thus, $D(x, y, z)$ cannot be determined. Consequently, the value of the distance function is approximate.

3.2 Approximation of the distance function *D*(*x, y, z*)

The approximation of the distance function between APs consists of three steps, as follows.

Step 1. Set the height of the MU.

The coordinates of the MU cannot be determined; however, the height of the MU and each AP can be set relative to the height of the ground. As a result, the variable z in $D(x, y, z)$ is set, and the function becomes $D(x, y)$. This function is the distance function of the testbed, as shown in Fig. 2.

Step 2. Search for the AP that received the maximum power.

AP_{imax}, the AP for which the RSSI measurement obtained during localization is the highest, is identified. In general, when the distance between nodes is shorter, the noise of the measurements is smaller [4]. It is inferred that the real position of the MU is near AP_{imax}.

Step 3. Approximate the coordinates (x_{imax}, y_{imax}).

In contrast to the identification of the position of the AP_{imax}, which requires only two steps, the identification of the real location of the MU requires a variable number of steps. However, it is understood that there is not much difference in each value of the distance function D. In addition, the value of D does not change drastically near AP_{imax} even if the MU is placed more than 10 m from the AP.

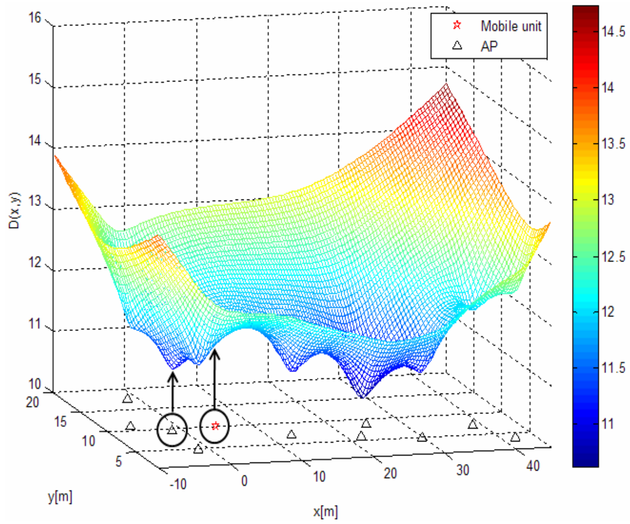

Fig. 2. Distribution of $D(x, y)$ on the testbed

Therefore, $D(x, y)$ can be approximated by $D(x_{imax}, y_{imax})$, which was obtained in the identification of AP_{imax}.

According to the above-mentioned steps, the unknown function D can be approximated, and the values of the offset P_0 can be determined using (3). However, the measurements P_i $[dBm]$ of the received power given by (2) are influenced by disturbances (e.g., multipath fading, reflection, and scattering). Moreover, because of the approximation of the distance function, a different result of the calculation is obtained every time when communicating for localization. Therefore, we updated the estimated value in the localization.

Table 1. Specification of the arrangement of APs

Sensor field	50 m × 20 m
Number of APs	10
Z-coordinate of AP(h_{AP})	1.2 m
Z-coordinate of MU(h_{MU})	m

3.3 Updating offset

When the P_0 value obtained from the measurements from the N-th trial is assumed to be α'_n, the actual P_0 used for localization is given by the following:

$$\alpha_n \leftarrow r_0\alpha'_n + r_1\alpha'_{n-1} + r_2\alpha'_{n-2} + \cdots + r_m\alpha'_{n-m} \quad (4)$$

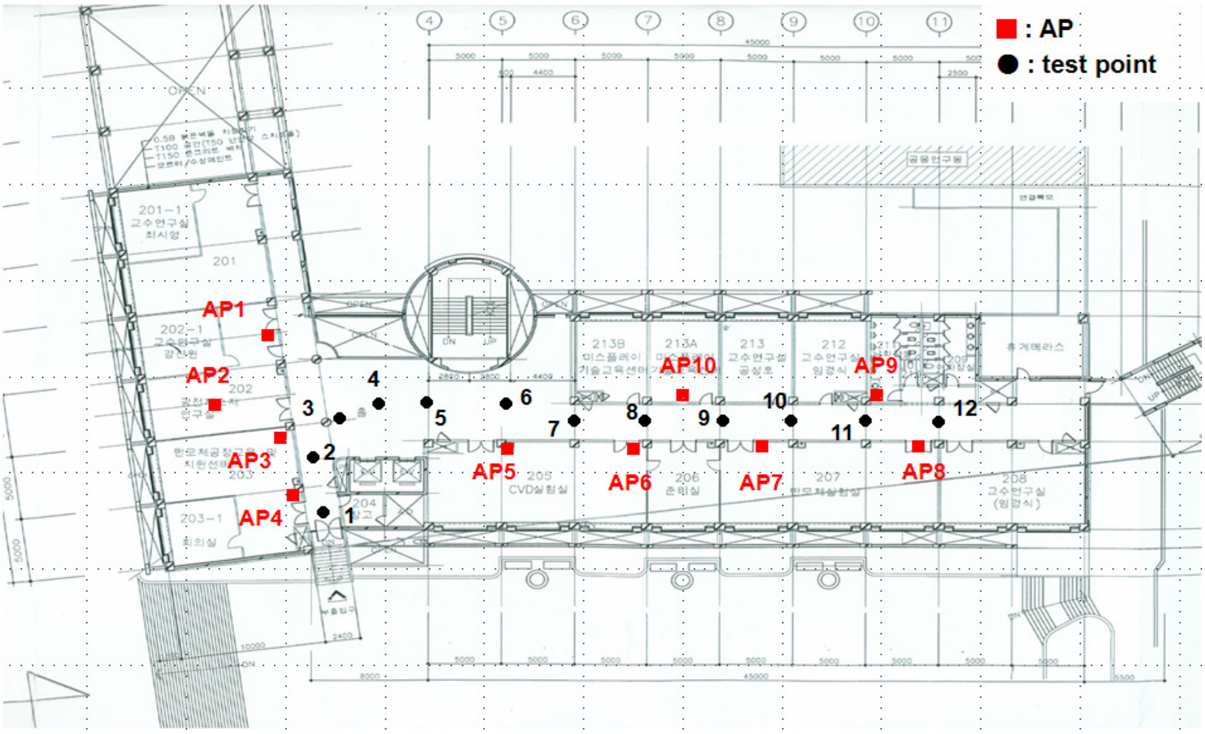

Fig. 4. Map of experimental test bed

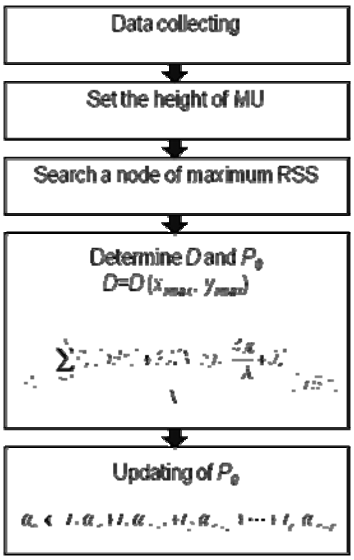

Fig. 3. Flowchart for P_0 estimation

where r_k ($k = 0, 1, \ldots, m$) are the weighting functions, and the summation is set to be 1 in this iterative approximation. In this way, by using not only the data from the latest m-th trial, the influence of the multipath fading or shadowing can be inhibited even if the last signal to be received is degraded in this way [5].

Furthermore, in the measured environment in which the propagation characteristic changes every time, it is possible to account for the change in the environment adequately by erasing the past data and using some values from the latest data. In this paper, the weighting functions r_k ($k = 0, 1, \ldots, m$) correspond to 1/m and $m = 3$. A flowchart explaining the procedure from the data collection to the estimation of P_0 is shown in Fig. 3.

4. Experimental Results

Fig. 4 shows our experiment testbed measuring 50 m × 20 m.

Ten APs were placed in this testbed at a height of 1.2 m. The MU was moved, generating 12 test points that were localized using the RSSI. Localization was performed in the same way for 300 times. The DARL algorithm was used in the localization [2]. A comparison of the results for each case is shown in Fig. 5.

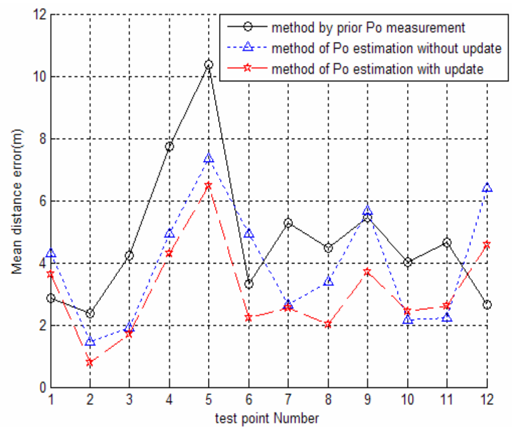

Fig. 5. The mean distance error of each case in the experiment

As shown in Fig. 5, the mean distance error of the total test point is reduced by about 2 m compared to the method by prior P_0 measurement. Specifically, the distance errors of test points 4 and 5 are about 4 m reduction. Consequently, it is thought that the distance information from the RSSI is improved by the recalibration P_0 during localization in poor propagation environment.

5. Conclusion

We developed a method to estimate the coordinates of the MU using parameter estimation of the propagation environment without investigating these parameters prior to localization. The mean distance errors from three methods of localization were evaluated. The results confirmed that the mean distance error of the proposed method is approximately 7% less than that of the P_0 estimation method without updating and 36% less than that of the method including prior P_0 measurement. Therefore, the proposed algorithm is an effective way to estimate the location of the MU.

Acknowledgments

This work has been supported by National GNSS Research Center program of Defense Acquisition Program Administration and Agency for Defense Development.

References

[1] N. Patwari, R. J. O'Dea, and Y. Wang, "Relative location in wireless networks," *Proc. IEEE VTC*, vol.2, 2001, p.1149-1153.

[2] C.B. Lim, S.H. Kang, H.H. Cho, S.W. Park, and J.G. Park, "An Enhanced Indoor Localization Algorithm Based on IEEE 802.11 WLAN Using RSSI and Multiple Parameters," *IEEE ICSNC,* Aug. 2010, p.238.

[3] Stephan Schuhmann, Klaus Herrmann, Kurt Rothermel, Jan Blumenthal, and Dirk Timmermann, "Improved Weighted Centroid Localization in Smart Ubiquitous Environments," *Ubiquitous Intelligence and Computing*, 2008.

[4] Altreyi Bose and Chuan Heng Foh, "A Practical Path Loss Model For Indoor WiFi Positioning Enhancement," *IEEE ICICS*, 2007

[5] K. Tateishi and T. Ikegami, "Estimation Method of Attenuation Offset During Localization in RSSI," *IS Communication and Information Technologies*, 2008, p. 482-487.

[6] K. Tateishi, Y. Sugiyama, K. Watanabe, and T. Ikegami, "An examination no Location Estimation to Consider Statistics of RSSI," *Proc. ICICE General Conf.*, A-21-3, 2007, p.394.

[7] A. Malekpour, T.C.Ling, and W.C.Lim, " Location Determination Using Radio Frequency RSSI and Deterministic Algorithm," *IEEE CNSRC*, 2008.

[8] S. Saha, K. Chaudhuri, D. Sanghi, and P. Bhagwat, "Location determination of a mobile device using IEEE 802.11b access point signals," *Proc. IEEE Wireless Communications and Networking Conf.*, Mar. 2003, pp. 1987- 1992.

[9] Alireza Nafarieh and Jacek Ilow, "A Testbed for Localizing Wireless LAN Devices Using Received Signal Strength," *IEEE CNSRC*, 2008.

[10] Y. Wang, X. Jia, H.K. Lee, and G. Y. Li, "An indoor wireless positioning system based on wireless local area network", Proceedings of The 6th International Symposium on Satellite Navigation Technology Including Mobile Positioning & Location Services, Melbourne, Australia, July 2003, paper 54.

[11] H.K. Lee, H.S. Kim, and J.J. Choi, "Modeling Heterogeneous Signal Strength Characteristics for Flexible WLAN Indoor Localization," Proceedings of ICROS-SICE International Joint Conference, Aug. 18-21, Fukuoka, 2009.

Hyun-Hun Cho received his B.S. degree in Electrical and Electronic Engineering from Kyungpook National University in 2010. He presently works at KISTI. His research interests include GPS and mobile software navigation.

Rak-Hee Lee is currently a B.S. student in Electrical and Electronic Engineering in Kyungpook National University. His research interests include GPS and mobile software navigation.

Joon-Goo Park received his B.S. and M.S. degrees in Control and Instrumentation Engineering from Seoul National University in 1994 and 1996, respectively. He received his Ph.D. degree in Electron Engineering from Seoul National University in 2001. He is presently a professor at the School of Electrical Engineering at Kyungpook National University. His research interests include GPS and mobile software navigation.