POSTER
Zero-Configuration Path Loss Model-Based Indoor Localization

Ryangsoo Kim, Wooyeol Choi, Hyuk Lim, and Jae-Hyung Jang

Department of Information and Communications
Gwangju Institute of Science and Technology (GIST)
Gwangju 500-712, Republic of Korea
hlim@gist.ac.kr

Abstract. In received signal strength (RSS)-based indoor localizations, the localization accuracy of a target node highly depends on the accuracy of estimated distances relative to anchors having a known location. Because RSS measurements are translated into distances by the path loss model (PLM), the accurate and prompt characterization of PLM parameters is crucial for improving the localization performance, especially as the wireless channel environment dynamically varies over time. Here, we propose a *zero-configuration* method based on inter-anchor measurements in order to accurately characterize PLM parameters with no offline onsite measurements. We then describe and compare two different approaches for converting the RSS measurements to the corresponding distances.

Keywords: Zero-configuration, localization, received signal strength, path loss model.

1 Introduction

With the advent of ubiquitous computing environments, received signal strength (RSS)-based indoor localization techniques have received considerable attention because of their advantage of easy implementation on existing wireless local area network (WLAN) infrastructure. In this paper, we consider a WLAN comprised of *anchors* with known locations and target nodes to be localized. For example, the access points (APs) of IEEE 802.11 WLAN deployment can serve as anchors in an indoor environment. Each anchor node periodically broadcasts beacons tagged with its ID, and records the RSS of beacon broadcasts. When a target node broadcasts a localization request packet, the anchor nodes measure the RSS of the request packet and estimates the location of the target node by using the path loss model (PLM), which characterizes the mapping between the RSS measure and the geographic distance.

A. Puiatti et al. (Eds.): MobiQuitous 2011, LNICST 104, pp. 219–223, 2012.
© Institute for Computer Sciences, Social Informatics and Telecommunications Engineering 2012

2 Proposed Localization Algorithm

2.1 Zero-Configuration Localization

In this paper, we propose a *zero-configuration* method [1] based on inter-anchor measurements, which periodically performs RSS measurements among the anchor nodes within the transmission range of each other, to realize the fully automated and online calibration of RSSs in the time and spatial domains. Because the RSS measure is susceptible to the physical characteristics of wireless networks, such as multi-path fading and signal attenuation due to the changes in temperature, humidity, and object mobility, parameters of the PLM change over time, such as the pass loss exponent and received power at a reference distance. Nevertheless, their accurate characterization is crucial for achieving an accurate localization. As the proposed localization method updates the PLM *online* with no offline onsite measurements, it can capture (in real-time) the effects of dynamic environmental changes and thereby improve the localization accuracy.

2.2 PLM Construction

We construct a simplified PLM based on inter-anchor RSS measurements. We first make the assumption that the signal strength is inversely proportional to d^α, where d is the geographical distance between the nodes and α is the path loss coefficient. Based on this assumption, the PLM can be approximately characterized by parameters α and β as follows:

$$p\ [\mathrm{dBm}] = \beta - 10\alpha \log_{10}(d) + n, \tag{1}$$

where p is the received power at the receiver, and n is the Gaussian random noise with zero mean and variance σ^2. In this case, the first step in constructing such a path loss model is to instruct each anchor node to periodically transmit beacon packets, to measure RSSs from the other nodes, and to estimate the parameters that characterize the PLM. Let $\mathbf{p}(b)$ denote a RSS measurement vector, whose element is the RSS measurement gathered in dBm by a beacon node b, and $\mathbf{d}(b)$ denote the corresponding distance vector. Then, for the RSS measurements, the PLM in (1) is represented as the linear system $\mathbf{p} = \beta \mathbb{1}_\ell - 10\alpha \log_{10}(\mathbf{d}) + \mathbf{n}$, where $\ell = |\mathbf{p}|$, $\mathbb{1}_\ell \in \mathbb{R}^\ell$ is the 1's column vector. The two parameters α and β are then given by the least square solution of the linear system, i.e.,

$$\begin{bmatrix} \alpha \\ \beta \end{bmatrix} = (\mathbf{A}^T \mathbf{A})^{-1} \mathbf{A}^T \mathbf{p}, \tag{2}$$

where $\mathbf{A} = [-10 \log(\mathbf{d})\ \ \mathbb{1}_\ell]$. This PLM is periodically updated by taking a weighted moving average of the RSS measurement whenever the anchor node receives a new sample of RSS measurement from its neighboring nodes.

2.3 Converting RSS to Distance

Once the PLM is obtained, the distances from the target node to the anchor nodes can be computed by inverting the PLM given in (1). Here, we consider two approaches for computing the distance corresponding to the measured RSS values. The first approach is to take the time average of the RSS values recorded for a certain time interval; the distance (denoted by d_a) is given by a function of the average RSS as follows:

$$d_a(\mathbb{E}[p]) = 10^{\frac{\beta-\mathbb{E}[p]}{10\alpha}}. \tag{3}$$

The other approach is to compute the distance for each RSS measurement using (1), and to use the average of the distances computed for a certain period as the final estimated distance. In this case, let d_i denote the distance for each RSS measurement, d_i is then given by $d_i(p) = 10^{\frac{\beta-p+n}{10\alpha}}$. However, the expectation of d_i is different from the actual distance d that can be obtained when $n = 0$ in (1) because it is biased, as was addressed in [2]. Here, the expectation of d_i is given by

$$\mathbb{E}[d_i] = d \cdot \mathbb{E}[10^{\frac{n}{10\alpha}}] = d \cdot \gamma(\alpha, \sigma), \tag{4}$$

where $\gamma(\alpha, \sigma) = \mathrm{e}^{(\frac{\sigma ln 10}{10\sqrt{2}\alpha})^2}$. This relation implies that when the estimated distance is obtained by taking the average of d_i, it is equal to the actual distance scaled by γ. Therefore, the actual distance can be accurately estimated by compensating for the bias of $\mathbb{E}[d_i]$ as follows:

$$d_c = \frac{\mathbb{E}[d_i]}{\gamma(\alpha, \sigma)}. \tag{5}$$

Once the distances to the anchor nodes are estimated, the geographic location of the target node can be determined using lateration algorithms [3–5].

3 Experiments

In this section, we evaluate the performance of the PLM parameter estimation and localization accuracy by using MATLAB in conjunction with an empirical RSS measurement data set obtained from the SPAN laboratory at the University of Utah [6]. The RSS measurement was obtained from 44 wireless devices in a 14 m x 13 m office area.

In order to characterize the PLM parameters, we randomly selected N nodes from among 44 wireless devices and computed α and β in (2) using their pairwise RSS measurements. Fig. 1 shows the estimated path loss exponent α with respect to N. In the figure, the mean value of α is approximately 2 regardless of the number of the selected nodes, which implies that the nodes are deployed under a line-of-sight channel environment. We can also see that the standard deviation is relatively high when N is small, due to the spatial diversity of wireless channel environments.

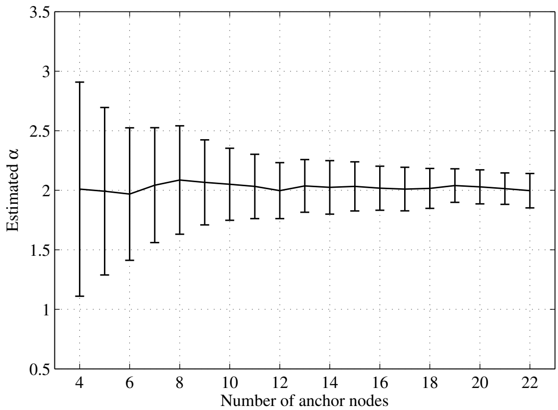

Fig. 1. Mean and standard deviation of the estimated path loss exponent α

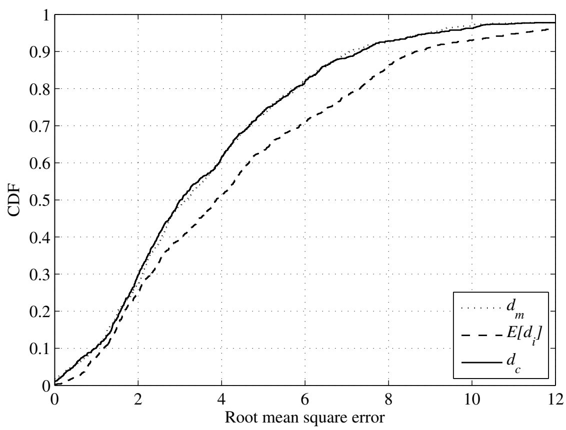

Fig. 2. Cumulative distribution of position errors for d_a, $\mathbb{E}(d_i)$, and d_c

We chose the five anchor nodes and then randomly selected the target nodes. The distances between the anchor nodes and the selected target nodes were obtained using (3)–(5), and the location of the target node was computed by the linear least square (LLS) approach in [7]. Note that the standard deviation of the measured RSS value was reported to be 3.92 (dBm) in [6]. Fig. 2 shows the cumulative distribution of the root mean square errors (RMSEs) of the target node location. We found that the localization obtained using the compensated distance (d_c) was approximately 30% more accurate than that with no bias compensation ($d_i(\mathbb{E}[p])$), and was almost the same as that obtained by d_a in (3).

4 Conclusion

In this paper, we proposed a zero-configuration method for the fully automated and online calibration of PLM parameters in order to cope with the temporal and spatial variation of wireless channel environments, and subsequently described two approaches for converting RSS measurements to the corresponding distances. The experimental results showed that if the distance estimate obtained by each RSS measurement is averaged over time, it is biased, which results in a poor estimation accuracy, though this can be accurately compensated for by using an appropriate scaling factor.

Acknowledgement. This research was partially supported by the UTRC program funded by DAPA and ADD, Leading Foreign Research Institute Recruitment Program through NRF funded by MEST (K20903001804-11E0100-00910), and the Center for Distributed Sensor Network at GIST.

References

1. Lim, H., Kung, L.-C., Hou, J.C., Luo, H.: Zero-configuration indoor localization over ieee 802.11 wireless infrastructure. Springer Wireless Networks 53(7), 405–420 (2010)
2. Zanca, G., Zorzi, F., Zanella, A., Zorzi, M.: Experimental comparison of RSSI-based localization algorithms for indoor wireless sensor networks. In: The ACM Workshop on Real-World Wireless Sensor Networks (2008)
3. Niculescu, D., Nath, B.: Ad hoc positioning system. In: IEEE Globecom (2001)
4. Nagpal, R., Shrobe, H., Bachrach, J.: Organizing a Global Coordinate System from Local Information on an Ad Hoc Sensor Network. In: Zhao, F., Guibas, L.J. (eds.) IPSN 2003. LNCS, vol. 2634, pp. 333–348. Springer, Heidelberg (2003)
5. Savvides, A., Han, C.-C., Strivastava, M.B.: Dynamic fine-grained localization in ad-hoc networks of sensors. In: ACM MobiCom (2001)
6. Patwari, N., Hero, A.O., Perkins, M., Correal, N.S., O'Dea, R.J.: Relative location estimation in wireless sensor networks. IEEE Trans. on Signal Processing 51(8), 2137–2148 (2003)
7. Yang, J., Chen, Y.: Indoor localization using improved rss-based lateration methods. In: IEEE Globecom (2009)