Dynamic Channel Model LMS Updating for RSS-Based Localization

Paula Tarrío, Ana M. Bernardos, Xian Wang, and José R. Casar

Data Processing and Simulation Group, Universidad Politécnica de Madrid, Madrid, Spain
{paula,abernardos,wang.xian,jramon}@grpss.ssr.upm.es

Abstract. Received signal strength-based localization systems usually rely on a calibration process that aims at characterizing the propagation channel. However, due to the changing environmental dynamics, the behavior of the channel may change after some time, thus, recalibration processes are necessary to maintain the positioning accuracy. This paper proposes a dynamic calibration method to initially calibrate and subsequently update the parameters of the propagation channel model using a Least Mean Squares approach. The method assumes that each anchor node in the localization infrastructure is characterized by its own propagation channel model. In practice, a set of sniffers is used to collect RSS samples, which will be used to automatically calibrate each channel model by iteratively minimizing the positioning error. The proposed method is validated through numerical simulation, showing that the positioning error of the mobile nodes is effectively reduced. Furthermore, the method has a very low computational cost; therefore it can be used in real-time operation for wireless resource-constrained nodes.

Keywords: Indoor localization, RSS, calibration, channel model, LMS.

1 Introduction

Many context-aware applications rely on the knowledge of the position of the user, and of the surrounding objects, to provide him with useful and personalized information and services. In indoor environments, where GPS cannot be used, several technologies have been proposed to calculate the position of a person or object, such as ultrasounds, artificial vision or infrared. However, due to the widespread use of wireless devices, radio-frequency localization techniques [1] and, in particular, those based on the measurement of the received signal strength (RSS), have become very popular and easy to deploy.

Either map-based or channel model based techniques can be used to locate a node from a set of RSS measurements. Channel model based techniques use a propagation channel model to establish a relation between the RSS and the distance between two nodes; then, a triangulation or positioning algorithm is used to calculate the position of a node from a set of distances to some anchor nodes with known positions. Map-based or fingerprinting techniques create a radio map of the environment by gathering, for each anchor node, a set of RSS measurements in different test points. When an unknown node needs to be localized, its RSS measurements are matched against the ones stored in the map, in order to find the closest correspondence. Both approaches require an initial calibration phase to obtain an appropriate fingerprint or channel model, valid for the specific deployment area.

The localization accuracy will depend on how accurately the propagation channel is characterized. The temporal variations of the propagation medium, originated by unstable environmental conditions (such as humidity), space reorganization (e.g. furniture movement or open-closed doors) and people's movement (temporal flow, human clusters around the mobile target, etc.), may therefore affect the localization accuracy. For example, [2] analyzes how the average position accuracy of a fingerprint-based system (offering 2.13m. of accuracy in standard conditions – no-blocking people, close-all-doors and 40% humidity level) is deteriorated in a 43.7% when the humidity level increases until 70%, in a 236.6% if the configuration changes to all-open-doors, and in a 85.9% when people clusters are present.

Due to the dynamic behavior of the propagation channel, the initial calibration may not be accurate enough after some time, so there is a need to repeat the calibration process in order to maintain the localization accuracy. In this paper, we present an automatic recalibration strategy for channel model-based localization systems, which is an enhanced version of our previous work [3]. We assume that the propagation channel adjusts to a theoretical lognormal model, with different parameters characterizing each of the anchor nodes. The proposed technique uses a set of reference points (with known positions) where RSS measurements from the anchor nodes are collected (either by a set of sniffers deployed at the reference points or by a mobile user that is detected at these particular points). These measurements are then integrated in a Least Mean Squares (LMS) algorithm that finds, iteratively, the values of the channel parameters that minimize the positioning error. The proposed technique can be implemented in real-time localization systems, as its computational and memory requirements are very low.

The structure of the paper is as follows. Section 2 reviews some previous proposals to automate calibration procedures for indoor localization systems. In Section 3, our localization scenario is fully described. Section 4 describes the proposed algorithm, which is tested in Section 5 through a number of numerical simulations. Finally, Section 6 concludes the work.

2 Related Work

RSS indoor localization systems usually rely on an off-line calibration phase, which aims at characterizing the electromagnetic environment by: 1) calibrating a theoretical propagation model with real RSS measurements or 2) building a RSS fingerprint (or radio map) of the localization area. Due to the changing environmental dynamics the reliability of the calibration does not last for a long time, thus, recalibration processes are necessary to maintain the positioning accuracy. Manual calibration and recalibration processes are costly and inefficient, so a line of research in indoor localization is devoted to propose solutions with zero or limited initial calibration and on-line recalibration.

Several fingerprinting localization approaches propose to update the radio map automatically without human interaction. This is usually achieved by using additional devices that listen to the transmitted signals. For example, Krishnan et al. [4] include sniffers in their RF deployment. When at least one sniffer observes a significant deviation on the RSS from any emitter, the radio map is recalculated using a spline interpolation technique on the sniffers data. Moraes and Nunes [5] also propose a sniffer-based technique to build a propagation map, in which each grid position is associated to a probability distribution. The map is rebuilt every T seconds or when significant variations in the RSS occur. A similar approach is followed by Yin et al. [6], who use a set of reference points (whose position is not needed) to measure the RSS from the anchor nodes of the deployment. These measurements and the ones collected from a mobile node are used in a multiple-regression based algorithm to update a linear relationship between the signal-strength values received by the reference points and those received by the client device.

With respect to channel modeling localization techniques, several methods have been proposed to calculate and update the channel model online. For example, Gwon and Jain [7] use inter-anchor RSS measurements to generate multiple linear functions (one for each pair of anchors) representing the relationship between RSS and distance. When the mobile node needs to be localized, it uses the mapping function corresponding to the first and second anchors with strongest RSS to convert the RSS into distance. A similar approach is followed by Barsocchi et al. [8]; they use the inter-anchor RSS measurements to calculate, adaptively, a RSS-distance model that, in this case, is logarithmic and includes, as parameters to update, a wall attenuation factor and the air attenuation factor (or path loss exponent). Lim et al. [9] take as input the on-line RSS measurements between anchors, and between a client and its neighboring anchors, to create a linear mapping between RSS and distance using the truncated singular value decomposition technique. The algorithm implicitly assumes a logarithmic path loss model and that the distance between a client and an anchor node is a linear combination of the RSS measurements between the client and all the anchor nodes. Our previous work [3] uses real-time RSS measurements from the anchor nodes obtained from a set of reference points to update the parameters of a logarithmic propagation model by using a LMS algorithm. We propose here an extension of this method that considers a different propagation model for each of the anchor nodes. In this way, the accuracy of the localization results is improved when the deployment area is such that different anchor nodes may be affected by different propagation conditions.

3 Localization Scenario

Our calibration scheme is targeted at dynamically adjusting the propagation channel models in model-based localization systems. This kind of systems are usually composed of N anchor nodes (e.g. WiFi or Bluetooth access points, or Zigbee motes) with fixed and known positions, and one or several mobile targets that need to be localized. The localization is based on using a channel model to compute each mobile-anchor node distance from the RSS measurements taken at the mobile device from the anchor nodes (or vice versa). The position of the target is then computed with a triangulation or positioning algorithm.

The most popular channel model for RSS-based localization is the lognormal model [10]:

$$P_{RX}(dBm) = A - 10\eta \log\frac{d}{d_0} + N(0,\sigma) \tag{1}$$

where P_{RX} is the received power, d is the distance between transmitter and receiver, A and η are the parameters of the channel model and N is a zero-mean Gaussian random variable with standard deviation σ. A depends on the antenna gains, the transmission power and the power loss for a reference distance d_0, and needs to be experimentally adjusted. The path loss exponent η has to be experimentally determined too. For example, in 2.4GHz IEEE 802.15.4 propagation, considering d_0 = 1 m, A may range between -50 and -85 dBm, while η may be between 1.9 and 3.5 [11].

In our case, we assume that each anchor node is characterized by different values of the parameters A and η of the lognormal channel model. Therefore, the distance between any point and anchor node i can be estimated from the received P_{RX} (in practice the RSS) using eq. 1 and given A_i and η_i. Then, from a set of, at least, three estimated distances to different anchor nodes, the target's position can be calculated. To this end, we use the hyperbolic positioning algorithm (detailed formulation is available in e.g. [10]), which estimates the position of the target according to the following expression:

$$\begin{bmatrix} \hat{x} \\ \hat{y} \end{bmatrix} = \left(H^T H\right)^{-1} H^T \tilde{b} \tag{2}$$

where:

$$H = \begin{bmatrix} 2x_2 & 2y_2 \\ \vdots & \vdots \\ 2x_N & 2y_N \end{bmatrix}; \quad \tilde{b} = \begin{bmatrix} x_2^2 + y_2^2 - \tilde{d}_2^2 + \tilde{d}_1^2 \\ \vdots \\ x_N^2 + y_N^2 - \tilde{d}_N^2 + \tilde{d}_1^2 \end{bmatrix} \tag{3}$$

$$\tilde{d}_i = 10^{\frac{A_i - RSS_i}{10\eta_i}} \tag{4}$$

being (x_i, y_i) the known coordinates of anchor node i, $\tilde{d}_i$ the estimated distance from the target to anchor node i, and RSS_i, the received signal strength to/from anchor node i. The origin of coordinates is situated in the anchor node $i=1$ (x_1=0, y_1=0).

In practice, the parameters A_i and η_i need to be continually updated or calibrated, as slightly biased estimations of A and η may result in significant localization errors [10]. To do so automatically, we define a number of reference points at fixed geographic positions, where a wireless device will take RSS measurements from the anchor nodes, which will be used to update the propagation model, according to the algorithm described in next section. These reference points, may be related to waypoints or objects capable of generating 'measurement events' (e.g. doors that detect users), or deployed as part of the communications infrastructure (i.e. an anchor node could serve as reference point).

Of course, this approach has many practical implementation details that are not directly addressed in this paper. For example, the number of reference points needs to be minimized, and the physical distribution of the reference points needs to be flexible, as it is not always easy to place new elements in daily-living environments. Additionally, reference points should be easily maintainable and admit dynamic reconfiguration. Assuming that a suitable deployment is feasible (as it is), the optimization algorithm used to calibrate the system is described in the next Section.

4 Proposed Adaptive Calibration Algorithm

The Least Mean Square algorithm is a kind of stochastic gradient algorithm, based on approximating the true gradient of the mean-square error of a function by its instantaneous estimate. The LMS algorithm is a simple and computationally efficient technique used to find the values of the parameters of a function that fit to a set of reference values.

In this case, we propose to use it in an adaptive filter to minimize the localization error (eq. 5) by recursively adapting the parameters A_i and η_i of the lognormal propagation models. A block diagram of the proposed scheme is shown in Fig. 1.

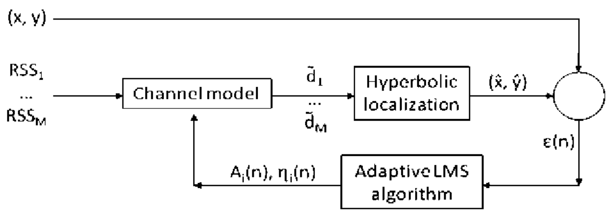

Fig. 1. Block diagram of the adaptive LMS algorithm

At each new iteration (n), the filter takes as input $M \leq N$ RSS measurements taken between a certain calibration/reference point and M anchor nodes. These measurements are used to estimate the distances $\tilde{d}_i$ from this reference point to the set of anchor nodes, using eq. 4 and the values of A_i and η_i calculated at the previous iteration (n-1). Then, the hyperbolic positioning algorithm (eq. 2) is used to estimate from these distances the position of the reference point ($\hat{x}, \hat{y}$), which is compared with its known real position (x, y) to evaluate the error:

$$\varepsilon(n) = \sqrt{\left(x(n) - \hat{x}(n)\right)^2 + \left(y(n) - \hat{y}(n)\right)^2} \tag{5}$$

This error serves as input to the LMS algorithm, which finds the parameters A_i and η_i at the current iteration n that minimizes this error. According to the LMS technique, the optimum values of these parameters can be calculated as:

$$\begin{aligned} A_i(n) &= A_i(n-1) - \frac{1}{2}\mu_{Ai}\frac{\partial E[\varepsilon^2(n)]}{\partial A_i} \cong A_i(n-1) - \mu_{Ai}\varepsilon(n)\frac{\partial \varepsilon(n)}{\partial A_i} \\ \eta_i(n) &\cong \eta_i(n-1) - \mu_{\eta i}\varepsilon(n)\frac{\partial \varepsilon(n)}{\partial \eta_i} \end{aligned} \tag{6}$$

where μs are the filter step sizes, which control the speed and stability of convergence, and the partial derivatives can be obtained from eqs. 2-5 after some calculations:

$$
\begin{aligned}
\frac{\partial \varepsilon(n)}{\partial A_i} &= \frac{1}{\varepsilon(n)} \cdot \frac{16 \cdot \ln 10}{\det \cdot 10 \cdot \eta_i(n-1)} \cdot \left[C_i \cdot (x(n) - \hat{x}(n)) + D_i \cdot (y(n) - \hat{y}(n)) \right] \cdot \tilde{d}_i^{\,2} && i = 2..N \\
\frac{\partial \varepsilon(n)}{\partial A_1} &= -\frac{1}{\varepsilon(n)} \cdot \frac{16 \cdot \ln 10}{\det \cdot 10 \cdot \eta_1(n-1)} \cdot \left[\sum_{i=2}^{N} C_i \cdot (x(n) - \hat{x}(n)) + \sum_{i=2}^{N} D_i \cdot (y(n) - \hat{y}(n)) \right] \cdot \tilde{d}_1^{\,2} && \\
\frac{\partial \varepsilon(n)}{\partial \eta_i} &= -\frac{1}{\varepsilon(n)} \cdot \frac{16 \cdot \ln 10}{\det \cdot \eta_i(n-1)} \cdot \left[C_i \cdot (x(n) - \hat{x}(n)) + D_i \cdot (y(n) - \hat{y}(n)) \right] \cdot \tilde{d}_i^{\,2} \log \tilde{d}_i && i = 2..N \qquad (7) \\
\frac{\partial \varepsilon(n)}{\partial \eta_1} &= \frac{1}{\varepsilon(n)} \cdot \frac{16 \cdot \ln 10}{\det \cdot \eta_1(n-1)} \cdot \left[\sum_{i=2}^{N} C_i \cdot (x(n) - \hat{x}(n)) + \sum_{i=2}^{N} D_i \cdot (y(n) - \hat{y}(n)) \right] \cdot \tilde{d}_1^{\,2} \log \tilde{d}_1 &&
\end{aligned}
$$

where

$$\tilde{d}_i = 10^{\frac{A_i(n-1) - RSS_i}{10 \cdot \eta_i(n-1)}}$$

$$C_i = x_i \cdot \left(y_2^2 + \ldots + y_N^2\right) - y_i \cdot \left(x_2 \cdot y_2 + \ldots + x_N \cdot y_N\right), \qquad D_i = y_i \cdot \left(x_2^2 + \ldots + x_N^2\right) - x_i \cdot \left(x_2 \cdot y_2 + \ldots + x_N \cdot y_N\right)$$

$$\det = \left(4 \cdot x_2^2 + \ldots + 4 \cdot x_N^2\right) \cdot \left(4 \cdot y_2^2 + \ldots + 4 \cdot y_N^2\right) - \left(4 \cdot x_2 \cdot y_2 + \ldots + 4 \cdot x_N \cdot y_N\right)^2$$

As it can be noticed, the proposed iterative technique just handles data of the previous temporal instant and is simple in its formulation, thus, it has minimum computational and memory needs. Therefore, it can be integrated in real-time localization systems without requiring significant resources or introducing serious operational delays.

5 Performance Evaluation

In order to evaluate the performance of the proposed method, Matlab was used to simulate a wireless deployment in a noisy environment. The simulation scenario was composed of 8 anchor nodes and 20 reference points, as shown in Fig. 2.

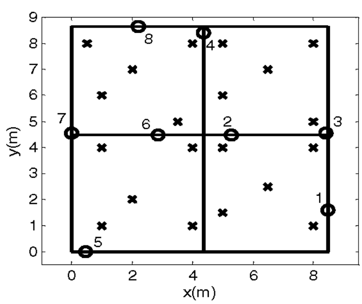

Fig. 2. Scenario for simulation: 4 rooms, 8 anchor nodes (o) and 20 reference points (x)

The positions of the reference points were chosen to have enough spatial diversity in each room with a moderate number of nodes (5 per room, located near the corners and the center). For each reference node, we generate 200 data arrays, each one containing RSS measurements from the 8 anchor nodes. These RSS measurements are simulated using eq. 1, with $P_{TX\text{-}sim}$ = 0 dBm, $d_{0\text{-}sim}$ = 1 m and σ_{sim} = 1 dB. The channel parameters were set to $A_{sim\text{-}i}$ = -60 dB and $\eta_{sim\text{-}i}$ = 2.3 for the first four anchor nodes (i=1..4) and to $A_{sim\text{-}i}$ = -65 dB and $\eta_{sim\text{-}i}$ = 2.6 for the other four (i=5..8).

The algorithm is initialized with a set of initial values for the parameters of the channel models of the different anchor nodes (A_{0i} and η_{0i}). Then, in the first iteration, one of the reference points provides a set of RSS measurements from the 8 anchor nodes. The initial channel model parameters are used to convert these measurements into distances (using eq. 1), which are introduced into the hyperbolic localization algorithm (eq. 2) to obtain a first position estimation of the reference point. Then, equations 6-7 are used to update the values of A_i and η_i that minimize the position error. Those values are to be used by the localization algorithm in the next iteration.

Fig. 3 shows the evolution of the position error (Euclidean distance between the real position and the estimated position) for a set of 100 mobile nodes randomly distributed in the simulation area. In this case, the initial values of the channel model parameters were set to A_0 = -65 dB and η_0 = 2.4 for the first 4 anchors, and to A_0 = -60 dB and η_0 = 2.7 for the other four. It can be seen that the algorithm converges in this case after approximately 25 samples (i.e., 25 measurement events, with 8 RSS measurements at each event: one for each anchor node). When the difference between the initial values of the channel model parameters and their "true" value is higher, the convergence is slower. For example, when if the initial values of the channel model parameters are set to A_0 = -70 dB and η_0 = 2.4 for the first 4 anchors, and to A_0 = -55 dB and η_0 = 2.7 for the other four, approximately 100 samples are needed to calibrate the model (Fig. 3b).

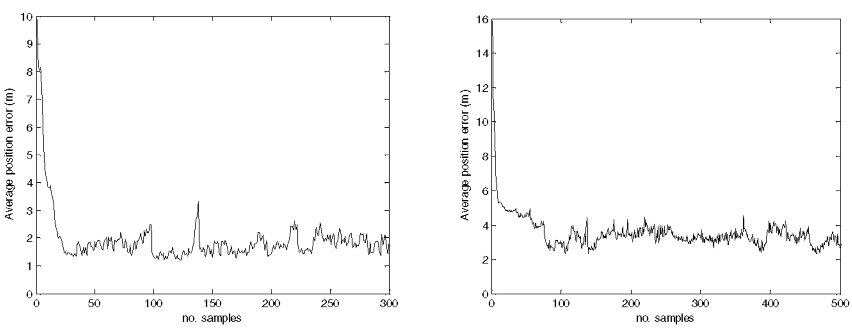

Fig. 3. Evolution of the positioning error using a LMS filter with μ_A = 0.8, μ_η = 0.01. The initial values of the model parameters were a) A_i = -65 dB and η_i = 2.4 for i = 1..4, and A_i = -60 dB and η_i = 2.7 for i = 5..8, b) A_i = -70 dB and η_i = 2.4 for i = 1..4, and A_i = -55 dB and η_i = 2.7 for i = 5..8.

As comparison, we have also evaluated the convergence of the real-time calibration algorithm proposed in [3], which also uses a LMS technique to minimize the error, but assumes a unique and isotropic channel model for the entire environment. Fig. 4 shows the evolution of the positioning error under the same simulation environment as in Fig. 3a. As it can be seen, the new method provides better results: the convergence is quicker and the final positioning error is lower.

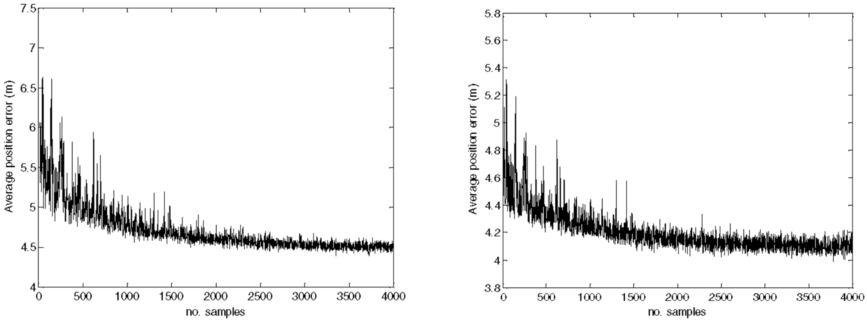

Fig. 4. Evolution of the positioning error using the LMS filter in [3] with $\mu_A = 0.8$, $\mu_\eta = 0.01$. The initial values of the model parameters were a) A = -65 dB and η = 2.4, b) A = -60 dB and η = 2.7.

A significant factor for the LMS algorithm are the filter step sizes (μs), which control the pace to convergence but also the stability of the estimation. For our experiments, the step sizes have been empirically chosen among those that where offering a reasonable convergence time (in terms of needed number of RSS tuples) while providing a reasonably stable convergence value for A_i and η_i. Although there are other values which may be effectively used, Fig. 3 shows how the convergence works for the distance error when the filter step sizes have been set to $\mu_A = 0.8$, $\mu_\eta = 0.01$. As shown in Fig. 5, higher values of μ may accelerate the convergence (fewer samples are needed to reach the possible minimum error in distance), but may also provide a less stable convergence.

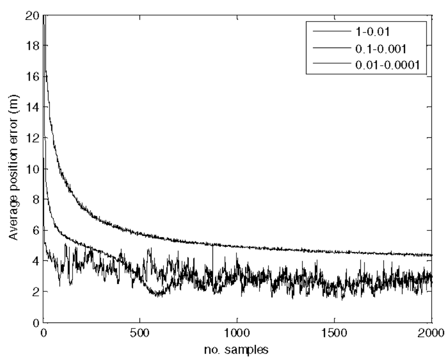

Fig. 5. Effects of the value of the LMS filter coefficients <μ_A, μ_η> on the mean error evolution (in m.). LMS initialization: A_i = -70 dB and η_i = 2.4 for i = 1..4, and A_i = -55 dB and η_i = 2.7 for i = 5..8.

6 Conclusions

This paper describes a strategy to automatically adapt the parameters of the lognormal channel models in order to minimize localization errors when using a hyperbolic localization technique. Preliminary numerical results show that the strategy achieves good localization results after a short convergence time. Furthermore, its computational and memory requirements are very low. Therefore, it is a promising technique to use in resource-constrained devices to automate the calibration procedure.

From a practical viewpoint, we have deployed a testbed with MicaZ devices and we are starting to carry out some experimental test to assess the performance of the algorithm in a real situation. Further work is focused on demonstrating the stability and feasibility of the proposal in real time operation; in particular, it is necessary to study how to set the LMS step sizes effectively, and to analyze the relationship between the number of reference points, their geometrical distribution and the LMS algorithm accuracy.

Acknowledgements. This work has been supported by the Government of Madrid under grant S-2009/TIC-1485 and by the Spanish Ministry of Science and Innovation under grant TIN2008-06742-C02-01.

References

1. Gezici, S.: A survey on wireless position estimation. Wireless Personal Communications 44(3), 263–282 (2008)
2. Chen, Y.C., Chiang, J.R., Chu, H.H., Huang, P., Tsui, A.W.: Sensor-assisted WiFi Indoor Location System for Adapting to Environmental Dynamics. In: 8th ACM Int. Symposium on Modeling, Analysis and Simulation of Wireless and Mobile Systems, pp. 118–125 (2005)
3. Bernardos, A., Casar, J.R., Tarrío, P.: Real time calibration for RSS indoor positioning systems. In: Int. Conf. on Indoor Positioning and Indoor Navigation (2010)
4. Krishnan, P., Krishnakumar, A.S., Ju, W.-H., Mallows, C., Ganu, S.: A system for LEASE: Location Estimation Assisted by Stationary Emitters for Indoor RF Wireless Networks. In: IEEE INFOCOM, vol. 2, pp. 1001–1011 (2004)
5. Moraes, L.F.M., Nunes, B.A.A.: Calibration-Free WLAN Location System Based on Dynamic Mapping of Signal Strength. In: 4th ACM Int. Workshop on Mobility Management and Wireless Access, pp. 92–99 (2006)
6. Yin, J., Yang, Q., Ni, L.: Adaptive Temporal Radio Maps for Indoor Location Estimation. In: 3rd IEEE Int. Conf. on Pervasive Computing and Communications (2005)
7. Gwon, Y., Jain, R.: Error Characteristics and Calibration-free Techniques for Wireless LAN-based Location Estimation. In: 2nd Int. Workshop on Mobility Management & Wireless Access Protocols, pp. 2–9. ACM Press, New York (2004)
8. Barsocchi, P., Lenzi, S., Chessa, S., Giunta, G.: A Novel Approach to Indoor RSSI Localization by Automatic Calibration of the Wireless Propagation Model. In: 69th Conf. on Vehicular Technology, pp. 1–5 (2009)
9. Lim, H., Kung, L.-C., Hou, J.C., Luo, H.: Zero-configuration, robust indoor localization: Theory and Experimentation. In: IEEE INFOCOM, pp. 1–12 (2006)
10. Tarrío, P., Bernardos, A.M., Casar, J.R.: An RSS Localization Method based on Parametric Channel Models. In: Int. Conf. on Sensor Technologies and Applications, pp. 265–270 (2007)
11. Tarrío, P., Martín, H., Bernardos, A.M.: Enhancing the Performance of Propagation Model-Based Positioning Algorithms. In: 3rd Int. Workshop on User-Centric Technologies and Applications, pp. 123–132 (2009)