Enhancing the Performance of Propagation Model-Based Positioning Algorithms

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Abstract. Object localization in wireless networks through Received Signal Strength (RSS) measurements requires a precise estimation of the signal attenuation model in order to produce meaningful results. The popular lognormal channel model, widely adopted to describe the signal strength attenuation as a function of the distance between nodes, turns out to be too simplistic when applied to a real scenario. In this paper, we analyze two possible improvements to this model: on one hand, we build a different channel model for each reference node in the network, with the aim of tackling the anisotropy of the environment. On the other hand, we explicitly append to the lognormal model a term to account for walls attenuation. A thorough experimental testbed demonstrates the potentials of the two approaches, with the second one being especially useful to counteract the effect of the limited sensitivity of practical wireless receivers.

Keywords: RSS, Localization, Lognormal channel model, Hyperbolic and Circular positioning

1 Introduction

Ambient intelligence and augmented reality are receiving an increasing deal of attention due to their applicability to logistics, medicine, education, tourism, domotics, and many other fields [1]. In order to provide useful information, all of these systems are supposed to estimate, with sufficient accuracy, the position of people and objects in the environment, as a starting point for further processing. Most commercial wireless devices include nowadays the possibility of measuring the *received signal strength* (RSS) of the radio signal at a specific node. This information can be collected easily with current off-the-shelf equipment, and has become therefore one of the most popular techniques for inferring the relative positions of the nodes in the wireless network.

In the literature, two main approaches have been proposed to solve the localization problem. In the first one [2-8], a channel model is used to establish a relation between the RSS and the distance between two nodes. Since the radio signal attenuates as it propagates through the space, the received signal strength can be used to estimate the distance from the transmitter to the current node. The location of a node can then be determined from a set of these distances using some positioning algorithm [9][15]. Conversely, the second approach [8-11] creates a radio map of the environment by gathering, for each node, a set of RSS measurements in different positions, uniformly spaced on a regular grid. These “fingerprints” are then stored in a database; 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. The main drawback of this approach is that a large number of onsite measurements is required in order to obtain a fine-granularity localization, which unavoidably entails an increase of the operational cost of the system. Moreover, this kind of systems requires a preliminary calibration phase before the actual measurements collection, which is often infeasible in real-field situations.

In this work we focus on the model-based approach, by analyzing the effect of more sophisticated channel models on the localization performance. Our contribution consists in evaluating two possible ameliorations to the popular lognormal model, reviewed in Section 2.1. Specifically, we observe that in a practical deployment, the isotropy assumption of the lognormal model is misleading, as the presence of objects and obstacles in the room make the signal attenuation significantly deviate from the theoretical behavior. We propose and critically analyze two possible improvements to the baseline model that aim at dealing with these real field issues. The first one targets the anisotropy of the environment by estimating a different model for each reference node in the room. The second enhancement regards the effects of obstacles like walls, which are specifically accounted for by adding an ad hoc term in the channel equation.

The rest of this paper is organized as follows. Section 2 discusses the fundamentals of model-based localization, highlighting the main limitations of the traditional approaches. In Section 3 we describe the proposed channel model enhancements, while Section 4 presents the experimental deployment and their results. Finally, Section 5 draws some concluding remarks.

2 Model-based methods for indoor positioning

Model-based RSS localization systems have been proposed thoroughly in the literature for different radio technologies, such as WiFi [8], Bluetooth [17], IEEE 802.15.4 [16]. All of these systems share a common methodology for estimating the nodes positions given the signal strength measurements. In this section, we first briefly review the basic ideas of model-based positioning, in order to subsequently put in evidence their advantages and drawbacks.

2.1. Model-based localization

Consider the problem of localizing a mobile node in a wireless network. We assume that the positions of some of the nodes, hereafter named *reference nodes*, are known. The position of the mobile node can then be calculated using the model-based approach as follows. First, the mobile node collects RSS measurements from the reference nodes. Then, these measurements are matched against a channel model in order to estimate the distances between the mobile node and each reference node; the so-obtained distances are finally used to determine the location of the node using a positioning algorithm.

Among the number of channel models proposed for outdoor and indoor environments [12] (Nakagami, Rayleigh, Ricean, etc.), the most popular channel model for RSS-based localization, due to its simplicity, is the lognormal shadowing path loss model [13], which expresses the relation between the received power (P_{RX}) and the transmitter-receiver distance as:

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

where A is a constant term which accounts for the transmission power of the nodes, d is the distance between transmitter and receiver, η is the path loss exponent, and N is a zero-mean Gaussian random variable with standard deviation σ. The parameters A and η have to be determined experimentally.

After estimating the distances to the different reference nodes, a positioning algorithm must be applied in order to calculate the position of the mobile node. The two most popular positioning algorithms adopted for RSS-based localization are the circular and the hyperbolic positioning algorithms [15], which leverage a Least-Squares (LS) procedure to determine the node location. Intuitively, the basic idea of the circular positioning algorithm is to find the closest intersection of a set of spheres centered in each reference node, with radii given by the previously estimated distances. Let (x_i, y_i) be the position of reference node i, i = 1, 2,…, N, where N is the total number of reference nodes; let also $\tilde{d}_i$ be the estimated distance between the node under consideration and reference node i. The circular positioning algorithm estimates the coordinates (x,y) of the mobile node as the ones that minimize the following cost function:

$$\varepsilon = \sum_{i=1}^{N} \left(\sqrt{(x_i - x)^2 + (y_i - y)^2} - \tilde{d}_i \right)^2 \tag{2}$$

This is a highly non-linear function of (x,y), which can be minimized iteratively by using for instance a gradient descent method. The initialization of this procedure can be performed, without loss of generality, as proposed in [15].

The hyperbolic positioning algorithm converts the non-linear localization problem into a linear one, which can therefore be solved by means of linear algebra operations. The position of the mobile node can be calculated as:

$$\hat{\bar{x}} = \left(H^T H\right)^{-1} H^T \tilde{b} \tag{3}$$

where $\hat{\bar{x}} = \begin{bmatrix} \hat{x} \\ \hat{y} \end{bmatrix}$, $H = \begin{bmatrix} 2x_2 & 2y_2 \\ \vdots & \vdots \\ 2x_N & 2y_N \end{bmatrix}$ and $\tilde{b} = \begin{bmatrix} x_2^{\,2} + y_2^{\,2} - \tilde{d}_2^{\,2} + \tilde{d}_1^{\,2} \\ \vdots \\ x_N^{\,2} + y_N^{\,2} - \tilde{d}_N^{\,2} + \tilde{d}_1^{\,2} \end{bmatrix}$.

2.2 Limitations of current model-based localization approaches

In practice, using a channel model such as the one described above can hardly capture the complexity of a real radio channel. In ideal conditions, the signal strength decays as the inverse of the square distance between the transmitter and the receiver. However, in real indoor deployments the actual behavior deviates from the theoretical one due to other environmental factors, such as the size and surface of objects in the scene. Furthermore, the channel in practice is far from isotropic, being its characteristics strongly dependent on the environmental conditions surrounding the node [18]. Moreover, in real applications, the radio channel has to be estimated from a limited number of noisy RSS measurements, which might not be sufficient to properly condition the estimation process, leading to a poor reconstruction of the environment characteristics. This may introduce additional errors in the RSS-to-distance conversion, and, consequently, deteriorated localization performance. The neat result of all these effects is that the model-based systems proposed thus far in the literature can hardly achieve a precision higher than 2 or 3 meters, both indoors and outdoors.

3 Proposed channel-model enhancements

Channel models used for RSS-based localization are usually isotropic and do not consider obstacles like people or walls interposed between the transmitter and the receiver. While taking into account moving objects is generally a complex task, which must be targeted e.g. by adding some tracking module in the system, other influencing factors are easier to account for in the model description. For instance the attenuation of the signal produced by the walls in the deployment area has been considered in previous works, such as the RADAR localization system [8].
In this section, we propose two improvements to the channel model in (1) which directly aim at overcoming the limitations of the standard lognormal model.

3.1 Reference nodes

The first enhancement to the channel model that we consider tackles directly the possible anisotropy of the environment. Typically, a channel model will change depending on the direction of the transmission, the position of the objects which may interfere with the propagation, etc. To take into account these effects, we propose to consider a different channel model for each reference node. The different models are then used in place of the global isotropic one in the distance estimation phase, as described in Section 2.1.

3.2 Wall attenuation

When the radio signal travels through a wall, it gets attenuated in a rather predictable way. We use this observation to introduce a wall attenuation factor in our model. In order to correctly account for the wall attenuation, one would need to know in advance the number of walls crossed by the radio wave, which requires in turn a pretty good localization of the mobile node. This chicken-and-egg problem can be solved using an iterative approach. First, we compute an initial estimate of the node position using the general channel model of (1); then, we use this approximate position to compute the number of walls traversed by the radio signal (the environment geometry is known at the moment of the deployment). The number of wall-crossings obtained in this way is then embedded in the channel-model to refine the position of the node. This procedure can be repeated until some convergence criterion is met. In light of the above consideration, the channel-model equation (1) can be updated as:

$$P_{RX}(dBm) = A - 10\eta \log \frac{d}{d_0} + n \cdot A_p + N(0,\sigma) \tag{4}$$

where n is the number of walls that the signal crosses in its propagation, A_p is the attenuation that a wall introduces and the other parameters are the same as in (1). Clearly, this new way of modeling the propagation subsumes some previous calibration stage to estimate the attenuation suffered by the signal when a wall is crossed, which depends on its thickness and composition.

4 Experimental evaluation

In this section we describe the results of some experimental tests carried out to analyze and evaluate how the channel model improvements depicted above affect the accuracy of the localization. A WiFi network and a wireless sensor network composed of MICAz motes [14] were used for these experiments.

4.1 Experimental setup

In the first experiment, we deployed four WiFi access points in an office area and we measured the RSS with a PDA in various points following an 80x80cm grid. Fig. 1a shows the deployment area with the position of the access points and the measurement points. In each of the measurement points we took 4 different RSS measurements, one for each orientation of the person who held the PDA (north, east, west and south). Altogether, 689 RSS values were taken from each access point.

In the second experimental setting, we deployed a MicaZ sensor network composed of twelve reference nodes, situated at fixed positions (see Figure 1b). We then collected a minimum of 3 RSS values (from distinct reference nodes) in 2780 different positions, as illustrated in Figure 1b.

The frequency band used in both cases is the 2.4 GHz ISM band, and we tried to reproduce as much as possible realistic working conditions, e.g. people were allowed to move in the rooms, etc.

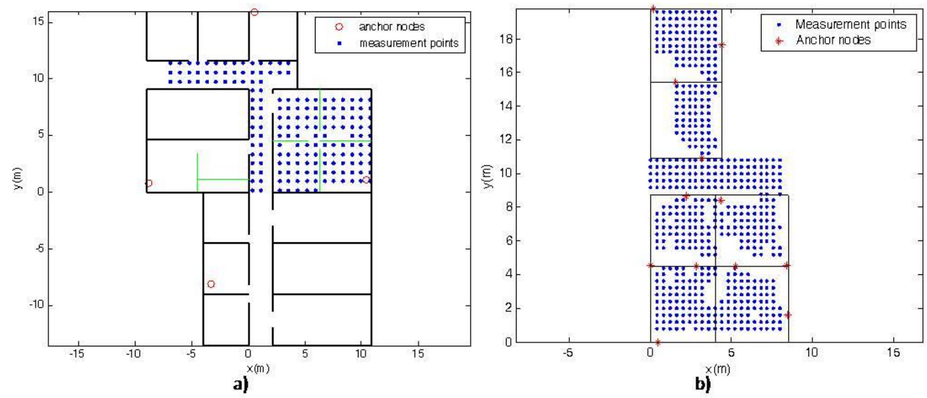

Fig. 1. Deployment area in the WiFi experiment and in the Zigbee sensor network experiment.

4.2 Channel models evaluation

For both the WiFi and the MicaZ network deployments described in the previous paragraph, we compared the three approaches outlined in Section 3 in order to evaluate the performance improvement due to the changes in the channel model estimation.

Global channel model. Figure 2 depicts the estimated global channel attenuation as a function of the distance for both the WiFi (Figure 2a) and the MicaZ (Figure 2b) cases. The parameters A and η of the model have been obtained according to equation (1), i.e. a common isotropic channel model is supposed to underlie all the measurements. Note that the two transmission technologies correspond to very different parameters, and in the WiFi case the channel curve stays "above" the one of the MicaZ network; this is due to the superior transmission power employed by WiFi devices with respect to MicaZ motes, which ends up in a better SNR at the receiver. As a side-effect, the reduced power used by MicaZ motes finally leads to worse estimation accuracy. In fact, the actual range of the measurements is constrained by the equipment sensitivity: in other words, the mobile nodes cannot sense signals whose power is below the minimum one detectable by the node hardware (-96 dBm in this case). This sort of threshold effect implies that the curve of the estimated model is biased upwards, i.e. at low RSS the distances matched by the model are overestimated with respect to the actual ones.

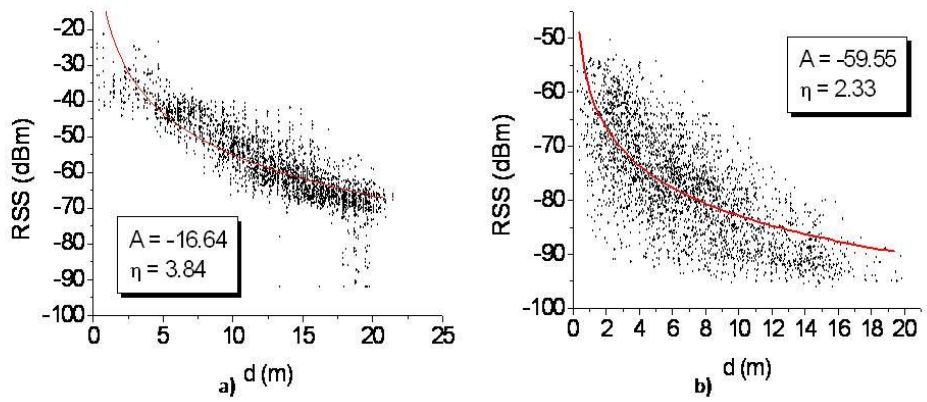

Fig. 2. Experimental RSS measurements for different distances between reference and mobile nodes in the WiFi (a) and MicaZ (b) deployments. The lognormal channel model curve fitting is represented as well.

Local channel models. We have also estimated the parameters of the channel model for each reference node in both WiFi and MicaZ scenarios, as described in Section 3.1. The results are reported in Tables 1 and 2. Note that in both cases, the average value of the parameter is approximately the same as the global case (see Figure 2), as expected. However, using a different model for each reference node enables to capture local propagation variations, due e.g. to obstacles or walls which may occlude the line of sight between the nodes. In table 1 we notice that the fittings 1 and 2 have similar values, which are deviated from the ones of the fittings 3 and 4. This is due to the fact that the RSS measurements were taken at points which were far away from these access points and thus, the fitted curve is not as steep as if we had some measurements at shorter distances.

Table 1 Estimated model parameters for each reference node, in the case of the WiFi network

A	-3.86	5.32	-24.89	-12.68
η	5.11	5.73	2.63	4.19

Table 2 Estimated model parameters for each reference node, in the case of MicaZ motes network.

A	-65.37	-57.21	-65.60	-57.09	-65.12	-63.00	-65.04	-50.39	-52.11	-54.75	-76.10	-82.11
η	2.56	2.06	2.69	2.12	2.78	2.46	2.62	2.03	1.96	2.10	3.01	3.45

Wall-attenuation model. When the walls influence is taken into consideration, one first needs to estimate the specific attenuation induced by the wall. To this end, we observe that, in the presence of a wall, the channel attenuation exhibits a discontinuity, as is apparent for instance in Figure 3, where just one wall has been traversed by the signal. Therefore, once that all the measurements have been collected, we can separately estimate the model for the two branches of the curve created by the wall discontinuity. To estimate the attenuation we assumed that the path loss exponent η is the same at both sides of the wall; thus, the global fitting problem of (1) is split into two constrained LS problems, where the only unknown parameter is A. The difference between the two values of A is the attenuation of the wall, which experimentally has been assessed to be around 3 dB. In our experiments, we have used the same attenuation value for all the walls in our testing room. In order to determine the number of walls traversed by the signal we have assumed that we know in which room the mobile node is placed, so we can directly introduce the attenuation of the walls in the RSS measurements using (4) and estimate the position with the procedure explained in 2.

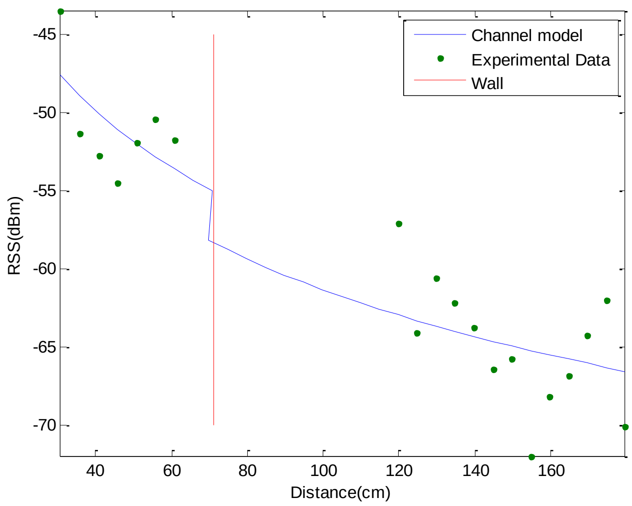

Fig. 3 Attenuation in the presence of a wall.

4.3 Localization performance

In this section, we assess the impact of the different channel models discussed in Section 3 on the localization accuracy. In order to do so, we measure the average and standard deviation of the localization errors for both the hyperbolic (3) and circular (2) positioning algorithms. The experimental setup is the one described in Section 4.1.

The results for the MicaZ and for the WiFi networks are reported, respectively, in Table 3 and 4. The two methods presented in Section 3 are abbreviated here for convenience as "Local" and "Walls", and are contrasted with the general model in (1). At a glance, a first consideration about the results involves the difference between the hyperbolic and circular positioning techniques: the second can localize the mobile nodes with much higher precision than the hyperbolic algorithm. This is due to the fact that the cost function in the circular algorithm is exactly the average error, while the hyperbolic method minimizes a related, but distinct, quantity. Thus, by construction, it is reasonable to obtain this kind of results (for a more detailed analysis of the two techniques see [15]). For the hyperbolic algorithm, the highest improvement on the baseline global model is attained by the wall attenuation model. This is especially true for the MicaZ network, which, as mentioned in Section 4.2, uses a lower transmission power which affects negatively the channel estimation at low RSS values. The rationale behind these improvements resides in the gain of accuracy yielded by the wall model, which is particularly beneficial to contrast the distance overestimation due to the sensitivity of the nodes hardware. Conversely, the marginal gain yielded by the wall model for the WiFi scenario confirms that, for this scenario, the model estimation is more robust to the sensitivity of the equipment.

The contribution of the local channel models to the overall performance is instead quite moderate, for both the hyperbolic and the circular algorithms. This is due to the fact that estimating a channel model for each reference node can well capture peculiar effects introduced by one reference node, but it is poor in offering an explanation of other environment-specific factors, since it does not care of the relative orientation between nodes.

Table 3 Average errors and standard deviations in meters of the different methods in the MICAz scenario.

Error / variance (m)	Hyperbolic	Circular
General	10.60/3.91	4.05/1.43
Local	9.28/5.72	3.51/1.58
Walls	5.06/1.91	4.14/1.88

Table 4 Average errors and standard deviations in meters of the different methods in the WiFi scenario.

Error / variance (m)	Hyperbolic	Circular
General	7.73/19.95	4.19/3.93
Local	7.29/16.43	4.13/3.61
Walls	6.69/12.90	4.67/2.99

5 Conclusions

In this paper we have analyzed the impact of the channel model estimation in the localization problem in wireless networks. It turns out that the channel estimation phase is crucial for the subsequent positioning phase, yet the popular lognormal channel model alone is unable to capture the variability of a real deployment. We have proposed two enhancements, namely considering different channels for each node and embedding in the lognormal model the attenuation due to walls. Among these two modifications, the most promising one, considering the hyperbolic localization algorithm, is for sure to consider the effect of walls, especially when the transmission power of the nodes is constrained. The results of the circular algorithm are not improved using this technique. Other improvements, such as trying to account for the local behavior of the channel, are still in a preliminary stage and will be subject of future research.

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