Use of Negative Information in Positioning Algorithms

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Abstract. Wireless communication networks exploit positioning information to deliver personalized, context-aware services. On the other side, positioning information can improve the network performance through location aware routing, coverage management, enhanced security, power saving etc. Availability of position information strongly depends on existing infrastructure, such as cellular base stations and GPS satellites. In order to enhance the performance of indoor localization systems, where infrastructure is not available, the innovative solution presented in this paper considers also the negative information.

Keywords: Distance estimation, data fusion.

1 Introduction

The availability of positioning information is an enabler for location based services as part of context aware applications. Especially in indoor environments, where Global Positioning System (*GPS*) does not perform well because of the absence of Line of Sight transmission between satellite and receiver, it is still a challenge to design a system able to provide accurate positioning information. In this paper, we address an indoor WiFi scenario, assuming that the access points coordinates are known. Typically, positioning algorithms assume a fraction of nodes that are aware of their own location, called anchor nodes. Those nodes are used as references for other, unknown nodes to estimate their positions. Unknown nodes estimate their distances to anchor nodes based on measurements of received signal strength (*RSS*), time of arrival (TOA) or angle of arrival (AOA). Since the RSS value is commonly available in any IEEE 802.11 interface, it is the most appropriate measurement to use, although sophisticated models are needed to translate the received power level into distance. Once a sufficient number of distance estimates to anchor nodes are available (for n-dimensional space, $n+1$ distance estimates are required), the node can compute its position using least squares (LS) algorithm. Besides the processing of measurements between nodes, localization procedure can include the information of all available environment information. Most algorithms ignore the negative information, i.e., information gathered when nodes are not detected.

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In this paper, we propose a novel solution to increase the localization performance. Basically, this is achieved by incorporating information about anchor nodes that are *not* in range, which allows us to eliminate candidate solutions.

The rest of the paper is organized as follows: the next section gives an overview on related work; in Section 3 we describe our model and the procedures of collecting measurements and data fitting; in Section 4 we present the obtained results; and finally Section 5 concludes the paper.

2 Related Work

Indoor localization has been a motivating research topic and many methods have been proposed so far, including WiFi, RFID and UWB localization. The *Active Badge System* was an early system developed to localize mobile devices within a building[1]. Every badge identifies itself periodically, sending unique infrared signals to the receivers. Although it provides accurate location, the drawbacks of the system are poor scalability due to limited range of IR, and deployment cost. The system *RADAR*[2], based on WiFi fingerprinting, uses signal strength information from multiple receiver locations. The main idea is to record radio signals and build models for the signal propagation during off-line analysis. However the system's main disadvantage is its dependence on empirical data. PlaceLab[3] uses connectivity from GSM base stations and 802.11 access points. If the node density is high enough, the system achieves accuracy of 15-20 meters, which is even lower than GPS, but unlike GPS it is capable to perform localization for both indoor and outdoor environments. Both passive and active RFID devices have been considered in [4] to provide connectivity based localization.

Cooperative positioning algorithms are widely used in indoor scenarios where a line of sight connection to anchor nodes is not always available, due to short communication range, obstacles and a harsh environment. For sparse sensor networks the most widely used method is multi-dimensional scaling (MDS), a statistical dimensionality reduction technique that uses pair-wise distance measurements as input data[5,6]. Similarly, pair-wise distance measurements are used as convex constraints[7], and linear and semi-definite programming (SDP) techniques[8] are used to estimate locations of free nodes. Another broadly used approach is the iterative multilateration scheme, where unknown nodes, once being localized, serve as virtual anchors for the rest of unknown nodes in subsequent iterations[9,10,11]; one major drawback of this method is error propagation, resulting from using erroneous virtual anchors. Moreover, in [10] the authors take into account the channel behavior to provide accurate indoor positioning and importantly reduce error propagation. In [11] the authors develop an error control mechanism based on characterization of node uncertainties.

Negative information had few applications for localization in wireless networks. Most of the work targeted problems for mobile robot localization[12,13,14]. In Markov localization for mobile robots, the absence of an expected measurement can be used to improve localization. One difficulty in implementing a system that uses negative information is that there are two main reasons for the lack of an expected measurement reading: the target may not be there or the sensor may not be able to detect the target. To avoid false negatives, the model needs to consider possible obstructions[12]. Nevertheless, even a false attempt to detect a target can be exploited in tracking applications, based on Bayesian approach to target tracking[13]. Negative information can be integrated by generating an artificial measurement. However, all these works only consider cases where an *expected* observation is missing. In [14] the authors have shown how negative information can be incorporated into *FastSLAM*, a system that is alternative to the complex Extended Kalman Filter approach for robot localization. In wireless sensor localization, Monte-Carlo localization algorithms make use of negative information[15]. However, it can be useful only in obstacle-free areas, and leads to localization errors otherwise.

3 Proposed Technique

3.1 Composing Different Sources of (Negative) Information

This subsection proposes a technique to fuse different types of information to perform the localization of a unit. The technique described is as abstract as possible, since it aims only at showing the general idea. Subsection 3.2 will refine the technique towards the implementation in a simple wireless scenario, and Section 4 will provide information about the implemented system.

We propose a model where localization procedure makes use of different sources of information, that can comprise sources of negative information. In this respect, positive information means that some data is saying "you can be here", while data bearing negative information is saying "you can not be here". The main idea behind the system is to provide a framework to compose different kinds of information that can contribute to the localization process. Instead of applying only positive reasoning, an alternative way is to consider all the locations in the area, and provide a technique to evaluate how "unlikely" a mobile unit to be located in a given position. At the end of the day, "when you have eliminated the impossible, whatever remains, however improbable, must be the truth"[18]. In fact the proposed system exploits all the available information to all possible mobile locations, resulting in a normalized probability map of probable locations.

For each possible location on the probability map, the predicted measurement is computed, and then the predicted noise is applied to it, to get a probability distribution function for the measurement. Let us describe the location by its coordinates (x, y) in the plane, the error e we would need to match the prediction with the measurement is:

$$e = V_{x,y} - m \tag{1}$$

where $V_{x,y}$ is the predicted signal in (x, y) and m is the measurement. Let us now call F the pdf of the error and p the pdf for the localization, p is function of the required measurement error e, and is parametric in (x, y):

$$p_{x,y}(m) = F_{x,y}(e) = F_{x,y}(V_{x,y} - m) \quad (2)$$

The composition of different types of information is done by considering all the measurements with their own error, and by considering these errors as independent. Given a measurement m_1 taken from a source of information, for example the RSS from an access point, the probability for a unit to be in a given location (x, y) depends on the expected measurement $\mu_1(x, y)$, the expected error of the signal $\sigma_1(x, y)$, and the predicted distribution of the signal at the location (x, y). Let us consider that p_1 is the probability for a measurement to be m_1. Since we are considering independent information sources, if the probability to be in the same location (x, y) given a measurement m_2 from a different information source is p_2, the probability for that location is $p_1 p_2$.

Now, for all possible mobile positions, we apply the same kind of reasoning to check the "compatibility" of each measurement with the expected signal. If at a given stage of the computation, the probability map is $M(x, y)$, after a given measurement is applied, the probability map is modified to $M'(x, y)$:

$$M'(x, y) = M(x, y)p_{x,y}(m) = M(x, y)F_{x,y}(V_{x,y} - m) \quad (3)$$

If we start from a probability map where all the probabilities are, for example, equal to 1, we will end up with a map where a number of locations are ruled out, while a set of locations are still quite probable. Now we apply the normalization process, where all the probabilities are multiplied by the same number such that the maximum value in the probability map is 1.

In principle, an approach could first display the probability distribution of a node's position based on signal strength measurements from all access points that are in range. Afterwards, we update this distribution by incorporating negative information: if a signal measurement is missing, we consider it as a signal that is too weak to be received, and we set its value as some conventional value. The fact that a node is not able to sense certain access points gives us the possibility to update the probability distribution, by ruling out some potential solutions to the localization problem. For visualization purposes, it is possible to apply a threshold τ to the probability map, to consider that the mobile unit can be in all the locations where the probability value is higher than τ, while it can't be in the locations where the probability is lower than τ.

The proposed technique is able to provide two main benefits:

– composition of information from multiple sources: every source of information is considered with its error and its distribution, to evaluate the compatibility of the measurement with a given location (x, y). Moreover, the probability of location (x, y) is just the multiplication of all the probabilities that are extracted from the single measurements;
– exploitation of negative information: we are not giving value only to information that validates a given location. On the opposite, we consider valuable all

the information, for example the absence of the RSS from an access point. In this case, the system would estimate the probability for the signal to be low enough not to be received, and would exploit that probability for generating the probability maps.

3.2 Implementing the Proposed Technique

This subsection proposes the design of a prototype for the localization system. The scenario that we consider is a wireless scenario, where a mobile unit (e.g.: a laptop) is in range with a number of IEEE 802.11 access points.

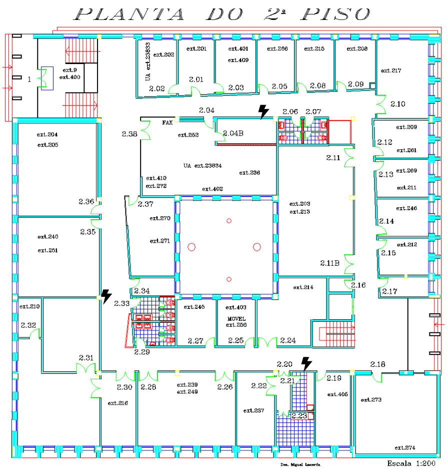

Fig. 1. Floor 2 of the Instituto de Telecomunicações, and access points' location

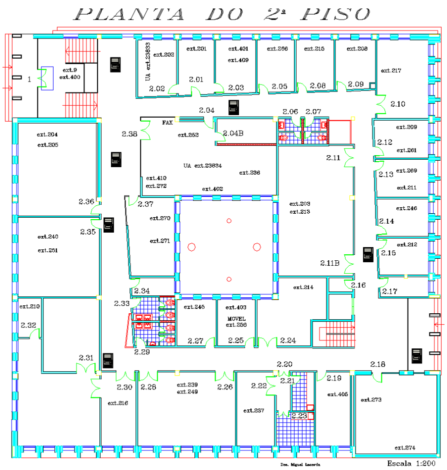

Fig. 2. Locations where data were taken for the tuning of the mobility model

When a node is sensing available access points, some of them can be detected and the others not. Our information is increased by knowing the fact that some of the access points could not be sensed. The measurements of interest are the RSS values, since these are readily available in IEEE 802.11 interfaces. During the scanning phase, a node performs sensing to identify all the available access points.

We limit the system to using a lognormal signal model[19] to translate the RSS values to distances, and hence to probabilities for given locations. We are aware of the limitations of this model in terms of predicting power for the RSS, but we chose it on purpose to test our proposed technique against poor signal processing techniques. If the system will be able to perform reasonably, we can conclude that applying refined signal processing techniques and a more reasonable signal propagation model, such as the ones described in [21] and [22], would further improve the localization performance.

We consider that a tuning phase has been executed in the area, with the goal of finding the parameters of the lognormal signal model, and we consider that for each access point, some of the area is behaving like a Line of Sight (LoS) signal transmission, while the rest is behaving like a non Line of Sight (nLoS) signal transmission. Thus, for the prediction of the signal RSS, we use two functions, one for LoS distances and one for nLoS distances, with d the Euclidean distance between the access point and the location (x, y). Both the functions are of the form:

$$V_{x,y} = RSS_0 - 10 * n_p * \log(d/d_0) \quad (4)$$

where RSS_0 is the received power at reference distance d_0 (we assume the usual value for reference distance $d_0 = 1m$), n_p is the path loss exponent. The functions for LoS and nLoS differ only for the values of RSS_0 and n_p, and this translates into considering two system-wide set of parameters for the signal propagation, one set applied to all the access points with LoS access, and the other set applied to access points with nLoS. In both cases, we consider that the error on the signal has Gaussian statistics, with a width that is 5 dBm for the LoS signal, and 7 dBm for the nLoS signal, as suggested in [20]. When a signal is missing, we consider it as a poor signal, and we set its RSS to the value of -70 dBm.

Although The tuning phase adds a setup time to our technique since it is necessary to perform the tuning for every single scenario, one motivation for the lognormal signal model is that it uses only 2 parameters to describe signal propagation, and hence a limited number of measures can be sufficient for fitting the wireless channel parameters.

4 Experiments

We illustrate our model based on measurements performed on the second floor of the Instituto de Telecomunicações building (Figure 1). The dimensions of the area are about 50 m by 50 m. There are three access points in an indoor environment (represented on Figure 1 by a small thunder). We recorded measurements from a laptop to the access points, at several locations in the building. Communications are performed by using the WLAN 802.11b standard.

4.1 Tuning of the System

The first phase of the experiment was to collect 10 measurements from the 3 access points that are in the area. The measurements were taken on the locations shown in Figure 2. WiFi Hopper[16] was used as a tool to record the received signal strength at the mobile station from the infrastructure (access points). WiFi Hopper is a WLAN utility with the ability to display network details like type of network, network mode (infrastructure or ad-hoc), received signal strength

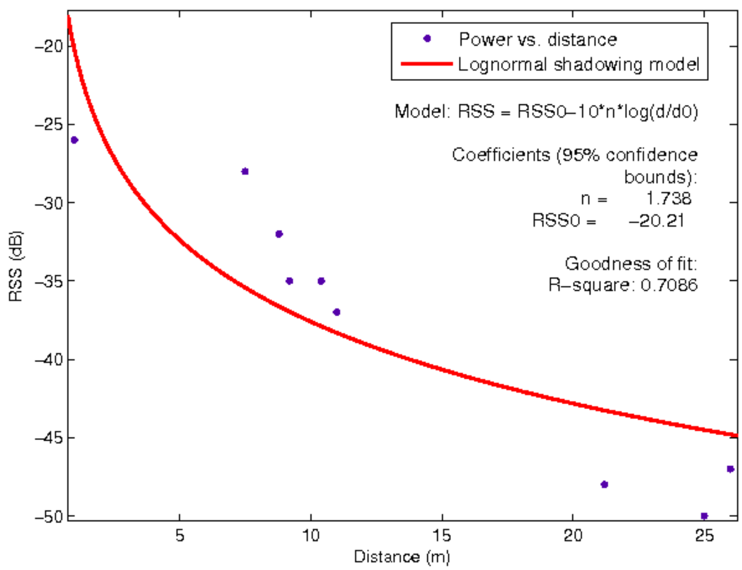

Fig. 3. Fit for the lognormal parameters, access points in Line of Sight

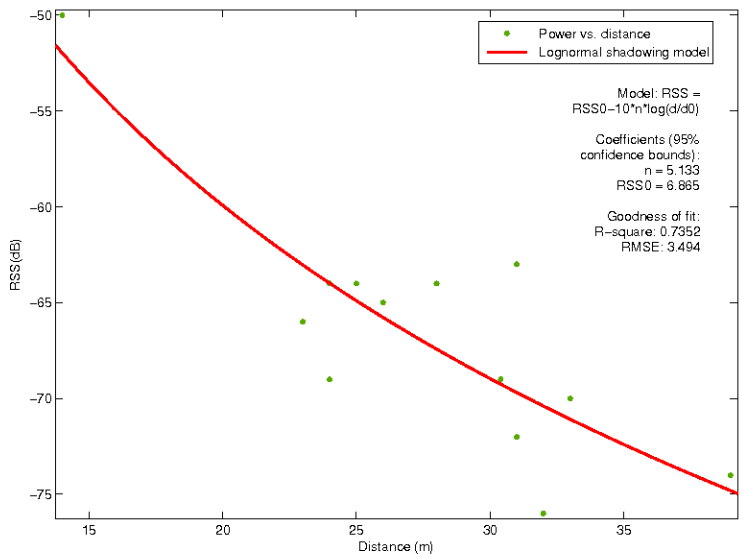

Fig. 4. Fit for the lognormal parameters, access points NOT in Line of Sight

indication (RSSI), frequency and channel, encryption type etc. We performed several measurements inside the building. RSS values from all three access points were collected, both with and without Line of Sight. As stated in Subsection 3.2, to translate RSS values into distances d, we use the lognormal shadowing model, shown in Equation 4, where RSS_0 is the received power at reference distance d_0 (we assume the usual value for reference distance $d_0 = 1m$), n_p is the path loss exponent.

Based on the collected data we estimated the values of the path loss exponent n_p and reference power RSS_0 (power at reference distance) for the lognormal shadowing model using MATLAB curve fitting toolbox[17]. As we can see from Figure 3, for the case when measurements were taken from access points that have Line of Sight connection, the data fit returned values $n_p = 1.738$ and $RSS_0 = -20.21dB$. For the non Line of Sight case, we attained different values for the parameters, namely $n_p = 5.133$ and $RSS_0 = 6.865dB$ (see Figure 4).

The small number of total measurements (7 measurements for 3 access points, for a total of 9 measurement for the LoS signal propagation and 12 for nLoS propagation) provided us a rough approximation of the parameters for the lognormal model. In both cases, the fit that we used reported a pretty unprecise matching with the values, hence we can predict that the localization system will not provide perfect localization, but will have to exploit the composition of all available information, with the goal of providing a good localization of the mobile unit.

4.2 Localization of the Mobile Unit

The experiments involved measuring the RSS values from the three access points, computing for each measurement the pdf, and multiplying these three probability densities to find out the probability density of a given location. The visualization process was performed by applying a mask to the floor plant, where the dark areas refer to the possible mobile locations.

Figures 5, 6, 7 and 8 show the localization of the same mobile unit, represented in the figures by a small white + sign. The first three figures represent the probability maps for each of the access points (where + is the mobile unit, and the small thunder is the access point). Even though the real location of the mobile unit matched with the probability map, the localization was not precise since a number of locations featured a high compatiblity with the RSS measurement. Figure 8, on the other hand, constitutes the composition of the probability map of all the access points. The result shows that the mobile unit is considered to be in a well defined area, either in the corridor, which is its actual position, or in the room nearby.

Figures 9, 10, 11 and 12, show more probability maps. In each of the figures, all the three RSS measurements were used, and the real location is represented by a small + sign. Figures 9 and 10 compare the localization results when a mobile unit moves from a location where it has just one LoS access point, to a location where it has two LoS access points. Figure 11 shows the behavior of the

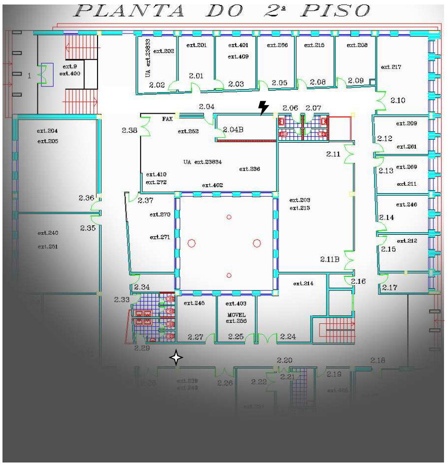

Fig. 5. Probability map when using only the first access point

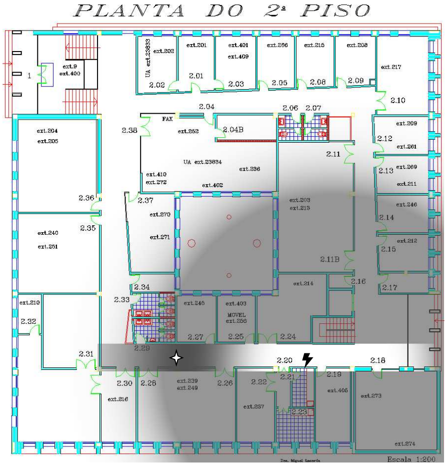

Fig. 6. Probability map when using only the second access point

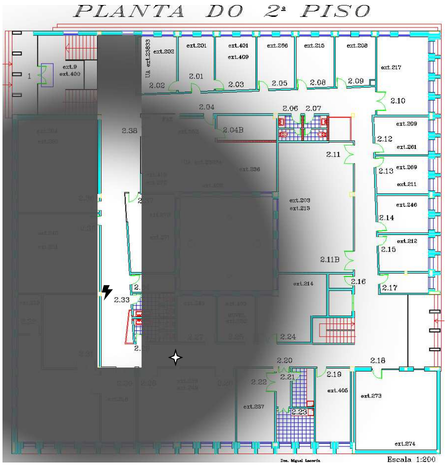

Fig. 7. Probability map when using only the third access point

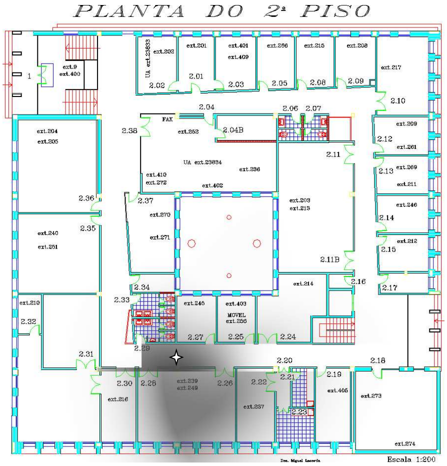

Fig. 8. Probability map when combining all available information

technique when there are no access points in LoS, and it confirms the limitations of the signal model we are using (lognormal). Finally, Figure 12 shows another scenario with only one LoS access point, and the localization is quite precise. We see that in some cases the method gives fairly good results. Nevertheless, we have to keep in mind that the applied channel model is very simple, serving only to illustrate the proposed scheme.

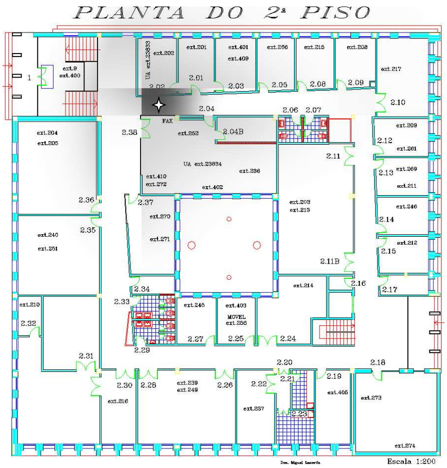

Fig. 9. Localization with one access point with LoS, two with nLoS

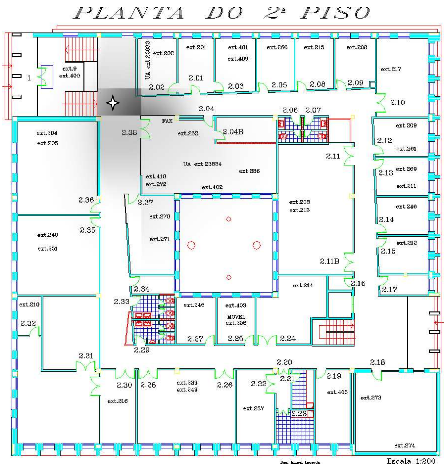

Fig. 10. Localization with two access points with LoS, one with nLoS

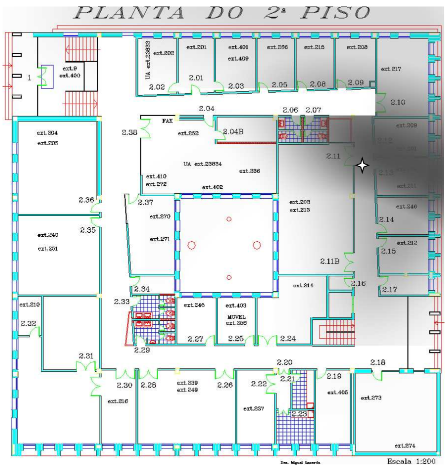

Fig. 11. Localization with three access points with nLoS

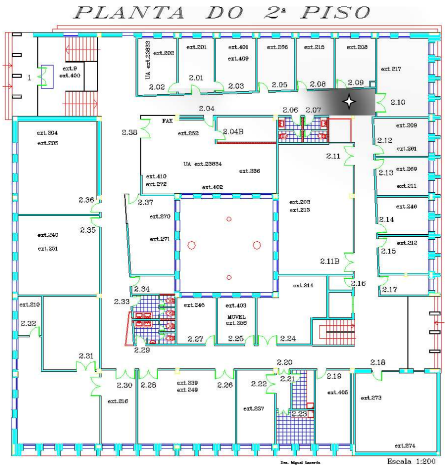

Fig. 12. Localization with one LoS access point, two nLoS access points

5 Conclusions

Indoor localization is still a challenging research topic. One way to improve the positioning procedure is to make use of all available environmental information. In this paper we have shown how negative information (information about where the mobile unit *is not*) can be incorporated into an indoor positioning scenario.

The paper showed the merits of this novel localization technique, but is a "work in progress". Future work will focus on integrating more realistic indoor channel models, as well as exploiting refined signal processing techniques with the common goal to enhance positioning performance.

In this paper, for illustration purpose, we used a simple lognormal shadowing model without taking into account spatial correlation. However, correlated shadowing is shown to have significant impact on system performance in WLAN networks[23]. If a signal in a certain direction is attenuated by an obstruction, it is very likely that a received signal in close proximity is experiencing a similar shadowing effect. The assumption that shadowing losses are correlated among nearby links has been verified by experimental measurements[24]. Therefore is it important to improve statistical propagation models and include them in localization algorithms, what we intend to do in our future work.

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