Dynamic path-loss estimation using a particle filter

Javier Rodas[1] and Carlos J. Escudero[2]

[1] Department of Electronics and Systems, University of A Coruña
A Coruña, 15071, Campus de Elviña, Spain

[2] Department of Electronics and Systems, University of A Coruña
A Coruña, 15071, Campus de Elviña, Spain

Abstract

The estimation of the propagation model parameters is a main issue in location systems. In these systems, distance estimations are obtained from received signal strength information, which is extracted from received packets. The precision of these systems mainly depends on the proper propagation model selection. In this paper we introduce an algorithm based on Bayesian filtering techniques, which estimate the path-loss exponent of a log-normal propagation model. This estimation is made dynamically and in real time. Therefore, it can track propagation model changes due to environmental changes.

Keywords: *path-loss, RSS, WSN, Bluetooth, particle filter, Bayesian filtering, propagation model.*

1. Introduction

Modeling signal propagation is an important topic in some applications such as location systems using Wireless Sensor Networks (WSN) [1]. The most typical information used to estimate mobile node locations in a WSN is the Received Signal Strength (RSS). This parameter is relatively easy to obtain in most WSN architectures like Wifi, ZigBee or Bluetooth. Location systems usually consider anchor nodes in fixed and known positions, which obtain RSS information and then estimate mobile node positions using the gathered information.

It is well known that the power of the transmitted signal decays exponentially with distance, depending on the obstacles that surround or interpose between the transmitter and the receiver, environment characteristics (indoor, outdoor), etc. [2]. Moreover, RSS varies randomly depending on the environment characteristics. This variability can be interpreted by means of small and large-scale propagation models [2], which statistically represent changes in signal levels.

In this paper, we use a classical path-loss propagation model, which is defined as:

where $P_L(d)$ is the received signal power with distance d, $P_L(d_0)$ is the power with reference distance d_0, n is the path-loss exponent and X_σ represents the noise, by using a normally distributed random variable, with zero mean and σ_L standard deviation. As shown, the model assumes log-normal variations of the power with distance. Both n and σ_L parameters are usually estimated using off-line linear regression analysis from real RSS data obtained at several distances in the environment.

The path-loss n value typically varies between 1 and 3 in indoor environments when there is a clear line-of-sight (LOS) between a transmitter and a receiver, and it suddenly changes when the line-of-sight is blocked, that is, in the non line-of-sight (NLOS) case. Therefore, if the real path-loss (n) value changes significantly with respect to the considered value in the location algorithm, the system accuracy will surely be lower or even null.

In [3] we introduced a method to jointly estimate propagation model path-loss parameter and position, and we also showed the magnitude of the path-loss estimation error in the system accuracy. In the case of this paper, we do not jointly estimate position and path-loss parameter values. Instead, we are going to estimate the path-loss value in a continuous manner when node positions are known. The main advantage of this new approach is the possibility to track the n value in a real-valued range between two fixed limits, that is, without forcing the possible n values to a fixed set of discrete values, extracted from off-line measurements. Now, we can detect channel conditions in real time between two nodes with known positions. For instance, we could detect the loss of the LOS among the WSN anchor nodes after performing a cross measuring process, to obtain RSS information among themselves. With this information, we could take some decisions about prioritization or calibration of some of the anchor nodes.

$$P_L(d)[dB] = P_L(d_0) + 10n\log\left(\frac{d}{d_0}\right) + X_{\sigma_L} \qquad (1)$$

Therefore, in order to achieve a reliable location system, it is mandatory to track propagation model changes by estimating its parameters frequently.

Other different approaches can be found in the bibliography. To consider these changes in the propagation model, [4] and [5] consider transitions among different situations using a two node Markov model, which takes into account the probability of LOS between transmitter and receiver. In [6] they also identify LOS and NLOS channel conditions but they study it using an UWB network and time-of-arrival (TOA) approach applied to location systems. In [7] the unknown propagation model parameters are deduced from mathematical formulation, and in [8] parametric propagation models are proposed as a feasible way to track the channel. Our approach considers Bayesian filtering (particle filter) in order to estimate the path-loss parameter and, therefore, to detect channel conditions.

This paper is organized as follows. Section 2 introduces the propagation model problem, emphasizing possible changes that could take place in model parameters. Section 3 introduces our proposed algorithm based on particle filtering to estimate the path-loss parameter of a log-normal propagation model. Section 4 shows the results obtained by simulation, which prove the advantages of the proposed algorithm. Finally, section 5 summarizes the conclusions and future lines of work.

2. Propagation model

In this paper we consider the simplified log-normal propagation model defined in (1). Typically, this path-loss model is considered known a priori by assuming a perfect free-space channel, or extensive channel measurement and modeling is performed prior to system deployment. Such an assumption is an oversimplification in many applications and scenarios, where no extensive channel measurement is possible (i.e. hostile of inaccessible environments). In some other scenarios, such as indoor scenarios with moving people or devices, the channel characteristics tend to change considerably over a short period of time, mainly because of the loss of the line-of-sight (LOS). In some outdoor scenarios, instead, the channel tend to change over a long period of time due to seasonal and accidental reasons [9].

Moreover, it is not guaranteed that all anchor nodes radiate in the same manner. Even with identical anchor hardware from the same manufacturer, depending on their antenna orientation and tolerance, pigtail lengths, etc., radiation could be different, producing different n and σ_L values. It is well known that the noise deviation increases

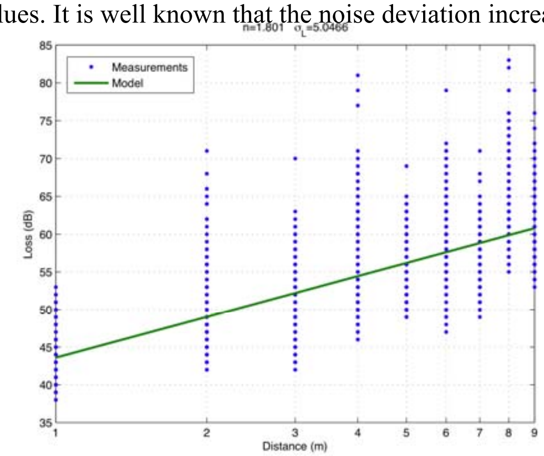

Fig 1. Power loss versus distance in line-of-sight (LOS) case.

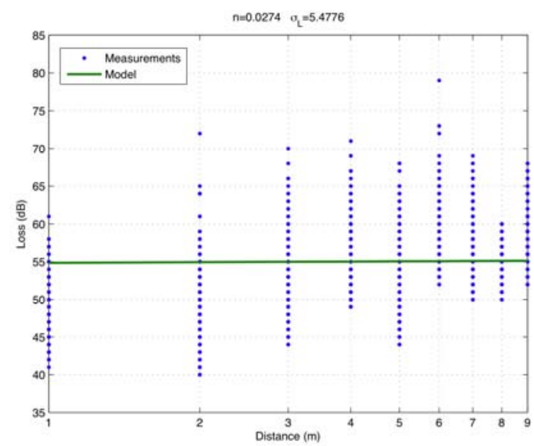

Fig 2. Power loss versus distance in non line-of-sight (LOS) case.

with the distance in indoor environments, due to multipath fading effects produced by obstacles.

The problem is that usually the n value is assumed to be constant. However, this consideration is not valid for real environments when n can change suddenly due to the loss of LOS. It should only be considered constant for a certain period of time, and a reliable location algorithm needs to optimally accommodate and adapt to changing or unknown channel conditions.

At least, path-loss n value should be estimated frequently, while it is enough to set an upper bound for σ_L, based on an estimated value obtained from off-line measurements. Note that, in order to guarantee good results and the convergence of our algorithm, this σ_L assumed upper bound must be greater than any real value this parameter could take in real life. For this reason, we should always choose the worst observed σ_L value, measured at the longest distance our location system can reach, or even a greater value.

In the section 4 we are going to perform some experiments based on RSS values and channel conditions that usually appear in real indoor scenarios when using a real WSN. Figures 1 and 2 show the fitting curve of the log-normal propagation model in eq. 1 for the LOS and NLOS cases, respectively. These measurements were obtained at different distances between an anchor node and a mobile device, from 1 to 9 meters, in a 6×10 meter real scenario, using a Bluetooth sensor network. They were taken during four minutes at each position in order to obtain enough samples. For the NLOS case, we put an obstacle at 40 cm in front of the device to be located, blocking the line of sight. As shown, $n = n_{LOS} = 1.8$ and $\sigma_L = 5.0466$ for the LOS case whereas for NLOS case these parameters are $n = n_{NLOS} \simeq 0$ and $\sigma_L = 5.4776$.

In some other scenarios these n_{LOS} and n_{NLOS} values will be surely different when using the same WSN, and both also can vary depending on new obstacles and moving people. However, these path-loss values obtained from off-line measurements can give us a good idea of the kind of values that path-loss and σ_L can take in real life. And assuming them as fixed within a location algorithm is always a bad idea, as shown in [3] in the CDF curves about the loss of accuracy.

Therefore, it is desirable to have a system that could blindly track the real path-loss n value in real time, as the one introduced in this paper.

3. Particle filter

A particle filter is a Monte Carlo (MC) method for implementing a recursive Bayesian filter [10]. It is based on a set of random samples, named particles, associated to different weights that represent a probability density function (pdf). Basically, the objective is to construct the a posteriori pdf recursively, $p(n_i(t)|z(t))$, where $n_i(t)$ is the state of the i-th particle and $z(t)$ is an observation at a given instant t.

In this paper, the state of the i-th particle is only composed by the channel parameter n, which estimates the real path-loss exponent value. The σ_L value is constant and an upper bound based on the worst deviation value observed from off-line measurements. After a random initialization of the N_p particle states and all their weights as $w_i = 1/N_p$, the algorithm performs several consecutive iterations. Each iteration is divided into the following steps: prediction, update, resampling and estimation.

3.1 Prediction

The prediction step computes the state of each particle with respect to the previous one, based on the dynamic model that indicates how the parameters must be updated. In our case, n_i is the n value for the i-th particle, and the dynamic model is as simple as shown:

$$\begin{aligned} n_i(t) &= n_i(t-1) + n_n \Delta t \\ n_n &\sim \mathcal{N}(0, \sigma_n) \\ n_i(t) &\in [min_n, max_n] \end{aligned}$$

where $\mathcal{N}(\mu, \sigma)$ is a Gaussian distribution with μ mean and σ standard deviation, Δt is the interval of time between iterations (RSS samples), σ_n models the variations of the dynamic model, and min_n, max_n are, respectively, the minimum and maximum values allowed for n. Note that in the first iteration, the n_i values are updated with a Uniform distribution $\mathcal{U}(min_n, max_n)$. Note that particles update their state in a random way.

3.2 Update

Each particle has an associated weight $w_i(t)$ directly related to $p(n_i(t-1)|z(t-1))$ [11].

These weights are updated and normalized as follows:

$$w_i(t) = \overline{w}_i(t-1) p(z(t)|n_i(t)), \quad \overline{w}_i(t) = \frac{w_i(t)}{\sum_{j=1}^{N_p} w_j(t)}$$

where $\overline{w}_i(t)$ stands for the normalized weights. In the update process, the conditioned probability of the observations with respect to the state depends on the propagation model in (1). Taking into account the Gaussian noise, we obtain the following expression for the j-th anchor node:

$$p(z(t)|n_i(t)) = \frac{1}{\sigma_L \sqrt{2\pi}} exp\left(-\frac{(z(t) - P_{L,i}(d))^2}{2\sigma_L^2}\right)$$

where $P_{L,i}(d)$ is defined by the propagation model shown in (1), but applying the appropriate n_i parameter stored in the i-th particle:

$$P_{L,i}(d)[dB] = P_L(d_0) + 10n_i \log\left(\frac{d}{d_0}\right) + X_{\sigma_L}$$

3.3 Resampling

To avoid degeneration problems in the particle system, new particles are generated when many of them have low weights after some iterations and the majority of the overall weights is accumulated in only a few particles [10], [12].

We consider a bootstrap approach, where the N_p particles are replaced by using each i-th sample replicate probability based on its $w_i(t)$ weight. Therefore, the strongest particles, that is, the particles with highest weights, will tend to be replicated while the weakest ones will tend to disappear.

This resampling step is only performed when an effective number of samples, N_{eff}, is lower than a threshold N_{th}:

$$\left(N_{eff} = \frac{1}{\sum_{i=1}^{N_p}(w_i(t))^2}\right) < N_{th}$$

3.4 Estimation

Finally, the parameter estimation is computed by means of a weighted sum of the state information from all the particles. It is computed as follows:

$$n(t) = \sum_{i=1}^{N_p} \overline{w}_i(t) n_i(t)$$

4. Experimental results

We have made some experiments to show the way our algorithm estimate the path-loss parameter, n, in the environment described in section 2. We considered a particle filter with $\sigma_n = 0.5$, $min_n = 0$, $max_n = 3$ and a sampling period (time between algorithm interactions) $\Delta t = 1$ sec. The noisy simulated measurements were always generated using a $\sigma_{L_{real}} = 5$ dBm, to simulate a harsh environment like the real scenario described in section 2.

Figures 3 and 4 show the n value temporal evolution and the estimation achieved by the particle filter. We have considered a value of $n = 1.8$, for the LOS case, and a change to $n = 0$ in the middle of the experiment, to simulate the loss of the line-of-sight due to an obstacle. As it was shown in section 2, this kind of values is typical in some real indoor scenarios. The figures show how our algorithm tracks n dynamically when different assumptions in the σ_L value were considered. In Figure 3 we have considered a fixed value of $\sigma_L = 5$, equal to the real value used in the simulation to generate the noisy measurements ($\sigma_{L_{real}}$). Note that the mean error of the n estimation is very low (0.061), which means that the estimation is centered on the real n value. In Figure 4 we show the effects of considering a wrong σ_L parameter. The worst situation happens when σ_L is lower that its real value. Nevertheless, greater values than the $\sigma_{L_{real}}$ obtains a correct path-loss estimation, even when much higher values are considered. The only effect in these cases is a lower speed of convergence in n estimation. Although it is not realistic, we even considered an over-sized value for σ_L, 27 dB greater than the real value, to show the effect in n estimation.

Therefore, it is even better to choose a slightly higher value for σ_L to guarantee that we never fall into the problematic case.

As soon as we have a stable estimation of n, after detecting that the variance of some consecutive $n(t)$ estimations is very low, we can easily assume that the environment is not changing to much and that the path-loss value is close to the mean of $n(t)$ over a certain interval of time. Instead of, if a high variance in the n prediction is detected over a certain period of time, we can easily assume that the channel condition is changing and we can take the appropriate decisions over the anchor nodes.

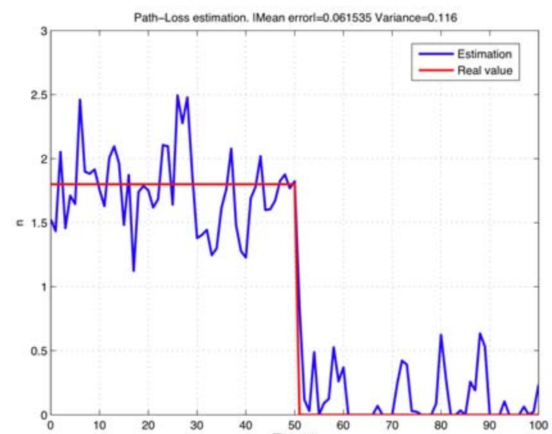

Fig 3. Path-loss n estimation for a real path-loss $n = 1.8$ and the right $\sigma = \sigma_{L_{real}} = 5$.

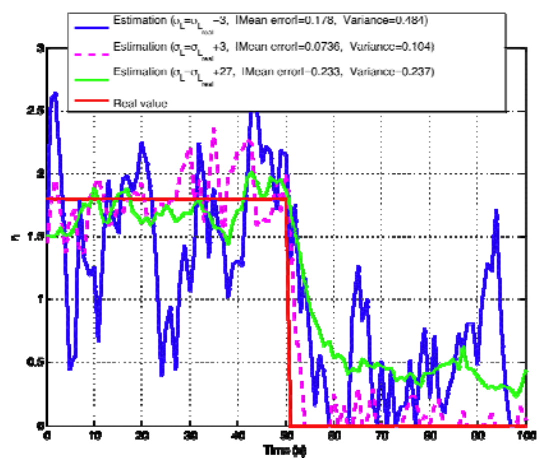

Fig 4. Path-loss n estimation for a real path-loss $n = 1.8$ and wrong σ_L.

It is important to note that log-normal model (1) is suitable when there are not many multipath components. Therefore, in some real indoor scenarios this model can not be applied and we should study other more complex models like Nakagami [1]. Authors are working in a solution, based on the results here described, for this kind of models.

5. Conclusions

In this paper we presented a particle filter algorithm for the estimation of the path-loss n parameter of a log-normal propagation model. The importance of good estimation of propagation model parameters to achieve good results in applications as, for instance, location systems, is well known.

The introduced algorithm can dynamically estimate this parameter. In the experimental results section we have shown the effect of possible deviations in the estimation of this parameter in order to analyze the algorithm accuracy. We can conclude that the particle filter is very flexible and suitable to solve the raised problem.

As a future line of work we should study the possibility of using other more complex propagation models, not as simple as the log-normal model used in this paper, to take into account multipath fading effects, very present in some real indoor scenarios.

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Javier Rodas González. He received a M.Sc degree in Computer Engineering from the Univertity of A Coruña in 2007.
His area of interest is indoor positioning combined with short range communications, wireless sensor networks (WSN), ad-hoc networks, signal processing techniques for indoor localization, hybrid positioning using both WSN and GNSS systems, and embedded system designs and prototyping.

Carlos J. Escudero Cascón. He received a M.Sc degree in Telecommunications Engineering from the University of Vigo in 1991 and a PhD degree in Computer Engineering from the University of A Coruña in 1998. He received two grants to stay at the University of Ohio State as a research visitor, in 1996 and 1998. In 2000 he was appointed Associate Professor, and more recently, in 2009, Government Vice-Dean in the Faculty of Computer Engineering, University of A Coruña. His area of research is the signal processing, digital communications, wireless sensor networks and location systems. He has published several technical papers in journals and conferences, and supervised one PhD thesis.