PATH LOSS FACTOR ESTIMATION FOR RSS-BASED LOCALIZATION ALGORITHMS WITH WIRELESS SENSOR NETWORKS

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ABSTRACT

We address the problem of estimating the path loss factor and its integration in RSS-based localization algorithms with wireless sensor networks. We propose an algorithm that relies on a stochastic characterization of the uncertainties in the propagation model. Due to that the path loss factor is unknown and the localization is only based on RSS measurements whose distances from the beacons to the target are also unknown. This is a problem for which we propose an iterative algorithm which estimates the factors, the locations and the distances. The algorithm is tested with three RSS-based localization algorithms: circular trilateration, weighted centroids and ratiometric vector iteration. The results of our simulations show that the proposed algorithm gives good estimations of the path loss factors and gives improvements over the original localization algorithms.

1. INTRODUCTION

Many applications require accurate knowledge of sensor locations [1,2]. For instance, in environmental monitoring applications, it is meaningless to sense data without knowing the sensor locations. That is the case in precision agriculture, water quality monitoring, etc.

Localization with Wireless Sensor Networks (WSN) requires intersensor measurement techniques (e.g., [1-8]). Based on the type of basic measurements these techniques can be broadly classified into three categories: Received Signal Strength (RSS), Angle of Arrival (AOA), and propagation time based. Among them, the RSS based localization algorithms have attracted great interest due to its simplicity and their impact on local power consumption, sensor size and cost is minimal.

In this paper we are interested in distance-based localization where distance is estimated from the RSS measurements. We study the signal strength by means of a propagation model [3] that includes parameters like the transmitted and received power, signal frequency, propagation distance, antenna gain, etc. Among all parameters, the path loss factor (PLF) is one of the most important and an accurate knowledge of the PLF is necessary. Many techniques to estimate the PLF obtain the RSS through extensive channel measurements prior to system deployment where the distances are known [7,9,10], other techniques use online calibration without relying on distance measurements [8]. In this paper we introduce an algorithm to estimate the path loss factor that can be used in the localization algorithms.

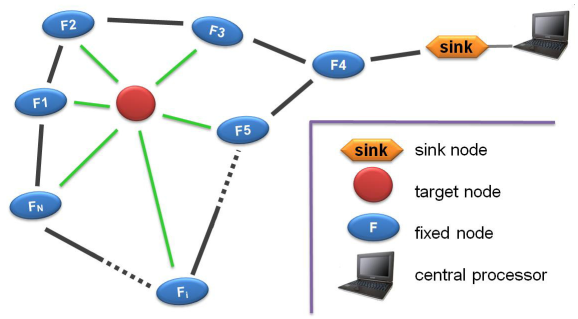

Figure 1 – Scheme of the simulated WSN for localization.

In section 2, we state the localization problem and explain the simulation environment. The simulator that we have developed is intended to reproduce realistic scenarios.

In section 3, we explain the propagation model putting emphasis on the uncertainties of the model and their stochastic character. These uncertainties may be due to distance errors, RSS measurement errors, insufficient knowledge of some parameters like antenna gains, etc. Also, the base equation s to be used in the development of the PLF estimation algorithm are presented.

In section 4, we describe some RSS-based localization algorithms (e.g., trilateration, weighted centroids). In their description the effect of the PLF is emphasized. Particularly, the importance of the PLF on the distance estimations is clearly stated and it is formulated in such a way that it can be used in the algorithms.

In section 5, we propose an algorithm that estimates the path loss factors and the sensor locations. It is developed considering several uncertainty sources that are identified in the propagation model. These uncertainties lead us to set up an iterative estimation algorithm which alternates between the PLF and the location of the target node. At the end of the algorithm we have the path loss factors, the location of the target and its distances to the fix nodes as a by-product.

In section 6, we present our experiments, which are developed in two scenarios. In one of them we study the PLF estimation algorithm when there is no error in the intersensor measurements. In the other one, we perform localization experiments in outdoor locations close to a building. Our results on PLF show that the proposed algorithm performs very well even when there are errors in the intersensor measurements. The localization experiments show that we can achieve improvements on location estimation with respect to the case where no PLF compensation is made.

2. PROBLEM STATEMENT AND SIMULATION ENVIRONMENT

Localization in Wireless Sensor Network (WSN) means the process of position estimation of wireless nodes. The result of the process is the knowledge of actual position of the nodes under localization. The localization is performed by means of an algorithm that uses information from intersensor measurements. We work on distance-based localization where distance is estimated from the RSS measurements. The signal strength measurements are related to the propagation model where the PLF is a key parameter. An accurate knowledge of this parameter is necessary to obtain accurate estimates of the intersensor distance from the corresponding RSS measurements. The PLF depends on propagation conditions which may vary along time. The problem we are dealing with is to locate the position of nodes through the application of localization algorithms in which PLF compensation is a key issue.

All experiments in this paper have been made by means of a simulation program for outdoor communications. For this purpose, we have developed a simulator with a typical scenario for localization systems with WSN as illustrated in Figure 1. The nodes, F_i $\{i=1, ,N\}$, are deployed with a communication range *'R'*. It is a multihop network with a specified maximum number of possible hops to guarantee that all packets can arrive to their destination. The communication subsystem emulates the IEEE 802.15.4 radio communication standard [11]. Some parameters considered in the simulations regarding the standard are; antenna height, transmission power, carrier frequency (2.4-2.4835 GHz), direct sequence spread spectrum technique, O-QPSK modulation/demodulation,symbol/chip generation and detection, bit error rate estimation, packet format, etc. Other parameters such as atmospheric absorption, reflections (e.g., walls), diffraction, multipath propagation, additive noise, 3D building structures, etc. were also considered.

In our simulator we distinguish between fixed and target nodes. We have considered that all fixed nodes are beacons whose exact positions are known. The targets can communicate with at least three/four beacons in order to make 2D/3D localization. Irrespective of the simulated topology (which is out of the scope of this paper) we assume that every packet sent by any node arrives to its destination, the sink node, which is connected to a central processing unit. Thus, our system operates in a centralized mode. The localization process works as follows: the target node sends a set of packets and the RSS are measured at the beacon nodes. Then, these RSS measurements are transformed into Received Signal Strength Indicator (RSSI) by emulating the Chipcon CC2420 radio [11,13] and they are incorporated in the data payload of the packets to be forwarded to the sink. In the central unit the positions of the beacons and the RSS measurements are used by localization algorithms to estimate the target localization.

Our simulator also includes a module that simulates the Telos Rev. B motes from Crossbow [13]. The radiation pattern of the Inverted-F, antenna gain, allowed transmission power, etc. are considered in the module.

3. PROPAGATION MODEL

Our propagation model starts from a generalization of the Friis free space equation [3] expressed as

$$p_i^{'} = \frac{p_t \lambda^2 g_t g_{ri} l_{it}}{(4\pi)^2 \left\|\mathbf{x}-\mathbf{s}_i\right\|^{\alpha_i}} + n_i = p_i + n_i; \qquad i = 1, \cdots, N \quad (1)$$

where $\mathbf{x}$ is the unknown emitter (target) position vector that must be estimated, $\mathbf{s}_i$ is the (known) position vector of the i-th beacon node, N is the number of fixed nodes, p_t and $p^{'}_i$ are the transmitted and the received power, λ is the wavelength, g_t and g_{ri} are the gains of the transmitter and reception antennas and l_{it} includes all losses (e.g., in the transmitter and receiver circuits). The PLF, α_i, measures the rate at which p_i decreases with distance. In free spaces this factor is α_i=2 being the Friis equation a particularization of (1). For simplicity, in (1) we take $\|\mathbf{x}-\mathbf{s}_i\|=d_i$ as the distance in meters and we assume that the noise level is very low, $n_i \ll p_i$.

In real situations the free space conditions do not exist due to multipath fading, shadowing of the RF channel, complex interactions among the signal rays from different propagation paths (i.e., we may have reflections in several bordering surfaces like ground and walls), etc. Among these conditions in this paper we are mainly interested in surface reflections because they are very common in WSN-based localization systems. The PLF covers deterministic parameters such as the height of the antennas, reflections and multipath propagation, etc [7]. A multi-ray model is here adopted since it is more realistic than the one based on a free space. In practical situations it has been reported [9,10] that α_i takes values in a given range, e.g. $\alpha_i \in [1,5]$. For instance in [3], in urban areas it has been empirically found that $\alpha_i \in [2.7,3.5]$, in some building line-of-sight situations $\alpha_i \in [1.6,1.8]$, etc.

We can express (1) in logarithmic form, so we have in (2) all magnitudes of (1) in decibels (dB).

$$P_i^{'} = K_i + G_t + G_{ri} + L_{it} - 10 \cdot \alpha_i \cdot \log_{10} d_i + N_i^{'} \qquad (2)$$

where P'_i is the received power on the i-th node, G_{ti} and G_{ri} are antenna gains for transmitter and i-th receiver node, L_{it} includes all losses, and K_i contains all constants in (1) like p_t, $(\lambda/4\pi)^2$, etc. In equation (1) and (2) the distance d_i and the path loss factor, α_i, are the unknowns that we must estimate for our localization algorithm. Unfortunately, these are not the only unknowns. For example, although we can know the radiation pattern of the antennas [13], the losses L_{it} in the electric circuits, etc, for real wireless devices it is unfeasible to know them with absolute accuracy, causing, thus, uncertainties in the model. Nevertheless, the most pernicious error sources for the localization algorithms are the errors introduced by the device in charge of measuring the RSS (P'_i), and the errors in estimating the distances. These errors pose the problem of the necessity to estimate parameters for which we do not have enough information. Clearly, we have a set of N equations like (2) and $2N$ unknowns, d_i and α_i.

Our first step to tackle this problem is made by defining an *"uncertainty"* term that includes all errors in (2).

We consider that N_i is a stochastic term that picks up the effect of all error sources. We assume it to have a Gaussian probability density function (pdf). Now, rearranging the elements in equation (2), we get a simplified equation as

$$P_i = -10 \cdot \alpha_i \cdot \log_{10} d_i + N_i \quad (3)$$

where P_i is a corrected term that includes the received power P'_i, K_i and the nominal values of L_{it}, G_t, G_{ri}. The N_i is an uncertainty term that integrates the errors in the knowledge of the RSS, d_i, L_{it}, G_t, G_{ri}, etc. As we have stated previously, the path loss factor and the distance depend on complex interactions of several parameters in (2). In section 5, the joint estimation of all N pairs d_i and α_i is addressed.

4. RSS-BASED LOCALIZATION ALGORITHMS WITH WIRELESS SENSOR NETWORKS

There is a great diversity of methodologies for localization algorithms based on RSS measurements. In this paper we are focused on some of the most promising of them. For each algorithm, we give a short description where the dependency with respect to the α_i factor is highlighted through the term $(k_i/p_i)^{1/\alpha_i}$ thus opening the algorithms to use the estimated factors.

4.1 Circular lateration and Multilateration

The Circular Multilateration Algorithm (CLA) is one of the most widely suggested algorithms for localization purposes [1,2]. It uses the estimated distances d_i among the beacons and the target nodes to be localized. The algorithm derives from a simplified version of (1).

$$p_i = k_i \big/ \left\| \mathbf{x} - \mathbf{s}_i \right\|^{\alpha_i} \quad (4)$$

where k_i is assumed to be known and integrates all terms in (1) except the denominator term, being noise contribution is neglected. Rearranging the equation (4) we obtain (5).

$$\left\|\mathbf{x}\right\|^2 + \left\|\mathbf{s}_i\right\|^2 - 2 \cdot \mathbf{x}^T \mathbf{s}_i = \left(k_i / p_i\right)^{2/\alpha_i} = d_i^{\,2} \quad (5)$$

As we can see in (5), the term $(k_i/p_i)^{1/\alpha_i}$ has dimension of distance. Since the real distance, $\hat{d}$, is an unknown the quotient in (5) plays a surrogating role, and it can be considered as the estimated distance, $d_i=(k_i/p_i)^{1/\alpha_i}$. Therefore, the more realistic its value is the better the algorithm performs. If we have N fixed nodes for the localization estimation then we can set out a system of equations where the estimation of the emitter position vector **'x'** is given by (6), where $C_{N-1}=-2\cdot(\mathbf{s}_i-\mathbf{s}_1)^T$ and

$\delta_{N-1} = (d_i^{\,2} - d_1^{\,2}) - (\left\|\mathbf{s}_i\right\|^2 + \left\|\mathbf{s}_1\right\|^2)$.

$$\mathbf{x} = \left[(C_{N-1}^T \cdot C_{N-1})^{-1} C_{N-1}^T \right] \delta_{N-1} \quad (6)$$

4.2 Weighted centroid

The Weighted Centroid Algorithm (WCA) is a simple and efficient algorithm [1,2]. The location $\mathbf{x}$ of the emitter is estimated by means of an expression like (7).

$$\mathbf{x} = \left(\sum_1^{N-1} \mathbf{w}_i \cdot \mathbf{s}_i \right) \Big/ \sum_1^{N-1} \mathbf{w}_i \quad (7)$$

where the $\mathbf{w}_i$ are normalized weighting factors that act on the position of the fixed nodes, $\mathbf{s}_i$*'s*. It is very common to use the received power (e.g., through the RSS's) at the beacon nodes [4,10] to define the weights. In this paper, we make a definition of the $\mathbf{w}_i$ that is based on the inverse of the estimated distances. In this sense, the closer a given fixed node is the more reliable it is considered for the estimation purposes. We have defined the $\mathbf{w}_i$ factors as

$$\mathbf{w}_i = \left\| \mathbf{x} - \mathbf{s}_i \right\|^{-1} \Big/ \sum_{j=1}^{N} \left\| \mathbf{x} - \mathbf{s}_j \right\|^{-1} \quad (8)$$

Therefore, we have chosen to define them as a relation of Euclidian distances among fixed nodes and the target node. Recalling (4), we can replace the unknown distances in (8) by an expression in terms of k_i and p_i defined as:

$$\mathbf{w}_i = \left(k_i / p_i\right)^{-1/\alpha_i} \Big/ \sum_{j=1}^{N} \left(k_j / p_j\right)^{-1/\alpha_j} \quad (9)$$

4.3 Ratiometric vector iteration

The Ratiometric Vector Iteration (RVI) algorithm is based on the estimation of relative distances instead of absolute [4] ones. Starting from an initial estimate (e.g., through CLA or WCA) it makes successive iterations in order to update the estimated locations, $\mathbf{x}_{j+1}=\mathbf{x}_j+\mathbf{v}_j$, such that $\mathbf{x}_{j+1}$ approaches $\mathbf{x}$. Vector $\mathbf{v}_j$ is a translation vector whose expression is

$$v_j = \sum_{k=1}^{N} (g_i - g_{ij}) \left(\overrightarrow{s_i x_j} \Big/ \left| \overrightarrow{s_i x_j} \right| \right)$$

where g_i and g_{ij} are normalized ratios expressed as (10).

$$g_{ij} = \left| \overrightarrow{s_i x_j} \right| \Big/ \sum_{k=1}^{N} \left| \overrightarrow{s_k x_j} \right|$$
$$g_i = \left(k_i / p_i\right)^{-1/\alpha_i} \Big/ \sum_{k=1}^{N} \left(k_k / p_k\right)^{-1/\alpha_k} \quad (10)$$

The g_{ij} are given by a normalized ratio of distances from the estimated target location, $\mathbf{x}_j$, to the beacons position, $\mathbf{s}_i$, at iteration '*j'*. The algorithm terminates when it arrives to a stationary point. Generally speaking, as the algorithm iterates, the closer the g_{ij} to the normalized surrogate distances, g_i, the smaller the translation vector thus arriving to the stationary location point.

5. PATH LOSS FACTOR AND LOCATION ESTIMATION ALGORITHM

As we have seen before, all algorithms depend on the path loss factor, α_i, in a decisive manner. For each localization of the target node we will have different radiofrequency paths among transceivers (fixed and target nodes). Then, we will also have different values for α_i. Therefore, given that the path loss factor varies with the relative emitter-receiver position and the propagation phenomena, it is useful for localization to make a good estimation of α_i. These estimations are used in (5), (9) and (10) in a preprocessing step previous to the location estimation with the algorithms.

To start with, we write the equation (3) in matrix form:

$$\mathbf{P} = \mathbf{C} \cdot \boldsymbol{\alpha} + \mathbf{N} \quad (11)$$

where $\mathbf{C}$=diag([-10log$_{10}d_1$, ..., -10log$_{10}d_N$]) is a diagonal matrix of logarithmic distances, $\boldsymbol{\alpha}=[\alpha_1,\ldots,\alpha_N]^T$ is the *Nx1* vector of path loss factors, $\mathbf{P}=[P_1,\ldots,P_N]^T$ is the *Nx1* vector of corrected terms, $\mathbf{N}=[N_1,\ldots,N_N]^T$ is the *Nx1* vector of uncertainties, and N is the number of beacons. Let's define a distance vector as $\mathbf{d}=[d_1,\ldots,d_N]^T$. The unknowns in (11) are vectors $\boldsymbol{\alpha}$ and $\mathbf{d}$. That is, there are 2N unknowns.

In the section 3, N_i was considered as a random variable with a Gaussian pdf, therefore from (11) we can assume **N** as a N-dimensional Gaussian distributed variable whose pdf is

$$p_N \propto \exp\{-(\mathbf{p}-\mathbf{C}\cdot\boldsymbol{\alpha})^T \mathbf{Q}^{-1} (\mathbf{p}-\mathbf{C}\cdot\boldsymbol{\alpha})/2\} \qquad (12)$$

where **Q** is the diagonal covariance matrix and $(\mathbf{p}-\mathbf{C}\boldsymbol{\alpha})^T$ is the estimation error vector. Initially, vector $\boldsymbol{\alpha}$ and matrix **C** are unknown. Since there are N equations and 2N unknowns, we will find the optimum of $\boldsymbol{\alpha}$ and **d** by means of an alternating maximization of (12) using a surrogating function defined as $f(\boldsymbol{\alpha})=(\mathbf{p}-\mathbf{C}\boldsymbol{\alpha})^T\mathbf{Q}^{-1}(\mathbf{p}-\mathbf{C}\boldsymbol{\alpha})$.We can maximize (12) through the minimization of $f(\boldsymbol{\alpha})$ by means of an iterative method. We employ the Newton-Raphson method [12] over $f(\boldsymbol{\alpha})$ as

$$\boldsymbol{\alpha}_k = \boldsymbol{\alpha}_{k-1} - \nabla_\alpha f(\boldsymbol{\alpha})\cdot\mathbf{H}(\boldsymbol{\alpha})^{-1} \qquad (13)$$

where $\mathbf{H}(\boldsymbol{\alpha})=2\mathbf{C}^T\mathbf{Q}^{-1}\mathbf{C}$ and $\nabla_\alpha f(\boldsymbol{\alpha})=-2(\mathbf{p}-\mathbf{C}\boldsymbol{\alpha})^T\mathbf{C}^T\mathbf{Q}^{-1}$ are the Hessian and the gradient of $f(\boldsymbol{\alpha})$, respectively. The algorithm is summarized as follows:

1. **Initialization.** In the first step we consider that α is known, $\boldsymbol{\alpha}_0=[2,..,2]^T$.
2. **Update C**. For $k\geq 1$ use the estimates α_{k-1} in a localization algorithm to locate the target and from the location estimate the distances to compute **C.**
3. **Update** $\boldsymbol{\alpha}$**,** the path loss vector through (13) from the previously updated C.
4. **Alternate** steps 2 and 3 until a prescribed number of iterations K. In our experiments K=3.

Note that in the last iteration (K) we not only obtained the PLF vector ($\boldsymbol{\alpha}^e$), but also the sensor locations (s_i^e) and their distances ($\mathbf{d}^e$) to the target as a by-product. The PLF estimation error at the *i-th* sensor is measured as $\Delta_i^\alpha=\alpha_i^e-\alpha_i$.

6. SIMULATION RESULTS

The simulations comprise two main groups. On the one hand, we have evaluated our algorithm (13) in two circumstance; a) the received power values and the distances are exactly known and b) the actual received power measurements are artificially affected by errors. For each sensor, independent uniformly distributed zero mean random errors, δ_i, are added to the actual power (p_i) values, that is, we make $p_i(1\pm\delta_i)$, $\forall i$. This is done previously to the iterations (13). With this simulation we emulate the errors due to uncertainties in the RSS measurements. On the other hand, we evaluate the location estimates by means of (6), (7) and (10) in a realistic outdoor scenario with and without using the estimated path loss factors with (13). The target node emission power is 0 dBm, the received noise level is -110dBm, the receiver sensitivity is -90dBm and $\mathbf{Q}=10\times\mathbf{I}_{NxN}$ (**I**, identity matrix).

6.1 Evaluation of the estimation of the path loss factors

For these simulations we have created a virtual scenario (see Figure 2.a) with two nodes: one is fixed and the other one is a target. There are two parallel walls with reflection coefficient ρ=-0.9 and a floor with reflection coefficient ρ=-0.2. The height over the terrain of the fixed node is 2 meters while for the target node it is 1.2 m. In this scenario there are four rays arriving to the receiving node, one is direct and the others are reflected on the two walls and the floor. Initially, the target node is located one meter apart from the fixed node. The distances from the target to the fixed node varies from 1 to 100 m. in steps of 25 cm. In such a controlled scenario we know the actual values of the PLF's.

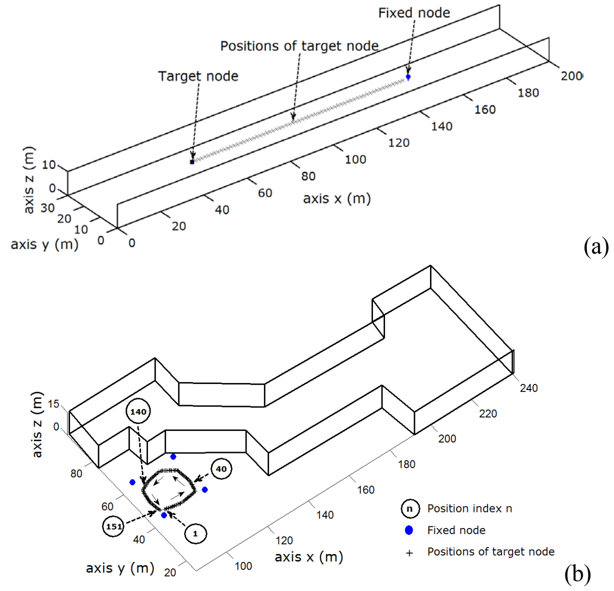

Figure 2 – Scenarios for the simulations in the estimation of α (a) and estimation of localizations (b).

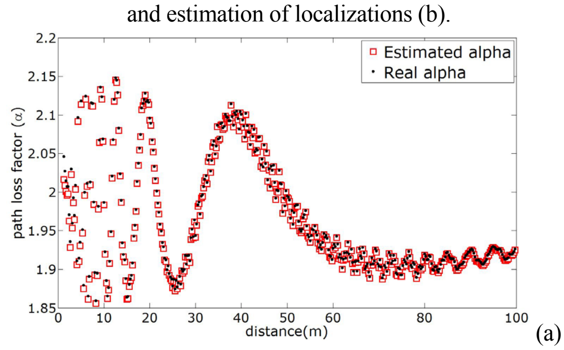

Figure 3 – Results for the estimation of α.

In Figure 3 we show the actual (dots) and the estimated (squares) path loss factors when the actual received power and distance values are exactly known. As we can see, the estimated factors are very precise. An interesting result is that the higher estimation errors are found for short distances. This is because for short distances ($d_i\leq 5$ m) the rays arrive with similar powers and the resulting signal suffers from high interactions. Nevertheless, the absolute errors are very small.

In Figure 4 we show the experiments in which the received RSS measurements are distorted. In Figure 4 the distortion is uniformly distributed in $\delta\in[-0.1,0.1]$ (10%). For each distance we have performed 100 runs and in the plots we represent the mean and the deviation (margin) of the Δ_i^α . As we can see, when compared to the actual PLF values, the estimation method is very robust, the mean and deviations are quite independent from the distance. Similarly to the previous experiments, the estimation errors for short distances are higher than for long distances. The results suggest that our estimation algorithm for the PLF can benefit the localization algorithms for short and long distances.

6.2 Location estimation

In Figure 5 we show the location results in terms of the mean distance errors (over the four locations) with respect to the

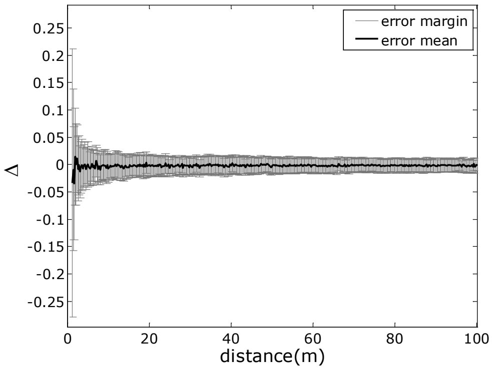

Figure 4 – Path loss factor estimation error for $\delta \in [-0.1, 0.1]$.

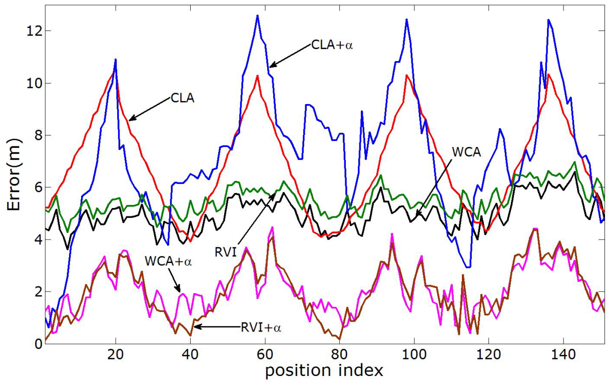

Figure 5 – Location estimation errors with and without the α.

real locations achieved by the localization algorithms, with and without the estimated α. We have simulated an outdoor scenario (Fig. 2.b) with four 3 m high fixed nodes, which are placed in the vertices of a 20x20m square. The target node is 0.5 m. high and its location varies along 151 positions that represent different difficulties for location estimation with regard to the relative location of the target and the fixed nodes. Broadly speaking, there are two types of results, with the estimated α's as explained in section 5 (solid lines) and without them. As we can see, the CLA shows the worst results. Still, it is difficult to decide whether the algorithm of section 5 really represents an improvement. The WCA and the RVI algorithm are clearly better than the CLA with and without using the PLF estimations. On average, for these algorithms the improvements are around 60%.

7. CONCLUDING REMARKS AND FUTURE WORK

We have introduced an algorithm to estimate the path loss factor and the location of targets nodes with wireless sensor networks. We have made considerations about the uncertainties in the propagation model and their consequences on the RSS measurements. These considerations have conducted us to set up an iterative algorithm that gives the location of the targets, the path loss exponents, and the distances as a by-product. The results of our simulations clearly suggest that the proposed algorithm is a good estimator of the PLF and leads to improve the RSS-based localization algorithms. In our future work we will perform extensive experiments in real scenarios in an attempt to validate our simulation results. We are working through simulation and experimentation on the introduction of our algorithm as part of a tracking algorithm for which we can apply Kalman filtering, particle filtering, etc. Research work will also be conducted to integrate our algorithm in localization and tracking methods based on pattern matching.

8. ACKNOWLEDGEMENT

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9. REFERENCES

[1] Ferrari, G.; "*Sensor Networks: where theory meets practice*," Springer-Verlag, Berlin Heidelberg, 2010.
[2] Boukerche, A.;"*Algorithms and Protocols for Wireless Sensor Networks*," John Wiley, New Jersey, 2009.
[3] Rappaport, T.S.; *Wireless Communications: Principles & Practice*, Prentice Hall PTR, 1996.
[4] Lee, J.; Cho, K.; Lee, S.; Kwon, T.; Choi, Y.;"Distributed and energy-efficient target localization and tracking in wireless sensor networks.", *Computer Communications*, vol. 29, pp. 2494–2505, 2006.
[5] Papamanthou, C.; Preparata, F.P.;Tamassia, R.; "Algorithms for Location Estimation Based on RSSI Sampling," *Lecture Notes in Computer Science*, vol. 5389, pp. 72-86, 2008.
[6] Kumar, P.; Reddy, L.; Varma, S.;"Distance measurement and error estimation scheme for RSSI based localization in Wireless Sensor Networks," *Fifth IEEE Conference on Wireless Communication and Sensor Networks (WCSN)*, 2009, pp.1-4, Dec. 15-19, 2009.
[7] Moravek, P.; Komosny, D.; Simek, M.; Jelinek, M.; Girbau; D. Lazaro, A.; "Signal Propagation and Distance Estimation in Wireless Sensor Networks," *International Conference on Telecommunication and Signal Processing, TSP 2010*. 2010.
[8] Mao, G.; Anderson,B.; Fidan,B.; "Path loss exponent estimation for wireless sensor network localization". Ed. Elsevier Science Direct, *Computer Networks* 51 2467–2483, (2007).
[9] Andersen, J. B.; Rappaport, T.S.;Yoshida, S.; "Propagation Measurements and Models for Wireless Communications Channel", *IEEE Communications Magazine*, Jan. 1995.
[10] Erceg, V.; Greenstein, L. J.; Tjandra, Sony Y.; Parkoff, S. R.; Gupta, A.; Kulic, B.; Julius, A. A. and Bianchi, R.; "An Empirically Based Path Loss Model for Wireless Channels in Suburban Environments," *IEEE Journal On Selected Areas In Communications*, vol. 17, no. 7, Jul. 1999.
[11] IEEE Std. 802.15.4-2006. Part 15.4: Wireless Medium Access Control (MAC) and Physical Layer (PHY) Specifications for Low-Rate Wireless Personal Area Networks (WPANs).
[12] Golub, G.;Van Loan, C.F.; "*Matrix Computations*" The Johns Hopkins University Press, 1989.
[13] Date, February 18th, 2011.
http://www2.ece.ohio-state.edu/~bibyk/ee582/telosMote.pdf