

# Non-Parametric and Semi-Parametric RSSI/Distance Modeling for Target Tracking in Wireless Sensor Networks

Janani.G<sup>1</sup>, Nandhitha.M<sup>2</sup>, Swetha.N<sup>3</sup>, S.Chidambaram<sup>4</sup>

UG Scholar, Department of ECE, Adhiyamaan College of Engineering, Hosur, Tamilnadu, India<sup>1,2,3</sup>

Associate Professor, Department of ECE, Adhiyamaan College of Engineering, Hosur, Tamilnadu, India<sup>4</sup>

**ABSTRACT:** This paper introduces two main contributions to the wireless sensor network (WSN) society. The first one consists of modelling the relationship between the distances separating sensors and the received signal strength indicators (RSSIs) exchanged by these sensors in an indoor WSN. In this context, two models are determined using a radio-fingerprints database and kernel-based learning methods. The first one is a non-parametric regression model, while the second one is a semi-parametric regression model that combines the well-known log-distance theoretical propagation model with a non-linear fluctuation term. As for the second contribution, it consists of tracking a moving target in the network using the estimated RSSI/distance models. The target's position is estimated by combining acceleration information and the estimated distances separating the target from sensors having known positions, using either the Kalman filter or the particle filter. A fully comprehensive study of the choice of parameters of the proposed distance models and their performances is provided, as well as a study of the performance of the two proposed tracking methods. Comparisons to recently proposed methods are also provided.

**KEYWORDS:** Distance estimation, Kalman filter, machine learning, particle filter, radio-fingerprints, RSSI, target tracking.

## I.INTRODUCTION

Recently, wireless sensor networks (WSNs) have received much concern because of their practical applications in nowadays world. WSNs are rapidly gaining importance in many fields, especially in the healthcare and industrial domains [1],[2]. They are also being deployed to track enemy vehicles in military applications [3], and to follow the movement of wild animals in environmental monitoring [4]. In all applications, awareness of location information is fundamental, since collected data are meaningless without any geographical context. Typically, stationary sensors broadcast signals in the network, while targets collect these signals for location estimation. Many localization algorithms using stationary sensors have been proposed. They are mainly based on estimating the distances between the stationary sensors and the targets to be localized. Estimating these distances can be based on several types of measurements, such as received signal strength indicators (RSSIs) [5], angle of arrival [6], time difference of arrival [7] and time-of-arrival [8]. The RSSI based techniques exploit the attenuation of the signal strength with the traveled distance to estimate the distances separating the emitters from the receivers. These techniques exhibit favorable properties with respect to power consumption, size and cost. Nevertheless, it is important to highlight that distance estimation using RSSI can be really challenging, since the measurements of signals' powers could be significantly altered by the presence of additive noise, multi-path fading, shadowing, and other interferences.

## II.TRACKINGUSINGTHEPARTICLEFILTER

The objective in this section is to find the target's position estimates using the particle filter, the distances estimated by either one of the kernel-based distance models of Section III and the acceleration information of the target. Unlike the Kalman filter, the particle filter makes no restrictive assumption about the dynamics of the

state-space or the density function. The observation model can be non-linear, and the initial state and noise distributions can take any required form. Finally, the last step in the filtering process is the resampling. In this step, the particles with negligible weights are replaced by new particles in the proximity of the particles with higher weights. It is applied only when the effective number of particles  $N_{\text{eff}}$  becomes less than a threshold value  $N_{\text{th}}$ , with  $N_{\text{eff}}$  given by:

$$N_{\text{eff}} = \frac{1}{\sum_{m=1}^{N_{\text{PF}}} (w^m(k))^2}$$

The threshold  $N_{\text{th}}$  is usually taken equal to 10% of the particles number  $N_{\text{PF}}$ . Having calculated the weights of the particles, the target's position at time step  $k$  is then given using the following:

$$\hat{x}(k) = \sum_{m=1}^{N_{\text{PF}}} x^m(k) w^m(k).$$

Compared to the Kalman-based method, this algorithm needs more computations, due to the generation and resampling of the particles; however, it is more robust when the distances errors are non Gaussian.

### III. EVALUATION OF THE ACCURACY OF THE PROPOSED DISTANCE MODELS

We now propose to evaluate the accuracy of the proposed distance models, in the case of real data and simulated data.

The proposed models are compared to the log-distance propagation model, and to the polynomial model introduced in [13]. The polynomial regression in [13] determines a mathematical relation between RSSIs and distances, without taking physical properties into consideration

$$d_{s_t, p_\ell} = a_0 + a_1 \rho_{s_t, p_\ell} + a_2 \rho_{s_t, p_\ell}^2 + \dots + a_q \rho_{s_t, p_\ell}^q$$

#### A. EVALUATION OF THE DISTANCE MODELS ON REAL DATA:

To evaluate the proposed distance models, we use the set of collected measurements available from [30]. In this work, the measurements are carried out in a room of approximately 10 m × 10 m, where 48 uniformly distributed EyesIFX sensor nodes are deployed. Furniture and people in the room cause multi-path interferences affecting the collected RSSI values. Now, for our evaluation, we consider that 5 sensors over the 48 are denoted as fixed sensors. The 43 remaining are used to collect the measurements for the training phase. Fig. 1 shows the topology of the testbed.

Note that it is the collected measurements that are needed in the test phase with the 5 fixed sensors, not the 43 remaining ones. It is also worth noting here that the training data for our algorithm could be collected by using one sensor, as explained in Section II, and this only once at the beginning of the experiments.

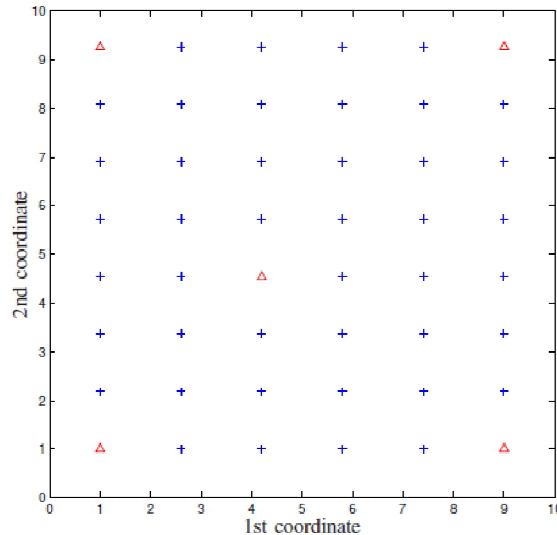


Fig. 1: Topology of the testbed (real data), where  $\Delta$  represents the sensors and  $+$  represents the training positions.

where is its bandwidth that controls, together with the regularization parameter  $\eta_i$ , the degree of smoothness, noise tolerance, and generalization of the solution. The kernel parameters are chosen in a way to minimize the error on the training set. The value of this error for the computed models is given in Table I, along with the error on the training set for the physical log-distance propagation model used in [9], [10], [11] and for the polynomial model of [32], for several degrees  $q$ . We also use the leave-one-out (LOO) technique in order to evaluate the performance of the proposed model in the case of data that are not part of the training set. The LOO technique involves using a single observation from the collected data as the validation data, and the remaining observations as the training data. This is repeated 43 times, such that each observation is used once as the validation data. This technique is interesting because it allows us to compare the proposed models to the log-distance model, even though the set of collected data is not really large. Finally, the mean estimation error (in meters) is stored in Table I for the computed models. For convenience, in the comparison tables, let us denote the non-parametric model of Subsection III-A by NPM, and the semi-parametric model of Subsection III-B by SPM. We also denote the log-distance propagation model, that is known for being a physical model, by PM and the polynomial model by PolyM. One can see from Table I that the proposed models yield better results than the log-distance model, when comparing the mean estimation error. Moreover, the two proposed models yield really close results.

## B. EVALUATION OF THE DISTANCE MODELS ON SIMULATED DATA

In this subsection, we evaluate the accuracy of the distance models on simulated data, in the case of two different scenarios. In the first paragraph, we present the first scenario, where an area without walls is considered. We then compare the results obtained using the proposed distance models to the results obtained with the log-distance propagation model. In the second paragraph, we consider a different scenario, where the signals are attenuated because

of the presence of walls in the proposed topology. As it will be shown in the following, such topology allows a better comparison between models. We start with the first scenario, where a  $100 \text{ m} \times 100 \text{ m}$  area is considered, with  $N_s = 16$  sensors and  $N_p = 100$  reference positions distributed over the area. Fig. 2 illustrates the considered topology, where no walls or obstacles are present. The RSSIs for the training phase are obtained using the theoretical log-distance propagation model [9] given in (6), with  $n_P$  set to 4 as often given in the literature, and

$\rho_0$  set to 1 dBm. As for the test phase, 100 positions are randomly generated in the studied area, and their RSSIs are also obtained using (6). Finally, a zero mean additive white noise  $\epsilon_{i,\ell}$  is added to all the RSSIs, with  $\sigma_{\epsilon}$  being its standard deviation. Here, we take  $\sigma_{\epsilon}$  equal to 1 dBm.

TABLE I: Comparison between models (error in meters) for real data.

Considered model	Mean training error	Mean LOO error
PM	1.36	1.41
PolyM, $q = 2$	1.30	1.40
PolyM, $q = 3$	1.29	1.48
PolyM, $q = 4$	1.29	1.74
NPM	1.21	1.33
SPM	1.17	1.33

TABLE II: Estimation errors for simulated data in the case of the first scenario.

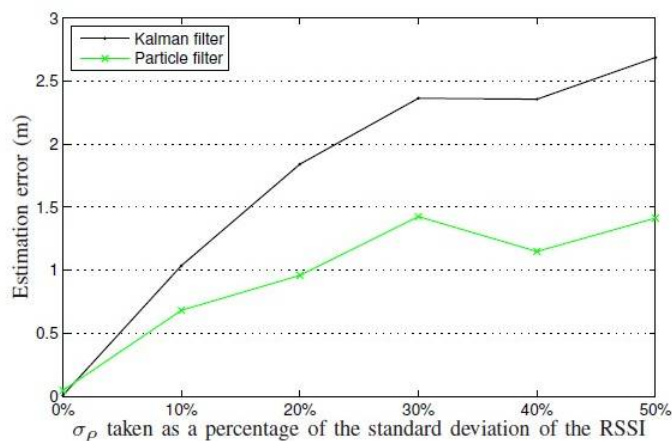
Considered model	Mean training error	Mean test error
PM	2.26	2.59
PolyM, $q = 2$	2.74	2.94
PolyM, $q = 3$	2.23	2.57
PolyM, $q = 4$	2.22	2.60
NPM	2.18	2.57
SPM	2.09	2.59

Therefore, we consider the average walls model described in [33] to generate the RSSI measures. This model is a modified version of the log-distance model that explicitly takes into account the attenuations due to walls. The received signal strength indicator is then given by the following:

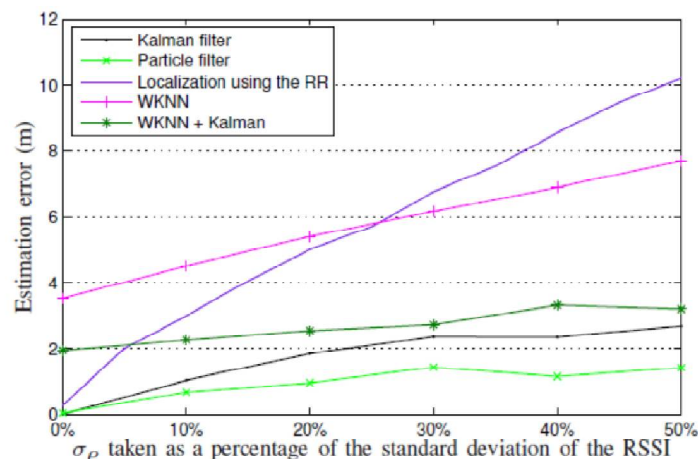
$$\rho_{s_i,p_\ell} = \rho_0 - 10 n_p \log_{10} d_{s_i,p_\ell} - N_{w_i} L_{w_i} + \epsilon_{i,\ell},$$

where the quantities  $L_{w_i}$  and  $N_{w_i}$  denote respectively the loss due to walls and the number of penetrated walls. The quantity  $L_{w_i}$  is taken equal to 6.9 dBm, since we consider the case of heavy thick walls [33]. Now for the test phase, 100 positions are randomly generated in the studied area, and their RSSIs are obtained using (20).

Estimation error as a function of the noise on the RSSI.



Estimation error as a function of the noise on the RSSI, using different methods.



#### IV. CONCLUSION

In this paper, we proposed two original regression models that relate the received signal strength indicators (RSSIs) to the distances separating sensors in a wireless sensor network. Then, we solved the tracking problem using the estimated distances and two new methods that take into account the target's motion. We provided a fully comprehensive study of the proposed distance models and their performances. Simulation results show that our models yield accurate distance estimation. Results also show that our tracking methods allow accurate position estimation, and are proved to be robust in the case of noisy data. Both proposed tracking methods outperform tracking using recently developed methods based on the WKNN method and the Kalman filter or some other learning strategy. Future work will handle further improvements of this work, such as wisely choosing a group of sensors instead of using all the available distance information. Solutions to cases where zones of the surveillance area are not covered by all sensors could also be provided.

#### V. REFERENCES

1. P. Honeine, F. Mourad, M. Kallas, H. Snoussi, H. Amoud, and C. Francis, "Wireless sensor networks in biomedical: body area networks," in *Proc. 7th International Workshop on Systems, Signal Processing and their Applications*, Algeria, 09–11 May 2011.
2. F. Salvadori, M. De Campos, P. Sausen, R. De Camargo, C. Gehrke, C. Rech, M. Spohn, and A. Oliveira, "Monitoring in industrial systems using wireless sensor network with dynamic power management," *IEEE Transactions on Instrumentation and Measurement*, vol. 58, no. 9, pp. 3104–3111, 2009.
3. S. H. Lee, S. Lee, H. Song, and H. S. Lee, "Wireless sensor network design for tactical military applications : Remote large-scale environments," in *Military Communications Conference*, 2009, pp. 1–7.
4. A. Tovar, T. Friesen, K. Ferens, and B. McLeod, "A dtn wireless sensor network for wildlife habitat monitoring," in *23rd Canadian Conference on Electrical and Computer Engineering (CCECE)*, 2010, pp. 1–5.
5. E.-E.-L. Lau and W.-Y. Chung, "Enhanced rssi-based real-time user location tracking system for indoor and outdoor environments," in *International Conference on Convergence Information Technology*, 2007, pp. 1213–1218. [6] L. Zhang, Y. H. Chew, and W.-C. Wong, "A novel angle-of-arrival assisted extended kalman filter tracking algorithm with space-time correlation based motion parameters estimation," in *9th International Wireless Communications and Mobile Computing Conference (IWCMC)*, 2013, pp. 1283–1289.
6. J. Wendeborg, J. Muller, C. Schindelbauer, and W. Burgard, "Robust tracking of a mobile beacon using time differences of arrival with simultaneous calibration of receiver positions," in *Int. Conf. on Indoor Positioning and Indoor Navigation (IPIN)*, 2012, pp. 1–10.
7. E. Xu, Z. Ding, and S. Dasgupta, "Target tracking and mobile sensor navigation in wireless sensor networks," *IEEE Transactions on Mobile Computing*, vol. 12, no. 1, pp. 177–186, 2013.
8. A. Medeisis and A. Kajackas, "On the use of the universal Okumura- Hata propagation prediction model in rural areas," *Vehicular Conference Proceedings*, vol. 3, 2000.

**International Journal of Innovative Research in Science, Engineering and Technology**

An ISO 3297: 2007 Certified Organization

Volume 6, Special Issue 3, March 2017

5<sup>th</sup> National Conference on Frontiers in Communication and Signal Processing Systems (NCFCSPS '17)

13<sup>th</sup>-14<sup>th</sup> March 2017

Organized by

**Department of ECE, Adhiyamaan College of Engineering, Hosur, Tamilnadu, India.**

9. N. Patwari, J. Ash, S. Kyperountas, A. Hero, R. Moses, and N. Correal, "Locating the nodes: cooperative localization in wireless sensor networks," *IEEE Signal Processing Magazine*, vol. 22, no. 4, pp. 54 – 69, July 2005. [11] A. Zanella and A. Bardella, "Rss-based ranging by multichannel rss averaging," *IEEE Wireless Communications Letters*, vol. 3, no. 1, pp.10–13, February 2014.
10. [13] J. Yang and Y. Chen, "Indoor localization using improved rss-based lateration methods," in *IEEE Global Telecommunications Conference GLOBECOM.*, Nov 2009, pp. 1–6.
11. [30] G. Zanca, F. Zorzi, and A. Zanella, "RSSI measurements in indoor wireless sensor networks."
12. [Online]. Available: <http://telecom.dei.unipd.it/pages/read/59/>
13. L. Wang, Y. Liu, X. Xu, and X. Wang, "Wsnmultilateration algorithm based on landweber iteration," in *International Conference on Electronic Measurement Instruments*, August 2009, pp. 1–250–1–254.
14. C. Andrade and R. Hoefel, "IEEE 802.11 WLANs: A comparison on indoor coverage models," in *Electrical and Computer Engineering (CCECE), 2010 23rd Canadian Conference on*, May 2010, pp. 1–6.