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A Pragmatic Approach of Localization and Tracking Algorithms in Wireless Sensor Networks

Ph.D Dissertation by

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A l'Èlia,

Un camí,
quina cosa més curta de dir,
quina cosa més llarga de seguir.

Poema de Nadal
Josep Maria de Segarra

Abstract

THE last advances in wireless communications and electronics have motivated the appearance of Wireless Sensor Networks. These networks are formed by a new kind of low-power and low-cost sensors able to operate across short ranges. Their simplicity and autonomy have motivated the development of many final applications in a large variety of fields. Nevertheless, sensor nodes are equipped with limited data processing and communication capabilities. Hence, several design challenges appear when an application has to be developed. These restrictions justify the design of highly distributed and energy-efficient applications.

Localization and tracking algorithms are one of those emerging applications that have become an interesting field to the researchers. The information routing is often supported by their localization. Besides, the location knowledge gives to the data sensed a geographic sense. Instead of using the existing global localization methods, such as GPS, that are more complex and costly, recent advances have demonstrated the viability of local methods.

In this PhD dissertation, we have focused our study of the localization and tracking algorithms for WSN on the RSS-based distributed approaches. One of the major issues is to obtain the simplest possible method, and RSS range measurements have become the simplest existing measurements. Besides, we have also presented methods that are able to optimize the trade-of between accuracy versus energy-efficiency.

First, RSS-based cooperative localization algorithms in static indoor networks are considered. The use of RSS measurements requires the knowledge of a propagation model in order to obtain inter-node distance estimates. We introduce an on-line path loss estimation method that obtains the model by means of RSS measurements. Hence, we avoid the need of an a priori estimation of the propagation model. Moreover, the cooperative approaches used increase the number of nodes that cooperate with a non-located node in the location estimation procedure. Two major issues have to be taken into account when a large number of nodes are used. On the one hand, the larger

the number of cooperating nodes, the larger the number of messages exchanged, and, hence, the higher the energy consumption. On the other hand, the probability of using further nodes is increased, hence, the higher the distance, the higher the error distance estimates, when RSS measurements are used. These features have motivated us to propose three different node selection criteria in order to reduce the energy consumption maintaining the accuracy.

Finally, we have considered the mobility of the non-located nodes inside a fixed network. The interest is to locate and track a node moving across a WSN. We have considered two different scenarios: an outdoor one, in which the velocity is medium-high, and, an indoor one, where the velocity is lower. In both cases, we have still used an RSS-based cooperative algorithm. Besides, we introduce the Kalman Filter and its derivatives, because, they have become a common approach used for tracking purposes. In both scenarios, the mobility of the node causes a high variability of the RSS measurements. These errors reduce the accuracy. In that sense, we propose a window-based RSS correction method in order to counteract these negative effects.

Resum

ELS últims avenços en comunicacions sense fils i electrònica ha motivat l'aparició de les xarxes de sensors sense fils. Aquestes xarxes estan formades per un nou tipus de sensors de baixa potència i de baix cost que són capaços d'operar en rangs propers. La seva senzillesa i autonomia ha motivat el desenvolupament de moltes aplicacions en una gran varietat de camps. No obstant això, els nodes estan equipats amb uns recursos de processament de dades i capacitats de comunicació limitats. Per tant, el desenvolupament de qualsevol aplicació planteja diversos problemes de disseny. Aquestes restriccions imposen un disseny d'aplicacions amb un caràcter distribuït i energèticament eficients.

Els algoritmes de localització i seguiment són una d'aquestes aplicacions emergents que s'ha convertit en un camp d'interès per als investigadors. La informació d'enrutament de les xarxes de sensors està sovint suportada en la localització dels nodes. A més, el coneixement de la posició permet donar, a les dades detectades, un sentit geogràfic. En lloc d'utilitzar els mètodes existents de localització globals, com el GPS, que són més complexos i costosos, els recents avenços demostren la viabilitat de mètodes locals.

En aquesta tesi, hem centrat el nostre estudi dels algoritmes de localització i seguiment, en xarxes de sensors sense fils, en solucions distribuïdes basades en mesures de potència. Una de la qüestions més importants és l'obtenció d'un mètode el més senzill possible, i les mesures de potència s'han convertit en les més simples. A més, també volem obtenir el millor compromís entre obtenir la major fiabilitat de l'algorisme i maximitzar l'eficiència energètica.

En primer lloc, hem considerat el desenvolupament d'algoritmes de localització cooperatius basats en mesures de potència rebuda en xarxes interiors estàtiques. Les mesures de potència imposen el coneixement d'un model de propagació per tal d'obtenir una estimació de la distància entre nodes. Nosaltres proposem la introducció d'un mètode que estima l'exponent de pèrdua de potència per propagació mitjançant les

mesures de potència fetes, en comparació a les normalment utilitzades campanyes de mesures fetes a priori. A més a més, els mètodes cooperatius en els quals basem la nostra proposta augmenten el nombre de nodes que cooperen durant el procediment d'estimació de la posició d'un node no localitzat . Dos són els problemes principals que no s'han de menystenir quan s'utilitza un major nombre de nodes. D'una banda, a major nombre de nodes cooperants, major intercanvi de missatges, i, per tant, major consum d'energia. D'altra banda, la probabilitat d'utilitzar nodes llunyans s'incrementa, i, com més gran sigui la distància entre nodes, l'error de la distància estimada serà major, puix que utilitzem mesures de potència. Aquesta característica ens ha motivat a proposar tres criteris de selecció de nodes diferents per tal de reduir el nombre de nodes cooperants i així reduir el consum d'energia sempre intentant mantenir l'exactitud.

Finalment, hem considerat la mobilitat dels nodes dins d'una xarxa fixa. L'interès és localitzar i seguir un node mòbil en una xarxa de sensor sense fils. En aquesta ocasió hem considerat dos escenaris diferents: una a l'aire lliure, on la velocitat és mitjana-alta, i un interior, on la velocitat és menor. En ambdós casos, també utilitzem un algorisme cooperatiu basat en mesures de potència. A més, el filtre de Kalman i els seus derivats s'introdueixen a la solució proposada, ja que s'han convertit en un solució d'ús comú als algoritmes de seguiment. En ambdós casos, la mobilitat del node produeix una alta variabilitat de les mesures de potència. Aquests errors poden causar una precisió inferior. En aquest sentit, es proposa un mètode de correcció de les potències rebudes basat en un enfinestrat, per tal de disminuir aquests efectes negatius.

Resumen

Los últimos avances en comunicaciones inalámbricas y electrónica ha motivado la aparición de las redes de sensores inalámbricos. Estas redes están formadas por un nuevo tipo de sensores de baja potencia y de bajo coste que son capaces de operar en rangos cercanos. Su sencillez y autonomía ha motivado el desarrollo de muchas aplicaciones en una gran variedad de campos. Sin embargo, los nodos están equipados con unos recursos limitados de procesamiento de datos y capacidades de comunicación. Por lo tanto, el desarrollo de cualquier aplicación plantea distintos problemas de diseño. Estas restricciones impone un diseño de aplicaciones que sean de carácter distribuidas y energéticamente eficientes.

Los algoritmos de localización y seguimiento son una de esas aplicaciones emergentes que se han convertido en un campo de interés para los investigadores. La información de enrutado de las redes de sensores a menudo se apoya en la localización de los nodos. Además, el conocimiento de la posición da lugar a que los datos detectados tengan un sentido geográfico. En lugar de utilizar los métodos existentes de loca-lización globales, como el GPS, que son más complejos y costosos, los recientes avances demuestran la viabilidad de los métodos locales.

En esta tesis doctoral, hemos centrado nuestro estudio de los algoritmos de localización y seguimiento, en redes de sensores inalámbricos, en soluciones distribuidas basadas en medidas de potencia recibida. Una de la cuestiones más importantes es la obtención de métodos lo más sencillos posible, y las medidas de potencia se han convertido, hoy en día, en las medidas más simples. Además, también queremos lograr métodos capaces de optimizar el compromiso entre la exactitud de los resultados y la eficiencia energética.

En primer lugar, hemos considerado el desarrollo de un algoritmo de localización cooperativo basado en medidas de potencia en redes interiores estáticas. Las medidas de potencia imponen el conocimiento de un modelo de propagación con el fin de obtener una estimación de la distancia entre nodos. Nosotros proponemos la in-

troducción de un método que estima el exponente de pérdida de potencia por propagación mediante las medidas de potencia hechas, en comparación a las, normalmente utilizadas, campanyas de medidas hechas a priori. Además, los métodos cooperativos aumentan el número de nodos que coopera con un nodo no localizado en el momento de estimar la posición. Dos problemas principales tienen que ser tenidos en cuenta cuando se utiliza un mayor número de nodos. Por un lado, a mayor número de nodos cooperantes, mayor es el intercambio de los mensajes, y, por lo tanto, mayor será el consumo de energía. Por otro lado, la probabilidad de utilizar más nodos lejanos se incrementa, por lo tanto, cuanto mayor sea la distancia entre nodos, el error de estimación de distancia será mayor debido a la utilización de medidas de potencia. Estos problemas nos ha motivado a proponer tres criterios de selección de nodos distintos con el fin de reducir el consumo de energía, tratando de mantener en todo momento la exactitud en las posiciones estimadas.

Por último, hemos considerado la movilidad de los nodos dentro de una red fija. El interés es localizar y seguir un nodo móvil en una red de sensores inalámbricos. En esta ocasión hemos considerado dos escenarios diferentes: uno al aire libre, en el que la velocidad que se supone es media-alta, y uno interior, donde la velocidad que se supone es menor. En ambos casos, utilizamos, también, un algoritmo de cooperación basado en medidas de potencia. Además, los filtros de Kalman y sus derivados se introducen en la solución propuesta, ya que se han convertido en una solución de uso común en los algoritmos de seguimiento. En ambos casos, la movilidad del nodo produce una alta variabilidad en las medidas de potencia. Estos errores causan una precisión inferior. En ese sentido, se propone un método de corrección de potencias basado en un enventanado, con el fin de disminuir estos efectos negativos.

Contents

Notation

Boldface upper-case letters denote matrices, boldface lower-case letters denote column vectors, upper-case italics denote sets, and lower-case italics denote scalars.

$\log_a(\cdot)$	Base-a logarithm.
$\log(\cdot)$	Natural logarithm.
$\|\mathbf{x}\|$	Euclidean norm of the vector **x**.
$E[\cdot]$	Mathematical expectation.
$f(\mathbf{x}\|\mathbf{y})$	Joint probability density function.
$p(\mathbf{x}\|\mathbf{z})$	Posterior density of random variable **x** conditioned to **z**.
$\triangleq$	Defined by.
arg	Argument.
max, min	Maximum and minimum.
∇	Gradient operator.
$\approx$	Approximate as.
$\mathbb{N}(\mathbf{m},\mathbf{c})$	Real Gaussian vector distribution with mean **m** and covariance matrix **C**.
$\bar{\mathbf{x}}$	Mean value of **x**.
$\exp(\cdot)$	Exponencial.
$I(\cdot)$	Indicator function.
$\bar{\mathbf{x}}$	Mean Value of vector **x**.
$\hat{\mathbf{x}}$	Estimate value of **x**.
$\mathcal{U}(a, b)$	Uniform distribution with upper and lower values b and a, respectively.
x^-	A priori state estimate of x.
$\mathbf{X}^T$	Transpose of the matrix **X**.
$\mathbf{X}^{-1}$	Inverse of the matrix **X**.
$\mathbf{I}$	Identity matrix.

Acronyms

1DKF	One Dimensional Kalman Filter
AOA	Angle Of Arrival
APIT	Approximate Point In Triangle
ASS	Adaptive Sensor Selection
CB-DEM	Consensus-Based Distributed Expectation Maximization
CRB	Crámer-Rao Bound
D-LMS	Distributed-Least Mean Squares
DLS	Distributed Least Squares
DOA	Direction Of Arrival
DV-Hop	Distance Vector-Hop
EKF	Extended Kalman Filter
EM	Expectation Maximization
FG	Factor Graphs
GDOP	Geometric Dilution Of Position
GNS	Global Node Selection
GPS	Global Positioning System
KF	Kalman Filter
LNS	Local Node Selection
MDS	MultiDimensional Scaling
MGA	Micro-Genetic Algorithm
ML	Maximum Likelihood
MLE	Maximum Likelihood Estimator
MMSE	Minimum Mean Square Error
MRC	Maximum Ratio Combining
MSO	Mass Spring Optimization
LS	Least Squares
OLPL-NS-LS	On-Line Path Loss- Node Selection-Least Squares

PF	Particle Filters
PL	Path Loss
RARE-Area	Reduced Area REporting-Area
RARE-Node	Reduction of Active node REdundancy-Node
RF	Radio Frequency
RMS	Root Mean Square
RMSE	Root Mean Square Error
RTOA	Roundtrip Time Of Arrival
RTT	RoundTrip Time
RSS	Received Signal Strength
SDP	SemiDefinite Programming
SeRLoc	Secure Range-independent Location
SS	Spatial Split
TDOA	Time Difference Of Arrival
TOA	Time Of Arrival
UWB	Ultra Wide Band
WITS	Wireless Indoor Tracking System
WLS	Weighted Least Squares
WSN	Wireless Sensor Networks

Chapter 1

Introduction

1.1 Motivation

DISTRIBUTED sensor networks have been a recurrent field of study for more than 30 years, but the recent advances in wireless communications and electronics have allowed to bring into reality wireless sensor networks [Mao09]. These advances have enabled the development of low-cost, low-power and multi-functional sensors that are small in size and can communicate over short distances. The increasing interest to deploy these sensor networks has motivated the appearance of many applications for monitoring and controlling different environments.

Location estimation in wireless sensor networks has become an important field of interest from researchers [Bac05, Bou07, Mao09]. This is due to the demand of the knowledge of the node position by the majority of applications. In environmental monitoring, such as fire or agriculture control, a basic premise to give sense to all the data measured is to know their location, otherwise data could be considered as meaningless information. The obtention of node positions gives the opportunity of increasing the number of possible applications.

The main purpose of a localization or a tracking algorithm is to estimate the position of those non-located nodes with the following information: a priori knowledge of some nodes positions and inter-sensor measurements, such as time difference of arrival, angle of arrival or connectivity. Hence, the majority of existing localization methods applied in WSN tries to achieve the best accuracy considering the restrictions that this kind of networks imposes. Although nowadays there are many methods of localization in wireless networks, such as GPS or radar-based geolocation techniques, there exist many challenges that limit their usage. Wireless sensor nodes have normally low-cost hardware with a limited computational capability. Hence, the localization algorithms have to take into account them in order to achieve the best trade-off between cost, size, energy consumption and accuracy. For that reason, localization has become a challenging field.

Moreover, it is possible that the nodes have mobility. Besides the inherent problems due to the nature of the nodes, the mobility causes a major uncertainty to the measurements done by nodes. For that reason, to give solution to the location of mobile nodes the, so called, tracking algorithms have appeared.

Within this framework, this PhD dissertation provides a contribution to the study of pragmatic approaches devoted to localize and track wireless sensor nodes. More concretely, based on Received Signal Strength (RSS) range measurements, we are able to obtain accurate solutions. Moreover, node selection mechanisms are proposed in order to achieve a better energy efficient algorithm. Besides, control mechanism are introduced in the tracking algorithm in order to overcome the challenges introduced by the mobility.

1.2 Outline

The objective of this dissertation is the study of pragmatic approaches of localization and tracking algorithms for Wireless Sensor networks (WSN). Compared to existing methods in the literature, we try to reduce the complexity of the solution in order to achieve easy-to-implement solutions. More concretely, the solutions adopted are feasible solutions based on the Received Signal Strength range measurements that have been validated in a real network. Next, we describe, in more detail, the organization of the text.

Chapter 2 presents an overview of the localization and tracking algorithms. Furthermore, a special attention in the RSS-based algorithms for location and tracking has been given.

Chapter 3 is devoted to the localization algorithms of multiple static nodes in an indoor WSN. More concretely, an RSS-based distributed cooperative solution is presented. Our basic purpose is to develop a pragmatic algorithm that achieves the best possible trade-off in terms of accuracy versus energy consumption. In that sense, we present three different node selection criteria in order to reduce the energy consumption and increase the reliability of the information that cooperating nodes give to the non-located node. Besides, an on-line path loss estimation mechanism is introduced in order to obtain the radio propagation model needed when RSS range measurements are adopted. Different scenarios are assumed in the simulations and experimental results carried out.

Chapter 4 is focused on the localization and tracking of mobile nodes in WSN. In this chapter two different environments are considered, outdoor and indoor, and, hence, two different solutions are presented. Again, RSS-based tracking algorithms are adopted. The purpose of the chapter is minimizing the bad effects that the movement causes at the RSS measurements. To do so, window-based RSS Correction mechanism is proposed. The main purpose is to achieve a pragmatic approach that does not increase the complexity and the cost of the network. The outdoor solution proposed is devoted to locate medium-high velocity mobile nodes. In the indoor case, low velocity mobile nodes are assumed. Simulation and experimental results are presented and discussed for both environments.

Chapter 5 concludes this PhD dissertation with a summary and a discussion of the obtained simulation and experimental results. Some suggestions for future work are also presented.

1.3 Contributions

The main contribution of this thesis is the study of pragmatic approach of localization and tracking wireless sensor nodes based on RSS-measurements. Next, the details of research contributions in each chapter are presented.

Chapter 3

The main results of this chapter that addresses the on-line path loss and node selection localization algorithm of static sensor nodes have been published in one book chapter, one journal paper, two conference papers and two COST Action meetings:

- A. Bel, J. L. Vicario, G. Seco-Granados, "A Pragmatic Approach to Cooperative Positioning in Wireless Sensor Networks", chapter in Microwave and Milimeter Wave Circuits and Systems. Emerging Design, Technologies and Applications, ed. A. Georgiadis, H. Rogier, L. Roselli and P. Arcioni, John Willey & Sons, pp. 135-172, Sept. 2012.

- A. Bel, J. L. Vicario, G. Seco-Granados, "Localization Algorithm with On-line Path Loss Estimation and Node Selection", in *Sensors*, Volume 11, Number 7, pp. 6905-6925, Jul 01 2011.

- A. Bel, J. L. Vicario and G. Seco-Granados, ”Node selection for Cooperative Localization: Efficient Energy vs. Accuracy Trade-off”, in *IEEE International Symposium on Wireless Pervasive Computing (ISWPC),* May 05 2010.

- A. Bel, J. L. Vicario and G. Seco-Granados, ”Real-Time Path Loss And Node Selection For Cooperative Localization In Wireless Sensor Networks”, in *Proc. IEEE International Workshop on Advances in Positioning and Location-Enabled Communications APLEC (in conjunction with PIMRC'10)*, Sep 26 2010.

- A. Bel, J. L. Vicario, G. Seco-Granados, ”RSSI-based Cooperative Localization with Energy-efficient Node Selection for Wireless Sensor Networks ”, COST ic0803 RFCSET, Oct 07 2009.

- A. Bel, J. L. Vicario, G. Seco-Granados, ”Cooperative Localization in WSN based on Real-Time Pathloss Model and Node Selection”, COST ic0803 RFC-SET, Feb 24 2010.

Chapter 4

The results within the chapter have been published in a patent and a journal paper is in preparation.

- A. Bel, J. L. Vicario, A. Morell, ”Método y Sistema de Localización y Seguimiento de un Dispositivo Móvil en una Red de Nodos Inalámbrica” (*patent pending*)

Other Research Contributions

The author of this PhD dissertation has contributed as the main author in another research contribution related to wireless networks whose content is not included in the present document. This contribution is:

- A. Bel, J. L. Vicario, G. Seco-Granados, ”The Benefits of Relay Selection in WiMAX Networks”, in *Proc. ICT Mobile Summit*, Jun 2008

Finally, other research works where the author has contributed are:

- J. L. Vicario, A. Bel, J. A. Lopez-Salcedo, G. Seco-Granados, ”Opportunistic Relay Selection with Outdated CSI: Outage Probability and Diversity Analysis”, in *IEEE Trans. on Wireless Communications, Vol. 8, No. 6, pp: 2872-2876*, Jun 2009

- J. L. Vicario, A. Bel, A. Morell, G. Seco-Granados, "Outage Probability vs. Fairness Trade-off in Opportunistic Relay Selection with Outdated CSI", in *EURASIP Journal on Wireless Communications and Networking: Special Issue on Fairness in Radio Resource Management for Wireless Networks*, 2009

- J. L. Vicario, A. Morell, A. Bel, G. Seco-Granados, "Optimal Power Allocation in Opportunistic Relaying with Outdated CSI", in *Proc. IEEE SAM*, Jul 2008

- J. Abad, A. Angles, A. Aynos, A. Bel, O. Chabrera, J. L. Vicario, R. Munoz, C. Pena, F. Santiago, I. Sanz, G. Seco-Granados, D. Soro, "InterRural: Internet Rural mediante Redes Heterogeneas e Itinerantes", in *URSI*, Sep 2008

- J. L. Vicario, A. Bel, A. Morell, G. Seco-Granados, "A Robust Relay Selection Strategy for Cooperative Systems with Outdated CSI", in *IEEE VTC Spring 2009*, Apr 26 2009

Chapter 2

An Overview of Cooperative Positioning and Tracking Algorithms

NOWADAYS, the great interest in localization of nodes on a WSN has motivated the development of a large number of algorithms. The different existing approaches try to overcome the different restrictions that a WSN inherently has, such as, limited hardware, energy or computational capabilities. The scenario where the algorithm has to work imposes some requirements that guide us in the decision of choosing between the different existing algorithms. In order to decide which is the suitable algorithm, they are grouped in different classifications depending on their characteristics. In the following subsections, a brief presentation of these classifications is made.

2.1 Introduction

A first classification divides existing methods in two main categories: range-based and range-free approaches. These approaches differ in the way of obtaining inter-node information. On the one hand, range-based approaches estimate inter-node distance or angle through ranging measurements. On the other hand, range-free approaches are based on the connectivity between adjacent nodes. Range-free methods present less accuracy than range-based methods,but they are a simple and cost-effective approach.

A second classification is cooperative versus non-cooperative algorithms. This second classification differentiates between those algorithms that allow the exchange of measurements between all nodes inside the network (cooperative) and those algorithms that only allow, the non-located nodes to exchange of messages with the nodes that know their position, a.k.a anchor nodes (non-cooperative).

The last classification refers to centralized versus distributed algorithms. Localization algorithms could be executed in a central node which becomes responsible for collecting all the network information and estimating the nodes' positions. On the other hand, in distributed algorithms each node is responsible for the estimation of its own position. Hence, the necessary calculations are distributed along the network.

Furthermore, in the last section a brief review of target tracking techniques applied in wireless sensor networks is presented. Tracking moving objects has also waken up the interest of researchers. The basic idea idea is to detect moving objects inside a network and reproduce the path of their movements. Tracking through WSNs can have several advantages [Vee07]. On the other hand, the highly restrictive constraints of WSNs introduces new challenges in wide field of tracking moving objects, in this case mobile sensor nodes.

2.2 Measurement Characterization

The measurement characterization divides the existing localization algorithms in two main categories: range-based and range-free methods. The measurement characterization provides a classification based on how the algorithms obtain the inter-node information.

In the following subsections the main differences between both methods are presented as well as their pros and cons. At the end, a brief summary of both techniques is presented.

2.2.1 Range-free

Range-free methods are based on connectivity information. Connectivity measurements allow each node to determine how many nodes are inside its radio range. But, as it will be seen it is also possible to obtain an estimation of the inter-node distances.

These methods are presented as the simplest measurements that a localization algorithm can use, because the basic idea is to decide if a node is connected with an adjacent node or not. Hence, the complexity introduced by ranging methods is avoided.

The connectivity information is usually obtained from RSS measurements. Considering perfect circle radio coverage, any node that receives an RSS above a threshold is supposed to be connected to the receiving node. Also a node can be considered inside the coverage range of another node by measuring the number of received packets. The commonest algorithms based on connectivity measurements are: centroid [Bul00], DV-HOP [He03], APIT [Nic03] or SeRLoc [Laz04].

Centroid

One of the simplest method existing in the literature is the Centroid algorithm [Bul00]. The nodes estimate their position through the information transmitted by anchor nodes (nodes with known location) present in the network.

The algorithm is quite simple. Non-located nodes detect how many anchors are inside their radio range coverage. The anchors broadcasts a message with their location coordinates. Hence, non-located nodes have the coordinates (x_{aj}, y_{aj}) from the anchors inside their radio range. With this information, non-located node position (x_i, y_i) is obtained as:

$$(x_i, y_i) = \left(\frac{\sum_{j=1}^{n} x_{aj}}{n}, \frac{\sum_{j=1}^{n} y_{aj}}{n} \right). \tag{2.1}$$

The centroid method is based on the assumption of having different overlapping regions of coverage (see Figure 2.1). If a node detects more anchors it will have a more accurate position estimate. With a lower number of overlapping regions, the algorithm reduces the number of possible locations that a non-located node could take and the estimates are less accurate.

In order to improve the accuracy of the centroid algorithm many works introduce weights (e.g. [Blu07]) in to the algorithm, and the new formula is:

$$(x_i, y_i) = \left(\frac{\sum_{j=1}^{n} w_{ij} x_{aj}}{\sum_{j=1}^{n} w_{ij}}, \frac{\sum_{j=1}^{n} w_{ij} y_{aj}}{\sum_{j=1}^{n} w_{ij}} \right), \tag{2.2}$$

being each weight w_{ij} equal to:

$$w_{ij} = \frac{1}{(d_{ij})^g}, \tag{2.3}$$

where d_{ij} is the estimated distance between node i and anchor j and g the degree. This degree allows us to control the impact of remote anchor or the estimates.

The authors in [Bul00] present some results of the centroid algorithm. The authors considered an ideal outdoor environment and a network formed by four anchor nodes with ideal spherical transmission range (see Figure 2.1). In that case an average localization error of 1.83 m is obtained, being the scenario a 10 m x 10 m area.

The difference in terms of accuracy of a weighted centroid compared to a plain centroid algorithm is shown in [Blu07]. The results show that the introduction of a weight improves the accuracy. Moreover, the higher the degree, the more stable the error with long range transmissions. In other words, a high degree gives to the further anchors the opportunity of giving a more reliable information to the non-located node. Nevertheless, when the degree g becomes higher the position moves towards the closest anchor and, hence, the positioning error increases.

Both proposed schemes could be easily deployed in a large scale network. The major problem of these methods when applied to a WSN is that the accuracy is directly related with the number of anchor nodes. The accuracy could be increased if the number of overlapped reference nodes is increased. Nevertheless, the inclusion of more anchor nodes increases the cost of the network, as anchor nodes have to know their own location.

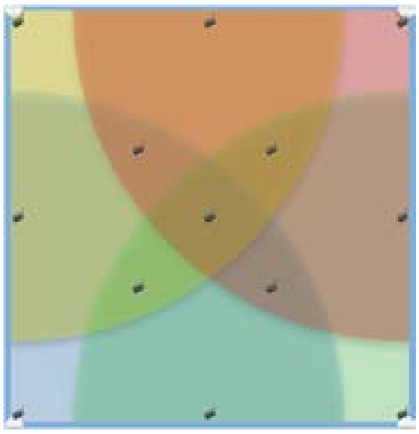


Figure 2.1: Centroid method with the different possibilities of positioning

DV-HOP

The Distance Vector-HOP algorithm [Nic03] is another method that is based on connectivity measurements. Although DV-HOP is more complex than the centroid, more accurate estimations are achieved.

The algorithm works as follows (see Figure 2.2). First, a broadcast message is sent by all the nodes. The message contains the information about which are their neighbour nodes (anchors or non-located). With this information each non-located node can construct a table with the different possible paths, in terms of number of hops, in order to reach every possible anchor. Then, they have to choose the shortest possible path. Once having these hop-distances, anchors broadcasts the average distance per hop to neighbours (achieved when a message from an anchor is received by another anchor). Finally, an average distance between a non-located node and all anchors reached are obtained. Then, the algorithm converts the shortest number of hops path to meters with the average hop distance value. Finally, a trilateration or multilateration method is used to estimate the non-located node position.

The DV-HOP algorithm is characterized by the simplicity of the procedure, as it does not require extra hardware. Moreover, the location estimation is distributed along the network. On the contrary, the great amount of transmissions necessary to construct all the possible paths causes an increase in the energy consumption.

Compared to the previous algorithm, the accuracy does not only depend on the connectivity with the anchors. Now the accuracy depends on the connectivity with any node (anchor or not anchor). Hence, similar accuracy values could be achieved with a reduction of the anchors density, e.g. the cost of the network could be reduced. At the end of the subsection a comparison between the first three range-free algorithms will be done.

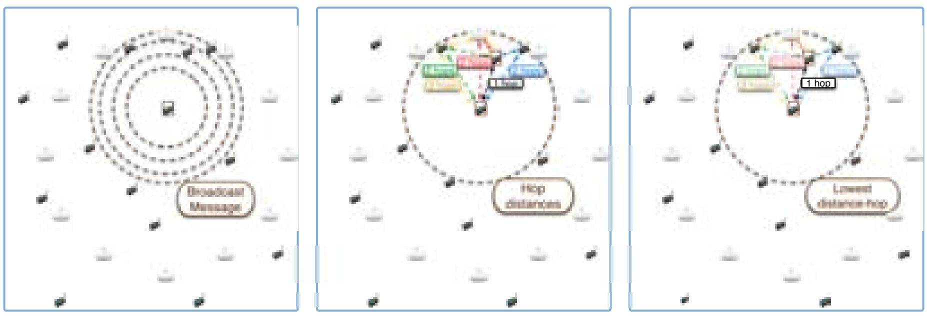


Figure 2.2: DV-HOP procedure.

APIT

The Approximate Point In Triangle Test (APIT) [He03] is included in a different category to range-free methods. APIT is classified as an area-based approach. The algorithm is basically divided in 4 steps: each node receives the location of many anchors as possible; given all possible combinations of three different anchors, each node has to form triangles with them; then, each non-located node has to determine whether it is or not within each triangle; and finally the position is obtained by calculating the gravity center of the intersection of all triangles selected (see Figure 2.3).

As the previous approaches, APIT algorithm is capable of providing global coordinates (thanks to the use of anchor nodes) and none extra hardware is required (no increase in node cost). But, in comparison with the DV-Hop, APIT algorithm depends only on communications with anchor nodes. APIT and centroid algorithm are considered non-cooperative methods, because they do not take advantage of communication between non-located nodes. Hence, the accuracy of the solution will depend, in part, on the density of anchor nodes or on having long-range transmission anchors, able to be sensed at long distances.

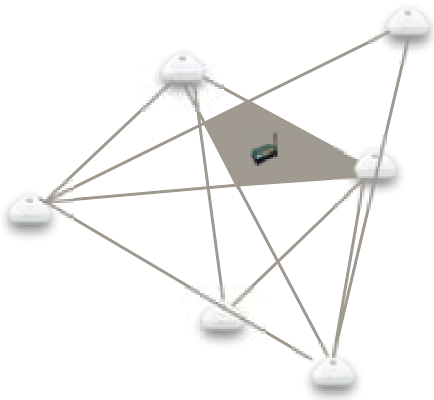


Figure 2.3: APIT estimation

A comparison of these methods is presented in [He03]. Authors analyse the dependence of the accuracy of these three methods or different parameters such as anchor density, radio range ratio or non-located nodes density. The results reflect that no single algorithm can be used in all scenarios. The centroid algorithm has the largest localization error (mean error achieved is 1.25 times the radio range R in meters), but it is not dependent on features such as node density. Furthermore, this is the algorithm with less exchange of information and more simple to implement. DV-HOP algorithm requires more exchange of messages through the network and a greater density of nodes (non-located and anchors) is necessary in order to obtain good accuracy. DV-HOP achieves a mean error equal to the radio range R. The APIT algorithm obtains similar results in terms of accuracy but non-located nodes have to have more anchors nodes inside their radio range. The parameter that negatively affects all the algorithms is the anchor node range. The work study the effect of reducing the anchor node density by means of increasing the anchor node range. But, as the transmission range of the anchors increases, the error also increases (worse results are achieved by the centroid algorithm). There exists a trade-off between the anchor density and the anchor node transmission range. APIT algorithm achieves a mean error 0.75 times the radio range R.

Although the three algorithms are compared in terms of accuracy, this is not the only figure of merit to be considered. Better results in a localization algorithm mean, normally, a reduction of the accuracy error. However,accuracy can also be improved by increasing the cost of the network, i.e. increasing the number of anchor nodes, the calculus complexity, or the nodes hardware requirements. When a localization algorithm is designed, the accuracy should not be the only figure of merit. Cost of the nodes or energy consumption have to be taken also into account.

SeRLoc

The Secure-Range Independent Localization (SeRLoc) algorithm is also considered an area-based approach [Laz04]. Following the idea of APIT, this localization method also obtains the node's position by means of calculating the center of gravity of an overlapping region. In this case the localization algorithm assumes a network with anchor nodes equipped with directional sectored antennas and non-located nodes equipped with omnidirectional antennas.

The algorithm has four steps. First, anchors transmit directional beacons within a sector. Non-located nodes collect this information and they determine the search area or sector in which they believe to be located. Then, the overlapping sector region is computed. Finally, the position is obtained by means of calculating the center of gravity of the overlapping section obtained at the previous step. Figure 2.4 illustrates the procedure.

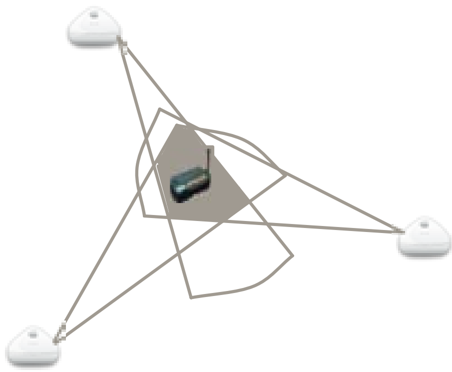


Figure 2.4: SeRLoc estimation

A comparison in terms of location accuracy versus the mean number of anchors heard is presented in [Laz04]. The best result is obtained with a SeRLoc algorithm in comparison with other methods such as APIT, Centroid o DV-HOP. More concretely the error is equal to 0.5 times the radio range R. On the other hand, the SeRLoc algorithm also achieves good results in terms of number of transmissions needed. In this occasion the centroid algorithm obtains the best results. However, SeRLoc achieves the best trade-off in terms of accuracy versus transmissions needed. The major drawback of SeRLoc algorithm is the necessity of having anchors equipped with directional sectored antennas.

2.2.2 Range-based

The range-based classification groups all the methods that estimate the inter-node distances or angles with the use of range information. The use of range information in order to extract distance estimates gives to the algorithm a better accuracy because the inter-node information obtained is more accurate than those obtained with range-free approaches. As commented previously, usually a gain in accuracy means an increase of the cost or the complexity. The use of range-based approach is more recommendable when the accuracy is the major purpose.

In this subsection the different signal metrics used to obtain distances estimates are presented. These distances are then used to determine the nodes positions.

Time of Arrival (TOA)

Time of arrival (TOA) measurement reflects the time at which any kind of signal arrives at a receiver [Li10]. More specifically, TOA is equal to the transmission time plus the propagation delay between a transmitter and a receiver, which reflects the inter-node distance between them. Hence, assuming a constant propagation velocity, it is easy to obtain an estimated distance. This velocity depends on the type of signal, e.g. 1 ms becomes to 0.3 m for an acoustic propagation and 1 ns becomes 0.3 m for an RF signal.

The major sources of error that affect time of arrival measurements are noise and multipath signals. Moreover, another limitation that imposes TOA measures is the synchronization between nodes. Maintaining the same reference clock among all the network is a must because if nodes do not have it, the estimated propagation time at the receiver will have an inherent error.

Errors about 2% are achieved over a communication range of 3-6 m [Yu09]. Moreover, the nodes clocks resolution should be of the order of nanoseconds. TDOA is a range measure usually used in wireless or satellite networks [Guv09] (in which base stations and mobile nodes are synchronized), but a recent trend uses time measurements approaches with Ultra Wide Band signals [Mao07, Shi03, Gez05]. The UWB signal achieves a high accuracy because the transmitted pulses have a wide bandwidth, hence a very short pulse waveform. With the recovery of this transmitted pulse it is possible to estimate the distance between receiver and transmitter. Moreover, UWB signals achieve very high temporal resolutions.

Time Difference of Arrival (TDOA)

The synchronization requirement of the TOA measurements could be an important disadvantage that limits their use in WSN. Although time measurements are also affected by noise and multipath the obtained accuracy is high. For this reason another time measurement approach is presented. This new approach avoids the necessity of having an entire network synchronized. This method is known as time difference of arrival (TDOA). TDOA is based on two different ideas [Bou07].

- The first TDOA method [Mao07] is based on the measurement of the difference between the arrival times of a signal sent by a transmitter at two receivers. This method assumes that the receiver locations are known and that the two receivers are perfectly synchronized (it could also be two synchronized transmitters and one receiver). It is not necessary to synchronize the entire network, only the receivers. For that reason, it is mostly used in the uplink cellular networks where the complexity of base stations is considerably relaxed.

- TDOA can also be understood as the difference of the arrival times of two different signals sent by a unique sender to a unique receiver (see [Pri00, Sal04]). With this idea is avoided the necessity of synchronizing any node inside the network, neither senders neither transmitters. This TDOA method is based on sending two different kind of signals with different propagation velocities. This is necessary in order to achieve this time difference at the arrival time. Hence, it is possible to measure the one-way propagation time. It can be done if nodes include extra hardware in order to transmit different signals.

As already said, the first case is more appropriate in cellular networks due to the necessity of having the receiving terminals synchronized. In this kind of networks, base stations have less stringent requirements in terms of complexity or cost. Hence, it is possible to synchronize them having a priori knowledge of their position; being them able to act as the receivers for estimating the TDOA.

On the other hand, the second TDOA approach could be more suitable in a WSN. The major disadvantage is the necessity of including extra hardware in the entire network, thus, increasing the cost of the terminal. Moreover, WSN nodes are usually battery-powered terminals. The requirement of sending two signals will increase the energy consumption.

Both approaches obtain good accuracy. In [Sal04] the results show an average error of the distance estimates between 29 cm and 8 cm. However, both methods neither increase the complexity of the network (first TDOA method requires synchronized reference nodes) or the cost of nodes (second TDOA method requires more integrated hardware in order to transmit to different signals).

Round-trip Time of Arrival (RTOA)

As previously discussed, WSN nodes are simple low-power devices. For that reason, any algorithm that has to be applied to these devices is highly restricted. Both time measurement techniques presented, although they could be used in WSN, increases the cost and the complexity of the nodes. The previous time measurement techniques achieve good distance estimates but impose a higher cost and complexity to the network. In order to take advantage of the good accuracy achieved by time measurements but trying to minimize these high requirements, a two-way time measurement technique is presented.

The Round-Trip Time method [Maz11] avoids the synchronization constraint that TOA or first TDOA methods impose, and also the hardware requirements of the second TDOA method. The measurement starts when a node A sends a packet to a node B. When the node B receives the packet, it retransmits it to the node A. At the end, node A receives the packet; hence, it can calculate the propagation time because the difference between the sending time and the receiving time at node A is twice the propagation time plus the processing time at node B (obtained from specifications or estimated at calibration time).

The major advantage of RTT method is the avoidance of the clock synchronization requirement or the inclusion of extra hardware. Nevertheless, a double transmission is necessary in order to obtain a time measurement. Furthermore, the time delay between the reception and the retransmission is not perfectly known, hence range measurements will have an inherent error. Numerical results based on different experimental setups are presented in [Maz11]. The results show that RTT measurements lead to an RMS error between a minimum of 75 cm and a maximum of 2.51 m. The difference in accuracy compared to that achieved by TOA or TDOA measurement is remarkable.

Furthermore, although the hardware and synchronization requirements are eliminated this technique needs the exchange of more packets in order to estimate the internode distance.

Received Signal Strength (RSS)

Received Signal Strength (RSS) is the power measured by a receiver [Yan09]. This measure is obtained from RF, acoustic or other kind of signals. Thus, these measurements can be done during normal transmission without increasing the requirements in terms of bandwidth or energy consumption. For this reason, they become one of the simple and inexpensive ranging methods, compared to AOA or TOA-based approach.

However, distance estimates obtained through RSS measurements suffer from many errors. The majority of these errors are induced by shadowing and multi-path effects. These effects are present in real channels and they depend on the environment. These two effects make the RSS measurements very difficult to model.

Usually, RSS-based distance estimations are based on the well-known radio propagation path loss model. This model assumes that the power decays proportionally to the distance, that is accordingly to $\frac{1}{d^{\alpha}}$, where α is the path loss exponent. In order to include the shadowing effects the received power is modelled as a log-normal variable (Gaussian if it is expressed in dBs), resulting in:

$$P_{R_x}(dBm) = P_0(dBm) - 10\alpha \log_{10}(d) - v_i, \tag{2.4}$$

where P_0 is the power received at a reference distance (usually 1 meter) and v_i represents the shadowing effects modelled as a Gaussian with zero mean and variance σ_{dB}^2 expressed in dBs.

The adoption of a log-normal model is motivated by experimental results such as those provided by [Pat01, Has93] and the analytical study by [Cou98]. Some results in terms of accuracy are presented in [Kum09]. The authors carried out a measurement campaign using TelosB motes. The average error achieved in the measured distances is 2.25 m, for distance between 1 and 8 meters. The RSS-based estimates achieve worse accuracy compared to that achieved with time measurements. However, the major advantage is that RSS provides a lower complex solution. Moreover, the accuracy of the distances estimates can be improved if a more accurate propagation model is used.

Angle of Arrival (AOA)

Compared to time or RSS measurements, AOA techniques do not estimate distances. AOA measurements estimate the direction of arrival of the signal transmitted by neighbour nodes [Pat05].

In [Pat05] two different ways of estimating angles are presented. First method, which is the most common, estimates the angle of arrival by means of using a sensor array; hence array signal processing is employed. Each sensor requires two or more sensors placed at a known location. These sensors could be microphones, if acoustic signals are sensed, or it could be antennas, if RF signals are used. The angle is estimated following the same approach as in time-delay estimation. On the other hand, in [Kul10] an AOA algorithm based on antenna arrays is presented. The measurement consists of two phases. At first phase, anchors transmit their location and a short omnidirectional pulse. Then, they transmit a beacon with a rotating radiation pattern. Taking the advantage of beamforming techniques, the anchors are able to transmit directional pulses every T seconds and changing the direction of the signal by a constant angular step $\triangle\beta$. Sensors have to register the arrival time between the first omnidirectional signal and the time of arrival of the pulse with maximal beacon power. This difference in time $(\triangle t)$ allows the sensor to estimate the angle of arrival as:

$$\beta = \triangle\beta \frac{\triangle t}{T} \tag{2.5}$$

The accuracy achieved in [Kul10] is an average error of 2 m in a scenario with 6 anchors and 100 non-located nodes uniformly distributed in a 50 m x 50 m area. Increasing the anchors one can achieve root mean square errors (RMSE) in the localization below the 1.5 m.

In [Ash04, Bac05], RSS measurements from directional antenna arrays on each node were also used to estimate arrival angles. Through the ratio RSS between these two antennas differently oriented it is possible to extract the angle of arrival of the signal. Accuracy errors below 1 meter are achieved compared to that achieved with distance-based algorithms.

However, the necessity of a higher number of antennas in the nodes makes these measurements not easy to implement. The increase of cost and size of the nodes makes the AOA a more complex solution although achieves good results in terms of localization accuracy.

The AOA measurements are used with the triangulation localization algorithm. The triangulation estimates the node position by means of angles between fixed node and reference nodes. Later, a similar method (lateration), but based on distances instead of angles, is presented.

Radio Interferometry

This technique [Mar05] is based on exploiting interfering radio waves. Although it is also based in RSS measurements, the procedure of extracting the distance is more complex. The basis of radio interferometry is to utilise two transmitters (two reference nodes with known location) to create an interference signal and compare the phase offset at two receivers. This phase offset can be measured using the RSS. By measuring this relative phase offset at different carrier frequencies, it is possible to obtain a linear combination of the distances between both transmitters and receivers and finally their relative position.

The accuracy that this method could achieve is considerably high. Results achieved in [Mar05] show that more than 50% of the range measurements achieve accuracy lower than a quarter of the wavelength. In [Fox03] a tracking algorithm based on radio interferometry measurements is presented. The mean absolute error achieved with the mobile experiment is between 0.94 meters and 1.96 meters. The error achieved with a stationary experiment is between 0.54 meters and 0.83 meters. The distance estimates by means of RSS measurements achieved are more accurate than simply using a propagation model. Nevertheless, the method presents some requirements, such as, synchronization of some nodes and signal processing units able to estimate the carrier offset.

2.3 Algorithms Classifications

The previous classification of the localization algorithms was referred to the internode distance or angle estimates. Once these distances are computed next step is to estimate node locations inside the network. This second phase, usually called location-update phase, could be classified in two main categories: cooperative versus non-cooperative methods and distributed versus centralized methods. These two classifications will be discussed in the following subsections.

2.3.1 Cooperative versus Non-cooperative

As previously discussed, if the localization algorithm wants to provide absolute locations, some nodes of the network have to know their position (through GPS measurements or having a priori knowledge of their coordinates). Those nodes are known as anchor nodes.

Non-cooperative approaches refer to those algorithms that allows a non-located node to establish communication only with anchor nodes. In other words, a non-located node position is only obtained using only the information transmitted by the anchors. Hence, the accuracy of those approaches are high-dependent on, on the one hand, the density of anchors inside the network or, on the other hand, on having the presence of long-range transmission anchor nodes.

This restrictive imposition limits the use of these techniques in large-scale networks. However, in small-scale networks, where nodes have a high probability of having a direct communication with a high density of anchor nodes, the use of a non-cooperative technique could become a great option.

Non-cooperative approaches are communication-restricted algorithms. On the other hand, cooperative algorithms have not restrictions in the communication between any nodes inside the network. Nodes are able to obtain information from all nodes inside the network. All nodes (being anchor or not) inside the radio range can cooperate with non-located nodes at the time of estimating their position. With this characteristic the accuracy is not only dependent on the density of anchor nodes, hence they can offer increased accuracy and coverage and be more suitable in a large-scale network, i.e. in networks with a high number of networks and considered very complex to manage.

It is shown in Figure 2.5 an example of both strategies.

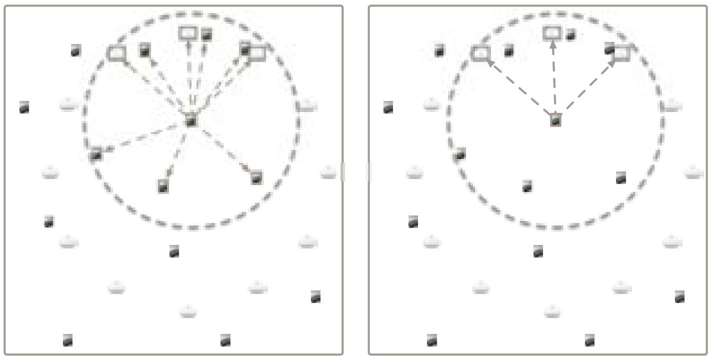


Figure 2.5: Cooperative and non-cooperative approaches

2.3.2 Centralized versus non-centralized

As previously commented, location-update phase has a second classification: centralized versus distributed. Centralized approaches are those algorithms in which one node becomes a central unit. This central unit is the one that has to collect all data and it is the only one that computes all the position estimates. On the other hand, in a distributed algorithm each node is responsible of estimating its own position.

In the following subsection different alternatives of both approaches are presented discussing their strong points and when the conditions when they are not appropiate.

Centralized Algorithms

In some applications it is appropriate to implement a centralized WSN due to the nature of the application, e.g. environmental monitoring, where the information should be controlled by a central point. In this situation, the use of centralized algorithms in order to locate the nodes inside the network is useful.

On the one hand, centralized algorithms provide good accuracy because the central node has information of the entire network. Moreover, these nodes are less restricted in terms of complexity. Hence, a more complex algorithm could be implemented. On the other hand, all the information collected at the network must be transmitted to the central node , and hence the traffic is increased. Furthermore, the centralization of all the information reduces the scalability of the algorithm. Finally, the higher computational capacity of the central node, the higher the cost of the central node.

MultiDimensional Scaling Multidimensional Scaling (MDS) [Bac05] was originally developed for use in mathematical psychology and has many variations.

The most usual approach is the MDS-MAP [Sha03], which is a direct application of the simplest kind of multidimensional scaling: the classic metric MDS. The basic idea is to arrange objects in a space of a certain number of dimensions trying to reproduce the dissimilarities observed in the objects.

Adapting to a localization algorithm, the objects are the nodes and the dissimilarities are the distance estimates. By means of using the law of cosines and linear algebra the MDS could reconstruct the relative positions of the points based on the internode distances. The last step of an MDS algorithm is transforming the relative map obtained to an absolute map based on the knowledge of the absolute position of some anchors.

MDS has become a potential solution in localization algorithms. These algorithms introduce the opportunity of constructing a relative map without knowing any absolute position. In [Sha03], authors present some accuracy results of the MDS methods. They show that the accuracy of the MDS-MAP is highly dependent on the connectivity with other nodes. In order to reduce the error, the algorithm needs a high density of neighbour nodes (a minimum number of 12 cooperating nodes). Another important point is the high accuracy achieved when range information is used instead of using connectivity information (range-free approach). In conclusion, it is possible to achieve an error of less than half the radio range of the nodes with a number of 12 cooperating nodes and 4 anchors.

A major drawback when the network becomes so large is the necessity of having all the information in a central node. The transmission and also the size of the matrix that has to be processed could limit the applicability of this method in large-scale networks.In order to avoid this problem can be reduced by means of using map-stitching techniques [Kwo08].

Although, MDS is originally developed as a centralized algorithm, distributed solutions have also appeared [Cos06].

SemiDefinite Programming The SemiDefinite Programming (SDP) is a subfield of convex optimization. SDP basically consists in minimizing a linear function subject to the constraint that an affine combination of symmetric matrices is positive semidefinite. Such a constraint is non-linear and non-smooth, but convex, so semidefinite programs are convex optimization problems.

The major problem of applying these techniques is that the localization problem is a non-convex problem. Hence, the basic idea of an SDP algorithm is to convert the non-convex quadratic distance constraints into linear constraints by introducing a relaxation to remove the quadratic term in the formulation.

Three different approaches applying SDP algorithms are presented in [Bis06]. The best result achieved is an error of the 5% of the radio range. This accuracy is highly affected by the noise factor.

Moreover, when the size of the network increases the solution of a large SDP becomes more complex. This problem can be solved by means of dividing the network into several clusters, reducing the complexity of the entire network [Bis06] and achieving a reduction in terms of computation time.

Maximum-Likelihood Estimation The MLE is a centralized localization algorithm [Pat01]. As it occurs with MDS it can be solved in a distributed fashion. MLE is a popular statistical method used for fitting a statistical model to data, and providing estimates for the model's parameters. One of its advantages is its asymptotic efficiency. In [Pat01], simulations carried out in a scenario with 40 non-located nodes achieve a root mean square of 2.1 m.

Although it is possible to achieve a good accuracy two major problems appear when this method is used. ML estimation is very sensitive to model perturbations, i.e. if data measurements deviates from the statistical model assumed, the results obtained could not be optimal. Moreover, ML is a biased estimator [Rah08]. For that reason authors in

[Rah06] present an Optimisation to Maximum Likelihood algorithm in order to reduce the bias introduced by the sum-of-squares.

Distributed Algorithms

In a distributed algorithm each node processes all the data that it collects from the network. They themselves are responsible of estimating their own coordinates. This is possible because the nodes share their position information. A distributed algorithm is usually considered more efficient, in terms of computational cost, and scalable (an important characteristic for large scale networks). On the other hand, distributed algorithms have lower accuracy compared to that achieved with a centralized algorithm due to the fact that the calculus is done at the nodes which have less computational capacities.

Three distributed methods are presented: lateration, Bayesian and non-Bayesian algorithms. Bayesian approaches consider nodes coordinates $(\mathbf{x})$ as a realization of a random variable, while non-Bayesian and lateration approaches consider $\mathbf{x}$ as a deterministic parameter.

Lateration This first method is based on the triangulation concept. In this case, the lateration methods use the distances to some reference nodes instead of using angles. This method is known as trilateration if three nodes are used or multilateration when more than three nodes are used.

Taking advantage of the estimated distances obtained from neighbour nodes, non-located nodes obtains their location by means of calculating the intersection point of the circles centred at reference node positions with radius equal to the estimated distances (see Figure 2.6). Hence, this technique is significantly affected by the errors on the distance measurement (ranging).

Once a non-located node estimates its position, it could become a new reference node that could help the rest of the nodes, giving to non-located nodes the possibility of exchanging information with other non-located nodes. Hence, a lateration method can be considered a cooperative localization algorithm.

Non-bayesian Estimators The non-bayesian estimators [Wym09] are one of the categories inside the distributed algorithms. The basic idea is the minimization of a cost function, such as LS or ML ((2.6)and (2.9) respectively), in a distributed way.

Each node estimates its own position following a three-step algorithm. The procedure starts with the distribution of their coordinates to their neighbours. Then each

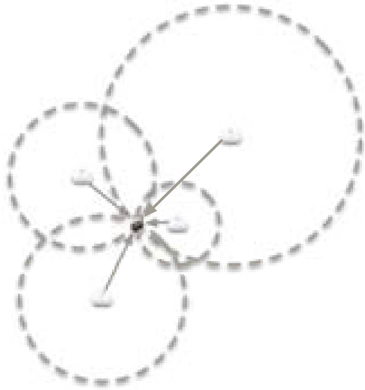


Figure 2.6: Lateration example.

node estimates the internode distances, using range metrics, to those nodes from which the node has received their coordinates. Finally, the nodes recalculate their position estimates by means of using both data. These steps are repeated until a convergence.

The problem that presents these methods is the possibility of not converging to a global minimum. This fact is related with the use of a good starting point. Hence, the selection of this initial point has to be taken into account when the algorithm is designed. If an initial point near to the final solution is not used, the algorithm could not converge to a global solution, affecting the global accuracy of the algorithm.

The cost function of a LS method minimizes the error between both distances is:

$$C_{LS}(\mathbf{x}) = \sum_{i=1}^{N_2} \sum_{j \epsilon S_i} ||z_{j\rightarrow i} - \mathrm{f}(\mathbf{x_i} - \mathbf{x_j})||^{\mathbf{2}}, \tag{2.6}$$

where $z_{j\rightarrow i}$ is the distance estimate between node i and node j, and $\mathrm{f}(\mathbf{x_i} - \mathbf{x_j})$ is a function that provides distance between node i and j using the coordinates of them.

On the other hand, ML position estimation depends on a statistical information of the RSS. Having a vector $\mathbf{p}_i$ that contains all the received RSS measurements made by non-located node *i* and assuming that the communication channels are independent, the likelihood function L is the probability, assuming that the position estimates are correct ($\mathbf{x}$), of the power that we would received and it is defined as:

$$L = \prod_{i=1}^{N_2} \prod_{j \in S_i} exp\left(-\frac{1}{2}\left(\frac{p_{ij} - RSS_{ij}}{\sigma_{dB}}\right)^2\right), \tag{2.7}$$

where p_{ij} is the power that we expect to receive given the position estimates.

The maximum likelihood method the position estimates are obtained as the values that maximizes the likelihood function, or, the values that minimizes the negative log-likelihood function that is defined as:

$$f(\mathbf{p}|\mathbf{x}) = -\log(L) = \sum_{i=1}^{N_2} \sum_{j \in S_i} \frac{1}{2} \left(\frac{p_{ij} - RSS_{ij}}{\sigma_{dB}} \right)^2. \tag{2.8}$$

Assuming the pathloss and shadowing model of the RSS of eq. (2.4), the ML position is obtained by:

$$\mathbf{x} \triangleq \arg\min_{\mathbf{x}} f(\mathbf{p}|\mathbf{x}) = \arg\min_{\mathbf{x}} \sum_{i=1}^{N_2} \sum_{j \epsilon S_i} \left(\frac{10\alpha}{4\sigma_{dB} \log 10} \right)^2 \left(\log \left(\frac{z_{j \to i}}{\mathrm{f}(\mathbf{x}_i - \mathbf{x}_j)} \right) \right)^2. \tag{2.9}$$

Hence, the ML cost function is given by:

$$C_{ML}(\mathbf{x}) = b^2 \sum_{i=1}^{N_2} \sum_{j \epsilon S_i} \left(\log \left(\frac{z_{j \to i}}{\mathrm{f}(\mathbf{x}_i - \mathbf{x}_j)} \right) \right)^2, \tag{2.10}$$

where $b = \frac{10\alpha}{4\sigma_{dB} \log 10}$. The major difference between both methods is that ML approach takes advantage of the statistics of noise sources and LS approach does not. A comparison between both methods is shown in [Den06], where more concretely the LS approach is a weighted one. All results presented show that the ML approach achieves better accuracy in terms of positioning errors. The mean error values obtained with the ML algorithm are between 1.2 and 1.5 meters in comparison to that obtained with a WLS algorithm (values between 1.4 m and 1.75 m).

Bayesian Estimators Other methods used in the localization algorithms are those based on the Bayesian estimators. First approaches of these methods were basically developed for the localization of robots [Thr00]. Nowadays, many works have been developed for sensor localization and tracking algorithms.

The basic idea is: given sensors measurements $\mathbf{z}$, what is the probability of being at position $\mathbf{x}$ ($p(\mathbf{x}|\mathbf{z})$). This posterior density over the random variables $\mathbf{x}$ conditioned to all received measurements $\mathbf{z}$ is usually called belief [Fox03]. By means of computing the belief, it is possible to obtain the position estimate.

These methods are mostly divided in two different approaches [Dhi10]: Kalman Filter (and their derivatives) and Sequential Monte Carlo filters (a.k.a particle filters). The difference of both methods is that Kalman filters assume a Gaussian probabilistic distribution of the system. The results in [Dhi10] present different algorithms that obtain the position estimates using a Bayesian approach such as Kalman filter or particle filter. Results in [Fox03] show that both methods achieve a good accuracy but, in terms of adaptability to the environment, the particle filter implementation is the best option.

In [Wym09], the authors present a distributed approach called factor graphs (FG) that is a successive refinement method used to estimate the probability density of sensor network parameters. These methods are particularly promising for sensor localization. Their procedure is done in three steps. First, each sensor initializes their belief. Then, all nodes broadcast their beliefs to neighbours. Finally, each node updates their belief with their own belief and the information extracted from the neighbour beliefs, i.e. nodes iteratively refine their position. Results obtained in [Wym09] show that the distributed approach achieves similar results to those obtained with a centralized approach. Results show that the 90% of the nodes achieve an error below 1 meter. Compared to the results achieved by non-bayesian LS algorithm in which only the 40% achieves error values below 1 meter.

2.3.3 Summary

The first classification presented was between range-free and range-based methods. Although both methods are suitable to be used in a localization algorithm for WSN, the choice between one or another is based on the requirements of the final application. On the one hand, range-free methods provide less accuracy but the complexity of the measurements is lower. On the other hand range-based methods present a higher accuracy but the obtention of the range measurements is more complex. Time-based measurements present high accuracy in terms of range error, but all the approaches presented have high complexity that makes them not be the most suitable solution for WSN. The same problem appears with the AOA method. Angle measurements require extra hardware that increases the cost of the nodes and also the size. At last, in order to achieve a good trade-off between accuracy and cost one of the most appropriate options is the RSS-based range measurements. RSS-based methods present worse measurement results in terms of accuracy but they are the simplest range-based methods that could be applied in a WSN.

A brief comparison between cooperative and non-cooperative algorithms has also been presented. Cooperative algorithms have become an accurate approach for localization algorithms in sensor networks. By allowing the cooperation with the entire network, and not only with the anchor nodes, can increase the accuracy of the final position estimate. An important objective is to achieve a good trade-off in terms of accuracy versus network complexity and cost, and the cooperative approaches are the kind of algorithms that could achieve that. Furthermore, in a cooperative approach, where the cooperation between all nodes from the network is allowed, the number of anchor nodes inside the network or the necessity of having long-range transmission anchors could be reduced without affecting the localization accuracy. Also, a cooperative algorithm is a scalable solution because it does not only depend on the number of anchors nodes.

The last classification presented compares the centralized versus the distributed algorithms. As discussed before, centralized approaches give a higher accuracy due to the possibility of developing a more complex algorithm. Distributed approaches have to be computed in each node so they have to be as simple as possible. On the other hand, a centralized approach needs a higher traffic exchange, because all data has to be sent to the central node and limits the capability of scaling the network.

2.4 RSS-based Cooperative Positioning

As previously commented, finding a method suitable to be used in all scenarios is practically impossible. In the previous section, the principal pros and cons of the different methods have been presented.

In this section, the discussion is focused on a cooperative approach based on RSS measurements. The main restrictions that a WSN inherently imposes have to be taken into account in order to achieve the best possible algorithm. The economic and computational costs and the complexity of the algorithm should be as lower as possible, maintaining a certain position accuracy. Although RSS-based methods provide a limited distance estimate accuracy, it is the simplest possible approach. Furthermore, cooperative approaches leads to the algorithm the possibility of increasing the robustness and the scalability.

Let us consider a wireless sensor network with N nodes. There are N_1 nodes, whose exact locations are known (anchor nodes). The rest of the nodes $N_2 = N - N_1$ do not know their position (non-located nodes). Those algorithms are normally divided in two steps. The first one is the measurement phase in which the algorithm uses some range measurement in order to obtain distance estimates. The second one is the location-update phase, in which by means of using the estimates obtained at the first phase and the nodes state information, the algorithm computes the position estimates.

2.4.1 Measurement Phase

As commented above, this section focuses on RSS-based cooperative approach. In this kind of algorithms the first phase of the algorithm consists in obtaining internode distances, in this case, by means of RSS measurements.

The simplicity of RSS-based measurements arises from the fact that they are extracted from normal transmission. Hence, they do not require extra hardware to be measured. Although they are more unpredictable measurements, they become a very attractive ranging method for practical implementation.

The most common sources of error that affect RSS-based distance estimations are shadowing and multipath signals, which complicate the modelling of the channel that nodes need to know a priori. Usually, RSS measurements are modelled through the well-known radio-propagation path loss and shadowing model [Pat01]. Received power is modelled as a log-normal distributed random variable with a distance dependant mean. Hence, power received in node *j* from a signal transmitted by node i, P_{ij} , is expressed as:

$$RSS_{ij} = P_{ij} = P_0 - 10\alpha_{ij} \log_{10} d_{ij} - v_{ij} \tag{2.11}$$

where P_0 is the power received in dBm at 1 m distance, d_{ij} is the distance between nodes i and j in meters, parameter α_{ij} is the path loss exponent, i.e. the rate at which the power decreases with distance, and $v_{ij} \approx \mathcal{N}(0, \sigma_{dB}^2)$ represents log-normal shadow-fading effects, where the value of the standard deviation σ_{dB} depends on the characteristics of the environment. The small-scale fading effects are diminished [Pat01] by time averaging; hence they do not affect the distribution of v_{ij}. Since, static scenarios are considered the major sources of error are shadowing and path loss.

In [Has93], the authors discuss that the lognormal distribution is often used to explain the large scale variations of the signal amplitudes in multipath fading environments. References inside [Has93] present the validity of this model for modelling an indoor radio channel. Some results show that lognormal fits better than the Rayleigh model. Furthermore, large scale variations of data collected at 900 MHz, 1800 MHz and 2.3 GHz for transmission into and within buildings were found to be lognormal.

Given the received power RSS_{ij} in Equation (2.11), the density of P_{ij} is [Pat03]:

$$f_{P|\gamma}(P_{ij}|\gamma) = \frac{\frac{10}{\log 10}}{\sqrt{2\pi\sigma_{dB}^2}} \frac{1}{P_{ij}} \exp\left(-\frac{1}{8} \left(\frac{10\alpha}{\sigma_{dB} \log 10} \right)^2 \left(\log \left(\frac{d_{ij}^2}{d_0 \left(\frac{P_0}{P_{ij}} \right)^{\frac{2}{\alpha}}} \right) \right)^2 \right). \tag{2.12}$$

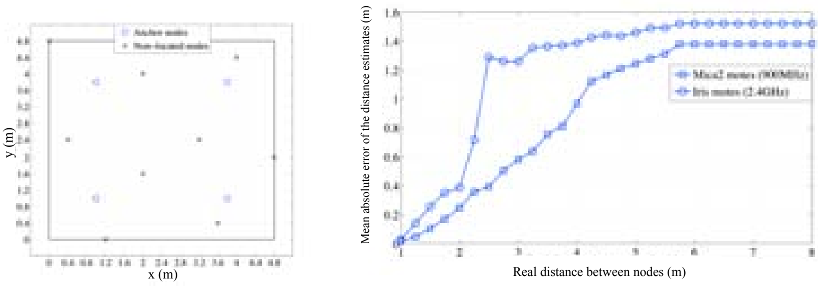
It is worth noting that P_0 and P_{ij} are not expressed in dBm, they are expressed in lineal. Having the equation in (2.12), an ML estimate of the distance d_{ij} could be derived as [Pat03]:

$$\delta_{ij} = 10^{\frac{P_0 - RSS_{ij}}{10\alpha_{ij}}} \tag{2.13}$$

An important result of the log-normal model is that RSS-based distance estimates have variance proportional to their actual range [Pat05]. The standard deviation in decibels is considered constant with range. This consideration implies that the multiplicative factors are constant with range; hence, this explains the multiplicative error present in the RSS-based distance estimates.

Accuracy Results

In order to check the accuracy of the distance estimates obtained through RSS measurements different experimental values are shown below. The experimental values are extracted in different scenarios and for different motes. In Figure 2.7 a comparison between mica2 and iris motes from Crossbow [Xbo] is shown. Mica2 motes transmit at 900 MHz while Iris motes transmit at 2.4 GHz. Results demonstrate that the higher distance between nodes the higher the error of the distance estimate. The presence of a multiplicative error presented in [Pat05] is observed in the obtained results. Also one can observe that RF transmissions at 900 MHz are less affected by the shadowing and multipath effects. Hence the accuracy of the distance estimates are better than those obtained at 2.4 GHz.

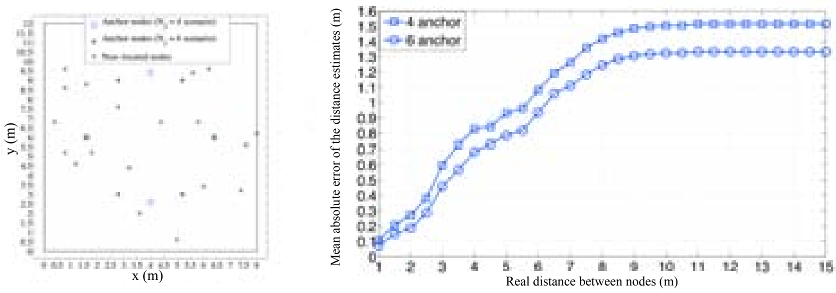


(a) Experimental scenario

(b) Mean error on distance estimates (δ_{ij}) vs. real distance between nodes

Figure 2.7: Accuracy of distance estimates in an indoor scenario (Comparison between two different motes)

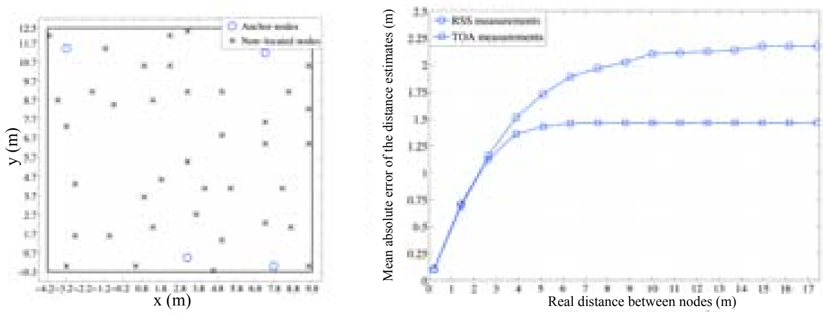
In Figure 2.8(b) both results are based on mica2 measurements. The density of nodes is increased by means of increasing the number of anchor nodes (N_1). The resulting effect is a reduction of the distance estimates' error. The improvement obtained oscillates between 0.1 and 0.2 cm. The difference between having a high density of nodes, hence a high number of closer nodes, is minimally shown in these results because node density has only varied from 0.25 $\mathrm{nodes/m^2}$ to 0.27 $\mathrm{nodes/m^2}$.



(a) Experimental scenario (b) Mean error on distance estimates (δ_{ij}) vs. real distance between nodes

Figure 2.8: Accuracy of distance estimates in an indoor scenario *(Comparison between different number of anchors (N_1))*

Finally in Figure 2.9(b) a comparison between TOA and RSS-based distance estimation accuracy is shown. The time and power measurements are obtained from [Pat]. The results show that the best accuracy, as expected, is obtained with time measurements. The difference between both methods is, approximately, 75 cm. The accuracies of both measurements are only comparable when the real distance between nodes are below 3 meters.



(a) Experimental scenario (b) Mean error on distance estimates (δ_{ij}) vs. real distance between nodes

Figure 2.9: Accuracy of distance estimates in an indoor scenario (*Measurements extracted from [Pat]*)

2.4.2 Location Update Phase

Once the relative distances between nodes are obtained, the main goal is to estimate the location of the non-located nodes with the help of anchor nodes and the rest of nodes in the network.

As previously commented, in a distributed cooperative algorithm each node estimates its own position by means of using information of all its neighbours. These kind of methods could increase the accuracy and the scalability. From the previous distributed approaches presented, this chapter will be focus in a non-bayesian Least Square approach, which is a method that achieves a good accuracy with a reduced complexity. The proposed methods that will be presented in the following chapter are based on this method due to its simplicity. Moreover, the distributed LS method has become an easy-deployable method able to be used in WSN, as it will be seen later.

The position estimates for each non-located node are obtained by means of the least squares (LS) criterion. The localization algorithm has to obtain the set of non-located node positions that minimize the difference between estimated distances at the first phase (δ) and the distances computed using such position estimates (d). In particular, the problem consists in minimizing the following cost function:

$$C_{LS}(\mathbf{x}) = \sum_{i=1}^{N_2} \sum_{j \epsilon S_i} \left(\delta_{ij} - d_{ij}\left(\mathbf{x_i} - \mathbf{x_j}\right)\right)^2 . \tag{2.14}$$

where $d_{ij}(\mathbf{x}_i - \mathbf{x}_j) = \|\mathbf{x}_i - \mathbf{x}_j\|$ is the distance between nodes *i* and *j*, calculated with the estimated position (or real coordinates if node *j* is an anchor) of nodes *i* and *j*, $S_{\ i}$ is the group of nodes (anchor and non-located) that cooperates in the position estimation of non-located node i, and **x** are the coordinates of nodes.

The cost function is minimized by means of optimizing the non-located nodes coordinates. The minimization will be obtained by means of calculating the derivative of (2.14) with respect to $\mathbf{x}_{\,i}$:

$$\frac{\partial C_{LS}}{\partial \mathbf{x_i}} = \sum_{j \in S_i} \frac{\left(\delta_{ij} - d_{ij}\right)^2}{\partial \mathbf{x_i}} + \sum_{k \in S_i} \frac{\left(\delta_{ki} - d_{ki}\right)^2}{\partial \mathbf{x_i}} . \tag{2.15}$$

Measurements of the second summation are not available in node i [Wym09], i.e. the RSS_{ki} is the measurement of the power received at the node k from node i. If we want to include these measurements, each node k should retransmit this value to the node i. The number of message is increased. As a result, the cost function adopted by each node can be rewritten as:

$$C_{DLS}(\mathbf{x}_i) = \sum_{j \in S_i} \left(\delta_{ij} - d(\mathbf{x}_i - \mathbf{x}_j)\right)^2 . \tag{2.16}$$

A distributed cost function results, so each node is responsible of obtaining the minimization of this cost function. Many methods could be applied in order to solve this minimization. A gradient descent is one of the simplest approaches. Hence, the distributed cost function in (2.16) is iteratively minimized. These algorithms may not reach a global minimum when a good starting point is not used. Nevertheless, it is a simple method with a low computational complexity.

The gradient of the cost function is:

$$\nabla_{\mathbf{x}_i} C_{DLS}(\mathbf{x}_i) = \nabla_{\mathbf{x}_i} \left(\sum_{j \epsilon S_i} (\delta_{ij} - ||\mathbf{x}_i - \mathbf{x}_j||)^2 \right) = \sum_{j \epsilon S_i} \left(\delta_{ij} - d_{ij}\left(\mathbf{x}_i - \mathbf{x}_j\right)\right) \mathbf{e_{ij}}, \tag{2.17}$$

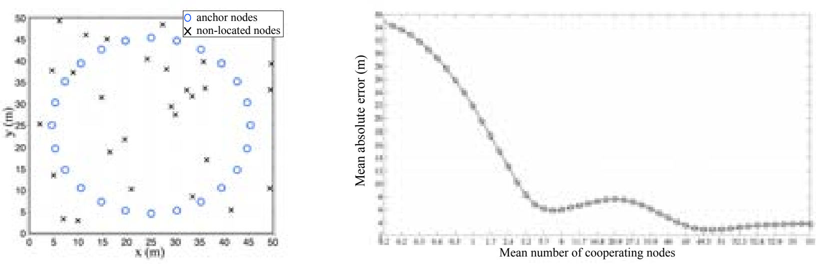
where $\mathbf{e_{ij}} = \frac{\mathbf{x_i} - \mathbf{x_i}}{||\mathbf{x_i} - \mathbf{x_j}||}$ is the unit vector that takes the orientation between the node i and node j. So, the estimate of $\mathbf{x_i}$, can be iteratively computed by using the gradient descent algorithm as follows:

$$\hat{\mathbf{x}}_i(t+1) = \hat{\mathbf{x}}_i(t) + \gamma \sum_{j \epsilon S_i} (\delta_{ij} - d_{ij}) \mathbf{e_{ij}}, \tag{2.18}$$

where γ is the step length factor.

This algorithm becomes a simple, low computational approach that obtains position estimates in a cooperative and distributed way by means of RSS measurements.

Accuracy Results



(a) Experimental scenario

(b) Mean absolute error versus mean number of cooperating nodes (24 anchor nodes).

Figure 2.10: Accuracy of the location update phase (Distributed LS algorithm).

In Figure 2.10, a WSN scenario of 50 m x 50 m with 24 anchor nodes and 30 non-located nodes normally distributed is considered. One can observe in Figure 2.10(a) that the anchors are distributed following the optimal position presented in [Ash08].

The mean absolute error obtained in the position estimates as a function of the number of cooperating nodes is presented in Figure 2.10(b). As commented previously, the higher the number of cooperating nodes, the lower the error obtained. However, it is remarkable that the error is not monotonically decreasing and the error is saturated for high values of cooperating nodes. This is basically due to the effect commented previously: having a node further away produces a higher error in the distance estimate.

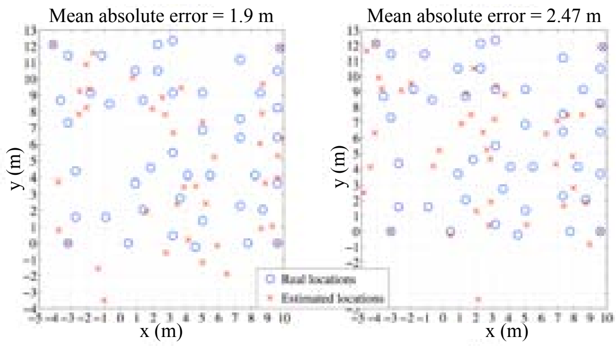


Figure 2.11: Comparison of position estimates obtain with TOA-based vs. RSS-based

Taking the measurements of [Pat] the results show the difference, in terms of accuracy, between TOA-based or RSS-based measurements. As it is shown previously in Figure 2.9(b), the accuracy of the internode distance estimates is higher when TOA-based is used. This fact is reflect in the mean absolute error obtained with both cases. The location coordinates obtained with TOA-based have, in mean, a mean error 0.5 m lower than the results of RSS-based algorithm. As previously commented, if the accuracy is the major requirement of the algorithm, TOA-based approaches are the most suitable solutions. On the contrary, if the algorithm considers that the simplicity is more important that the accuracy, RSS-based solutions will be more suitable.

2.5 Tracking Algorithms in Wireless Sensor Networks

The actual increase trend of implanting wireless sensor networks has helped the appearance of many different applications. One of them is the target tracking. The final purpose of this application is to determine the presence of an object inside the network and to estimate the path that this object follows. The introduction of these techniques could be applied to many final applications.

Moreover, wireless sensor networks have some limitations that have to be taken into account at the time of designing a tracking algorithm. Limitations in energy, the processing capacity of nodes, a reduced bandwidth of transmissions or the looses of communication in large networks are the main drawbacks that a wireless sensor network suffers. Trying to obtain algorithms that avoid these obstacles has become of interest, in recent years, for researchers.

In [Li10, Bha09], both works present a classification of the different existing methods. A very useful classification is the one based on the network architecture. The authors in [Li10] propose two different kind of networks: hierarchical and peer-to-peer. Tracking algorithms are divided in two main categories depending on the structure of the network in which the algorithm will be used. In Figure 2.12, a network-based classification tree is presented.

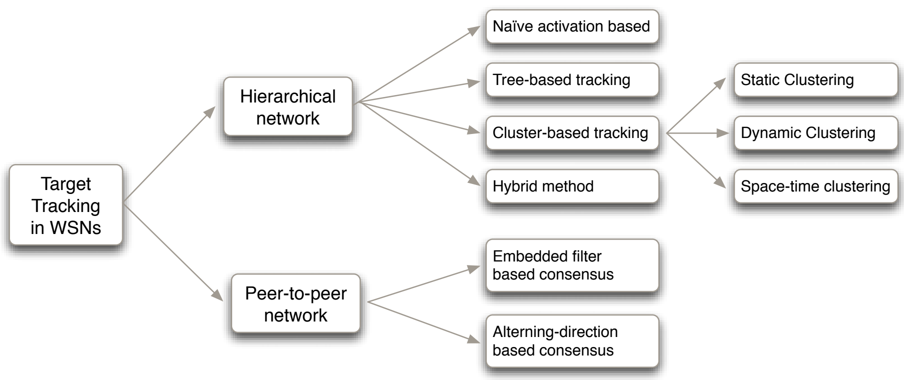


Figure 2.12: Classification of tracking algorithms in WSNs Classification extracted from [Li10]

In the following subsections the different tracking methods, organized using the classification in Figure 2.12, will be presented.

2.5.1 Tracking Methods for Hierarchical Networks

Hierarchical networks are those networks in which nodes are able to monitor and report the information to a sink or central node in a multihop-based communication. It is possible to differentiate between normal nodes and sink nodes. First ones are those nodes that report the information collected to the sink nodes; and sink nodes are those that receives all information and transmit they to an outdoor network. Hence, the network force a hierarchy between normal nodes and sinks.

Naïve-based Activation Tracking

The naïve-based tracking algorithms [Guo03] are those methods in which all nodes are active during all time. Nodes recollect measurements and they send them to a base station, which is the responsible of estimating the position and predicting the track of the target. These methods are similar to the centralized approaches presented in section 2.3.2. On the one hand, they offer a good accuracy. On the other hand, they are the worst algorithms in terms of energy efficiency.

Tree-based Tracking

In order to improve the efficiency of the previous algorithms, tree-based tracking is proposed. One can find in the literature different methods such as: STUN [Kun03], DCTC [Zha04], DAT [Lin06] and DOT [Tsa07].

- **Scalable Tracking Using Networked sensors (STUN)**

  In this tree-based algorithm nodes that are the responsible to track the target are the normal nodes. Although they do not estimate the target path. The information collected by these normal nodes is sent to the sink nodes using intermediating nodes.

  In order to avoid sending correlated information, these intermediating nodes do not act only as repeating nodes. When they receive information they compare with the information sent at a previous time. If the information is similar to the previous one, the intermediating node discard this new packet received.

  Moreover, STUN algorithms are also characterized by the assignation of a cost value to every link. These cost is related with the Euclidean distance between nodes. Hence, the algorithm give a higher weight to closer nodes in order to achieve a higher tracking accuracy.

- **Dynamic Convoy Tree-Based Collaboration (DCTC)**

  The DCTC is an algorithm that relies on a tree structure that is dynamically changed. The algorithm has the possibility of including or extracting nodes from the tree as the target moves. Once the target enters in a detection region, the nodes that detect the target collaborate between them to form a tree and select a root. This root collects all the information and tries to refine the information collected by the nodes. The root is the responsible for estimating the future path of the target and, hence, activate or deactivate the necessary nodes.

- **Deviation Avoidance Tree (DAT)**

  The DAT algorithm propose a new tree structure for the tracking algorithm. The algorithm has to different stages: firstly the approach tries to reduce the update cost, while the second part tries to reduce the query cost. The first stage tries to reduce the communication cost of location update through two different solutions: the deviation-avoidance tree and the zone-based deviation-avoidance tree. A query cost reduction algorithm is developed for the second stage, that adjusts the tracking tree formed at the previous stage in order to minimize the cost.

  Results in [Lin06] show that Z-DAT and DAT offers similar results and outperforms the results obtained with a Naïve algorithm. In both features analysed, query cost and update cost, the two developed approaches obtain better results.

- **Dynamic Object Tracking (DOT)**

  The DOT is developed in order to obtain an accurate and energy efficient tracking algorithm. The algorithm achieves an energy consumption reduction through the activation of only the necessary nodes. The nodes collect the neighbour information through a hello message. Thanks to this information, the nodes create links with their neighbour nodes, forming the Gabriel graph. Then the source that wants to track the target sends a request to the nodes of the network. Nodes that sense the target judges whether they are near-node or not. If this node considers that is a near-node, it replies with a message to the source. Then the near-nodes awake the neighbouring nodes that will help to track the path of the mobile node.

Cluster-based Tracking

The main purpose of the appearance of these methods is to facilitate the collaborative data processing in centralized networks. The major cons is the lower grade of scalability of these kind of networks. These algorithms divides the network into clusters. These clusters are formed by a cluster head and several slave nodes. The different clustering methods are presented in the following paragraphs.

- **Static Clustering**

  Static clustering has become the simplest strategy. The different clusters are decided at the beginning and they are fixed. Although it is a simple method, this method has many drawbacks. The algorithm is not adaptable to dynamic scenarios. The first distribution decided a priori could not be the optimal one in order to accurately track the target. Also, the possibility of sharing information between slave nodes of different clusters is prohibited. Hence, the cooperation between is really limited. Moreover, when the network distribution is fixed, the failure of a cluster head node could cause a failure of the entire algorithm; because, cluster head are the only nodes that could communicate with another clusters through the other cluster heads.

- **Dynamic Clustering**

  Compared to the previous scheme, dynamic algorithms form the cluster depending on different events. The normal procedure is the following. When a node senses a signal of interest with a high signal-to-noise ratio (SNR), it offers itself to act as a cluster head. If more than one node is offered, a decentralized procedure is applied in order to decide the best node. The rest of volunteer nodes are invited to become members of the cluster. In these algorithms, only one cluster is active, hence, the redundancy of information sensed by more than one anchor would be reduced. Moreover, a node could dynamically belong to as many cluster as necessary. Hence, at each time the dynamic clustering is using the best possible nodes. Although these algorithms reduce the energy consumption and take advantage of the most suitable nodes, the complexity is increased, compared to the static clustering.

  An example of a dynamic clustering algorithm is presented in [Olu07]. The algorithm works as following: when a node detects a target, it takes some measurements and gives them a weight through the Reduced Area REporting-Area (RARE-Area) algorithm. If this weight is above a threshold, node sends a beacon and waits until it receives two beacons from two different nodes. With the beacon information received the node is able to estimate the position through a trilateration method and to send the position estimate to the sink node.

  Moreover, authors also propose to use a Reduction of Active node REdundancy-Node (RARE-Node) algorithm. The main difference between using or not the RARE-Node algorithm as a complement of the RARE-Area algorithm is the following: if the RARE-area algorithm is only applied, the node that has a detection above a threshold and receives information from two different nodes sends the position estimate to the sink; if a RARE-Node algorithm is also applied, the nodes has to verify if there is any other node sending a broadcast message. Hence, the algorithm tries to minimize the redundancy of information sent to the sink.

- **Space-time Clustering**

  The authors in [Pho03] present an algorithm with a high accuracy. As the previous approaches, the DSTC dynamically organises the cluster in order to better sense the target. The DSTC Localization algorithm [Fri03] is based upon the Closest Point of Approach (CPA) of a target to the nodes in the sensor network. CPA works as follow: sensor nodes receive a local maximum of an acoustic signal in time. Then, this sensor broadcasts the receiving time and the intensity value that it has sensed. After a set time, if a node has received at least 4 other CPAs, and is the receiver of the highest intensity CPA in its local area, then it declares itself to be a local cluster head, and estimates the source location as a weighted mean of CPA positions, with the square root of the CPA intensity as the weight. Only one source is the responsible of estimating the location per local spatial intensity maximum. The error obtained [Pho03] is approximately 4 meters when the number of nodes inside the cluster is higher than 20.

Hybrid Methods

The hybrid methods are those methods that accomplish different requirements of different methods. The following approaches form part of this category: Distributed Predictive Tracking (DPT) [Yan03], Dynamic Clustering for Acoustic Tracking (DCAT) [Che04] and Hierarchical Prediction Strategy (HPS) [Wan08].

The main purpose of the DPT is to obtain a distributed and energy efficient tracking algorithm through a clustering algorithm. Once the clusters are formed, the border nodes of the clusters are always awake in order to sense if a node enter or leave the cluster. On the other hand, the other nodes only are able to sense if the cluster head allows them. The results show that the algorithm is robust in front of a possible node or estimation failure and it is capable to have a quick recovery to these failures.

The DCAT is a decentralized dynamic clustering based single target tracking algorithm. The algorithm forms the cluster through the Voronoi diagrams. Only one node, which receives an acoustic signal above a threshold, becomes an active cluster head. Then, it is the responsible of asking to the other nodes if they want to join the cluster. Hence, this new cluster is the responsible of estimating the target position. Once the position is estimated the cluster head retransmits the position to the network sink. The results [Che04] show an average error of 4.35 meters. Moreover, the lower value of messages transmitted compared to other approaches makes this algorithm be energy efficient.

The HPS algorithm forms the cluster through the Voronoi division and the target is positioned through a Least Square Method. The network is formed by two different nodes: normal nodes (NN) and cluster heads (CH). A hierarchy is assumed in the network in which NNs are only able to communicate with their CH, and CHs are able to communicate with other CHs and the NNs inside their cluster. The accuracy obtained is analysed depending on different features, such as the active radius, the number of clusters, etc. The accuracy achieved oscillates between 0.5 meters and 0.2 meters.

2.5.2 Tracking Methods for Peer-to-Peer Networks

In all the previous cluster or tree methods, many nodes are active to sense and all the information sensed by this nodes has to be processed at a central or cluster node. Hence, the central node has to be able to process a great amount of information. Furthermore, if a central node fails, the network could also fail.

Another kind of network structure is also deployed. The peer-to-peer networks offers the possibility of limiting the number of active nodes, as nodes only rely on one hop communication with their neighbours. Hence, many of the limitations that previous schemes have are not present in peer-to-peer networks. In the following sections the usual strategies are presented.

Embedded Filter Based Consensus

In peer-to-peer WSN is common to use distributed estimation algorithms that basically are based on successive refinements of the information collected by all nodes. As it is commented previously, these distributed strategies are formed by two stages. But the distributed strategies presented in section 2.3.2 are focused on a static environment. Hence, the dynamic case is still not contemplated.

The most common algorithms that takes into account the mobility of the nodes are the well-known Kalman Filter and their variants (Distributed Kalman Filter (DKF), Unscented Kalman Filter (UKF) or Extended Kalman Filter (EKF)). The role of consensus filters is to estimate global information but with the use only of neighbour information. In [OS07], the authors present three different DKF approaches. The first one is a modification of the work present in [OS05]. This method is a continuous-time DKF. The two following approaches, inspired in this first algorithm, are discrete-time Kalman-Consensus filtering. The followed objective of these two approaches is to reduce the disagreement of the estimates between nodes. In order to achieve this purpose, in the second approach is added an ad hoc consensus step, and a consensus term is added in the third approach. The best results are achieved with the third algorithm although the second DKF algorithm has a similar performance.

Another method inside this category are the Particle Filters (PF) [Aru02, Ahm10]. The PF is a suboptimal nonlinear filter that performs estimation using sequential Monte Carlo methods to represent the probability density function of the target state. Compared to the KF approaches, PF does not assume that the system and the measurement processes are linear. The major advantages between PF-based algorithms in front of nonlinear filter approaches, such as EKF, are: the presence or absence of the target is modelled by the probability function; the algorithm is able to track random movements of a target; the non-Gaussian noise in sensor readings could be incorporated in the filter; and, the detection of targets could be done at different levels.

The work presented in [Ahm10] divides the PF algorithm operation in three parts. First, the target model is presented. It is based in a binary Markov process that models the detection or not the target. Then the sensor model is presented. In this work, acoustic measurements are done. The nodes is made by calculating the variance of 1000 acoustic samples, that are model approximately as a Gaussian distributed measurement. Finally, the estimation algorithm is developed. The basic function of a particle filter is to approximate the posterior density of the target state, given all measurements, by a set of P points, called particles, and corresponding weights.

Alternating-direction Based Consensus

The appearance of the alternating-direction based consensus algorithms has been motivated by the continuously changing environment in which tracking algorithms are applied. All the approaches presented are based on the alternating-direction method of multipliers developed in [Ber97]. This numerical method has been proved to be efficient in solving the distributed estimation in [Sch08b, Sch08a].

This algorithms are considered adaptive algorithms based on in-network processing of distributed observations and they are useful for tracking signals in peer-to-peer networks. In [Sch09] a fully distributed distributed least mean squares (D-LMS) is developed. It offers a simple and flexible algorithm that minimizes the squared error cost. The algorithm is also robust in front of node failures that could affect the accuracy of the algorithm.

The authors in [For08] have also developed a distributed algorithm based on the expectation-maximization (EM) concept, more concretely a Consensus-based distributed expectation-maximization (CB-DEM) is presented. The EM algorithms are based on two steps. The E-steps rely on local information. The novelty of this algorithm is the reformulation of the M-step. In this step, the data collected is maximized. The presented algorithm divides the maximization into local subproblems that nodes has to solve iteratively by only communicating with their single-hop nodes, until a global consensus is reached. The simulations carried out demonstrate that the centralized and the distributed approaches presented reaches the same consensus, hence the distributed approach is a valid solution to be used.

2.6 RSS-based Tracking Algorithms

As it has been discussed previously in Section 2.2.2, the RSS measurements have become the simplest range measurements usable in wireless sensor networks. Our interest is focused on this kind of measurements due to their simplicity. Although the previous works can be used with any range measurement, a brief revision of the state-of-the-art of the RSS-based tracking algorithms is presented. In order to classify the methods, the algorithms will be divided depending on the model of the RSS measurements. Three different classifications will be used: connectivity-based, RSS radio map-based, and pathloss and shadowing-based algorithms.

2.6.1 Connectivity-based Algorithms

The tracking algorithm presented in [Cab07] is based on a dynamic weighted multidimensional scaling algorithm. The internode information is obtained through connectivity information. The authors use these range-free approaches instead of estimating distances using range measurements. This decision is made due to the poor accuracy that RSS-based distance estimates could offer. In this case RSS measurements are used to determine whether if nodes are connected or not.

Different results of the reconstruction error are presented. The values show that the higher value of the coverage radius, the higher the reconstruction error. Also the error is higher when the root mean square error (RMS) of the anchor positions is increased.

2.6.2 RSS Radio Map-based Algorithms

A work based on radio map is the one presented in [Zho06]. The Wireless Indoor Tracking System (WITS) needs a previous measurement campaign of the RSS. Different footprints at various known locations are collected at the final scenario. These measurements are stored and they are able to be used by the fixed network. When the mobile node receives a signal from a fixed access point, it obtains the RSS from the measurement and it retransmits the measurement to the access point. The access point converts the RSS measured by the mobile node into a position through the RSS radio map constructed a priori.

The authors in [Mor06] present a tracking system based on a priori map of RSS measurements. More concretely, the RSS received y_l at the mobile node position $\mathbf{x}_t$ is based on a log-normal stochastic model as:

$$y_l\left(\mathbf{x}_t\right) = \bar{y}_l\left(\mathbf{x}_t\right) + v_{l,t}\left(dBm\right), \tag{2.19}$$

where $\bar{y}_l\left(\mathbf{x}_t\right)$ is the effects of the static obstacles and attenuation propagation, a deterministic value obtained with a previous measurement campaign, and the random effects of people or small objects moving are represented as $v_{l,t} \sim \mathcal{N}\left(0, \sigma_l^2\left(\mathbf{x}_t\right)\right)$. Both variables, $\bar{y}_l\left(\mathbf{x}_t\right)$ and $v_{l,t}$, are deterministic and obtained through a previous measurement campaign. The same model is used in [Ber08].

2.6.3 Pathloss & Shadowing Model-based Algorithms

The work in [Guv03] obtains distance estimates through the RSS measurements. The authors has made an experimental study of the indoor attenuation. The attenuation between two nodes separated a distance d, known as Path Loss (PL) is given by:

$$PL = FSPL_{REF} + 10n\log_{10}(d), \tag{2.20}$$

where n is the attenuation factor or path loss exponent and the $FSPL_{REF}$ is the path loss calculated at the far-field of the antenna. The authors has carried out different experimental measurements and they present different polynomial function that fits the signal strength data for different floors. Also they present a table with the attenuation that presents different materials. Finally, they present a comparison between different bayesian tracking models. The best result is obtained with a Kalman smoother (it obtains a 2.48 m of mean error).

In [Ber08], authors have also presented another tracking system modelling the RSS measurements with the pathloss and shadowing model (see (2.4)). The mobile node sends a broadcast message to the network. The anchors store those messages that have an RSS higher than a RSS threshold. Then anchors estimate the distance thanks to the ML estimator of (2.13). They send these distance estimates and their IDs to the mobile node. Then, mobile node estimates its position by means of three different estimators: Maximum Likelihood, Least Squares and Maximum Ratio Combining. The results obtained show that ML obtains the best results. Errors oscillate between 0.2 m and 1.2 m. MRC obtains the worst errors. They oscillate between 0.25 m and 4.5 m.

Chapter 3

On-line Path Loss Estimation & Node Selection Localization Algorithm

WHEN a positioning algorithm is presented and compared with similar approaches the first figure of merit that developers remark is the accuracy that the algorithm offers. As previously commented, accuracy is not the unique purpose that a localization algorithm has to pursue and at some occasions, it could be less important than other figures of merit, such as energy consumption, scalability, complexity, etc.

In this chapter, we propose the introduction of two proposals: a node selection and an on-line path loss estimation mechanism. With both of them we try to fulfil the requirements imposed by the WSN characteristics by means of obtaining good accuracy results.

3.1 Introduction

One of the important characteristics of the WSN is that their components should be as energy efficient as possible. The nodes that conform a WSN are normally battery powered elements. An important purpose is to achieve a long-life network, hence it is necessary to save energy limiting the transmissions and developing energy-efficient algorithms.

In order to reduce the energy consumption, our proposal is to reduce the message exchange. Basically, our proposal reduces the energy consumption by means of introducing a node selection mechanism that will limit the number of nodes cooperating. With this mechanism, we try to achieve a good trade-off between accuracy versus energy consumption.

Furthermore, the simplest the method, the lowest the energy consumed. RSS measurements are the simplest way to obtain inter-node distances, hence a good option to be energy-efficient. As previously explained, these are the range-based measurements that offer less accuracy. This is highly related with the model used to obtain the distance estimates. Hence, the better the model, the more accurate estimates. For that reason, our proposal is to introduce an on-line path loss estimation. With this estimation, we to provide a better model that is able to adapt to every environment.

Moreover, the algorithm need not only be able to adapt to the environment, it also should be able to adapt to the size of the network. Scalability is another important design feature that has to be taken into account. Distributed approaches allow more scalability to the localization algorithm giving the opportunity to implement it in a small-scale or in a large-scale network. As previously commented, a distributed cooperative LS is the selected algorithm that will be modified by our proposals.

In this work, we focus on a cooperative distributed localization method based on RSS measurements. The choice of a distributed strategy is motivated by the desire to reduce the necessity of transmitting all the network information to a central node. With this adoption each node modifies, in the second phase, its own state through those estimated metrics and the nodes state information. We also adopt a cooperative technique. Although cooperative techniques could increase localization accuracy, cooperation with distant nodes could introduce a higher degradation in the estimate if RSS measurements are used. This is because the error introduced in the measurements can be multiplicative to the distance when RSS measurements are considered. In addition, allowing the cooperation with more nodes increase the consumption of energy. The introduction of node selection strategies allow to the localization algorithms to minimize the energy consumption and the cooperation with further nodes while maintaining location accuracy.

3.2 Scenario Description

Let us consider a wireless sensor network with N nodes. There are N_1 nodes, whose exact locations are known (anchor nodes). The rest of the nodes $N_2 = N - N_1$ do not know their position (non-located nodes). The main goal is to estimate the location of the non-located nodes with the help of anchor nodes and the rest of nodes in the network by means of a cooperative strategy. We consider an RSS-based distributed cooperative algorithm for location estimation. In the following table 3.1 are defined the basic parameters used in this chapter.

Table 3.1: Scenario Parameters.

Parameter	Description
N_2	Number of Non-Located Nodes
N_1	Number of Anchors
S_i	Vector of cooperating nodes
N_{S_i}	Number of elements of cooperating group
δ_{ij}	Distance estimate through RSS measurements
d_{ij}	Distance estimate through node coordinates
RSS_0	Received signal strength at a reference distance
α_{ij}	Path Loss exponent

3.2.1 First Phase - Measurement Phase

The first phase of a range based localization algorithm consists in obtaining internode distances through, in our case, RSS measurements. As previously commented, RSS-based distance estimates are obtained by means of modelling the power received with a radio propagation model. The most usual model used is the well known radio-propagation path loss and shadowing model. A more detailed explanation is presented in subsection 3.5.2.

3.2.2 Second Phase - Location-Update Phase

Once the relative distances between nodes are obtained, the position estimates for each non-located node are estimated by means of the least squares criterion. Position estimates are calculated by obtaining the set of non-located node positions and path loss exponents that minimize the difference between estimated distances at the first phase and the distances computed using such position estimates. In particular, the problem consists in minimizing the following cost function:

$$C_{LS}(\mathbf{x}, \boldsymbol{\alpha}) = \sum_{i=1}^{N_2} \sum_{j \epsilon S_i} (\delta_{ij}(\alpha_{ij}) - d_{ij}(\mathbf{x}_i, \mathbf{x}_j))^2, \tag{3.1}$$

where $d_{ij}(\mathbf{x}_i, \mathbf{x}_j) = ||\mathbf{x}_i \mathbf{x}_j||$ is the distance between nodes i and j, calculated with the estimated position (or real coordinates if node j is an anchor) of nodes i and j, S_i is the group of nodes (anchor and non-located) that cooperates in the position estimation of non-located node$i$, **x** are the coordinates of nodes, and α the set of all path loss exponents of all links. The minimization of the cost function is carried out in a distributed fashion by means of using a gradient descent approach. We adopt a distributed strategy due to its scalability and robustness. A more in-depth explanation is carried out in subsection 3.5.4.

3.3 Energy Consumption

Wireless sensor networks nodes rely on low data rates, very long battery life (several months or even years) and very low computational complexity associated with the processing and communication of the collected information across the WSN. In order to maintain the battery life, the reduction of the energy consumption is an important point in WSN. In that sense, many works present different approaches to model the energy consumed by a WSN [Zou03, San09, Wan06, Mal07, Hei02].

The majority of these works presents a model that depends on the energy transmission per bit, hence, per message. The models presented in [Zou03, San09] model the energy consumption as the sum of the energy cost of transmission and the energy cost of reception. Hence, as the number of nodes that receive or transmit increases, the energy consumed by a node is higher.

In [Mal07], the authors present the transmission and the reception costs, using the CC2420 specifications. The transmission cost is composed by the sum of two terms: the transmission startup cost P_{T0}, and the cost of the power amplifier to transmit the packet P_{TA}. More concretely, the total energy consumed per transmission is:

$$P_T = P_{T0} + P_{TA} = V\, P_{ROON}\, T_{startup} + C_{plevel}\, (L/T_{rate}), \tag{3.2}$$

where V is the voltage determined by the current battery voltage; P_{ROON} is the current usage of the state *Radio On Oscillator On*; $T_{startup}$ is the time needed to start the node; C_{plevel} the current necessary to transmit at a certain power level; *L* is the packet length in bits; and, T_{rate} is the necessary transmission rate in bits. On the other hand, the reception cost is modelled as:

$$P_R = V\, C_{Rx}\, (L/T_{rate}), \tag{3.3}$$

where C_{Rx} is the necessary current to receive a message. This model depends on the length in bits of the messages received or transmitted by the nodes.

The authors in [Hei02] introduces also a distance dependency on the power consumed at the transmission time. The model presented is:

$$E_T(d) = \begin{cases} E_{Telec} + \epsilon_{fs}\, d^2 & d < d_0 \\ E_{Telec} + \epsilon_{mp}\, d^4 & d \geq d_0 \end{cases} \tag{3.4}$$

where E_T is the energy consumed; E_{Telec} are energy consumption per bit not distance-dependant; ϵ_{fs} and ϵ_{mp} are energy consumption for both models, the free-space (fs) and the multipath (mp); d the distance between nodes; and d_0 a distance threshold. Another distance-dependent energy consumption model is presented in [Wan06]. In this occasion the model is defined by:

$$P_T(d) = P_{T0} + \frac{\epsilon\, d^{\alpha}}{\eta}, \tag{3.5}$$

where ϵ is a constant that depends on the power transmitted and the characteristics of the receiving and transmitting antennas; d is the distance; α is the pathloss exponent; and η is the ratio between of RF output power to DC input power and is called the drain efficiency. Both methods includes the necessity of knowing the distance between both nodes in order to estimate the power consumption necessary to reach a node located at a distance d.

Having in mind the different methods present in the literature, we notice that the energy consumption is basically dependant on the number of transmissions that are done by the nodes. Nodes only interact with their group of cooperating nodes. The reduction of cooperating obtained with our proposed node selection mechanism should imply an important reduction of the energy consumption. Now we present our energy consumption model in order to reflect the effects produced in the network.

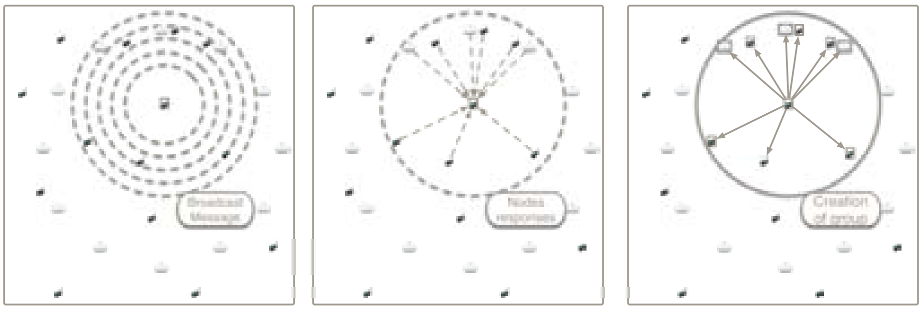


Figure 3.1: Creation of group S_i

Each node *i* has to create its own group of cooperating nodes S_i (see Figure 3.1). At the beginning, each node *i* sends a broadcast message with its coordinates. Only those nodes that receive this message answer with their node id and their location coordinates. With the received messages, each non-located node can create its own S_i group. Once these groups are created, the exchange of messages is only done between cooperating nodes.

Having the total number of cooperating nodes, we assume that the total amount of energy consumed by the network follows the model:

$$\epsilon = (\mu_{R_x} + \mu_{T_x}) \left(\sum_{i=1}^{N_2} N_{S_i} - N_2 \right) \kappa, \tag{3.6}$$

where κ is the number of iterations of the algorithm, N_{S_i} the number of nodes inside S_i, and μ_{R_x} and μ_{T_x} (e.g. a value equal to 400 nJ/sec is used in [Zou03]) are the energy consumption dedicated for peer to peer transmission and reception procedures, respectively. It is noticeable, that this model presents some differences compared with the model presented in [Zou03]. It is supposed that the energy per transmission is always the same instead of having an energy consumption depending on time. The purpose behind a node selection mechanism is the reduction of the traffic. Hence, the energy consumption model presented only reflects the impact that selection mechanisms could produce. Furthermore, it is only taken care of the energy consumption at the transmission and reception time.

The energy consumption is an increasing function on the number of cooperating nodes (N_{S_i}). The introduction of a node selection mechanism reduces the number of cooperating nodes; hence the energy consumption decreases.

Our energy consumption model reflects only the consumption in terms of messages transmitted. The node selection mechanism proposed is devoted to reduce the cooperation with more nodes; hence, less messages exchanged. For that reason, we only take into account the number of messages transmitted by a node inside a network, hence, we assumed a more general method that could be refined, if it takes into account issues such as, cost per bit or the cost of the power amplifier.

3.4 Node Selection Mechanisms

In this chapter, we focus on a cooperative distributed localization method based on RSS measurements. A cooperative approach allows the algorithm achieve better accuracy results. Nevertheless, the computational cost is increased because nodes receive more information from more cooperating nodes. Furthermore, a higher packet exchange in the network will be necessary; hence, it exists a higher probability of loosing packets due to a collision. Besides, cooperation with distant nodes could introduce a higher degradation in the estimate due to RSS measurements are considered. This is because the error introduced in the measurements are multiplicative to the distance.

The introduction of node selection strategies allow to the localization algorithms to minimize the energy consumption and the cooperation with further nodes while maintaining location accuracy.

More concretely, the benefits of a node selection mechanism are:

- Reducing the number of cooperating nodes; hence, following the previous energy consumption model, a reduction of the energy consumption.
- Reducing the number of packet exchanges inside the network; hence, the probability of packet collisions is reduced.
- Decreasing the probability of working with further nodes; hence, the multiplicative errors of the RSS-based distance estimates achieved are lower.

The results of Figure 2.10 of the previous chapter show that a reduction of the number of cooperating nodes does not seriously affect the accuracy of the localization algorithm. The mean absolute error versus the mean number of cooperating nodes ($\bar{N}_{S_i}$) is not a monotonically decreasing function. A local minimum, that has a similar value to the global minimum, is achieved with a lower number of cooperating nodes.

3.4.1 Related Work

In order to avoid the use of a large number of cooperating nodes, i.e. having a lower number of nodes inside each group S_i, different node selection mechanisms are proposed. The major purpose behind the node selection is to reduce the packet exchange inside the network, thus the reduction of computational effort done by each node and the energy consumed by them. Some works have presented different approaches in order to select those nodes that will cooperate with each non-located node.

In [Tam06], authors present a non-cooperative micro-genetic algorithm (MGA) in order to select nodes and improve the localization in WSN. The adaptation of the MGA presented is based on 3 steps: a first construction of a small population of chromosomes based on the best-values of position estimation; secondly, a genetic operator called descend-based mutation is applied; and finally a second genetic operator called crossover operator is used. The basic idea is to first select best nodes (done at the first step) and then applying both genetic operators to the chromosomes (a.k.a. nodes) in order to converge to a final solution. The results obtained are, in mean, 0.2 times the node range *R*.

In [Lie08] the authors propose to select nodes by means of the Crámer-Rao Bound (CRB), instead of using the closest nodes. The algorithm calculates the CRB of all the reference nodes that a node receives and selects those nodes with a lower CRB. Results obtained show that with a number of 8 reference nodes the location error is, approximately, 7 meters if RSS-based distance measurements are used. On the other hand, 0.8 meters of error is achieved if TOA-based distance estimates are used.

In [Das11], the authors present a censoring method based also on the CRB. The algorithm censors those nodes with unreliable estimation. Based on the CRB calculation, the authors propose a criterion that will reflect the quality of the information that a node transmits as well as the geometry of the positions of the anchors and non-located nodes. Three methods of censoring are presented in the work: the first one is the one in which nodes can censor itself, i.e. each node can decide not to broadcast its own information; the second one, blocks the reception of information from the neighbours considered not reliable; and finally, the last one is created to avoid an unnecessary transmission when a node is censored by all their neighbours, i.e. a node receive the order of not transmitting because all their neighbours have censored it. All these censoring methods are executed through the calculation of the CRB and its comparison with a threshold imposed by the algorithm. With the inclusion of all these censoring methods, the authors obtain a reduction in complexity and in network traffic, while the position accuracy is maintained.

All methods achieve in their results a high reduction of messages exchanged. A comparison between distance-based and CRB-based selection is done in [Lie08]. On the one hand, better results are achieved when the CRB is used to select cooperating nodes, e.g. differences between 2.5 meters with 3 cooperating nodes and 0.3 meters with 10 cooperating are presented in the location error. On the other hand, the distance-based selection does not require any extra calculation at the time of deciding which nodes are the best to cooperate.

In the works developed in [Kap06a, Kap06b], the author present two different node selection mechanisms: a global node selection (GNS) and a local node selection (LNS) mechanism. GNS and LNS are mainly based on obtaining an active set of nodes $\mathcal{N}_a$ that minimizes the mean square position error. The difference between the GNS and LNS is the possible candidates to be part of the active set. In the GNS there is no restriction. All the nodes could take part in the localization algorithm. On the other hand, in the LNS the possible candidates are only those nodes that have been active at the previous snapshot. The algorithm also introduces a second stage, called discovering stage, that allows to inactive nodes the possibility of joining the active set.

Finally, in [Zog10] the authors present a comparison between two different selection algorithms: the GNS presented in [Kap06a] and a modification of the closest approach called Spatial Split (SS). Based on the GDOP concept the SS algorithm creates a number of partitions of the radio region, selects the closest nodes and calculates a cost function. Then, it changes the starting point for partitioning and begins another time the previous steps. The active set $\mathcal{N}_a$ will be these set with the lowest value of the cost function. The authors also present an Adaptive Sensor Selection (ASS) algorithm that adapts the number of active nodes depending on an innovating vector. The error achieved by the SS and the GNS, when a number of 6 active nodes is used, is approximately 5 meters. If those algorithms uses the ASS the RMS position error that the tracking algorithm achieves is approximately 1 meter (when 6 nodes are active).

All the methods presented, although they obtained good accuracy results, are complex. The major premise that we follow is to achieve an algorithm as simple as possible. For that reason, our proposals want to reduce the complexity of calculation of the works presented. More concretely, we want to achieve a node selection mechanism easy to implement but without loosing accuracy.

Which is the best criterion in order to select the nodes that will cooperate in the location-update phase? With this question in mind, and taking a look in existing methods presented at the beginning of the section, three node selection criteria are proposed and studied.

The purpose that the node selection approach has to maintain is not to increase the complexity of the localization algorithm. All the node selection mechanisms are related with the measurements that a node can do without any extra requirement.

In order to take the advantage of the RSS measurements, the node selection mechanisms presented will depend on them. Hence node selection criteria does not impose any extra measurement. With those selection mechanisms a reduction of the number of nodes that cooperates in the location algorithm and also of the energy consumption of the network is achieved.

3.4.2 RSS-based Criterion

The basic idea of an RSS-based criterion is to select only those nodes that have an RSS above a threshold. In other words, considering a cooperative scenario, one node is only allowed to cooperate with those nodes having an RSS higher than a specific threshold RSS_{th} (i.e., node j cooperates with node i if $RSS_{ij} \geq RSS_{th}$).

In Figure 3.2 it is shown that lower errors can be obtained with a lower threshold, i.e. by allowing the cooperation with a higher number of nodes. However, it is remarkable that the error is not monotonically decreasing and the error is saturated for

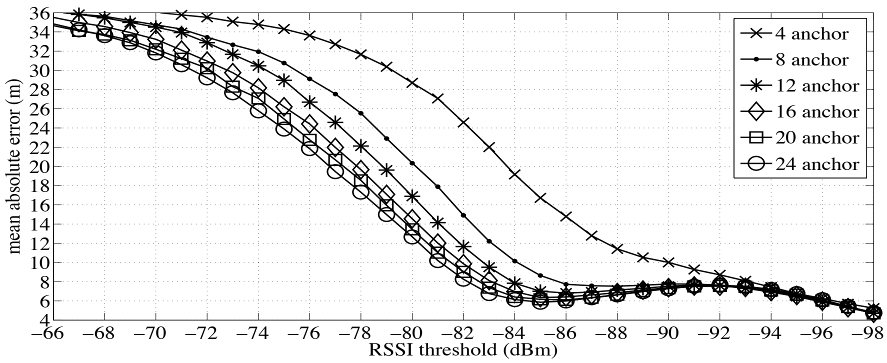


Figure 3.2: Mean absolute error versus RSS_{th} for different number of anchor nodes

low thresholds values. This is basically due to the effects commented previously that having a further node becomes in a higher error in distance estimate.

Furthermore, the error obtains the global minimum when the RSS_{th} is decreased. This effect is due to the existence of more anchor nodes inside the cooperating group S_i. Those nodes provide a more reliable information to the non-located node. Hence, more accurate results should be obtained.

As the difference between the global and the local minimum, in terms of accuracy, is not remarkable (a difference of few cm is obtained), a node selection criterion is proposed to be used. We propose to limit the number of cooperating nodes by selecting a threshold value that provides an appropriate error value in terms of position accuracy. The use of a selection threshold is aligned with the WSN philosophy in terms of reduced complexity, size and cost of the terminals. By doing so, the number of cooperating nodes, those within group S_i, is reduced and energy efficiency can be improved. For example, the difference in terms of error is minimal with a threshold of -88 dBm or -95 dBm but the number of cooperating nodes can be further reduced with the first option, i.e. thus reducing energy consumption.

In order to select an appropriate RSS threshold, the use of an exhaustive search based on computer simulations is mandatory, due to the complexity involved in the problem at hand. The procedure is even more complex when the large variety of possible scenarios is taken into consideration. In order to avoid that, a simpler method is proposed.

Basically, the idea is to select the highest RSS threshold that assures that a minimum number of anchor nodes are cooperating with the considered non-located node. Clearly, this criterion also implies that a set of non-located nodes will be also present in the region of interest for cooperation purposes. In particular, the mean number of anchors is firstly fixed and, using this number, the RSS threshold is obtained. This methodology provides a closed-form expression to obtain the required threshold for each possible scenario. In the following lines, it is presented how such closed-form expressions could be obtained.

The number of anchor nodes inside the range of node i is (see Figure 3.3):

$$N_{anchor}^{(x_i,y_i)} = \sum_{j=1}^{N_1} I(||(x_i, y_i) - (x_j^a, y_j^a)|| < r_{th}) \tag{3.7}$$

where $I()$ is the indicator function (i.e. $I(a)$=1 if a is true) and (x_i, y_i) and (x_j^a, y_j^a) are the coordinates of the non-located node i and anchor node j, respectively.

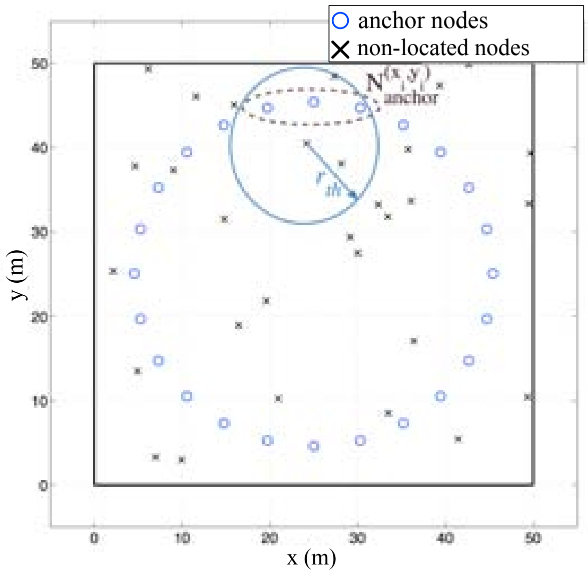


Figure 3.3: Number of anchor nodes inside the radio range of a node

Then, the mean number of anchor nodes inside the range of node i is:

$$N_{m_i} = \int_x \int_y N_{anchor}^{(x_i,y_i)} f(x_i, y_i) dx_i dy_i \tag{3.8}$$

where $f(x, y)$ is the p.d.f of the nodes position distribution along the area. Without loss of generality, a uniform distribution of the non-located nodes in the network is considered (for a given time realization). Introducing (3.7) in (3.8) we obtain:

$$N_m = \int_x \int_y \sum_{j=1}^{N_1} I(||(x_i, y_i) - (x_j^a, y_j^a)|| < r_{th}) \frac{1}{A} dx_i dy_i \tag{3.9}$$

where A is the total area of the considered scenario. Since the nodes are uniformly distributed the mean number of anchor nodes inside a radius r_{th} becomes:

$$N_m \approx \sum_{j=1}^{N_1} \pi r_{th}^2 \frac{1}{A} = \frac{N_1 \pi r_{th}^2}{A} \tag{3.10}$$

Once the closed-form expression in (3.10) is obtained, the dependency of the coverage range radius with the RSS threshold has to be established. Two different approximations based on different propagation models will be considered.

Pathloss model

In this case, the pathloss model dependency is only considered. In other words, the received power is modelled as a function inversely proportional to the distance elevated to the pathloss exponent.

$$RSS^{PL} = \frac{P_0}{r^\alpha} \tag{3.11}$$

If the expression of r_{th} obtained from (3.10) is introduced in (3.11), the RSS threshold becomes:

$$RSS_{th}^{PL} = \left(\frac{N_1 \pi P_0^{2/\alpha}}{N_m A} \right)^{\alpha/2} \tag{3.12}$$

Pathloss & shadowing model

In this case, the effects of path loss and shadowing that appear in (2.11) are both considered. The relation between radio range radius and received power is expressed as follows:

$$RSS^{PL\&S} = \frac{P_0}{r^\alpha} z \tag{3.13}$$

being z a log-normal variable, $\mathbf{z} = \mathbf{10^{v/10}} \sim \log\mathcal{N}(\mathbf{0}, \sigma_{\mathbf{v}}^{\mathbf{2}})$. Therefore, the mean number of anchor nodes is, in this case, a random variable $\mathbf{n_m}$. Taking this into account, the mean value of $\mathbf{n_m}$ has to be search. Using the value of the r_{th} in (3.10) and being $E[z] = e^{\mu_v + \frac{1}{2}\sigma_v^2}$ the mean of a lognormal variable, it can be written:

$$\begin{aligned} N_m = E[\mathbf{n}_m] &= \frac{\pi N_1}{A} \left(\frac{P_0}{RSS_{th}^{PL\&S}} \right)^{2/\alpha} E[\mathbf{z}^{2/\alpha}] \\ &= \frac{\pi N_1}{A} \frac{P_0^{2/\alpha}}{\left(RSS_{th}^{PL\&S}\right)^{2/\alpha}} e^{\frac{1}{2}\frac{4\sigma_v^2 (\log 10)^2}{\alpha^2 100}} \end{aligned} \tag{3.14}$$

As in the previous case, this dependency is combined with (3.10) and the result is the following RSS threshold:

$$RSS_{th}^{PL\&S} = \left(\frac{N_1 \pi P_0^{2/\alpha} e^{\frac{\sigma_v^2 2(\log 10)^2}{100\alpha^2}}}{N_m A} \right)^{\alpha/2} \tag{3.15}$$

As observed, (3.12) and (3.15) allow the computation of the required threshold in terms of the desired mean number of anchor nodes (N_m).

In order to show the validity of the obtained expressions, in Figure 3.4 such approximations are compared with the real dependency of N_m with the RSS threshold obtained by means of computer simulations. The three different thresholds shown are: RSS_{th}^{sim}, which is the RSS threshold obtained with simulations that assures a number N_m of anchor nodes; RSS_{th}^{PL}, which is the RSS threshold obtained with (3.12) (pathloss model); and $RSS_{th}^{PL\&S}$, which is the RSS threshold obtained with (3.15) (pathloss & shadowing model).

As observed in Figure 3.4, both equations achieve a good approximation when high values of RSS threshold are considered. For low values of RSS threshold the behaviour of both approximations becomes worse. This is because the N_m value of the (3.8) is obtained by disregarding the edges of the area (see Figure 3.5). Therefore, as the RSS threshold is reduced, the coverage radius increases and an extra area outside the edges is considered. As observed in the following, this effect has not a big impact on the presented design as it is focused on selecting only the closest nodes. Besides, Figure 3.4

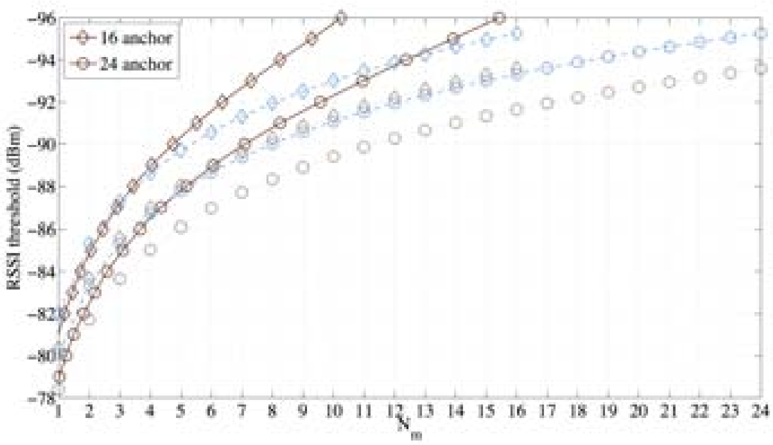


Figure 3.4: RSS threshold versus mean number of anchor nodes (*(solid line* RSS_{th}^{sim}*, dashed line* RSS_{th}^{PL}*, dashed-dotted line* $RSS_{th}^{PL\&S}$*)*)

shows that the best approximation is obtained with the pathloss model ((3.10)) and for that reason we focus on this scheme in the sequel. The problem with the approximation given by (3.15) is that the shadowing effects over-estimate the RSS when the power is expressed in lineal (as adopted in (3.15)).

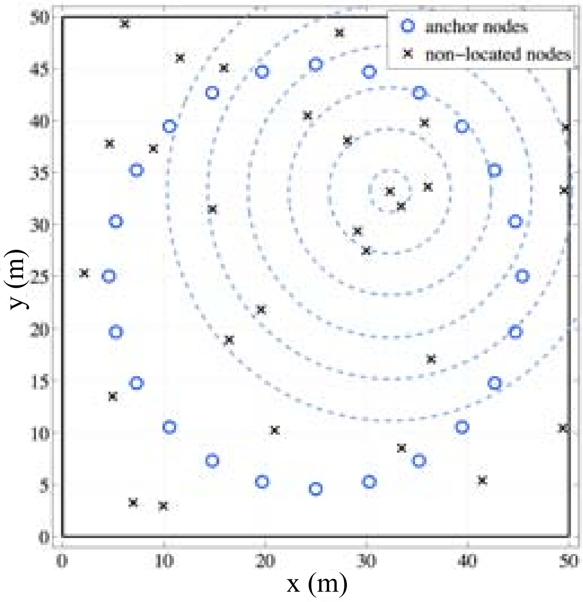


Figure 3.5: Effect of increasing the RSS threshold

3.4.3 Distance-based Criterion

The second selection criterion proposal selects those nodes with lower values of distance estimates, i.e. those nodes closer to the non-located nodes. RSS-based distance estimates have an error multiplicative to the distance; hence the selection of closer nodes will choose those nodes with a lower distance estimate. The higher the distance, the higher the error of the distance estimates. This multiplicative error is due to the log-normal model used have a variance proportional to their actual range. The model assumed is distributed as:

$$f(RSS_{ij}|\mathbf{x}_i) = \mathcal{N}(R\bar{S}S_{ij}, \sigma_{dB}^2), \tag{3.16}$$

where the mean value of the RSS_{ij} is equal to $R\bar{S}S_{ij} = RSS_0 - 10\alpha_{ij}\log_{10}(d_{ij})$. The standard deviation in decibels is considered constant with range. This consideration explains the assumed multiplicative error to the distance. For that reason the mechanism tries to reduce this effect selecting the closest nodes to the non-located node i.

Given now all the distance estimates of the nodes inside the coverage of node i:

$$\delta_{i1} \leqslant \delta_{i2} \leqslant ... \leqslant \delta_{in} \; 1, ..., n \in S_i, \tag{3.17}$$

where in this case δ_{i1} and δ_{in} are the lowest and highest distance estimate, respectively. The new group of cooperating nodes becomes:

$$S_i^{NS} = \{i1, i2, ..., in_\delta\}, \tag{3.18}$$

with n_δ standing for the number of selected nodes.

When distance estimates are obtain through RSS measurements, the distance-based selection criterion prioritizes the use of those nodes that has a lowest error in those estimates. Hence the algorithm are taking the advantage of those nodes with high reliability.

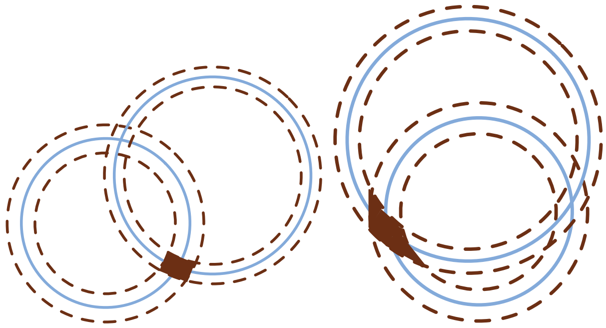
Moreover, the complexity of the criterion is low. By including this censoring method, the calculation complexity of the algorithm is not increased. This is a major objective that is important to take into account due to the nature of the wireless sensor networks and their devices.

3.4.4 GDOP-based Criterion

The major disadvantage of the previous method is taht the geometry of the selected cooperating nodes is not contemplated by the criterion. As the authors in [Das11] mentioned, the geometry of the configuration also affects the positioning performance. For that reason, we proposed a node selection criterion based on the GDOp concept.

The Geometric Dilution of Position (GDOP) is a navigation term used in geometric engineering to describe the geometric strength of the reference node configuration on the accuracy of the estimated location [Zha09]. Mostly used in satellite networks, the GDOP gives a measure of the effect of the geometry of the reference nodes used to estimate the location. More concretely, GDOP is defined as the ratio between the computed coordinate error and the measurement error [Pri05]. In order to obtain a better position estimation, the GDOP value should be as small as possible. Hence, when a node receives signal from many nodes, it should find the best combination of nodes that obtains the lowest GDOP value.

In [BD10], the authors show the dependency of the error to the geometry between, in this case, the satellites and the receiver (see Figure 3.6). Furthermore, they emphasize that minimizing the GDOP value would not guarantee the best positioning accuracy, as many other issues has to be optimized, such as received signal power and ionosphere/troposphere effects. The authors propose a method of satellite connection using convex geometry. Being the convex hull of a finite set of points S the smallest convex set that contains the points of S, it provides the set of points that provides the largest polytope. The authors said that the set of satellite positions defining the largest polytope are those that yield approximately the smallest GDOP. Hence, the nodes that conforms the convex hull of S_i will provide the best geometry in order to obtain the best position accuracy.



(a) Good geometry (b) Bad Geometry

Figure 3.6: Effect of different geometries between two references and a receiver

If one observes Figure 3.7 extracted from [BD10], the points that conforms the convex hull are those nodes that are in the border of the cooperating nodes. These method really simplifies the search of the best cooperating nodes, because it is not necessary to calculate the GDOP for all possible combinations of N_{S_i} nodes. On the contrary, selecting those border nodes would not be the best option when RSS measurements are used. As commented before, the further the distance the higher the error of distance estimate. For that reason a simplified Spatial Split (SS) [Zog10] method is presented.

The basic idea of the GDOP-based node selection criterion is to divide, assuming a circular radio range of coverage, the radio range in N sectors and selecting the closest node. The basic difference with the work presented in [Zog10] is that our criterion does not iterate among all the possible N selected nodes. The selection method (see Figure 3.8) procedure is as follows. Firstly, the angle between node i and each node j of the

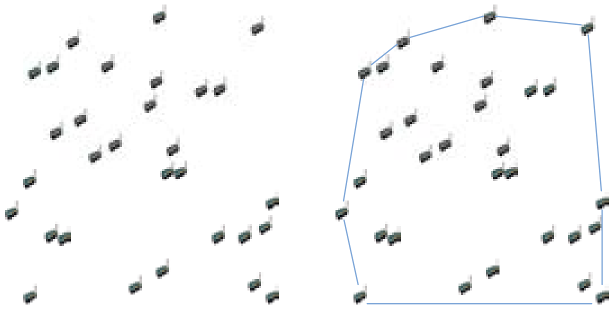


Figure 3.7: Point set and its convex hull

cooperating group are estimated:

$$\beta_{ij} = \arctan \frac{y_i - y_j}{x_i - x_j} \; \forall j \in S_i. \tag{3.19}$$

With this angle estimates we group all the nodes belonging to sector m_i defined as:

$$m_i = \left[\frac{2\pi}{m-1}, \frac{2\pi}{m}\right) \; \forall m = 1, 2, \cdots, M. \tag{3.20}$$

The subgroups obtained become:

$$S_{m_i} = \{abc \cdots f\} \; j = a, ..., f \forall \beta_{ij} \in m_i. \tag{3.21}$$

Then, the distance estimates of each subgroup S_{m_i} are sort as:

$$\delta_{m_i 1} < \delta_{m_i 2} < \cdots < \delta_{m_i n} \; 1, ..., n \in S_{m_i}, \tag{3.22}$$

where $\delta_{m_i 1}$ and $\delta_{m_i n}$ are the lower and the higher, respectively, distance estimates of the cooperating sector group S_{m_i}. The final new cooperating group are composed for all the nodes that has the lower distance estimate from each sector $m_i = 1, ..., M$:

$$S_i^{NS} = 11, 21, ..., M1 \tag{3.23}$$

The major drawbacks that will affect the accuracy of the node selection criterion are mainly two: the distribution among the different sections is done with an initial position estimation done at the first iteration; and the selection of the closest nodes of each sector depends on the accuracy of the model used (also estimated by the algorithm). These effects will be studied in the simulations and experimental results presented in Sections 3.6 and 3.7.

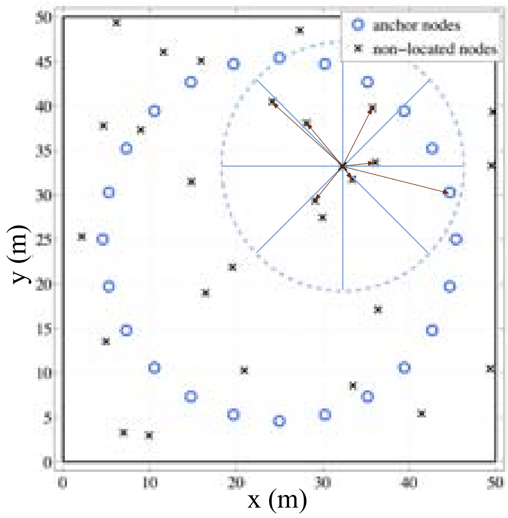


Figure 3.8: GDOP-based selection criterion

3.5 Joint Node Selection and Path Loss Estimation

RSS-based distance estimations depends on the knowledge the propagation model. This model is usually obtained with a previous measurement campaign. But the idea of repeating a measurement campaign in every possible scenario in which the algorithm has to work is not a good decision. For that reason, an on-line path loss estimation is introduced in order to dynamically estimate the transmission model and allowing to the algorithm to estimate the model that best fits to the current scenario.

In this section, all the steps that the localization has to do in order to obtain position estimates is presented . In Figure 3.9, the different stages of the node localization algorithm with on-line path loss estimation are presented. A more in-depth explanation of the different blocks is presented in the following subsections. All the procedure are summarized at the end of the section in Algorithm 1.

3.5.1 Discovering Cooperating Group S_i

The first necessary step is to discover which nodes are inside the radio range of each non-located node i. In order to do that, each non-located node, broadcasts a message with their node id. Nodes that are able to receive this message, i.e. are inside the node i radio range, send an answer to the non-located sender, with their node id an their

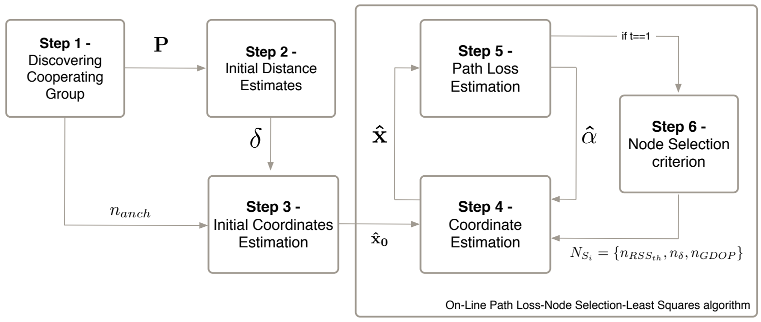


Figure 3.9: On-Line Path Loss and Node Selection LS Algorithm Procedure

position. Thanks to that, each node can form its own group and can know the number of anchor and non-located nodes that are inside its radio range.

The number of cooperating nodes N_{S_i} depends on the radio characteristics of the RF transmitter. Depending on the sensitivity of the radio chip and the transmission power of the nodes, each node could have a very variable number of nodes inside its group S_i. Hence, in a low density scenario, if a node wants a high number of cooperating nodes, it is necessary long-range capabilities of radio transceivers.

3.5.2 Initial Distance Estimates and Anchor Nodes Placement

As previously commented, we consider an RSS-based distributed cooperative algorithm for location estimation. The first phase of the algorithm consists in obtaining inter-node distances through RSS measurements. Power received is modelled through the well known radio-propagation path loss and shadowing model. The RSS can be expressed as the power received in node j from a signal transmitted by node i, P_{ij}, as:

$$RSS_{ij} = P_{ij} = P_0 - 10\alpha_{ij}\log_{10} d_{ij} - v_{ij}\,(dBm), \tag{3.24}$$

Given the power received RSS_{ij} in (4.10), an ML estimate of the actual distance can be derived as:

$$\delta_{ij} = 10^{\frac{P_0 - RSS_{ij}}{10\alpha_{ij}}} \tag{3.25}$$

The algorithm initially estimates these distances using assuming an equal value of the path loss exponent. Then, the estimates will be updated, once the algorithm obtains the first path loss exponents estimates.

3.5.3 Initial Position Estimation and Anchor Nodes Placement

The next step is giving an initial value to the position estimates of the non-located nodes. As discussed before, a gradient descent approach could not converge to the global solution if a biased initial value is used. Hence, it is important to give a good starting point in order to converge to a global solution. In that sense many works present different options [Sat08, Eng07, Li07]. All the works propose to combine two different approaches. The first one in order to obtain an initial estimation that is refined by another kind of algorithm

In [Eng07], authors make a comparison between four initial algorithms that then are refined by two different approaches. They propose to use as an intial estimation the following algorithms: DV-HOP, DV-Distance, N-HOP and TERRAIN. The two refinement algorithms are the Minimum Mean Square Error and the Mass-Spring Optimization. Results oscillates between 2.5 m and 5 m, when MMSE is used, and between 0.7 m and 4 m when and MSO is used. The authors in [Li07] obtain a previous estimate by means of using an MDS algorithm and then implement a refinement algorithm, such as ML non-bayesian approach. On the one hand, this solution obtains good results in terms of accuracy. On the other hand, this method is more complex compared to previous solutions. Moreover, it is possible to give a random initialization to all non-located nodes. It is a low complex but inaccurately method. Following with the general purposes presented previously, the starting point procedure has to achieve a good trade-off between accuracy and complexity.

A simple method to initialize each node is the use of a centroid method. Once each node forms its own cooperating group S_i, all the non-located nodes are able to compute its initial position with a weighted centroid algorithm based on the use of anchors inside their group S_i. The computation becomes:

$$\hat{\mathbf{x}}_i(t=0) = \sum_{a=1}^{n_{anch}} \mathbf{x}_a w_a, \tag{3.26}$$

where $\mathbf{x}_a$ are the coordinates of the anchor $a \in S_i$ and w_a is the weight assigned. In order to give an in-depth study of this initialization method, some simulation are presented in the sequel.

With the weighted centroid we could achieve a closer initial point; hence we could obtain a better performance of the gradient descent approach. Although, the centroid algorithm presents a low accuracy it is a simple method and it is only used to obtain the initial coordinates that we later refine with a non-bayesian LS method.

Besides, an important point of decision when a WSN has to be designed is the number and location of the anchor nodes. The presence of these nodes influences the global performance of the localization algorithm. Hence, it is important to study how their position affects the position accuracy.

Concerning the anchor nodes placement, the approach presented in [Ash08] is initially adopted, where the authors present that the best anchor placement is a centred circumference with radius equal to the root-mean-square (RMS) of the non-located nodes distances to the centre (see Figure 3.10(a)). In order to obtain these distances a uniform distribution of the nodes is assumed.

The RMS of the distance to the centre (RMS_{dc}) of N nodes uniformly distributed in a squared area of d_{sq} x d_{sq} m^2 is:

$$\begin{aligned} RMS_{dc} &= \sqrt{\frac{\sum_i^N d_i^2}{N}} = \sqrt{\frac{\sum_i^N \left(x_i - \frac{d_{sq}}{2}\right)^2}{N} + \frac{\sum_i^N \left(y_i - \frac{d_{sq}}{2}\right)^2}{N}} = \\ &= \sqrt{\left(RMS_{\mathbf{x}}^2 - 2d_{sq}\bar{\mathbf{x}} + \frac{d_{sq}}{2}\right) + \left(RMS_{\mathbf{y}}^2 - 2d_{sq}\bar{\mathbf{y}} + \frac{d_{sq}}{2}\right)}. \end{aligned} \tag{3.27}$$

The mean value of a uniform distribution with limits a and b is defined as:

$$\bar{\mathbf{x}} = \frac{b+a}{2}, \tag{3.28}$$

and the RMS of a variable **x** is defined as:

$$RMS_{\mathbf{x}} = \sqrt{\bar{\mathbf{x}} + \sigma_{\mathbf{x}}^2}, \tag{3.29}$$

being $\bar{\mathbf{x}}$ and $\sigma_{\mathbf{x}}^2$ the mean and the variance, respectively, of the uniform variable x.

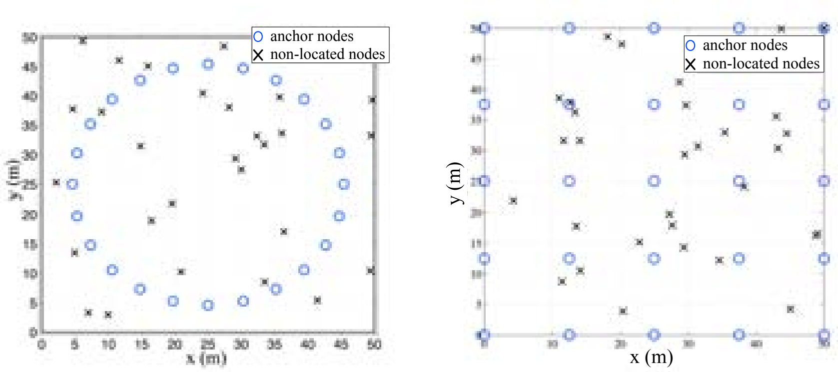
Hence, the RMS of the distance could be defined as:

$$RMS_{dc} = \sqrt{2\sigma_{\mathbf{x}}^2}, \tag{3.30}$$

being $\sigma_{\mathbf{x}}^2 = (b-a)^2/12$ the variance of the coordinate **x** (is the same as **y**) uniformly distributed.

Although this distribution of the anchors in a centred circumference was demonstrated to be the best one in [Ash08], it could be not the most optimal when a centroid algorithm is used as initial position estimate. For that reason, a grid-based positioning (see Figure 3.10(b)), a common anchor distribution in many works, is also proposed as an alternative.

In the simulation and experimental results both approaches are used in order to achieve a better comparison between them.



(a) Circular Simulation scenario (b) Grid-based Simulation Scenario

Figure 3.10: Two different anchor distribution

3.5.4 On-line Path Loss Estimation and Node Selection Least Squares Algorithm (OLPL-NS-LS)

The use of RSS measurements has the need of a good propagation model. Otherwise, less accurate distance and position estimates are obtained.

Usually, this model is based on experimental values obtained in a previous measurement campaign. Hence, with a more complete measurement campaign, the model reflects better the scenario behaviour. Moreover, these high accuracy is reflected in the localization algorithm performance. The main issues that has to be solved is the scenario dependency of this measurement campaign and the previous work that is necessary to be carried out.

With the introduction of on-line path loss estimation, the localization algorithm is the responsible of obtaining the node coordinates and the path loss estimation; hence the necessity of a previous modelling is avoided.

Following the procedure of Figure 3.9, next step presented is the minimization of the LS cost function:

$$C_{DLS}(\mathbf{x}_i, \alpha_{i1}, \alpha_{i2}, ..., \alpha_{in}) = \sum_{j \in S_i} \left(\delta_{ij}(\alpha_{ij}) - d_{ij}(\mathbf{x}_i - \mathbf{x}_j)\right)^2 . \tag{3.31}$$

The objective is to minimize the difference between both distances, optimizing the node coordinates and also the set of path loss exponents. The node coordinates $(\mathbf{x}_i)$ and the set of path loss exponents $(\alpha_{ij} \, \forall \, j \, \epsilon \, S_i)$ affect the computation of both distances, d_{ij} and δ_{ij}, respectively. In order to solve the cost function of (3.10), a Gauss-Seidel algorithm is adopted in [Ber97]. This non-linear algorithm is based on a circular iterative optimization with respect to one set of variables while maintaining the rest of the variables fixed. Hence, the minimizations are carried out successively for each component. Considering a generic cost function F that depends on a set of variables β, the desired minimization of F is formally defined as [Ber97]:

$$\beta(t+1) = \arg\min_{\beta_i} F\left(\beta_1(t+1), ..., \beta_{i-1}(t+1), \beta_i, \beta_{i+1}(t), ..., \beta_m(t)\right). \quad (3.32)$$

At time instant $t+1$, the F function is minimized by means of optimizing β_i component. Components between β_1 and β_{i-1} have been already optimized while components from β_{i+1} to β_m (being m the total number of components) have not been yet optimized. These last components must remain constant while the other components are being optimized. By using the Gauss-Seidel approach, it is possible to divide the optimization in two steps: firstly a minimization of the cost function by means of optimizing the node coordinates (fixing the path loss exponents) could be carried out; secondly, another minimization is done by means of the optimization of the path loss exponents (fixing the nodes coordinates). As the convergence of the non-linear Gauss-Seidel algorithm can be achieved using a descent approach (see [Pat05]), both minimizations could be carried out through a gradient descent mechanism. The basic idea is summarized in the following Figure 3.11.

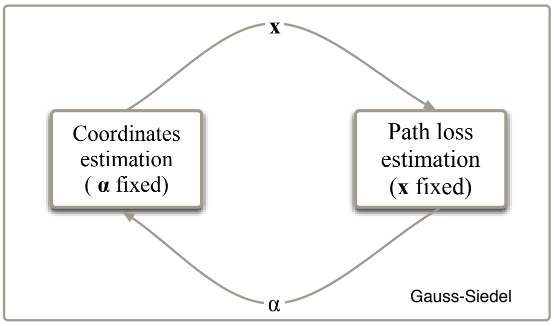


Figure 3.11: Optimization of the nodes coordinates and path loss exponents using a Gauss-Siedel algorithm

Coordinates Estimation

The estimation is done following the algorithm described in the previous section. The algorithm minimizes, by means of a least squares criterion, the difference between the estimated distance and the distance calculated with node coordinates. With the use of a gradient descent approach the algorithm is able to converge to a minimum of the cost function presented before.

We initially obtain a minimization of the cost function by optimizing the nodes coordinates. We first maintain all the α_{ij} fixed $\forall\ j\ \epsilon\ S_i$. As $d_{ij}(\mathbf{x}_i, \mathbf{x}_j) = f(\mathbf{x_i}, \mathbf{x_j}) = ||\mathbf{x_i} - \mathbf{x_j}||$ depends on the coordinates $\mathbf{x}_i$ the gradient of the cost function is:

$$\begin{aligned} \nabla_{\mathbf{x_i}} C_{DLS}(\mathbf{x}_i, \boldsymbol{\alpha}_{S_i}) &= \nabla_{\mathbf{x_i}} \left(\sum_{j \epsilon S_i} (\delta_{ij}(\alpha_{ij}) - ||\mathbf{x}_i - \mathbf{x}_j||)^2 \right) \\ &= \sum_{j \epsilon S_i} (\delta_{ij}(\alpha_{ij}) - d_{ij}(\mathbf{x}_i, \mathbf{x}_j)) \mathbf{e}_{ij} \end{aligned} \tag{3.33}$$

where $\mathbf{e}_{ij} = \frac{\mathbf{x}_i - \mathbf{x}_j}{||\mathbf{x}_i - \mathbf{x}_j||}$ is the unit vector that takes the orientation between the node i and node j. So, the estimate of $\mathbf{x}_i$, can be iteratively computed by using the gradient descent algorithm as follows:

$$\hat{\mathbf{x}}_\mathbf{i}(t+1) = \hat{\mathbf{x}}_i(t) + \gamma \sum_{j \epsilon S_i} (\delta(\alpha_{ij}) - d(\mathbf{x}_i, \mathbf{x}_j)) \mathbf{e}_{ij} \tag{3.34}$$

As previously commented, the main drawback of a gradient descent algorithm is that the result highly depends on the initial estimation used. For that reason, a deep study of the influence of the initial estimation different approximations are done in the simulation section.

Path Loss Estimation

This step is necessarily done after a previous position estimate. The algorithm has obtained the previous coordinates by means of using an arbitrary and equal value of the path loss exponent. At the second step, each non-located node estimates a path loss exponent for each link. Following the Gauss-Seidel approach, it is now minimized the cost function of (3.10) by means of optimizing the path loss exponents. Following the same methodology applied in Subsection 6.2.2 it is necessary to calculate the gradient of the cost function. The estimated distance $\delta_{ij} = \mathrm{f}(\alpha_{ij}) = 10^{\frac{P_0 - RSS_{ij}}{10\alpha_{ij}}}$ depends on the path loss exponent α_{ij}; hence, the cost function is minimized by means of calculating the derivate with respect to the path loss exponent of each individual link. In that case, the fixed variables are the coordinate estimates and the rest of the path loss exponents $(\alpha_{ik} \forall k \neq j)$. The gradient of cost function is:

$$\begin{aligned}\nabla_{\alpha_{ij}} C_{DLS}\left(\mathbf{x}_i, \alpha_{S_i}\right) &= \nabla_{\alpha_{ij}} \left(\left(10^{\frac{P_0 - RSS_{ij}}{10\alpha_{ij}}} - d_{ij}\left(\mathbf{x}_i, \mathbf{x}_j\right)\right)\right)^2 = \\ &= -\log(10)\frac{P_0 - RSS_{ij}}{5}\frac{1}{\hat{\alpha}_{ij}^2}\delta_{ij}\left(\delta_{ij} - d_{ij}\right). \end{aligned} \quad (3.35)$$

Each node estimates their own path loss exponents for all the links in an iteratively fashion as:

$$\hat{\alpha}_{ij}(t+1) = \hat{\alpha}_{ij}(t) - \gamma_\alpha \log(10)\frac{P_0 - RSS_{ij}}{5}\frac{1}{\hat{\alpha}_{ij}^2}\delta_{ij}\left(\delta_{ij} - d_{ij}\right). \quad (3.36)$$

It is a distributed method that minimizes the cost function through an iterative gradient descent strategy. The algorithm is able to estimate the path loss exponents by means of using RSS measurements. The presented algorithm maintains the philosophy of having a low complex and low cost localization algorithm.

Node Selection Mechanism

Finally the node selection mechanism is applied. With this node selection the localization algorithm modifies the cooperating group formed at the beginning of the algorithm. Hence, the algorithm reduces the traffic exchange among the network, allowing the network to decrease the total amount of energy consumed. The algorithm selects n number of nodes based on the different criteria presented in the previous section 3.4. With this selection mechanism each cooperating group S_i is reduced following the: RSS-based, distance-based or GDOP-based selection criterion.

3.6 Simulation Results

This section presents the performance of the proposed location algorithm with online path loss estimation and node selection. In order to evaluate the accuracy of the algorithm different simulation results are presented. The simulated scenario and the assumed simulation parameters are presented in Table 3.2.

Path loss exponents take values between a maximum value of 5 and a minimum value of 2 (the uniform distribution of the path loss exponents between 2 and 5 are based on experimental results obtained in [Maz09]). Hence, path loss values are simulated with a uniform distribution ($\alpha \,\epsilon\, \mathcal{U}(2, 5)$). An initial value of the path loss equal to 3.5, which is the middle value of the random values used in the uniform distribution, is assumed.

Algorithm 1 LS Localization Algorithm with On-Line Path Loss Estimation

Discovering Cooperating Group S_i:
node i transmit a broadcast message
nodes able to receive answers with their id and their coordinates
RSS-based distance estimates δ:
for $i = 1$ to N_2 **do**
  for $i = 1$ to N_{S_i} **do**
    $\delta_{ij} = 10^{\frac{P_0 - P_{ij}}{10\alpha_{ij}}}$
  end for
end for
Previous Coordinate Estimation:
for $i = 1$ to N_2 **do**
  $\hat{\mathbf{x}}_i(t = 0) = \sum_{a=1}^{n_{anch}} \mathbf{x}_a w_a$
end for
On-Line Path Loss-Node Selection-Least Squares algorithm
for $t = 1$ to t_{iter1} **do**
  Coordinate Estimation:
  for $t' = 1$ to t_{iter2} **do**
    for $i = 1$ to N_2 **do**
      $\hat{\mathbf{x}}_i(t) = \hat{\mathbf{x}}_i(t-1) + \gamma_{\mathbf{x}} \sum_{j \epsilon S_i} (\delta_{ij} - d_{ij})\mathbf{e}_{ij}$
    end for
  end for
  Path Loss Estimation:
  for $t' = 1$ to t_{iter2} **do**
    for $i = 1$ to N_2 **do**
      for $j = 1$ to N_{S_i} **do**
        $\hat{\alpha}_{ij}(t) = \hat{\alpha}_{ij}(t-1) - \gamma_\alpha \log(10) \frac{P_0 - RSS_{ij}}{5} \frac{1}{\alpha_{ij}^2} \delta_{ij}(\delta_{ij} - d_{ij})$
        $\delta_{ij} = 10^{\frac{P_0 - P_{ij}}{10\alpha_{ij}}}$
      end for
    end for
  end for
  Node Selection Criterion
  if $t == 1$ **then**
    $S_i = \{i1, i2, ..., iN_{S_i}\}$
    if RSS-based criterion **then**
      $N_{S_i} = n_{RSS_{th}}$
    else if Distance-based criterion **then**
      $N_{S_i} = n_\delta$
    else if GDOP-based criterion **then**
      $N_{S_i} = n_{GDOP}$
    end if
  end if
end for

Table 3.2: Simulation Parameters.

Simulation Parameters	Parameter Value
Size of Sensor Field	50×50 m
Number of Non-Located Nodes (N_2)	30
Number of Anchors (N_1)	4–25
Path Loss Exponent α_{ij}	2–5
Standard Deviation σ_v	1 dB
First-Meter RSS P_0	-50 dBm
Energy Consumption to Transmit or Receive μ_{T_x} or μ_{R_x}	400 nJ

3.6.1 Initial Position Estimation

The use of a gradient descent algorithm requires a good starting point in order to achieve better results. The initial position estimate proposed previously is a centroid method due to its simplicity. The initial accuracy given by the centroid method could be affected by the anchors position and also by the number of nodes $n_{\,anch}$ used by the centroid. For that reason, in the following lines a study of different scenarios and approaches in order to obtain the best possible performance of the localization algorithm is presented.

In order to achieve a sufficient accurate initial position estimate without increasing the complexity of the algorithm, we propose to use a centroid algorithm. It is a simple algorithm that could give an approximate value near the real position. As commented in the previous chapter, the centroid algorithm could achieve a better accuracy including a weight. Hence, we present different options of weights (see table 3.3) in order to decide which is the suitable one able to be used in our localization algorithm. Moreover, we

Table 3.3: Proposed weights.

w_1	$w_a = 1/n_{anch}$
w_2	$w_a = \frac{RSS_a}{\sum_{i=1}^{n_a}\left(1-\frac{RSS_i}{\sum_{i=1}^{n_a} RSS_i}\right)}$
w_3	$w_a = \frac{\frac{1}{\delta_a}}{\sum_{i=1}^{n_a}\left(\frac{1}{\delta_i}\right)}$
w_4	$w_a = \frac{\frac{1}{\delta_a^3}}{\sum_{i=1}^{n_a}\left(\frac{1}{\delta_i^3}\right)}$
w_5	$w_a = \frac{\frac{1}{\delta_a^5}}{\sum_{i=1}^{n_a}\left(\frac{1}{\delta_i^5}\right)}$

also study which is the effect that produces the number of anchors used by the centroid. The centroid algorithm is highly dependent on the number of anchors used.

Table 3.4: Accuracy of the initial position estimation *(circular anchor distribution)*.

$n_{anchors}$ \ w_a	w_1	w_2	w_3	w_4	w_5
1	12.83	12.33	10.50	11.83	12.26
2	10.83	11.32	10.05	8.53	10.90
3	13.89	12.94	10.84	8.98	11.03
4	15.80	14.98	11.29	8.62	11.3
5	17.06	15.91	13.89	8.75	12.5
10	20.04	19.82	14.61	8.54	13.98
15	20.04	19.82	14.61	8.54	13.98

Table 3.5: Accuracy of the initial position estimation *(Grid anchor distribution)*.

$n_{anchors}$ \ w_a	w_1	w_2	w_3	w_4	w_5
1	7.62	9.20	6.96	7.32	7.57
2	7.31	8.00	6.62	6.74	6.93
3	7.11	7.65	6.02	5.93	6.5
4	9.09	9.86	7.15	6.42	6.57
5	10.41	11.21	7.64	6.86	6.62
10	13.98	13.92	9.94	7.51	6.74
15	15.93	15.93	11.13	7.94	7.3

If one observes the results the best initial estimates are obtained when a centroid with a weight equal to δ_{ij}^3. This fact is valid at both anchor distributions. On the other hand, the circular distribution only requires two anchor nodes to achieve the lowest value instead of the three that the grid distribution scenario needs.

In the sequel we present the accuracy of the proposed solution comparing when the algorithm estimates the path loss exponent and when not. Furthermore, a comparison between the presented algorithm and two other localization algorithms (a distributed and a centralized) is also presented.

3.6.2 Accuracy of the path-loss and distance estimates

The RSS-based measurements are those range measurements used in localization algorithms that are less complex but with a low accuracy. They are highly affected by the path-loss and shadowing effects. Their accuracy depend on how good is the model used, usually obtained through an off-line measurement campaign. The major cons is that a recalibration process is needed when the environment changes.

In our case, the RSS measurements are modelled through the well-known path-loss and shadowing model (see (2.11)). In order to extract the distance an ML estimation is used (see (2.13)).In order to estimate the distance, the path-loss exponent of the environment has to be known.

In the proposed algorithm an on-line estimation of the path-loss is introduced, that, using the RSS measurements, the algorithm estimates for each individual link its correspondent path-loss value. Figure 3.12 shows the error achieved by the algorithm compared to the use of a constant value equal to 3.5, which is the middle value that this exponent takes.

	Selection Criteria	RSS-based	Distance-based	GDOP-based
Circular-based	OLPL	0.68	0.69	0.59
	$\alpha = 3.5$	0.95	0.86	0.95
Grid-Based	OLPL	0.64	0.65	0.58
	$\alpha = 3.5$	0.99	0.95	0.85

Figure 3.12: Accuracy of the Path-loss exponent ($N_1 = 16$)

	Selection Criteria	RSS-based	Distance-based	GDOP-based
Circular-based	OLPL	7	4.5	6.9
	$\alpha = 3.5$	9	5.2	9.5
Grid-Based	OLPL	9.4	6.5	6.1
	$\alpha = 3.5$	12.5	7.5	6.9

Figure 3.13: Accuracy of the distance estimates ($N_1 = 16$)

All the results shown by these two tables, 3.12 and 3.13, reflect the best results obtained by the On-line Path-Loss (OLPL) localization algorithm. Lower values of error are achieved by means of estimating the path loss value on line. Hence, the estimation carried out by the localization algorithm is better than considering a fixed value for all the links.

The introduction of the OLPL proposed in the localization algorithm improves both values, the path loss and the distance estimates. The errors reflected at both tables show that if the path loss value is estimated by the algorithm, the results are improved, and, moreover, the algorithm is able to change the values dynamically as the environment changes.

3.6.3 Performance of the Node Selection Mechanisms

Now we study the performance of the different node selection criterion at both scenarios presented. For each criterion, we present different results. The first are devoted to explore which is the best number of nodes that should be selected under the node selection criterion. Then, we present the gain in terms of energy consumption. They are obtained by means of comparing the number of cooperating nodes when the node selection mechanism is used or not. Finally, the mean absolute error mean versus the number of anchor nodes are presented. The results are done by means of comparing both anchor distributions and between selecting or not the cooperating nodes.

RSS-based Criterion Performance

The first node selection criterion analysed is the RSS-based Selection. This method fixes an RSS threshold that guarantees a minimum number, in mean, of anchor nodes inside each cooperating group S_i. Hence, the nodes are selected depending on their received RSS. If RSS_{ij} is greater than the RSS_{th}, then the node j is selected to conform the modified cooperating group.

As previously commented, the path loss exponents take different values for each link. Compared to the work developed in [Bel10], where the path loss exponent was considered constant, now we obtain the mean value between all the cooperating nodes inside group S_i in order to estimate the RSS threshold.

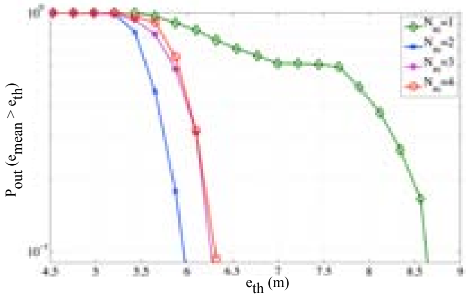
$$\bar{\alpha}_{S_i} = \frac{\sum_{i=1}^{N_{S_i}} \alpha_{ij}}{N_{S_i}} \tag{3.37}$$

$$\tag{3.38}$$

Once the algorithm has estimated a position and a value of all the path loss exponents, the RSS threshold is estimated by means of using (3.12) with the mean value of the path loss exponent (3.38). With these equations each non-located estimates its RSS_{th} in order to discard those nodes inside the initial cooperating group that has a lower value of RSS.

Selection of the number of cooperating nodes This is an important point when a node selection mechanism is included in the localization algorithm. The first parameter that has to be defined is the number of nodes that has to be selected by the criterion. This number should be the one that achieves the best trade-off between accuracy versus energy consumption.

Simulation results are presented in order to decide which is the suitable number of cooperating nodes, because it is not straightforward to obtain the value of cooperating nodes that optimize the system behaviour.

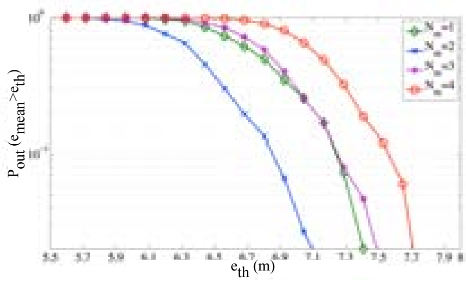


(a) Outage Probability ($N_1 = 25$)

N_m	mean num. of coop. nodes	Mean absolute error (m)
1	4,22	7,48
2	8,9	5,64
3	13,05	5,91
4	15,7	5,97

(b) Table of results

Figure 3.14: RSS-based node selection with a circular anchor distribution



(a) Outage Probability ($N_1 = 16$)

N_m	mean num. of coop. nodes	Mean absolute error (m)
1	4,07	7,09
2	8,7	7,03
3	12,13	7,09
4	14,4	7,16

(b) Table of results

Figure 3.15: RSS-based node selection with a grid-based anchor distribution

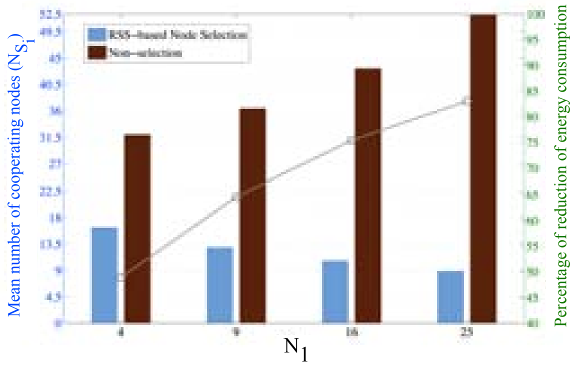
Observing the results shown in Figures 3.14 and 3.15, the best results are achieved with a mean number of anchors equal to two. The probability of having an error higher to an error threshold e_{th} shows that having a mean number of two anchor nodes inside each group S_i offers the best accuracy to the location algorithm. With this value of N_m, every non-located node is able to fix an RSS_{th} in order to select their cooperating nodes.

Energy efficiency and number of nodes cooperating comparison Moreover, the RSS-based node selection fixes an RSS threshold but the number of nodes inside the cooperating is not fixed. These values varies depending on the proximity of more or less neighbours; hence the node density of the network. Also having a higher number of anchor nodes inside the area of the network helps to increase the RSS threshold and, hence, the reduction of the mean number of cooperating nodes. This fact is reflected in the Figure 3.16.

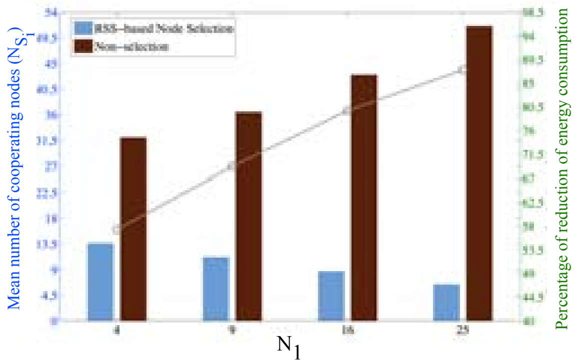
Results reflect that the higher the number of anchors, the higher the node density, and hence, the lower the mean number of cooperating nodes. As previously commented, the energy consumption is directly related with the number of cooperating nodes. One could observe the difference in terms of mean number of cooperating nodes between a localization algorithm with and without a node selection mechanism in Figure 3.16. This difference is reflected in the percentage of reduction of the energy consumption. Results of the circular anchor distribution (see Figure 3.16(a)) oscillates between a 50% (with $N_1 = 4$) and 83% (with $N_1 = 25$). On the other hand the grid anchor distribution scenario (see Figure 3.16(b)) obtains values between 58% and 89% (with $N_1 = 4$ and $N_1 = 25$ respectively). As it is expected, a high density of anchor nodes becomes in a reduction of the number of cooperating nodes and, hence, a reduction of the energy consumption. The major difference between both scenarios is that with a grid distribution the results achieved are better when the number of anchors is higher. On the other hand, when the number of anchors is reduced, the grid-based anchor distribution achieves a better energy efficiency.

One can notice that the no-selection algorithm stills achieves a percentage of reduction. The hardware is limited by its sensitivity in terms of RSS level. Nodes can only receive messages with an RSS above a threshold. For that reason, a no-selection algorithm can achieve a certain level of energy reduction.

Accuracy of the localization algorithm In Figure 3.17, the mean absolute error for different values of N_1 is plotted. The results show, in both anchor distributions, grid and circular, at the RSS-based node selection localization algorithm achieves a better



(a) Circular anchor distribution



(b) Grid anchor distribution

Figure 3.16: Mean number of Cooperating nodes and percentage of reduction of the energy consumption ($N_m = 2$)

accuracy than an LS localization algorithm without node selection mechanisms. As the results commented from the previous Figure 3.16, the grid-based distribution achieves the best results only with an scenario with 25 anchors. On the contrary, with lower values of anchor nodes the circular distribution scenario present a higher accuracy. One can also see that, when $N_1 = 16$, the mean absolute error of both scenarios is comparable.

Distance-based Criterion Performance

Selection of the number of cooperating nodes As previously commented, we first present the results of the probability of outage, that allows us to know the most suitable

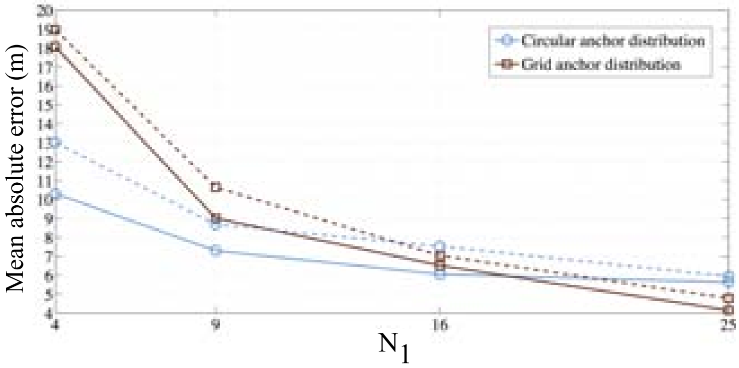
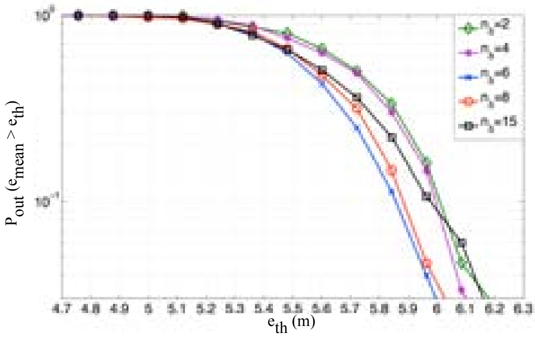


Figure 3.17: Mean absolute error versus mean number of anchor nodes*(solid line: RSS node selection, dashed line: Non-selection)*

number of cooperating nodes. We want to discover the value that achieves the better performance in terms of accuracy.



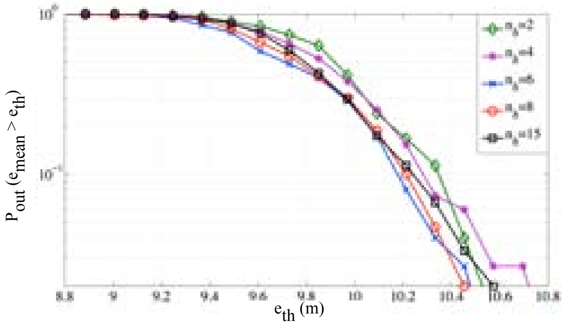
(a) Outage Probability $(N_1 = 16)$

n_δ	Mean absolute error (m)
2	5,7
4	5,7
6	5,5
8	5,6
15	5,61

(b) Table of results

Figure 3.18: Distance-based node selection with a circular anchor distribution

Observing the results shown in Figures 3.18 and 3.19, the best results are achieved with 6 cooperative anchors. Hence, the node selection mechanism selects $n_\delta = 6$ nodes to cooperate with each non-located node (see Figures 3.18(a) and 3.19(a)). Although, the differences between the different number of anchors are not so reliable, it is shown in the respective tables that the best best position accuracy is achieved with 6 nodes cooperating. For that reason, the following simulations will assume a number of 6 cooperating nodes.



(a) Outage Probability ($N_1 = 9$)

n_δ	Mean absolute error (m)
2	9,91
4	9,88
6	9,7
8	9,78
15	9,83

(b) Table of results

Figure 3.19: Distance-based node selection with a grid-based anchor distribution

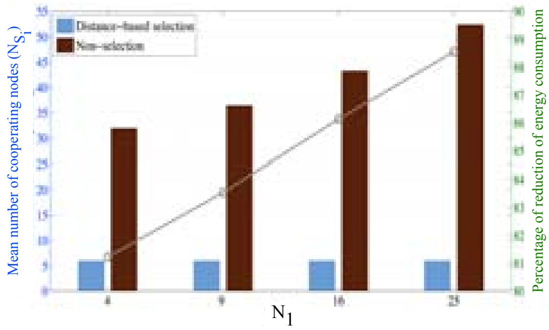
Energy efficiency and number of nodes cooperating comparison In order to reflect the efficiency in terms of energy consumption, Figure 3.20 shows the differences in terms of nodes used and the percentage of reduction of the energy consumption.

As the node selection criterion imposes a fixed number of cooperating nodes the percentage of reduction of the energy consumption is practically linear as the number of anchors increases (see Figure 3.20). The results in terms of percentage of reduction of $\epsilon_{consumed}$ oscillate between an 81% and the 88% for both anchor distributions. The efficiency in terms of energy consumption has been demonstrated with the results achieved.

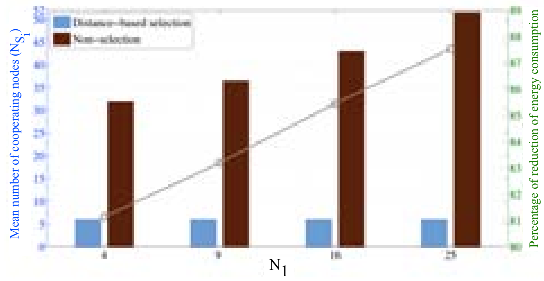
Accuracy of the localization algorithm The results shown in Figure 3.21 reflects that the accuracy between our On-Line Path Loss Node Selection (OLPL-NS) localization algorithm and a non-selection localization algorithm is similar . Hence, in terms of accuracy, our proposal maintains a satisfactory performance.

However, the results presented previously demonstrate that the node selection localization algorithm is more energy efficient compared to a localization algorithm without this node selection mechanism.

It is also remarkable that the grid-based anchor distribution scenario offers a poorer results in terms of accuracy when the number of anchors are lower or equal than 16 anchors. The best results are achieved with a number of 25 anchors an a grid distribution. The error mean values are



(a) Circular anchor distribution



(b) Grid anchor distribution

Figure 3.20: Mean number of Cooperating nodes and percentage of reduction of the energy consumption ($n_\delta = 6$)

GDOP-based Criterion Performance

Selection of the number of cooperating nodes As it has been done with the previous methods, we first observe which is the suitable value of sectors that obtains the best accuracy in terms of positioning error.

Observing the results shown in Figures 3.22(a) and 3.23(a), the best results are achieved when the algorithm divides the radio range in 10 sectors.

In this case, as it has happened with the RSS-based node selection mechanism, using 10 sectors does not mean that the number of cooperating is 10. The node selection criterion divides in 10 sectors but it could occur that in some sector there is not node or the angle estimation done could not be correct, and, hence, the selection is not done as correct as one wants. The total number of cooperative nodes, in mean, are reflected in Tables 3.22(b) and 3.23(b). In both cases, having 10 different sectors results in a mean number of cooperating nodes equal to, approximately, 6.

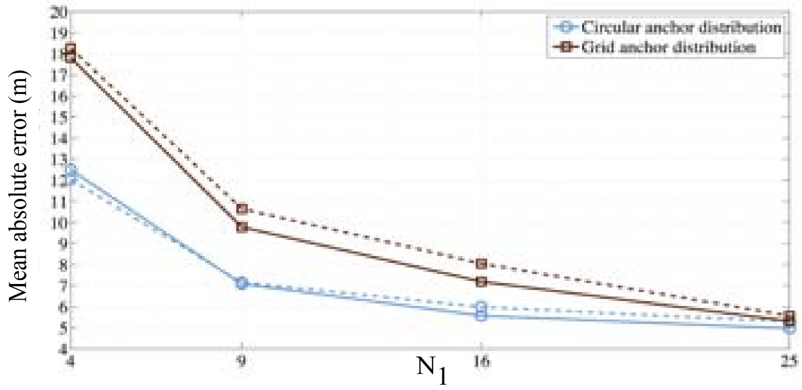
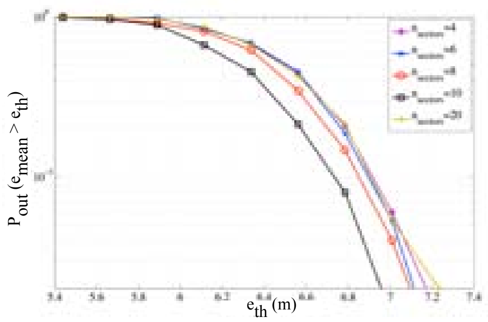


Figure 3.21: Mean absolute error versus mean number of anchor nodes*(solid line: Distance-based node selection, dashed line: Non-selection)*



(a) Outage Probability ($N_1 = 25$)

num. of sectors	mean num. of coop. nodes	Mean absolute error (m)
4	2,8	6,45
6	3,85	6,35
8	4,83	6,3
10	5,87	6,2
20	10,46	6,45

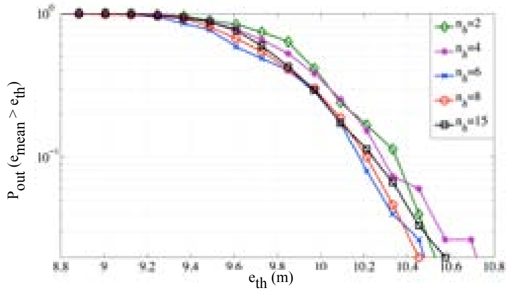
(b) Table of results

Figure 3.22: GDOP-based node selection with a circular anchor distribution

Although results in terms of efficiency are very similar, the best results is achieved with 10 sectors. In terms of accuracy, the difference between having more or less sectors are, depending on the case, not so much remarkable. But, if one talks in terms of energy efficiency, the node selection has a big impact on them, that is reflected in the following results.

Energy efficiency and number of nodes cooperating comparison In order to reflect the efficiency in terms of energy consumption, Figure 3.24 shows the differences in terms of nodes used and the percentage of reduction of the energy consumption.

The results reflect an average percentage reduction between 83% and the 89% with

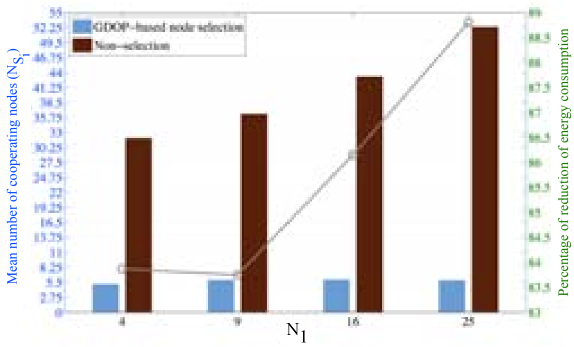


(a) Outage Probability $(N_1 = 4)$

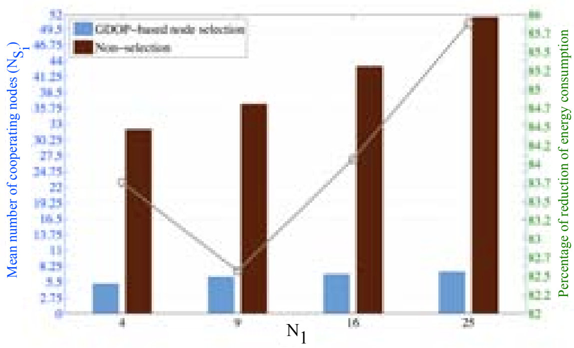
num. of sectors	mean num. of coop. nodes	Mean absolute error (m)
4	2,66	19,54
6	3,72	19,2
8	5,22	19,42
10	6,35	19
20	7,35	18,9

(b) Table of results

Figure 3.23: GDOP-based node selection with a grid-based anchor distribution



(a) Circular anchor distribution



(b) Grid anchor distribution

Figure 3.24: Mean number of Cooperating nodes and percentage of reduction of the energy consumption $(n_{sectors} = 10)$ (GDOP-based node selection)

respect to a circular anchor distribution and 82% and the 86% with respect to a grid-based anchor distribution. These results reflect the average value of reduction. As in the RSS-based node selection criterion, the GDOP-based criterion fixes the number of sectors, but the final number of nodes that will cooperate is not exactly known. These number will depend on the accurate estimation of the classification inside the different sectors.

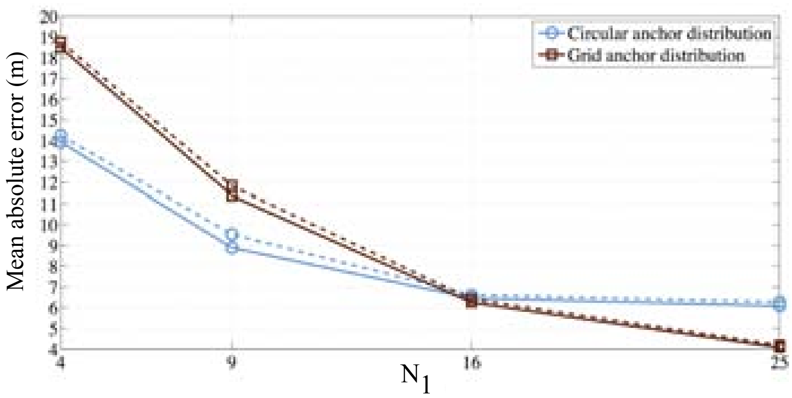


Figure 3.25: Mean absolute error versus mean number of anchor nodes*(solid line: GDOP-based node selection, dashed line: No-selection)*

Accuracy of the localization algorithm The results shown in Figure 3.25, as in the distance-based node selection, reflects a similar accuracy between an algorithm with node selection in comparison with a non-selection localization algorithm. the benefit that introduces the node selection mechanism is more reflected in terms of energy consumption. Moreover, the network reduces its traffic, and, hence, the possibility of packet loses or errors.

Again, the grid-based anchor distribution achieves a higher accuracy when $N_1 = 25$. For lower values the circular anchor distribution achieves a higher accuracy. Only remark, the very similar accuracy obtained in the case of a 16 anchor scenario, at both scenarios.

Summary

The results reflect two different situations. When the anchor nodes are distributed in a circular distribution the best results are achieved by the distance-based selection criterion. On the other hand, when the anchor distribution is grid-based, the best results are achieved with the GDOP-based criterion. These results reflects an idea commented before. Not all the algorithms are suitable to be used in all situations or scenarios.

The GDOP-based criterion works better when the anchors are distributed following a grid, because the distribution of the anchors are geometrically-distributed better. More concretely, each non-located node has more probability of being inside an are covered by more than one anchor node. This anchor distribution is, under a geometrical point-of-view, more similar to the convex-hull; hence, better distributed to achieve a lower GDOP value. Moreover, the best results are achieved when the number of anchor nodes are higher than 9.

On the contrary, the distance-based algorithm is better when the circular distribution is used. The geometry of the anchors inside each cooperating group are not equitable as before. Hence, the distribution of the anchors also affects the overall performance. With this distribution, the number of anchor nodes in each cooperating group, when a GDOP-based criterion is used, is lower, hence, each non-located node has less reliable information. For that reason, the distance-based criterion works better.

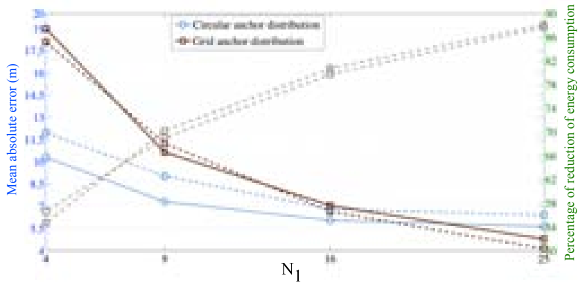
3.6.4 Comparison with Existing Methods

In this subsection we will compare our proposed algorithm On-Line Path Loss Node Selection Least Squares (OLPL-NS-LS) with two different existing solutions: a distributed method based on a Maximum Likelihood algorithm (ML) and centralised algorithm based on Multidimensional Scaling (MDS). We apply the on-line path loss estimation to all the methods in order to achieve a fair comparison between them. Only our OLPL-NS-LS method present the node selection method proposed. Moreover, the three criteria are used. We will compare the performance of our method in terms of both energy consumption and positioning accuracy.

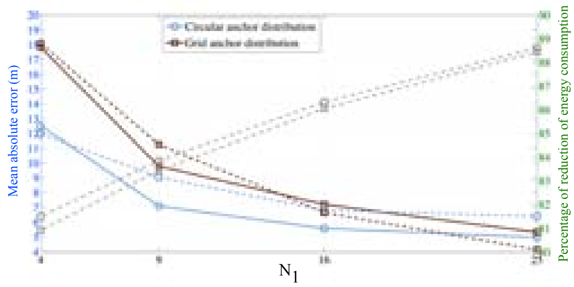
Comparison with Maximum Likelihood Localization Algorithm

The Maximum Likelihood, as presented in the chapter 2, is also a non-bayesian estimator. The major difference between LS and ML methods is that ML approaches take advantage of the statistics of noise sources and LS approach does not. The cost function that characterizes the ML algorithms, and the one that has to be minimized, is the following:

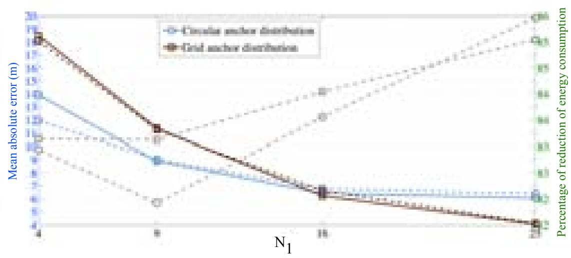
$$C_{ML}(\mathbf{x}) = b^2 \sum_{i=1}^{N_2} \sum_{j \epsilon S_i} \left(\log \left(\frac{z_{j \to i}}{\mathrm{f}(\mathbf{x}_i - \mathbf{x}_j)} \right) \right)^2 . \tag{3.39}$$



(a) Comparison with RSS-based node selection mechanism



(b) Comparison with Distance-based node selection mechanism



(c) Comparison with GDOP-based node selection mechanism

Figure 3.26: Mean absolute error mean vs. N_1 *(solid line: OLPL-NS-LS algorithm, dashed line: ML algorithm)*

In Figure 3.26, the results obtained by the three different node selection mechanisms are shown. In Figure 3.26(a) the accuracy achieved by th OLPL-NS-LS algorithm is very similar to the achieved by the ML algorithm. The similarity is higher when the grid-based anchor distribution is used. As occurs at the previous results, the accuracy obtained in a grid-based anchor scenario with N_1 higher than 16 is better. This conclusions could be transferred to the results of the distance-based node selection mechanism presented in Figure 3.26(b), because the behaviour of the accuracy is the same as in the RSS-based node selection case. Finally, in Figure 3.26(c), they are shown the comparison between the GDOP-based mechanism and the ML algorithm. One can see, that the results are, approximately the same. The difference, in terms of mean absolute error, are almost negligible.

Although the results in terms of accuracy are almost the same in all the simulations presented, there exists a feature that improves the performance of the OLPL-NS-LS. The results in terms of energy efficiency are highly improved by our proposal. The benefit introduced by the node selection criteria used makes considerably more efficient the OLPL-NS-LS versus the ML algorithm. The percentage of reduction of the energy consumption of the network oscillates between the 50$\%$, with a value of $N_1 = 4$, and 90$\%$, with a value of $N_1 = 25$. Hence, the introduction of a node selection criterion does not affect the accuracy of the localization algorithm and increases the efficiency in terms of energy consumption.

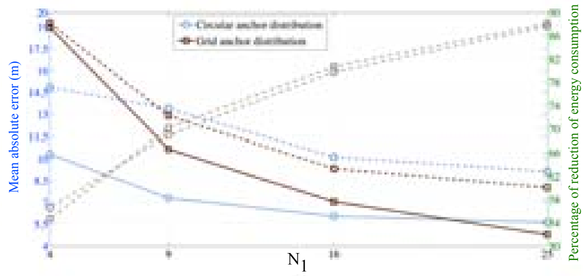
Comparison with MultiDimensional Scaling Algorithm

The MDS algorithm is a simple centralized approach that builds a global map using classical MDS [Sha03]. MDS works well on networks with relatively uniform node density but less well on more irregular networks.

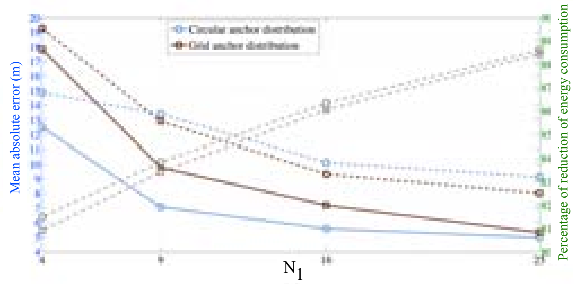
As observed in Figure 3.27 the proposed OLPL-NS-LS algorithm outperforms the MDS localization algorithm. This gain is achieved thanks to the introduction of node selection criteria. In this case it is compared a distributed method (OLPL-NS-LS) with a centralized method (MDS). On the one hand, a centralized method includes more distant nodes. Then, nodes with a high error on their distance estimates are used. On the other hand, all possible nodes inside each group S_i are also used in the path loss estimation process. Probably, these nodes that are not near to a node i would not have a similar propagation conditions compared to those nodes that are closer. For that reason a node selection scheme allows to reduce the mean absolute error results in an RSS-based distance estimated.

Furthermore, it is also important to remark the reduction of the energy consumption. According to our energy consumption model, the use of a reduced cooperating group S_i produces a reduction in the energy consumed by the network. The reduction of the energy consumption achieved by the OLPL-NS-LS algorithm oscillates, again, between 50$\%$ and 90$\%$, compared to the energy consumed by a method without node selection mechanism (see Figures 3.27(a) 3.27(b) and 3.27(c)).

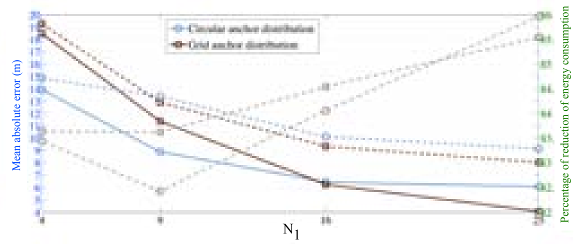
In this case there exists a benefit in both features: the accuracy and energy con-



(a) Comparison with RSS-based node selection mechanism



(b) Comparison with Distance-based node selection mechanism



(c) Comparison with GDOP-based node selection mechanism

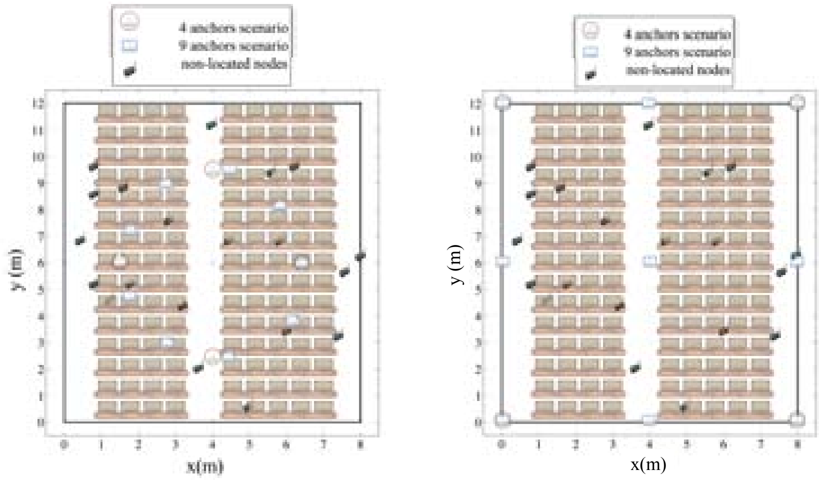
Figure 3.27: Mean absolute error mean vs. N_1 *(solid line: OLPL-NS-LS algorithm, dashed line: MDS algorithm)*

sumption. It is remarkable the benefit achieved in the mean absolute error. The difference oscillates between 3 and 5 meters.

3.7 Experimental Results

In this section experimental results are presented. The measurements done in an indoor scenario have been carried out with the Mica2 motes @ 915MHz of Crossbow [Xbo] and Z1 motes @ 2.4GHz of Zolertia [zol]. Two different kind of hardware are used in order to compare the differences between the two frequency regimes. The scenario is presented in Figure 3.28.

There are $N_2 = 20$ non-located nodes and two different number of anchors N_1: 4 and 9. The non-located nodes are normally distributed in an 8 x 12 meters scenario, while the anchors are distributed with a circular and a grid-based distribution (3.28).



(a) Circular anchor distribution (b) Grid-based anchor distribution

Figure 3.28: Experimental Scenario

3.7.1 Circular Anchor Distribution

In Figure 3.29 the results obtained are shown for the three different node selection criteria. The results of the RSS-based node selection mechanism is presented in Figure 3.29(a). Although the results between the two different hardware are approximately the same, better accuracy is achieved by the mica2 motes. The path-loss and shadowing model used depends on the frequency band used. The path-loss and shadowing model is modelled as [Gol05]:

$$RSS_{ij} = P_{T_x} + K - 10\alpha_{ij}\log_{10}(d_{ij}), \tag{3.40}$$

where P_{T_x} is the power transmit by a node and K a unitless constant that depends on the antenna characteristics and the average channel attenuation. More concretely, when a omnidirectional antenna is assumed, the K values is obtained as:

$$K = 20\log_{10}\frac{c/f}{4\pi d_0}. \tag{3.41}$$

With a higher value of frequency, the K value becomes higher; hence, more propagation looses. In our case, the values at 900 MHz and 2.4 GHz are -31.5 dB and -40 dB, respectively.

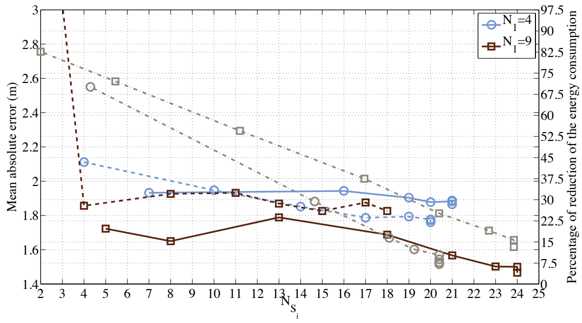
Furthermore, the major difference is achieved in the scenario with 4 anchors. One could also observe that the behaviour of the error is similar at the obtained with the simulations. With a higher number of nodes cooperating the error is slightly better (approximately 20 cm), but the energy consumption is higher.

If one observes the results of the Distance-based node selection criterion (Figure 3.29(b)) the difference between both hardware used is very remarkable. Lower accuracy are obtained with the mica2 motes. This is due to this method highly depends on the accuracy of the distance estimates and mica2 motes works at 900 Mhz; hence, the pathloss and shadowing affect less at this frequency band, as explained before. Furthermore, the mean number of nodes that achieves a better accuracy is equal to 6. The same value obtained at the simulation scenarios presented at the previous section.

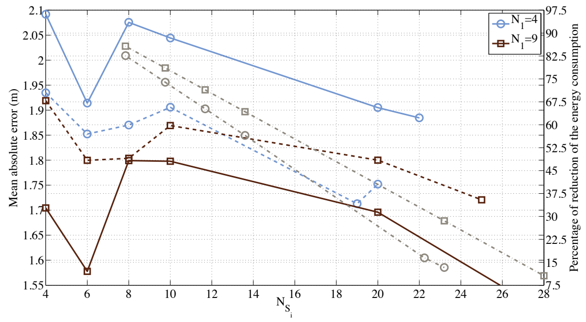
Finally, the results achieved by the GDOP-based node selection criterion are shown in Figure 3.29(c). Again, the best value for the N_{S_i} is 6. With this value of cooperating the accuracy achieved is equal to 1.67 and 1.63 meters, when the z1 and mica2 motes are used respectively, with $N_1 = 9$, and 2 and 1.96 meters with $N_1 = 4$. The differences between both hardware are not so high. The GDOP-based algorithm does not only take into account the distance estimate of the cooperating. The selection mechanism also incorporates the geometry information, hence both hardware used has a similar performance.

3.7.2 Grid-based Anchor Distribution

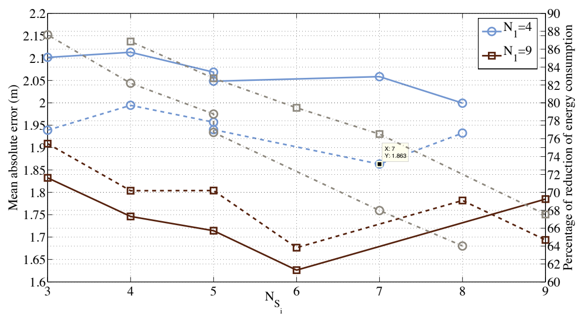
The grid-based anchor distribution results are shown in Figure 3.30. The results of the RSS-based node selection mechanism is presented in Figure 3.30(a). The results between the two motes are very similar when there are 9 anchors. With lower number of anchors the results achieved by the Z1 motes are worse. The grid anchor distribution positions the 4 anchor nodes at the scenario corners; hence, compared with the circular distribution, non-located nodes located far away from the corners have a lower probability of having an anchor node inside theri cooperating group. This fact is reflected in the results. As previously commented, the Mica2 motes have better results at the time of estimating the distances (see Figure 2.9(b)), and this fact is reflected in the accuracy



(a) RSS-based node selection



(b) Distance-based node selection

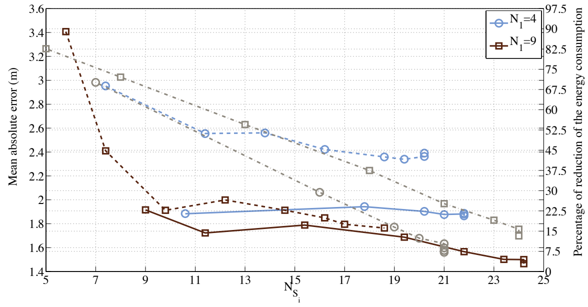


(c) GDOP-based node selection

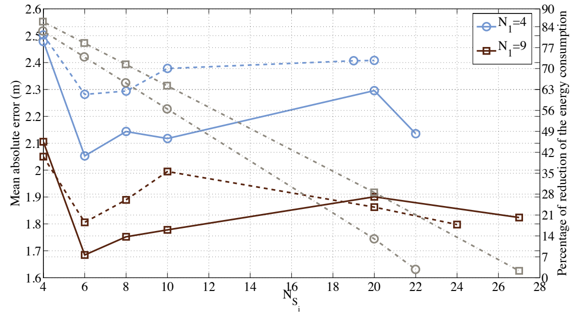
Figure 3.29: Mean absolute error mean vs. N_{S_i} (Circular anchor distribution) *(solid line: mica2 motes, dashed line: z1 motes)*

results. Only when the number of anchors is increased, and the proximity of them to the rest of the nodes is higher, the accuracy of both motes is comparable.

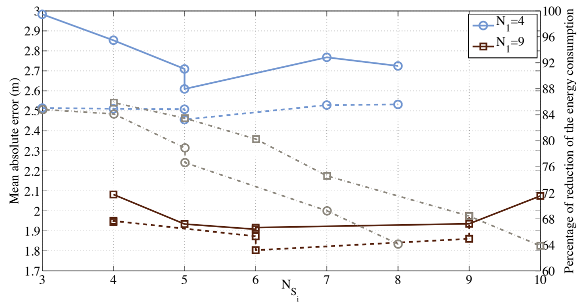
Moreover, the results of distance-based node selection results show a difference



(a) RSS-based node selection



(b) Distance-based node selection



(c) GDOP-based node selection

Figure 3.30: Mean absolute error mean vs. N_1 (Grid anchor distribution) *(solid line: mica2 motes, dashed line: z1 motes)*

with respect to RSS-based selection criterion (see Figure 3.30(b)). The distance-based selection relies on the selection based on their distances instead of the RSS; hence, the criterion includes the estimation of the path loss done by the algorithm. Now, although the best accuracy is achieved by the mica2 motes, the z1 motes achieves better performance. Furthermore, the best result in all scenarios is achieved with a mean number of 6 nodes cooperating validating the value achieved with the simulation results.

The GDOP-based node selection criterion are shown in Figure 3.30(c). Again, the best value for the N_{S_i} is 6. The differences between both hardware are not so high, but in this occasion the z1 motes outperforms the mica2 motes. The error achieved with 4 anchor nodes is 2.45 with z1 motes and 2.6 meters with mica2 motes. In a 6 anchor nodes scenario, z1 motes achieved 1.8 meter error and the mica2 motes an error equal to 1.9 meters.

3.7.3 Comparison

In tables 3.31 one could observe the gains achieved by the different section criteria in terms of mean absolute error and energy consumption, when mica2 motes are used. As it occurs at the simulation results, the best selection criterion, when the circular distribution is used, is the distance based criterion. As the results reflects, we do not achieve a gain in terms of positioning error but the difference of mean absolute error is only of 4 cm with $N_1 = 4$ and 5 cm when $N_1 = 9$. The node selection mechanism does not achieve better results but the energy consumption is considerably reduced. The selection mechanism allows to obtain a gain equal to 82.3% with $N_1 = 4$ and 85% with $N_1 = 9$. On the other hand, with a grid based anchor distribution, the best performance is achieved with a GDOP based selection criterion. In this case, the mean absolute error achieved is lower compared to the non-selection case. Moreover, the energy consumed when the selection method is done is, again, lower than with a non-selection localization algorithm.

	Selection Criteria	RSS-based	Distance-based	GDOP-based
Circular-based	$N_1 = 4$	-1.5%	-2.6%	-2.4%
	$N_1 = 9$	-7.4%	-2.3%	-4.3%
Grid-Based	$N_1 = 4$	-0.6%	-2.08%	3.7%
	$N_1 = 9$	-7.4%	-2.53%	4.5%

(a) Gain in terms of mean absolute error

	Selection Criteria	RSS-based	Distance-based	GDOP-based
Circular-based	$N_1 = 4$	67.5%	82.3%	77%
	$N_1 = 9$	57%	85%	79%
Grid-Based	$N_1 = 4$	67.5%	75%	78%
	$N_1 = 9$	57%	83.5%	80%

(b) Gain in terms of energy consumption

Figure 3.31: Gain results of mica2

If we focus now on the results of the z1 motes, the results (see 3.32) reflect the same behaviour as those obtained with the simulations. The best selection criterion is the distance based when a circular distribution of the anchors is assumed, and the GDOP based when the grid distribution is used. Moreover, the energy consumption is considerably reduced. The node selection algorithm performance is better in both features, the mean absolute error and the energy consumption is reduced.

Selection Criteria		RSS-based	Distance-based	GDOP-based
Circular-based	$N_1 = 4$	-16%	7.18%	-1.5%
	$N_1 = 9$	-1%	1.88%	1.3%
Grid-Based	$N_1 = 4$	-1.5%	3.3%	3.9%
	$N_1 = 9$	-7.4%	-1.09%	6.25%

(a) Gain in terms of mean absolute error

Selection Criteria		RSS-based	Distance-based	GDOP-based
Circular-based	$N_1 = 4$	40%	82%	77%
	$N_1 = 9$	35%	85%	79%
Grid-Based	$N_1 = 4$	50%	72%	78%
	$N_1 = 9$	65%	73%	82%

(b) Gain in terms of energy consumption

Figure 3.32: Gain results of z1

3.8 Summary

The basic issue that we follow is to implement a pragmatic localization algorithm as simple as possible, energy efficient but without sacrificing the accuracy.

Based on an RSS-based Least Squares localization algorithm we introduce two modifications in order to achieve a good trade-off between accuracy versus energy efficiency: an on-line path loss estimation and a node selection mechanism.

With the introduction of an on-line path loss estimation, the proposed algorithm is able to achieve better estimates of the inter-node distances. The major advantage is the avoidance of giving to the nodes a model of the environment, done with an a priori measurement campaign. Moreover, the adaptability of the algorithm is increased in front of other localization algorithms based also on RSS range measurements. We estimate this parameter using the RSS measurements; hence, we maintain our purpose of simplicity.

WSN are battery powered networks and it is necessary be as energy-efficient as possible. In that sense, we propose to limit the nodes that cooperate; hence, we reduce the exchange of messages, reducing the possibility of packet loses due to collisions and reducing the information that a node has to process. Three are the different approaches proposed: RSS-based, distance-based and GDOP-based node selection criterion.

In order to study the viability of these proposals different simulations and experimental values are carried out. The results show that the accuracy achieved by distance-based node selection mechanism achieves the best trade-off between accuracy versus energy consumption when the anchors are circularly distributed. With a grid-based distribution, the GDOP-based node selection criterion shows the best trade-off between accuracy versus energy consumption. Reducing the number of cooperating nodes by means of a node selection mechanism allows to achieve an energy consumption gain that oscillates between the 70% and the 83%. The reduction of cooperating nodes allows to the algorithm reduce the number of messages and the information to process but the localization accuracy is maintained. These results are reflected in the simulated and experimental results.

We also reflect the impact of having an on-line path loss estimation. Results show that better distance estimates are obtained. Moreover better behaviour in terms of mean absolute error is achieved. As previously discussed, this estimation is done with the RSS measurements obtained with the normal messages sent by all the nodes; hence, we do not increase the cost of the nodes with extra equipment.

We could summarized that the proposals introduced in an RSS-based distributed cooperative LS localization algorithm allows us to achieve a good trade-off between accuracy versus energy consumption. This summary is reflected at the experimental results. They show that the distance-based criterion achieves gains, in terms of mean absolute error, that oscillate between the 2% and the 8%. The gains achieved by the GDOP-based criterion oscillates between the 4% and the 6.25%.

Chapter 4

Mobile Node Localization and Tracking

THE increasing interest on WSNs has motivated the appearance of different applications. Sometimes, an application needs to know the position of a mobile node. This requirement has motivated the appearance of tracking algorithms devoted to locate mobile nodes. But the mobility of the nodes causes some problems to estimate the position, and hence, to track a mobile node. For that reason, in this chapter we propose an RSS-based tracking algorithm.

4.1 Introduction

In chapter 2, different works aimed at tracking mobile nodes in WSN have been presented. For example, in [Vu08] the authors present a positioning method of fixed nodes based on the minimization of an ML function that is latter used as a tracking method. Basically, they propose to follow the movement of a node by repeatedly using the MSE algorithm over a predefined period of time. In [Ber08], authors have also presented another RSS-based tracking system in which the mobile node estimates their position by means of using three different estimators: Maximum Likelihood, Least Squares and Maximum Ratio Combining.

Although all these methods are used and developed for tracking purposes, they do not include other features that characterizes a moving target, such as: velocity, acceleration, etc. In order to include these features many other methods have been developed in the literature. Methods such as kalman filters, and its derivatives, and the particle filters include these features. As commented previously, PF algorithms [Aru02, Ahm10] is a suboptimal non-linear filter that performs estimation using sequential Monte Carlo methods to represent the probability density function of the target state. These approaches do not assume that the system and the measurement processes are linear. The Kalman Filter (KF) [OS07, Cac09, Di08] has become the most common method used to track mobile nodes. KF bases their functionality on two steps: a prediction step followed by a correction step. Although the KF is a method that assumes a linear signal model, posterior extensions, such Extended KF or Uscented KF, consider a non-linear systems. All of them are characterized by assuming that all error terms and measurements have a Gaussian distribution.

Another important issue is to obtain a good accuracy by means of using low-complex and low-cost methods, able to be used in a WSN. At the previous chapter the feasibility of using RSS-based measurements in localization algorithms has been presented. RSS-based measurements are the simplest range-based way to achieve distance estimates; moreover, these measurements consume less resources and do not impose any cost increase in hardware. Some works such as [Vu08, Ber08, Guv03, Cac09], have used these range measurement as the way to obtain inter-node distance estimates. Authors in [Cac09] say that the use of RSS-based tracking algorithms are not very extended. Hence, their use make the development of a tracking algorithm more challenging.

In this chapter, we present an RSS-based tracking algorithm based on a Kalman Filter. Our proposal is to increase the accuracy of the RSS-based methods by means of introducing a Window-based RSS correction mechanism that improves performance when compared to existing methods. Moreover, we prove the proposed tracking algorithm in two different scenarios: outdoor and indoor. The errors that affect the RSS measurements in both scenarios are very different. Nevertheless, we adapt our Window-based mechanism to both environments achieving a higher accuracy compared to other existing methods.

4.2 Overview of the Kalman Filter

Our proposals are both based on a Kalman Filter, more concretely in a KF for the outdoor algorithm and an EKF for the indoor algorithm. For that reason, we present both solution with more details in the following subsections.

The Kalman Filter was first introduced by Rudolph Emil Kalman in [Kal60]. The presented algorithm estimates an unknown variable using measurements affected by noise. The main advantage is that the estimation is done over time, i.e., KF does not only use a single measurement. The basic functionality of this filter is based on a prediction-correction operation and it is considered optimal due to its final purpose is to minimize the estimated error covariance [Wel01]. Since its first publication, the Kalman Filter has become a recursive field of research study and vastly applied in the area of autonomous or assisted navigation.

The KF works in a two-step process: the prediction step, where the algorithm estimates the current state variable, and the correction step, where, thanks to the corrupted measurements, the KF update the estimation done at the previous step. This algorithm basically assumes that the system is a linear dynamical one, and the error and the measurements are Gaussian distributed [Aru02].

When the dynamics cannot be represented as a linear combination of the state variables, there exist some approximations to the optimal solution as the Extended Kalman Filter (EKF) or the Unscented Kalman Filter among others. In recent years, KF has been used in the field of navigation because it is considered a simple and robust filter.

4.2.1 Kalman Filter

The basic characteristic of the Kalman Filter is its recursive behaviour. The KF only uses the previous estimate and the current measurements; hence, the filter could be consider as a memoryless algorithm.

The KF is normally conceptualized in two different phases: predict and correction. At the prediction phase the algorithm calculates an state estimate by means of using the previous time state estimate. Then, the correction time step refines the current state estimate using the current measurements.

The first step is characterized by two variables: $\hat{\mathbf{x}}^{-}(k+1)$, the a priori state estimate at time $k+1$, and $\mathbf{P}(k+1)^{-}$, the a priori error covariance matrix which is an estimated accuracy of the state estimate.

The state estimate is obtained as:

$$\hat{x}^{-1}(k+1) = \mathbf{F}(k)\hat{x}(k) + \mathbf{V}(k)v(k), \tag{4.1}$$

$v(k)$ are the noise of the process and the observations modelled as Gaussian variable with zero mean covariance $\mathbf{R}$, the $\mathbf{F}$ matrix relates the process state with the previous state, and $\mathbf{V}$ the input/control matrix. Moreover, the estimate covariance is estimated as:

$$\mathbf{P}^{-}(k+1) = \mathbf{F}(k+1)\mathbf{P}(k)\mathbf{F}(k+1)^{T} + \mathbf{Q}(k+1), \tag{4.2}$$

[1] we denote the a priori estimation with the superscript -

where $\mathbf{Q}$ is the process noise covariance matrix.

As previously said, the basis of a Kalman filter is to obtain a posteriori estimator $\hat{\mathbf{x}}(k+1)$ thanks to a priori estimator $\hat{\mathbf{x}}^{-}(k+1)$ and the correction through the observation prediction error $\mathbf{H}\hat{\mathbf{x}}^{-}(k+1)$; hence is considered a predictor-correct estimator.

At the second step, the filter corrects the a priori estimation by means of introducing the measurement equations to finally obtain a posteriori estimation of the process state. The equations in order to obtain the a posteriori estimate are the following:

$$\mathbf{K}(k+1) = \mathbf{P}^{-}(k+1)\mathbf{H}^{T}\left(\mathbf{H}\mathbf{P}^{-}(k+1)\mathbf{H}^{T} + \mathbf{R}\right)^{-1} \tag{4.3}$$

$$\hat{\mathbf{x}}(k+1) = \hat{\mathbf{x}}^{-}(k+1) + \mathbf{K}(k+1)\Big(\mathbf{z}(k+1) - \mathbf{H}\hat{\mathbf{x}}^{-}(k+1)\Big) \tag{4.4}$$

$$\mathbf{P}(k+1) = (\mathbf{I} - \mathbf{K}(k+1)\mathbf{H})\mathbf{P}^{-}(k+1), \tag{4.5}$$

where $\mathbf{R}$ is the covariance matrix of the measurement noise.

In this stage the KF estimates the so-called Kalman gain $\mathbf{K}(k+1)$, that takes into account the current statistics of the state and the measurement noise. This gain is used later to minimize the covariance of the a posteriori error. Another important factor is the residual or the observation innovation's $\Big(\mathbf{z}(k+1) - \mathbf{H}\hat{\mathbf{x}}^{-}(k+1)\Big)$. The residual reflects the divergence between the predicted estimate $\mathbf{H}\hat{\mathbf{x}}^{-}(k+1)$ and the current measurements $\mathbf{z}(k+1)$. In addition to the previous gain, the filter is capable to correct the a priori estimation.

All these equations and the global procedure of the Kalman filter is summarized in Figure 4.1.

A major cons that could affect the performance of the KF is the estimation of the noise covariances $\mathbf{Q}$ and $\mathbf{R}$. These two matrices are very difficult to estimate. Nevertheless, they are not the only issue that affects the optimality of the KF. If an optimal KF is desired, then white Gaussian noise and a model that perfectly fits the real system are also necessary.

Although, KF could not achieve its optimal performance, it is a highly used algorithm in order to track moving objects in WSNs [Di08, Nab08].

4.2.2 Extended Kalman Filter

The KF basically estimates a state x of a discrete-time process modelled with a linear equation. But: *it is possible to model any process in a linear way?*.

Moreover, the measurements could not have a linear relationship with the process. The Extended Kalman Filter (EKF) is a suboptimal alternative that linearises the model at each step; hence, we are able to use a non-linear model.

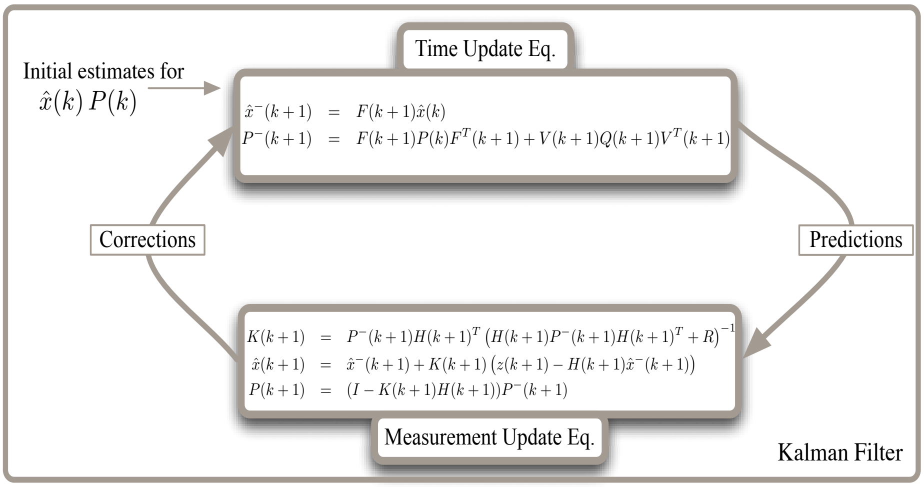


Figure 4.1: Kalman Filter Procedure

In this case, the equations presented at the previous subsection should be modified, as, now, the process is modelled as a non-linear stochastic difference equation:

$$\mathbf{x}^-(k+1) = \mathrm{f}\left(\mathbf{x}(k), \mathbf{u}(k)\right) \tag{4.6}$$

with a measurement $\mathbf{z}$ equal to:

$$\mathbf{z}(k+1) = \mathrm{h}\left(\mathbf{x}^-(k+1)\right), \tag{4.7}$$

where $\mathrm{f}\left(\mathbf{x}(k), \mathbf{u}(k)\right)$ and $\mathrm{h}\left(\mathbf{x}^-(k+1)\right)$ are non-linear functions that depend on the current state and time.

As previously discussed, the basic idea of the EKF is to linearise the equations (4.6) and (4.7), through the calculation of the partial derivatives of the process and measurements functions. Once the equations are linearised, the standard Kalman filter equations are applied. Hence, the EKF is also divided in two different stages.

The first stage is responsible to obtain the linearisation of the functions f and h and to convert them into the linear matrices $\mathbf{A}$ and $\mathbf{H}$. They are obtained as:

$$\mathbf{A}(k+1) = \left.\frac{\partial \mathrm{f}(\mathbf{x})}{\partial \mathbf{x}}\right|_{\mathbf{x}=\hat{\mathbf{x}}(k)} \tag{4.8}$$

$$\mathbf{H}(k+1) = \left.\frac{\partial \mathrm{h}(\mathbf{x})}{\partial \mathbf{x}}\right|_{\mathbf{x}=\hat{\mathbf{x}}^-(k+1)} \tag{4.9}$$

The equations that describe the EKF algorithm are summarized in the following equations, shown in the following Figure 4.2

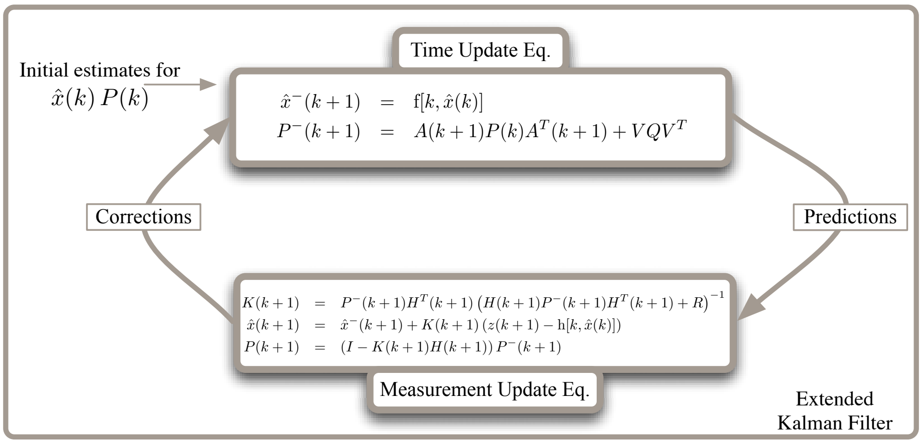


Figure 4.2: Extended Kalman Filter equations

The linearisation, i.e. the Jacobian, of f and h is computed each time step with current predicted states. Once these matrices are constructed, they are able to be used at the KF.

Compared to the KF, the EKF is not an optimal estimator. Moreover, the linearisation could cause a quickly divergence, if the initial estimate is not sufficiently accurate or the process is modelled incorrectly. Furthermore, another inconvenient is that the estimated covariance matrix tends to underestimate the true covariance matrix; hence, the algorithm could become inconsistent in the statistical sense.

Nevertheless, EKF has a valuable algorithm used in navigation systems, and mostly recent in tracking algorithms in WSNs [Liu08, Zhu06].

4.3 Outdoor Mobile Node Tracking

The first contribution is a method to track mobile nodes in outdoor scenarios.

More specifically, our purpose is to develop a tracking algorithm able to be used with med-high speed nodes (e.g car users). To do so, a fixed infrastructure is placed in an outdoor scenario. The benefits that we achieve using an algorithm based on WSN compared to other existing methods, such as GPS, are: more precision in urban environments due to the bad behaviour of GPS signals propagation in urban areas and a lower energy consumption.

In the following subsections, we present the scenario in detail, the procedure developed and the experimental results obtained.

4.3.1 Scenario Description

As previously commented, we consider a fixed WSN deployed in an urban scenario. Let us consider a wireless sensor network with N_1 anchor nodes, whose exact locations are known. The main goal is to estimate the location of a non-located node with the help of anchor nodes.

Figure 4.3: Example of and outdoor scenario

These nodes transmit a message that contains their positions. Thanks to the information collected and the RSS range measurements from the fixed nodes, the algorithm is able to detect, locate and track the mobile node.

RSS Measurements Model

As we consider an RSS-based tracking algorithm, we need to adopt the model that best fits the real propagation conditions. The most accepted option in WSN is to model the received power through the well known radio-propagation path loss and shadowing model. The RSS can be expressed as the power received in node j from a signal transmitted by node i, P_{ij}, as:

$$RSS_{ij} = P_{ij} = P_0 - 10\alpha_{ij} \log_{10} d_{ij} - v_{ij} \, (dBm), \tag{4.10}$$

As we will see later, the high variability of the RSS measurements will be simulated by means of assuming a higher value of the v_{ij}.

In the case of mobile nodes, some effects, such as Rayleigh fading, appears. These effects induced by the mobility are taken into account at the experimental validation in order to adapt the algorithm.

4.3.2 RSS-based Outdoor Tracking Algorithm

RSS-based algorithms have to raise certain challenges. RSS measurements offer a low accuracy but, however, they provide the simplest way to obtain inter-node distance estimates. Our basic interest is to offer a pragmatic solution easy to implement and low-cost. For that reason, although RSS measurements offer low accurate results, our proposal is to improve the existing solutions by means of correcting the RSS measurements.

Moreover, the med-high velocities assumed also affects these measurements. hence, when an algorithm is designed, one has to take into account all these limitations, that could, considerably, affect the overall performance.

Two major problems appear when practical RSS measurements are considered:

- **RSS errors:** Measurements reveal the appearance of different effects (such as Rayleigh) not present when fixed non-located nodes are considered. At the previous chapter, the principal range measurement error effect has been the shadowing effect. In this occasion, the obtention of an environment model is more complicated than in a static environment. Hence, the distance estimates obtained through the RSS measurements will have a higher error.

- **Connectivity errors:** The connectivity with the nodes would change faster than in a static scenario. This rapid change of the neighbour nodes that a mobile node could detect depends on the velocity that the mobile node takes. In the scenario proposed, the mobile node is inside a car, hence, the velocities that the node takes are considered to be med-high. The connectivity with the neighbour nodes in this scenario will have a high variation.

With the knowledge of all the issues that an outdoor tracking algorithm introduces, one has to wonder: *which is the most suitable tracking algorithm to be used?*

Proposed Solution

We have to, basically, take into account the two basic differences between the previous fixed proposals: the appearance of more error effects, and, high variability of the connectivity.

These effects induced by the mobility difficult to obtain a valid model of the RSS measurements. Hence the distance estimates can have a higher error. Hence, a weighted centroid algorithm seems to be more valuable compared to a trilateration method.

As commented at the beginning of this chapter, localization algorithms previously presented usually do not include many other parameters, such as velocity or direction, that could improve the position estimates. For that reason, methods, such as Kalman Filters, has been in last years proposed as a tracking method solution.

Moreover, the rapidly variability of the neighbours connectivity becomes in hopes back and forward of the position estimate. For that reason, a RSS Correction mechanism is proposed to be included. This modification allows us to minimize the bad effects due to the high velocities of the scenario; hence, trying to achieve a higher accuracy without increasing the complexity.

The localization and tracking algorithm procedure is shown in Figure 4.4. In the following lines, we explain with more detail all the parts that compose the outdoor tracking algorithm in order to adapt the method of the previous chapter to a mobile scenario.

Step 1 - Messages Reception

During a time period T, the mobile node recollect the messages transmit by the fixed network. The information extracted from the messages are the different RSS and the fixed node identifier. This information is saved in a matrix **P** as:

$$\mathbf{P} = \begin{bmatrix} RSS_1 & RSS_2 & \cdots RSS_{N_{S_i}} \\ Id_{R_x,1} & Id_{R_x,2} & \cdots Id_{R_x,N_{S_i}} \end{bmatrix}, \tag{4.11}$$

where RSS_i is the received power from node i in dBms and $Id_{R_x,i}$ is the value that indicates the existence of a measure, i.e. if $Id_{R_x,i}$ is equal to 1, this means that at that time the mobile node has received a message from node i. The RSS values are continously updating during all the time period. We do not erase any value, although

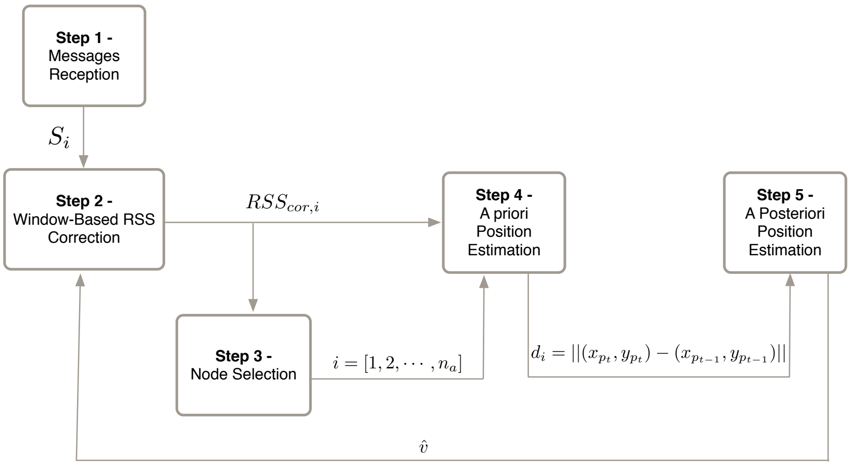


Figure 4.4: RSS-based Outdoor Tracking Procedure

the measurement has been done at the beginning of the time period. These errors are corrected with the work done at the step 2.

Step 2 - Window-based RSS Correction

This correction mechanism tries to reduce the bad effects explained before.

All the nodes that do not have any RSS measurement (i.e. their Id=0) or all of them that have a value of RSS lower than a threshold, modify their RSS value following our proposal.

The power received is modelled depending on the distance d and the exponent γ, that determines the decrease of the power depending on the distance, as:

$$RSS = P_0 - 10\gamma \log_{10}(d), \tag{4.12}$$

where P_0 is the power received at a reference distance of 1 meter (obtained experimentally). Hence, the propagation loses are estimated as:

$$L_{prop} = 10\gamma \log_{10}(d). \tag{4.13}$$

As shown in Figure 4.4, the Window-based corrector depends on the estimated velocity. We adapt the correction depending on the velocity. For that reason, we define different zones that the mobile node could take.

- range 1: $[v_{th1}, v_{th2})$

- range 2: $[v_{th2}, v_{th3})$
- range 3: $[v_{th3}, v_{th4})$

where the v_{thi} are the different thresholds that limits the different zones. Once we have decided the thresholds, we have to determine which are the values of the correction factors. Our proposal is to obtain them depending on the propagation loses formula (4.13). We first calculate the mean velocity of every range as:

$$\begin{aligned}
v_{m,range1} &= (v_{th1} + v_{th2}/2) \\
v_{m,range2} &= (v_{th2} + v_{th3}/2) \\
v_{m,range3} &= (v_{th3} + v_{th4}/2)
\end{aligned}$$

For every mean value of velocity, we can estimate the distance that a mobile node could move away as:

$$\begin{aligned}
d_{m,range1} &= v_{m,range1} t_{period} \\
d_{m,range2} &= v_{m,range2} t_{period} \\
d_{m,range3} &= v_{m,range3} t_{period}
\end{aligned}$$

With these distances we can obtain those looses with the equation (4.13), and, hence, we can update the values of the power that we should received as:

$$RSS(t+1) = RSS(t) - L_{prop,range_i}. \tag{4.14}$$

We update the previous measurement received $RSS(t)$ with the propagation loses depending on the velocity. Although the exponent γ value depend on the scenario, we assume a constant value equal to 2.5 that works in a general outdoor case.

The introduction of this window-based mechanism is motivated by the movement of the non-located nodes. The messages received suffer from variations and range measurement errors, and, moreover, these variations increase as the velocity increases. These problems in the connectivity and in the RSS values measured cause changes on the proximity in a short period of time (see Figure 4.5).

In a straight line scenario, the major problem is the possibility of having an estimated position that jumps forward and backward. With the proposed Window-based mechanism, we introduce a method that corrects the RSS variations by means of adapting the correction to the node velocity (see Figure 4.6).

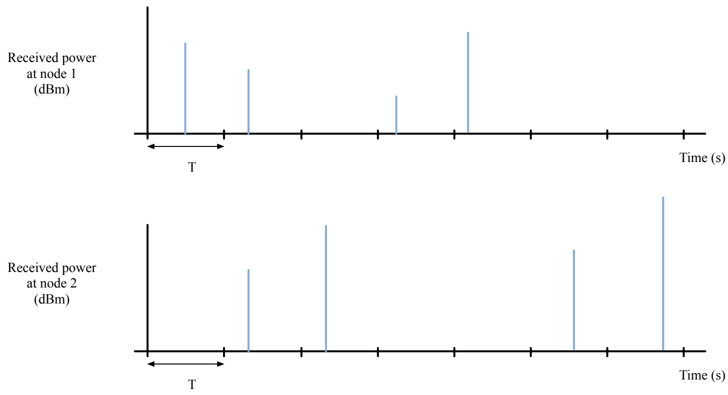


Figure 4.5: Temporal representation of the RSS measurements done at two nodes

Step 3 - Node Selection

As in the previous chapter, we introduce a node selection criterion in order to improve the overall performance. The closer the nodes, the more reliable information obtained from an anchor.

In our case, the closest nodes are those nodes with the highest RSS received. The node selection mechanism sort the RSS measurements received from higher to lower

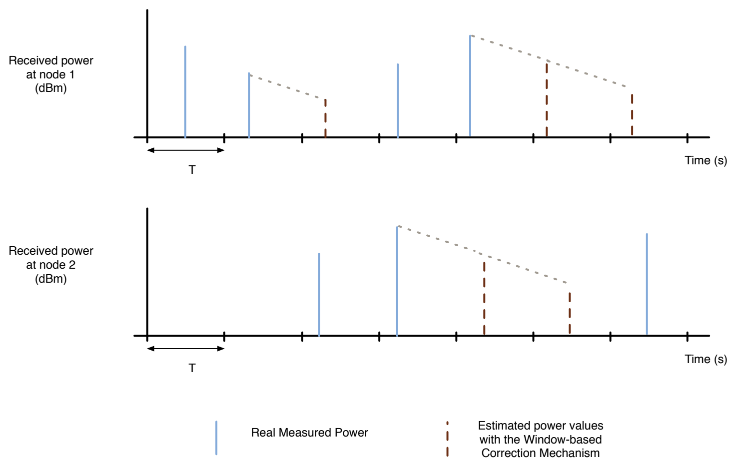


Figure 4.6: Temporal representation of the corrected RSS measurements done at two nodes

values. Being the sorted RSS measurements done the following:

$$RSS_a > RSS_b > ... > RSS_f \; \forall a, b, ..., f \in S_i \tag{4.15}$$

The node selection mechanism modifies the cooperating group S_i to:

$$S_i = [abc] \tag{4.16}$$

Finally, the number of anchors nodes n_a is fixed to three. Compared to the previous chapter, the number of the selected anchors are lower. The reason is that, now, the mobility of the nodes affects the RSS measurements received. The RSS can not reflect the real RSS, hence, we can erroneously use far away nodes. for that reason we have to limit the node selection to a lower number.

Step 4 - A Priori Node Position Estimation

If we want to guarantee a position inside the area of interest a better option is a centroid algorithm. This simple method, as previously commented in chapter 2, offers the possibility of estimating a node position thanks to the anchor coordinates. The higher the number of anchors the more precision of the position estimate. If the scenario is analysed in detail, one can see that the network offers a high number of fixed nodes; hence, a good accuracy could be obtain with a centroid method. Furthermore, the position of the node will be always inside the desired area.

In order to give a better accuracy to the position estimate offered by the centroid, a weight is introduced at the time of the estimation. Hence, the weighted centroid estimates the position as:

$$(x_m, y_m) = \left(\sum_{i=1}^{n_a} w_i x_i, \sum_{i=1}^{n_a} w_i y_i \right), \tag{4.17}$$

where the weights w_i are obtain as:

$$w_i = \frac{RSS_i}{\sum_{i=1}^{n_a} \left(1 - \frac{RSS_i}{\sum_{i=1}^{n_a} RSS_i}\right)}, \tag{4.18}$$

where RSS_i is the signal strength received from any anchor of the group n_a. In this occasion are selected the three anchor nodes with the highest RSS.

A weighted algorithm ensures to us a localization inside the network area. Nevertheless, the variability of the measures produces a high oscillation of the position estimates. As the scenario considered (see Figure 4.3) is a straight street, we can limit the possible path that a node can follow. Hence, the previous localization method could be improved by means of projecting the weighted centroid result onto the straight line in the middle of the street. Thanks to the projection of the positions, the localization algorithm will achieve a better representation of the position of the node (see Figure 4.7).

Figure 4.7: Projection of the weighted centroid estimates

As the anchors positions are known, it is straightforward to obtain the formula of a straight line in the middle of the area where the car moves. The projected weighted positions are estimated as follows:

$$\begin{bmatrix} x_m \\ y_m \end{bmatrix} = \begin{bmatrix} x_w \\ y_w \end{bmatrix} + \left(\frac{b - a_1 x_w - a_2 y_w}{a_1^2 + a_2^2} \right) \begin{bmatrix} a_1 \\ a_2 \end{bmatrix}, \tag{4.19}$$

where

$$\begin{aligned} m &= \frac{y_1 - y_0}{x_1 - x_0} \\ b &= y_0 - x_0 m \\ a_1 &= -m \\ a_2 &= 1. \end{aligned}$$

where (x_0, y_0) and (x_1, y_1) the coordinates of initial and final points that define the projected straight line, (x_w, y_w) the weighted mean coordinates estimates and (x_m, y_m) the projected coordinates.

Other Localization Methods The following methods are also simple methods to obtain an initial position estimate. We will present two different options that later will be compared with our proposal in terms of accuracy.

- Trilateration The first method presented is the trilateration. Hence, the mobile node needs 3 messages from 3 different anchor nodes. Instead of using a multilateration localization algorithm. The restriction to 3 cooperating nodes is motivated by the inherent multiplicative error of RSS distance estimates. The further the node, the higher the distance error. Hence, the algorithm selects those 3 nodes with the highest RSS received.

  Once the mobile node has select the cooperative nodes, given the power received RSS_{ij} in Equation (4.10), an ML estimate of the actual distance can be derived as:

$$\delta_{ij} = 10^{\frac{P_0 - RSS_{ij}}{10\alpha_{ij}}}. \tag{4.20}$$

  The algorithm estimates these distances assuming an equal value of the path loss exponent.

  Finally, the position is estimated as:

$$\mathbf{A} \cdot \mathbf{p_m} = \mathbf{b}, \tag{4.21}$$

  where

$$\begin{aligned} \mathbf{A} &= \begin{bmatrix} x_1 - x_2 & y_1 - y_2 \\ x_1 - x_3 & y_1 - y_3 \end{bmatrix} \\ \mathbf{b} &= \begin{bmatrix} x_1^2 - x_2^2 + y_1^2 - y_2^2 + \delta_2^2 - \delta_1^2 \\ x_1^2 - x_3^2 + y_1^2 - y_3^2 + \delta_3^2 - \delta_1^2 \end{bmatrix} \\ \mathbf{p_m} &= \begin{bmatrix} x_m \\ y_m \end{bmatrix} \end{aligned}$$

where (x_m, y_m) are the mobile nodes coordinates, $(x_i, y_i)\,\forall i \in [1,2,3]$ are the anchors coordinates and $\delta_i\,\forall i \in [1,2,3]$ are the distance estimates from the mobile node to the selected anchors.

This matrix equations could be solved through an LS closed-form solution as:

$$\mathbf{p_m} = \begin{bmatrix} x_m \\ y_m \end{bmatrix} = \left(\mathbf{A^T A}\right)^{\mathbf{-1}} \mathbf{A^T b}. \tag{4.22}$$

- Weighted Centroid The weighted centroid algorithm is the our proposed solution excluding the projection part. As commented before, we assure a priori position estimate inside the area of interest. Moreover, the inclusion of a weight helps to increase the accuracy of the algorithm, because we give more reliability to those nodes with higher RSS. Hence, we give a high ponderation to those nodes that are, probably, closer to the mobile node.

Step 5 - One Dimensional Kalman Filter

The major drawback that all the localization methods present is the high variability of the estimates obtained. Although this behaviour is not observable in an static figure, the position estimates backs down and up due to the variability of the RSS measurements. One has to take into account that the algorithm is using RSS-range based measurements in a rapidly environment (the mobile node is moving at velocities between 10 and 20 km/h) and this velocity is not taking into account by the projected weighted algorithm proposed.

For that reason, a Kalman filter is introduced in the localization and tracking procedure. The KF used is a one dimensional kalman filter, because the algorithm projects the position on a centred straight line, hence, it is only necessary to estimate how many meters has moved the mobile node through this line.

The equations that characterizes our 1DKF are:

- **State vector:** The state vector is formed by only two variables: the distance d that the mobile node has moved through the centred straight line and the velocity v of the mobile node.

$$\mathbf{x} = \begin{bmatrix} d \\ v \end{bmatrix} \tag{4.23}$$

- **State equation:** Each state is obtained through a position-velocity model as:

$$\mathbf{x}(n) = \begin{bmatrix} 1 & T \\ 0 & 1 \end{bmatrix} \mathbf{x}(n-1) + \begin{bmatrix} T^2/2 \\ T \end{bmatrix} v(n-1) \tag{4.24}$$

- **Observation equation:** the KF only considers the observation of the distance that the mobile node has moved away from the previous position estimate d. Hence, the observation equation becomes:

$$\mathbf{z}(n) = [1\ 0]\,\mathbf{x}(n-1) \tag{4.25}$$

The basic operation of the 1-Dimensional Kalman Filter (1DKF) is shown in the Figure 4.8.

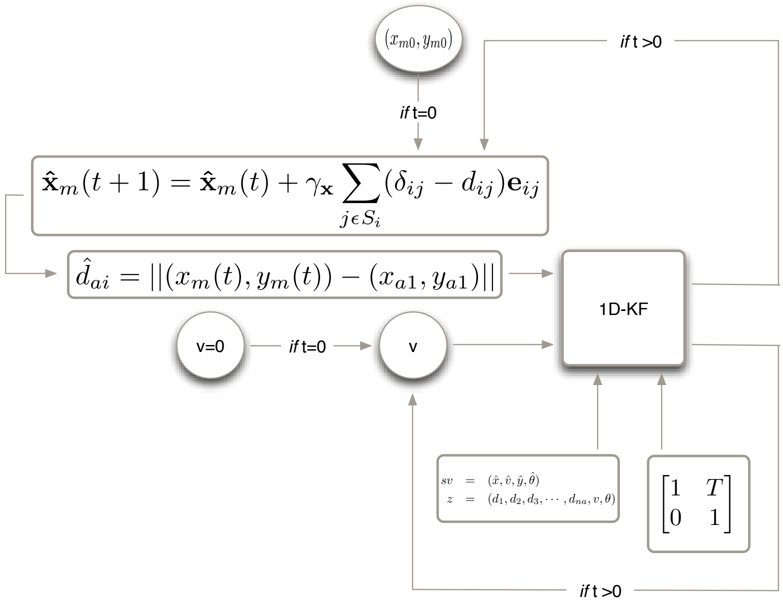


Figure 4.8: 1-Dimensional Kalman Filter

The procedure of the outdoor tracking algorithm is summarized in the Algorithm 2.

4.3.3 Simulation Results

We consider a fixed network composed by N_1 equal to 6 nodes and a mobile node moving at two different velocities. The nodes are divided in two different straight lines separated 10 meters. Moreover, the nodes at the same line are separated 5 meters. the parameters assumed at the simulations are summarized at the following table 4.1.

In the following subsections, we evaluate the performance of the two diffrent parts of the algorithm: the a priori and the a posteriori position estimate.

Algorithm 2 RSS-based Outdoor Tracking Algorithm

Messages Reception

$$\mathbf{P} = \begin{bmatrix} RSS_1 & RSS_2 & \cdots RSS_{N_{S_i}} \\ Id_{R_x,1} & Id_{R_x,2} & \cdots Id_{R_x,N_{S_i}} \end{bmatrix}$$

Window-based RSS Correction

if $v < v_{th1}$ **then**
  for $i = 1$ to N_{S_i} **do**
    $RSS_i(t+1) = RSS_i(t) - \gamma_1$
  end for
else if $v_{th1} < v < v_{th2}$ **then**
  for $i = 1$ to N_{S_i} **do**
    $RSS_i(t+1) = RSS_i(t) - \gamma_2$
  end for
else
  for $i = 1$ to N_{S_i} **do**
    $RSS_i(t+1) = RSS_i(t) - \gamma_3$
  end for
end if

Node Selection:

$being\, RSS_a > RSS_b > ... > RSS_f \; \forall a, b, ..., f \in S_i$

$then\, n_a = [abc]$

Coordinates Estimation:

$(x, y) = (\sum_{i=1}^{n_a} w_i x_i, \sum_{i=1}^{n_a} w_i y_i)$

Projected Coordinates:

$$\begin{bmatrix} x_m \\ y_m \end{bmatrix} = \begin{bmatrix} x \\ y \end{bmatrix} + \left(\frac{b - a_1 x - a_2 y}{a_1^2 + a_2^2} \right) \begin{bmatrix} a_1 \\ a_2 \end{bmatrix}$$

A Posteriori Position Estimate:

1Dimensional Kalman Filter

Table 4.1: Simulation Parameters.

Simulation Parameters	**Parameter Value**
Size of Sensor Field	10×15 m
Number of Anchors (N_1)	4
Path Loss Exponent α_{ij}	2.5
Standard Deviation σ_v	5 dB
First-Meter RSS P_0	-50 dBm
Velocity	$v_1 = $ 10km/h & $v_2 = $ 20km/h

A Priori Position Estimate

The a priori position estimation proposed is compared, in terms of accuracy, with two other proposals: a trilateration method and a weighted centroid. The projection of the weighted centroid results, which is our proposal, is done thanks to the a priori knowledge of the map. The results of the mean absolute errors achieved at both velocities are summarized in the table 4.9. The trilateration method obtain the worst results. The propagation model used is not sufficiently accurate in order to obtain good inter-node distance estimates. Hence, the trilateration method inherit these errors.

Moreover, the weighted centroid method obtains good results, although, the projected weighted centroid outperforms it. A gain of the 18 % with a v=10km/h and a of gain 10% with a v=20km/h are achieved.

Positioning Method	Velocity (km\h)	Mean Absolute Error (m)
Trilateration	10	>10
	20	>10
Weighted Centroid	10	2.14
	20	2.62
Projected Weighted Centroid	10	1.75
	20	2.35

Figure 4.9: A priori methods accuracy comparison

A Posteriori Position Estimate

In this section we simulate the effects of the introduction of our window-based RSS correction mechanism. The results show the increased accuracy achieved by our proposal. The errors produced by the high variability and rapid changes of the connectivity are minimized with the Window-based RSS mechanism. The differences between the proposed algorithm and the 1DKF are reflected in the gains achieved: a 65% with a low velocity and a 30% with a high velocity.

A Posteriori Position Estimation	Velocity (km\h)	Mean Absolute Error (m)
1D-KF	10	4.57
	20	2.55
Window-based & 1D-KF	10	1.57
	20	1.78

Figure 4.10: A posteriori methods accuracy comparison

Besides, our proposal achieves more accurate results than the a priori position estimate. Gains achieve are a 10% with 10 km/h and a 24% with 20 km/h.

4.3.4 Experimental Results

The experimental scenario is a street from a parking located inside the university campus. As shown in Figure 4.11, we placed 20 fixed anchor nodes along a straight street. The two queues of nodes were separated 10 meters and the distance between two nodes at the same line was 5 meters. The total longitude of the street is 50 meters. The different experimental results are obtained at two different velocities: 10 km/h and 20 km/h.

XALOC Project

This work has been experimentally demonstrated in the framework of project XALOC (Regional Project[2]). For that reason, in the following lines we briefly present the XALOC scenario and the purposes of the project.

The main purpose of the project was the design of a car parking platform based on wireless sensor networks (WSN). UAB contributed with the development of WSN-

[2] INFOREGIÓ project XALOC - XArxes de sensors per a la gestió d'aparcaments públics i LOCalització

Figure 4.11: Outdoor scenario

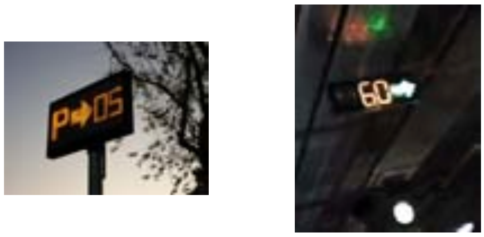
and WIFI-based positioning systems devoted to efficiently guide the drivers to available parking spaces. The platform developed is able to detect free parking spaces and localize vehicles. With this information, the system guides the drivers to the free parking spaces in the area of interest.

The XALOC project, apart from this navigation application, has developed a fixed platform based on a WSN. These nodes detect the presence or absence of a car at their parking place position. This information is transmitted through a central point that is connected to a central server that maintains an actualization of the total network. This information is processed and then sent to street panels (see Figure 4.12(a)) in order to inform to the drivers of the free spaces, taking the idea from the panels of an indoor parking (see Figure 4.12(b)), vastly extended.

Hence, the main objectives of the XALOC project could be summarized as follows:

- The detection of free parking spaces.
- Determine the localization of the users that want to find a free space.
- Guide the drivers to free parking spaces with the panels or messages to their navigators.

With this system is possible to achieve a better management of the traffic in urban environments, by means of reducing the no-direction navigation of the drivers that are



(a) Street panel indicator (b) Indoor parking panel

Figure 4.12: Example of indicator panels

searching a free parking. In addition, a diminution of the traffic could become in an improvement of the circulation and, moreover, it is possible to reduce the pollution caused by the car residues.

A Priori Position Estimation Results

The results of the different a priori methods presented in the previous step 4 are presented here. In order to compare the benefits that we achieved with our proposal we first present the trilateration method and, then, the weighted centroid.

Trilateration The reliability of the trilateration algorithm is mostly dependent on the distance estimates δ_i. When RSS range measurements are used, the higher the distance, the higher the distance estimate error. In our proposal, the node selection mechanism propose tries to select those nodes with more reliable distance estimates, e.g. those closer nodes.

The results are shown in Figures 4.13 and 4.14. The environment changes very rapidly as the mobile node moves. Moreover, the higher the velocity, the higher the errors obtained. With this high variations of the environment, the obtention of a good model and, hence, the good estimation of the internode distances is more difficult.

Furthermore, some measurements could estimate a position outside the area of interest. Although trilteration is a good localization algorithm, the low accurate distance estimates affects so much the positions accuracy.

Weighted Centroid The weighted centroid algorithm is introduced in order to reduce the errors achieved with the trilateration method. As previously commented, the weighted centroid does not depend on the distance estimates, hence we assure a position inside the desired area and we avoid the necessity of obtaining a good propagation

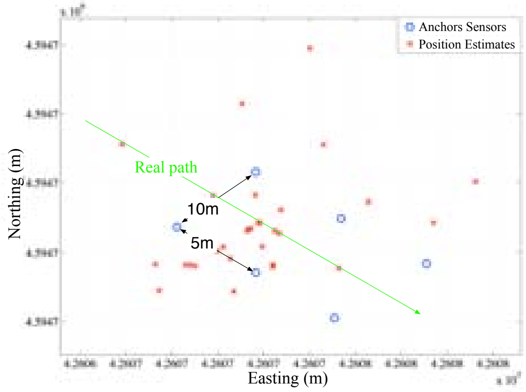


Figure 4.13: Position tracking done at low velocity ($\approx 10km/h$)

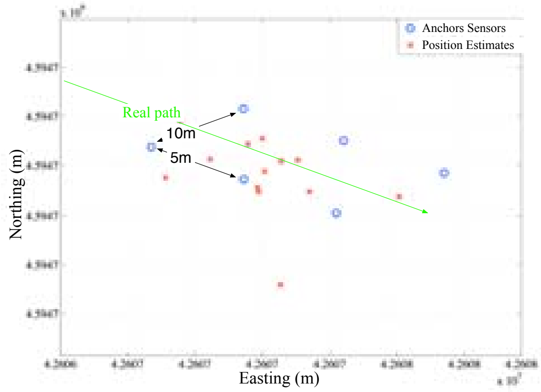


Figure 4.14: Position tracking done at high velocity ($\approx 20km/h$)

model to transform the RSS measurements to distance.

The accuracy of this method is reflected in Figures 4.15 and 4.16. The position estimates are now always inside the area of interest. For that reason the weighted centroid method achieves a better accuracy compared to that achieved by the trilateration.

Although weighted centroid guarantees that the position estimation will be inside the measurement region it does not offer an accurate position to the mobile node. The majority of the positions shown at both Figures are concentrated in an area and they do not reflect the real movement of the mobile node along the area.

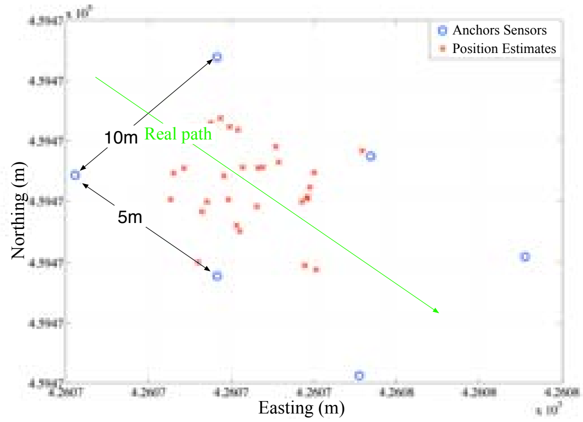


Figure 4.15: Position tracking done at low velocity ($\approx 10km/h$)

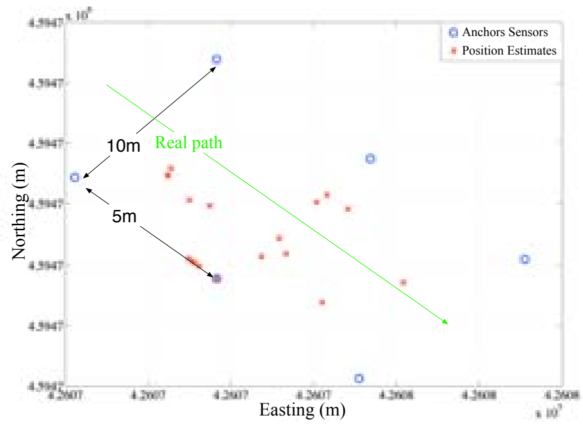


Figure 4.16: Position tracking done at high velocity ($\approx 20km/h$)

Projected Weighted Centroid A comparison between having or not the projection of the position is done in Figures 4.17 and 4.18. As commented before, as we know the map of the scenario we can take the advantage of this knowledge and projecting the position estimates to the a priori known path that the node could follow.

The benefits could be shown in both Figures. The position estimates are now always located inside the desired area and have less variations. Moreover, thanks to the projection method, the algorithm could offer a more stable position estimate to the user.

At the end of this section, a brief summary, in terms of mean absolute error is

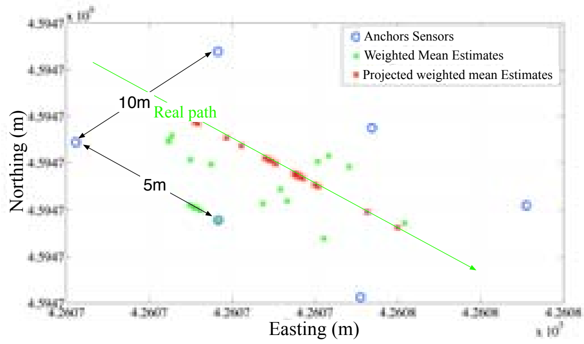


Figure 4.17: Position tracking done at low velocity ($\approx 10km/h$)

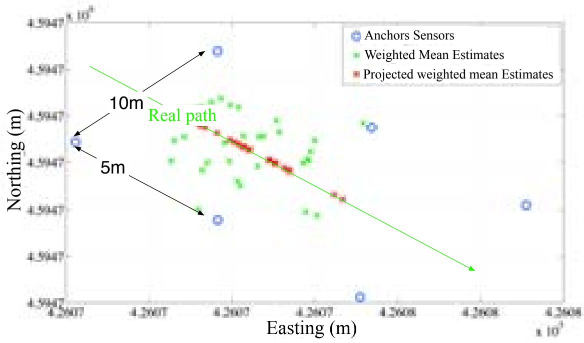


Figure 4.18: Position tracking done at high velocity ($\approx 20km/h$)

presented.

A Posteriori Position Estimate Results

In this part we are evaluating the accuracy obtained with our 1D-KF with the Window-based correction mechanism compared to the accuracy of a 1D-KF without the correction mechanism. Both methods uses the projected weighted centroid as a priori position estimation. Now the measurements are done every 2.5s (the time period assumed). Compared to the previous results, now we do not estimate the position when four messages are received.

In Figures 4.19 and 4.20 the performance, when the 1D-KF is introduced, is shown. One could observe that the estimates obtained reflect better the path followed by the mobile node. The major drawback still observed is the jumps that the estimates have. Although the track is, more or less, followed, it exists some points at which the position goes back. Moreover, this fact becomes in huge jumps of position estimates that not reflects the reality.

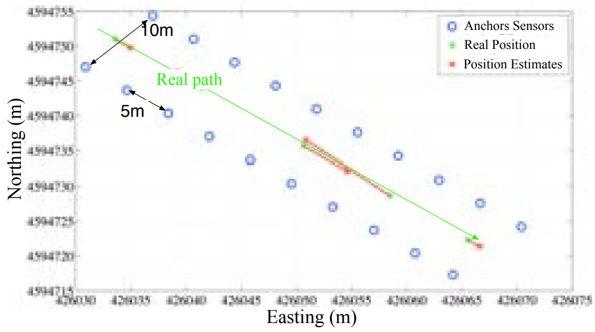


Figure 4.19: Position tracking done at low velocity ($\approx 10km/h$)

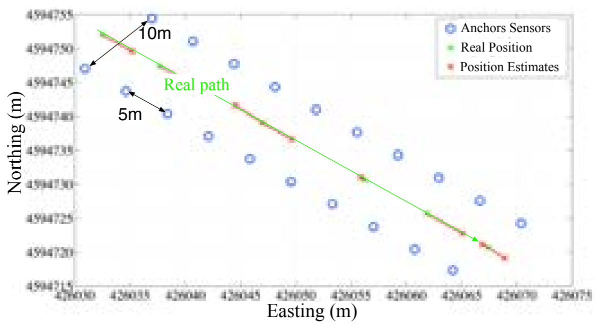


Figure 4.20: Position tracking done at high velocity ($\approx 20km/h$)

If one compares the results obtained in 4.19 and 4.20 with the results in Figures 4.21 and 4.22, the hopes forward and backward are practically avoided. With the Window-based correction, the tracking algorithm improves their overall performance achieving a better results in terms of accuracy. We achieve a gain of 37.79% with v=10 km/h and of 61.74% with v=20km/h. Moreover, the uncertainty of the RSS measurements is controlled with our proposal.

Summary

The experimental results validate the proposed strategy. With respect to the a priori position estimate step, the projected weighted centroid have increased the accuracy of

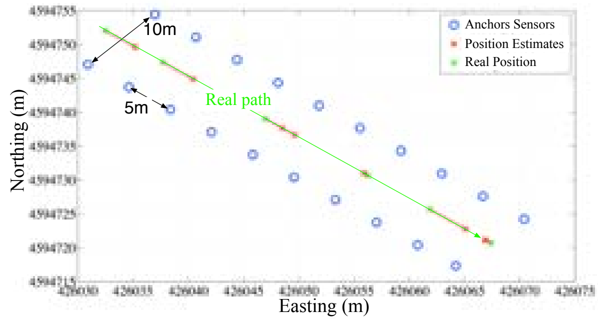


Figure 4.21: Position tracking done at low velocity ($\approx 10km/h$)

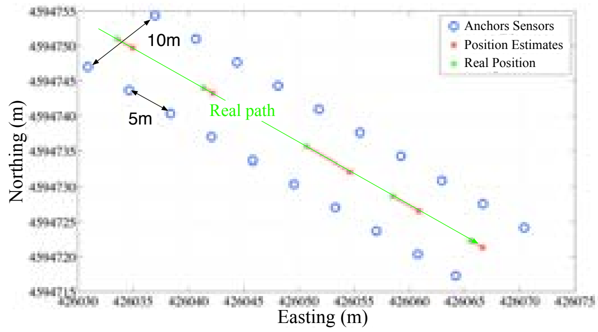


Figure 4.22: Position tracking done at high velocity ($\approx 20km/h$)

the tracking algorithm. The results have demonstrated that the inclusion of a priori knowledge of the possible path that the mobile node could follow reduces the mean absolute error. Moreover, we have validated the disregard of the distance-based method presented (trilateration), because it is very difficult to obtain an accurate propagation model (see table 4.23(a)). Furthermore, the a posteriori position estimation based on a KF has shown that increases the accuracy. Nevertheless, the variability of the measurements due to the mid-high velocities considered still affects the 1D-KF performance. The Window-based RSS correction mechanism proposed has reduced this variability problem, and, hence, it has increased the accuracy of the tracking algorithm (see table 4.23(b)).

Compared to the algorithm without using the window-based correction mechanism, our proposal achieves a gain of 37.8% with 10 km/h and of 61.7% with 20 km/h. If that comparison is done between the a priori position estimate and the a posteriori estimate obtained with our proposal tha gains achieved are 16.4% and 21.7% with 10 and 20

Positioning Method	Velocity (km\h)	Mean Absolute Error (m)
Trilateration	10	>10
	20	>10
Weighted Centroid	10	3.22
	20	2.68
Projected Weighted Centroid	10	2.91
	20	2.02

(a) A Priori Position Estimation

A Posteriori Position Estimation	Velocity (km\h)	Mean Absolute Error (m)
1D-KF	10	3.91
	20	4.13
Window-based & 1D-KF	10	2.43
	20	1.58

(b) A Posteriori Position Estimation

Figure 4.23: Experimental Accuracy Results

km/h, respectively.

4.4 Indoor Mobile Node Tracking

The indoor localization is a widely field under study in the past literature as explained 2. The easy-deployment of WSN in indoor environments has impulsed an interest on the development of tracking algorithms devoted to this kind of networks. The indoor tracking method could be applied in different final applications, such as: to monitor patients in a hospital (as in [Red10]); to monitor elder people who lives alone; or to control the packaging inside a warehouse. The advantage of developing a tracking algorithm in a WSN is that the tracking algorithm could be complemented with any other features that are sensed by the nodes.

In order to achieve an easy-deployable and energy-efficient algorithm, an indoor localization based on RSS range measurements is proposed.

Compared to the previous section, now we want to solve the same problem but new impairment appear as we consider an indoor environment. Although the velocities consider in indoor scenarios are much lower than before, other effects, such as multipath and obstacles, badly affect the RSS measurements.

Compared to other works that includes inertial navigation systems [Sch11, Kli08, Fan05], our pragmatic approach avoids the use of additional sensors such as accelerometers, gyroscopes, etc.

4.4.1 Scenario Description

In this case the tracking algorithm is applied in an indoor WSN. The idea is to develop a system to track a person or a moving object inside a building.

The mobile node is able to estimate their position thanks to a given number of fixed nodes distributed along the scenario (see Figure 4.24). Mobile node receives messages from this fixed nodes. With the information transmitted the node is able to estimate and track its position.

Following the approach presented in the outdoor case, our proposal is to minimize the bad effects explained with another window-based RSS control mechanism. In this case, we propose, as before, a tracking algorithm composed by two parts: a firts stage in which the node estimates a priori position that is then corrected at the second stage by means of using a Kalman Filter, in this occasion a 2D KF.

RSS Measurements and Distance Modelling

As previously commented, we consider an RSS-based tracking algorithm. RSS measurements are used to obtain inter-node distance estimates. Power received is modelled through the well known radio-propagation path loss and shadowing model. The RSS can be expressed as the power received in node j from a signal transmitted by node i, P_{ij}, as:

$$RSS_{ij} = P_{ij} = P_0 - 10\alpha_{ij} \log_{10} d_{ij} - v_{ij}\,(dBm), \tag{4.26}$$

Given the received power RSS_{ij} in equation (4.26), an ML estimate of the actual distance can be derived as:

$$\delta_{ij} = 10^{\frac{P_0 - RSS_{ij}}{10\alpha_{ij}}} \tag{4.27}$$

In order to reflect the high variability of the RSS measurements, we assume a variance higher than this assumed in the previous fixed localization algorithms. This difference is reflected in the different RSS measurements shown in Figures 4.25. In both Figures, the RSS measurements received by two anchor nodes during a time period are shown. The variability of the measurements produces errors at the time of estimating the mean value of the RSS measurements.

4.4.2 RSS-based Indoor Tracking Algorithm

The tracking algorithm proposed wants to take advantage from the RSS measurements. As commented in the previous chapter, the RSS measurements are badly affected by the pathloss and shadowing effects. Hence, a good propagation model is necessary, if

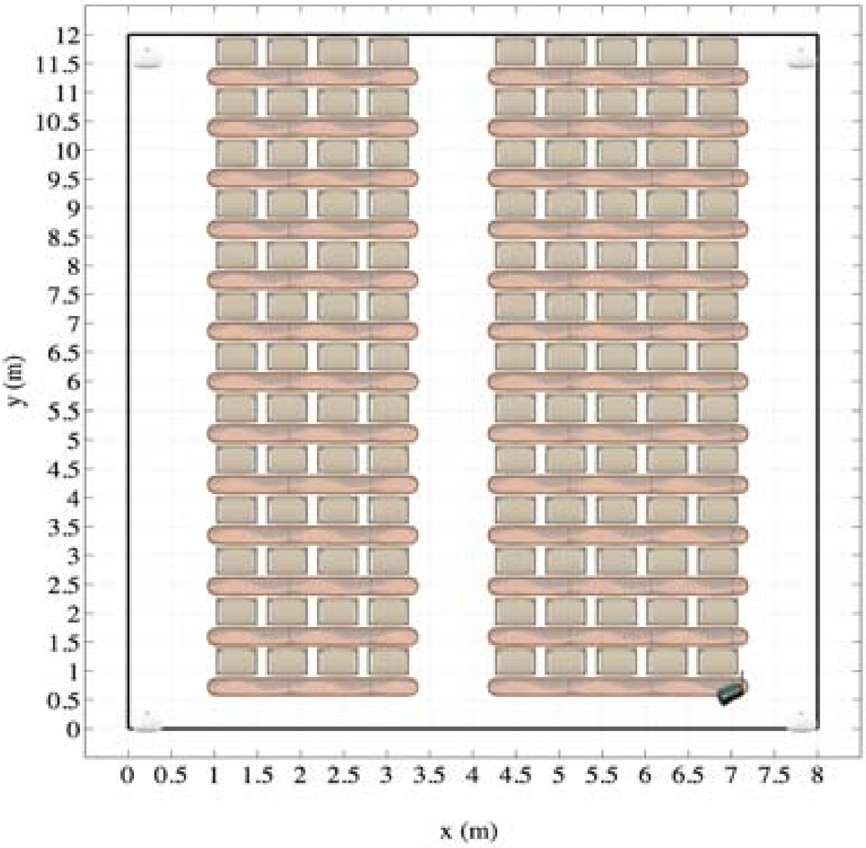
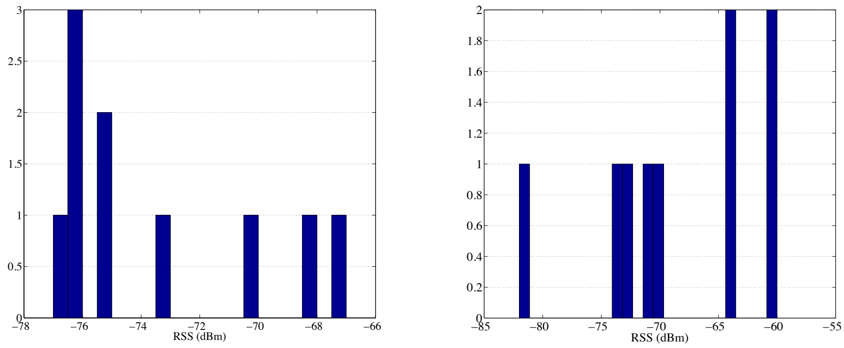


Figure 4.24: Example of an indoor scenario

RSS-based distance estimates are used. In this occasion, and compared to the outdoor scenario, the distance between the mobile nodes and the anchor nodes are lower than in the previous outdoor scenario. Hence, the multiplicative error of the distance estimates will be lower. For that reason, we will take advantage of this estimates at the time of estimating the position.

Moreover, our proposal differs from the previous localization methods in one sense: the velocity of the node. Although the mobile node moves slower than before, the velocity still increases the variability of the range measurements. Experimental campaigns reveal that the uncertainty is very high. The major drawback that affects the range measurements done is the possible reception of messages with a higher RSS



(a) Mean value=-73.3 dBm Estimated variance=13.3 (b) Mean value=-68.87 dBm Estimated variance=53

Figure 4.25: Example of indoor measurements

compared to the expected value of the RSS model. *Which is the best option to implement?*

- **A Priori Position Estimation** As commented above, a tracking algorithm based on a Kalman Filter estimates a process state, thanks to series of measurements. The measurements, in our case are the calculated distances through the following equation:
$$d_{mi} = \sqrt{(x_m - x_i)^2 + (y_m - y_i)^2}, \tag{4.28}$$
where (x_m, y_m) and (x_i, y_i) are, respectively, the mobile and anchor node coordinates.

  These mobile node coordinates are obtained through a localization algorithm. Our proposal is to use a weighted LS algorithm. The results obtained at the previous chapter reveal the viability of using this approach in an indoor environment. The accuracy provided by these localization algorithm is good and the complexity needed is not so high. Moreover a node selection mechanism is also introduced, hence, the energy consumption is also reduced.

- **A Posteriori Position Estimation** The positions obtained a priori are then introduced as measurements at the EKF, that refines those position estimates. In this case, we base our proposal on an Extended Kalman Filter. The process that defines our tracking algorithm is a not linear one; hence, it is necessary to use this suboptimal solution.

  The major drawback that we comment previously is the high variability of the

RSS range measurements. High values of variance are achieved with the experimental measures done. The estimation of the RSS variances allows to us to propose two mechanisms in order to improve the performance of the tracking algorithm.

First proposal is related with the parameters that regulates the EKF. As explained previously, the EKF model equations are affected by white Gaussian errors. These errors are reflected on the parameters R and Q. Although they are normally assumed fixed, our proposal is to update the values of these parameters depending on the variance. Hence the EKF adapts their behaviour to the RSS measurements.

Our second proposal is to introduce a mechanism that controls the variability of the range measurements, similar to the previous window-based RSS control mechanism. The main difference is that, now, instead of using the velocity, the estimated RSS variance is the feature that controls the correction.

In the following section the different parts of the algorithm are presented in order to gives an in depth explanation of the proposed tracking algorithm. This procedure is shown in the Figure 4.26. All the procedure are summarized at the end of the explanation in the Algorithm 2.

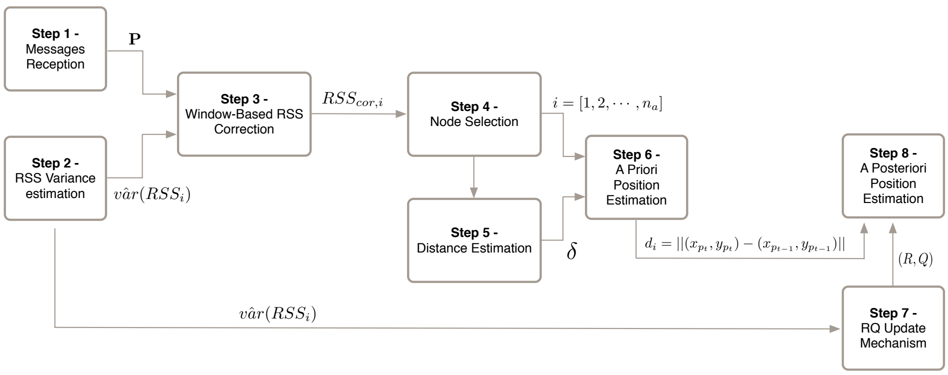


Figure 4.26: RSS-based Indoor Tracking Procedure

Proposed Solution

Step 1 - Messages Reception

During a time period T, the mobile node recollect the messages transmit by the fixed network. The information that extracted from the messages are the different RSS and the fixed node identifier. This information is saved in a matrix **P** as:

$$\mathbf{P} = \begin{bmatrix} \mathbf{RSS}_1 & \mathbf{RSS}_2 & \cdots & \mathbf{RSS}_{N_{S_i}} \\ n_{PckR_x,i} & n_{PckR_x,i} & \cdots & n_{PckR_x,i} \end{bmatrix}, \tag{4.29}$$

where $\mathbf{p}_{R_x,i}$ is the vector with all the received power from node i in dBms and $n_{PckR_x,i}$ is the value that indicates the number of measures done. All the RSS values are saved during all the time period. We do not erase any value, although the measurement has been done at the beginning of the time period. The final value used is the mean value of all the messages received as:

$$R\bar{S}S_i(t+1) = \frac{\sum_{j=1}^{n_{PckR_x}} RSS_j}{n_{PckR_x}} \tag{4.30}$$

Step 2 - RSS Variance Estimation

As previously explained, the RSS measurements done in an static indoor scenario suffer from a high variability. Moreover, when the node has mobility this feature is increased .

This high variability of the measurements is reflected in the variance of the RSS values received during a time period T. The higher the variance, the higher the measurements errors. For that reason, we propose to estimate this variance in order to take advantage of it. The values are obtained as:

$$var_i = \frac{\sum_{j=1}^{n_{PckR_x,i}} \left(RSS_j - \frac{\sum_{j=1}^{n_{PckR_x,i}} RSS_j}{n_{PckR_x}} \right)^2}{n_{PckR_x}} \tag{4.31}$$

Thanks to the RSS variance estimates, we can control and reduce this bad effect by means of using the proposed window-based RSS correction (Step 3). Moreover, with the RQ update mechanism (Step 7) we could inform to the Kalman filter that the measurements from these nodes are less reliable, and, hence, we could adapt the RQ Kalman parameters to increase the EKF accuracy. Finally, we also used them to introduce the velocity measurement to the Kalman Filter (Step 8).

Step 3 - Window-based RSS Correction

As previously commented , in an indoor environment the RSS measurements suffer from shadowing and path loss effects. These factors are present in the propagation looses (L_{prop}).

$$RSS = P_0 - L_{prop}. \tag{4.32}$$

But the uncertainty introduced is more evident when the non-located node is moving along the scenario. This highly variation could produce non-realistic measurements that could seriously affect the tracking algorithm performance. For that reason, and taking advantage of the RSS variance estimations, we propose an RSS control mechanism. The basic purpose is trying to reduce the error that suffers the RSS measurements. We can remark that we avoid the use of inertial sensors, such as gyroscopes or accelerometers. They increase the cost of the nodes and can consume more energy resources that limits the battery life of the hardware.

The control mechanism performance works as follows. Depending on the value of the variance, the control mechanism applies a correction factor to the RSS measured.

As in the outdoor case, we now define different variance ranges as:

- range 1: $[var_{th1}, var_{th2})$
- range 2: $[var_{th2}, var_{th3})$
- range 3: $[var_{th3}, var_{th4})$

where the var_{thi} are the different thresholds that limits the different zones.

Once we have the thresholds, we have to decide which are the values of the correction factors. Our proposal is to use the estimated variance multiplied by a factor. The values are obtained as:

$$\begin{aligned} L_{range1} &= var_i \gamma_{range1} \\ L_{range2} &= var_i \gamma_{range3} \\ L_{range3} &= var_i \gamma_{range3} \end{aligned}$$

With these values, we can update the values of the power that we should received as:

$$P_{Rx}(t+1) = P_{Rx}(t) - L_{rangei}. \tag{4.33}$$

We update the previous measurement received $P_{Rx}(t)$ with the estimated correction factors. Although the exponent γ value depend on the scenario, we assume a constant value equal to 2.3, that, in a general case works.

Step 4 - Node Selection

As in the previous chapter, we introduce a node selection criterion in order to improve the overall performance. The closer the nodes, the more reliable information obtained from the anchor.

In our case, the closest nodes are those nodes with the highest RSS received. The node selection mechanism sort the RSS measurements received from higher to lower values. Being the sorted RSS measurements the following:

$$RSS_a > RSS_b > ... > RSS_f \; \forall a, b, ..., f \in S_i \tag{4.34}$$

As commented previously, the mobility of the nodes induces bad effects to the RSS measurements. The introduction of an on-line path loss estimation based on this RSS measurements can be affected by these mobility errors. For that reason, we assume a fixed value of the path loss exponent, hence, the RSS-based node selection criterion used becomes the same as the distance-based used at the previous Chapter.

The node selection mechanism modifies the cooperating group S_i to:

$$S_i = [abcd] \tag{4.35}$$

Finally, the number of anchors nodes n_a is fixed to four. Now, we use 4 anchors instead of the 3 used at the outdoor case because, now, the velocity assume is lower and the real distances between the mobile node and the anchors distributed in the indoor environment are lower.

Step 5 - Distance Estimation

Given the corrected RSS values from the selected nodes and considering the path loss and shadowing model presented before (see equation (4.10)), an ML estimate of the actual distance can be derived as:

$$\delta_{ij} = 10^{\frac{P_0 - RSS_{ij}}{10\alpha_{ij}}} \tag{4.36}$$

The algorithm estimates these distances assuming an equal value of the path loss exponent. We do not introduce the on-line path loss estimation because

Step 6 - A Priori Position Estimation

The Kalman Filter depends on a set of measurements done at each time step. In our tracking algorithm these measurements are the distance between mobile node and each anchor obtained through their coordinates $\left(\hat{d}_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}\right)$. Hence, an important point is having the best a priori mobile node position estimate, in order to give the best possible measurements to the KF.

In that sense, we propose to use a distributed weighted LS. Compared to the outdoor scenario presented in the previous section, the indoor scenario has a lower density of anchor nodes. As the area is considerably reduced, the number of anchors necessary should be reduced. For that reason, we propose to use a weighted LS localization algorithm, because, the weighted centroid, as seen in chapter 2, has a better performance when the anchor density is high. Furthermore, a weight based on the inter-node distance estimates are introduced in order to give a higher reliability to those closer anchor nodes.

These step is formed by two substeps:

$$\begin{aligned}
&\text{Weight Estimation} \quad && w_i && = \frac{\frac{1}{\delta_{ai}^2}}{\sum_{i=1}^{n_a}\left(\frac{1}{\delta_{ai}^2}\right)} \\
&\text{Position Estimation} \quad && \hat{\mathbf{x}}_m(t+1) && = \hat{\mathbf{x}}_m(t) + \gamma_{\mathbf{x}} \sum_{j \epsilon S_i} w_i(\delta_{ij} - d_{ij})\mathbf{e}_{ij}
\end{aligned}$$

Other Localization Methods We want to compare the proposed weighted LS algorithm with the previous weighted centroid method.

- **Weighted Centroid:** The weighted centroid algorithm used at the previous proposal is a simple approach that assures a position inside the scenario desired. The position estimate is obtained as:

$$(x, y) = \left(\sum_{i=1}^{n_a} w_i x_i, \sum_{i=1}^{n_a} w_i y_i\right) \tag{4.37}$$

  The weight is the same as the previously defined for the weighted LS.

Moreover, we will also compare the performance of both algorithms with the weight used in the outdoor case. Being the weight:

$$w_i = \frac{RSS_i}{\sum_{i=1}^{n_a}\left(1 - \frac{RSS_i}{\sum_{i=1}^{n_a} RSS_i}\right)} \tag{4.38}$$

In the simulation and experimental results we will see the comparison, in terms of accuracy, of our proposal and these other localization methods.

Step 7 - RQ Update Mechanism

Our proposal to improve the performance of a basic EKF is based on taking advantage of the variance estimates done at the beginning. The covariance noise of the measurements (R) and of the process (Q) are normally assumed constant, although they could be obtained at each time step.

The process and the measurements are highly dependant on the RSS measurements. The variance estimates reflects, in part, the accuracy of those measurements.

Due to this dependency, our proposal is to update these two factors depending on the estimated variances. Following the idea of the Window-based RSS control of the third step, the covariance update procedure modifies the R and Q values based on the same ranges presented before. Depending on the zone in which the mean variance value is placed, the R and Q values are updated.

$$R_{range1}, Q_{range1} = var_{mean}\eta_{range1}$$
$$R_{range2}, Q_{range2} = var_{mean}\eta_{range2}$$
$$R_{range3}, Q_{range3} = var_{mean}\eta_{range3}$$

This RQ update mechanism allows to reduce the mobility errors through the RSS variance estimates. With these measurements we can avoid the use of extra inertial sensors that increase the cost of the nodes.

Step 8 - A Posteriori Position Estimation

The last step of the tracking algorithm studied is the introduction of, in this case, the Extended Kalman Filter used to obtain a in order to a refined a posteriori position estimate. As commented previously, the use of a localization algorithm from the chapter 2 is not the suitable option to track a mobile node. Features such as velocity or direction are not contemplated in the majority of these algorithms. For that reason the Kalman Filter and their suboptimal solutions has become, in recent years, a trending topic used for tracking mobile nodes.

As the relationship between the measurements and the process matrix with the process state is not linear, we propose a tracking algorithm based on an Extended Kalman Filter. The equations that characterizes the KF used are:

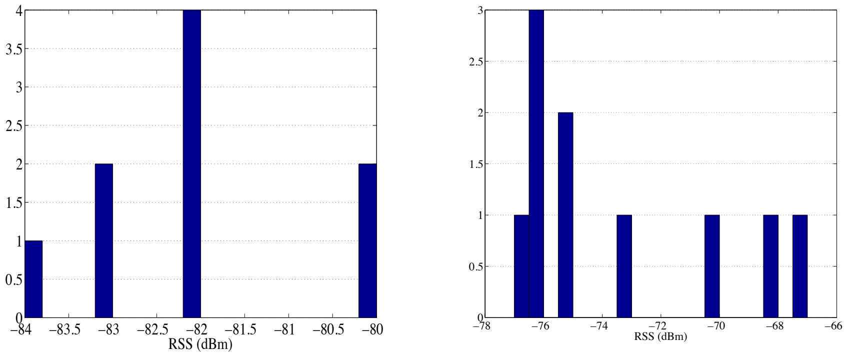
- **State vector:** The state vector is formed by four variables: x and y are the mobile node coordinates, the velocity v of the mobile node and θ the direction of the mobile node.

$$\mathbf{sv} = \begin{bmatrix} \hat{x} \\ \hat{v} \\ \hat{y} \\ \hat{\theta} \end{bmatrix} \tag{4.39}$$

- **State equation:** Each state is obtained through a position-velocity model as:

$$\mathbf{sv}(t) = \begin{bmatrix} 1 & Tcos(\theta) & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & Tsin(\theta) & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \mathbf{sv}(t-1) + \begin{bmatrix} 3T & 0 \\ 2T & 0 \\ 0 & 3T \\ 0 & 4T \end{bmatrix} w(t-1) \tag{4.40}$$

- **Observation equation:** The EKF considers the observation of the distance between the mobile node and all anchors d. Moreover, the velocity, although it is not estimated directly using an inertial sensor, is also introduced as a measurement. Basically, if the variance is above a threshold, we assume a constant velocity of 1 m/s. Figure 4.27 shows the difference of the RSS received and their RSS variance estimates between static measurements (4.27(a)) and mobile measurements (4.27(b)). The observation equation becomes:



(a) Estimated variance=1.75

(b) Estimated variance=13.3

Figure 4.27: Comparison of variance estimates with and without movement

$$\mathbf{z}(t) = [d_1 \; d_2 \; d_3 \cdots d_{n_a} \; v \; 0] \tag{4.41}$$

- **Linearization of f and h non-linear equations** Following the equations (4.8) and (4.9) the EKF linearise the non-linear equations that model the process and the measurements. Both matrices become as:

$$\mathbf{A}(n) = \begin{bmatrix} 1 & Tcos(\theta) & 0 & -Tvsin(\theta) \\ 0 & 1 & 0 & 0 \\ 0 & Tsin(\theta) & 1 & Tvcos(\theta) \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{4.42}$$

$$\mathbf{H}(n) = \begin{bmatrix} \frac{(\hat{x}-x_{a1})}{||(\hat{x},\hat{y})-(x_{a1},y_{a1})||} & 0 & \frac{(\hat{y}-y_{a1})}{||(\hat{x},\hat{y})-(x_{a1},y_{a1})||} & 0 \\ \frac{(\hat{x}-x_{a1})}{||(\hat{x},\hat{y})-(x_{a1},y_{a1})||} & 0 & \frac{(\hat{y}-y_{a1})}{||(\hat{x},\hat{y})-(x_{a1},y_{a1})||} & 0 \\ \vdots & \vdots & \vdots & \vdots \\ \frac{(\hat{x}-x_{an_a})}{||(\hat{x},\hat{y})-(x_{an_a},y_{an_a})||} & 0 & \frac{(\hat{y}-y_{an_a})}{||(\hat{x},\hat{y})-(x_{an_a},y_{an_a})||} & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{4.43}$$

All the functionality of the EKF is summarized in Figure 4.28

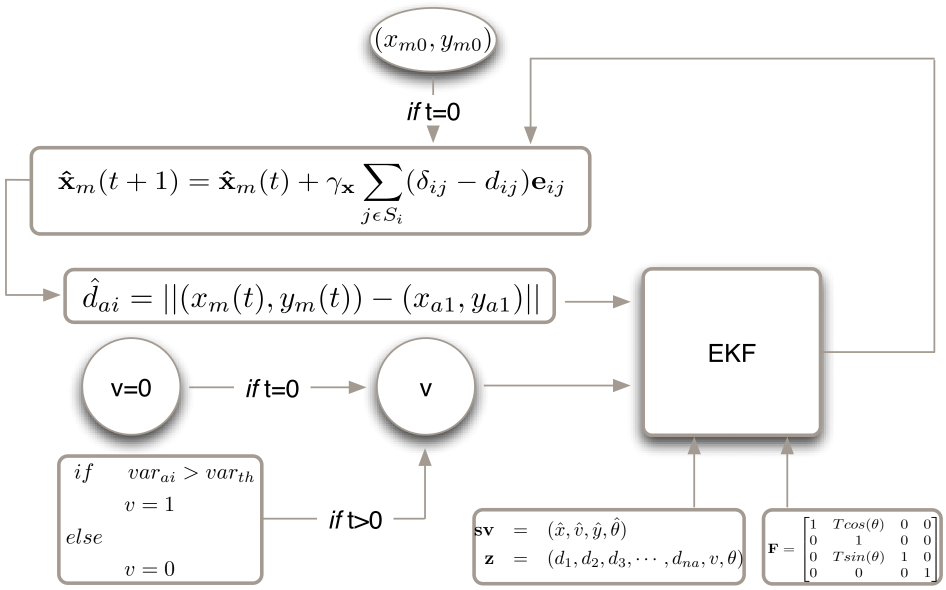


Figure 4.28: EKF algorithm

In the following Algorithm 3 is summarized the Indoor Tracking procedure.

4.4.3 Simulation Results

This section presents the performance of the proposed location and tracking algorithm. The simulated scenario and the assumed simulation parameters are presented in Table 4.2. Two different paths are done (see Figure 4.29) and only four anchors, located at the corners, are used.

The results achieved are summarized in tables 4.30(a) and 4.30(b). But we will talk in more detail in the following sections.

Algorithm 3 Tracking Algorithm Procedure

Messages Reception

$$\mathbf{P} = \begin{bmatrix} \mathbf{RSS}_1 & \mathbf{RSS}_2 & \cdots & \mathbf{RSS}_{N_{S_i}} \\ n_{PckR_x,i} & n_{PckR_x,i} & \cdots & n_{PckR_x,i} \end{bmatrix}$$

Variance Estimation:

for $i = 1$ to n_a **do**

$$var_i = \frac{\sum_{j=1}^{n_{PckR_x}} \left(RSS_j - \frac{\sum_{j=1}^{n_{PckR_x}} RSS_j}{n_{PckR_x}} \right)^2}{n_{PckR_x}}$$

end for

Window-based RSS Correction

for $i = 1$ to N_{S_i} **do**

if $var_i < var_{th1}$ **then**

$R\bar{S}S_i(t+1) = R\bar{S}S_i(t+1) - \gamma_1$

else if $var_i < var_{th2}$ **then**

$R\bar{S}S_i(t+1) = R\bar{S}S_i(t+1) - \gamma_2$

else

$R\bar{S}S_i(t+1) = R\bar{S}S_i(t+1) - \gamma_3$

end if

end for

Node Selection

$being\, RSS_a > RSS_b > ... > RSS_f \; \forall a, b, ..., f \in S_i$

$then\, n_a = [abcd]$

Distance Estimation

for $i = 1$ to n_a **do**

$\delta_i = 10^{\frac{RSS_0 - RSS_i}{10\alpha}}$

end for

A Priori Position Estimate

$\hat{\mathbf{x}}_m(t+1) = \hat{\mathbf{x}}_m(t) + \gamma_{\mathbf{x}} \sum_{j \epsilon S_i} (\delta_{ij} - d_{ij}) \mathbf{e}_{ij}$

RQ Update

if $var_{mean} < var_{th1}$ **then**

$\{R, Q\} = var_{mean}\eta_1$

else if $var_{mean} < var_{th2}$ **then**

$\{R, Q\} = var_{mean}\eta_2$

else

$\{R, Q\} = var_{mean}\eta_3$

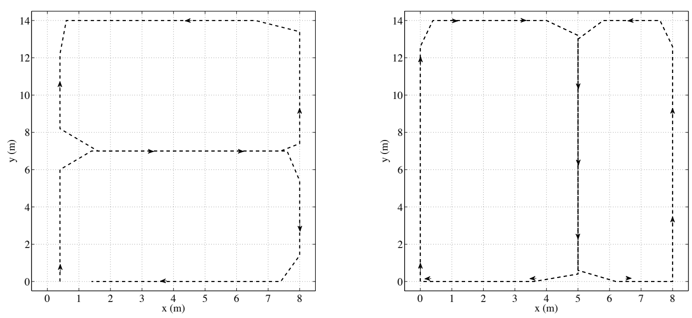
end if

A Posteriori Position Estimate

Extended Kalman Filter

Table 4.2: Simulation Parameters.

Simulation Parameters	Parameter Value
Size of Sensor Field	8.4×14 m
Number of Anchors (N_1)	4
Path Loss Exponent α_{ij}	2.35
Standard Deviation σ_v	10 dB
First-Meter RSS P_0	-49 dBm



(a) Path 1 (b) Path 2

Figure 4.29: Indoor Scenario Simulated

A Priori Position Estimation

The a priori estimation proposed, i.e. the weighted (w_2) LS algorithm, will be compared with: a weighted LS with another weight (w_1) and a weighted centroid with the same weight. In the following table 4.3 are summarized the different methods and both weights.

Weighted LS: comparison of both weights The comparison between the proposed weights based on the distance estimates and the weight w_1 based on RSS measurements is very remarkable. Our proposal achieves a gain of the 15%, at path 1, and a 28% of gain at path 2. In a reduced scenario, as the one simulated, the difference of RSS levels are not sufficiently high to have a remarkable impact on the position method accuracy. The differences between the RSS of the selected nodes are not sufficiently high in order to have an impact on the weight. Hence, the weighted LS with w_1 results are similar to those obtained without weight.

Window-Based RSS Control	Update RQ	Weighted LS (w_2)	Weighted LS (w_1)	Weighted Centroid (w_2)	Mean absolute error (m)
x	x	x			2.26
	x	x			2.31
x		x			2.64
		x			2.94
x	x		x		2.65
	x		x		2.88
x			x		3.56
			x		3.93
x	x			x	2.39
	x			x	2.58
x				x	3.25
				x	3.58

(a) Path 1

Window-Based RSS Control	Update RQ	Weighted LS (w_2)	Weighted LS (w_1)	Weighted Centroid (w_2)	Mean absolute error (m)
x	x	x			2.26
	x	x			2.52
x		x			2.69
		x			2.88
x	x		x		3.15
	x		x		3.32
x			x		3.9
			x		4.19
x	x			x	2.62
	x			x	2.73
x				x	3.28
				x	3.46

(b) Path 2

Figure 4.30: Simulation Accuracy Results

Weighted LS versus Weighted Centroid On the other hand, the comparison of our weighted LS with the weighted centroid is done with the same weight (w_2). Once again, our proposal achieves a gain at both paths, a 5% and a 14% at path 1 and path 2, respectively. Although, the gain for the path 1 is not so high, for the path 2 the accuracy is more improved. For that reason, our proposal is the best option to be used as an priori position estimation procedure.

Table 4.3: A Priori Positioning Methods

Positioning method	Position estimation	Weight
Least Squares & weight w_2	$\hat{\mathbf{x}}_m(t+1) = \hat{\mathbf{x}}_m(t) + \gamma_{\mathbf{x}} \sum_{j \epsilon S_i} w_i(\delta_{ij} - d_{ij})\mathbf{e}_{ij}$	$w_i = \frac{\frac{1}{\delta_{ai}^2}}{\sum_{i=1}^{n_a}\left(\frac{1}{\delta_{ai}^2}\right)}$
Centroid & weight w_2	$(x,y) = \left(\sum_{i=1}^{n_a} w_i x_i, \sum_{i=1}^{n_a} w_i y_i\right)$	$w_i = \frac{\frac{1}{\delta_{ai}^2}}{\sum_{i=1}^{n_a}\left(\frac{1}{\delta_{ai}^2}\right)}$
Least Squares & weight w_1	$\hat{\mathbf{x}}_m(t+1) = \hat{\mathbf{x}}_m(t) + \gamma_{\mathbf{x}} \sum_{j \epsilon S_i} w_i(\delta_{ij} - d_{ij})\mathbf{e}_{ij}$	$w_i = \frac{RSS_i}{\sum_{i=1}^{n_a}\left(1 - \frac{RSS_i}{\sum_{i=1}^{n_a} RSS_i}\right)}$

A Posteriori Position Estimation

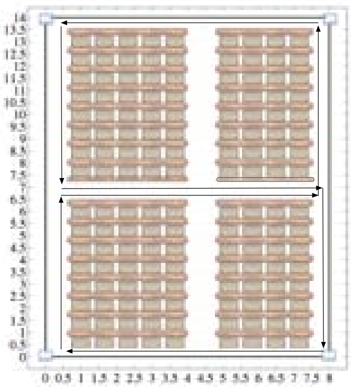
In this section, we present the behaviour of both proposals: the window-based RSS correction and the RQ-update mechanism.

Window-based RSS Correction performance The Window-based RSS correction allows to the algorithm to correct those RSS measurements that highly deviates from thier real values due to the multipath and obstacles present in an indoor scenario. Our pragmatic proposal outperforms an Extended Kalman filter without it. the gain achieved is: 3% at path 1 and a 11% at path 2. The mechanism correct some RSS measurements deviations and allows to increase the overall performance, and hence, the accuracy of the tracking algorithm.

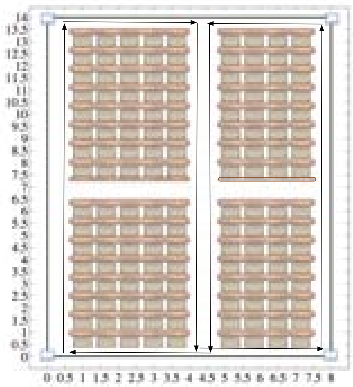
RQ-update Mechanism The RQ-update mechanism is introduced in order to adapt the noise covariances matrices of the EKF. Although, they are normally considered fixed, if we adapt these matrices depending on the estimated RSS variances, we give to the EKF more information of how reliable are the model and the measurements. Again, our mechanism achieves a better performance. The gain achieved is, approximately of: a 14% at path 1 and a 16% at path 2. one can notice that the improvement offered by the RQ-update mechanism is a little bit higher than those offered by the window-based RSS correction mechanism. Nevertheless, both proposals increases the accuracy of the tracking algorithm.

4.4.4 Experimental results

All the experiment results are done in an indoor scenario of 8 m x 14 m squared area. We consider $N_1 = 4$ anchor nodes located at the corners of the scenario. Furthermore, two different paths are done (see Figure 4.31) in order to obtain different behaviours of the algorithm in an indoor environment.



(a) Path 1



(b) Path 2

Figure 4.31: Indoor Scenario

A Priori Position Estimation Results

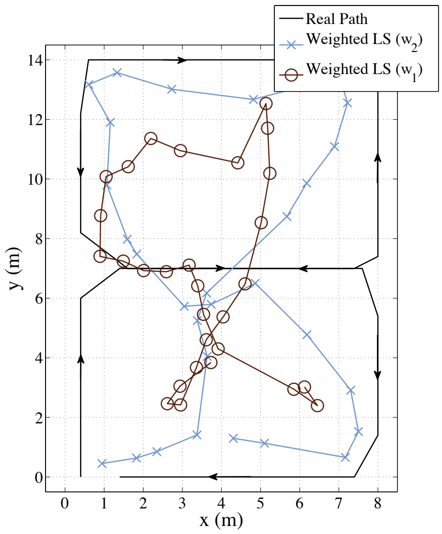
In this occasion, we also show two comparisons:

- Our proposal based on a weighted LS with a weight w_2 compared to a weighted LS with a weight w_1
- Our proposal based on a weighted LS with a weight w_2 compared to a weighted centroid with a weight w_2

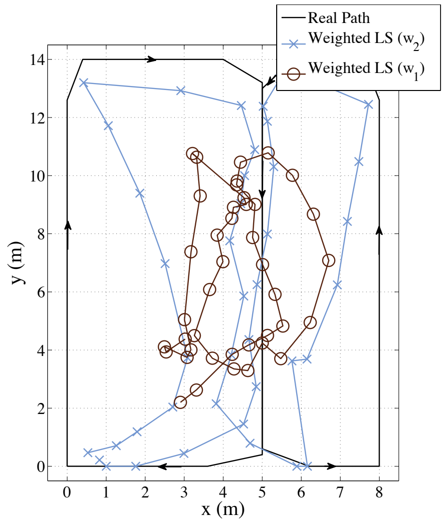
The results of a weighted centroid with the weight w_1 is not presented since their results are not sufficiently accurate. The major problem is that the difference of the RSS measured are not significant; hence, the weights are practically equal. Without the influence of the weights, the centroid method estimates a position at the center of the scenario, hence very far away from the real positions.

Weighted LS: comparison of both weights The comparison of the different weights applied to a distributed LS localization algorithm is shown in Figures and 4.32. The best results are obtained with our proposal at both paths. The gain achieved at path 1 (4.32(b)) is a 47% while in path 2 (4.32(a)) the gain is a 32%. The difference in terms of accuracy is significantly increased.

The weight w_1 depends on the difference between the RSS values. As commented previously, these differences are not sufficiently different, hence, the weights obtained are very similar. For that reason the effect of the weights are practically negligible.



(a) Path 1

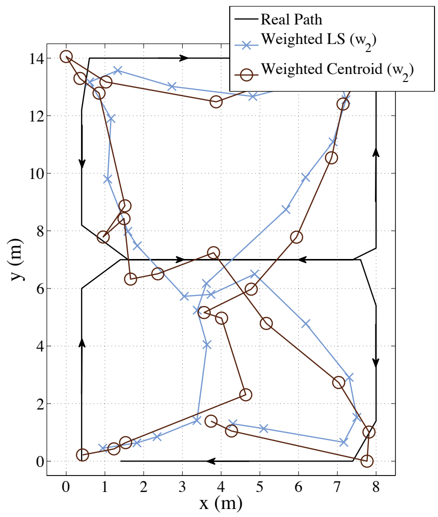


(b) Path 2

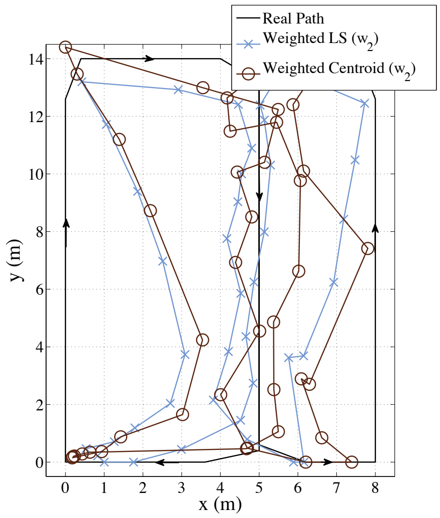
Figure 4.32: Weighted w_1 LS vs Weighted w_2 LS

Weighted LS versus Weighted Centroid Now the comparison is between our distributed LS with a weight w_2 compared to a weighted centroid with the same weight. The results are shown in Figures 4.33(b) and 4.33(a). In this occasion, although again our proposal has a better performance, the gain achieved is not so high as before. The gain at path 1 is a 29% and at path 2 a 14% meters. One can note that the weight w_2 based on the estimated distances is better instead of using the RSS (used in weight w_1). This occurs because, as commented previously, the difference between the RSS received is not sufficiently high, hence the effect of the weights are not reflected.

Moreover, the results achieved with the weighted centroid are less accurate as expected. The centroid accuracy is highly related with the number of anchors. The lower the number of anchors, the lower possible position estimates. The proposed weighted LS provides better results.



(a) Path 1



(b) Path 2

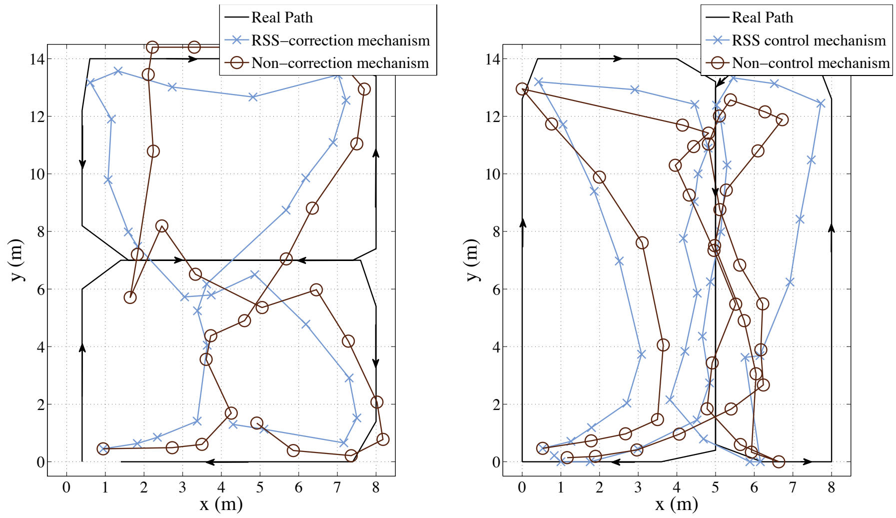
Figure 4.33: Weighted LS vs Weighted Centroid

A Posteriori Position Estimation

Window-based RSS Correction performance The high variability of the RSS measurements, reflected in the RSS variance estimates, produces an error that affects the performance of the tracking algorithm. With the proposed Window-based mechanism we are able to minimize this bad effect, and, hence, improving the overall performance.

Both results are shown in Figure 4.34. If one observes the results of path 1 (Figure 4.34(a)) our proposal achieves a better performance. The mean error achieved with the Window-based control mechanism is 1.8 meters. On the contrary, the mean error of a tracking algorithm without the proposed control mechanism is 2 meters. We achieve an improvement of a 10%. The same behaviour is achieved at the second path. The mean absolute error achieved with our proposed control mechanism is 1.6 meters while without this mechanism the error achieved by the tracking algorithm is 2 meters. In this case, we obtain a gain of the 40%.

The improvement of the tracking algorithm is achieved at both experimental paths. Moreover, our proposal is only based on the RSS measurements; hence, we are not increasing the cost of the network requiring extra hardware.



(a) Path 1 (b) Path 2

Figure 4.34: RSS Control mechanism vs Non-Control Mechanism

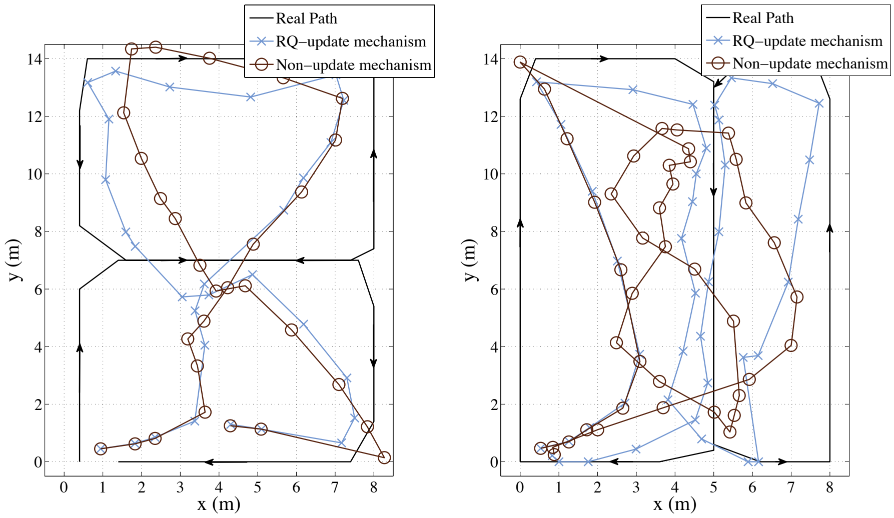
RQ-update Mechanism Finally we compare the performance of our proposal, that contains an RQ-update mechanism, with a tracking algorithm without this mechanism (see Figures 4.35(b) and 4.35(a)). It is usually assumed fixed values to these values. But the RSS variance estimates reflects the error that the measurement and the process could have. For that reason, we take advantage of the variance estimates knowledge to update the R and Q values and, hence, we could give more valuable information to the EKF to improve their behaviour.

This update mechanism again allow to our proposal to achieve a better performance. The gain between both methods is a 36% at the path 1 and a 5% at the path 2.

Summary

The inclusion of the proposed mechanisms helps the algorithm to increase the accuracy. Two tables (4.36(a) and 4.36(b)) summarize all the comparisons for the two paths. The results reflects the good performance achieved by our proposal.

Moreover, both mechanisms depend on the RSS variance estimations. Those estimates are obtained though the RSS measurements done. These measurements does not increase the cost of the network, as they are obtain from the propagation signals without increasing the required hardware. Hence, as we want, our pragmatic approach



(a) Path 1 (b) Path 2

Figure 4.35: RQ Update mechanism vs. Non-update mechanism

increases the accuracy of the tracking algorithm in indoor environments. The gain achieved with the path 1 is a 40.96% and with the path 2 is a 23.73%.

4.5 Summary

The RSS-based tracking algorithms have become in the last years a very challenged field of research. The simplicity of these range measurements allows to achieve a simple algorithm that would also be energy efficient. But their lower accuracy could badly affects the performance accuracy.

In this chapter we have presented two different proposals: an outdoor and an indoor algorithm. The different problems inherent to the use of RSS measurements have motivated us to developed two different tracking algorithms. Both algorithms introduces a control mechanism based on window levels.

The outdoor measurements reflect a high variability of the connectivity between the mobile node and the anchor nodes. The window-based mechanism helps to control this high variability giving to the tracking algorithm more stability. This fact helps to achieve a higher performance and, as we want, using the simplest range measurements that a node could do.

At the indoor measurements, we do not have problems with this connectivity vari-

Window-Based RSS Control	Update RQ	Weighted LS (w_2)	Weighted LS (w_1)	Weighted Centroid (w_2)	Mean absolute error (m)
x	x	x			1.6
	x	x			1.97
x		x			2.5
		x			2.71
x	x		x		3.07
	x		x		3.19
x			x		3.1
			x		3.59
x	x			x	2.26
	x			x	3.03
x				x	2.48
				x	3.76

(a) Path 1

Window-Based RSS Control	Update RQ	Weighted LS (w_2)	Weighted LS (w_1)	Weighted Centroid (w_2)	Mean absolute error (m)
x	x	x			1.8
	x	x			2
x		x			1.9
		x			2.36
x	x		x		2.66
	x		x		2.76
x			x		2.82
			x		3.12
x	x			x	2.1
	x			x	2.32
x				x	2.26
				x	2.65

(b) Path 2

Figure 4.36: Experimental Accuracy Results

ability but the measurements suffer a higher uncertainty. These variability of the RSSs measured by the mobile node badly affects the overall performance. The main problem is the false measurements that moves far away the position estimate from its real location. For that reason, an RSS-control mechanism is introduced. Taking advantage of the estimated variance of the RSS received, we propose a window-based control mechanism that tries to correct the measured RSSs. Moreover, we also propose to adapt the noise error covariances of the EKF, also with the RSS variance estimates. Another Window-based mechanism is also used to adapt, at each time step, these KF factors.

Both mechanisms introduced are based on the RSS variance estimates. Our proposals achieves gains of the 23.7% and of the 40.9% without using additional sensors, such as gyroscopes or accelerometers.

The experimental results at both proposals demonstrates the viability of implementing at a real environment and validates the simulation done at the outdoor and indoor scenarios. The simplicity of the algorithm makes it feasible to be used in a real network.

Chapter 5

Conclusions and Future Work

THIS PhD dissertation has explored RSS-based localization and tracking algorithms in Wireless Sensor Networks (WSN) and justified their applicability in real environments. First, we have considered an indoor static wireless sensor network composed of nodes with known positions (anchors) and nodes with unknown location (non-located nodes). In this scenario, we have derived an on-line path loss estimation mechanism. The radio propagation model necessary to obtain distance estimates from RSS range measurements is estimated by the localization algorithm. Hence, we have avoided the necessity of making an a priori measurement campaign and we have given to the localization algorithm an on-line adaptability to every environment. Apart from the adaptation of the algorithm to the scenario, three node selection criteria have been proposed to improve the overall performance. The selection mechanism results have obtained good accuracy. Moreover, the use of selected nodes has achieved a reduction in terms of energy consumption. Apart from the localization of fixed nodes, we have studied the localization and the tracking of a mobile sensor node in an outdoor and an indoor environment. The RSS-based measurements suffers from many errors and the mobility of the nodes increases them. In this scenario, we have proposed a correction mechanism devoted to diminishing these bad effects, and, hence, increasing the accuracy of the tracking algorithm.

5.1 Conclusions

After motivating the PhD thesis, a review on cooperative schemes for wireless sensor networks (WSN) has been provided in Chapter 2. Among all of them, a special emphasis has been given to RSS-based measurement techniques, because they provide suitable solutions for practical implementations.

Although RSS-based measurements are the simplest method, their accuracy depends on how accurate is the propagation model. In order to avoid to make an off-line modelling of the environment, in Chapter 3 a cooperative localization algorithm that dynamically estimates the path loss exponent has been proposed. This estimation is carried out by means of using the RSS measurements devoted not to increase the cost of the network.

Afterwards, the reduction of the complexity and the message exchange is the reason that motivates the investigation of this kind of algorithms and also to propose three different node selection criteria: the first one based on the RSS range measurements; the second one based on estimated inter-node distances; and finally one based on Geometric Dilution Of Position concept. The proposed node selection criteria have been easily integrated in the localization algorithm due to they also use the RSS range measurements.

Finally, a comparison with other existing methods have been presented. Results have shown that, by selecting nodes, better results in terms of a good trade-off between accuracy and energy efficiency have been achieved. One can observe that results show that with a circular anchor distribution, the best criterion is the distance-based, while, with a grid-based anchor distribution, the GDOP-based criterion works better. Besides, practical examples based on real WSN have been presented that achieve gains in terms of mean absolute error between the 2% and the 8%.

Chapter 4 has been devoted to the study of an outdoor and an indoor tracking algorithm. More concretely, we have proposed two different RSS-based distributed tracking algorithm devoted to locate a mobile node. In this mobile scenario, the RSS range measurements have present a high variability that difficult their usage. For that reason, a Window-based RSS correction tracking algorithm has been proposed in order to diminish the errors that the range measurements suffers due to the movement. Both proposals are based on a Kalman Filter approach in order to refine the position estimates.

The outdoor scenario measurements have presented a high variability in terms of RSS measurements and inter-node connectivity due to mid-high velocities considered. This RSS variations, that affects the tracking algorithm performance, have been corrected by means of using a window-based mechanism. Depending on the velocity estimated by the KF, we have proposed to correct those RSS measurements with a velocity-adapted correction value. Simulation and experimental results have shown that the accuracy is improved, the error is reduced a 37.8% at 10 km/h and a 61.7% at 20 km/h, without increasing the cost and the complexity of the algorithm.

The indoor scenario measurements have also presented a high variability although the velocity assumed is lower. Following the outdoor correction mechanism, we have developed another Window-based RSS correction mechanism, but, now, depending on the RSS variance estimates; hence, without using inertial sensors. Besides, an RQ update mechanism is introduced in order to increase the accuracy of the Extended Kalman Filter used to refine the position estimate. Again, simulation and experimental results that we have carried out have shown that the proposed tracking algorithm achieves a considerable gain (between a 23.7% and a 40.9%) without increasing the complexity and the cost of the network nodes.

5.2 Future Work

In the following we detail some of the questions that should be addressed in future extensions of this dissertation. In Chapter 3 some of the possibilities are:

- To make an exhaustive campaign of measurements at different environments in order to have a more in-depth study of the radio propagation characteristics. An in-depth knowledge of the propagation characteristics is important to take into account more errors that the environment could introduce at the time of developing the on-line channel estimation characteristics proposed.

- Proving the viability of our proposals for a 3D positionig algorithm. The introduction of the third dimension gives the opportunity to give more added value to our algorithm.

- To extend the experimental measurements to a large scale network in order to revalidate the simulation results obtained. The behaviour when the number of nodes is increased have not been experimentally done and it would be interesting having these measurements.

In Chapter 4 we consider the following extensions:

- To include more mobile nodes inside the network. The multiple nodes tracking algorithm is an interesting application in order to study cooperative approaches, studied at chapter 3, in mobile nodes.

- To compare the behaviour of the proposed solution with a tracking algorithm assisted with inertial systems.

- Make an study of an scenario composed by different rooms separated by walls, in order to investigate how the scenario distribution affects the RSS measurements, and, hence, how we can tune our window-based mechanism in order to reduce these bad effects.

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