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Posicionamento Cooperativo para Redes sem Fios Heterogéneas

Cooperative Positioning for Heterogeneous Wireless Systems

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Dissertação apresentada à Universidade de Aveiro para cumprimento dos requesitos necessários à obtenção do grau de Doutor em Electrotécnica, realizada sob a orientação científica do Doutor Jonathan Rodriguez do Instituto de Telecomunicações e do Doutor Manuel Violas, Professor do Departamento de Electrónica, Telecomunicações e Informática da Universidade de Aveiro.

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Palavras-chave

Palavras-chave: estimação de localização, cooperação, tecnologias de acesso rádio, seleção de links, redes heterogéneas, CRLB

Resumo

As tendências nos mercados emergentes caminham na direção dos servios baseados em posicionamento, criando uma nova perspectiva na forma como podemos obter e utilizar informação de posicionamento. Por um lado, as inovações em tecnologias da informação e sistemas de comunicação sem fios permitiram o desenvolvimento de inúmeras aplicações baseadas em localização, tais como a navegação e monitorização de veículo, aplicações de redes de sensores, domótica, gestão de ativos, segurança e serviços de localização sensíveis ao contexto. Por outro lado, as próprias redes sem fios podem beneficiar da informação de localização dos utilizadores de forma a melhorarem as performances de diferentes camadas de rede. Routing baseado em localização, sincronização e cancelamento de interferência são os exemplos mais representativos de áreas onde a informação de localização pode ser útil.

Soluções de localização típicas dependem de medições e de aproveitamento de métricas de sinal dependentes da distância, tais como a potência do sinal recebido, o tempo ou ângulo de chegada. São mais baratos e fáceis de implementar do que sistemas de localização dedicados com base em fingerprinting, com a desvantagem da perda de precisão. Consequentemente, algoritmos inteligentes de localização e técnicas de processamento de sinal têm de ser aplicados para compensar a falta de precisão das estimativas de distância. A cooperação entre nodos é usada nos casos em que as técnicas convencionais de posicionamento não têm um bom desempenho devido à inexistência de infraestrutura adequada, ou a um ambiente interior com obstruções. O objetivo é ter uma arquitetura híbrida, onde alguns nós têm pontos de ligação a uma infraestrutura e simultaneamente estão interligados através ligações ad-hoc de curto alcance. A disponibilidade de equipamentos mais capazes permite cenários mais inovadores que tiram proveito de múltiplas redes de acesso de rádio, bem como ligações peer-to-peer, para o posicionamento.

A seleção de ligações é usada para otimizar o equilíbrio entre o consumo de energia dos nós participantes e da qualidade da localização do alvo. A diluição geométrica de precisão e a Cramér Rao Lower Bound podem ser utilizadas como critrio para a escolha do conjunto adequado de nodos de ancoragem e as medições correspondentes antes de realizar a tarefa de estimativa de localização. Este trabalho analisa as soluções existentes para a seleção de nós, a fim de melhorar o desempenho de localização e propõe um novo método baseado em funções de utilidade. O método proposto é então estendido para ambientes móveis e heterogéneos. Foram realizadas simulações bem como avaliação de dados de medições reais. Além disso, alguns casos específicos foram considerados, tais como a localização em cenários mal-acondicionados e uso de informação negativa. As abordagens propostas revelaram uma melhoria na precisão da estimação, ao mesmo tempo que reduziram significativamente a complexidade do cálculo, o consumo de energia e o overhead do sinal.

Keywords Location estimation, cooperation, radio access technologies, link selection, heterogeneous environment, CRLB.

Abstract

Future emerging market trends head towards positioning based services placing a new perspective on the way we obtain and exploit positioning information. On one hand, innovations in information technology and wireless communication systems enabled the development of numerous location based applications such as vehicle navigation and tracking, sensor networks applications, home automation, asset management, security and context aware location services. On the other hand, wireless networks themselves may benefit from localization information to improve the performances of different network layers. Location based routing, synchronization, interference cancellation are prime examples of applications where location information can be useful.

Typical positioning solutions rely on measurements and exploitation of distance dependent signal metrics, such as the received signal strength, time of arrival or angle of arrival. They are cheaper and easier to implement than the dedicated positioning systems based on fingerprinting, but at the cost of accuracy. Therefore intelligent localization algorithms and signal processing techniques have to be applied to mitigate the lack of accuracy in distance estimates. Cooperation between nodes is used in cases where conventional positioning techniques do not perform well due to lack of existing infrastructure, or obstructed indoor environment. The objective is to concentrate on hybrid architecture where some nodes have points of attachment to an infrastructure, and simultaneously are interconnected via short-range ad hoc links. The availability of more capable handsets enables more innovative scenarios that take advantage of multiple radio access networks as well as peer-to-peer links for positioning.

Link selection is used to optimize the tradeoff between the power consumption of participating nodes and the quality of target localization. The Geometric Dilution of Precision and the Cramer-Rao Lower Bound can be used as criteria for choosing the appropriate set of anchor nodes and corresponding measurements before attempting location estimation itself. This work analyzes the existing solutions for node selection in order to improve localization performance, and proposes a novel method based on utility functions. The proposed method is then extended to mobile and heterogeneous environments. Simulations have been carried out, as well as evaluation with real measurement data. In addition, some specific cases have been considered, such as localization in ill-conditioned scenarios and the use of negative information. The proposed approaches have shown to enhance estimation accuracy, whilst significantly reducing complexity, power consumption and signalling overhead.

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List of Acronyms and Abbreviations

2G	2^{nd} Generation
2LKF	Two Level Kalman Filter
3G	3^{rd} Generation
4G	4^{th} Generation
A-GPS	Assisted Global Positioning System
AHLoS	Ad Hoc Localization System
ANN	Artificial Neural Networks
AOA	Angle Of Arrival
AWGN	Additive White Gaussian Noise
BLUE	Best Linear Unbiased Estimator
B-FIM	Bayesian Fisher Information Matrix
BS	Base Station
CAP	Collinear Anchor aided Positioning
CDF	Cumulative Distribution Function
CR	Cognitive Radio
CSI	Channel State Information
DME	Distance Measurement Error
EKF	Extended Kalman Filter
EM	Expectation Maximization
ESA	European Space Agency
FCC	Federal Communications Commission
FIM	Fisher Information Matrix
GDOP	Geometric Dilution of Precision
GLONASS	Global Navigation Satellite System
GNSS	Global Navigation Satellite System
GPS	Global Positioning System
GSM	Global System For Mobile Communications
HDF	Hybrid Data Fusion
ICMP	Internet Control Message Protocol
ICT	Information And Communication Technology

IEEE	Institute Of Electrical And Electronics Engineers
ILS	Incremental Least Squares
KF	Kalman Filter
LAN	Local Area Network
LBS	Location Based Services
LLS	Linear Least Squares
LOS	Line Of Sight
LS	Least Squares
LTE	Long Term Evolution
LWLS	Linear Weighted Least Squares
MAC	Medium Access (Medium Access Layer)
MANET	Mobile ad-hoc network
ML	Maximum likelihood
MS	Mobile Station
MT	Mobile Terminal
NE	Nash equilibrium
NLOS	Non Line Of Sight
NLS	Nonlinear Least Squares
NTU	Non-transferable utility
OFDM	Orthogonal Frequency-Division Multiplexing
P2P	Peer-to-Peer
PAN	Personal Area Network
PHY	Physical (Physical Layer)
PSAP	Public-Safety Answering Point
QoS	Quality Of Service
RAN	Radio Access Network
RAT	Radio Access Technology
RF	Radio Frequency
RFID	Radio Frequency Identification
RMSE	Root Mean Square Error
RSS	Received Signal Strength
RSSI	Received Signal Strength Indication
RTT	Round Trip Time
RX	Receiver
SLAM	Simultaneous Localization and Mapping
SMS	Short Message Service
SNR	Signal To Noise Ratio
TDOA	Time Difference Of Arrival

TOA	Time Of Arrival
TU	Transferable utility
TX	Transmitter
UE	User Equipement
UMTS	Universal Mobile Telecommunications System
UWB	Ultra Wide Band
WHERE	Wireless Hybrid Enhanced Mobile Radio Estimators (Phase 1)
WHERE2	Wireless Hybrid Enhanced Mobile Radio Estimators (Phase 2)
WiFI	Wireless Fidelity
WiMAX	Worldwide Interoperability For Microwave Access
WLAN	Wireless Local Area Network
WLS	Weighted Least Squares
WNLS	Weighted Nonlinear Least Squares
WPAN	Wireless Personal Network
WSN	Wireless Sensor Network

Chapter 1

Introduction

The availability of position information already plays an integral role in todays wireless communication networks and current trends suggest that it will form a pivotal part of future systems. Innovations in information technology and wireless communication systems enabled the development of numerous location based applications such as vehicle navigation and tracking, sensor networks applications, home automation, asset management, security and context aware location services. On the other hand, communication networks themselves may benefit from localization information to improve the performances of different network layers. Location based routing, synchronization, interference cancellation are some examples of fields where location information can be useful.

In this introduction, we start with motivations to investigate the localization problem. Then a brief overview of localization techniques is provided in Section 1.2. The scope of the thesis is specified in Section 1.3, while 1.4 outlines the focus of each chapter. Finally, the novel contributions of the thesis are described in Section 1.5.

1.1 Motivation

Position information is necessary to provide location based services to the users, and also contribute to enhancements on the network side. Our research is motivated by the need for location based services in personal, professional and public domain. In this section, we list the most common applications.

1.1.1 Navigation and tracking

Navigation is the original localization application. Navigation services are based on mobile users who need directions within their current geographical location. The main location-based navigation solution is the global navigation satellite systems (GNSS), for vehicles and pedestrians in an outdoor environment.

Tracking consists in determining the position of the user at each time step. The time step can be fixed by the user or by the system. One popular example refers to tracking postal packages so that both companies and clients know where their goods are at any time [2]. Examples of asset tracking applications are fleet management such as emergency vehicles and taxi companies, cargo tracking and asset tracking at manufacturing sites and hospitals. A similar application allows companies to locate their field personnel.

1.1.2 Emergency and Security

The most famous emergency services are E911 in the United States and E112 in the European Union. The U.S. Federal Communications Commission (FCC) has adopted rules requiring wireless service providers to provide the public-safety answering point (PSAP) with the location of the caller. Phase I rules required to provide the location of the cell site or base station transmitting the call. Phase II required to deliver the location accurate to within 50 to 300m [3].

For the 112 emergency calls in Europe, a recommendation of the European Commission requires the operators to provide the best information available as to the location of the caller, to the extent technically feasible.

1.1.3 Monitoring

Monitoring is based on Wireless Sensor Networks (WSN). In many applications, sensors' locations must be known for their data to be meaningful. Examples of these applications are environmental monitoring (collecting information such as temperature, humidity, pressure) [4], logistics (monitoring and controlling goods), or health care monitoring [5].

1.1.4 Location based services

Yellow pages services, finding the nearest service such as ATM, gas station or restaurant, accessing traffic news, obtaining a local street map are few examples of location-based informative services that can be offered to the user. Social networking, mobile games and activities like geocaching are some attractive fields especially for young and teen users.

Advertising applications pinpoint users location and provide location-specific advertisements on their mobile devices. However, user's privacy has to be respected, and a user may not accept that service providers have an unauthorized access to personal location information.

Location sensitive billing allows the mobile operators to charge different rates to their users depending on their location. One example is allowing flat rate when the user is at home, in order to be able to compete with rates from landline operators.

1.1.5 Network enhancement

Location information can be used for enhancing wireless communication systems at different network layers. Wireless communication systems have to provide a variety of services for an increasing number of mobile users. Therefore an efficient use of wireless communication systems is necessary to cover the increased demand for data rate. Frequency spectrum as the main and most valuable resource in wireless communications is limited. An efficient use of this resource is one of the main design objectives in the development of future wireless communication systems. Some examples are:

- Location based routing

  Location based routing protocols in mobile ad hoc networks (MANETs) improve network scalability by reducing the total routing overhead [6]. The idea is to use location information in order to reduce propagation of control messages, control packet flooding, or make simplified packet forwarding decisions. Location based routing has also been adopted in wireless sensor networks, mainly for the purpose of energy saving.

- Interference cancellation

  Location information can be exploited in order to coordinate inter-cell interference, enhance interference cancellation algorithms, and resource scheduling [7].

- Synchronization

  The location information can be used to compute the distances to neighboring base stations (BS). By measuring the time-of-arrival of the signal transmitted by the BSs, a common reference time can be obtained and synchronization signals coming from different base stations can be timely related. Hereby additional signal energy can be used for synchronization and the signals from these BSs are no longer considered as interfering with each other [7].

- Cooperative communication and relaying

  Position information can be useful in relay selection techniques. Both WLAN and cellular network management can establish relayed or cooperative communication if it is the best available connection with the mobile station. The impact that terminal's position information has on cooperative relaying schemes are for example awareness of line of sight (LOS) conditions, or possibility to obtain the partial channel state information (CSI) such as channel mean and channel covariance through exploitation of the positioning information [8]. A potential problem that arises with the use of relays is that these additional nodes also impose additional interference to nodes of adjacent cells. Example of cooperative communications and relaying is shown in Figure 1.1.

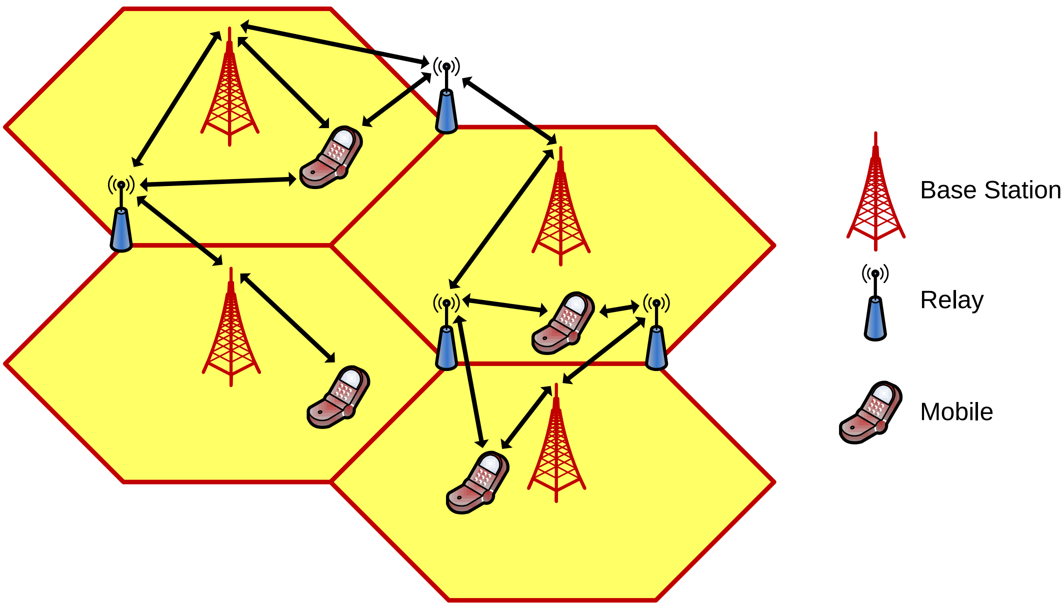


Figure 1.1: Cooperative communications and relaying

- Radio resource management

  Wireless users can benefit from higher data rates through more effective use of resources, due to exploiting a precise estimation of mobile terminals position information. The goal of radio resource management is to optimize the utilization of bandwidth (capacity) and Quality of service (QoS). There are static, dynamic resource or mixed allocation schemes [9]. The concept can be further improved in terms of capacity and power consumption at the terminals if the locations of the terminals are known [10].

1.2 Historical overview

In this section we provide a brief historical overview of location systems, showing their capabilities and their domains of application.

1.2.1 Global Navigation Satellite System

The global navigation satellite systems (GNSSs) are among the fundamental localization solutions. Satellite systems rely on a constellation of satellites rotating in well-known orbits and continuously transmitting signals used by the mobile terminals to perform pseudo-range measurements based on the time of flight of transmitted signals

Any GNSS is made up of three parts: the space segment, consisting of satellites orbiting the Earth; control segment, made of monitoring stations on Earth; and the user segment, i.e., user receiver equipment capable of receiving and processing the GNSS signals. Currently, the Global Positioning System - GPS, which was first developed for military use in the United States, is the only commercially available GNSS solution. Galileo, which is developed by the European Union and European Space Agency (ESA), is scheduled to be operational in 2014.

Over the last decades, several improvements to the GPS have been implemented. New satellites are being launched to update the constellation. The availability of small size, low power GPS chips allows their implementation in a wide range of devices, such as mobile phones and computers.

The GNSS localization systems perform well only if the receiver is in line of sight with at least four satellites. Especially in dense urban or indoor environments, navigation based on GNSS becomes inaccurate or impossible, since the necessary amount of 4 directly visible satellites is not reached. Therefore GNSS based localization may not be adequate for applications that require precise location estimates, and for indoor scenarios. An analysis of the GPS localization error in various environments is provided in [11].

Besides GPS and Galileo, other GNSSs have been developed or are currently under development. The Global Navigation Satellite System (GLONASS) system, which was originally started by the Soviet Union, has been recently restored by the Russian government. The Compass system is a Chinese GNSS which became operational in China in 2011 and the global system should be ready by 2020.

GPS assisted localization

Besides the standalone mode, where a GPS-capable mobile phone determines its position based on signals received from GPS, it can also operate in the assisted mode. In that case, it receives assistance data from terrestrial wireless networks (e.g. cellular networks) [12]. The data rate of the GPS broadcast signal is only 50 bits per second, thus it can take several minutes to obtain the first position fix. In assisted GPS (A-GPS), the GPS receiver gets the initial position information from the cellular network, which helps to reduce the time it takes the receiver to calculate its first position. This allows the receiver to stay in idle mode when positioning is temporarily not needed, and reduces its power consumption. The A-GPS is currently used in many GPS-capable cellular phones or mobile stations (see Figure 1.2).

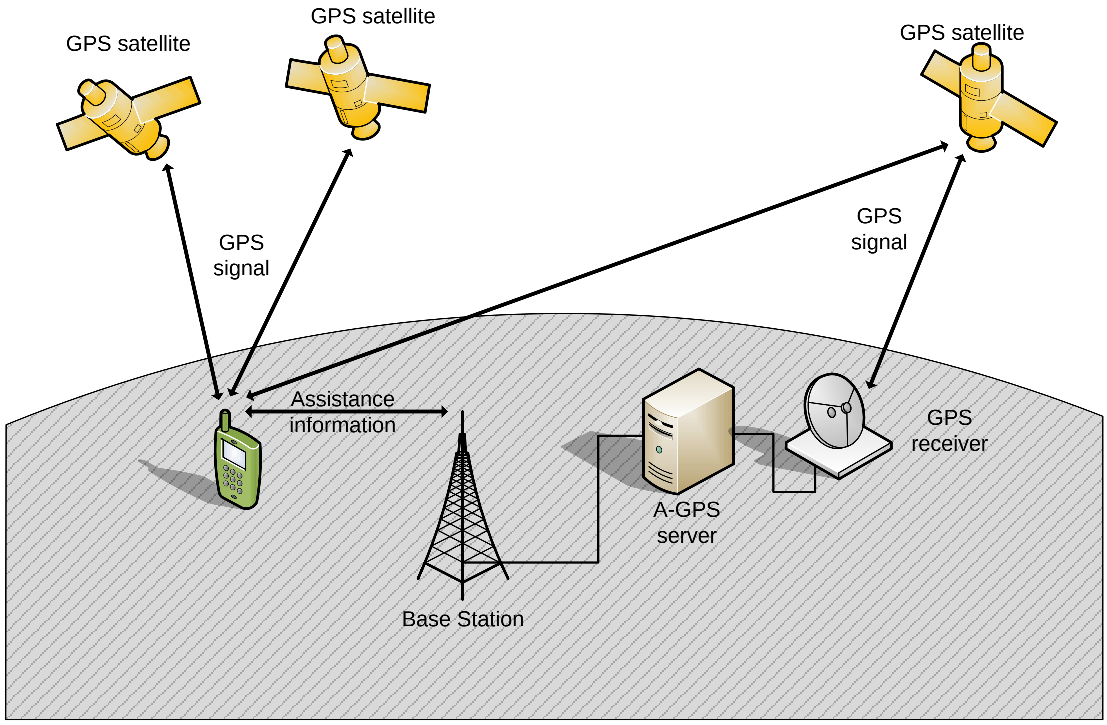


Figure 1.2: Assisted GPS

1.2.2 Network based Location Systems

Network based location systems take advantage of the existing wireless network infrastructure. Because of the variety of wireless terrestrial systems, different approaches have been adopted so far to enable localization by exploiting network infrastructure. These systems cover either a large area, such as a large cell in a cellular system (e.g. GSM, UMTS), or a smaller one (e.g. WiFi, UWB and Bluetooth).

Cellular networks

The simplest technique is cell-ID, where the mobile device is located inside the coverage area of a base station. Depending on the cell size, the accuracy ranges from few hundred meters in urban areas, to tens of kilometers in rural zones. A classical application of cellular positioning is the localization of the origin of an emergency call. A more accurate method is the Time Difference of Arrival (TDOA), where at least three synchronized base stations provide measurements to the target [13].

With the recent development of the indoor femtocell concept, cellular location could be much more accurate especially in indoor because of the small area covered by each cell [14]. Currently, there is still no universal and efficient cellular solution available for indoor environments.

Wireless Local Area networks

The IEEE 802.11a, b, g and n standards, also known as WiFi are generally used to provide a wireless internet connection to mobile terminals through access points in indoor environments. The broad deployment of Wireless local area networks (WLANs) offers a realistic solution for indoor localization. The access points are usually set at known, fixed locations, so it is possible to locate the connected devices with respect to these access points. Most solutions rely on measuring the received signal strength to the access point, and then perform either trilateration or a fingerprinting algorithm. More on this topic will be provided in Chapter 2. The main advantage of using WLAN technology is that it is already a common feature in most mobile devices and widely used. There are numerous applications for WLAN positioning, including home entertainment, automotive industry, or consumer electronics.

Wireless Personal Area networks

Wireless personal area networks (WPANs) are short-range wireless networks, where communicating devices are characterized by their low complexity and low power consumption. WPANs are based on the working group IEEE 802.15 which consists of several task groups such as Bluetooth (IEEE 802.15.1) or Zigbee (IEEE 802.15.4). The localization solutions in WPANs rely on received signal strength, connectivity and proximity information, or time-of-arrival measured using ultra-wideband UWB signals. The UWB technology has been specified in the amendment IEEE 802.15.4a, an alternative PHY standard providing high throughput, precise ranging capability and low power usage.

The standard 802.15.4 is attractive for wireless sensor networks because of their low cost, and low power consumption feature. The knowledge of the relative sensors locations improves the localization performance, and different cooperative methods involving mobile-to-mobile radio links and measurements can also be used to localize all the sensors in the network [15].

Heterogeneous networks

Mobile communication devices are becoming more intelligent and reconfigurable in nature, supporting an increasing number of communication standards. Thus they are capable to exploit a heterogeneous communication infrastructure, comprising for instance 2G, 3G, LTE, WLAN and WiMAX. Moreover, mobile devices will have available peer-to-peer (P2P) communication capabilities. In the traditional localization scenario, wireless terminals use measurement based techniques to obtain distance estimates from the transmitter and calculate their position. The availability of more capable handsets make way for more innovative scenarios that take advantage of multiple radio access networks (RANs) as well as peer-to-peer links for positioning. In particular, P2P links allow extending the coverage and improving the accuracy of positioning especially in sufficiently dense populated environments (e.g. office buildings).

1.2.3 Autonomous Location Systems

Autonomous location systems rely on their own embedded hardware and software capabilities. They eliminate the need for a priori topological knowledge of the environment, or additional infrastructures as is the case with GNSS and wireless networks. One example is the Simultaneous Location and Mapping (SLAM). SLAM is a research subject in the area of robotics, and is defined as the problem of building a model leading to a new map, or repetitively improving an existing map, while at the same time localizing the robot within that map [16].

1.2.4 Radio Frequency Identification (RFID) tags

Radio-frequency identification (RFID) uses radio-frequency electromagnetic fields identify and track tags attached to objects or carried by persons. The RFID reader can read data emitted from RFID tags. Tags are small and cheap devices that can be active or passive. The active tag is battery supplied and autonomously transmits signals, while the passive tag reflects the signal transmitted from and operates without battery. RFID readers and tags use a defined radio frequency and protocol for data transmission. The transmission range is usually less than few meters [17], whereby active tags have more range. The main reason why RFID does not provide accurate location sensing is the fact that readers do not provide the signal strength of a tag directly. Instead, they report if the tag is being detected or not detected in a given range. Solutions to improve performance of RFID in dynamic environments have been presented in [18].

1.2.5 Other Location Systems

Other localization systems are based on acoustic [19], infrared [20], or magnetic [21] measurements. These systems are usually deployed in local areas for short-range applications. Although these systems can be very accurate, they face several limitations. Acoustic systems, which usually use ultrasonic frequencies, are very expensive and a dedicated infrastructure is needed. Infrared systems impose the line of site requirement. Their range is limited to a few tens of meters, however the accuracy can be as low as tens of centimeters [20]. Magnetic systems consist of sources of magnetic signals and by magnetometers, thus special devices are needed. One example of commercial systems is Polhemus [22].

Table 1.1 presents an overview of major contributions on localization systems, from prevailing ones such as GPS and network based positioning, to more specific ones, considering indoor, cooperative, distributed and heterogeneous scenarios.

Authors	Contribution
[23] Enge 1994	A tutorial describing GPS signals, measurements and performance
[24] Caffery 1998	An overview of radiolocation in cellular systems
[25] Spirito 2001	Accuracy analysis of location estimation techniques for cellular networks
[26] Patwari 2003	Derivation of performance bounds of cooperative localization in wireless sensor networks
[27] Qi 2003	Accuracy limits for time delay based and signal strength based positioning
[28] Liu 2007	Survey on indoor location systems
[29] Mayorga 2007	Positioning in heterogeneous networks, combining Wi-Max and Wi-Fi peer-to-peer links
[30] Liu 2008	Error control mechanism based on characterization of node uncertainties
[31] Wymeersch 2009	SPAWN, a fully distributed cooperative algorithm based on UWB measurements
[32] Denis 2009	Joint update of ranging measurements and position information
[33] Bargshady 2010	Heterogeneous localization, combining Wi-Fi and UWB links
[34] Das 2010	Transmit and receive censoring for distributed cooperative positioning
[35] Zorzi 2011	Improving localization performance by exploiting opportunistic interactions between heterogeneous nodes
[36] Zirari 2012	Link selection criteria in heterogeneous localization

Table 1.1: Major contributions addressing localization systems

1.3 Scope of the thesis

The localization problem can be examined from three aspects, namely:

1. Ranging

   Ranging refers to estimation of distances between location-aware nodes, called anchors and the target with unknown position. Ranging can be examined from different perspectives, and its performance will differ depending on what technology is used, which signal metric is observed, and what models are used to translate that signal metric into inter-node distance. One critical aspect of the ranging stage is the parameter extraction for the corresponding model. These parameters are usually obtained by means of experiments and calibration [37], [38].

2. Positioning

   In the positioning phase, the ranging information is used as input to the localization algorithm. Signal processing and optimization techniques are deployed in order to calculate the target coordinates based on the available information. Improvements can be made, e.g., by exploiting cooperation [26],[31] performing node selection [39], or discarding unreliable anchor nodes [34].

3. Communication

   The communication aspect considers the message exchange between nodes. It examines the protocols that are used for communication and signalling caused by transmitting position information.

We focus on the central part, the positioning part, while the ranging models are assumed. This thesis is focused on positioning in heterogeneous environments. The associated node discovery schemes and message exchange protocols are beyond the scope of this thesis. Moreover, we focus our attention on a multimodal target, able to simultaneously connect to both infrastructure elements and peer nodes. The evaluation of the localization performance was evaluated mainly using the following metrics:

- Accuracy, expressed either as the root mean square error or in terms or error cumulative distribution function.
- Computational complexity, measured as the time needed to perform the algorithm.

- Signaling overhead, which is represented as the number of additional messages that have to be exchanged for localization purposes.

More details on performance metrics are given in Section 2.5 in Chapter 2. We review the ranging methods in Section 2.1, and adopt one of the models from literature in further work, namely the lognormal shadowing model for received signal strength measurements. We use the recommended model parameters according to the scenario, while parameter extraction and calibration is out of scope of this thesis.

1.4 Outline of the thesis

The outline of the thesis is presented in the following. In the introduction the possible applications and services that use positioning information are described.

- Chapter 2: The second chapter presents the general overview of indoor positioning as well as the state of the art on existing localization techniques and systems. We start by listing the most common ranging techniques and their sources of error. The fundamental principles of localization algorithms are described, and classified in two main categories: probabilistic and deterministic algorithms. Particular emphasis is put on cooperative positioning, as it is the main focus of this thesis. Most important aspects of localization in heterogeneous networks are analysed and state of the art is presented. At the end of the chapter, we present the metrics used to evaluate and compare localization systems.

- Chapter 3: The third chapter is the core of the thesis. We consider the importance of anchor node selection in order to optimize the tradeoff between the power consumption of participating nodes and the quality of target location estimated. The main algorithm treated in this chapter is iterative multilateration. In this algorithm, non-anchor nodes serve as virtual anchors after having obtained their position estimate. Shortcomings of iterative multilateration are the error accumulation and propagation, originating from the use of imperfect anchor positions which contaminate the localization process through iterations.

  The Geometric Dilution of Precision and the Cramer-Rao Lower Bound can be used as criteria for choosing the appropriate set of anchor nodes and corresponding measurements before carrying out the location estimation task itself. This work analyzes the existing solutions for node selection in order to improve localization performance, and proposes a novel method based on utility functions. The main contribution is a selection principle that accounts for imperfect anchor locations.

- Chapter 4: Here we apply the node selection in a dynamic scenario. Different accuracy indicators are used as selection criteria in order to localize a moving target. We propose a solution for energy efficient tracking in a heterogenous environment. We analyzed a specific scenario, and also evaluated the performance averaged over random located node configurations, that correspond to realistic indoor environments. By analysing different setups, we determine the best trade-off between desired accuracy and cost.

  Furthermore, in Section 4.2.1 we evaluate the node selection scheme with data obtained from real measurements campaigns that were conducted within the FP7 European projects WHERE and WHERE2.

- Chapter 5: Here we consider two specific non-cooperative cases of positioning. The first one is a low-complexity method for a scenario when anchor nodes are near collinear, which is considered an ill-conditioned scenario. Its localization accuracy outperforms conventional algorithm used in the same scenario, with significantly reduced complexity.

  The second case, described in Section 5.2.5 is based on probability maps, where we exploit negative information, e.g., information about where the mobile unit is *not*. Since we applied a simple channel model, and assumed independent measurement errors, the work serves as proof of concept for the proposed strategy. The approach has been extended to exploit the history of mobile terminal's location to assist the computation of the terminal location.

- Chapter 6: The contributions of the thesis are summarized in the last chapter. We present an overview of individual contributions per chapter and provide some concluding remarks. Our suggestions for future research are outlined thereafter in Section 6.2.

Notation

Throughout the thesis, we use the following notations. Bold lower-case letters are used for vectors, and italic lower-case letters for vector elements. Bold capital letters refer to matrices, italic capital letters to matrix elements, and subscripts reveal matrix dimension. P_{ij} refers to power transmitted from node i and received at node j. Distance d_{ij} is the distance between nodes i and j.

$()^T$ and $()^{-1}$ represent matrix transpose and inverse, respectively. $E()$ is the expectation of a random variable, and $var()$ its variance. Variables with a tilde $\sim$ represent estimated values, while those without tilde are the true values.

1.5 Novel contributions

The novel contributions of the thesis include the following:

- In Chapter 3, a utility based node selection scheme for static localization has been proposed [39]. Cooperative positioning solutions result in higher signalling overhead and computation cost than conventional positioning methods. Therefore the number of actively participating nodes should be kept at a minimum. Compared to the present approaches that consider nearest neighbor and random node selection scheme, simulation results show that selecting subsets of nodes with highest utility values leads to more accurate position estimates. The efficiency of using coalitional game theory for localization has been demonstrated [40], and further improvements in node selection in terms of complexity reduction have been proposed [41].

- In Chapter 4, we extend the static node selection scheme to a mobile heterogeneous scenario. We analyzed a specific scenario, and a generalized one that corresponds to realistic indoor environments. We presented an extensive study of different setups in order to determine the best trade-off between desired accuracy and cost [42].

- In Chapter 5, we considered the use of negative information in positioning and tracking algorithms [43], [44]. Negative information had few applications for localization in wireless networks. It has been mainly used for mobile robot localization [45, 46], however it has been proved to be useful in wireless sensor localization as well [47]. In order to enhance the performance of Wi-Fi based localization systems, the innovative solution presented in this section considers so called 'negative information'. To some extent, the concept of negative information has been exploited in robot localization, but not for wireless communication.

The aforementioned contributions resulted in the following list of scientific publications. These include:

Conference papers

S. Hadzic, J. Bastos and J. Rodriguez: "Enhanced Localization in Wireless Ad Hoc Networks through Cooperation", in Proceedings of ICST International Conference on Mobile Lightweight Wireless Systems - MOBILIGHT, Barcelona, Spain, Vol. 1, pp. 1 - 12, May 10-12, 2010.

S. Hadzic, J. Rodriguez: "Cooperative positioning for heterogeneous wireless systems", in 6th International Conference on Wireless and Mobile Communications (ICWMC 2010), Valencia, Spain, September 20-25, 2010.

M. Albano, S. Hadzic, J. Rodriguez: "Use of negative information in positioning algorithms", 6th International Mobile Multimedia Communications Conference (MOBIMEDIA 2010), Lisbon, Portugal, September 6-8, 2010.

S. Hadzic and J. Rodriguez, "Utility based node selection scheme for cooperative localization", in International Conference on Indoor Positioning and Indoor Navigation (IPIN), Guimares, Portugal, September 21-23, 2011.

S. Hadzic, Joaquim Bastos, Jonathan Rodriguez, "Reference node selection for cooperative positioning using coalition formation games", 9th Workshop on Positioning, Navigation and Communication 2012 (WPNC'12), Dresden, Germany, March 15-16, 2012.

V. Sucasas, S. Hadzic, H. Marques, J. Rodriguez and R. Tafazolli: "Performance evaluation of RSS based localization systems in mobile environments", 17th IEEE International Workshop on Computer-Aided Modeling Analysis and Design of Communication Links and Networks (CAMAD 2012), Barcelona, Spain, September 17-19, 2012.

Journal papers

M. Albano, S. Hadzic, J. Rodriguez: "Use of negative information in positioning and tracking algorithms", Springer Journal on Telecommunication Systems, Volume 53, Number 3, July 2013.

S. Hadzic, D. Yang, M. Violas, J. Rodriguez: "Energy efficient mobile tracking in heterogeneous networks using node selection", in Eurasip Journal of Wireless Communications and Networking, Volume 2014, Number 1, January 2014.

S. Hadzic, D. Yang, M. Violas, J. Rodriguez: "RSS-based near-collinear anchor aided positioning algorithm for ill-conditioned scenario", accepted in International Journal of Wireless Communications and Mobile Computing, Science Publishing Group, February 2014.

Book chapters

S. Hadzic, S. Mumtaz and Jonathan Rodriguez: "Cooperative game theory and its application in localization algorithms", Chapter in Game Theory Relaunched, Intech International Publisher, In-Tech, 2013.

Chapter 2

Wireless localization systems

Generally, the localization process assumes a number of location aware nodes, called anchors. In a typical two-stage positioning system, the first phase is the ranging phase, where nodes estimate the distances to their neighbors by observing time of arrival, received signal strength or some other distance dependent signal metrics. In the second phase, nodes use the ranging information and the known anchor position for calculation of their coordinates.

In this chapter, we begin by describing the most common ranging techniques, their sources of error and statistical models in Section 2.1. In Section 2.2 we present the fundamental positioning algorithms, both deterministic and stochastic, followed by fingerprinting methods. Nonetheless, we put particular emphasis on cooperative positioning algorithms, and review them in Section 2.3. Since this thesis focuses on positioning in heterogeneous networks, in Section 2.4 we give an overview on the state of the art solutions for localization in such environments. When it comes to performance evaluation of localization algorithms, we intuitively think of accuracy. However, there are other metrics that contribute to the quality of a certain system. At the end of the chapter, in Section 2.5 we list the most commonly used performance metrics.

2.1 Ranging techniques

In the first positioning stage, packets are exchanged between neighboring nodes. From the physical waveforms corresponding to these packets, the receiver can extract information regarding its distance to the transmitter by measuring or estimating one or more signal metrics. Errors and uncertainties in localization arise from these signal metrics, which are subject to various sources of errors, such as noise, multipath, obstacles, interference, clock drifts, and environmental effects. The errors affecting the metrics are realizations of random variables, and the knowledge of their statistical properties are very important for localization algorithms, as the development of efficient probabilistic estimators relies on this knowledge. In the following, we list several common measurements and describe their use in localization and their sources of error. Note that there are also localization methods based on connectivity between nodes. They estimate the target coordinates based on information reliant on the subset of connected nodes. One example is the centroid algorithm [48], where position is estimated as the centroid of all anchors it is connected to. It requires a large number of anchors. These methods are usually very simple to implement, but do not provide very accurate results.

2.1.1 Received signal strength (RSS)

RSS based methods are based on the fact that signal attenuation is proportional to the distance between transmitter and receiver. It is one of the most popular parameters to be used in localization, since most wireless devices are capable of measuring the RSS in a simple and inexpensive way. A path loss model is needed for estimating the distance from the RSS value. Several factors, such as shadowing and reflection, may affect the radio signal propagation as well as the received power. Unfortunately, these factors are environment dependent and unpredictable. Time-varying errors caused by noise and interference can be averaged out. As the shadowing effects cannot be precisely tracked, they are usually modeled as a zero-mean lognormally distributed random variable. A widely accepted model for characterizing the RSS is given by:

$$P_r = P_0 - 10\alpha \log_{10}(\frac{d_{ij}}{d_0}) + X \tag{2.1}$$

where P_r is the received power in decibels, P_0 is the received power at reference distance d_0 (usually at one meter) from the transmitter in decibels. d_{ij} is the distance between node i and node j. α is the path loss exponent, while X is a zero mean Gaussian random variable with variance σ^2 in decibels and represents the shadowing component. X accounts for randomness of the environment.

As can be seen, the model is nonlinearly dependent on the position of the transmitter. If channel parameters, i.e., P_0 and α, are known, the maximum likelihood estimate of the distance between node i and j can be obtained as:

$$\tilde{d}_{ij} = d_0 10^{\frac{P_0 - P_r}{10\alpha}} \tag{2.2}$$

It can be shown that the distance estimate obtained in 2.2 is biased. An unbiased estimate for the distance can be derived as:

$$\tilde{d}_{ij} = d_0 10^{\frac{P_0 - P_r}{10\alpha}} e^{-\frac{1}{2}\frac{10\alpha}{\sigma \ln 10}} \tag{2.3}$$

The lower-bound on the variance of any unbiased distance estimator based on RSS measurements can be obtained as [27]:

$$\mathrm{var}(\tilde{d}) \geq \sigma^2 d^2 (\frac{\ln 10}{10\alpha})^2 \tag{2.4}$$

This bound is increasing with the square of the distance d. When $\alpha = 3$ and $\sigma^2 = 4$dB, its value is about $9.4m^2$ for $d = 10m$. It also shows that larger path loss exponent α leads to more accurate distance estimate. This can be explained by the fact that the average power is more sensitive to distance for larger path loss [49]. Note that if the path loss exponent α or reference power P_0 are unknown, they must be treated as nuisance parameters when estimating distance based on RSS [26]. For free space the path loss exponent $\alpha = 2$, and for indoor scenarios this parameter is highly environment dependent. In some indoor environments, the value of α can even be less than 2, due to the waveguide effect [50]. An RSS based model considers the randomness across a set of deployed environments. This method is still the most convenient one, since almost all wireless radio devices can report the received signal strength. However, due to multipath fading and shadowing present in indoor environment, the accuracy of distance estimates may not always be satisfactory.

The fingerprinting method consists in constructing the RSS or shadowing maps via measurements campaigns or calibration tools. This method is presented in section 2.2.3.

2.1.2 Time of arrival (TOA)

For TOA methods, distance is estimated based on the time the signal travels between two devices. The physical position of the target can be estimated via trilateration. Figure 2.1 illustrates the cellular case with three base stations. On the left side the distance estimates are exact, hence the circles (with radius equal to the distance between BS and MT) intersect in one single point. On the right side however, distance estimates are erroneous and thus the circles do not intersect at one point, but form an area. For signals propagating in free space at the speed of light ($c \approx 3 * 10^8$m/s), the distance between the target node and the anchor node i is given by $d_i = c(t_i - t_0)$ where t_0 is the time instant at which the emitter node begins transmission and t_i is the time of arrival at the receiver node.

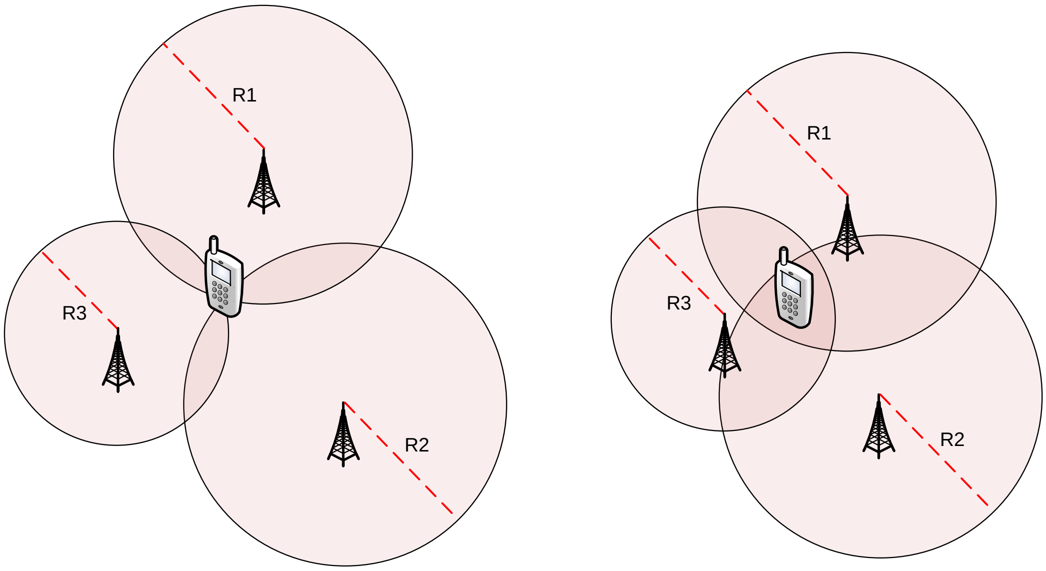


Figure 2.1: Time of arrival based localization in a 2-dimensional space.

The need for time synchronization can be overtaken by measuring the round trip delay, which is the time elapsed between the transmission of a signal and the reception of an acknowledgment. The TOA estimate is commonly obtained by employing correlator or matched filter receivers.

There are two ways to obtain the TOA: 1) one-way ranging which requires synchronization between transmitter and receiver, and 2) two-way ranging where the distance between two nodes is computed using the round-trip delay estimation without the need for a common time reference. For time-of-arrival in asynchronous networks, a common practice is to use two-way (or round-trip) TOA measurements. In this method, the first node transmits a signal to a second node, which immediately replies with its own signal. At the first sensor, the measured delay between its transmission and its reception of the reply is twice the propagation delay plus a reply delay internal to the second sensor. This internal delay is either known, or measured and sent to the first sensor to be subtracted.

Figure 2.2 illustrates Round Trip Time (RTT) measurements from the MS to the AP using the DATA-ACK frames of the IEEE 802.11 MAC layer. The RTT is the time the signal spends travelling from a transmitter to a receiver and back again to the transmitter; thus the TOA estimate is obtained by halving the RTT. RTT measurements are performed instead of directly measuring TOA in order to avoid the need of time synchronisation between the WiFi nodes. In each MAC layer data-ACK exchange, an ICMP Ping echo request is piggybacked: the transmitter(MS) waits for the reception of the ICMP (Internet Control Message Protocol) Ping echo request from the AP before sending the next ICMP request [51]. The period between sending and receiving the data frame constitutes an RTT. A timer exists to avoid blockage in case the MS does not receive the Echo response. In case the MS receives the corresponding ACK and the ICMP echo response, the timer stops and the pending RTTs counter decreases in one unit. In case of several collisions the timer can reach timeout limit [51]. Due to the noise in the measurements, RTT is treated as a random variable, and therefore statistical post-processing is required.

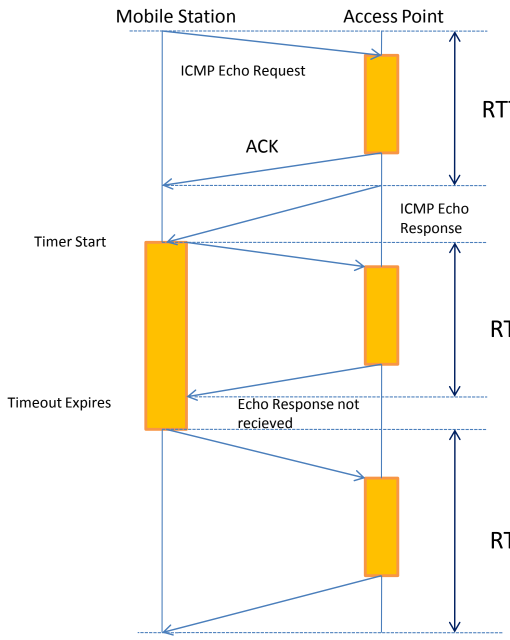


Figure 2.2: Round trip time (RTT) measurements

In TOA ranging, a timing error of 1 microsecond corresponds to a ranging error of 300 m and a timing error of 1 nanoseconds corresponds to a ranging error of 0.3 m. Thus, for most indoor applications, the error must not exceed a few nanoseconds. The main sources of error are:

- Multipath

  In multipath propagation, several components of the same signal arrive at the receiver via different propagation paths. In the absence of multipaths, a simple receiver computes the TOA by maximizing the cross-correlation between the received signal and the known transmitted waveform. In multipath propagation, the LOS path might not be the strongest path and the receiver detects the first arriving path and not the one with the highest peak. A common detection technique consists in measuring the time when the cross-correlation first crosses a given threshold. Generally, wider bandwidths are necessary to obtain greater temporal resolution, as the peak of autocorrelation function is inversely proportional to the bandwidth. Errors caused by multipath are often greater than those caused by the additive noise. A trend in propagation time measurements is the use of ultra wide band (UWB) signals for accurate distance estimation. Due to a wide transmission bandwidth these signals have very short pulse duration, and the fine delay resolution makes it possible to resolve multipath components [52].

- Additive noise

  Even in LOS conditions and in absence of multipath signals, additive noise limits the accuracy of TOA. For a given bandwidth and a signal-to-noise ratio (SNR), assuming that the bandwidth is much lower than the center frequency, the lower bound on variance of unbiased TOA estimation is given by [15]:

  $$\mathrm{var(TOA)} \geq \frac{1}{8\pi^2 BTF_c^2 \mathrm{SNR}} \tag{2.5}$$

  where B is the signal bandwidth in Hertz, T is the transmitted symbol duration in seconds, F_c is the center frequency in Hertz and SNR is the signal-to-noise ratio.

- Non-line of sight (NLOS)

  When the direct path is blocked, the receiver can only observe NLOS components, and the estimated distance is positively biased. While some of NLOS mitigation approaches perform by identifying and discarding the NLOS observations, others perform by solving a weighted least squares (assigning higher weights to links with high LOS probability), or by assuming statistical models of the NLOS bias and applying a probabilistic estimation technique. A survey of the different NLOS mitigation techniques is given in [53].

- Timing errors

  Synchronization errors, clock errors and drift, estimation of the reply delay in two-way ranging contribute to errors in TOA estimation. Synchronization errors refer to time differences between different clocks, while the clock errors refer to an individual node‘s offset against absolute time. The reply delay has been illustrated in 2.2.

Statistical model

Short ranging measurements have shown that ranging errors can be roughly modeled as Gaussian distributed in case of LOS propagation [15]:

$$T \sim N(\frac{d}{c} + \mu_T, \sigma_T^2) \tag{2.6}$$

Here, d is the inter-node distance, c is the speed of light and thereby $\frac{d}{c}$ is the time needed for the signal to travel between nodes. μ_T represents the measurement bias, thus the term $\frac{d}{c}+\mu_T$ is the mean value of the normal distribution, while σ_T is the standard deviation of the time measurement error. In the case of NLOS and obstructed and severely attenuated LOS signals, other models have been proposed to account for errors that can take large values, for example a mixture of Gaussian distributions or Gaussian and exponential distributions [54].

2.1.3 Time difference of arrival (TDOA)

The idea of TDOA ranging is to examine the difference in time at which signals arrive at multiple receivers, rather than the absolute time of arrival. A straightforward method for estimating the TDOA is to cross-correlate the signals arriving at a pair of anchor nodes. The cross-correlation of two signals $r_1(t)$ and $r_2(t)$, is given by

$$R_{1,2}(\tau) = \frac{1}{T} \int_0^T r_1(t) r_2(t+\tau) dt \tag{2.7}$$

where T represents the observation interval. The estimate of the delay is provided by the argument τ, which is the parameter that maximizes $R_{1,2}$. This method is widely used especially in cellular systems [55]. TDOA ranging techniques have also been applied to WLAN [56], eliminating the need for synchronization in the conventional methods. The advantage of the TDOA based method over the TOA based method is that it only requires the anchor nodes to be synchronized with each other. It also does not depend on the clock bias of each node. As for the TOA measurements, the error originates from the additive noise, multipath and NLOS. The error model is zero-mean Gaussian.

2.1.4 Angle of arrival (AOA)

Angle of arrival techniques are based on measuring the angles between target and anchor nodes. In order to apply these techniques, the nodes have to be equipped with antennas capable of measuring the angles. The most common method is the use of array antennas, which imply large device size. The angle of arrival is estimated from the differences in arrival times at each of the array elements. The second approach uses the RSS ratio between directional antennas.

In a 2-dimensional space, each AOA defines a straight line along which the target node is located, and a minimum number of two AOA observations are needed for computing the target coordinates. The advantages of this method are that it requires less observations than other methods, and synchronization of the anchor nodes and target node clocks are not a requirement. However, the hardware complexity is a drawback. Small errors in the angle estimation result in a high localization error, especially when the target node is far from the anchor nodes.

The major sources of error are NLOS conditions, multipath and array precision. The resulting AOA measurements are typically modeled as Gaussian, with the mean equal to the real angle to the target, and the standard deviation σ_α.

2.1.5 Comparison of ranging methods

The choice of the ranging method depends on the technology used for localization. For example, it is unfeasible to measure the received signal strength from the GPS satellites. Angle of arrival methods require special antennas, and are mainly used in the scope of cellular networks based localization. Therefore it does not make sense to compare the ranging methods without considering the scenario. In Table 2.1 we give an overview of ranging methods with respect to the underlying technology.

Having in mind the scenario that we will examine, the most appropriate ranging method is the RSS. Note that the TDOA technique cannot be applied because the distances between MSs are so small that small errors in TDOA estimations would result in huge errors when estimating their positions.

Technology	Meas. techniques	Accuracy	Pros	Limitation
GPS	TDOA	10-20 m	Earth scale	Expensive and outdoor only
A-GPS	TDOA	<5 m	Country scale	Expensive, limited indoor
Cellular	TDOA	50-500 m	Wide area	Synchronized BS needed
	AOA	>1° 50 m, for 3 km cell size	1-3 km urban	Smart antennas needed
	Cell ID	Cell size	3-20 km suburban	Low precision
WiFi	RSS	1-5 m	Widely used High data rate Relatively wide area (<1 km)	High accuracy only for fingerprinting
	TOA	50-500 m		
	AOA	<100 m		
ZigBee	RSS	1-10 m	Low power consumption Up to 50m coverage	Low scalability
UWB	TOA	0.1-1 m	Highly accurate for short range indoor	Short range (10-20 m)

Table 2.1: Localization technologies and ranging methods

2.2 Range based positioning algorithms

Indoor localization techniques can be classified into two main groups: 1) The first group uses dedicated infrastructure for positioning; in this case dedicated devices have to be installed, and 2) the other group employs previously available wireless communication infrastructures. The latter group is a cost efficient solution with large coverage, while high accuracy, availability and reliability can be attained. On the other hand, there is a need for more intelligent algorithms to compensate for the low performance of measurement techniques. Most Wi-Fi-based location approaches correspond to radio maps (fingerprinting). Although high accuracy is attainable, a complex training process is required to develop the fingerprinting database, specifically each time the environment changes. Cooperative positioning techniques are used in scenarios where non-cooperative solutions are not feasible, or do not perform well in terms of accuracy, cost and complexity. The challenge is to allow nodes which are not in range of a sufficient number of anchors to be located, and hereby increase localization performance in terms of both accuracy and coverage. While positioning and navigation have been investigated for a long time, cooperative positioning schemes have to extend those existing algorithms by making use of peer-to-peer measurements among location-unaware nodes.

Given an underlying transmission technology, localization performance is also dependent on the specific algorithm used in the location-update phase. Here we will list the most common algorithms, which can be classified into deterministic and probabilistic ones. We also give an overview on the most popular fingerprinting methods.

2.2.1 Deterministic positioning techniques

Deterministic approaches to localization are based on least squares (LS). Here we will review the nonlinear least squares (NLS), weighted least squares (WLS) and linear least squares (LLS) for the positioning problem.

Nonlinear least squares

Least squares algorithm is used in order to minimize the error between the estimated position $\tilde{\mathbf{x}}$ and the real position. A nonlinear least squares algorithm for positioning tries to minimize the following cost function:

$$\tilde{\mathbf{x}} = \arg\min_{x} \sum_{i=1}^{N} (y_i - f(x_i))^2 \tag{2.8}$$

where y_i , $i = 1, ..., N$ are the observations, and $f(x_i)$ are transformations of desired state x_i. In case of localization, y_i are estimated distances between the target and anchor node i, and $f(x_i)$ are the true distances between them.

Weighted least squares (WLS)

When the variances of measurement errors are available, the NLS can be formulated as a weighted nonlinear least squares (WNLS):

$$\tilde{\mathbf{x}} = \arg\min_{x} \sum_{i=1}^{N} w_i(y_i - f(x_i))^2 \tag{2.9}$$

For the selection of weights, several strategies have been adopted. Most works set the weights equal to the inverse of estimated variances of the measurements (i.e., $w_i = \frac{1}{\sigma_i^2}$), [57],[58],[59]. In [60] the weights are exponentially decreasing with the measured distances. Basically the weights have to reflect the quality of the distance estimates. In general, the WNLS solution coincides with the ML estimate if measurement errors are independent individual distributed Gaussian.

Linear least squares (LLS)

The obvious approach in solving this positioning problem is to treat the coordinates of the target $\mathbf{x} = (x, y)$ as the point of intersection of several circles, whose centers are the locations of the N anchor nodes (x_i, y_i) for $i = 1, ..., N$. The exact distances between the anchors and the target, d_i, are the radii of the individual circles. The equation for any of these circles is

$$(x_i - x)^2 + (y_i - y)^2 = d_i \tag{2.10}$$

The point of intersection of these circles is obtained by solving the resulting N nonlinear equations, but first we have to linearize them. For two-dimensional positioning, when the exact distances from three anchors are available, the solution of the system of equations is completely determined. In general, for (N-1)-dimensional case, distances to N anchors are needed. We can write a set of N equations:

$$\begin{pmatrix} (x_1 - x)^2 + (y_1 - y)^2 \\ (x_2 - x)^2 + (y_2 - y)^2 \\ ... \\ (x_N - x)^2 + (y_N - y)^2 \end{pmatrix} = \begin{pmatrix} d_1^2 \\ d_2^2 \\ ... \\ d_N^2 \end{pmatrix} \tag{2.11}$$

By subtracting one of the equations, e.g. the last one, from all previous ones, we eliminate one unknown and obtain a linear set of (N-1) equations:

$$\begin{pmatrix} x_1 - x_N & y_1 - y_N \\ x_2 - x_N & y_2 - y_N \\ ... & ... \\ x_{N-1} - x_N & y_{N-1} - y_N \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix} = \frac{1}{2} \begin{pmatrix} d_1^2 - d_N^2 - x_1^2 + x_N^2 - y_1^2 + y_N^2 \\ d_2^2 - d_N^2 - x_2^2 + x_N^2 - y_2^2 + y_N^2 \\ ... \\ d_{N-1}^2 - d_N^2 - x_{N-1}^2 + x_N^2 - y_{N-1}^2 + y_N^2 \end{pmatrix} \tag{2.12}$$

This linear system can be rewritten into a matrix form: $\mathbf{Ax} = \mathbf{b}$. Since the measured distances d_i are only approximate estimates, we need to determine x such that $\mathbf{Ax} \approx \mathbf{b}$.

The least squares method finds its optimal solution when the sum of squared residuals is a minimum. A residual is defined as the difference between an observed variable and the predicted value from the estimated model. Minimizing the sum of squares of residuals:

$$\mathbf{r^T r} = (\mathbf{b} - \mathbf{Ax})^{\mathbf{T}}(\mathbf{b} - \mathbf{Ax}) \tag{2.13}$$

leads to equation

$$\mathbf{A^T A x}{=}\mathbf{A^T b} \tag{2.14}$$

Assuming that the anchor nodes are reasonably placed (non collinear), the matrix $\mathbf{A^T A}$ is non-singular and well conditioned. Now the LS solution can be obtained as:

$$\tilde{\mathbf{x}} = (\mathbf{A^T A})^{-1}\mathbf{A^T b} \tag{2.15}$$

For least-squares problems there are efficient algorithms and software implementations for solving the problem to high accuracy and with high reliability. The least-squares problem can be solved in a time approximately proportional to $m^2 * N$, where m is the dimension of the target (we usually consider the 3-dimensional case), and N the number of anchor nodes.

The linear version of the weighted least squares algorithm is given by:

$$\tilde{\mathbf{x}} = (\mathbf{A^T W}^{-1}\mathbf{A})^{-1}\mathbf{A^T W}^{-1}\mathbf{b} \tag{2.16}$$

where $\mathbf{W}$ is a diagonal matrix with diagonal values equal to w_i. One important feature of the LLS method is the covariance matrix of the LS estimator. This covariance matrix represents a measurement of uncertainty in the position estimate [61]:

$$\begin{aligned}
\mathbf{P} &= E\left[\{\tilde{\mathbf{x}} - E(\tilde{\mathbf{x}})\}\{\tilde{\mathbf{x}} - E(\tilde{\mathbf{x}})\}^T\right] = E\left[\{\tilde{\mathbf{x}} - \mathbf{x}\}\{\tilde{\mathbf{x}} - \mathbf{x}\}^T\right] \\
\mathbf{P} &= (\mathbf{A}^T\mathbf{W}^{-1}\mathbf{A})^{-1}\mathbf{A}^T\mathbf{W}^{-1}E\left[\eta\eta^T\right]\mathbf{W}^{-1}\mathbf{A}(\mathbf{A}^T\mathbf{W}^{-1}\mathbf{A})^{-1} \\
\mathbf{P} &= (\mathbf{A}^T\mathbf{W}^{-1}\mathbf{A})^{-1}
\end{aligned} \tag{2.17}$$

Here the parameter η represents the noise component added to the model. Equation (2.17) results in:

$$\mathbf{P} = (\mathbf{A}^T\mathbf{W}^{-1}\mathbf{A})^{-1} \tag{2.18}$$

To form a linear least squares problem, we need to find a signal model that is linear in the unknown parameters. Therefore in the case of RSS based ranging, first we have to estimate the distances based on the methods described in the previous section, and then apply LLS on these estimates. In case of TOA, LLS techniques can be applied directly to the measurements multiplied by the speed of light c.

2.2.2 Probabilistic positioning techniques

While the previously presented algorithms are deterministic, e.g., their aim is to find the deterministic location, the statistical/probabilistic approach proposes an approximate solution. Generally, the aim is to estimate the maximum a posteriori node location using a set of observations (distance estimates) and a priori probability distributions of nodes locations. Probabilistic algorithms exploit the available probabilistic models on the measurements (i.e., likelihood functions) and positions (i.e., a priori information). There are two approaches to the parameter estimation problem: Maximum Likelihood (ML) and Bayesian estimation.

Maximum Likelihood Estimator

In the ML approach the unknown parameter θ is treated as deterministic. The estimation is then based on maximizing the likelihood function, e.g., the density of the observations y conditioned on the parameter vector.

$$\tilde{\theta}_{ML} = \arg\max_{\theta} p(y|\theta) \tag{2.19}$$

where $p(y|\theta)$ is the likelihood function. In case of localization, observations are measurements and corresponding distance estimates d_i so (2.19) becomes:

$$\tilde{\theta}_{ML} = \arg\max_{\theta} p(d_i|\theta) \tag{2.20}$$

The ML estimator is asymptotically efficient. This means that it converges to the Cramer Rao Lower Bound (CRLB) at low error variances, when the statistics of the measurement errors are known. In practice it is difficult to obtain a priori knowledge of the full statistics of measurement errors. The algorithm itself is computationally demanding. The ML cost function is highly nonlinear and contains multiple local minima and maxima. Therefore the ML formulation has been relaxed to a convex optimization problem in the form of a semidefinite program [62]. However, due to its optimality, ML is a good benchmark for evaluation of localization algorithms.

Bayesian estimators

In the Bayesian approach, the unknown parameter is treated realization of a random variable of known a priori distribution. Two common Bayesian estimators are the minimum mean square error (MMSE) and the maximum a posteriori (MAP) estimators, which are maximizing the density of the parameter vector conditioned on the observations.

In general MAP estimators have superior performance than ML estimators, assuming that the prior distributions used are the correct ones. When the assumed models deviate from the true distributions, the estimation accuracy in principle degrades. If the prior distributions are not known, a method known as Bayesian inference can be used. The belief propagation algorithm is a graphical model for distributed statistical inference, widely used for positioning. The amount of computation is proportional to the number of links in the graph. Non parametric belief propagation (NBP) is more acceptable for localization in wireless networks, because of its ability to accommodate non-Gaussian distance estimation errors and provide an estimate of the remaining uncertainty in each node location [63]. NBP techniques are widely used for cooperative localization. The main drawback of these algorithms is that convergence is not guaranteed in networks with loops [64].

Kalman filter (KF) remains one of the mostly used Bayesian techniques. The filter defines a set of equations, which in a recursive manner can estimate the state of an unknown noisy process. The traditional Kalman filter yields the optimal minimum mean squared error (MMSE) estimate under assumptions that the noise is Gaussian, and that state equations are linear [65]. The Kalman filter is a two-step process: prediction and correction (Figure 2.3). In the prediction step, the filter predicts the next position and its estimated error based on the previous position and its estimated error with a movement model. During the correction step, the filter calculates the new position and its estimated error by updating the predicted position using acquired measurements. The filter can start with either step but will begin by describing the correction step first. The correction step makes corrections to an estimate, based on new information obtained from sensor measurements.

The Kalman filter model assumes that the real state at time k evolves from the state at $k-1$. Thus the process equation is given as:

$$\tilde{\mathbf{x}}_k = \mathbf{A}\tilde{\mathbf{x}}_{k-1} + \mathbf{B}\mathbf{u}_{k-1} + \mathbf{w}_{k-1} \tag{2.21}$$

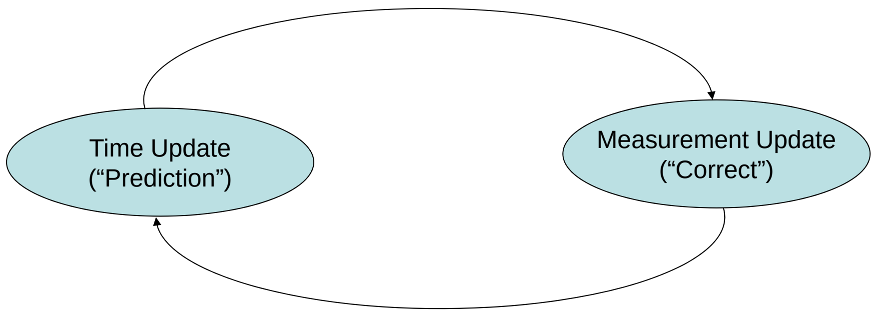


Figure 2.3: Kalman filtering cycle: cyclic sequence of prediction and correction

The scale transition matrix $\mathbf{A}$ defines the relation between the previous state and the current one, matrix $\mathbf{B}$ relates the previous external input vector $\mathbf{u}_k$ with the actual state $\mathbf{w}$ is the process noise and is a zero-mean Gaussian normal variable. $\mathbf{w}_{k-1}$ stands for the process noise at the previous time instance. The output/observation vector is given by:

$$\mathbf{z}_k = \mathbf{H}\tilde{\mathbf{x}}_k + \mathbf{v}_k \tag{2.22}$$

Here $\mathbf{H}$ is the state transition matrix and represents the relation between the present state $\tilde{\mathbf{x}}_k$ and the measurement $\mathbf{z}_k$ expected for that state $\tilde{\mathbf{x}}_k$. The measurement error $\mathbf{v}_k$ is a random zero-mean Gaussian variable. It is assumed that the measurement noise $\mathbf{v}$ and the process noise $\mathbf{w}$ are mutually independent random variables.

The starting values for the state $\tilde{\mathbf{x}}_{0|0}$ and the error covariance estimator $\mathbf{P}_{0|0}$ are system dependent. For $\tilde{\mathbf{x}}_{0|0}$ it shall be the expected value of the state at time t_0. Concerning the $\mathbf{P}_{0|0}$ it is commonly initialized with the covariance matrix $\mathbf{Q}$. The prediction state of the Kalman filter is given by:

$$\begin{aligned} \hat{\mathbf{x}}_{k|k-1} &= \mathbf{A}_k\hat{\mathbf{x}}_{k-1|k-1} + B_k\mathbf{u}_{k-1|k-1} \\ \mathbf{P}_{k|k-1} &= \mathbf{A}_k\mathbf{P}_{k-1|k-1}\mathbf{A}_k^T + \mathbf{Q}_k \end{aligned} \tag{2.23}$$

and the prediction phase by:

$$\begin{aligned} \mathbf{K}_k &= \mathbf{P}_{k|k-1}\mathbf{H}_k^T(\mathbf{H}_k\mathbf{P}_{k-1|k-1}\mathbf{H}_k^T + \mathbf{R}_k)^{-1} \\ \hat{\mathbf{x}}_{k|k} &= \hat{\mathbf{x}}_{k|k-1} + \mathbf{K}_k(\mathbf{Z}_k - \mathbf{H}\hat{\mathbf{x}}_{k|k-1}) \\ \mathbf{P}_{k|k} &= (\mathbf{I} - \mathbf{K}_k\mathbf{H}_k)\mathbf{P}_{k|k-1} \end{aligned} \tag{2.24}$$

The positioning process is illustrated in diagram in Figure 2.4.

However, location estimation in wireless communication systems is often a nonlinear

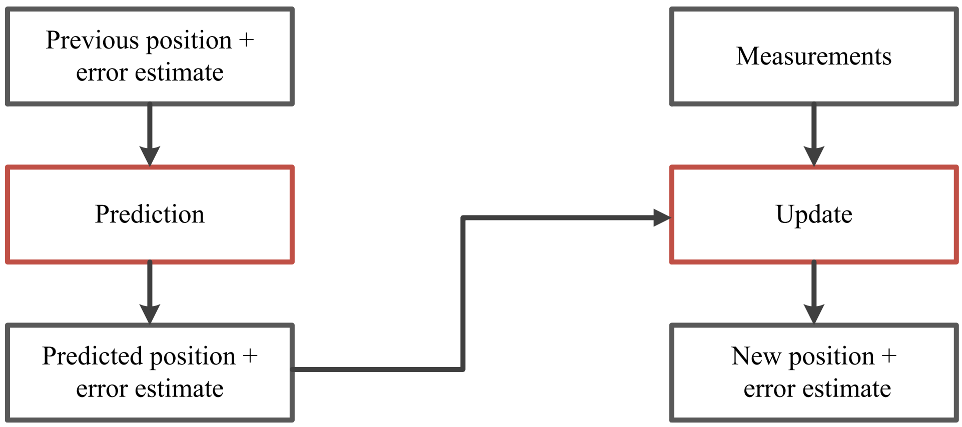


Figure 2.4: Position estimation based on Kalman filter

problem. Here the solution is the suboptimal extended Kalman filter (EKF), which assumes linearization of the prediction and measurement functions, based on a Taylor series expansion. The computational efficiency of a KF is maintained. The drawback of the EKF is that the convergence is not guaranteed in the case that the propagation error can not be properly approximated by a linear function. The linearization process can also have a high impact concerning the errors in the estimated mean and covariance.

2.2.3 Fingerprinting

The first part of the fingerprinting method is the offline phase where data collection is performed. Location dependent parameters of the signals are measured at selected locations, and then processed and saved in a database. What follows is the online phase where the target acquires the measurements of location dependent parameters, and compares it to the values in the database. The target location is computed from the locations associated to the database entries that best match the measurements.

Some fingerprinting and pattern recognition approaches are listed below. Active Badge was an early system developed to localize mobile devices within a building using infrared tags [20]. Targets are equipped with badges that transmit infrared signals providing information about their location through a sensor network. RADAR system [66] is implemented in WLAN nwtworks. The key idea is to record radio signals and build models for signal propagation during off-line analysis.The median resolution of the RADAR system is in the range of 2 to 3 meters, about the size of a typical office room. The systems main disadvantage is its dependence on empirical data. PlaceLab [67] uses connectivity from GSM base stations and IEEE 802.11 access points. The coverage and accuracy of Place Lab depend on the number and mix of beacons in the environment. Certain environments may be more tolerant to a more granular grid spacing because of the radio propagation conditions. Cricket [19] is a decentralized location support system based on RF and ultrasound. Incorporating ultrasound hardware was necessary because a purely RF-based system did not provide satisfactory results. It takes into account user privacy and does not depend on underlying network technology. Still, the systems granularity is a portion of a room. In [68] the authors implemented an indoor WLAN location system based on artificial neural networks (ANN). First the macro-location of the device is derived, knowing with which access point the user is associated and using information about its coverage. Micro-location is obtained based on RF fingerprinting and trained ANN, with an average error below two meters.

Compared to range-based techniques, fingerprinting requires huge amount of resources and time especially to establish and to populate the database. Each time the environment changes, the cost of the localization system may increase, since regular updates are required. One of the solutions which considered the issue of reducing the calibration effort has been presented in [38]. It consists of reducing the number of locations at which measurements are collected at the cost of reduced accuracy.

2.3 Cooperative positioning

Cooperation between nodes is used in cases when conventional positioning techniques do not perform well due to lack of existing infrastructure, limited number of reference nodes or obstructed indoor environment. The position of the target is then estimated based on known positions of a number of anchors and also using measurements to other location-unaware nodes (Figure 2.5). The existing cooperative positioning algorithms are mainly intended for homogeneous networks under relatively high network connectivity and density. Thus, significant efforts still have to be made to adapt, extend and optimize these promising schemes into heterogeneous network architectures under realistic operating constraints.

Main performance metrics for cooperative positioning algorithms are position estimation accuracy and latency, whereby the level of accuracy depends on the application for which the system is being used. Latency or response time is an important issue for delay-stringent applications. In fact the two major cost parameters are the amount of commu-

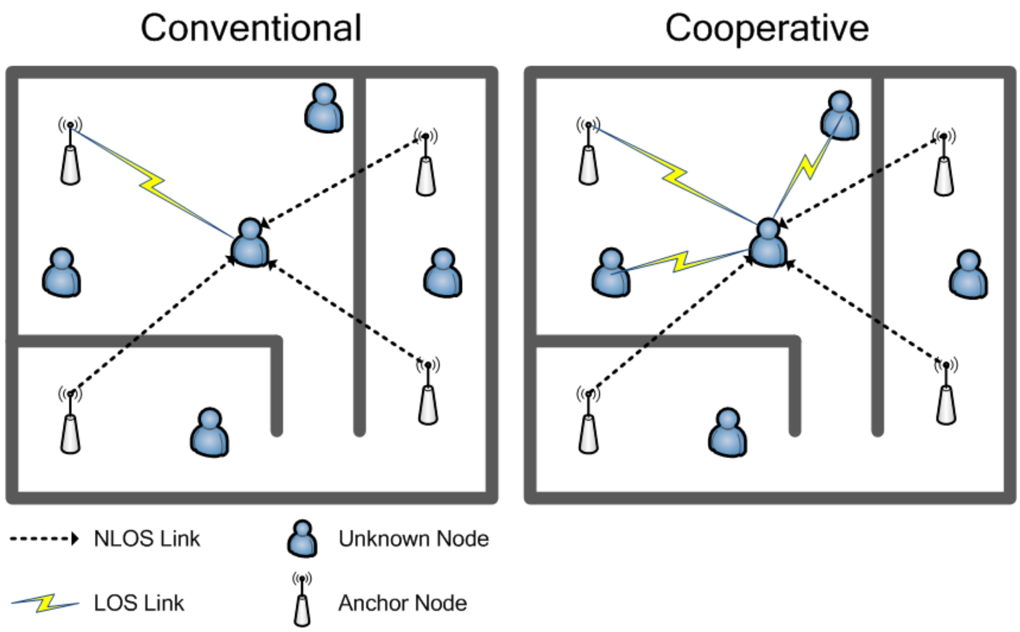


Figure 2.5: Example of cooperative scenario

nication between nodes, and the computation process in the nodes. Cooperative solutions have to achieve the desired cost-performance trade-offs. The number of actively participating nodes should be kept to a minimum, and therefore an appropriate cooperation subset has to be chosen, while the other nodes can be ignored. Such a restrictive and selective use of references is crucial in networks with limited resources.

In the following, we will survey the most popular cooperative localization algorithms. First we will extend the previously described ML and LS estimators to the cooperative case, and then describe some centralized cooperative methods such as multidimensional scaling, convex sets and semidefinite programming. In the end, we will list the categories of distributed positioning algorithms. Centralized localization algorithms are based on global optimization, while distributed solutions use local information only. The basic idea is to decompose the global estimation task into subtasks which comprise local computation only.

2.3.1 Centralized cooperative localization techniques

Centralized algorithms are sometimes unavoidable when the nodes do not have sufficient computational capacity. Measurements are sent to a central processor where all the computation is performed.

Maximum Likelihood Estimator

If there exists a statistical model for distance estimation (e.g., Gaussian), then a maximum likelihood estimator can be implemented. The ML algorithm finds the solution of a set of nonlinear equations by iterative minimization of a cost function. In [26] the authors developed a maximum likelihood estimator for cooperative positioning for both RSS and TOA measurements, assuming that TOA- based ranging errors are Gaussian, and using a lognormal model for RSS measurements. Several targets aim to estimate their locations at the same time, and besides measurements to fixed anchor nodes, they also exchange information between themselves. There are in total M nodes, N of which are anchor nodes and the remaining $M-N$ nodes have to be localized. Therefore, the parameter to be estimated is a matrix $\tilde{\mathbf{X}}$, consisting of $M-N$ rows (unknown nodes) and 2 columns (x and y coordinate).

When assuming that the measured power P_{ij} at node i transmitted by node j is lognormal, the random variable $P_{ij}(dBm) = 10log_{10}P_{ij}$ is Gaussian:

$$\begin{aligned} P_{ij}(\text{dBm}) &\sim N(\overline{P_{ij}}(\text{dBm}), \sigma^2_{\text{dB}}) \\ \overline{P_{ij}}(\text{dBm}) &= P_0(\text{dBm}) - 10\alpha\log_{10}(\tfrac{d_{ij}}{d_0}) \end{aligned} \tag{2.25}$$

where $\overline{P}_{ij}$ is the mean power in dBm, σ^2_{dB} is the variance of the shadowing, $P_0(\text{dBm})$ is the received power in dBm at reference distance d_0 (usually 1m), and α is the path loss exponent. For the RSS case the estimator is:

$$\tilde{\mathbf{X}} = \arg\min_{\mathbf{X}} \sum_{i=1}^{N} \sum_{j=N+1}^{M} \left[\ln \frac{\tilde{d}^2_{i,j}}{d^2_{i,j}} \right]^2 \tag{2.26}$$

In TOA case, with Gaussian distribution denoted as $T_{i,j} \sim N(\frac{d_{i,j}}{c}, \sigma^2_T)$, the MLE estimator is:

$$\tilde{\mathbf{X}} = \arg\min_{\mathbf{X}} \sum_{i=1}^{N} \sum_{j=N+1}^{M} (cT_{i,j} - d_{i,j})^2 \tag{2.27}$$

In [26], in addition to the ML estimator, an analytical expression for the Cramer-Rao lower bound (CRLB) for cooperative localization has been provided. More details on the CRLB will be given in the next chapters.

Least squares

The cost function to be minimized in the cooperative case is of the same form as (2.8), but here we assume that besides N anchor nodes, there are also $M-N$ non-anchor nodes that are estmating their positions simultaneously:

$$\tilde{\mathbf{X}} = \arg\min_{\mathbf{X}}(\sum_{i=1}^{N} (y_i - f(x_i))^2 + \sum_{i=N+1}^{M} (y_i - f(x_i))^2) \tag{2.28}$$

Similarly, the cost function for weighted least squares will be:

$$\tilde{\mathbf{X}} = \arg\min_{\mathbf{X}}(\sum_{i=1}^{N} w_i\,(y_i - f(x_i))^2 + \sum_{i=N+1}^{M} w_i\,(y_i - f(x_i))^2) \tag{2.29}$$

In general, the WLS solution coincides with the ML estimate if measurement errors are independent and identically distributed (i.i.d.) Gaussian random variables. In the above equations, the term y_i corresponds to estimated distances, $\tilde{d}_i$, while the term $f(x_i)$ represents true distances d_i. Iterative methods are applied to solve this kind of optimization problems, such as Gauss-Newton or Levenberg-Marquardt method [69].

Semidefinite programming

Since ML and NLS methods yield nonconvex optimization problems. If the estimator is not initialized with values close to the true solution, it can occur that the global maxima are not found. Convex relaxation techniques can be employed to solve them in an efficient way. In [70] pair-wise distance measurements are used as convex constraints. If two nodes can communicate with each other, there is a proximity constraint between them, given a limited radio range. The network can be seen as a graph with M nodes as vertices and bidirectional connectivity constraints among them as edges. Positions of the first N nodes are known, and the task is to find the coordinates of the remaining $M-N$ unknown nodes, such that the connectivity constraints are satisfied. The mathematical solution is based on linear and semi-definite programming (SDP) techniques. Performance increases with the number of additional constraints, or the tighter these are. However, the method does not yield good performance if anchors are placed in the interior of the network. An SDP relaxation based method is used in [57] to estimate locations of free nodes. Here the non-convex quadratic constraints are converted into linear constraints, and the method overcomes the problem of anchor placement.

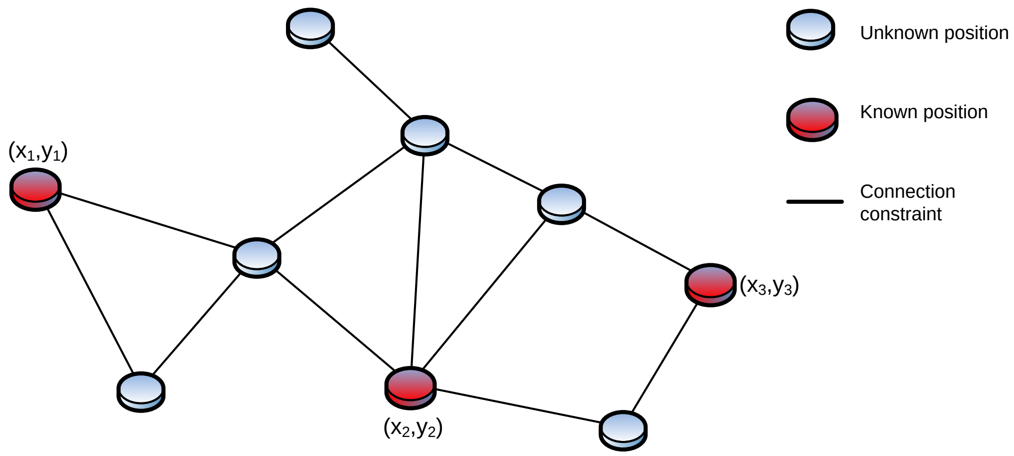


Figure 2.6: Distance measurements as convex constraints

Multidimensional scaling

For relatively sparse sensor networks the most widely used method is multi-dimensional scaling (MDS), a statistical dimensionality reduction technique for data analysis that uses pair-wise distance measurements as connectivity constraints [71]. MDS assumes N points, suspended in a volume, whereby the positions of the points are not known, but the distance between each pair of points are known. The distance between every pair of objects measures their dissimilarities.

When nodes are uniformly positioned, MDS gives very good results and it localizes all nodes at the same time, in contrast to trilateration based methods where nodes are being localized one by one. Nevertheless, it assumes the knowledge of all mutual ranges between sensors.

2.3.2 Distributed cooperative localization techniques

Distributed algorithms do not require the existence of a central processor, and this fact makes them more scalable and attractive for large networks.

Successive refinement

Successive refinement algorithms are based on least squares [32], weighted least squares, or maximum likelihood [72]. At each iteration, one or several nodes update their estimates by minimizing local cost functions and send them to nodes in their vicinity, until a convergence criterion is met. An initialization phase is required and significantly affects the accuracy and final convergence. In [32] initial estimates are obtained during the first phase by performing a coarse connectivity based positioning, such as DV-hop. [73]. TOA based ranging for UWB is used for further refinement, and the distributed LS is solved using the gradient descent method. In [72] two methods have been proposed, one based on WLS and solved using Levenberg-Marquardts algorithm, and another one based on distributed log-likelihood maximization.

A distributed version of MDS has been considered in [74]. Another successive refinement schemes have been elaborated in [75], [76].

Message passing

Message passing algorithms are based on Bayesian inference. The network is represented as Markov fields or factor graphs. Statistical models for the measurements have to be assumed, in order to define the potential functions between every pair of connected nodes in the graph. Each node computes its posterior marginal distribution from its local a priori information and messages received from neighboring nodes. Examples of these algorithms are nonparametric belief propagation [64], [63], variational message passing [77] and factor graphs [31].

Iterative multilateration

Iterative multilateration is a way to expand localization coverage throughout the network in a step-by-step fashion, also allowing the nodes which are not in range of a sufficient number of references to be localized. It follows an iterative scheme: once an unknown node estimates its position, it becomes an anchor and broadcasts its position estimate to all neighboring nodes. The process is repeated until all nodes that can have three or more reference nodes obtain a position estimate [78]. AHLoS (Ad Hoc Localization System) algorithm [75] uses TOA as the primary ranging method, and maximum likelihood multilateration as the basis for position calculation. This work identified two main problems: 1) it requires a high degree of network connectivity and anchor density, and 2) it suffers from error propagation. As a newly localized node becomes a new anchor for its neighbors, the estimation error of the first node can propagate to other nodes and eventually get amplified. Through successive iterations, the error could spread throughout the network leading to a proliferation of error in large topologies. In [79] the authors proposed an iterative algorithm that takes into account the behavior of the channel to provide accurate indoor positioning and importantly reduce error propagation. The error behavior of TOA measurements depends on the channel conditions, and there are three classes of behavior: dominant direct path, non-dominant direct path, and undetected direct path. The realistic indoor channel model was developed using UWB measurements, and was used to model the Distance Measurement Error (DME). DME establishes different statistical behavior, depending on whether the received signal is direct path or not. Besides the quality of link indicator, also the quality of estimate parameter has been provided. Simulations showed that inaccurate ranging has a bigger impact on error propagation than the use of estimated (and therefore erroneous) locations as anchors.

In [80] an error control mechanism has been developed, that consists of three components: 1) error characterization, addressing the uncertainty of estimate, 2) neighbor selection, excluding nodes with high uncertainty, and 3) update criterion, rejecting a new estimate if its uncertainty is too high. The mechanism is distributed and uses only local information, and computation is performed using multilateration. Localization error in every unknown node comes from two sources: 1) the uncertainty in each anchor position, denoted vertex error, and 2) uncertainty in each distance estimate, denoted edge error. Error characterization is iterative: once a node derives its own error characteristics, its overall error becomes the vertex error for its neighbors. Expressing uncertainty is a difficult task, and in [32] several simplifications are made. All variables are assumed to be Gaussian and independent, so the uncertainty can be expressed as variance or covariance, for scalar values and vectors, respectively. These assumptions are not accurate; however they provide a way to accomplish error characterization.

2.4 Heterogeneous networks

Although there are many works on cooperative positioning, there is not much attention given to the heterogeneity of the networks. By heterogeneity we mean the various and different radio access technologies (RATs) to which a mobile device can be conjointly connected; some works use the notation *hybrid*. However, in terms of localization, this may refer to different ranging technologies for the same RAT (combining RSS and TOA - hybrid data fusion). In the area of WSN localization *heterogeneous sensors* may refer to combination of different types of sensors such as audio and video, or image and RF. Throughout this thesis, we refer to the use of different technologies. The work in [29] proposed a cooperative positioning system where the Base station-MT link adopted the IEEE

802.16e standard and Time Difference of Arrival (TDOA) based distance estimation, while the MT-MT link adopted the IEEE 802.11a standard and RSS based distance estimation. Simulations showed a high benefit from cooperation using short-range links between mobile terminals. Most of the work concerning positioning in heterogeneous networks is considering Wi-Fi complementing cellular networks [81]. The combination of cellular and Wi-Fi radio interfaces in mobile devices, and the fact that the position estimation techniques are basically the same for both technologies, makes it a popular case scenario.

In [82] the mobile stations are equipped with two different technologies, able to establish long range links to cellular base stations, as well as short range links allowing communication among mobile devices themselves. To overcome the problem of different positioning characteristics for different technologies, a Two Level Kalman Filter (2LKF) is proposed, to decouple relative localization using ad hoc links from the absolute localization using long range cellular links. It is assumed that relative localization is performed using RSS measurements between mobiles, while for absolute localization TOA and AOA are used. The problem of integration of short- and long-range technologies is solved by decoupling of estimators, so they can operate independently. Distributed computation is feasible to a certain extent.

When it comes to short range technologies, combination of various RATs by exploiting their individual advantages such as the

- robustness of Wi-Fi under harsh environments
- accuracy of UWB under LOS conditions
- low cost features of ZigBee

provides us with better overall localization results in GPS denied environments.

The work in [33] considers a mobile robot in an indoor environment. Ranging between fixed anchors and mobile robots is achieved through Wi-Fi RSS-based techniques, while robot-robot ranging is performed through UWB TOA-based techniques. Different models for link errors using RSS and TOA, while the position is estimated by means of trilateration. In [35] two ranging techniques have been applied: one based on the RSSI measurements obtained with ZigBee sensor nodes, and the other one based on the TOA measurements on UWB devices. In case of RSSI based ranging, short distances have smaller ranging error, while the probability distribution of the ranging error provided by TOA does not depend on the actual distance. Main result shows the positive impact of heterogeneity. The accuracy increases with the number of possible interactions between nodes (larger communication range). A heterogeneous indoor Wi-Fi/ZigBee environment has been considered in [36]. Different link selection strategies for static scenarios have been compared, such as Geometric Dilution of Precision (GDOP) and CRLB. The results show a high correlation between predicted selection criteria and the actual positioning error.

2.5 Performance metrics of localization techniques

The choice of localization method will depend on the application and its requirements, in sense that some will require highly accurate results, while others may prefer robustness or ease of deployment. There are no unique criteria to evaluate and compare positioning algorithms. In this section, we survey the principal factors that are considered when choosing a localization technique.

2.5.1 Accuracy

The accuracy of a positioning system depends on several factors: the nature of measurements, conditions of the wireless propagation channel, the used RAT, the number and geometric configuration of anchor nodes, and the localization algorithm. In general, time based measurements are more precise than RSS, but also the accuracy differs from technology to technology.

Different positioning algorithms can be compared based on different accuracy metrics. The most common ones are the cumulative distribution function and the root mean square error, but sometimes also the instantaneous location error at a certain time stamp.

Cumulative distribution function

Due to randomness of measurement errors or network deployment, the error vector e is random. The cumulative distribution function (CDF) of position error is defined as the probability that the error is smaller than a certain value, that is:

$$P_{\|e\|}(error) = \Pr(\|e\| \leq error) \tag{2.30}$$

Usually we observe the errors at 50% and 90%, since they represent the average performance (median error), and "worst case" error (robustness metric), respectively. Another typical value is the 67% percentile error.

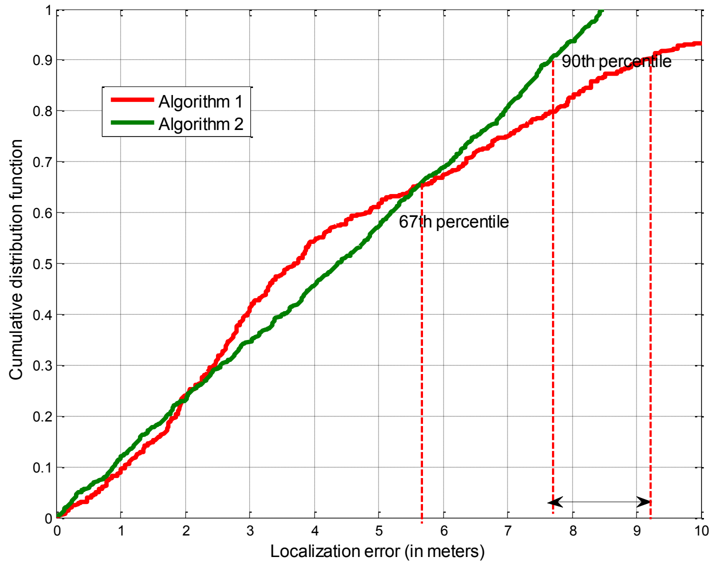


Figure 2.7: Comparison between two CDFs..

The CDF gives more insight into the performance of positioning algorithms than absolute error values. For example, two different algorithms may have relatively different performances for different error intervals. The example in Figure 2.7 shows the CDF of the position error for Algorithm 1 and Algorithm 2.

The x-axis contains the localization error in meters. The y-axis is the probability that the algorithm output will provide an estimate with the error smaller than the value on the x-axis. For example, the 67th percentile has the same value for both algorithms. This means, both algorithms will provide an error lower than 5.7 meters in 67 % of cases.

Root mean square error

The root mean square error (RMSE) is defined as

$$RMSE = \sqrt{E(\|\tilde{x} - x\|^2)} \approx \sqrt{\sum_{k=1}^{K} \|\tilde{x}(k) - x\|^2} \tag{2.31}$$

where $\tilde{x}(k)$ are location estimates of target x for the kth realization of noise and/or node deployment. Distinct random measurements are given at each network deployment k. Instead of the average error, maximum or median error can be useful in some scenarios.

The CDF gives more insight into the performance of positioning algorithms than RMSE which gives one value. For example, it can happen that two different algorithms have relatively different performances for different error intervals. In Figure 2.7 Algorithm 1 outperforms Algorithm 2 at 50th percentile, as they will have median errors of 3.7 m and 4.4 m, respectively. However, it performs far worse at 90th percentile. Here the Algorithm 1 will have an error of 9.2 m in 90% of cases, while Algorithm 2 will have the error of only 7.7 m.

Accuracy of a localization system is usually the main quality indicator. However, there is usually a tradeoff between position estimation accuracy and other factors that has to be achieved.

2.5.2 Robustness

Robustness of a localization technique refers to its capability to perform well in case of changes in the environment, such as node failures or changes in the wireless channel. Sensitivity to outliers (measurements with large errors) also affects the system's robustness. Several methods have been proposed for dealing with outliers and NLOS conditions [83]. A robust localization system should be resistant to irregular network topologies and distributions of anchor nodes.

2.5.3 Deployment cost

Deployment cost is an important factor for commercial applications. Apart from installation cost, there is also the cost of updating and maintenance. One example of a system with high deployment cost is fingerprinting. In order to decrease the cost, one option is to employ previously available wireless communication infrastructures. Energy is another cost factor of a system.

2.5.4 Implementation cost

Here we refer to practical issues in algorithm implementation. Other than deployment cost, where economic aspects of hardware installation are considered, here the term 'cost' refers to undesired conditions that occur during the localization process. The additional latency, data traffic and processing for localization may affect the performance of the underlying communication network. The following factors are a trade-off to accuracy.

1. Communication overhead

   Additional data traffic will occur while exchanging messages for sake of positioning (coordinated, values of location dependent parameters, RSS, etc.). In general, RSS based localization systems are most cost effective from this point of view, since the strength of received signal is being measured between nodes during the neighbor discovery phase, and does not require additional packet exchanges like TOA measurements.

2. Latency

   Latency occurs because of the time needed to obtain all the measurements, and the time needed for the positioning algorithm to converge. This metric is crucial for dynamic scenarios, since node locations change with time and might outdate if the algorithm does not perform fast enough. Topology changes trigger the localization update procedures that can cause excessive overhead in terms of delay.

3. Computational complexity

   Algorithm complexity determines the computational complexity in time and space. It can be expressed by means of time needed to perform certain operations, or by means of number of operations involved in computations. Usually matrix inversions increase the complexity to a high extent.

4. Power consumption

   Power consumption is a crucial factor in low-power sensor networks. It involves power used to send and receive messages, as well as power needed to perform local processing. In centralized location systems a central unit calculates the estimated locations It is usually a powerful device with higher processing capability and sufficient power supply and memory. In case of distributed localization, where calculations are performed at the node itself, the effects of complexity become more evident.

2.5.5 Coverage

Localization coverage refers to the number or percentage of target nodes that can be localized, regardless of accuracy. The geometry and the node density have the most effect on coverage. For a target to be positioned successfully, there should be enough measurements taken from the surrounding anchors. Cooperative solutions increase the coverage significantly. Scalability refers to the ability to perform the localization well in large scale networks.

2.5.6 Combined metrics

Instead of evaluating the algorithm according to different metrics individually, one can consider a composite metric where different criteria are combined. For example, the cost metric defined in [84] is an example of a composite metric which merges accuracy and complexity in one metric.

We can conclude that there is no unique way to compare two localization algorithms. Different positioning approaches can be evaluated based on a number of metrics, e.g., the ones presented in this section.

2.6 Conclusion

In this chapter we described the basic principles of localization in wireless networks. The distance estimation techniques presented here, particularly the RSS based ranging method, will be used as input for positioning algorithms in the following three chapters. We provided a comparison of different ranging methods with respect to the underlying technology. In most algorithms we will use the WNLS technique described in Section 2.2.1. However, the ML from 2.2.2 method will also be used, mainly as a benchmark.

Since this thesis considers cooperative localization in heterogeneous environments, we put particular emphasis on these two topics. However, chapter 5 deals with special cases of non-cooperative scenarios.

Chapter 3

Utility based anchor node selection

In this chapter we will focus on principles and methods for selecting the set of anchor nodes to be used in the localization process. First we will describe the scenario, and the principles of the iterative multilateration algorithm. Several criteria have been proposed in the literature, depending on the scenario requirements and the algorithms used. After the scenario description, we continue with presenting the state of the art solutions on node selection in wireless localization. In the following, we will review the selection criteria, such as GDOP and CRLB, with emphasis on their modifications which include anchor uncertainty. Since this work applies the iterative multilateration algorithm as a solution for cooperative localization, this raises key challenges in terms of managing anchor uncertainty. We will also review some concepts from game theory and see how these concepts can be adapted to the localization problem. At the end of the chapter, we will present the simulation results and analysis of our proposed node selection method, together with some improvements with respect to computational complexity. Since the selection procedure itself is computationally demanding, we apply some simplifications based on spatial correlation in order to reduce the complexity.

3.1 Scenario

Measurements from heterogeneous infrastructure (Wi-Fi access points, ZigBee anchors) are complemented by peer-to-peer measurements between mobile devices. In particular, we intend to use the WLAN standard, since it can operate in both infrastructure and ad hoc mode, and combine these links with some short range IEEE 802.15.4 ad hoc links. In the proposed scenario a multi-mode mobile terminal device is assumed, thus the peer-to-peer links can be both through WLAN or WPAN. In particular, we will consider a distributed localization approach, namely iterative multilateration, illustrated in Figure 3.1. Once an unknown node estimates its position, it becomes a virtual anchor and broadcasts its position estimate to all neighboring nodes. The process is repeated until all nodes that have three or more reference nodes in their vicinity are able to obtain a position estimate.

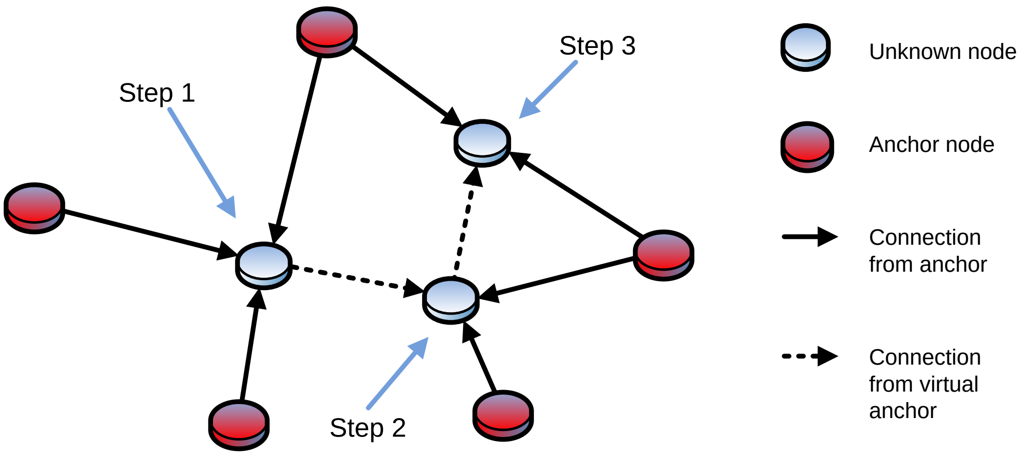


Figure 3.1: Iterative multilateration

The above mentioned only involves information within local neighborhood and hence reduces communication cost. However, it suffers from error propagation. As a newly localized node is becoming a new anchor for its neighbors, the estimation error of the first node can propagate to other nodes and eventually get amplified. Excessive iterations could lead to widespread error distribution throughout the network, leading to abundant error in large topologies. The effect may also arise in global methods such as multidimensional scaling (MDS) or semi-definite programming (SDP), but the global constraints are likely to balance against each other. For this reason the global methods are less vulnerable to error accummulation. Hence it is important to choose reference nodes carefully and hereby reduce error accumulation by taking into account uncertainties in reference nodes estimates. The procedure is illustrated in Figure 3.2, where the target can localize itself using neighboring anchor nodes, but also using so called virtual anchors, i.e., nodes that have obtained their location estimates in previous iterations. Anchor nodes can be Wi-Fi access points and deterministically placed ZigBee anchors, while the role of virtual anchors is taken by other mobile devices connected through Wi-Fi direct (P2P links), or a ZigBee sensor whose position was initially unknown and has been obtained in the meantime. Virtual anchors have different degrees of uncertainties in their location estimates.

Localization error is a function of several factors, such as the number of anchor nodes, node density, network topology etc. In addition to noisy distance estimates and reference node geometry, the error propagation problem is also resulting from the use of erroneous estimates as virtual anchors in subsequent iterations.

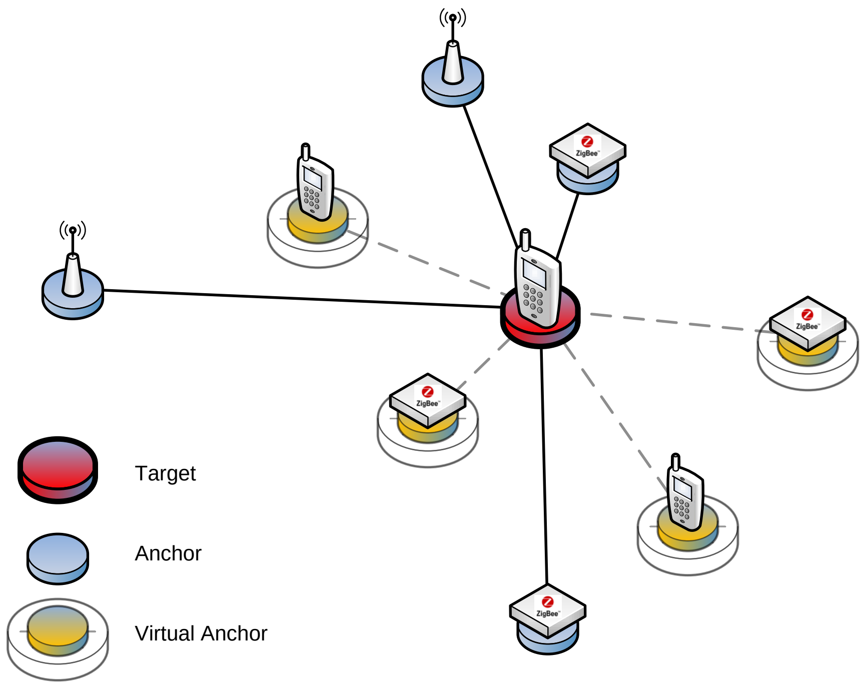


Figure 3.2: Multilateration with virtual anchors

An unknown node receives information from many neighbors, some of which are virtual anchors with a degree of uncertainty in their estimates. Therefore not all of those links have the same level of usefulness, even if localization accuracy increases with the number of used reference nodes, from the information theory perspective. Especially the geometry of used reference nodes has been shown to have a high impact on lateration.

Degree of uncertainty in the accuracy of the virtual anchors position obtained through successive iterations can be estimated based on the properties of the localization algorithm. Thus in case of LS position calculation, uncertainty is represented by the trace of the covariance matrix. The location estimates and the corresponding covariance matrix for all these estimates can also be derived by the Best Linear Unbiased Estimator (BLUE) [59].

The information about uncertainty in a node's location estimate is very important for some applications. Position uncertainty is unavoidable in a context-aware application and should not be hidden from the users. One example of a confidence-based application is choosing a safe retreat route for firefighters. The system would only choose a safe route if it is within a 95% confidence-level region. In the next section we will illustrate the error propagation in the iterative multilateration approach.

3.1.1 Error propagation

In order to illustrate error propagation, we assume a scenario consisting of 30 nodes, 6 of them are anchor nodes and the remaining ones are unknown. The positioning process start from unknown nodes which are able to identify at least three anchors within their communication range. Then they become virtual anchors and serve as reference nodes to their neighbors. We plot the cumulative distribution function (CDF) of the positioning error after first iteration, where only nodes with exactly known positions are being used as references. The average localization error $\bar{E}$ is defined as

$$\overline{E} = \frac{1}{N} \sum_{i=1}^{N} \sqrt{(\tilde{x}_i - x_i)^2 + (\tilde{y}_i - y_i)^2} \tag{3.1}$$

where N is the total number of localized nodes, $(\tilde{x}_i, \tilde{y}_i)$ and (x_i, y_i) are the estimated and true position of node i.

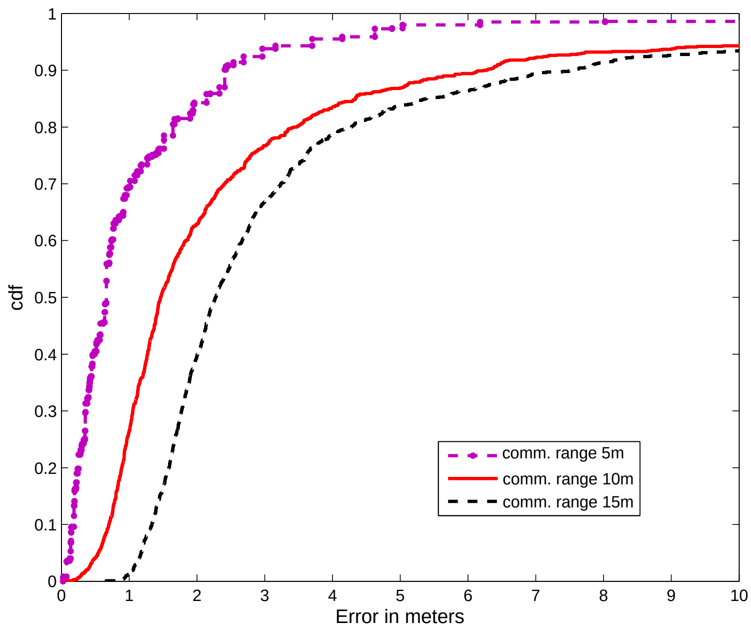


Figure 3.3: Positioning error for first iteration

The positions were estimated based on the least quares algorithm, using distance estimates based on the lognormal shadowing model. We used the typical values from the literature for the path loss exponent α, namely 2, and the shadowing variance has been set to 4 dB. The CDF in Figure 3.3 shows the percentage of localized nodes whose error is smaller than a certain value. The communication range has been set at 5 meters, 10 meters and 15 meters, respectively.

After the second iteration the positioning error significantly increases, as shown in Figure 3.4.

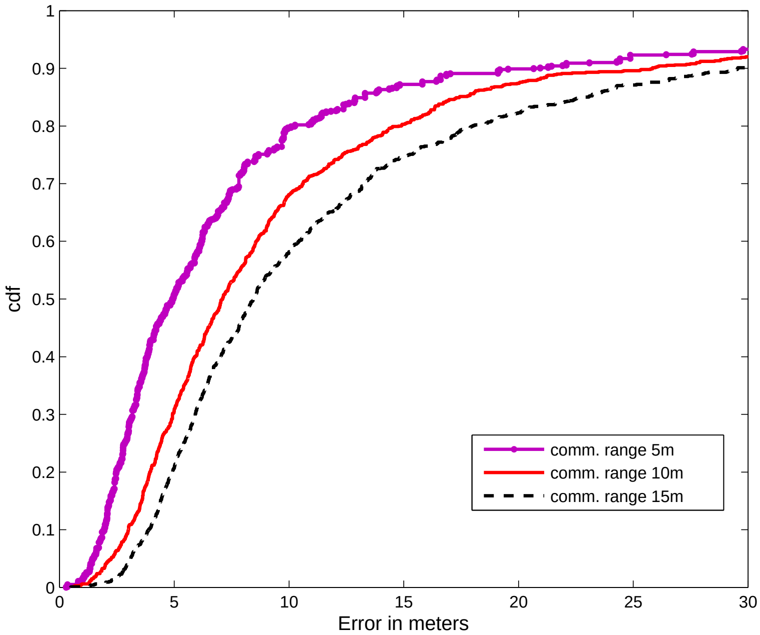


Figure 3.4: Positioning error for second iteration

It is evident that communication range will have an impact on localization coverage. Even though the errors for smaller communication ranges are lower, the number of iterations needed to achieve full localization coverage will be higher.

3.2 State of the art

The node selection problem arises in various applications, including robotics [85], target tracking [86], [87], and wireless sensor networks. The node selection problem can be formulated in a Bayesian framework [88] and an information theoretic framework.

Several works have considered anchor node selection for improving localization accuracy. In [89] the geometrical impact has been addressed and compared against the approach of using the closest reference nodes. More recent approaches consider cooperative scenarios, and the selection criteria are mainly based on theoretical localization performance limits such as the Cramer Rao Lower Bound [34], [32]. The algorithm in [34] includes both transmit and receive censoring. Transmit censoring prevents unreliable position estimates to be broadcasted, while receive censoring discards inadequate links once measurements are collected. All censoring decisions are distributed and based on a modified CRLB. In [32] unreliable links are sequentially discarded based on CRLB analysis during the coarse positioning phase - purely connectivity based, without distance estimation. This leads to resources savings, because the number of packets exchanged in the refined TOA based ranging phase is reduced. Some works also apply concepts from coalitional games and utility functions.

To model the tradeoff between power consumption and localization performance, a coalitional game theory based scheme has been proposed in [90], where coalition formation within the set of neighboring anchors helps to reduce communication costs. In [91] and [92] methods based on minimization of mean square error (MSE) are discussed, where utility of each set consisting of N nodes is defined as the reciprocal of the mean square error. The work in [93] uses notions from game theory, and utility is defined as information gain from a node, i.e. the mutual information between the prior density of target position and the measurement. Additionally, a price for transmission is included to account for the current energy level in the nodes, and the energy needed for data transmission. Our work is also based on principles of utility functions and cooperative game theory. Therefor we will continue with an overview on cooperative game theory and its use in localization algorithms.

3.3 Selection criteria

In this section we will derive the metrics used for node selection in localization algorithms.

3.3.1 Geometric dilution of precision

The concept of Geometric dilution of precision (GDOP) is taken from the GPS technology, where it is used to specify the effect of satellite geometry on the precision of position estimate. In case of terrestrial localization, it is also ued as a metric of precision. It depends only on the angular distribution of anchor nodes around the target, and not on the distance between target and anchors [25]. The GDOP does not depend on the ranging method, as it only takes into account the relative geometry between nodes. It can be calculated as [94]:

$$GDOP = \sqrt{tr(G^T G)^{-1}} \tag{3.2}$$

where **G** is the following geometry matrix:

$$\mathbf{G} = \begin{bmatrix} a_{1x} & a_{1y} & 1 \\ a_{2x} & a_{2y} & 1 \\ ... & ... & ... \\ a_{Nx} & a_{Ny} & 1 \end{bmatrix} \tag{3.3}$$

The term $a_i = (a_{ix}, a_{iy})$ is the unit vector from target t to anchor i:

$$\begin{aligned} a_{ix} &= \frac{x_i - \tilde{x}_t}{\sqrt{(x_i - \tilde{x}_t)^2 + (y_i - \tilde{y}_t)^2}} \\ a_{iy} &= \frac{y_i - \tilde{y}_t}{\sqrt{(x_i - \tilde{x}_t)^2 + (y_i - \tilde{y}_t)^2}} \end{aligned} \tag{3.4}$$

When selecting the ideal set of anchor nodes, one should try to identify the constellation that provides the minimum GDOP.

3.3.2 Cramer Rao lower bound

The Cramer-Rao lower bound for the localization problem has been derived in [26]. It indicates the lower bound on variance that an unbiased estimator can achieve.

Cramer Rao lower bound for RSS based localization

Assuming the lognormal propagation model, the Fisher information matrix (FIM) for a network consisting of N anchor nodes with positions (x_i, y_i) and one target with unknown position (x_T, y_T) is given by:

$$\mathbf{F} = \begin{bmatrix} F_{xx} & F_{xy} \\ F_{xy}^T & F_{yy} \end{bmatrix} \tag{3.5}$$

Here the elements are:

$$F_{xx} = b\sum_{i=1}^{N}\frac{(x_T - x_i)^2}{d_i^4}, \qquad F_{yy} = b\sum_{i=1}^{N}\frac{(y_T - y_i)^2}{d_i^4}, \qquad F_{xy} = b\sum_{i=1}^{N}\frac{(x_T - x_i)(y_T - y_i)}{d_i^4} \tag{3.6}$$

and

$$b = (\frac{10\alpha}{\ln 10\sigma_{RSS}})^2 \tag{3.7}$$

The Cramer-Rao lower bound is obtained as the trace of the Fisher information matrix and is given by:

$$CRLB_{RSS} = \frac{F_{xx} + F_{yy}}{F_{xx}F_{yy} - F_{xy}^2} = \frac{1}{b}\frac{\sum\limits_{i=1}^{N} d_i^{-2}}{\sum\limits_{i=1}^{N-1}\sum\limits_{j=i+1}^{N}\frac{d_{\perp ij}d_{ij}}{d_i^2 d_j^2}} \tag{3.8}$$

where d_{ij} is the distance between anchor nodes i and j and $d_{\perp ij}$ is the shortest distance from the target node to the line segment connecting nodes i and j.

Eq. B.2 provides the lower bound on the accuracy of target coordinates. Considering the one-dimensional case, i.e., the RSS ranging, the standard deviation of the distance estimate will be of the form:

$$\sqrt{\mathrm{var}(\tilde{d}_{ij})} \geq \frac{\ln 10}{10}\frac{\sigma}{\alpha}d_{ij} \tag{3.9}$$

We see in the above equation that the accuracy of the distance estimation is proportional to the distance itself. Therefore, in order to keep the distance estimation error less than a certain value e_{min}, the target has to be in the range of:

$$r_0 = \frac{10}{\ln 10}\frac{\alpha}{\sigma}e_{\min} \tag{3.10}$$

Since the parameters σ and α are determined by the channel characteristics, there is little we can do to control and improve the distance estimation accuracy. Thus the received signal strength based distance estiation is limited to short-range positioning.

Cramer Rao lower bound for TOA based localization

In case of TOA based distance estimation, the elements of the Fisher information matrix in Eq. 3.5 are the following:

$$F_{xx} = \frac{1}{c^2\sigma_T^2}\sum_{i=1}^{N}\frac{(x_T - x_i)^2}{d_i^2}, F_{yy} = \frac{1}{c^2\sigma_T^2}\sum_{i=1}^{N}\frac{(y_T - y_i)^2}{d_i^2}, F_{xy} = \frac{1}{c^2\sigma_T^2}\sum_{i=1}^{N}\frac{(x_T - x_i)(y_T - y_i)}{d_i^2} \tag{3.11}$$

Again, the CRLB for location estimation using N anchors is calculated as the trace of the FIM:

$$CRLB_{TOA} = c^2\sigma_T^2 N\left[\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\left(\frac{d_{\perp ij}d_{ij}}{d_i d_j}\right)^2\right]^{-1} \tag{3.12}$$

Other than the RSS case, here we are able to control the system performance by adjusting the effective bandwidth W and/or the SNR [27]:

$$\sqrt{\mathrm{var}(\tilde{d}_{TOA})} \geq \frac{c}{2\sqrt{2}\pi}\frac{1}{W}\frac{1}{\sqrt{SNR}} \tag{3.13}$$

Therefore,the TOA based method can perform well for long-range positioning.

3.3.3 Squared position error bound

The squared position error bound (SPEB) is a metric derived in [95], but in [96] the imperfect a priori location knowledge of the anchor nodes is taken into account, and the SPEB is derived in a closed-form, considering RSS based distance estimates. The closed-form indicates that the effect of the imperfect knowledge of anchor locations on SPEB is equivalent to the increase of the variance of RSS-based distance estimation:

$$SPEB = \frac{\sum_{i=1}^{N}\frac{1}{\beta_i}}{\left(\sum_{i=1}^{N}\frac{\cos^2\phi_i}{\beta_i}\right)\left(\sum_{i=1}^{N}\frac{\sin^2\phi_i}{\beta_i}\right) - \left(\sum_{i=1}^{N}\frac{\sin\phi_i\cos\phi_i}{\beta_i}\right)} \tag{3.14}$$

where ϕ_i denotes the angle from i-th anchor to the target, i.e., $\phi_i = \tan^{-1}\frac{y_t - y_i}{x_t - x_i}$, and β_i accounts for both anchor uncertainty (ω_i^2 is the variance of a priori knowledge of anchor location) and distance estimation uncertainty [27]:

$$\beta_i = \omega_i^2 + \varepsilon d_i^2 \tag{3.15}$$

The existence of this closed-form expression facilitates the node selection when uncertainties in anchor positions have to be considered.

To illustrate the motive for using geometry for node selection, we show in Figure 3.5 a target trying to select the best three neighbors out of 6 that will be used for positioning. Considering the links individually, anchor nodes A1, A2 and A3 might be the best ones, since they are ZigBee anchors. However with respect to target‘s location nodes A2 and A3 cannot contribute any additional information, as they all provide information in one direction. The same holds for anchor nodes A5 and A6.

GDOP helps us identify geometric conditions, thus we can discard redundant information from an angular point of view. CRLB and SPEB go beyond geometry and also contain information about channel conditions and reliability of the anchor positions.

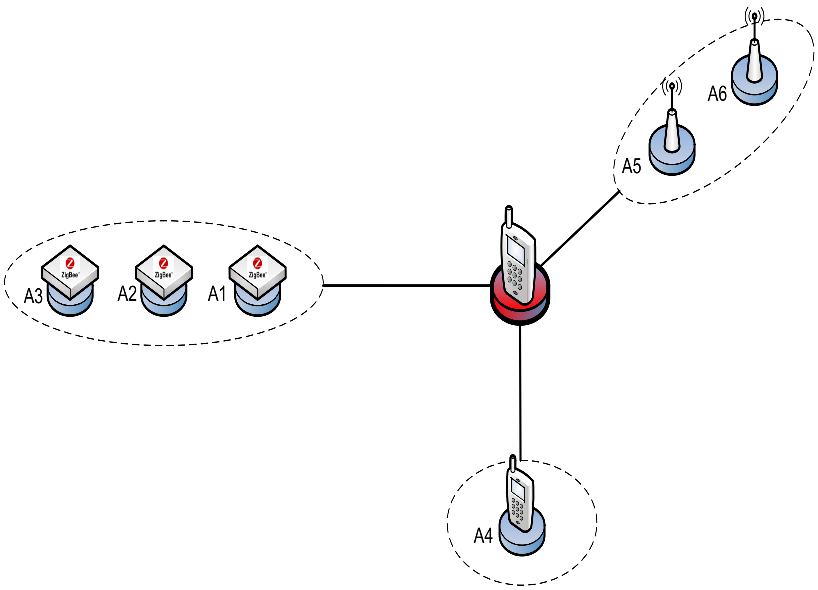


Figure 3.5: Redundant information from angular diversity perspective

3.4 Cooperative game theory and its applications in localization algorithms

Cooperative game theory provides a convenient framework for modeling collaboration in multiagent systems. It has been used in several topics in wireless communication systems, such as resource allocation, scheduling, cognitive radio (CR) etc. It is also very appropriate for localization problems, where it allows forming optimal coalitions of nodes to localize a target node.

Game theory is a field of applied mathematics for analyzing complex interactions among entities. It is basically a collection of analytic tools that enables distributed decision process. Game theory (GT) provides insights into any economic, political, or social situation that involves individuals with different preferences. GT is used in economics, political science and biology to model competition and cooperation among entities, and the role of threats/punishments in long term relations. The formation of coalitions or alliances is omnipresent in many applications. For example, in political games, parties, or individuals can form coalitions for improving their voting power. Recently, computer science and engineering have been added to the list of scientific areas applying GT. While in optimization theory the goal is to optimize a single objective over one decision variable, game theory studies multi-agent decision problems. In social sciences and economics, the focus of game is the design of right incentives/payoffs; in engineering it comes to efficiency on how to design efficient decentralized schemes that take into account incentives. However, there are still similarities when applying game theory to different disciplines. For example, a measurement allocation framework for localization in wireless networks, based on the idea to allocate more measurements to the nodes which contribute more, mimics a capitalist society where the gains are mostly reinvested where more profit is expected. It also replicates the concept of natural selection in population genetics.

In general, a game consists of a set of players (decision makers), while each player has its strategy, whereby utility (payoff) for each player measures its level of satisfaction. Each players objective is to maximize the expected value of its own payoff [97]. There are two main branches of game theory: cooperative and non-cooperative. Non-cooperative GT addresses interactions among individual players, each aiming to achieve their own goal, namely improving its utility, or reducing its costs. By contrast, in cooperative games the utility does not only depend on a single nodes strategy, but also on the strategies of other nodes within a coalition. Hence, cooperative game theory is more elaborate. Especially in realistic situations where entities can participate in several coalitions, the potential structure of these coalition allocations is more complex; thus there is a need for approaches that are able to reduce the complexity, without identifying and comparing all of the $2^n - 1$ possible coalitions, n being the number of players. A normal form representation of a game is given by

$$\mathrm{g} = \langle N, S_i, \{u_i\}\rangle \tag{3.16}$$

where $\mathrm{N} = \{1, ..., \mathrm{n}\}$ is the set of n players. We indicate an individual player as $i \in N$ and each player i has an associated set $S_i = \{{s_i}^1, \ldots, {s_i}^m\}$ of possible strategies from which, in a pure strategy normal form game, it chooses a single strategy $s_i \in S_i$ to be realized. $\mathrm{s} = \{s_1, \ldots, s_N\}$ is the strategy profile of N players, i.e., the outcome of the game, while s_{-i} is the strategy profile of all players but the i-th, and $\{u_i\} = \{u_1, \ldots, u_N\}$ is the utility function of the i-th player. The utility function measures the preferences of each player to a given strategy, assuming the strategies of other players are known. If s is a strategy profile played in a game, then $u_i(s)$ denotes a payoff function defining is payoff as an outcome of s.

One of the concepts for solving non-cooperative games is the Nash equilibrium (NE). Nash equilibrium is a stable solution of the game such that no player has reason to unilaterally change its action, since it may not improve its utility function. More precisely, a strategy profile set $\mathrm{s}^* = \{s_1^*, \ldots, s_N^*\}$ is a NE if for $\forall s_i \in S_i$ and for $\forall i \in N$, $u\left(s_i^*, s_{-i}^*\right) \geq u\left(s_i, s_{-i}^*\right)$. A strategy set that corresponds to the Nash equilibrium signifies a consistent prediction of the outcome of the game. In other words, if all players predict that Nash equilibrium will occur, there is no player in the game that has incentives to choose a different strategy. Any game allowing mixed strategies has at least one NE. However, some pure strategy normal form games may not have a NE solution at all. Therefore it is relevant to formulate the utility function in such a way that the game has at least one equilibrium point. When efficiency is important, Pareto Optimality is used. The existence of Nash Equilibrium does not assure that the outcome of a game will be beneficial for all players. Mathematically formulated, a strategy set $\mathrm{s} = \{s_1, \ldots, s_N\}$ is Pareto optimal if and only if there exists no other strategy set $\mathrm{t} = \{t_1, \ldots, t_N\}$such that $u_i(\mathrm{t}) \geq u_i(\mathrm{s})$ for $\forall i \in N$, and for some $k \in N$, $u_k(\mathrm{t}) > u_k(\mathrm{s})$. In other words, Pareto optimal outcome cannot be improved upon without hurting at least one player.

3.4.1 Coalitional games in wireless communications

From the communication networks perspective, there is a need for developing distributed and flexible wireless networks, where the units make independent and rational strategic decisions. In addition, low complexity distributed algorithms are required, to capably represent collaborative scenarios between network entities. Srivastava [98] proposed a mapping of network components to game components according to Table 3.1.

A coalition formation game is uniquely defined by the pair (N, v). $\mathrm{N} = \{1, 2, \ldots, \mathrm{N}\}$ denotes the set of players, e.g., network entities, pursuing to form sets in order to collaborate with each other. Any nonempty subset $\mathrm{S} \in \mathrm{N}$ is called a coalition. Coalitions with cardinality $|\mathrm{S}| = 1$, are called singleton coalitions and N is called the grand coalition. The set of all coalitions in a game is called coalition structure and is denoted by P. v denotes the coalition value which quantifies the worth of a coalition in a game.

Network component	Game component
Nodes	Players
Available adaptations	Action set
Performance metrics	Utility function

Table 3.1: Mapping of network components to game components

Coalitional games in characteristic form are classified into two types based on the distribution of gains among users in a coalition:

1. A transferable utility (TU) game where the total gain achieved can be apportioned in any manner between the users in a coalition subject to feasibility constraints, and

2. A non-transferable utility (NTU) game where the apportioning strategies have additional constraints that prevent arbitrary apportioning. Each payoff is dependent on joint actions within coalition.

In TU games, the cooperation possibilities of a game can be defined by a characteristic function v that assigns a value $v(S)$ to every coalition S. Here $v(S)$ is called the value of coalition S, and it characterizes the total amount of transferable utility that the members of S could gain without any help from the players outside of S. In general, we use the term coalition structure to refer to any mathematical structure that describes which coalitions (within the set of all $2^n - 1$ possible coalitions) can effectively negotiate in a coalitional game.

In case of TU games, goal is to find a coalition structure that maximizes the total utility, while in NTU games it is the structure with Pareto optimal payoff distribution. A centralized approach can be used, but it is generally NP-complete. The abbreviation NP refers to "nondeterministic polynomial time", and the most notable characteristic of NP-complete problems is that no fast solution to them is known. The reason is that finding an optimal partition requires iterating over all the partitions of the player set N. The number of partitions grows exponentially with the number of players in N. For example, for a game where N has 10 elements, the number of partitions that a centralized approach has to go through is 115975 (easily computed through the Bell number [99]. Therefore, using a centralized approach for finding an optimal partition is, generally, computationally complex and not very practical. Nevertheless, many applications require the coalition formation process to take place in a distributed manner, so that the players have autonomy on the decision whether or not to join a coalition. Indeed, the complexity of the centralized approach has initiated a growth in the coalition formation literature, with the goal to find low complexity and distributed algorithms for establishing coalitions. A novel classification of coalitional games has been proposed in [99]. Games are grouped into three types: canonical games, coalition formation games and coalitional graph games. Their properties are shown in Table 3.2.

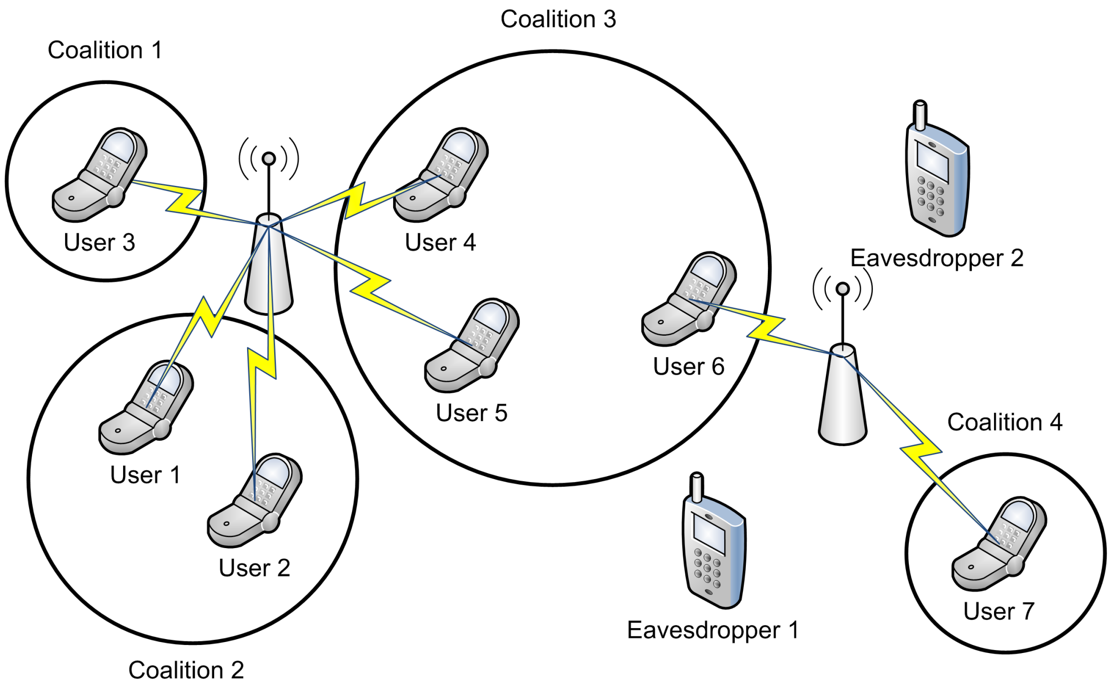
Canonical coalitional games	Coalition formation games	Coalitional graph games
Grand coalition is the optimal structure	Resulting coalitional structure depends on gains and costs	Interaction of players depends on communication graph structure
Goal: stabilize the grand coalition	Goal: form appropriate coalition structure	Goal: stabilize grand coalition or form network topology taking into account the communication graph

Table 3.2: Classification of coalitional games

Game theory can be applied to communication networks from several aspects: at the physical layer, link layer and network layer. However, there are certain challenges when applying game theory principles to wireless networks. For example, GT assumes that the players act rationally, which does not exactly reflect real systems. Furthermore, realistic scenarios necessitate complex models, yet the main challenge is to select the appropriate utility function, due to a lack of analytical models that would map each nodes available actions to higher layer metrics.

Non-cooperative games have been mainly applied for applications such as spectrum sharing, power control or resource allocation, hence mainly settings that can be seen as competitive scenarios. On the other hand, cooperative game theory provides analytical tools to study the behavior of rational players in cooperative scenarios. In particular, coalitional game theory is proven to be a very powerful tool for designing fair, efficient and robust cooperation strategies in communication networks.

Physical layer security has been studied via coalitional games in [100], [101]. In a distributed way, wireless users organize themselves into coalitions while maximizing their secrecy capacity - maximum rate of secret information sent from a wireless node to its destination in the presence of eavesdroppers [100]. The process is illustrated in Figure 3.6. This utility maximization is taking into consideration the costs occurring during information exchange. On the other hand, [101] introduces a cooperation protocol for eavesdropper (attacker) cooperation. Here the utility function is formulated to capture the damage caused by the attackers, and the costs in terms of time spent for communication among the eavesdroppers. In both cases, independent disjoint coalitions will form in the network, as the grand coalition would involve various communication costs.



Non-cooperative TDMA transmission: 1 user per slot

User 1	**User 2**	**User 3**	**User 4**	**User 5**	**User 6**	**User 7**

Cooperative TDMA transmission: 1 coalition per slot (transmitting the data of the slot owner)

Coal. 2: Data of User 1	**Coal. 2:** Data of User 2	**Coal. 1:** Data of User 3	**Coal. 3:** Data of User 4	**Coal. 3:** Data of User 5	**Coal. 3:** Data of User 6	**Coal. 4:** Data of User 7

Figure 3.6: Example of wireless users organized into coalitions

The works in [102] and [103] consider coalition structures in a wireless network where users are permitted to cooperate, while maximizing their own rates. Here both transmitter and receiver cooperation in an interference channel is studied. Several models have been analyzed: a TU and an NTU model, and with perfect and partial cooperation. In [102], the feasibility and stability of the grand coalition for all cases was evaluated, while the work in [103] is focused on stable coalition structures. In [104] a game theoretical framework for virtual MIMO has been proposed, where single antenna transmitters self-organize into coalitions. The utility function denotes the total achieved capacity, and also includes the power constraint to account for the costs. In [105] the multi-channel spectrum sensing problem is formulated as a coalitional game, where players are secondary users that cooperatively sense the licensed channels of primary users. The utility of each coalition reflects the sensing accuracy and energy efficiency. Distributed algorithms have been proposed to determine a stable coalition structure, maximizing the overall utility in the system. More game theory based solutions for spectrum sensing in cognitive radio have been proposed in [106] and [99]. A network-level study using coalition formation has been performed in [107], considering a scenario where service providers are cooperating in order to enhance the usage of the available resources. Particularly, different providers may serve each others customers and thereby increase the throughput and reduce the overall energy consumption. The model supports multi-hop networks and is not limited to stationary users and fixed channel conditions. A game theory based framework is used to determine optimal decisions and a rational basis for sharing the aggregate utility among providers. The optimal coalition structure can be obtained by means of convex optimization. Other applications of game theory include packet forwarding in ad hoc networks, distributed cooperative source coding, routing problems, and localization algorithms, which will be more elaborated in the following.

3.4.2 Game theory for localization algorithms

Recently game theory has been applied in localization algorithms, mainly for modeling the cost-performance trade-off and for selection of reference nodes. The work in [93] applies game theory for sensor network localization, namely for measurement allocation among reference nodes localizing the target. The localization process has been modeled as a game belonging to the class of weighted-graph games. For such a representation, the vertices correspond to the players, and the coalition value can be obtained by summing the weights of the edges that connect a pair of vertices in the coalition with self-loop edges only considered with half of their weights. A weighted-graph game can therefore be well represented by $\frac{N(N-1)}{2} + N$ weights, in contrast to 2N numbers which are usually required to represent a cooperative game. The basic idea is to allocate more weights to nodes that contribute more to the localization process. The allocation algorithm has been integrated into a Bayesian estimator. In [108], utility is defined as the information gain from a node, i.e. the mutual information between the prior density of target position and the measurement. Additionally, transmission cost is included to account for the current energy level in the nodes, and the energy needed for data transmission.

The algorithm proposed in [109] assumes a number of static anchor nodes, strategically placed to guarantee coverage to all unknown nodes. Anchors transmitting with lower power can provide coverage to a smaller number of nodes; the aim is to minimize power consumption at the anchor nodes, while assuring desired localization accuracy. The metric for positioning quality is the GDOP. The problem has been formulated as a noncooperative game, using Nash equilibrium as a solution concept.

In [110] the coalition formation within the set of neighboring anchors helps reduce communication costs. Using only a subset of available reference nodes does not necessarily degrade the accuracy, since some of them provide redundant information. In some situations it might be even useful to discard ranging information from some reference nodes, after they have been identified as unreliable due to biases in the measurements. In this paper the localization problem has been defined as a coalitional non-transferable utility (NTU) game, where coalitions are formed based on the merge and split procedure. The utility function is defined to account for both a quality and cost indicator. While the quality function accounts for inconsistencies between each of the node's measured distance and the final joint estimated distance within the coalition, the cost function is related to communication costs. The target tracking task based on coalition formation has been implemented using a Kalman filter. For the coalition formation approach a higher mean estimation error has been observed than for the grand coalition, i.e., when all nodes contribute to the tracking process. Nevertheless, in terms of communication costs the proposed scheme provides significant savings.

[90] proposes a dynamic coalition formation algorithm used for energy saving in multiple target localization. Assuming that nodes in sleep mode do not record any measurements and thereby save energy in both sensing and transmitting data, the optimization problem is formulated to maximize the average sleep time of all nodes in the network, assuring that targets are localized with desired accuracy. An important contribution is the exploitation of spatial correlation of sensor readings. The accuracy metric used is the determinant of the Bayesian Fisher information matrix (B-FIM). The characteristic function is formulated in a way that larger coalitions of sensors do not necessarily lead to longer sleep times. This is mainly due to the fact that the B-FIM, depending on both relative angles and distances of sensors to the target, does not automatically increase as the number of sensor nodes in

a coalition increases. The trade-off between performance and average sleep time allocated in the network is demonstrated via Monte Carlo simulations.

3.5 Utility based node selection scheme

Besides the use of theoretical localization performance limits, e.g., CRLB, as the selection criteria, concepts from coalitional games and utility functions have also been adopted in the proposed node selection approach. Given a set of candidate nodes $S = \{S_1, ..., S_n\}$, the problem is to determine the subset S' of $k < N$ nodes, which is referred to as the 'best set'. The 'best set' is the one which achieves a tradeoff between power consumption and quality of information with respect to positioning accuracy. This tradeoff can be modeled using the notions of utility and cost. Hereby 'utility' refers to the accuracy of collected information and its usefulness (i.e., by means of the mean square error), while 'cost' is associated with energy spent executing the performed task.

3.5.1 Formulating the utility function

The main challenge here is to choose the appropriate utility function, i.e., how a node values different levels of performance. Kaplan [92] defines the utility as the reciprocal of the expected mean square error performance of the extended Kalman filter (EKF). It is inspired by the GDOP and uses the predicted geometry to determine the best set of active nodes. Isler [87] formulates the sensor selection problem as a bicriteria optimization problem. Utility is related to the uncertainty of the measurements, while cost is measured by the number of sensors. The paper has formally proved the observation that a small number of anchors is sufficient for a good estimate. A decentralized selection scheme has been proposed in [108] for EKF tracking. The utility function consists of two components: one to quantify the amount of information gain, and the second to reflect a virtual price paid for data transmission.

We can formulate the node selection optimization as the one that maximizes the accuracy subject to constraints given by nodes limited processing capacity. The following parameters are relevant for reference node selection: number of references, their uncertainty (in case of virtual anchors), quality of range estimates and geometry. Since the CRLB gives the upper bound on accuracy, the general approach defines the utility function as inversely proportional to the CRLB. In fact, CRLB is computed as the trace of the Fisher Information matrix (FIM), and actually represents the sum of the squares of the estimate's confidence region. Similarly, the FIM's determinant represents the volume, and the smallest eigenvalue the length of the largest axis of the confidence region. There is no actual advantage in using one of these functions over others.

Besides the quality indicator, utility function also has to reflect the cost. Cost is related to the energy spent for message exchanges between nodes, and is proportional to the distances of target node to reference nodes. Having in mind the power consumption if all reference nodes were used for localization, the grand coalition is not optimal. Therefore we define the problem as a non-superaditive cooperative game.

Knowing that at least three nodes are needed in order to perform localization, we set the coalition value to zero for all subsets containing less than three elements.

Assuming that the communication range is R, we define the utility function as:

$$v(C) = \begin{cases} 0, if|C| < 3 \\ \frac{1}{CRLB_{i \in C}} - \sum\limits_{i \in C} \frac{d_{i,t}}{R}, otherwise \end{cases} \tag{3.17}$$

Where $CRLB_i \in C$ is the CRLB for the coalition C, $d_{i,t}$ is the distance from node $i \in C$ to the target t, and R is the transmission range, used to normalize the cost function. The first term is the benefit indicator, while the second term represents the cost function related to the power consumption required for communication. A lower CRLB indicates higher accuracy, and therefore it is inversely proportional to the benefit. The cost function is formulated using the fact that distant nodes spend more energy for communication, and accordingly the cost is proportional to distance.

In order to illustrate the performance of coalition formation based node selection, we will perform an exhaustive search over all possible coalition sets containing three nodes. The results are presented in the next subsection.

Results

For evaluation purposes we consider one snapshot in the iterative algorithm, where a node analyzes its local neighborhood, and exchanges information with N_A reference nodes within communication range $R = 30m$. Among the candidate references the goal is to choose three of them, $N_S = 3$, which maximize the utility function. In our simulations, we assume that a node has 10 available candidate nodes, randomly placed within communication range of the unknown node. Position is calculated using the LLS algorithm, using erroneous distance estimates as in Eq. (2.3).

Ranging error is modeled using channel parameters $\alpha = 2.3$ and $\sigma = 3.92dB$, as in [26]. In this work we assume a random, independent ranging error and all links have the same channel conditions. The number of all possible combinations is:

$$\frac{N_A!}{N_S!(N_A - N_S)!} \tag{3.18}$$

where N_A is the total number of available reference nodes, and N_S is the number of nodes to be selected, i.e., the coalition size.

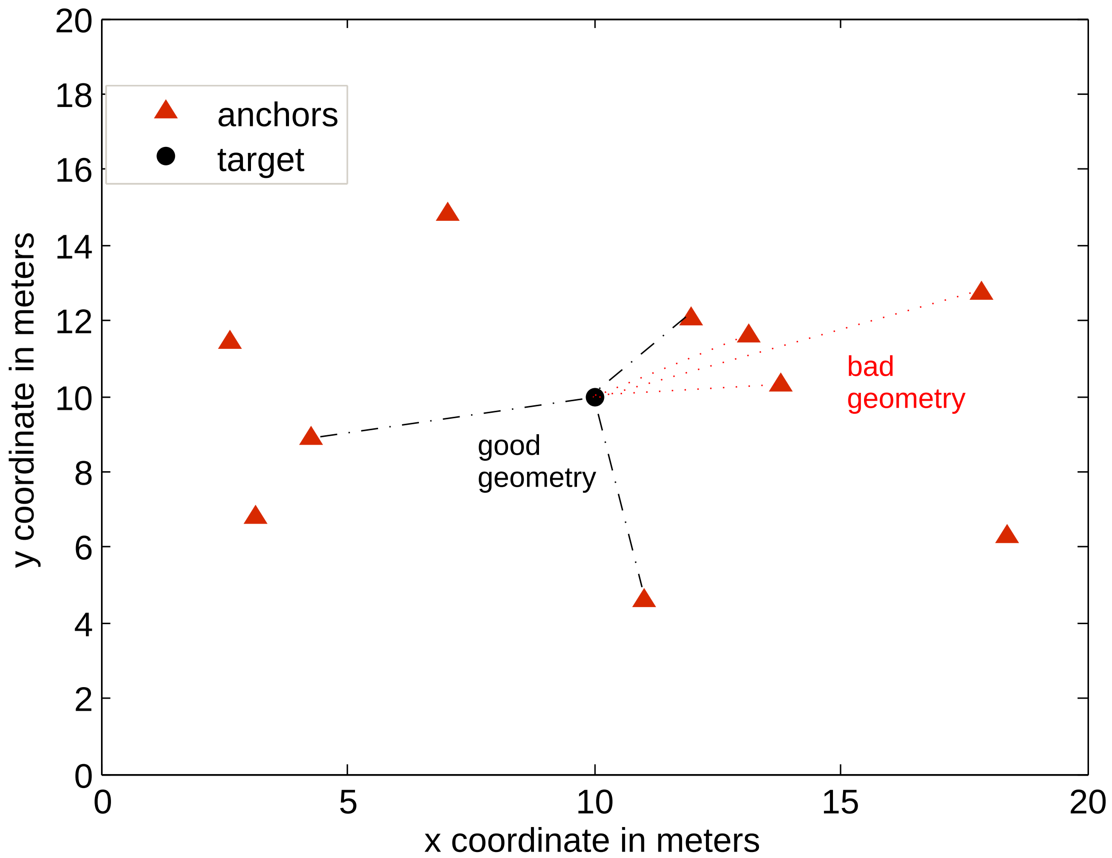


Figure 3.7: Simulation setup

For the evaluation scenario we assume $N_A = 10$ and $N_S = 3$. We examine 1000 random setups. One possible setup is shown in Figure 3.7, where we highlight examples of good and bad geometric conditions.

Since the network density is not high, and having in mind limited communication range, N_A is relatively small and the exhaustive search approach is applicable. Otherwise we would have to switch to the pruned search methods. Each combination represents a possible coalition, and for all of them the coalition value is calculated based on (3.17). The subset of nodes with the highest value for utility function is used to estimate the position. The set containing all N_A available reference nodes represents the grand coalition (the coalition of all nodes). However, since in our case there is cost associated with coalition formation, and we limit the selection to 3 nodes, the grand coalition will not form. Figure 3.8 shows through a scatter plot that higher coalition values lead to more accurate position estimates.

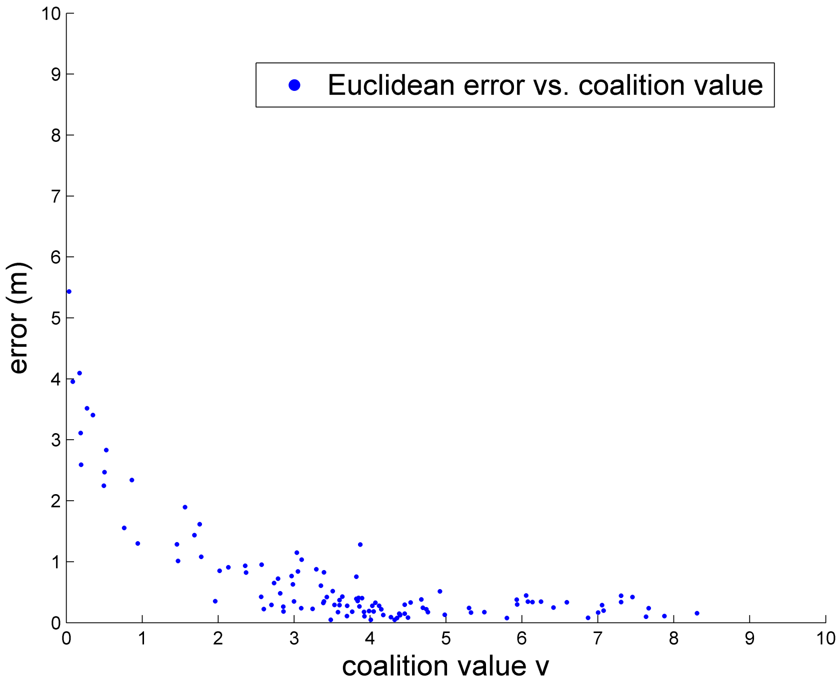


Figure 3.8: Localization error vs. coalition value

In Figure 3.9 we compare the error cumulative distribution functions (CDF) of our proposed selection strategy against selection based on closest distances, as well as purely random reference selection. We perform 1000 independent runs. The 90^{th} percentile for utility based selection is 3.5 m, which is an improvement of 39%, compared to 90^{th} percentile of 5.9 m for closest distance, and 51% improvement with respect to the 7.2 m error in the random case. In case of coalitions formed choosing more than three nodes, the gain achieved using utility based selection is less noteworthy. This is mainly due to the fact that the random selection and closest distance approach perform better when more anchor nodes are available. On the other hand, the computational complexity notably increases for larger coalition sets.

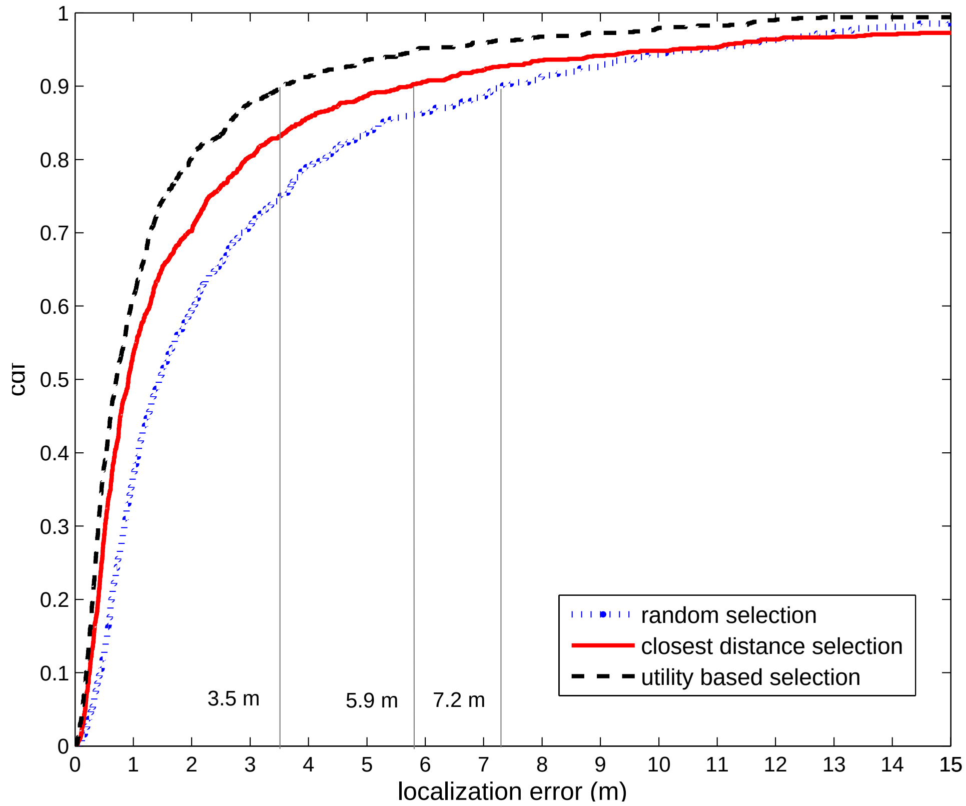


Figure 3.9: CDF of localization error

3.5.2 Node selection for localization exploiting spatial correlation

Besides the vast computational cost, exhaustive search also imposes memory cost, since we have to avoid checking a particular coalition repetitively. Therefore we propose a search method which exploits the spatial correlation among candidate reference nodes. In this manner, some of those nodes could be eliminated from the candidate list straightaway.

The concept of spatial correlation has been widely applied in WSNs, in order to place a number of low-power sensor nodes in sleep mode, and thus saving energy [12]. In the case of sensor networks, readings are mainly about the environment: temperature, humidity, etc. In our context, readings are position coordinates. Assuming that adjacent nodes report similar readings, the overall amount of available anchor nodes can be adequately represented by a reduced number of active nodes serving as anchors.

We propose to divide the coverage area of the target into correlation regions, as proposed in [111]. Here the correlation region refers to the region in which the nodes report similar readings. From the localization performance perspective, one can assume that spatially correlated nodes provide redundant information from the angular diversity point of view. Consequently, the entire coverage area is efficiently represented by a subset of active anchor nodes which perform such task well, comparable to that of the original setup. Such an approach helps reducing the search method complexity, since only a subset of anchors needs to be involved in the coalition formation procedure. The exploitation of spatial correlation has been applied to various aspects of wireless communications, with the goal to reduce redundancy. A concept that makes use of spatial correlation for localization has been proposed in [112]. The node coordinates are transformed into a polar coordinate system and the sensing area is divided into a number of partitions with equal angles with respect to the target. Then from each partition the node with the highest measured RSS is chosen. The work in [113] exploits the spatial correlation to measure the link quality of wireless sensor nodes. The intuition behind spatial correlation is that sensor nodes geographically close to each other may have correlated link quality. The history information of link quality for one node may be used for estimating not only its own link quality, but also that of other neighbor sensor nodes geographically close.

We performed simulations for different node densities and compared the performances for exhaustive search and spatial correlation based method, in terms of root-mean-square error (RMSE) and computation complexity. We assume that after a number of iterations, the target node is within coverage of several anchor nodes, some of which virtual anchors not perfectly aware of their locations, but with some uncertainty. The goal is to choose reference nodes which will provide the most accurate localization result, by evaluating the utility function over all subsets. The optimal method would be to perform an exhaustive search and evaluate the utility function over all possible combinations. This method is guaranteed optimal but the search time is exponential and the number of combinations is very large. Having in mind that with each iteration the number of available reference nodes increases significantly, we have to reduce the search time, i.e., the number of combinations. We apply the concept of spatial correlation based on clustering, as proposed in [111], and compare it with exhaustive search approaches. The assumption is that the nodes report similar values when they are close to each other. However, this closeness (θ) depends on the application requirements. In [111] the purpose is energy saving, but here we use the concept for localization. The correlation regions are formed as squared rectangles and nodes lying in the rectangle are assumed to be spatially correlated. Cluster formation procedure is assumed to be as described in [114].

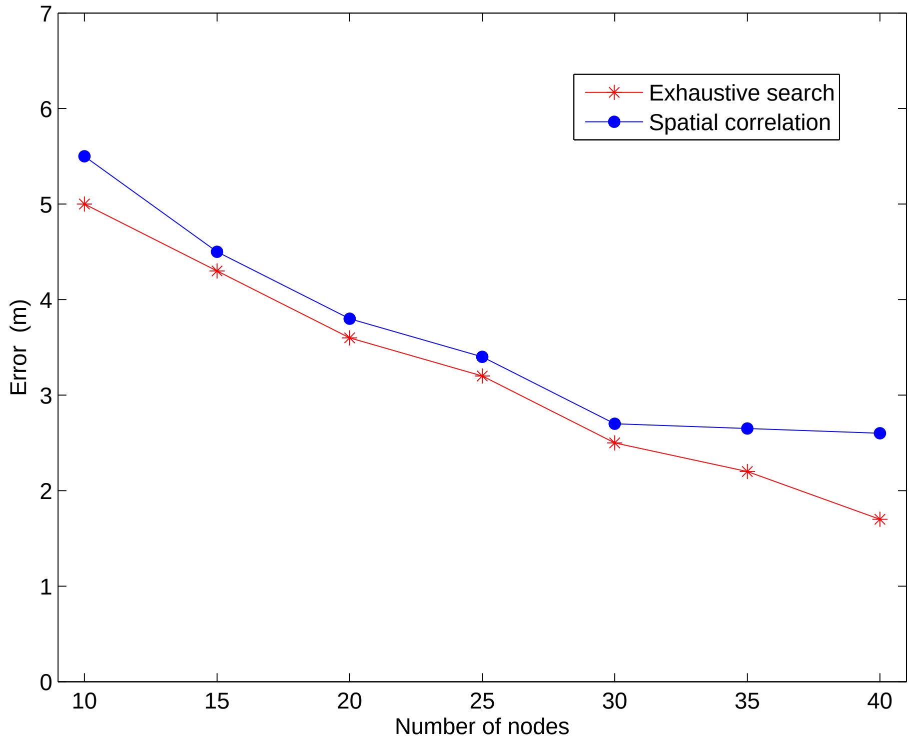


Figure 3.10: RMSE error vs. number of nodes

We performed 1000 runs for each setup. Each setup is a squared area 36 m x 36 m, with the target placed at the center of the area. The number of anchor nodes varies between 10 and 40, as represented on the x - axis of Figure 3.10. While the target is always placed at the center of the area. the anchors are randomly uniformly distributed, and we assume that 50% of them are virtual anchors, i.e., nodes that have obtained their location estimate and now act as anchors. Therefore the node selection criteria used is the SPEB explained in Section 3.3. The clustering resolution is 9 m x 9 m, thus we will have 16 regions in total. Note that due to the random nature of anchor placement some regions will be empty, especially in low density cases. Positions are computed using the same algorithm and parameters as in previous section. Figure 3.10 shows that applying spatial correlation results in a slight reduction of localization accuracy. We can also observe that the accuracy using spatial correlation does not improve much after the number of anchor nodes passes 30 nodes. This is due to the clustering resolution, which is fixed, as well as the size of the area. Thus for a large number of nodes and high density, the chosen representative nodes will often be the same ones.

Figure 3.11 shows a comparison of computational complexity, when increasing the number of anchor nodes. We define computational complexity as the amount of time spent on localization, in this case on a simulation run. The measurement of computation time is calculated using MATLAB functions *tic and* toc, which return the elapsed time in seconds. The computation time can be significantly reduced, especially as the number of nodes increases.

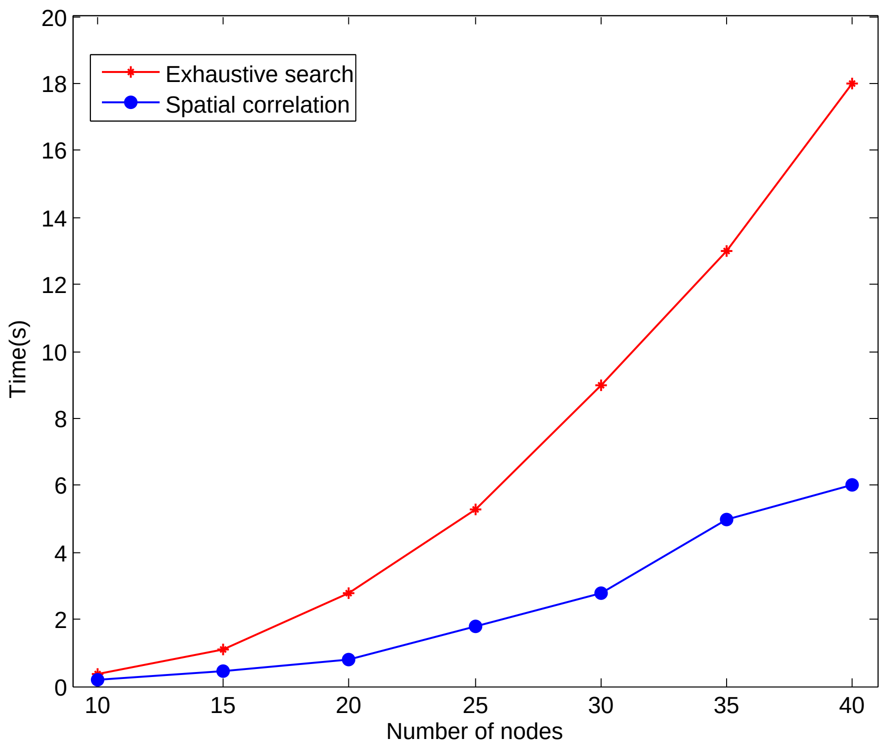


Figure 3.11: Computation time vs. number of nodes

3.6 Conclusion

In this chapter we address the node selection problem in cooperative localization. We model the localization process as a cooperative game, and formulate the corresponding utility function. Game theory proves to be a powerful tool for modelling various aspects of localization procedure, such as improved accuracy or energy saving. After giving an overview of the most significant contributions in the literature on this subject so far, we have proposed a localization procedure aiming to improve accuracy by selecting the references providing the best conditions in terms of channel conditions and node geometry. The utility function is defined in such a way that it captures node geometry, ranging quality and anchor node uncertainty. Besides providing enhanced performance, choosing only a subset of the available references contributes to resource saving. Computational complexity is reduced by using a randomized search method that exploits spatial correlation among coalition members.

Chapter 4

Node selection in mobile and realistic scenarios

After having reviewed the ranging methods and positioning algorithms in Chapter 2, and after describing the node selection methods in chapter 3, now we extend the anchor node selection to a dynamic, mobile scenario. Here, latency is the main issue. If it takes too long to perform localization, the node will have significantly changed its position since the measurement took place. Furthermore, the LOS/NLOS conditions might change while the target moves.

In Section 4.1.5 we will propose a node selection method for mobile tracking, and in 4.2.1 we evaluate the scheme using experimental data obtained during a WHERE2 measurement campaign. The Extended Kalman filter is the most popular tracking tool in robot applications. However, since a mobile scenario requires continuous and rapid localization, it is more pragmatic to use distributed algorithms.

4.1 Energy efficient mobile tracking in heterogeneous networks using node selection

Ranged-based positioning is capable of achieving better accuracy in heterogeneous network, where multi-RAT enabled mobile nodes are allowed to deploy not only the far-away access points but also high spatial density peer-nodes as anchor nodes. However, due to peer-node energy supply constraint and network capacity constraint, an efficient cooperation strategy is required. In this section, we propose a cooperation method to track the position of a moving target under required accuracy, and reduce the power consumption and signaling overhead via anchor selection. It is demonstrated by simulation that the proposed method is capable of reducing 34 % signaling overhead with about 0.5 meter degradation of accuracy compared to exhaustive cooperation in a practical scenario. We also evaluate the achievable performance averaged over random located node configurations, and compare the proposed scheme with the mostly used nearest-node selection algorithm [1] in terms of accuracy and cost.

4.1.1 Introduction

In the context of non-cooperative homogeneous networks, the number of anchor nodes such as Wi-Fi access points are small and far away from each other, which limits the localization accuracy. In the context of heterogeneous network, a multi-RATs aided mobile device is capable of communicating not only with the APs, but also peer nodes such as fixed Zigbee/Bluetooth sensors or other mobiles nodes if cooperation is supported. The spatial density of peer nodes is much higher than the one of APs. Using these nodes as anchor nodes could significantly decrease the distance estimation error, and improve the range-based positioning accuracy. However, peer-nodes are energy-constrained. Unlike the APs, they are not supposed to be always in transmission mode broadcasting their coordinates. In order to cooperate with peer nodes, training sequences and extra packets are required for distance estimation and location information exchange, which results in signaling overhead and additional power consumption. Hence, an efficient cooperation strategy is required so as to achieve the required positioning accuracy and minimize the resulting power consumption and traffic overhead.

We investigate a heterogeneous network containing fixed location-known Wi-Fi APs covering the area of interest and sufficient number of connected multi-modal (Wi-Fi and ZigBee) peer nodes. The goal is to estimate position of a moving node with required accuracy. We propose a cooperation method to reduce the signaling overhead via anchor node selection. The main idea is to select a subset of anchor nodes for location estimation. As the mobile moves, this selected subset remains the same until the required accuracy cannot be satisfied which triggers a re-selection process. Compared to the exhaustive cooperation, the proposed method is capable of reducing 34% signaling overhead with about 0.5 meter degradation of accuracy in a specific practical scenario. We also average out the performance over randomly generated node configurations, and compare the proposed scheme with the mostly used nearest-node selection algorithm [1] in terms of accuracy and cost. The rest of the section is organized as follows: in 4.1.2 we present the state of the art solutions in anchor selection. In section 4.1.3 we describe our target scenario. The proposed method is detailed in 4.1.4. The simulation results and discussion are shown in 4.1.5. The concluding remarks are given at the end of the chapter.

4.1.2 Related work

The accuracy of positioning algorithm is influenced by both measurement noise and the relative node geometry [115], [116]. A comparison of different selection criteria, namely CRLB and GDOP, and analysis of their correlation with localization error in both cooperative and non-cooperative scenarios have been given in [36]. Here the mobile scenario has been studied, so the selection criteria is used for predicting the best set of anchor nodes.

An important aspect in localization is energy saving. The use of coalitional games has been proposed in [90] with the purpose of determining which nodes can stay in sleep mode, while only a subset participates in the positioning algorithm. In [1] experiments were performed to increase the energy efficiency of a localization system in wireless sensor networks. The idea is to use the closest anchor nodes, and the remaining ones stay in semi active state. Besides radio localization, there are also works that consider multimedia (camera) sensors for energy aware target tracking [117].

Compared to previous works, here we investigate mobile tracking in a heterogeneous network with the following novel contributions:

a) The proposed method exploits the knowledge of indoor layout to improve the RSS-based distance estimation accuracy;

b) We proposed a new location accuracy indicator for Linear Weighted Least Square (LWLS) estimator, and demonstrated it outperforms the CRLB;

c) The proposed method deploys the AP to control cooperation with the aim of maximizing the performance given the affordable overhead.

4.1.3 Target scenario

The target scenario is illustrated in Figure 4.1, which shows a heterogeneous network containing three types of nodes: APs, peer-nodes and mobiles. Peer-nodes and mobiles are equipped with both Wi-Fi and ZigBee modules. APs and peer-nodes both know their positions, and serve as anchor nodes. However, they are different in two aspects: 1) APs are spatially separated covering long distance, while peer-nodes are densely packed with short-distance coverage. 2) APs periodically broadcast its position information, while peer-nodes do not due to power supply constraint. We are interested in the scenario having dense nodes, so that the moving multi-RATs mobile is always able to communicate with APs and more than three peer-nodes.

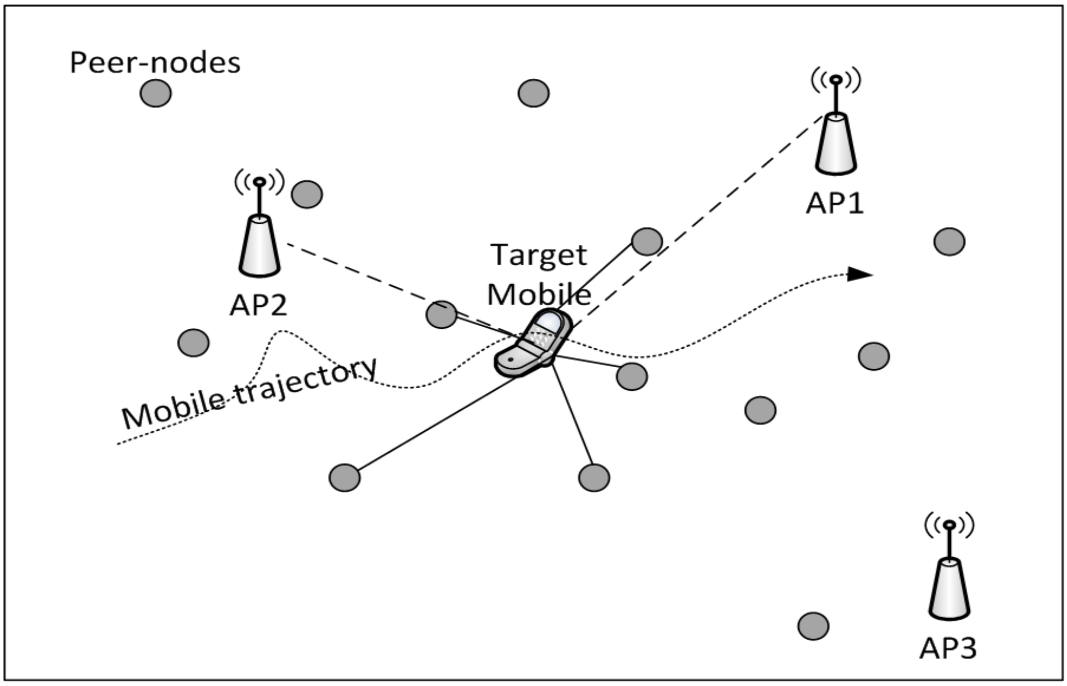


Figure 4.1: Heterogeneous network containing location-known access points, peer-nodes serving as anchor nodes, and one multi-RATs target mobile moving according to a certain trajectory

For the target mobile, we denote the set of reachable APs as N_{AP} , the set of reachable peer-nodes as N_p, the set of reachable anchor nodes as $\mathrm{N_A}(\mathrm{N_{AP}} \cup \mathrm{N_P})$, and their locations as $\mathbf{x}_n = [x_n, y_n]^T (n \in \mathrm{N_A})$ in 2-dimensional space. We assumed that there is at least one AP , $(|\mathrm{N_{AP}}| \geq 1)$ and at least 3 reachable peer-nodes $(|\mathrm{N_P}| \geq 3)$. The AP associated with the target node is called connected AP. The target node position is denoted as $\mathbf{x} = [x, y]^T$. The distance between the n-th anchor and the target node is denoted as $d_n = \sqrt{(x_n - x)^2 + (y_n - y)^2}$.

The estimated distance using ranging technical such as RSS/TOA is denoted as $\tilde{d}_n$ with mean value $\mathrm{E}\left(\tilde{d}_n\right)$ and variance $\mathrm{var}\left(\tilde{d}_n\right)$. The estimated target location is denoted as $\tilde{\mathbf{x}} = [\tilde{x}, \hat{y}]^T$. We employed Root Mean Squared Error (RMSE) to represent the estimation accuracy, which is formulated as

$$RMSE = \sqrt{tr(\mathbf{C}_{\tilde{\mathbf{x}}})} = \sqrt{\mathrm{E}\left((\tilde{x} - x)^2 + (\tilde{y} - y)^2\right)} \tag{4.1}$$

The notation $\mathbf{C}_{\tilde{\mathbf{x}}}$ represents the covariance matrix of estimated vector $\tilde{\mathbf{x}}$. The required accuracy is denoted as $RMSE_{\mathrm{req}}$ (unit: meter). Our goal is to select a subset of nodes $\mathrm{N_S}(\mathrm{N_S} \subseteq \mathrm{N_A})$ having fixed cardinality $|\mathrm{N_S}|$ such that: 1) the required accuracy can be achieved or approached as close as possible; 2) the remaining unselected anchors could remain silent so as to save power consumption and reduce traffic overhead.

4.1.4 Proposed method

The proposed method is illustrated in Figure 4.2.

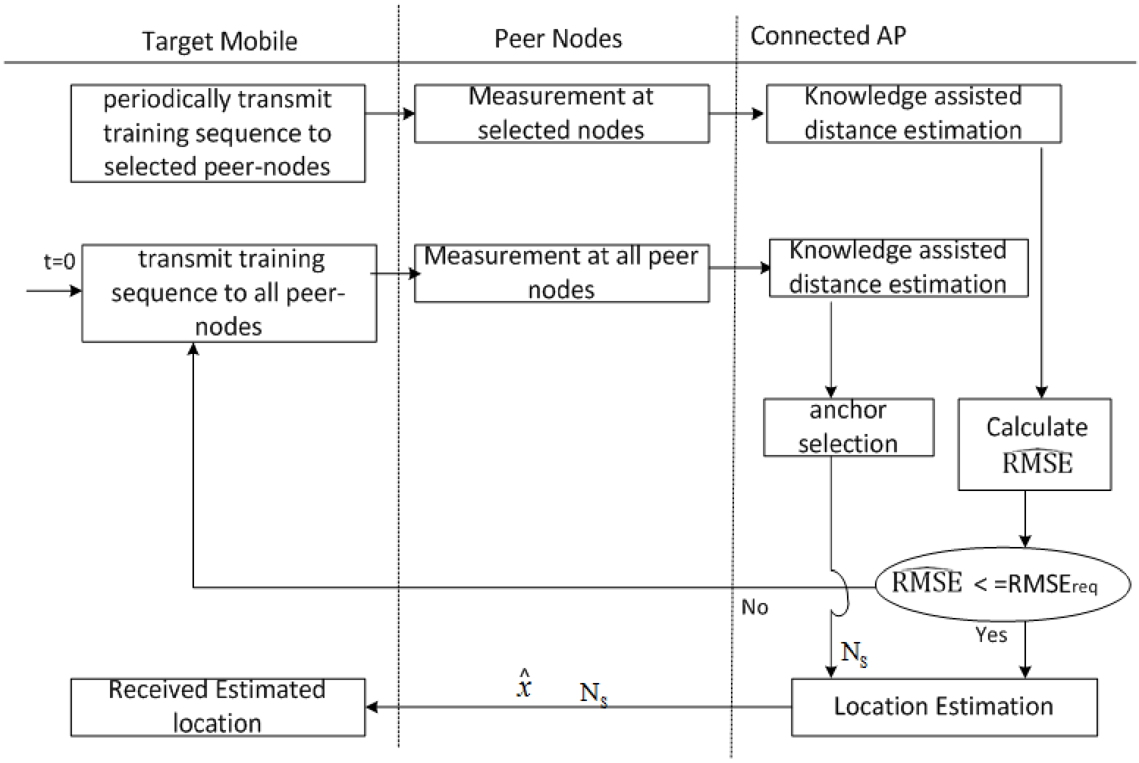


Figure 4.2: Illustration of the proposed method

At the beginning ($t = 0$), the target mobile node transmits training sequence at its highest transmit power, and seeks for assistance from all reachable peer-nodes. Peer-nodes measure the related signal parameters such as RSS/TOA and transmit measurement results to the connected AP. If peer nodes cannot communicate with the AP, the measurement results are sent via the target node. Upon receiving the measurements, the connected AP performs distance estimation, and then chooses the best set of anchors N_S over all possible combinations $S = \{\mathrm{N_S}\}$ which is expected to achieve the smallest RMSE. The estimation result $\tilde{\mathbf{x}}$ and the chosen set N_S are transmitted to the target node.

As the target node moves on, it will periodically transmit training sequences, and seeks assistance from those selected peer-nodes. Upon receiving the measurements, the connected AP will estimate the achievable RMSE using the selected set of anchors. If the required accuracy is satisfied, the estimation result $\tilde{\mathbf{x}}$ using this chosen set N_S is transmitted to the target node. Otherwise, a re-selection process is triggered, and a new set N_S will be chosen.

In addition, the indoor layout map is assumed to be available at the AP, which will be used to improve the RSS-based distance estimation as detailed in Section 4.1.5. The coordinates of all anchor nodes are also recorded and updated at the AP, which avoids the overhead traffic caused by exchanging location information between peer-nodes and the target node.

Location accuracy indicator

The pseudo-code of the proposed method is summarized in Algorithm 1.

Initialization: t=0; $\mathrm{N_S}^{(-1)} = \mathrm{N_{AP}}$

if $t > 0$ ***and*** $\widehat{RMSE}(N_S{}^{(t-1)}) \leq RMSE_{\mathrm{req}}$ **then**

  $\mathrm{N_S}^{(t)} = \mathrm{N_S}^{(t-1)}$;

else

  $\mathrm{N_A} = \mathrm{N_{AP}} \cup \mathrm{N_P}$;

  $S = \{\mathrm{N_S}\}, |\mathrm{S}| = \mathrm{C}_{|\mathrm{N_A}|}^{|\mathrm{N_S}|}$;

  for $i = 1 : |S|$ **do**

    Calculate $\widehat{RMSE}\,(S_i)$

  end

  $\mathrm{N_S}^{(t)} = \arg\min\limits_{S_i} \widehat{RMSE}(S_i)$

end

$\widehat{\mathbf{x}}\,(t) = \mathrm{f}\left(\mathrm{N_S}^{(t)}\right); t = t + 1$

Algorithm 1: Cooperative scheme with anchor selection at time (t), given the previous selected anchor set x

The key aspect is positioning accuracy estimation. In this section, we will detail two location accuracy indicators: estimated CRLB denoted as $\widehat{CRLB}$, and estimated RMSE for Linear Weighted Least Square estimator denoted as $\widehat{RMSE}_{LWLS}$. In the next section, we will compare these two indicators in terms of their correlation with the true RMSE.

Estimated CRLB

The target of range-based positioning is to estimate $\mathbf{x}$ based on the observation distance vector $\tilde{d}$. In estimation theory, the Cramer Rao Lower Bound is defined as the lower bound on variance of any unbiased estimator, which formulated as:

$$RMSE = \sqrt{tr(\mathbf{C}_{\widehat{\mathbf{x}}})} \geq \sqrt{CRLB} \tag{4.2}$$

The notation $tr(\mathbf{C}_{\widehat{\mathbf{x}}})$ represents the covariance matrix of estimated vector $\widehat{\mathbf{x}}$. CRLB has been introduced in Section 3.3. Supposed that the log-likelihood function of $\mathbf{x}$ given the distance vector $\tilde{d}$ is equal to the natural logarithm of the probability density function of $\tilde{d}$ given $\mathbf{x}$, formulated as $\ell(\mathbf{x}|\widehat{\mathbf{d}}) = \ln\left(\mathrm{p}(\widehat{\mathbf{d}}|\mathbf{x})\right)$, the CRLB is calculated as

$$CRLB = \frac{1}{tr\left(\mathbf{F}\left(\mathbf{x}\right)\right)}, \mathbf{F}\left(\mathbf{x}\right) = -\mathrm{E}\left(\frac{\partial^2 \ell(\mathbf{x}|\widehat{\mathbf{d}})}{\partial \mathbf{x}^2}\right) \tag{4.3}$$

The Fisher Information Matrix (FIM) $\mathbf{F}\left(\mathbf{x}\right)$ is a function of the second derivative of the likelihood function. If $\mathbf{F}\left(\mathbf{x}\right)$ contains any unknown parameters, which are replaced by their estimated values, the resultant bound is called the estimated CRLB, denoted $\widehat{CRLB}$. For example, the CRLB of RSS-based ranging in 2-dimentional space derived in [26] is a function of the unknown distance d_n. Hence, it is only feasible to calculate the estimated $\widehat{CRLB}$ using $\tilde{d}_n$.

RMSE for Linear Weighted Least Square Estimator

If the Linear Weighted Least Squared estimator is used, we can have a closed-form expression of $\tilde{\mathbf{x}}$ as:

$$\tilde{\mathbf{x}} = (\mathbf{A}^T\mathbf{C}_{\widehat{\mathbf{b}}}^{-1}\mathbf{A})^{-1}\mathbf{A}^T\mathbf{C}_{\widehat{\mathbf{b}}}^{-1}\widehat{\mathbf{b}} \tag{4.4}$$

The matrix $\mathbf{A}$ is a function of $\mathbf{x}_n$, vector $\widehat{\mathbf{b}}$ is a function of $\tilde{d}_n$ as well as anchor coordinates $\mathbf{x}_n$, and $\mathbf{C}_{\widehat{\mathbf{b}}}^{-1}$ is the inverse of covariance matrix of $\widehat{\mathbf{b}}$. Hence the covariance matrix $\mathbf{C}_{\widehat{\mathbf{x}}}$ also has a closed-form expression as:

$$\mathbf{C}_{\widehat{\mathbf{x}}} = (\mathbf{A}^T \mathbf{C}_{\widehat{\mathbf{b}}}^{-1} \mathbf{A})^{-1} \tag{4.5}$$

In the case of $\mathbf{C}_{\widehat{\mathbf{b}}}^{-1}$ is a function of unknown distance d_n , the estimated version $\widehat{\mathbf{C}_{\widehat{\mathbf{b}}}^{-1}}$ using $\tilde{d}_n$ is employed. We derive the location accuracy indicator as:

$$\widehat{RMSE}_{LWLS} = \sqrt{\left[(\mathbf{A}^T \widehat{\mathbf{C}_{\widehat{\mathbf{b}}}^{-1}} \mathbf{A})^{-1} \right]_{1,1} + \left[(\mathbf{A}^T \widehat{\mathbf{C}_{\widehat{\mathbf{b}}}^{-1}} \mathbf{A})^{-1} \right]_{2,2}} \tag{4.6}$$

4.1.5 Simulation results and analysis

Although the proposed method is not constrained by ranging techniques, RSS-based distance estimation is used in our simulation for its universal applicability and ease of implementation. Using the unbiased distance estimator, the estimated distance squared for the n-th anchor can be formulated as

$$\widehat{d_n^2} = e^{-\frac{2r_n}{\alpha} - \frac{2\lambda_n^2}{\alpha^2}} \tag{4.7}$$

It has zero mean and variance of $\mathrm{var}\left(\widehat{d_n^2}\right) = d_n^4 \left(e^{\frac{4\lambda_n^2}{\alpha}} - 1 \right)$.

We express the location accuracy indicators using these distance estimates. Thus the CRLB is formulated as:

$$\widehat{CRLB}_{RSS} = \sqrt{\frac{1}{b} \frac{\sum\limits_{n=1}^{N} \widehat{d_n^{-2}}}{\sum\limits_{n=1}^{N-1} \sum\limits_{m=n+1}^{N} \left(\frac{\widehat{d_{t\perp n,m}} d_{n,m}}{\widehat{d_n^2} d_{n,m}^2} \right)^2}} \tag{4.8}$$

where the distance between n-th and m-th anchors, and the term $\widehat{d_{t\perp n,m}}$ is the estimated shortest distance from target to the segment connecting n-th and m-th anchors. b has been explained in Section 3.3.

Using the Best Linear Unbiased Estimator (BLUE) proposed in [59], the estimated RMSE is formulated as Eq. 4.6 using:

$$\mathbf{A} = \begin{pmatrix} -2x_1 & -2y_1 & 1 \\ -2x_2 & -2y_2 & 1 \\ \vdots & \vdots & \vdots \\ -2x_n & -2y_n & 1 \end{pmatrix}, \widehat{\mathbf{C}_{\hat{\mathbf{b}}}^{-1}} = \begin{pmatrix} \widehat{\mathrm{var}\left(\hat{d}_1^2\right)} & & 0 \\ & \ddots & \\ 0 & & \widehat{\mathrm{var}\left(\hat{d}_n^2\right)} \end{pmatrix}^{-1} \quad (4.9)$$

In this rest of this section we describe the simulation for a) the specific scenario from Figure 4.3, and b) generalized scenarios with randomly distributed anchors and averaged performances over ten different constellations. We generated the deployment in MATLAB, and then determined the channel conditions based on the WINNER tool [118]. More details on the WINNER channel model are provided in the Appendix C.

A specific scenario

We consider a practical scenario illustrated in Figure 4.3, which consists of 1 Wi-Fi AP and 7 peer-nodes. The target moves from the corridor to a room. Along the movement trajectory, propagation conditions between the target and the other nodes change, according to LOS or NLOS modeled by the WINNER II channel model [118].

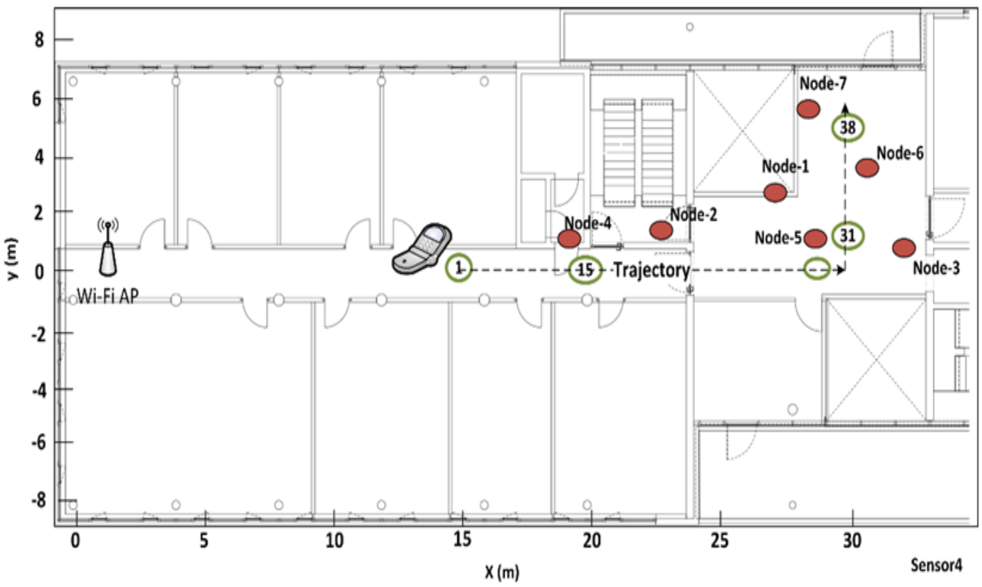


Figure 4.3: Simulation scenario consists of 1 Wi-Fi access point, 7 peer nodes, and one target mobile node moving from the corridor to a room

We assume that the map layout is known, hence we are perfectly aware of LOS/NLOS conditions at each point of the trajectory. The target node moves at a speed of 1 m/s. We trace the location of the target node every 1 second , which results in 38 foot-prints. The WINNER models [118] for indoor scenario at carrier frequency 2.4 GHz are used to simulate the channel between AP/peer-nodes and target node. The path loss parameter α is set to $\alpha_{LOS} = 1.85$ and $\alpha_{NLOS} = 3.68$. The variance of zero-mean lognormal shadowing σ^2 is set to $\sigma^2_{LOS} = 2dB$ and $\sigma^2_{NLOS} = 5dB$ respectively. α_{LOS} is lower than the path loss exponent in free space, because of the waveguide effect that may occur in corridors [119]. The true location RMSE is averaged over 1000 independent shadowing samples. Setting $|\mathrm{N}_S|$ and $RMSE_{\mathrm{req}}$ for different values, we simulate the following 4 schemes:

1. Scheme 1: $|\mathrm{N}_S| = |\mathrm{N}_{\mathrm{AP}}| + |\mathrm{N}_{\mathrm{P}}|$, $RMSE_{\mathrm{req}} = 0$, this is equivalent to exhaustive cooperation, where all reachable APs and peer-nodes are used for location estimation at every sampling time;

2. Scheme 2: $|\mathrm{N}_S| = 3$, $RMSE_{\mathrm{req}} = 0$, using $\widehat{CRLB}_{RSS}$ in Eq.4.8 as indicator, and LWLS/ML location estimator;

3. Scheme 3: $|\mathrm{N}_S| = 3$, $RMSE_{\mathrm{req}} = 0$, using $\widehat{RMSE}_{LWLS}$ in Eq.4.6 as indicator, and LWLS location estimator;

4. Scheme 4: $|\mathrm{N}_S| = 3$, $RMSE_{\mathrm{req}} = 1$ and 2, using $\widehat{RMSE}_{LWLS}$ in Eq.4.6 as indicator, and LWLS location estimator.

Location accuracy indicator comparison

Using the parameters set for Scheme 2, three out of eight anchors, which provide the lowest value of $\widehat{CRLB}_{RSS}$, are chosen at each sampling time. The true RMSEs using LWLS estimator and the maximum likelihood estimator are compared to the indicated value $\widehat{CRLB}_{RSS}$ in Figure 4.4. The ML estimator is the optimal RSS-based position estimator, however it is computationally very demanding and we use it for benchmark purposes. It is demonstrated that from the 15 sample onward, where the anchor nodes are dense and distributed in variable directions, the indicated RMSE using $\widehat{CRLB}_{RSS}$ has a good correlation with the true RMSE using ML estimator, but much lower than the true RMSE using LWLS estimator.

In the first few samples, the $\widehat{CRLB}_{RSS}$ values are low, but the true RMSE using either linear or ML estimators are very high. The reason is the closest 3 anchors are not in-line with the target, but almost collinear with each other. In this situation, the assumption

$\ell(\mathbf{x}|\widehat{\mathbf{d}}) = \ln\left(\mathrm{p}(\widehat{\mathbf{d}}|\mathbf{x})\right)$ does not hold anymore. In fact, given $\widehat{\mathbf{d}}$, the log-likelihood function of $\mathbf{x}$ achieves two peak values, one at the true location, the other at the mirror location symmetric to the approximate line connecting these to the near collinear anchors. Hence, $\widehat{CRLB}$ gives false accuracy estimation. It chooses the close, but near-collinear anchors, which results in high positioning error. The estimated error and the bound are not very close, thus it is not a reliable indicator.

Using similar parameters, Figure 4.5 compares the indicator $\widehat{RMSE}_{LWLS}$ and the true RMSE. Again, 3 out of 8 anchors, which provide the lowest value of $\widehat{RMSE}_{LWLS}$ are chosen at each sampling time. The results show that the indicated RMSE using $\widehat{RMSE}_{LWLS}$ has a good correlation with the true RMSE using LWLS estimator at all samples. Near collinear anchors are avoided during the first few samples.

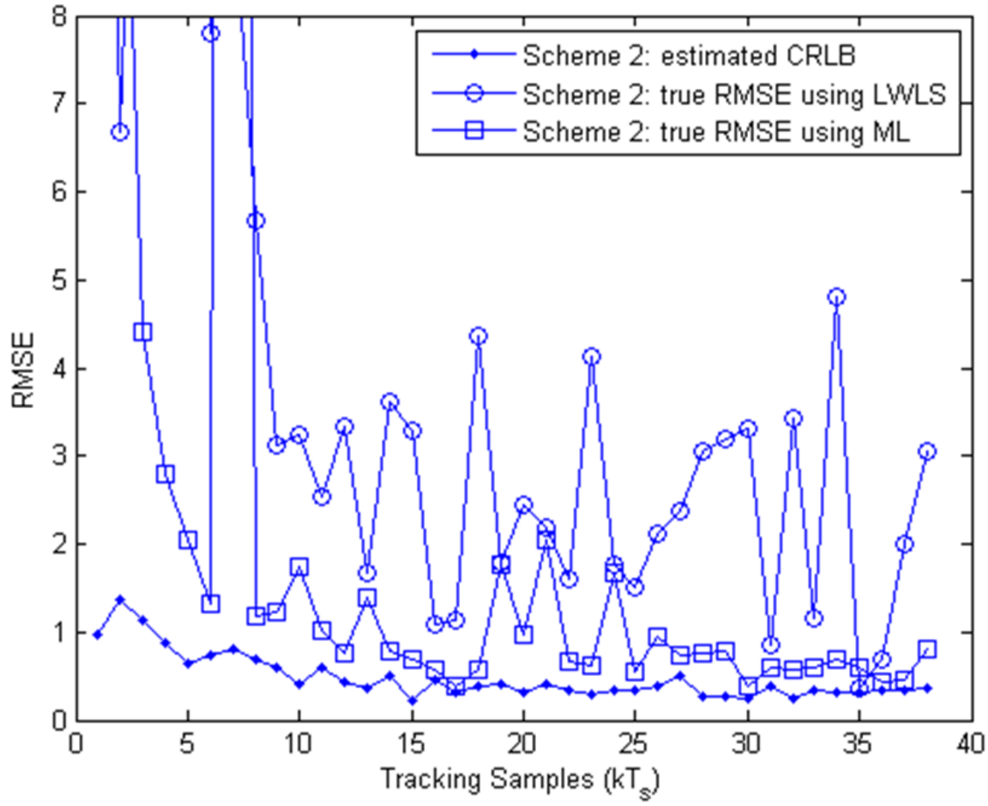


Figure 4.4: Comparison between the CRLB indicators and the true RMSE when using Scheme 2

Based on these two figures, we could conclude that $\widehat{RMSE}_{LWLS}$ is a better RMSE indicator than $\widehat{CRLB}$, which can avoid choosing near collinear anchors, and provides more accurate estimation of the achievable RMSE when LWLS estimator is deployed. Hence, we will use the $\widehat{RMSE}_{LWLS}$ indicator and LWLS estimator to evaluate the proposed method.

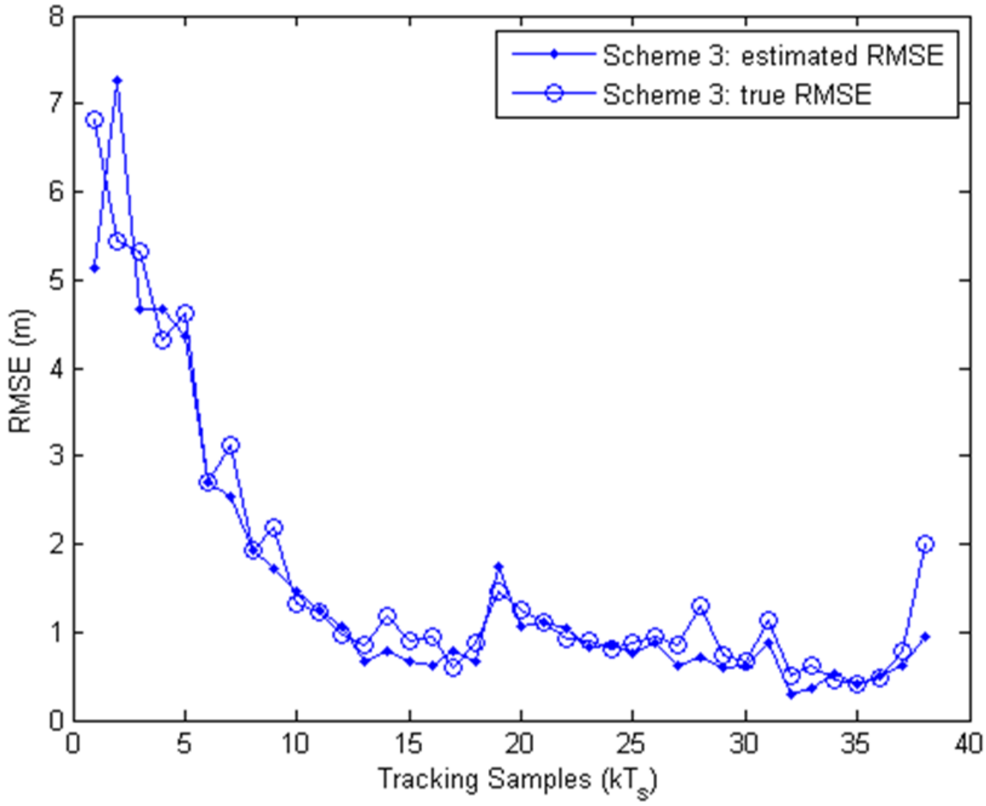


Figure 4.5: Comparison between indicator $\widehat{RMSE}_{LWLS}$ and the true RMSE when using Scheme 3

Exhaustive cooperation versus the proposed method

We simulate the proposed method and compare its RMSE to those using exhaustive cooperation. The parameters are summarized in Scheme 4 and Scheme 1, respectively. As shown in Figure 4.6, the degradation of accuracy is negligible. When using the proposed method with $RMSE_{\text{req}} = 2$, the average RMSE is about 0.53 (meter) higher than exhaustive cooperation. However, the total traffic overhead reduction is about 34% as shown in Figure 4.7. More explicitly, the proposed method does not always require messages from all anchors (in green). It only occasionally requires additional control packets from the AP (in blue) to invoke the re-selection process. Compared to exhaustive cooperation, the overall transmit overhead over 38 samples is reduced by 34% using the proposed method. The energy spent on this traffic overhead is saved. The higher error threshold value triggers less re-selections, thus the traffic is further reduced when $RMSE_{\text{req}} = 2$, instead of $RMSE_{\text{req}} = 1$.

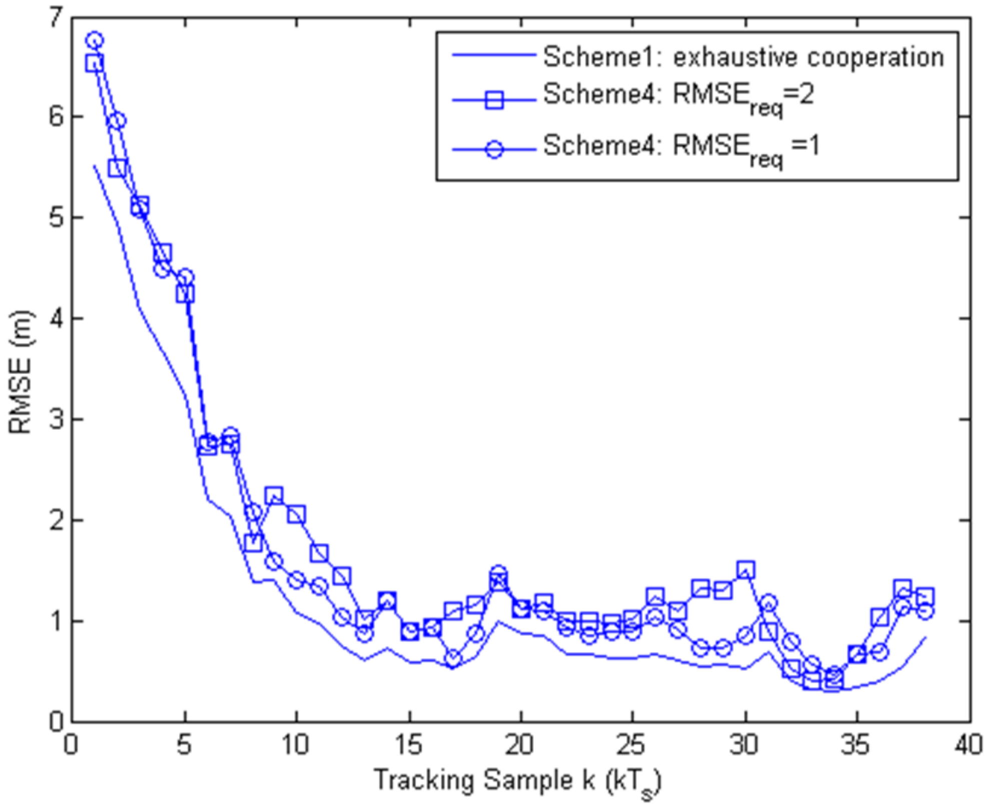


Figure 4.6: Comparison of the achievable accuracy RMSE between exhaustive cooperation using Scheme 1 and the proposed method using Scheme 4

Generalized scenario

In order to extend the validity of the results presented for the specific scenario from Figure 4.3, we evaluated the proposed method in more generalized scenarios. We consider a mobile moving across a 25 m x 10 m room. The number of anchors in the room is 20, where one of them is the access point ($|\mathrm{N}_{\mathrm{AP}}| = 1$) and the remaining ones are peer nodes ($|\mathrm{N}_{\mathrm{p}}| = 19$). We generated 10 setups having anchor nodes randomly distributed over the room, while the target node follows the same trajectory from the bottom-left side to the upper-right. The averaged performance at 30 sampled locations along the trajectory are evaluated. Again, the WINNER model for indoor scenario at carrier frequency 2.4 GHz are used with path loss parameter α set to $\alpha_{LOS} = 1.85$ and$\alpha_{NLOS} = 3.68$. The variance of zero-mean lognormal shadowing σ^2 is set to $\sigma^2_{LOS} = 2dB$ and $\sigma^2_{NLOS} = 5dB$ respectively. The true location RMSE is averaged over 1000 independent shadowing samples.

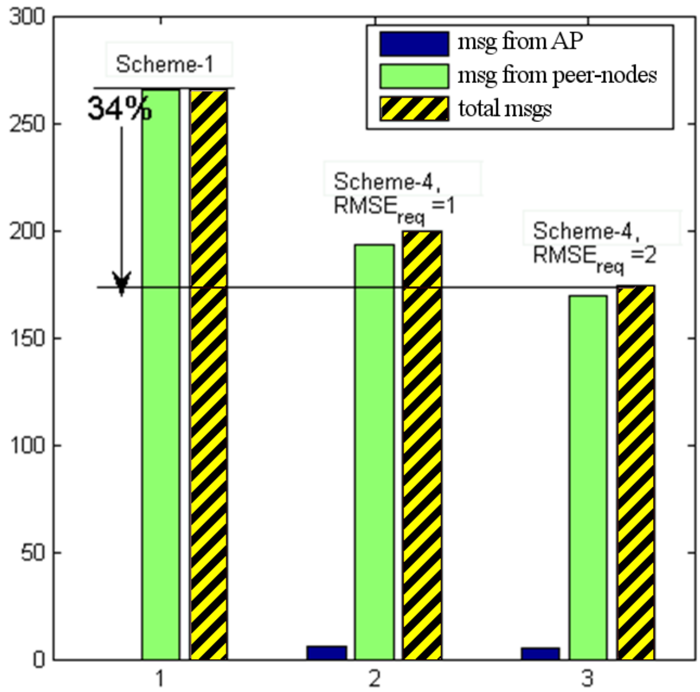


Figure 4.7: Comparison of packet overhead between exhaustive cooperative (Scheme 1) and the proposed method (Scheme 4)

We simulate the following two schemes:

- Proposed algorithm: using $\widehat{RMSE}_{LWLS}$ in Eq.4.6 as indicator, and LWLS location estimator, $RMSE_{\text{req}} = 0.6$ meter, and various combination of $|\mathrm{N}_S|$ and $|\mathrm{N_A}|$:

  $(|\mathrm{N}_S|, |\mathrm{N_A}|) = \{(3,7), (3,14), (3,20), (5,7), (7,7), (7,14), (20,20)\}$

- Three nearest node selection algorithm used in [1].

Comparison of different combination of $|\mathrm{N}_S|$ and $|\mathrm{N_A}|$

The averaged localization accuracy using the proposed algorithm with different combination of $|\mathrm{N}_S|$ and $|\mathrm{N_A}|$ are shown in Figure 4.8. First of all, the required accuracy $RMSE_{\text{req}} = 0.6$ meter is achieved for all settings from track sample 5 to 27, when the target moves in the central area of the room surrounded with sufficient number of anchor nodes.

By contrast, when the target moves in the edge of the room corresponding to samples 1-5 and 27-30, the accuracy requirement is only always achieved if $(|\mathrm{N}_S|, |\mathrm{N}_\mathrm{A}|) = (20, 20)$. It is because at edge areas, the number of reachable anchors is limit and they are not 360 degree spread. Second, as expected, the accuracy improves by increasing the number of selected nodes $|\mathrm{N}_S|$ or the cardinality of potential selection set $|\mathrm{N}_A|$. However, the performances using 3 selected nodes out of 7, 14 and 20 are very similar. The accuracy is significantly improved when increasing both $|\mathrm{N}_S|$ and $|\mathrm{N}_A|$ such as (5,7) and (7,14).

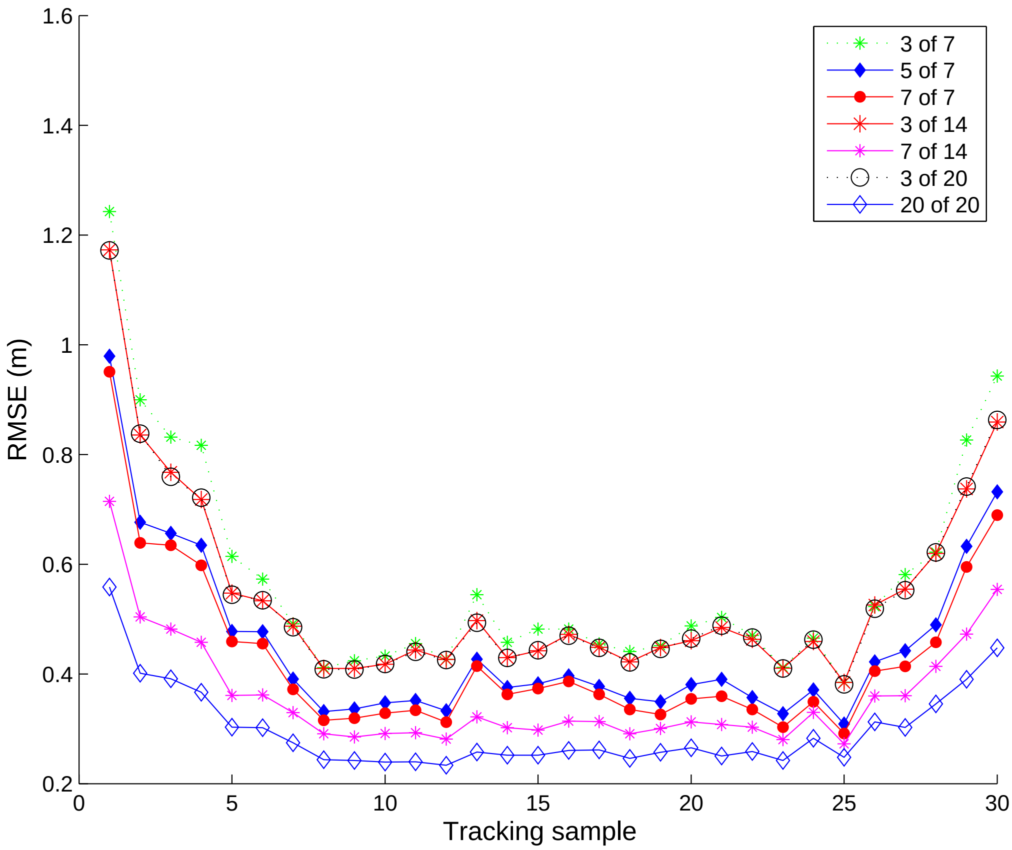


Figure 4.8: Comparison of different combination of $|\mathrm{N}_S|$ and $|\mathrm{N}_\mathrm{A}|$ using the proposed algorithm in terms of averaged localization accuracy

Figure 4.9 illustrates the traffic overhead accumulated from 30 tracking samples and averaged over 10 different setups. The traffic overhead consist of 1 message from $|\mathrm{N}_S|$ selected nodes at each tracking sample, 1 message from AP and $|\mathrm{N}_\mathrm{A}| - |\mathrm{N}_\mathrm{S}|$ messages from peer nodes at some tracking sample when re-selection is activated. Figure 4.8 shows that selecting 5 nodes of 7 candidates achieve the smallest traffic overhead, while selecting 3 nodes results in higher traffic overhead because it triggers more often re-selection.

Deploying the parameters stated in [120], we compare the energy needed for different schemes in Table 4.1. More explicitly, we assume that each message last for 1ms, and adopt the typical value of 32 mW (15 dBm) as transmit power of peer nodes, and 63 mW (18 dBm) as transmit power of APs [120]. The total energy required for transmitting the averaged traffic shown in Figure 4.9 is calculated, assuming that each message lasts 1 ms. Again, it demonstrates that (5,7) combination achieve the smallest energy consumption.

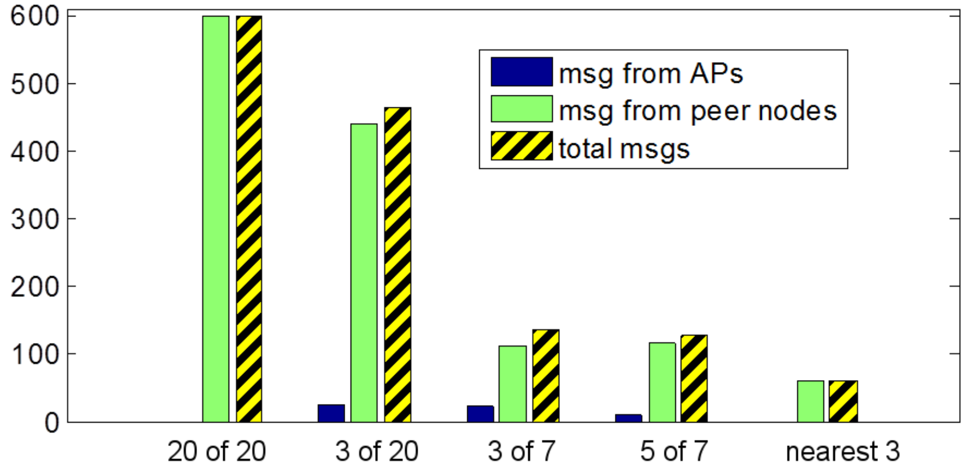


Figure 4.9: Averaged traffic overhead using 1) the proposed algorithm with different combination of $|N_S|$ and $|N_A|$; and 2) the nearest-3 node selection algorithm in [1]

Case	Proposed algorithm with different combination of —Ns— and —Na—				3 nearest nodes
	20 of 20	3 of 20	3 of 7	5 of 7	
Energy in mJ	19.2	16.315	5.903	3.661	1.92

Table 4.1: Power consumption for overhead messages

Nearest-nodes algorithm versus the proposed method

As a benchmark we used the approach of choosing the three closest nodes, as in [1], which is popular because of its simplicity. Although it has the lowest signaling overhead and power consumption as shown in Figure 4.9 and Table 4.1, we can see from Figure 4.10 that the accuracy requirement is much worse compared to the proposed algorithm. The main reason for this is that by choosing simply three nodes with the strongest RSSI we run the risk to choose three collinear nodes, or almost collinear which is an ill-conditioned scenario and yields large errors. This prenominal has been overlooked in [1], where anchor nodes are regularly placed. It is a reasonable assumption in sensor network as considered in [1], but no longer valid in our heterogeneous network. Finally, we summarize our analysis in terms of performance trade-offs in Table 4.2. In this sense, cost is related to communication overhead, power consumption, search complexity and computational complexity. For accuracy metrics, we used the mean RMSE.

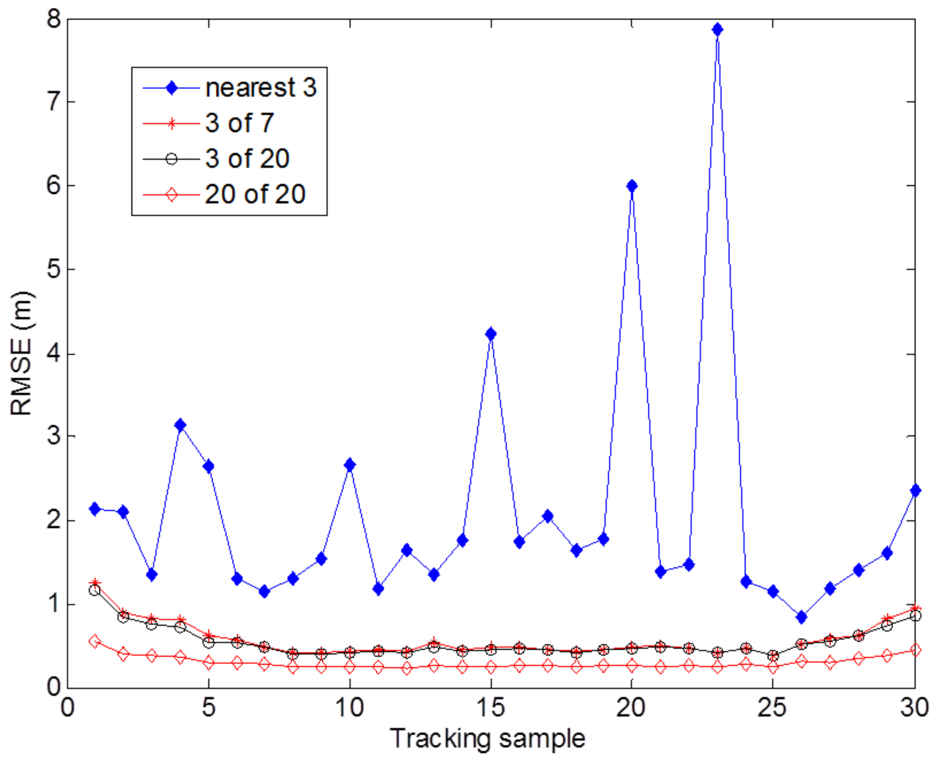


Figure 4.10: Comparison of the nearest-3-node selection algorithm to the proposed algorithm in terms of averaged localization accuracy

For the communication overhead metric we use the number of messages which are exchanged in the anchor selection process. The search complexity is the number of possible search space size, and the computational complexity arises from matrix inversions that have to be performed in WLS localization algorithm. The proposed algorithm provides the flexibility of achieving different trade-offs by manipulating the value of $|N_S|$ and $|N_A|$.

Performance metric		Mean RMSE (meter)	Comm. Overhead (packet number)	Size of search space	Comp. complexity (size of A in Eq.(4))
The nearest 3-nodes		2.109	60	1	3×3
Proposed algorithm	20 of 20	0.2975	600	1	20×20
	3 of 20	0.5424	465	1140	3×3
	3 of 7	0.5716	136	21	3×3
	5 of 7	0.4501	128	35	5×5

Table 4.2: Analysis of cost-performance trade-offs

4.2 Reference node selection in realistic localization contexts

In this section we show the benefits of a node selection scheme, using real measurement data obtained during measurement campaigns within the WHERE2 project at the premises of the German Aerospace Center (DLR).

The selection process is based on theoretical location performance bounds, such as the Cramer Rao Lower Bound, which captures information about both relative geometry and quality of received signal strength based distance estimates. In order to determine the optimum set of reference nodes, we perform an exhaustive search over all combinations and compute their CRLB values. We use setup 2 from [121] and consider ZigBee nodes only. Regarding RSSI measurements, the most relevant radio parameters of the used CC2431 chip are the operation frequency of 2.4 GHz with a bandwidth of 5 MHz, a TX power of 0 dBm and a RX sensitivity of -92 dBm.

All ZigBee anchors are located in a small open space area and the positioning system is over determined. This helps to evaluate the potential of more sophisticated cooperative positioning algorithms, GDOP reduction and link selection. To infer on the ranges from experimental RSSI readings we use the one-slope path loss model, whose parameters are the reference power P_0 at the distance $d_0 = 1m$, and the path loss exponent α, which characterizes the power decay versus distance. The deviations of experimental RSSI values from the path loss model are commonly modeled as realizations of a zero-mean Gaussian random variable with variance σ^2. Such path loss parameters are environment dependent and therefore must be determined empirically from a set of calibration measurements. The parameters extracted for this site-specific model as in [121] are $P_0 = -47dBm$, $\alpha = 2$, and $\sigma^2 = 5.8dB$.

4.2.1 Results

RSS-based range information is derived using estimators from [122], specifically the ML estimator: $\tilde{d}_{ML} = e^{M} e^{-S^2}$, where $M = \frac{(P-P_0)\ln 10}{10\alpha} + \ln d_0$ and $S = \frac{\sigma \ln 10}{10\alpha}$. Here we are assuming the path loss model from (2.1).

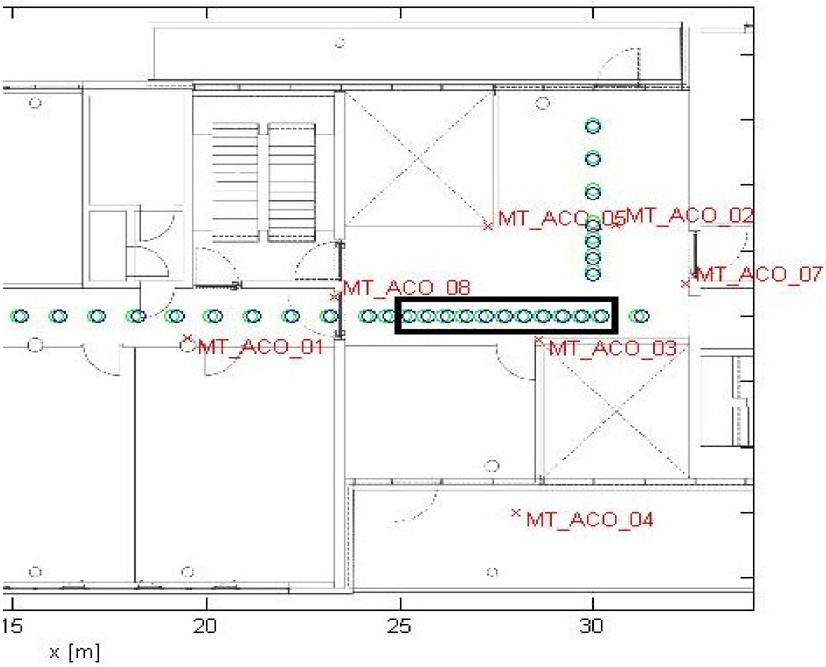


Figure 4.11: Scenario for evaluation: anchor locations are MT ACO, circles present the target trajectory.

We consider a real measurement campaign carried out at DLR premises where a multi-standard mobile terminal equipped with both a RSSI-enabled Zigbee node and an RTD-enabled OFDM device is assumed to be moving along a corridor. The physical environment is a 15mx33m indoor floor divided into multiple offices. The measurements are performed at stationary positions and a MT trajectory is emulated out of the tested positions. However, we only consider the ZigBee measurements. For 11 target positions shown at Figure 4.11, we evaluated the CRLB values for all combinations of three anchor nodes (in total 35 combinations of three anchors out of seven).

We kept track of combinations that result in lowest CRLB, and finally compared the cumulative distribution functions of positioning errors when using the anchor node combinations yielding lowest CRLB values and a random combination of anchor nodes. The estimator used for position computation was the WLS estimator. Results are shown in Figure 4.11.

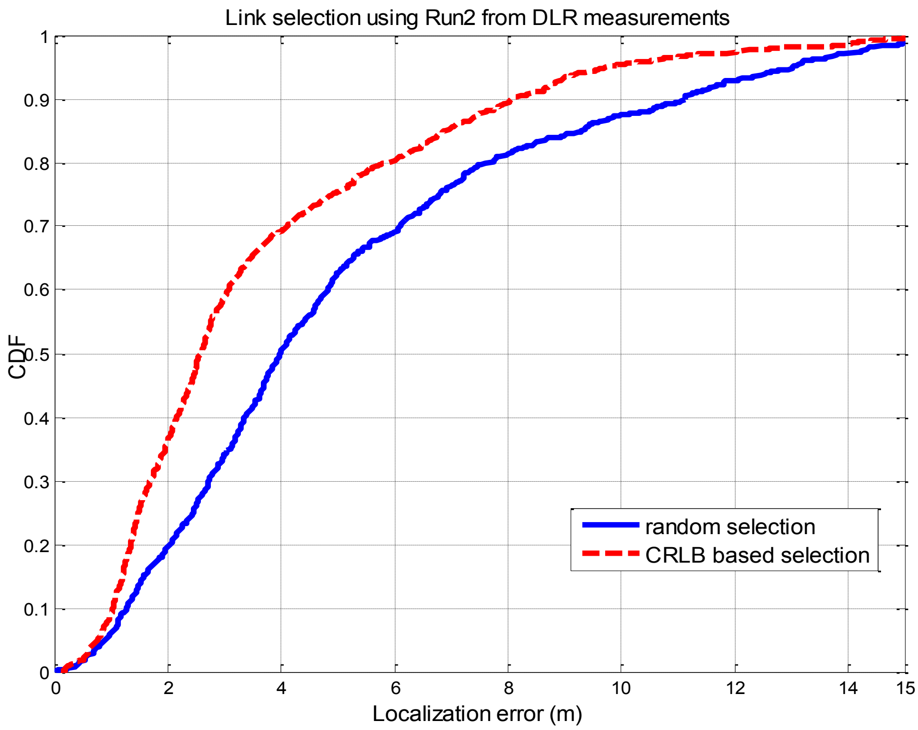


Figure 4.12: CDF of positioning errors when using a random combination of anchors, and combination yielding lowest CRLB values

We could also observe that the combination of anchors MT ACO 08, MT ACO 07 and MT ACO 04 (Figure 4.11) produced very large positioning errors for all target locations. This might be due to the fact that MT ACO 08 and MT ACO 07 are both almost in line with the target, and MT ACO 04 has multiple obstacles and therefore rather bad NLOS propagation conditions.

4.3 Conclusion

In Section 4.1.5 we proposed a cooperation method for range-based positioning in heterogeneous network via node selection in order to reduce communication and energy cost. Inactive nodes do not waste energy while collecting, processing, and communicating measurements. We analyzed a specific scenario, and a generalized one that corresponds to realistic indoor environments. We presented an extensive study of different setups in order to determine the best trade-off between desired accuracy and cost.

Furthermore, we evaluated the node selection for ZigBee nodes in an indoor environment using experimental data in Secton 4.2.1. We observed that combinations resulting from minimum CRLB provide better results than the random selection. The 90th percentile error for CRLB based selection is 8 meters, compared to 11 meters for random selection. We also observed that certain combinations lead to large errors even if the CRLB value is low.

Chapter 5

Special cases of non-cooperative positioning

In the previous chapters we considered a cooperative scenario, where nodes collaborate in order to enhance positioning accuracy. In this chapter two specific cases of non-cooperative positioning are described, namely a low-complexity algorithm for positioning in an ill-conditioned scenario with collinear anchor nodes in Section 5.1.4, and a map-assisted method that incorporates use of negative information in Section 5.2.5.

5.1 RSS based collinear anchor aided localization algorithm for ill-conditioned scenario

The conventional received signal strength based positioning algorithms such as LS and WLS estimation produce significant estimation errors when the anchor nodes positions approach a collinear scenario. In this section, we propose the CAP (Collinear Anchor aided Positioning) algorithm to provide robust positioning performance under ill-conditioned matrix conditions, whilst contributing toward overall low computational complexity. In this section, without loss of generality, we will focus on RSS-based lateration technique in a 2-dimensional space. The geometric method can be applied to TOA based distance estimates, without any restrictions.

5.1.1 Introduction

One limitation of lateration technique is that it requires distance measurements from at least 3 non-collinear anchors for calculating an objects position in 2-dimensional space. The accuracy of above-mentioned LS and WLS significantly degrades when the anchors are approaching collinear. The main reason for this degradation is that these two positioning algorithms involve matrix inversions which results in significant error injection when the matrix is ill-conditioned. The accuracy of high-complexity ML algorithm also degrades as well.

In this section, we consider an ill-conditioned scenario, in which the anchor nodes are nearly collinear, and the target does not lie on the same line as the anchors. Furthermore, we assume an indoor scenario where GPS does not work, and the positioning procedure relies exclusively on available anchor nodes. Although the probability decreases with the increase in the number of anchors, having near collinear anchor nodes is possible in practice. For example, it is possible that in public safety scenarios such as fire prevention, most of the well-planned indoor location sensors may be destroyed in a fire with only a few near collinear collocated sensors intact. Based on this scenario, we propose a Collinear Anchors-aided Positioning (CAP) algorithm, which provides significantly better localization results compared to the conventional LS/WLS algorithms. Its localization accuracy is comparable with ML, but with significantly reduced complexity.

The problem of anchor placement is a well-known subject in localization literature [115], [123]. Whether the localization algorithm is statistical and uses the Cramer-Rao lower bound as performance metric [123], or it introduces a new confidence metric for geometrical localization such as trilateration [115], the conclusions are similar - the best performance is given when anchor nodes are well separated around the target. One of the anchor constellations that have the biggest negative impact on localization performance is the collinear case, and several works have adopted methods to identify and discard such setups. It has been referred to as the pathological case [124], and the goal is to avoid it. Specific lower bounds on the degree of collinearity of anchor nodes sufficient to achieve optimal localization results have been proposed in [125]. The metric to measure collinearity is the height of the anchor triangle. The impact of anchor placement has also been studied in [126].

5.1.2 Preliminaries

The target scenario we consider in this section is illustrated in Figure 5.1 that depicts the target node position in a 2-dimensional space with near collinear anchors.

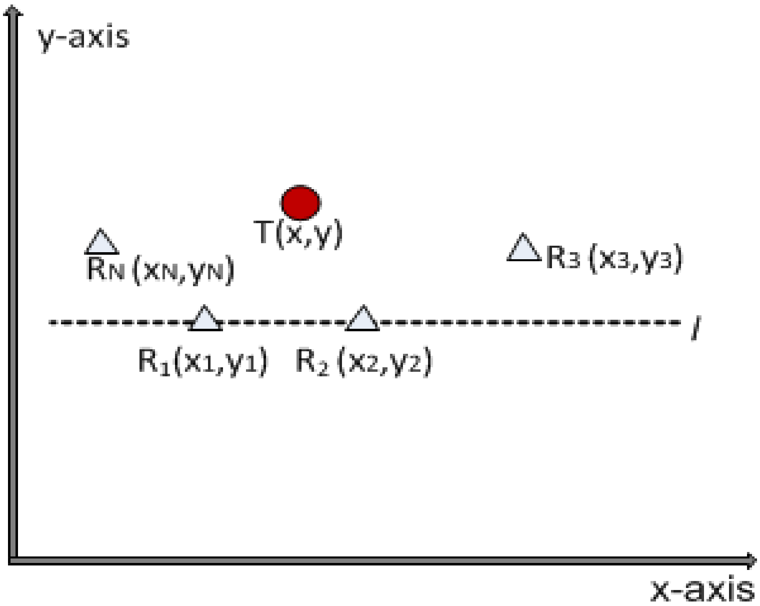


Figure 5.1: Target scenario with near collinear anchors

The target node T is located in 2-dimensional space with unknown coordinates (x, y) There are N fixed near collinear located anchors. In order to quantify the degree of collinearity between anchor nodes, we introduce the matrix A as in [124], which is formulated as:

$$\mathbf{A} = \begin{vmatrix} x_1 - x_N & y_1 - y_N \\ x_2 - x_N & y_2 - y_N \\ \vdots & \vdots \\ x_{N-1} - x_N & y_{N-1} - y_N \end{vmatrix} \tag{5.1}$$

This matrix contains information about geometrical configuration of anchor nodes. We use the condition number of matrix A as an indicator of collinearity: in the extreme case when all three anchors are collinear, the matrix is singular and the condition number $cond[A]$ is infinite. If the condition number is too large, the matrix (in our case the scenario) is said to be ill-conditioned.

From the expression for the LS solution (Eq. (2.12)), it can be seen that there are two factors affecting the estimation error of the target: 1) the distance estimation errors resulting from noisy measurements, which are part of the matrix b, and 2) the geometry of reference nodes. Information about anchor geometry is part of the matrix A. The estimation error is upper bounded [30]:

$$\frac{|\Delta \mathbf{x}|}{|\mathbf{x}|} \leq cond(\mathbf{A}) \frac{|\Delta \mathbf{b}|}{|\mathbf{b}|} \tag{5.2}$$

For collinear nodes, or if the number of reference nodes is less than three, matrix A is singular and its condition number is infinity. For a high value of even the minor perturbation in distance estimations would cause a large error in position estimate. If the reference nodes are well separated around the unknown node, matrix A is well conditioned.

There are several methods for distance estimation, such as [127], [128], etc. Even though in practice it has been shown that the RSS ranging performs well in addition to location maps (fingerprinting), we adopt RSS method in this section due to its simplicity. It is still the most easy-to-apply method for practical systems, because there is no need for any additional hardware, neither for synchronization. Suppose that the anchors R_i transmit a signal, and the long-term averaged received signal strength at reference distance d_0 is P_0 (dBm), the long-term averaged received signal strength P_i at the target is a shown in Section 2.1 in (2.1). Employing the unbiased estimator proposed in [59], and based on the results of [129], the unbiased estimate of the squared distance d_i^2 is:

$$\tilde{d}_i^2 = e^{-\frac{2r_i}{\alpha} - \frac{2\lambda_i^2}{\alpha^2}} \tag{5.3}$$

Here $r_i = 0.1 \ln(10)(P_i - P_0) - \alpha \ln(d_0)$, and $\lambda_i^2 = 0.01(\ln(10))^2 \sigma_i^2$.

Moreover, the variance of the estimation is formulated as:

$$\mathrm{var}(\tilde{d}_i^2) = d_i^4 (e^{\frac{4\lambda_i^2}{\alpha^2}} - 1) \tag{5.4}$$

Equation 5.4 demonstrates that the variance grows exponentially with the shadowing parameter. Since we assume equal channel conditions for all links, the variance of the distance estimates will be proportional to the distance itself. Here we have to mention that in case of TOA based ranging, the variance is not dependent on the distance, but is modeled by a zero-mean additive Gaussian noise.

Having the estimated distances $\tilde{d}_i^2$ and the knowledge of anchors locations (x_i, y_i), the target node is capable of estimating its own location coefficients (x, y) by exploiting the relationship $(x_i - x)^2 + (y_i - y)^2 = d_i^2$. The most common estimation algorithm is (linear)

Least Square [127], and its improved versions including the Weighted Least Square [58], incremental least square (ILS) [124] etc. However, the above-mentioned algorithms require at least 3 well-conditioned anchors. The Maximum-likelihood estimation algorithm [26] does not have this constraint, but it requires iterative operations, which results in high computational complexity. Motivated by the insufficiency of current estimation algorithms, we propose a new Collinear Anchor aided Positioning (CAP) estimation algorithm, which is described in the section 5.1.3.

5.1.3 Collinear anchor aided positioning algorithm

In this section, we describe the proposed algorithm given a scenario with $N = 3$ anchor nodes. The proposed algorithm can be extended to $N > 3$ scenario by first selecting 3 anchors having the most reliable estimation of distance according to Equation 5.4. Supposed there are three near collinear anchors R_1, R_2 and R_3 and $\mathrm{var}(\tilde{d}_1^2) \leq \mathrm{var}(\tilde{d}_2^2) \leq \mathrm{var}(\tilde{d}_3^2)$, the proposed CAP algorithm is detailed as follows:

Step 1: Employ the typical LS algorithm; obtain an initial estimation of the target nodes location, which is represented as $(\tilde{x}^(1), \tilde{y}^(1))$.

Step 2: By choosing first two anchors R_i, $i = \{1, 2\}$, we have the following two equations:

$$\begin{aligned} (x_1 - \tilde{x})^2 + (y_1 - \tilde{y})^2 = \tilde{d}_1^2 \\ (x_2 - \tilde{x})^2 + (y_2 - \tilde{y})^2 = \tilde{d}_2^2 \end{aligned} \tag{5.5}$$

where $\tilde{d}_i^2$ is the estimated distance between node R_i and node T using the unbiased algorithm of Equation 5.3. Coordinates $(\tilde{x}, \tilde{y})$ represent the estimated coordinates. Since the anchors lie on the line l, without loss of generality, we choose the x-axis in parallel with this line l to simplify the notations as shown in Figure 5.1. This condition can be easily achieved using transformations as translation, rotation and reflection. Hence, we have $y_1 = y_2$. By subtracting those two equations, after simple rearrangement we get an estimation of x:

$$\tilde{x}^{(2)} = \frac{\tilde{d}_2^2 - \tilde{d}_1^2 - (x_2^2 - x_1^2)}{2(x_1 - x_2)} \tag{5.6}$$

By substituting $\tilde{x}^(2)$ into Equation 5.5, we have:

$$
\begin{aligned}
\tilde{y}^{(2+)} &= \begin{cases} y_1 + \sqrt{\tilde{d}_1^2 - (x_1 - \tilde{x}^{(2)})^2} & \text{if} \tilde{d}_1^2 - (x_1 - \tilde{x}^{(2)})^2 \geq 0 \\ 0 & \text{if} \tilde{d}_1^2 - (x_1 - \tilde{x}^{(2)})^2 < 0 \end{cases} \\
\tilde{y}^{(2-)} &= \begin{cases} y_1 - \sqrt{\tilde{d}_1^2 - (x_1 - \tilde{x}^{(2)})^2} & \text{if} \tilde{d}_1^2 - (x_1 - \tilde{x}^{(2)})^2 \geq 0 \\ 0 & \text{if} \tilde{d}_1^2 - (x_1 - \tilde{x}^{(2)})^2 < 0 \end{cases}
\end{aligned} \tag{5.7}
$$

From 5.7 we conclude that two estimates $\tilde{y}^{(\pm)}$ can be calculated. In cases where the solution is an imaginary number, e.g., when there is no solution, we decided to assume the value $y = 0$. This situation appears in case of a high σ^2 value. We obtain two second-step estimations of y: $\tilde{y}^{(2+)}$ and $\tilde{y}^{(2-)}$.

Step 3: So far we have three estimation results: $(\tilde{x}^{(1)}, \tilde{y}^{(1)})$, $(\tilde{x}^{(2)}, \tilde{y}^{(2+)})$ and $(\tilde{x}^{(2)}, \tilde{y}^{(2-)})$. The final estimation is chosen as follows:

$$
\tilde{x}^{(3)} = \tilde{x}^{(2)} \tag{5.8}
$$

$$
\tilde{y}^{(3)} = \underset{\tilde{y}^{(2+)}, \tilde{y}^{(2-)}}{\arg\min} \left\{ \left| \tilde{y}^{(2+)} - \tilde{y}^{(1)} \right|, \left| \tilde{y}^{(2-)} - \tilde{y}^{(1)} \right| \right\} \tag{5.9}
$$

The advantage of the CAP algorithm is that it avoids ill-conditioned matrix inversion. Hence it outperforms traditional localization algorithms when having near collinear anchors as shown in the next section.

5.1.4 Analysis and simulation results

In order to evaluate the performance of our proposed algorithm, we perform simulations in MATLAB. We compare the performance of the CAP algorithm to the state-of-the-art algorithms, specifically LS, WLS and ML, and also include the Cramer Rao lower bound as a performance indicator. We consider a scenario having the minimum number of anchors (three) and one target. The target T is placed at fixed coordinates $(50, 50)$, namely in the center of a 100 x 100 m square area. We assume that the path loss value is the same throughout all area, namely $\alpha = 3$. We compute the root mean square error (RMSE) for different algorithms by running 1000 simulation runs, for shadowing variance values between -20 and 20 dB. In the first simulation, three anchors are fixed at coordinates (20, 20) and (70, 20), and (90, 30), which results in matrix condition number *cond(A)*=10.9. The position estimation RMSE versus shadowing variance using different positioning algorithms is illustrated in Figure 5.2.

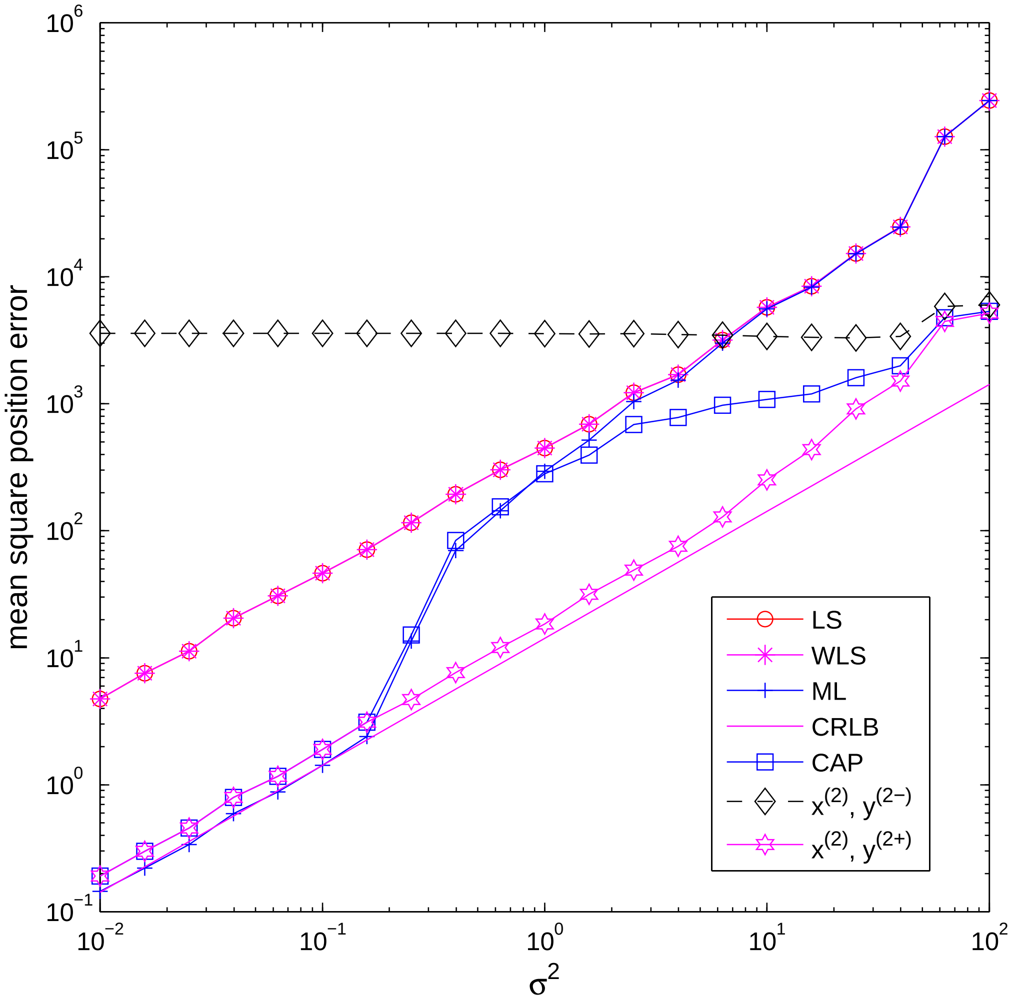


Figure 5.2: Position estimation RMSE versus shadowing variance for different positioning algorithms

It shows that for a low shadowing scenario $\sigma^2 = 0.1$, the RMSE using LS and WLS is 6.75 meter, whilst using the proposed CAP the RMSE is 1.37 meter. The proposed algorithm is about 5 times more accurate than the LS and WLS algorithms. Moreover, for medium shadowing scenario $\sigma^2 = 1$, the performance of the proposed CAP algorithm is reduced, but still showing better performance than the LS and WLS algorithm. Furthermore, for high shadowing cases $\sigma^2 = 10$, the estimation error using CAP becomes again significantly better than the conventional LS and WLS. In addition, Figure 5.2 also demonstrates that the performance of proposed CAP algorithm is comparable with the performance of the ML algorithm in low and medium shadowing conditions. The ML estimator is usually implemented using the expectation-maximization (EM) iterative algorithm, which may converge to a local maximum depending on starting values. The relatively poor performance of ML shown in Figure 5.2 is due to using the EM algorithm, and using LS estimates as its starting value. This implementation method works well for well-conditioned anchors. It also works well for near-collinear anchors having low shadowing values. As illustrated in Figure 5.2, the mean square error using ML is close to the CRLB when the shadowing variance is low, which means the distance estimation is relatively accurate. It increases as the shadowing variance increases, and finally converge to the curve using LS estimation. To better illustrate this phenomena, we demonstrate the spatial distribution of the estimated results using LS and ML for an ill-conditional scenario in Figures 5.3 and 5.4.

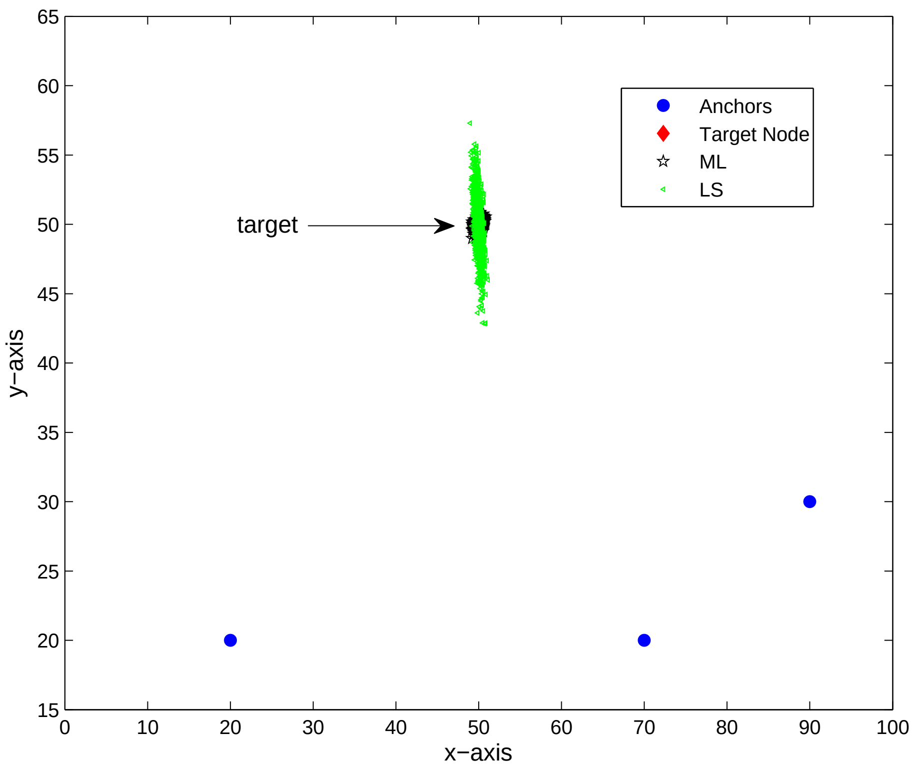


Figure 5.3: Spatial distribution of estimated values for LS and ML estimates; scenario includes 3 anchor nodes and one target node, shadowing variance is 0.01 dB

The ML estimates is capable of converging to the true target nodes when the shadowing value is 0.01.However, the ML estimates become similar to the LS estimates in a scenario with higher shadowing. Although randomly choosing multiple starting values can improve this drawback of EM, it still cannot guarantee the convergence to the global optimum, while it significantly increases the complexity.

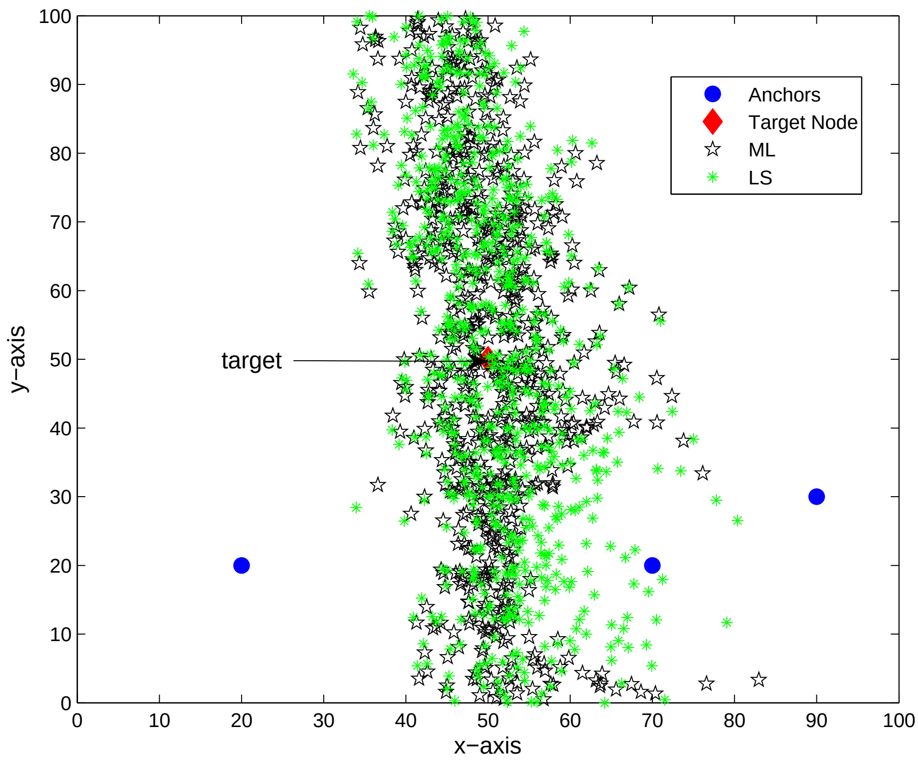


Figure 5.4: Spatial distribution of estimated values for LS and ML estimates; scenario includes 3 anchor nodes and one target node, shadowing variance is 6 dB

To sum up, ML should outperform our proposed algorithm in theory. However, using the practical EM algorithm, ML becomes worse than our proposed algorithm in practice. In a high shadowing scenario, the performance of the ML algorithm converges to the LS performance since it employs the LS estimate as its initial value before iteration. Having this implementation in mind, our proposed CAP algorithm slightly outperforms the ML solution at high values of shadowing variance. On the other hand, the proposed CAP algorithm is much more computationally efficient. Since the ML involves computationally demanding mathematical operations such as matrix inversion and matrix multiplication coupled with the iterative procedure, its complexity will be in the order of $N_iter * O(N^3)$, where N_iter is the number of iterations (in our simulations we used $N_iter = 20$), and N the number of anchor nodes. On the other hand, the CAP algorithm only involves simple algebraic operations, such as addition, subtraction and division. Therefore its computational complexity is in the order of $O(N)$.

In the second simulation, the first two anchors remain at $(20, 20)$ and $(70, 20)$, while the third anchor is moved along a circle with radius 45m in steps of 15 degrees. In Figure 5.5 we show the plot of the condition number versus the angle of the third anchor with respect to line l for a full 360 degrees circle. Furthermore, we compute the *gain* as the ratio between the RMSE for LS/ WLS and the RMSE of our CAP algorithm.

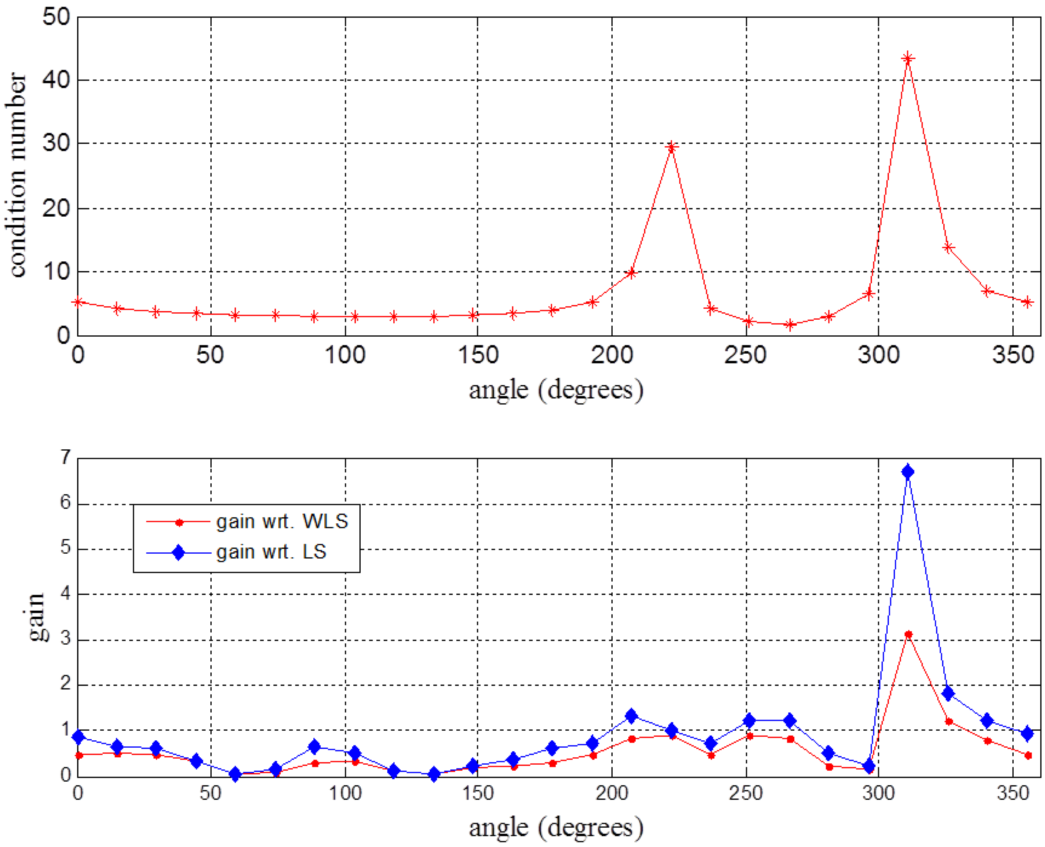


Figure 5.5: Condition number as metric for ill-conditioned scenario, and the gain of CAP vs. LS and WLS

Hence, if $gain \leq 1$, the proposed CAP algorithm provides less or equal estimation accuracy. If $gain > 1$, the proposed CAP algorithm provides higher estimation accuracy compared to the LS/WLS algorithm. As we can see from Figure 5.5, setting $\sigma^2 = 0.1$, our CAP algorithm outperforms both the LS and WLS for ill-conditioned scenarios having large matrix condition value. The gain over LS is larger than the gain over WLS, which indicates that the WLS is more robust to the ill-conditioned scenario than LS algorithm.

5.2 Use of negative information in positioning and tracking algorithms

5.2.1 Introduction

To avoid additional hardware deployment, indoor localization systems have to be designed in such a way that they rely on existing infrastructure only. Besides the processing of measurements between nodes, localization procedure can include the information of all available environment information. In order to enhance the performance of Wi-Fi based localization systems, the innovative solution presented in this section considers also the notion of negative information. An indoor tracking method inspired by Kalman filtering is also proposed.

In this section, we propose a novel solution to increase the localization and tracking performance. Basically, this is achieved by incorporating information about nodes that are *not* in range, which allows us to eliminate candidate solutions. The localization system reports the location of a mobile terminal via a map of possible locations, and the map resulted by a localization round is used, after a dispersal representing the user mobility, as the input for the successive localization round. Finally, we propose a metric to evaluate the trade-off between a correct location of the mobile terminal, and the size of the set of the possible locations, i.e. correctness vs precision.

5.2.2 Related Work

Indoor localization has been a motivating research topic and many methods have been proposed so far, including Wi-Fi, RFID and UWB localization. Indoor localization techniques can be classified into two main groups: 1) The first group uses dedicated infrastructure for positioning; in this case dedicated devices have to be installed, and 2) the other group employs previously available wireless communication infrastructures. The latter group is a cost efficient solution with large coverage, whilst high accuracy, availability and reliability can be attained. On the other hand, there is a need for more intelligent algorithms to compensate for the low performance of the measurement techniques.

Most Wi-Fi-based location approaches correspond to radio maps (fingerprinting). Although high accuracy is attainable, a complex training process is required to develop the fingerprinting database, specifically each time the environment changes.

The *Active Badge System* was an early system developed to localize mobile devices within a building [20]. Every badge identifies itself periodically, sending unique infrared signals to the receivers. Although it provides accurate location, the drawbacks of the system are poor scalability due to limited range of IR, and deployment cost. The system *RADAR* [66], based on WiFi fingerprinting, uses signal strength information from multiple receiver locations. The main idea is to record radio signals and build models for the signal propagation during off-line analysis. However the system's main disadvantage is its dependence on empirical data. The work in [130] uses neural networks based on Bayesian Regularization or Gradient Descent to obtain the location of mobile nodes from RSSI and LQI. PlaceLab [67] uses connectivity from GSM base stations and 802.11 access points. If the node density is high enough, the system achieves accuracy of 15-20 meters, which is even lower than GPS, but unlike GPS, it is capable to perform localization for both indoor and outdoor environments. Both passive and active RFID devices have been considered in [131] to provide connectivity based localization. These algorithms use signal parameters such as RSS to create a radio map of the environment. Afterwards, location is estimated by matching online measurements with the existing fingerprints, collected during the offline training phase. However, the fingerprinting method is a complex procedure that requires a training process to develop the fingerprinting database, specifically each time the environment changes. Cricket [19] is a decentralized location support system for sensors based on RF and ultrasound. Incorporating ultrasound hardware was necessary because a purely RF-based system did not provide satisfactory results. It takes into account user privacy and does not depend on underlying network technology. Still, the systems granularity is a portion of a room. Other localization techniques for wireless sensor networks are described in [132].

Particle filtering methods weigh the particles according to their likelihood. Monte Carlo estimation methods are mainly used for robot localization and tracking [133]. In principle, the procedure is divided into a prediction phase, where the robot moves and its positions uncertainty increases, and an update phase where new observations are integrated to filter and update data. Anyhow, the constraints in wireless sensors and ranging accuracy make node localization more difficult than robot localization [134].

Negative information had few applications for localization in wireless networks. Most of the work targeted problems for mobile robot localization [45, 46, 135]. In Markov localization for mobile robots, the absence of an expected measurement can be used to improve localization. The difficulties in implementing a system that uses negative information are mainly due to the lack of expected measurement readings: the target may not be there or the sensor may not be able to detect the target. To avoid false negatives, the model needs to consider possible obstructions [45]. Nevertheless, even a false attempt to detect a target can be exploited in tracking applications, based on Bayesian approach to target tracking [46]. Negative information can be integrated by generating an artificial measurement. The precondition for processing negative information is a refined sensor model. However, all these works only consider cases where an *expected* observation is missing. In [135] the authors have shown how negative information can be incorporated into *FastSLAM*, a system that is alternative to the complex Extended Kalman Filter approach for robot localization. In wireless sensor localization, Monte-Carlo localization algorithms make use of negative information [47]. However, it can be useful only in obstacle-free areas, and leads to localization errors otherwise.

The requirements on localization systems are even stricter when nodes are mobile, since for real time tracking there is a demand not mainly on accuracy, but also on latency and complexity. Kalman filtering is the most widely adopted technique for location tracking. One Kalman filter based solution making use of RSS measurements has been presented in [136]. Basically, the Kalman Filter (KF) offers an optimal solution for linear systems, where measurement errors follow a Gaussian distribution. Otherwise, the KF has to be transformed into the Extended Kalman Filter (EKF), suitable for non-linear systems [137]. The EKF consists of three phases:

1. the predict phase, which computes the a priori estimation based on the previous estimate, and

2. the update phase, that occurs when a new measurement becomes available;

3. finally, the a posteriori estimate is computed.

The current location of the node depends on the previous location, which is modeled by the state transition function; in localization problems this is basically the mobility (velocity) model.

5.2.3 Proposed technique

Composing different sources of (negative) information

This subsection proposes a technique to fuse different types of information to perform localization of a unit. The technique described is as abstract as possible, since it aims only at showing the general idea. Subsection 5.2.3 will refine the technique towards the implementation in a simple wireless scenario, and Section 5.2.4 will provide information about the implemented system.

We propose a model where localization procedure makes use of different sources of information, that can comprise sources of negative information. In this respect, positive information means that some data is saying "you can be here", while data bearing negative information is saying "you can not be here". The main idea behind the system is to provide a framework to compose different kinds of information that can contribute to the localization process. Instead of applying only positive reasoning, an alternative way is to consider all the locations in the area, and provide a technique to evaluate how "unlikely" a mobile unit to be located in a given position. Our approach to localization is based on the fact that "when you have eliminated the impossible, whatever remains, however improbable, must be the truth" [138]. In fact the proposed system exploits all the available information to all possible mobile locations, resulting in a normalized probability map of probable locations.

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

$$e = V_{x,y} - m \tag{5.10}$$

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

$$p_{x,y}(m) = F_{x,y}(e) = F_{x,y}(V_{x,y} - m) \tag{5.11}$$

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

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

$$M'(x, y) = M(x, y)p_{x,y}(m) = M(x, y)F_{x,y}(V_{x,y} - m) \tag{5.12}$$

If we start from a probability map where all the probabilities are, for example, equal to 1, we will end up with a map where a number of locations are ruled out, while a set of locations are still quite probable. Now we apply the normalization process, where all the probabilities are multiplied by the same number such that the maximum value in the probability map is 1. On the other hand, if we consider that we have already localized the mobile terminal, a special source of information that we can apply to the probability map is the history of the mobile terminal location. The map obtained in the previous localization step is used as input for the following localization round, after applying a dispersal algorithm to represent the user mobility.

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

It is possible to apply a threshold τ to the probability map, to consider that the mobile unit can be in all the locations where the probability value is higher than τ, while it can't be in the locations where the probability is lower than τ. The threshold is useful both for visualization purposes, and as a metric for the localization:

- From the point of view of the visualization, the threshold is used to show the final user a map with only the locations where the user is likely to be located.

- As a metric, while tuning up the technique, it is possible to consider the size of the "feasible locations" map, and the distance between this area and the real location of the user. The more stringent the threshold, the smaller the "feasible location" area, but the more probable that the real user location will fall out of the "feasible location" area. Hence, it is possible to experiment with the threshold to evaluate the trade-off between a correct location of the mobile terminal, and the size of the set of the possible locations, i.e. correctness vs precision.

The proposed technique is able to provide two main benefits:

- composition of information from multiple sources: every source of information is considered with its error and its distribution, to evaluate the compatibility of the measurement with a given location (x, y). Moreover, the probability of location (x, y) is just the multiplication of all the probabilities that are extracted from the single measurements;
- exploitation of negative information: we are not giving value only to information that validates a given location. On the contrary, we consider valuable all the information, for example the absence of the RSS from an access point. In this case, the system would estimate the probability for the signal to be low enough not to be received, and would exploit that probability for generating the probability maps.

Implementing the proposed technique

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

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

We limit the system to using a simple lognormal signal model [139] to translate the RSS values to distances, and hence to probabilities for given locations. We are aware of the limitations of this model in terms of predicting power for the RSS, but we chose it on purpose to test our proposed technique against poor signal processing techniques. If the system will be able to perform reasonably, we can conclude that applying refined signal processing techniques and a more reasonable signal propagation model, such as the ones described in [119] and [140], would further improve the localization performance.

When the user localization performed in a given round, is used as a basis for a new localization, a dispersal algorithm is applied to the map. In particular, it is considered that the user can move up to a speed v measured in meters/seconds, and that the localization algorithm uses measurements taken every θ seconds. In the rest of the discussion, we use the symbol M_i to address the localization map obtained after the application of the algorithm in round i, and M'_{i+1} for the map that is feed into the localization algorithm for round $i+1$. Both maps are functions of $M(x, y)$ from a pair of coordinates (x, y) to a number that is the probability density that a terminal is located in (x, y). The map M'_{i+1} is computed as follows:

1. for each location (x', y') of the map M'_{i+1}, area $A_{x',y'}$ is the set of points in M_i that are at most at distance $v\theta$ from (x', y'), that is,

$$\begin{aligned} A_{x',y'} &= \{(x, y) \in M'_{x',y'} \\ &\quad \textbf{with } (x - x')^2 + (y - y')^2 < (v\theta)^2\} \end{aligned} \tag{5.13}$$

2. for each point $(x, y) \in A_{x',y'}$, $M_i(x, y)$ is added to $M'_{i+1}(x', y')$, that is,

$$M'_{i+1}(x', y') = \sum_{(x,y)\in A_{x',y'}} M_i(x, y) \tag{5.14}$$

3. an optional step is to perform the normalization of the map M'_{i+1}, to have either

$$\max_{(x',y')} M'_{i+1}(x', y') = 1$$

or

$$\sum_{(x',y')} M'_{i+1}(x', y') = 1$$

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

$$V_{x,y} = RSS_0 - 10 * \alpha * \log(d/d_0) \tag{5.15}$$

where RSS_0 is the received power at reference distance d_0 (we assume the usual value for reference distance $d_0 = 1m$), α is the path loss exponent. The functions for LOS and NLOS differ only for the values of RSS_0 and n_p, and this translates into two system-wide set of parameters for the signal propagation, one set applied to all the access points with LOS access, and the other set applied to access points with NLOS. In both cases, we consider that the error on the received signal strength has Gaussian statistics, with 5 dBm width for the LOS signal, and 7 dBm for the NLOS signal, as suggested in [141]. When a signal is missing, we consider it as a poor signal, and we set its RSS to the value of -70 dBm.

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

5.2.4 Experiments

We illustrate our model based on measurements performed on the second floor of the Instituto de Telecomunicações building (Figure 5.6). The dimensions of the area are about 50 m by 50 m. There are three access points in an indoor environment (represented on Figure 5.6 by a lightning icon). We recorded measurements from a laptop to the access points, at several locations in the building. Communications are performed by using the WLAN 802.11g standard. The speed of the mobile terminal when performing tracking is $v = 1m/s$, and the measurements used to perform localization are taken every $\theta = 4s$.

Tuning of the system

Measurements were taken on the locations shown in Figure 5.7. WiFi Hopper[142] was used as a tool to record the received signal strength at the mobile station from the infrastructure (access points). WiFi Hopper is a WLAN utility with the ability to display network details like type of network, network mode (infrastructure or ad-hoc), received signal strength (RSS values), frequency and channel, encryption type etc.

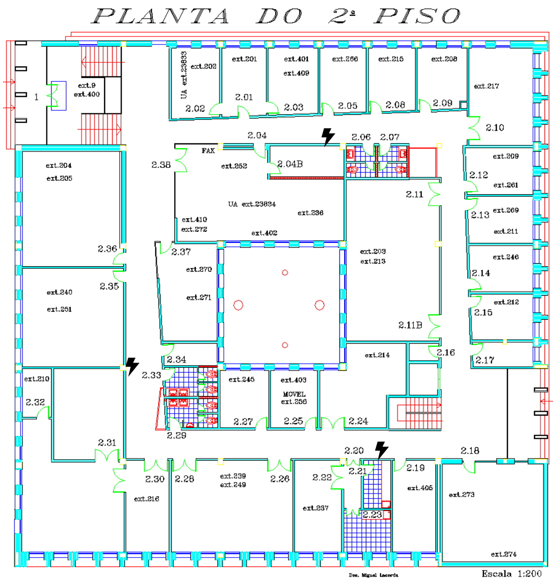


Figure 5.6: Floor 2 of the Instituto de Telecomunicações, and access points' location.

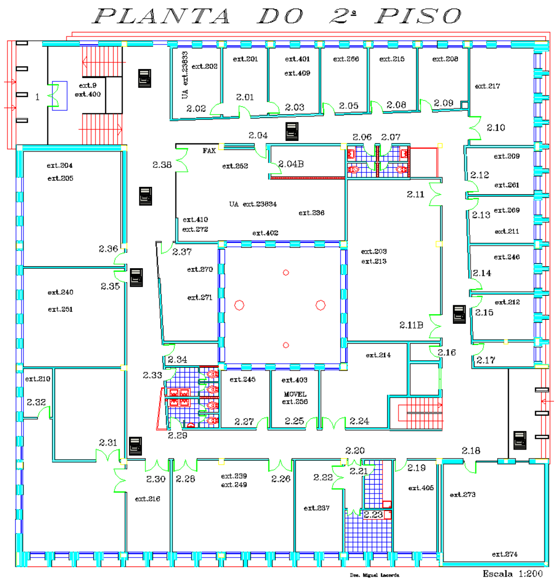


Figure 5.7: Locations where data were taken for the tuning of the mobility model.

We performed several measurements inside the building using a Toshiba Satellite laptop equipped with an Atheros network adapter, running Windows Vista and using the basic drivers the operating system is shipped with.

RSS values from all three access points were collected, both with and without Line of Sight. As stated in Subsection 5.2.3, to translate RSS values into distances d, we use the simple lognormal model, shown in Equation 5.15, where RSS_0 is the received power at reference distance d_0 (we assume the usual value for reference distance $d_0 = 1m$), n_p is the path loss exponent.

The simplified path loss model is defined for example on page 40 of [143] as:

$$P_r(\text{dBm}) = P_t(\text{dBm}) + K(\text{dB}) - 10\alpha \log \frac{d}{d_0} \tag{5.16}$$

In Equation 5.16, K is a constant which depends on the environment. When the simplified path loss model is used to approximate experimental measurements with line of sight, the value of K can be set to the free space path loss at reference distance d_0. Knowing that the EIRP for the access point is 15dBm, and the 2.4GHz frequency offers a path loss at reference distance $1m$ of 39.9dB (calculation based on the Free Space model), we adopt the value of -24.9dBm for RSS_0. As we can see from Figure 5.8, for the case when measurements were taken from access points that have Line of Sight connection, the data fit returned value $\alpha = -1.827$.

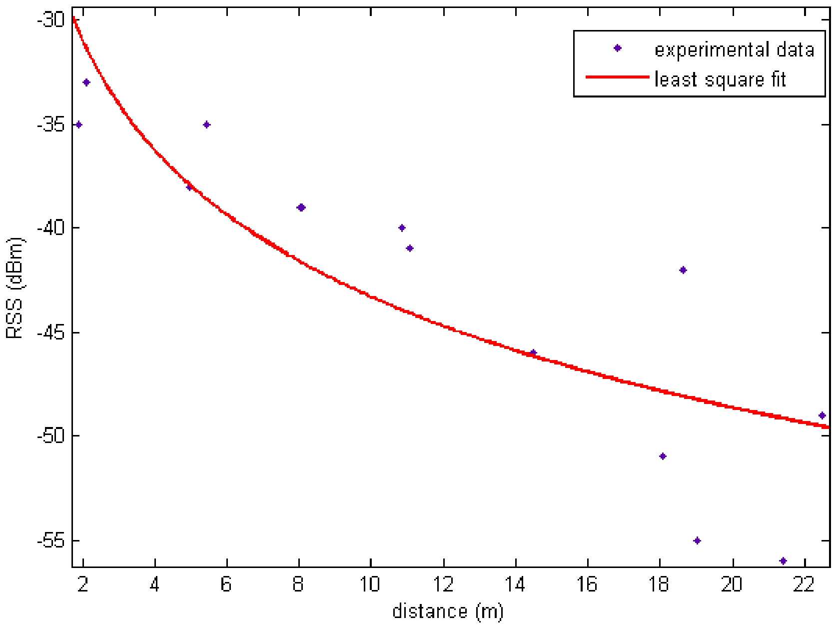


Figure 5.8: Fit for the simple lognormal parameters, access points in Line of Sight.

For the NLOS case we determine the constant K together with n_p by applying the least square fit to experimental data. Having in mind that the EIRP is identical as in the LOS case, we obtained the values $\alpha = -5.769$ for the path loss exponent, and $K = 11.58$. The fit based on experimental data can be seen in Figure 5.9. A rather small number of total measurements provided us a rough approximation of the parameters for the simple lognormal model.

However, for accurate modeling of propagation parameters, it would be essential to predict complete received signal statistics and consider the effect of variable shadowing due to the movement of people in the observed area[144]. Empirical calculation of those parameters needs to consider losses originating from obstacles of varying material, size and number[145]. In both cases, the fit that we used reported a pretty unprecise matching with the values, hence we can predict that the localization system will not provide perfect localization, but will have to exploit the composition of all available information, with the goal of providing a good localization of the mobile unit.

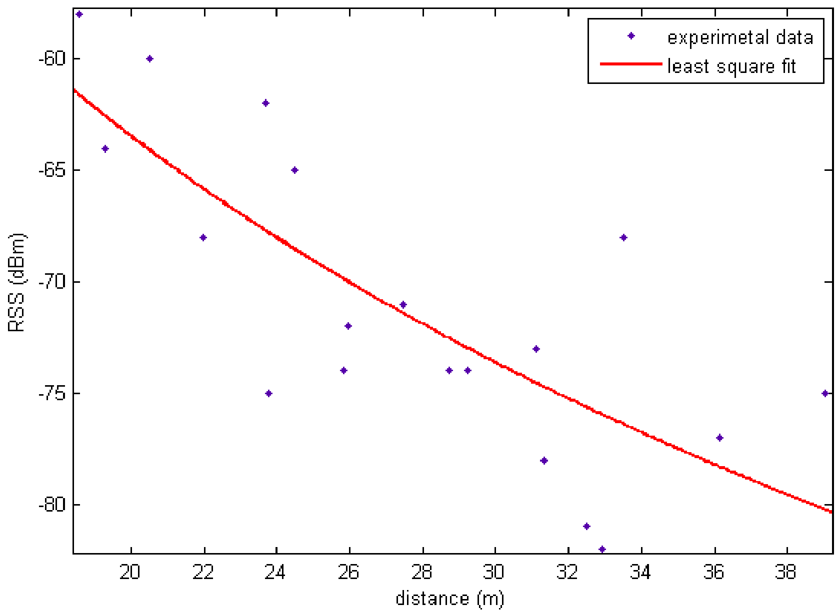


Figure 5.9: Fit for the simple lognormal parameters, access points NOT in Line of Sight.

Localization of the mobile unit

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

Figures 5.10, 5.11, 5.12 and 5.13 show the localization of the same mobile unit, represented in the figures by a small white + sign. The first three figures represent the probability maps for each of the access points (where + is the mobile unit, and the small thunder is the access point). Even though the real location of the mobile unit matched with the probability map, the localization was not precise since a number of locations featured a high compatiblity with the RSS measurement. Figure 5.13, on the other hand, constitutes the composition of the probability map of all the access points. The result shows that the mobile unit is considered to be in a well defined area, either in the corridor, which is its actual position, or in the room nearby.

Figures 5.14, 5.15, 5.16 and 5.17, show more probability maps. In each of the figures, all the three RSS measurements were used, and the real location is represented by a small

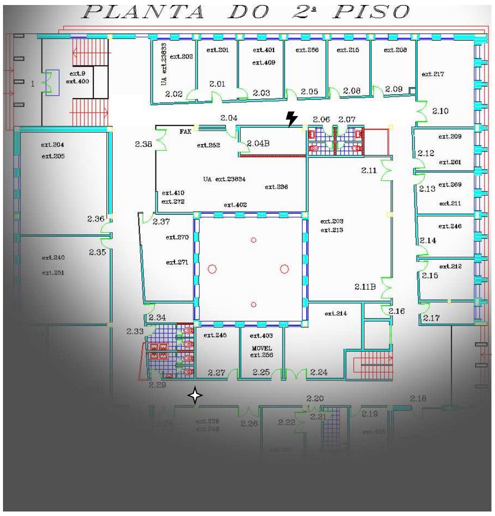


Figure 5.10: Probability map when using only the first access point.

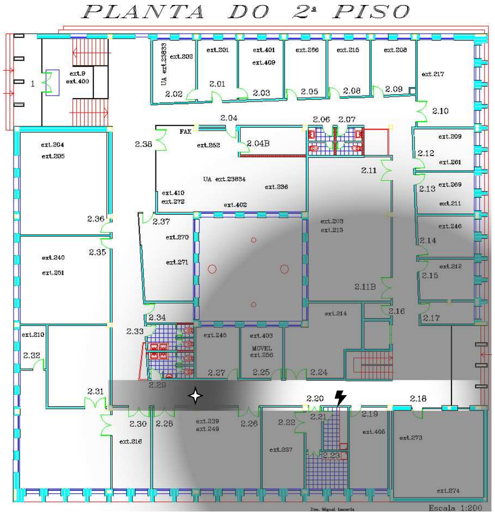


Figure 5.11: Probability map when using only the second access point.

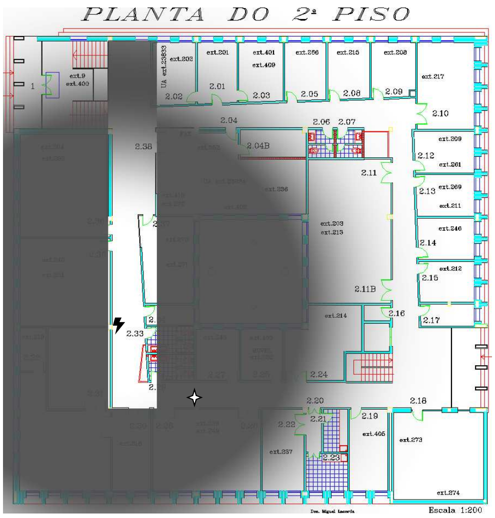


Figure 5.12: Probability map when using only the third access point.

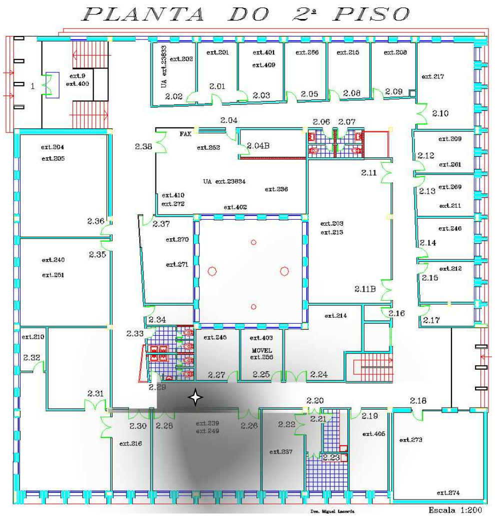


Figure 5.13: Probability map when combining all available information.

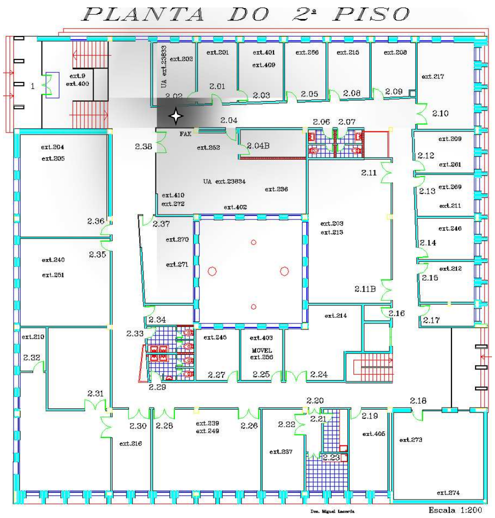


Figure 5.14: Localization with one access point with LOS, two with NLOS.

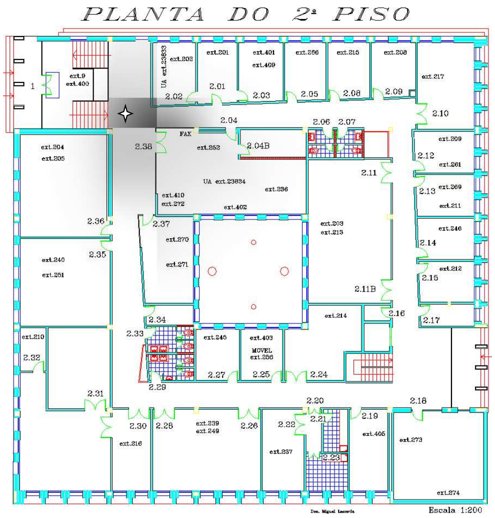


Figure 5.15: Localization with two access points with LOS, one with NLOS.

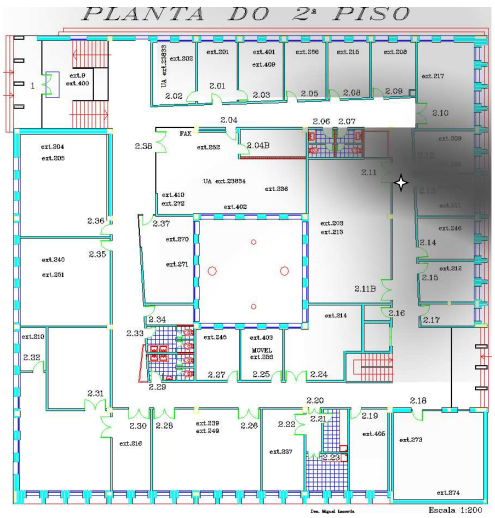


Figure 5.16: Localization with three access points with NLOS.

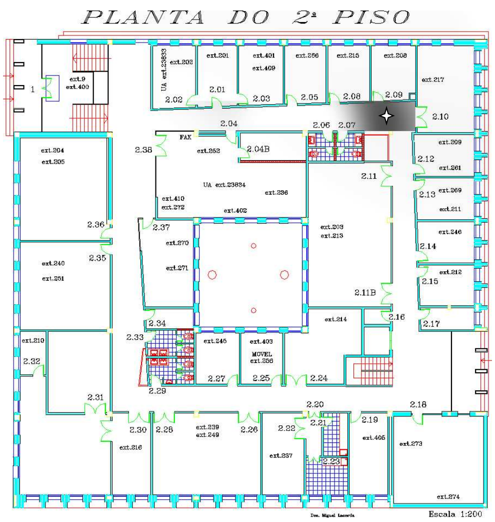


Figure 5.17: Localization with one LOS access point, two NLOS access points.

white + sign. Figures 5.14 and 5.15 compare the localization results when a mobile unit moves from a location where it has just one LOS access point, to a location where it has two LOS access points. Figure 5.16 shows the behavior of the technique when there are no access points in LOS, and it confirms the limitations of the signal model we are using (simple lognormal model). Finally, Figure 5.17 shows another scenario with only one LOS access point, and the localization is quite precise. We see that in some cases the method gives fairly good results. Nevertheless, we have to keep in mind that the applied channel model is very simple, serving only to illustrate the proposed scheme.

5.2.5 Tracking by means of probability map recycling

The experiments involving the tracking of a mobile unit involved using the posterior probability, computed at the end of a localization process, as the priori map for the successive round. Between the computation of the posteriori and its use as priori, a dispersion round is executed on the map, in which every location on the map adds to its own localization probability, the localization probability of all the locations in range, given a mobility model that predicts users will move at $1m/s$ and that the localization is executed once every 4 seconds.

The figures 5.18-5.27 provide a comparison of localization maps when the probability map is recycled, and when the previous state is ignored and localization is performed from scratch. In each figure, a small white + sign shows the real location of the mobile terminal. It is clear that the systems tracking capabilities improved the system by ignoring locations that do not match with previous estimates, hence reducing the set of potential solutions.

A metric to tune up the localization system

The metric proposed in Subsection 5.2.3 is applied here to the probability maps obtained by localization. In particular, figures 5.28-5.31 show the size of the "feasible location" areas, when the system considers respectively 1% and 0.5% of the best locations on the map. It is seen that "recycling" the old probability map gives a very good result in terms of the distance between the real location of the MT and the "feasible locations".

Figure 5.32 shows the results of an experiment when applying the different thresholds (1% and 0.5%) to the path analyzed in Section 5.2.5, both using and not using the old "a posteriori" map as the next "a priori". The figure shows the distance between the real location of the MT and the "feasible locations" map against the step of localization. Each

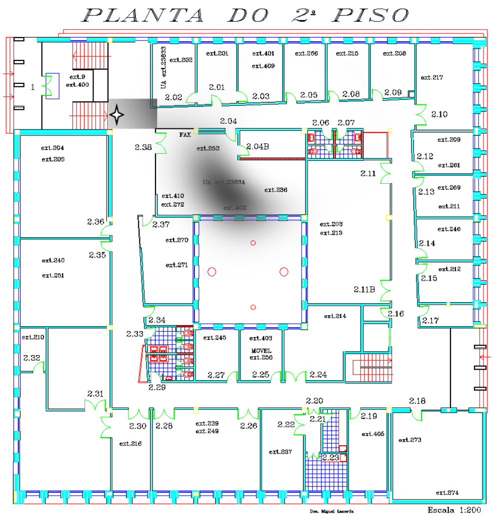


Figure 5.18: Localization *without* recycling the old map as an “a priori”.

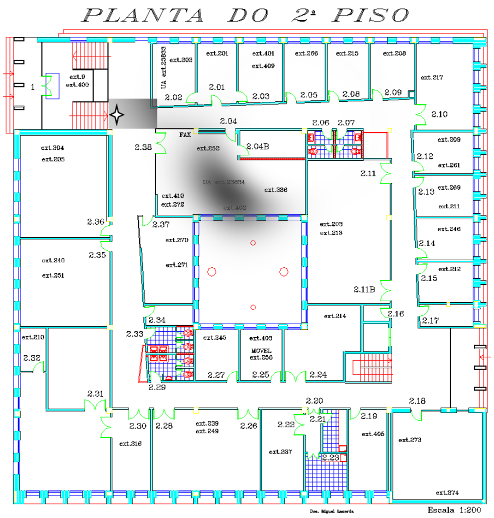


Figure 5.19: Localization using the old localization map as an “a priori”.

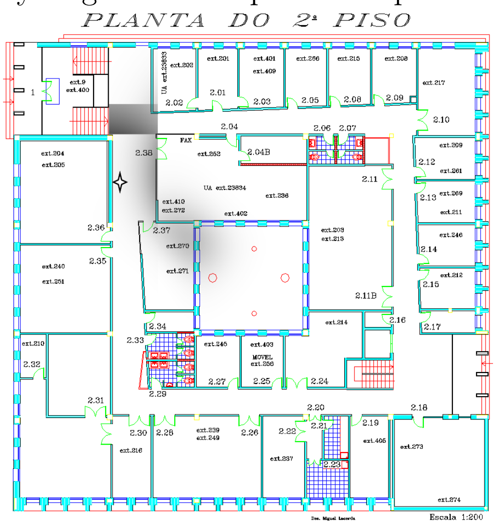


Figure 5.20: Localization *without* recycling the old map as an “a priori”.

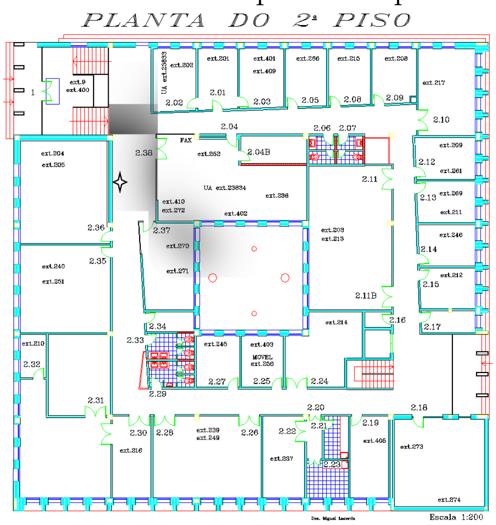


Figure 5.21: Localization using the old localization map as an “a priori”.

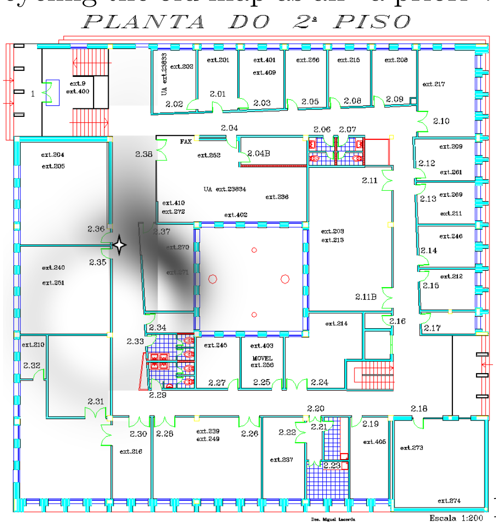


Figure 5.22: Localization *without* recycling the old map as an “a priori”.

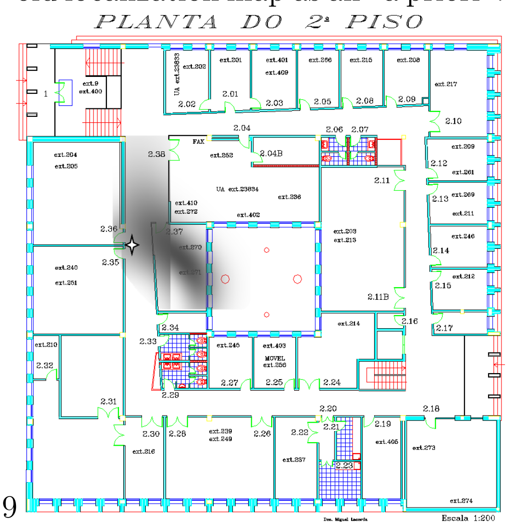


Figure 5.23: Localization using the old localization map as an “a priori”.

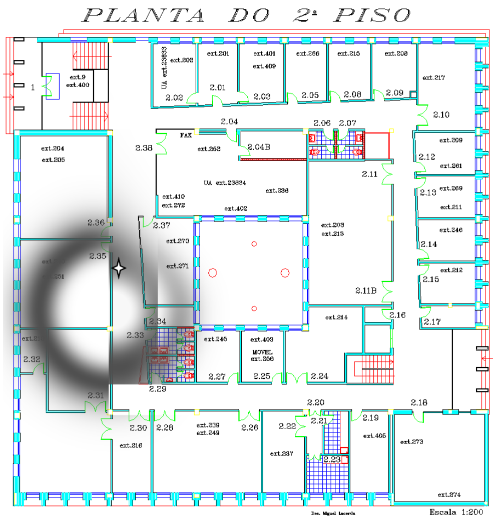


Figure 5.24: Localization *without* recycling the old map as an “a priori”.

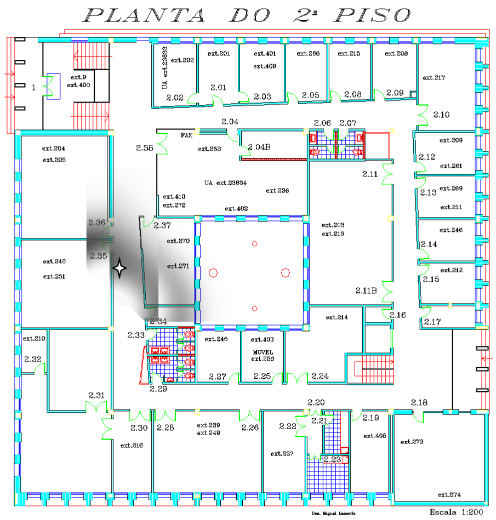


Figure 5.25: Localization using the old localization map as an “a priori”.

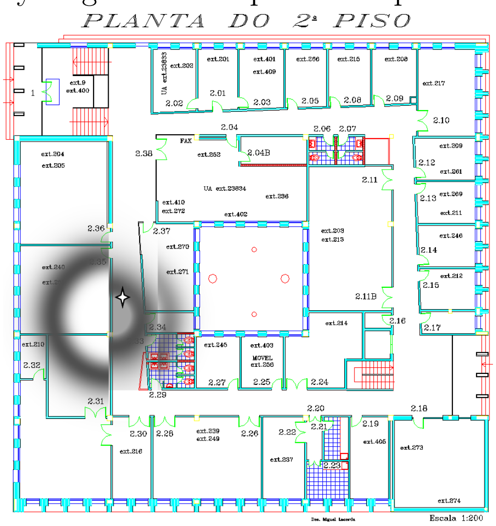


Figure 5.26: Localization *without* recycling the old map as an “a priori”.

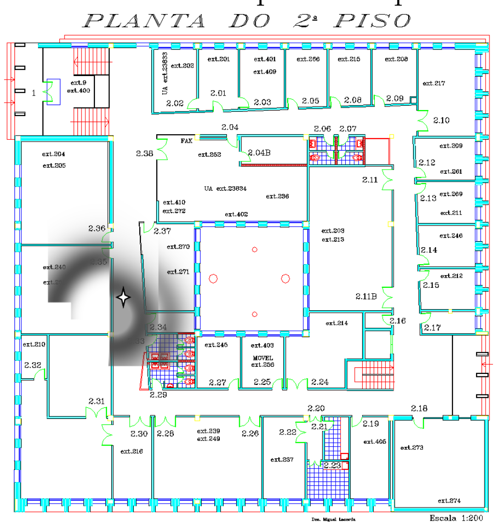


Figure 5.27: Localization using the old localization map as an “a priori”.

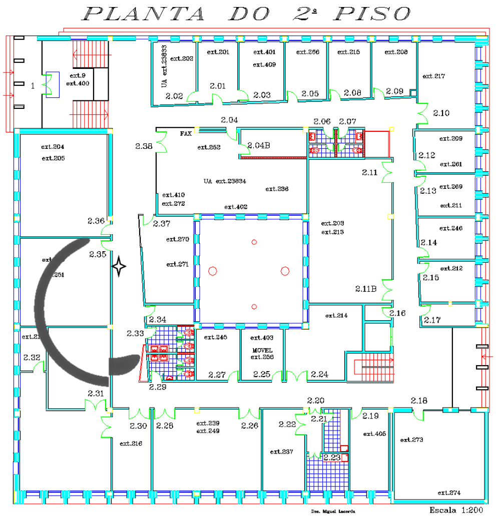


Figure 5.28: Localization *without* recycling the old map, threshold at 1%.

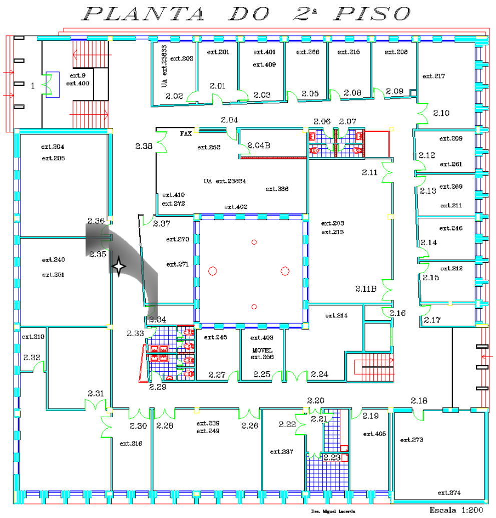


Figure 5.29: Localization using the old localization map as an “a priori”, threshold at 1%.

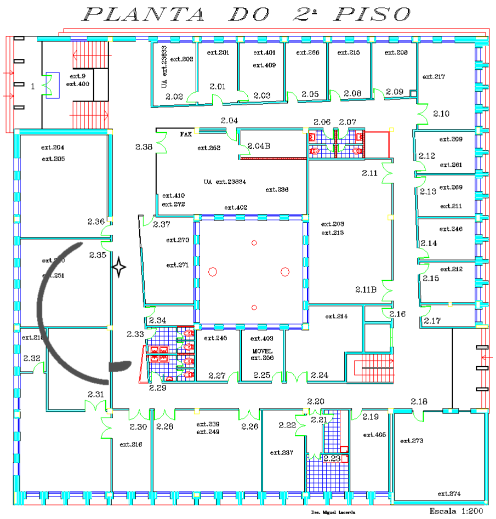


Figure 5.30: Localization *without* recycling the old map, threshold at 0.5%.

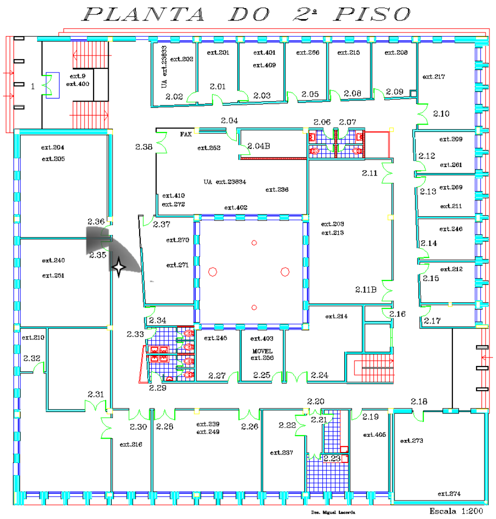


Figure 5.31: Localization using the old localization map as an “a priori”, threshold at 0.5%.

point represents a location on the map where we collected measurements about the signal strengths, computed the probability maps using the different strategies, and measured the distance between the real location and the closest point on the probability map. We collected 11 measurements for each strategy that was taken into account.

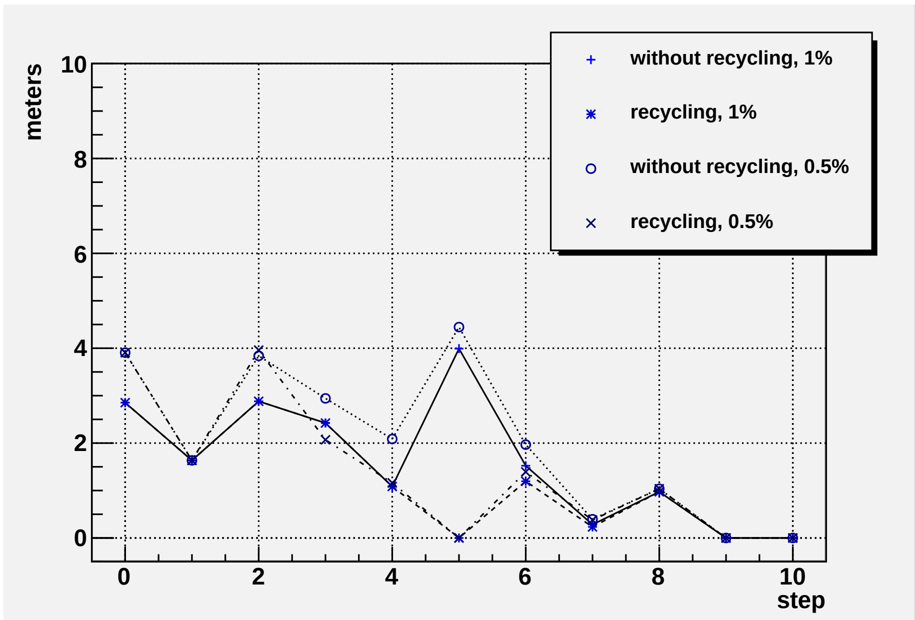


Figure 5.32: Comparison of "recycling the a priori" algorithm against localizing without an "a priori", using the metric of Subsection 5.2.3.

It is clear that there is a trade off between the size of the "feasible locations" map and the distance to the real location. The smaller the map is, the greater the precision of MT localization. On the other hand, it can be observed that in certain cases the real location of the MT is not inside the "feasible location" regions when the map is smaller, hence a lower threshold decreases the performance of the localization technique.

Thus, in a real deployment scenario, it will be necessary to consider the threshold for the "feasible locations" regions as a trade-off between precision and localization reliability.

5.3 Conclusion

In Section 5.1.4 we have proposed the CAP algorithm that performs well under ill-conditioned scenarios where the anchor nodes are almost collinear, which can likely occur in public safety scenarios. The proposed algorithm has been shown to provide up to seven times more accuracy than the traditional LS and three times more than WLS algorithms, whilst showing almost three orders of magnitude less in terms of complexity. In our future work we intend to apply different channel parameters for each link, since an identical channel model does not represent realistic indoor channel conditions appropriately. However, our assumption serves well for the proof-of-concept of the proposed method.

Indoor localization is still a challenging research topic. One way to improve the positioning procedure is to make use of all available environmental information. In Section 5.2.5 we have shown how negative information (information about where the mobile unit is *not*) can be incorporated into an indoor positioning scenario. We showed the proof of concept for the proposed strategy, given that we applied a simple channel model, and assumed independent measurement errors. In addition, inspired by tracking algorithms, we extended our approach by exploiting the history of mobile terminal's location to assist the computation of the terminal location. The method based on probability map recycling outperformed the basic implementation.

For illustration purposes, we used a simple lognormal model without taking into account spatial correlation. However, correlated shadowing is shown to have significant impact on system performance in WLAN networks [146]. If a signal in a certain direction is attenuated by an obstruction, it is very likely that a received signal in close proximity is experiencing a similar shadowing effect. The assumption that shadowing losses are correlated among nearby links has been verified by experimental measurements [147]. Therefore is it important to improve statistical propagation models and include them in the localization algorithms, which is an item for future work.

Chapter 6

Conclusion and future work

In this chapter, we summarize the obtained results and the reached conclusions and we give some directions for intended future work.

6.1 Conclusion

- In Chapter 1 we outlined the main motivations to investigate the problem of indoor localization. We presented the principal application areas and gave a historical overview on development of positioning techniques, from GNSS and cellular to short-range and indoor techniques.

- Chapter 2 contains the state of the art on wireless localization systems. We assessed the ranging techniques and the range-based positioning methods. The latter can be classified into deterministic and statistical techniques. We also provided a brief overview of fingerprinting solutions, although they are not the subject of this thesis. We place particular emphasis on cooperative positioning, and present the state of the art solutions, highlighting their advantages and drawbacks. Among the vast number of cooperative positioning applications, we emphasize the use in heterogeneous environments. This subject has not been well investigated yet, and might deliver the ultimate solution for indoor positioning [148].

  After presenting various algorithms and methods for position determination, we list the performance metrics used to evaluate and compare different approaches. Even though we intuitively think of accuracy when it comes to assessing the quality of localization algorithms, there are other metrics that we must cosider, such as cost (computational and deployment cost), robustness and scalability.

- In Chapter 3 we addressed the problem of the reference node selection. The problem has been widely addressed in the area of localization, but mainly for homogeneous networks. We present the most commonly used selection criteria, and propose a way to extend them to cover the aspect of heterogeneous networks. Furthermore, we also consider imperfect knowledge of the reference nodes, e.g., their uncertainty.

  One way to address the node selection problem is by modeling the localization process as a cooperative game. In Section 3.4 we reviewed the basic principles of cooperative game theory, and show how network components can be mapped to game components. Then we presented a utility based node selection scheme. Despite providing good results, the initial scheme suffers from drawbacks, such as vast computational requirements due to the combinatorial search complexity. Thus we proposed a randomized search method that exploits spatial correlation and still provides favourable results.

- In Chapter 4, we consider the node selection for a mobile target. The scenario is heterogeneous,i.e., a multi-RAT aided mobile device capable of communicating not only with the WI-FI access points, but also peer nodes such as fixed Zigbee sensors or other mobiles nodes (if cooperation is supported). The peer nodes have a higher spatial density and can thereby significantly improve the positioning accuracy, but since they are energy constrained their use should be kept to a minimum. Hence we propose an energy efficient cooperation strategy to minimize the power consumption while keeping the positioning accuracy at a required level. Inactive nodes will not waste energy while collecting, processing and communicating measurements.

  We also evaluate the node selection scheme using experimental data obtained during a WHERE2 measurement campaign at the premises of the German Aerospace Center (DLR). The setup contains ZigBee anchors that are located in a small open space area and the positioning system is over determined. We compared the localization accuracy when using a combination of anchors that provides the lowest CRLB with the randomly selected anchors approach.

- Chapter 5 considers two specific cases of wireless localization. First we proposed a low-complexity algorithm for ill-conditioned scenarios where conventional algorithms fail to provide reasonable results. Ill-conditioned scenarios are where the anchor nodes are almost collinear, that can occur in public safety scenarios among other places.

In the second part of Chapter 5 we proposed a novel solution to increase the localization and tracking performance. Basically, this is achieved by incorporating information about nodes that are not in range, which allows us to eliminate candidate solutions. The novelty of the method is based on exploiting negative information for indoor positioning and tracking scenarios. It is based on probability map recycling. As in most tracking algorithms, the history of mobile terminal's location can be exploited to assist the computation of the terminal location.

6.2 Future work

There are number of possibilities for future research. In the following, some research directions are mentioned:

- We began our investigations considering a static scenario, which we extended by incorporating mobility in the target node. However, in a realistic scenario the peer nodes from the scenario in Section 4.1.5 could also be moving. Such a scenario that incorporates both target and peer nodes mobility imposes several challenges that have to be considered. The peer nodes would have to frequently update and communicate their position to the access points, and thus the communication overhead would be excessive, in addition to impacting the latency. All these criteria will have to be studied and evaluated in more detail, imposing new design requirements on the localization approach.

- The utility based node selection scheme in 3.5 faces the problem of combinatorial search complexity. We addressed this issue by exploiting spatial correlation, discarding redundant reference nodes and thereby reducing the search space. Nevertheless, heuristic search methods could be applied to reduce the search complexity without the need for understanding the whole topology and nodes' mutual geometry. We aim at investigating further these methods, in a bid to advance further the node selection algorithm.

- Throughout this thesis we assumed a channel model based on parameters commonly assumed in the literature. The next step would be to evaluate the node selection scheme from Section 3.5 and the dynamic scenario from Section 4.1.5 using on-site experimental results, similarly to the preliminary results presented in Section 4.2.1.

Even though the indoor localization problem has been a research topic for more than a decade, the ultimate solution is still a topic for future research. Experts presume that mass-market indoor positioning will continue to improve slowly, using hybrid and heterogeneous schemes that take advantage of every radio source available [148].

Appendix A

Extended Kalman Filter

Kalman filter is a controlled process that is governed by a linear stochastic difference equation. This algorithm uses a statistical approach in object location estimation. In a situation where the process or system is non-linear, EKF is employed. The non-linearity of the system can be associated either with the process model, with the observation model or with both. The linearization ability is the major difference between EKF and KF algorithm.

In the extended Kalman filter, the state transition and observation models need not be linear functions of the state but may instead be differentiable functions. The solution uses a Taylor expansion and truncates the models in the linear terms, obtaining expressions for the models equivalent to equations (2.21) and (2.22) a. The difference is that the terms **A** and **H** are now the Jacobian matrices instead of model specific parameters. Thus, those Jacobian matrices can be defined as:

$$\mathbf{A} = \frac{\partial f}{\partial \tilde{x}} \left(\tilde{x}_{k-1}, U_{k-1}, 0 \right) \tag{A.1}$$

$$\mathbf{H} = \frac{\partial h}{\partial \tilde{x}} \left(\tilde{x}_{k}, 0 \right) \tag{A.2}$$

The prediction stage of the EKF is defined by:

$$\begin{aligned} \hat{x}_{k|k-1} &= f(\hat{x}_{k-1|k-1}, u_{k-1|k-1}, 0) \\ \mathbf{P}_{k|k-1} &= \mathbf{A}_k \mathbf{P}_{k-1|k-1} \mathbf{A}_k^T + \mathbf{Q}_{k-1} \end{aligned} \tag{A.3}$$

Correction:

$$
\begin{aligned}
&\mathbf{K}_k = \mathbf{P}_{k|k-1}\mathbf{H}_k^T(\mathbf{H}_k\mathbf{P}_{k-1|k-1}\mathbf{H}_k^T + \mathbf{R}_k)^{-1} \\
&\hat{x}_{k|k} = \hat{x}_{k|k-1} + \mathbf{K}_k(\mathbf{Z}_k - h(\hat{x}_{k|k-1}, 0)) \\
&\mathbf{P}_{k|k} = (\mathbf{I} - \mathbf{K}_k\mathbf{H}_k)\mathbf{P}_{k|k-1}
\end{aligned}
\tag{A.4}
$$

One of the drawbacks of the EKF approach for stochastic filtering is the linearization of the models. This linearization depending on the application can have a high impact concerning the errors in the estimated mean and covariance. The problem gets more and more evident with the increasing importance that higher order terms have in the nonlinear model.

Unlike its linear counterpart, the EKF in general is not an optimal estimator. Furthermore, if the initial state estimate is wrong, or if the process is modeled incorrectly, the filter may quickly diverge, owing to its linearization.

Appendix B

Simulation setup description

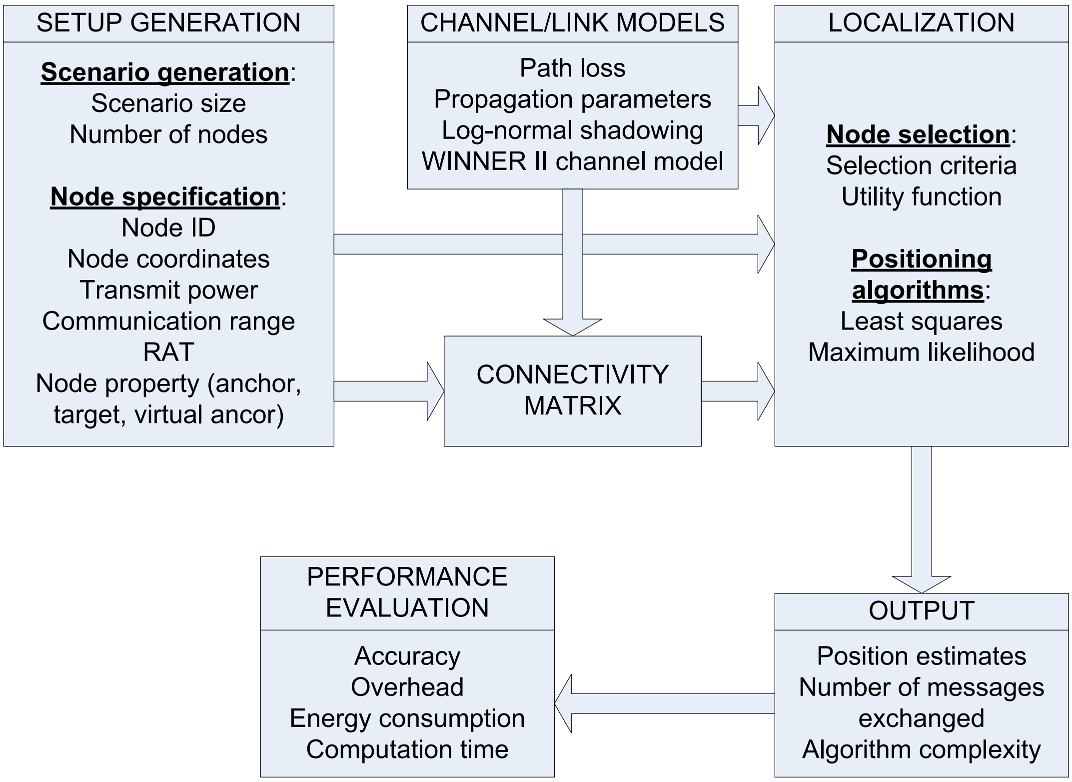


Figure B.1: Simulation setup

Here we describe our simulation modules. We start with the setup generation, where we specify the scenario size and the number of nodes. The nodes are placed either randomly or, in few cases, deterministically. Then we specify the nodes, by assigning attributes such as 'Node ID', position, transmit power and communication range. Since we consider a heterogeneous scenario, we also have to specify the RAT of each node. Finally, we have to distinguish between anchors, targets and virtual anchors.

The second module is the channel/link model block, where propagation parameters are generated. We consider RSS based localization, and the model we used is lognormal shadowing.

$$P_r = P_0 - 10\alpha\log_{10}(\frac{d_{ij}}{d_0}) + X \tag{B.1}$$

where P_r is the received power in decibels, P_0 is the received power at reference distance d_0 (usually at one meter) from the transmitter in decibels. d_{ij} is the distance between node i and node j. α is the path loss exponent, while X is a zero mean Gaussian random variable with variance σ^2 and represents the shadowing component. X accounts for randomness of the environment. Depending on the RAT, the communication range and channel parameters α and σ^2 will vary.

Based on the information of node coordinates and communication range, we form a connectivity matrix, whose elements are zero for nodes not connected to each other. This allows us to have an overview which nodes are able to communicate with each other.

The core part is the localization block. Here the computation takes place. We use as input the previously described modules, and before performing the localization itself, we analyze different setups based on reference node selection criteria. The selection criteria we used are the Cramer Rao lower bound (CRLB), Geometric dilution of precision (GDOP) and the Squared position error bound (SPEB) from 3.3.

B.1 Selection criteria

The CRLB for RSS based localization is:

$$CRLB_{RSS} = \frac{1}{b}\frac{\sum_{i=1}^{N} d_i^{-2}}{\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\frac{d_{\perp ij}d_{ij}}{d_i^2 d_j^2}} \tag{B.2}$$

where d_{ij} is the distance between anchor nodes i and j and $d_{\perp ij}$ is the shortest distance from the target node to the line segment connecting nodes i and j, and the term

$$b = (\frac{10\alpha}{\ln 10\sigma_{RSS}})^2 \tag{B.3}$$

accounts for channel parameters.

The GDOP is given by

$$GDOP = \sqrt{tr(G^T G)^{-1}} \tag{B.4}$$

where G is the following geometry matrix:

$$G = \begin{bmatrix} a_{1x} & a_{1y} & 1 \\ a_{2x} & a_{2y} & 1 \\ ... & ... & ... \\ a_{Nx} & a_{Ny} & 1 \end{bmatrix} \tag{B.5}$$

The term $a_i = (a_{ix}, a_{iy})$ is the unit vector from target t to anchor i:

$$\begin{aligned} a_{ix} &= \tfrac{x_i - \tilde{x}_t}{\sqrt{(x_i-\tilde{x}_t)^2 + (y_i - \tilde{y}_t)^2}} \\ a_{iy} &= \tfrac{y_i - \tilde{y}_t}{\sqrt{(x_i-\tilde{x}_t)^2 + (y_i - \tilde{y}_t)^2}} \end{aligned} \tag{B.6}$$

Finally, the SPEB in closed form for RSS localization is given by:

$$SPEB = \frac{\sum\limits_{i=1}^{N} \frac{1}{\beta_i}}{\left(\sum\limits_{i=1}^{N} \frac{\cos^2\phi_i}{\beta_i}\right)\left(\sum\limits_{i=1}^{N} \frac{\sin^2\phi_i}{\beta_i}\right) - \left(\sum\limits_{i=1}^{N} \frac{\sin\phi_i \cos\phi_i}{\beta_i}\right)} \tag{B.7}$$

where ϕ_i denotes the angle from i-th anchor to the target, i.e., $\phi_i = \tan^{-1}\frac{y_t - y_i}{x_t - x_i}$, and β_i accounts for both anchor uncertainty (ω_i^2 is the variance of a priori knowledge of anchor location) and distance estimation uncertainty:

$$\beta_i = \omega_i^2 + \varepsilon d_i^2 \tag{B.8}$$

The existence of this closed-form expression facilitates the node selection when uncertainties in anchor positions have to be considered. The exploitation of spatial correlation from Section 3.5.2 is also done in this block.

B.2 Algorithms

Different algorithms are used for position calculation, such as LS, WLS or BLUE. The ML estimator is usually used as a benchmark. In the ML approach the unknown parameter is treated as deterministic. In case of RSS based ranging, the estimator is give by:

$$\tilde{\mathbf{x}} = \arg\min_{\mathbf{x}} \sum_{i=1}^{N} (\ln \frac{\tilde{d}_{i,j}^2}{d_{i,j}^2})^2 \tag{B.9}$$

Here $\tilde{d}_{i,j}^2$ are estimated distances between target j and anchors i, while $d_{i,j}^2$ are the true distances.

The ML estimator is asymptotically efficient. This means that it converges to the Cramer Rao Lower Bound (CRLB) at low error variances, when the statistics of the measurement errors are known.

The linear lest squares algorithm has been described in detail in Section 2.2.1. The BLUE estimator, which we used for localization in Chapter 4, has been derived in [59]. We start from the equation, denoting the distance between the target and i-th anchor:

$$(x_i - x)^2 + (y_i - y)^2 = d_i \tag{B.10}$$

To convert the RSS measurements into linear models in x, we first introduce a range variable:

$$x^2 + y^2 = R \tag{B.11}$$

Now Eq. (B.10) becomes:

$$-2x_i x - 2y_i y + R = d_i^2 - x_i^2 - y_i^2 \tag{B.12}$$

or in matrix form $\mathbf{A}\theta = \mathbf{b}$. That is, $\mathbf{A}$ is a known matrix, θ is the parameter vector to be estimated and $\mathbf{b}$ is the observation vector. In practice, $\mathbf{b}$ is substituted with $\hat{\mathbf{b}}$ where d_i^2 are replaced by their unbiased estimates, denoted by $\hat{d}_i^2$. To solve for $\mathbf{A}\theta \approx \hat{\mathbf{b}}$ according to the BLUE, we need to find $\hat{d}_i^2$ and their covariance matrix:

$$\widehat{d_n^2} = e^{-\frac{2r_n}{\alpha} - \frac{2\lambda_n^2}{\alpha^2}} \tag{B.13}$$

and its variance $\operatorname{var}\left(\widehat{d_n^2}\right) = d_n^4 \left(e^{\frac{4\lambda_n^2}{\alpha}} - 1\right)$.

the noise covariance for $\hat{\mathbf{b}}$, denoted by $\mathbf{C}_{\mathbf{b}}$, is a diagonal matrix of the form:

$$\mathbf{C}_{\mathbf{b}} = \mathrm{diag}(d_1^4 \left(e^{\frac{4\lambda_1^2}{\alpha}} - 1 \right), d_2^4 \left(e^{\frac{4\lambda_2^2}{\alpha}} - 1 \right), ..., d_N^4 \left(e^{\frac{4\lambda_N^2}{\alpha}} - 1 \right)) \tag{B.14}$$

Finally, the solution for $\hat{\theta}$ is:

$$\hat{\theta} = (\mathbf{A}^T \mathbf{C}_{\widehat{\mathbf{b}}}^{-1} \mathbf{A})^{-1} \mathbf{A}^T \mathbf{C}_{\widehat{\mathbf{b}}}^{-1} \widehat{\mathbf{b}} \tag{B.15}$$

B.3 Performance evaluation

Based on the output (position estimates, number of messages exchanged, etc.), we analyze the performance metrics from 2.5. As accuracy metric we used are the error cumulative distribution function (CDF) or the root mean square error (RMSE).

The cumulative distribution function (CDF) of position error is defined as the probability that the error is smaller than a certain value, that is:

$$P_{\|e\|}(error) = \Pr(\|e\| \leq error) \tag{B.16}$$

Usually we observe the errors at 50% and 90%, since they represent the average performance (median error), and "worst case" error (robustness metric), respectively.

The root mean square error (RMSE) is defined as

$$RMSE = \sqrt{E(\|\tilde{x} - x\|^2)} \approx \sqrt{\frac{1}{K} \sum_{k=1}^{K} \|\tilde{x}(k) - x\|^2} \tag{B.17}$$

where $\tilde{x}(k)$ are location estimates of target x for the kth realization of noise and/or node deployment. Distinct random measurements are given at each network deployment k.

In order to cooperate with peer nodes, training sequences and extra packets are required for distance estimation and location information exchange, which results in signaling overhead and additional power consumption. Hence, an efficient cooperation strategy is required so as to achieve the required positioning accuracy and minimize the resulting power consumption and traffic overhead.

We assess the latency by means of time needed to execute the algorithm. The overhead is measured as the number of additional packets required for localization. In general, RSS based localization systems are most cost effective from this point of view, since the strength of received signal is being measured between nodes during the neighbor discovery phase, and does not require additional packet exchanges like TOA measurements. Power consumption is measured assuming that each message last for 1ms, and adopting the typical value of 32 mW (15 dBm) as transmit power of peer nodes, and 63 mW (18 dBm) as transmit power of APs.

Appendix C

WINNER II channel model

The WINNER II channel models have been developed within the WINNER project. WINNER (Wireless World Initiative New Radio) is a consortium of 41 partners coordinated by Nokia Siemens Networks working towards enhancing the performance of mobile communication systems.

The main purpose of the WINNER II channel model is to generate radio channel realisations for link and system level simulations of local area, metropolitan area, and wide area wireless communication systems. The covered propagation scenarios are indoor office, large indoor hall, indoor-to-outdoor, urban micro-cell, bad urban micro-cell, outdoor-to-indoor, stationary feeder, suburban macro-cell, urban macro-cell, rural macro-cell, and rural moving networks. In our simulations we used the indoor small office/ residential propagation scenario, called scenario A1 in WINNER literature. It supports LOS and NLOS conditions, low mobility (up to 5km/h) and frequencies ranging from 2-6 GHz. This specific scenario is depicted in Figure C.1.

Base stations (Access Points) are assumed to be in corridor, thus LOS case is corridor-to-corridor and NLOS case is corridor-to-room. In the NLOS case the basic path-loss is calculated into the rooms adjacent to the corridor where the AP is situated. For rooms farther away from the corridor wall-losses must be applied for the walls parallel to the corridors.

Parameters used in the WINNER II Channel Models have been specified from the measurement results or, in some cases, found from literature. The WINNER Channel Modelling Process is divided into three phases. The first phase starts from definition of propagation scenarios. The second phase of the channel modelling process concentrates on data analysis. Depending on the required parameters, different analysis methods and items are applied. For the post-processed data, statistical analysis is done to obtain parameter PDFs. The third phase of the channel modelling process covers the items required in simulation. Parameters are generated according to the PDFs, by using random number generators and suitable filters.

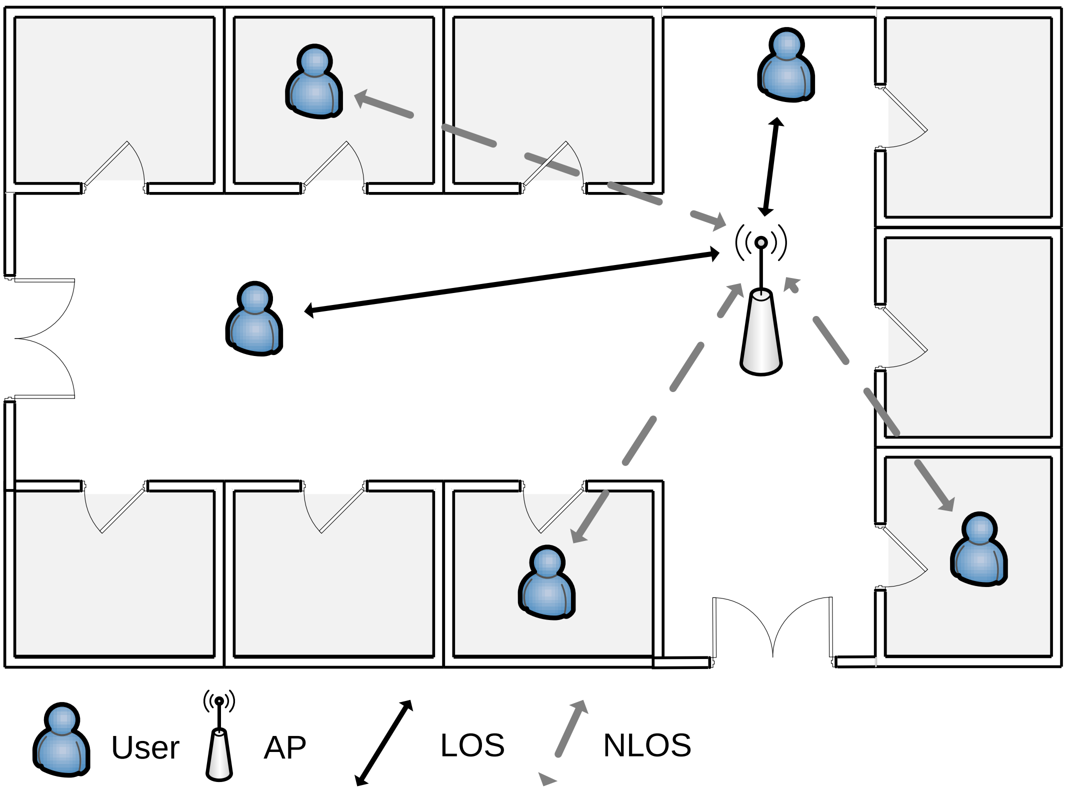


Figure C.1: WINNER II scenario A1 - indoor office

C.1 Path loss model

Path loss models for the various WINNER scenarios have been developed based on results of measurements carried out within the WINNER project, as well as results from the open literature. These path loss models are typically of the form of Eq. (C.1), where d is the distance between the transmitter and the receiver in meters, f_c is the system frequency in GHz, the fitting parameter A includes the path-loss exponent, parameter B is the intercept. Parameter C describes the path loss frequency dependence, and X is an optional, environment-specific term (e.g., wall attenuation in the indoor office NLOS scenario).

$$PL = A\log(d) + B + C\log(\frac{f_c}{5}) + X \tag{C.1}$$

The models can be applied in the frequency range from 2 6 GHz and for different antenna heights. The variables of Eq. (C.1) are either defined, or a full path loss formula is explicitly provided. For the indoor small office/ residential scenario, the variables have been provided depending on wheter it is LOS or NLOS link, and the final path loss formula is:

$$PL = \begin{cases} 18.7\log(d) + 46.8 + 20\log(\frac{f_c}{5}), & \sigma = 3 \\ 36.8\log(d) + 43.8 + 20\log(\frac{f_c}{5}) + 5(n_w - 1), & \sigma = 4 \end{cases} \tag{C.2}$$

Here n_w is the number of walls between the BS and the MS ($n_w > 0$ for NLOS).

C.2 Matlab implementation

WINNER II implementation in MATLAB supports a multi-base station and multi-mobile station network layout. The network layout includes information about the number and locations of MSs and BSs and the number of sectors in a BS (in case of a multi-cell network). Desired number of K links is formed by random BS-MS pairing (number of BSs and MSs is given implicitly during antenna selection). In the original implementation, random positions for all stations are generated, and random scenario and propagation conditions to all links are assigned. We manually edited the original files to support a specific setup, and generated the link conditions (LOS/NLOS) on our own.

The WINNER II channel model computation consists of two main parts:

- the random user parameter generation and
- the actual channel matrix computation.

Global simulation parameters could be classified into parameters defining model structure (also includes system dependant parameters like center frequency), and simulation control parameters. These parameters control sampling in time and delay, parameter initialization mode (random vs. manual), and format of output parameters (e.g. inclusion/exclusion of path-loss in channel matrix). The implementation is shown in the diagram in Figure C.2.

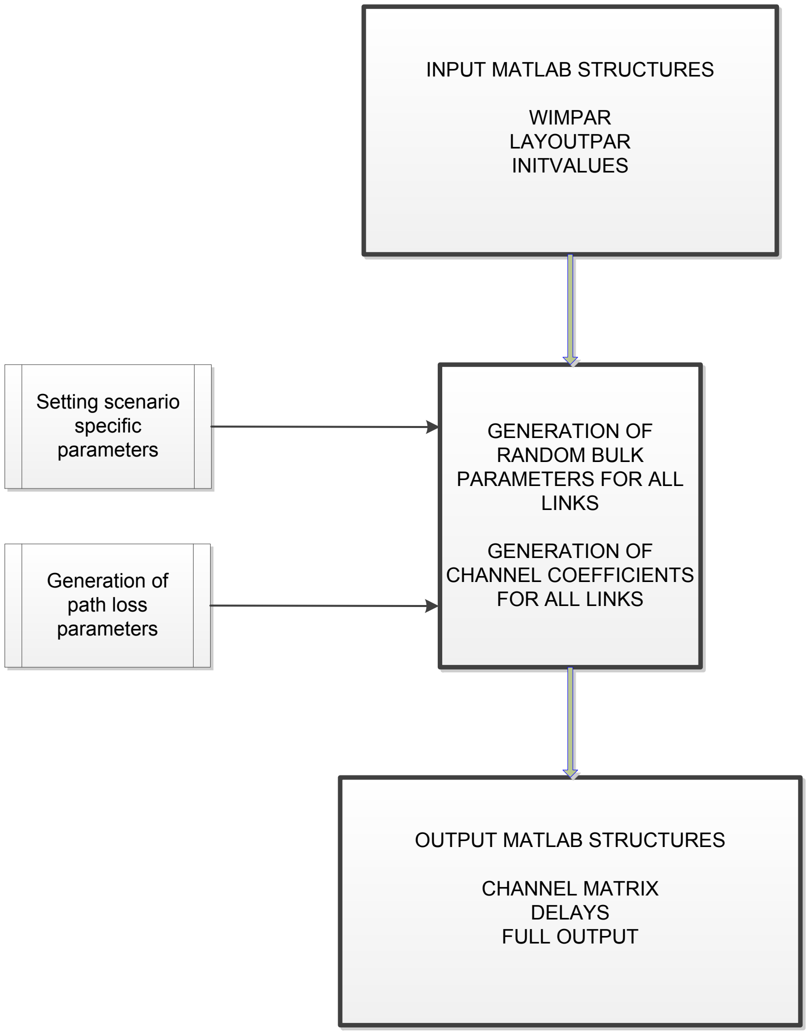


Figure C.2: WINNER II model MATLAB implementation

Input arguments are:

- WIMPAR - general simulation parameters;
- LAYOUTPAR - defines position of terminal stations, their assigned antenna arrays and gives links of interest for simulation;
- INITVALUES (optional) - parameters of the propagation channel. When this parameter is given WIM does not generate the channel parameters randomly, but uses the supplied initial channel values.

Output arguments are:

- Channel matrix H between all links;
- Multipath delays for all links;
- Full output - stores the randomly generated link parameters.

We did not make use of all the features provided by the WINNER model. However, it proved to be a very convenient tool for modeling link parameters, as well as saving different configurations in order to average them out, as we did in Section 4.1.5.

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