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COOPERATIVE POSITIONING STUDIES BASED ON WIRELESS LOCAL AREA NETWORKS (WLANs)

Master's thesis

Examiners: Adj. Prof. Elena Simona Lohan
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ABSTRACT

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Location information and location-based service have gained importance in recent years because, based on their concept, a new business market has been opened which encompass emergency services, security, monitoring, tracking, logistics, etc. Nowadays, the most developed positioning systems, namely the Global Navigation Satellite Systems (GNSS), are meant for outdoor use. In order to integrate outdoor and indoor localization in the same mobile application, several lines of research have been created for the purpose of investigating the possibility of wireless network technologies and of overcoming the challenges faced by GNSS in performing localization and navigation in indoor environments. The benefit in using wireless networks is that they provide a minimally invasive solution which is based on software algorithms that can be implemented and executed in the Mobile Station (MS) or in a Location Server connected to the network.

This thesis focuses on the development of localization approaches based on Received Signal Strength (RSS) and applied in WLANs. Such approaches demonstrated in recent research advances that RSS-based localization algorithms are the simplest existing approaches due to the fact that the RSSs are most accessible existing measurements. RSS measurements can be used with two main algorithms, which are addressed in this thesis: Fingerprinting method (FP) and Pathloss method (PL). These two methods can be applied in both cooperative and non-cooperative algorithms. Such algorithms are evaluated here in terms of Root Mean Square Error (RMSE) for both simulated and real-field data.

PREFACE

I would like to show my gratitude to all those who in one way or another, have contributed to the realization of this master thesis.

I acknowledge Adj. Prof. Elena Simona Lohan, who took me in and made me feel comfortable during the research stage and gave me the opportunity to carry out my master thesis. Her patience and invaluable help to my research was much appreciated.

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Tampere,

Tery Osmar Caisaguano Vásquez

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LIST OF SYMBOLS

(x_i, y_i, z_i)	Fingerprint location
(x_{MS}, y_{MS}, z_{MS})	Mobile station location
$(\hat{x}_{MS}, \hat{y}_{MS}, \hat{z}_{MS})$	Estimated mobile station location
(x_{ap}, y_{ap}, z_{ap})	Access point location
$(\hat{x}_{ap}, \hat{y}_{ap}, \hat{z}_{ap})$	Estimated access point location
N_{FP}	Number of fingerprints collected
N_{AP}	Number of APs deployed
N_{heard}	Number of heard APs
$RSS_{i,ap}$	Received signal strength collected from *ap-th* AP at the *i-th* fingerprint
$\mathcal{A}_{heard}$	Sub-set of all the AP in the scenario
$RSS_{ap_{heard}}^{(MS)}$	Received signal strengths measured at the ap_{heard}-*th* AP "heard" in the unknown location at the mobile
$RSS_{i,ap_{heard}}$	Received signal strength collected from ap_{heard}-*th* AP at the *i-th* fingerprint
$P_{RX_{i,ap}}$	Received signal strength collected from *ap-th* AP at the *i-th* fingerprint
N_{neigh}	Number of nearest neighbor to be averaged
$d_{i,ap}$	Distance between the *ap-th* AP and the *i-th* fingerprint
$\hat{d}_{i,ap}$	Estimated distance between the *ap-th* AP and the *i-th* fingerprint
$\hat{d}_{i,ap_{heard}}$	Estimated distance between the ap_{heard}-*th* AP and the *i-th* fingerprint
$P_{TX_{ap}}$	The *ap-th* AP transmit power

$\hat{P}_{TX_{ap}}$	The *ap-th* AP estimated transmit power
$\hat{P}_{TX_{ap_{heard}}}$	The ap_{heard}-*th* AP estimated transmit power
n_{ap}	Path-loss coefficient of the *ap-th* AP
$\hat{n}_{ap}$	Estimated path-loss coefficient of the *ap-th* AP
$\hat{n}_{ap_{heard}}$	Estimated path-loss coefficient of the ap_{heard}-*th* AP
$\eta_{i,ap}$	Noise factor between the *ap-th* AP and the *i-th* fingerprint
σ_{ap}	Noise factor standard deviation at the *ap-th* AP
$\hat{\sigma}^2$	Estimated noise factor variance
$\mathbf{P}_{\boldsymbol{RX_{ap}}}$	Received signal strength vector between the *ap-th* AP and the *i-th* fingerprint
$\mathbf{\Theta_{ap}}$	Vector of the unknown parameters per AP
$\mathbf{n}$	Noise factor vector
$\widehat{\mathbf{\Theta}}_{\mathbf{ap}}$	Vector of estimated parameters per AP
$p(i, ap_{heard})$	Probability density function related to *i-th* fingerprint and the *ap-th* AP
$d_{true}(MS\ 1, MS\ 2)$	True distance between mobile station 1 and mobile station 2
$d(i,j)$	Distance between the *i-th* fingerprint and the *j-th* fingerprint
ε	Distance error
ε_n^i	Distance error of the *n-th* tracking point at the *i-th* Monte Carlo realization
N_{TP}	Number of MS tracking points
N_R	Number of Monte Carlo realizations

LIST OF ACRONYMS

GPS	Global Positioning System
MS	Mobile Station
RMSE	Root Mean Square Error
RSS	Received Signal Strength
WLAN	Wireless Local Area Network
BS	Base Station
NLOS	Non Line-of-Sight
WPAN	Wireless Personal Area Network
WMAN	Wireless Metropolitan Area Network
WWAN	Wireless Wide Area Network
UWB	Ultra WideBand
IrDA	Infrared Data Association
RFID	Radio Frequency Identification
W-USB	Wireless Universal Serial Bus
WiMAX	Worldwide Interoperability for Microwaves Access
WiBRO	Wireless Broadband
MBWA	Mobile Broadband Wireless Access
ISM	Industrial, Scientific and Medical
PAN	Personal Area Network
PCS	Personal Communication Service

TDMA	Time Division Multiple Access
MAC	Media Access Control
FHSS	Frequency-Hopping Spread Spectrum
FH-CDMA	Frequency-Hopping Code Division Multiple Access
FSK	Frequency-Shift Keying
LR-WPAN	Low-Rate Wireless Personal Area Network
ASK	Amplitude-Shift Keying
BPSK	Binary Phase-Shift Keying
O-QPSK	Offset Quadrature Phase-Shift Keying
DSSS	Direct-Sequence Spread Spectrum
CSMA-CA	Carrier Sense Multiple Access with Collision Avoidance
CCA	Clear Channel Assessment
CS	Carrier Sense
ED	Energy Detection
GTS	Guaranteed Time Slot
IEEE	Institute of Electrical and Electronics Engineers
ETSI	European Telecommunications Standards Institute
Wi-Fi	Wireless Fidelity
WECA	Wireless Ethernet Compatibility Alliance
AP	Access Point
IEEE	Institute of Electrical and Electronics Engineers
ETSI	European Telecommunications Standards Institute
CSMA-CD	Carrier Sense Multiple Access with Collision Detection
LLC	Logical Link Control

HR-DSSS	High-Rate Direct-Sequence Spread Spectrum
OFDM	Orthogonal Frequency Division Multiplexing
BSS	Basic Service Set
IBSS	Independent Basic Service Set
ESS	Extended Service Set
DCF	Distributed Coordination Function
PCF	Point Coordination Function
RTS	Request to Send
CTS	Clear to Send
RSSI	Received Signal Strength Indicator
ACK	Acknowledgement
SIFS	Short Interframe Space
PIFS	Point Coordination Interframe Space
DIFS	Distributed Interframe Space
EIFS	Extended Interframe Space
PCS	Physical Carrier-Sensing
VCS	Virtual Carrier-Sensing
NAV	Network Allocation Vector
PHY	Physical Layer
IR	Infrared
CCK	Complementary Codes Keying
PLCP	Physical Layer Convergence Sublayer
PMD	Physical Medium Dependent
MIMO	Multiple-Input Multiple-Output

WLL	Wireless Local Loop
WiMAX	Worldwide Interoperability for Microwave Access
ADSL	Asymmetric Digital Subscriber Line
LOS	Line-of-sight
LMDS	Local Multipoint Distribution Systems
MMDS	Multichannel Multipoint Distribution Service
NLOS	Non-line-of-sight
MAN	Metropolitan Area Networks
CPE	Customer Premises Equipment
QoS	Quality of Service
SSCS	Service-Specific Convergent Sublayer
ATM	Asynchronous Transfer Mode
SAP	Service Access Point
DSA	Dynamic Service Addition
DSC	Dynamic Service Change
UGS	Unsolicited Grant Service
rtPS	Real-Time Polling Service
ertPS	Extended Real-Time Polling Service
nrtPS	Non Real-Time Polling Service
BE	Best Effort
FDD	Time Division duplex
TDD	Frequency Division Duplex
OFDMA	Orthogonal Frequency Division Multiple Access
SC	Single Carrier

ARQ	Automatic Repeat Request
HUMAN	High Speed Unlicensed Metropolitan Area Network
TOA	Time of Arrival
TDOA	Time Difference of Arrival
RTOF	Round-Trip Time of Flight
RTT	Round-Trip Time
AOA	Angle of Arrival
Cell-ID	Cell identifier
RSS	Received Signal Strength
NN	Nearest Neighbor
FP	Fingerprinting
PL	Pathloss
PDF	Probability Density Function
LS	Least Squares
MMSE	Minimum Mean Square Error
POCS	Projection Onto Convex Sets
WSN	Wireless Sensor Network
SDP	Semi-Definite Programming
MDS	Miltidimensional Scaling
MLE	Maximum Likelihood Estimation
P2P	Peer to Peer
NBP	Non-Parametric Belief Propagation
BP	Belief Propagation
SPA	Sum-Product Algorithm

SMC	Sequential Monte Carlo
LSE	Least Squares Estimation

1 Introduction

The new technology developments have increased the use of mobile phones in our lives. As time has passed, the hardware characteristics of phones have become more and more complex allowing the introduction of a wide range of services, and also, a new concept for mobile phones has been introduced, nowadays known as smartphones.

At the beginning of their introduction to the market, the typical use of mobile phones was to make voice calls and send SMSs, but today phones can even be used for social network applications, e-mails, uploading pictures online, retrieving location-based information, etc. This fact has allowed phones to turn into advanced social-networking tools, involving an increasing need to offer the consumers/users new services. All this implies an increment in research and development efforts towards more powerful and more versatile mobile phone engines.

Location information and location-based service have recently appeared in the new generation of smartphones, and it is now becoming a hot topic in society, industry and research. This new service has opened a new business market with a lot of power, which encompass emergency services, security, monitoring, tracking, logistics, etc. This fact has driven the manufacturers to build mobile handsets with the necessary embedded technology to provide location information with a high level of accuracy *anywhere and anytime* [1].

At the moment, the most popular commercial localization solution is the Global Positioning System (GPS), which is embedded in the current hardware designs of smartphones. However, it has to be pointed out that the GPS has several drawbacks, such as the lack of satellite signals in adverse environments, such as indoors and heavy urban scenarios, and its high battery energy consumption. From the point of view of signal availability, the signal blocking and multipath condition make it a difficult, if not impossible, task to receive the satellite signals in outdoors urban canyons, indoor environments and underground [1] [2], which actually represent the greatest interest of service providers.

In order to solve the localization problem for any environment, several lines of research have been created, which most of them focus on solving the localization problem in outdoor scenarios. Nevertheless, new lines focusing on indoor environments localization have been started in recent years too, whose purpose is to investigate if cellular and WLAN technologies can overcome the GPS challenges to achieve localization and navigation in indoor environments.

1.1 Motivation

There are several applications that offer the users outdoor localization services with sufficient accuracy, however, the number of indoor applications has been increasing in the past years. Moreover, the demand to integrate outdoor and indoor localization in the same mobile application has grown, for that reason it is necessary to improve the methods used to perform indoor localization. To this end, several companies have started working together as is the case of In-Location Alliance formed in August 2012 [3].

Researchers have studied the concept of cooperative localization by utilizing the additional information obtained from short-range links in order to enhance the location estimation accuracy in forthcoming cellular systems [1], and this method can easily be applied to indoor scenarios with a high level of accuracy. Moreover, the concept of Signals of Opportunity[1] (SoO) for outdoor positioning appears when the reception of GPS signals becomes unreliable [4]. The idea of cooperation between two or more communication links improves the position estimation if the Base Stations (BS) of each SoO is well known.

In [5] there are some experimental results introduced that were obtained in a real indoor scenario with a Wireless Local Area Network (WLAN) infrastructure, and they demonstrate the accuracy enhancement of localization considering also the information obtained from communication links between mobile stations (MS), i.e., MS-MS links. The results denote the better performance of cooperative schemes against non-cooperative schemes. On the other hand, [6] evaluates that the position error is directly proportional to the MS present in the scenario, and the metric used to evaluate it is the Average Root Mean Square Error (RMSE).

Another example is the research from [7] which addresses the human effects, such as hand-grip and mobile orientation when held in the hand, while performing Received Signal Strengths (RSS) for localization applications. Additionally, [7] highlights the importance of mitigating these error sources in order to enhance the positioning accuracy.

In the context of Wireless Sensor Networks (WSN) [8], the need to use low-computational load algorithms in limited hardware structures, i.e., wireless sensors, is important. Here RSS-based approaches are the best choice but one of the major issues is to find the best model to characterize the radio channel in order to obtain the inter-node distance estimates. Both methods, non-cooperative and cooperative, are simulated in different scenarios and, subsequently, their results are evaluated and discussed, concluding that the cooperation presents better performance in user localization and tracking.

[1] Signals of opportunity are those signals that are not originally intended (designed) for positioning but they are freely available all the time and everywhere (within a certain range, of course) [4]

The aforementioned studies indicate the viability of using WLANs for indoor positioning applications. Bearing this in mind, the objective of this thesis is to study the impact of WLANs combined with Cooperative and Non-Cooperative methods. By comparing to existing methods in the open literature, we try to reduce the complexity of the solution in order to achieve easy-to-implement solutions, in other words, the solutions adopted are feasible solutions for user devices. For that reason, RSS approach is selected. With the purpose to reduce the uncertainty in the accuracy, it is necessary to realize a reliable estimation of the wireless channel conditions, such as shadowing standard deviation (σ^2) and path loss exponent (n).

1.2 Author's contributions

The main objective has been to investigate the accuracy limits of various RSS-based localization methods used in cooperative and non-cooperative positioning algorithms. The algorithms are compared by simulating some possible environments and analyzing the errors that they perform during the estimation stage. The authors has contributed to the followings:

- Literature review of indoor localization methods nowadays, such as cooperative and non-cooperative localization methods
- Implementation (in Matlab) of an indoor WLAN localization simulator using both fingerprinting and path-loss approach in a two dimensional scenario
- Analysis of the impact of various modeling parameters (such as AP variability and shadowing effects) on the positioning accuracy
- Comparative analysis of the non-cooperative WLAN positioning with cooperative WLAN positioning based on the built simulator
- Testing of the algorithms with real-field measurement data available in the research group (measurements done in a university building in Tampere)

1.3 Outline

The organization of the thesis is described below in more detail.

Chapter 2 presents an overview of the current Wireless Network standards and their classification from the point of view of radius coverage, such as WPAN, WLAN, WMAN and WWAN. In this work we pays special attention to the IEEE 802.11 standard for WLAN, which is widely used nowadays. Also, some characteristics from the physical layer are described.

Chapter 3 addresses to non-cooperative localization methods. Two approaches are studied in more detail, namely Fingerprinting and Probabilistic/Path-Loss approaches. In the Training/Offline phase, we will describe how data measurements can be done and how to use these measurements to estimate the channel parameters. Subsequently, in the estimation phase we introduce the most common algorithms applied in both approaches. Finally, simulation results are presented to compare the performance between Fingerprinting and Path-Loss.

Chapter 4 presents an overview of the generic cooperative methods. Our basic purpose is to propose and develop approaches based in cooperative methodology.

Chapter 5 demonstrates to the reader the comparison between both, cooperative and non-cooperative methods and the approaches simulated, studying the accuracy effect achieved from each of them. This comparison is carried out showing the simulation results in merit metrics, such as the cost functions criteria, the RMSE and the Average RMSE.

Chapter 6 concludes with a discussion of the obtained results and, also, some suggestions for future work are presented.

2 Wireless Networks

Over the past five years, the wireless technology is permeating almost all the business fields, such as, communication, medicine, automation, security, etc. As a result, wireless technologies are one of the best options for networking applications, where free movement is needed. If users must be connected to a network by physical cables, their movement is dramatically reduced [9].

The remarkable advantages of wireless networks are [9]:

- *Mobility*, wireless network users can connect to existing networks and are then allowed to roam freely. These networks allow different levels of mobility:
    - No mobility, the receiver has to be in a fixed position.
    - Mobility in the range of the wireless transmitter.
    - Mobility between different wireless transmitters.
- *Flexibility*, the wireless infrastructure does not need to be reconfigured to add new users, which can be translated into independence of the number of users to be connected. This is an important attribute for service providers. Thanks to the flexibility, a new market that many equipment vendors and service providers have been chasing is the Wi-Fi Hot-Spots. The best way to increase the implicit benefits of attracting more customers to public gathering spots is by offering internet access. A point in case is a coffeehouse, shopping center, etc.

Although these networks have advantages, today they need to have a fixed infrastructure. Infrastructure networks not only provide access to other networks, but also include forwarding functions, medium access control etc. From the Figure 2-1, we can observe that in these infrastructure-based wireless networks, communication typically takes place only between the wireless nodes and the access point, but not directly between the wireless nodes [10].

Moreover, there are implicit disadvantages in the wireless networks[9]:

- Transmission speed is typically an order of magnitude lower than wired networks, e.g., Gigabit Ethernet (IEEE 802.3z) against from 450 Mbps of IEEE 802.11n.
- The use of radio spectrum resources, which is rigorously controlled by regulatory authorities through licensing processes. Wireless devices are constrained to operate in a certain frequency band. Each band has an associated bandwidth, which is simply the amount of frequency space in the band.
- Security on wireless networks is often a critical concern, because the signal transmissions are available to anyone within the range of the transmitter. It implies

that the sniffing task is much easier because the radio transmissions are designed to be processed by any receiver within range.

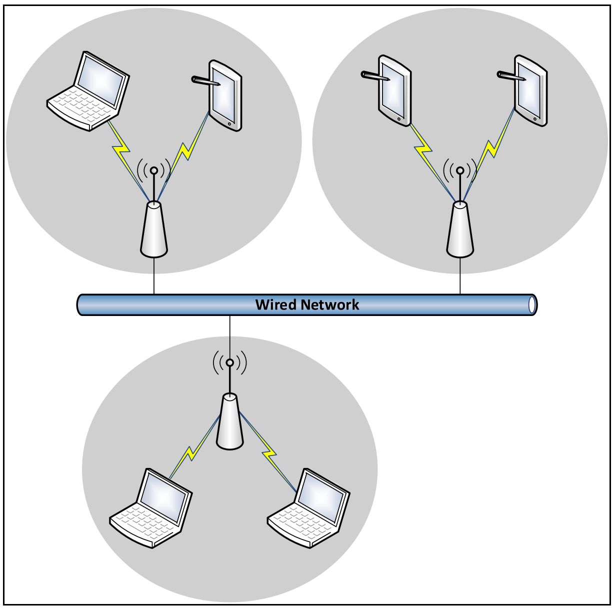

Figure 2-1.- Example of three infrastructure-based wireless network [10]

As mentioned previously, the radio spectrum resources are rigorously controlled by regulatory authorities, which have classified the spectrum in two regions, i.e., frequency bands: those that require license and those that do not [11].

- Licensed spectrum
  - The need to buy the right to use spectrum allocation in a specific geographic location from the government (e.g., AM/FM radio)
  - Prevents interference, because licensee can control signal quality. It implies better coverage and quality
  - Higher barriers for entrance
- Unlicensed spectrum
  - Anyone can operate in the spectrum (e.g., ISM[2] band for WLANs) but must maintain proper behavior in spectrum (max power level and frequency leakage, etc.)
  - The transceiver can have interference problems. This implies that coverage and quality are inconsistent
  - Fast rollout
  - More worldwide options

[2] Industrial, Scientific and Medical Band or ISM Band (see Table 2-1).

From the point of view of radius coverage, wireless networks can be classified as follows [12]:

- Wireless Personal Area Network (WPAN), with range of coverage up to 10 m. The current technologies are based on the IEEE 802.15 standard:
  - Bluetooth
  - ZigBee
  - WiMedia/Ultra WideBand (UWB)
  - Infrared Data Association (IrDA)
  - Radio Frequency Identification (RFID)
  - Wireless Universal Serial Bus (W-USB)
- Wireless Local Area Network (WLAN), with ranges up to 100 – 500 m. The most common technology is based on IEEE.802.11 standard, i.e., Wi-Fi.
- Wireless Metropolitan Area Network (WMAN) or Broadband Wireless Access (BWA), which covers areas up to 5 – 10 km.
  - WiMAX (Worldwide Interoperability for Microwaves Access), which belongs to IEEE 802.16 standard
  - WiBRO (Wireless Broadband) technology launched in South Korea in June 2006
- Wireless Wide Area Network (WWAN), with ranges up to 15 – 50 km. Its standard is the IEEE 802.20, i.e., Mobile Broadband Wireless Access (MBWA)

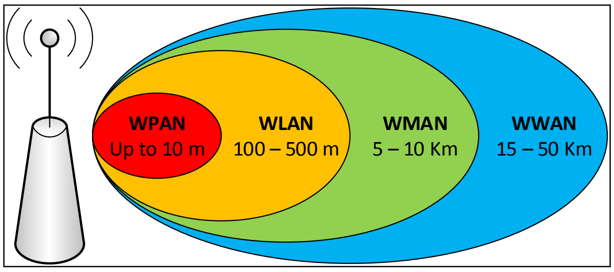

Figure 2-2.- Wireless Networks classification and their respective radius of coverage [12]

Table 2-1 shows the licensed and unlicensed frequency bands in use. These frequencies are classified according to the coverage and the continent.

What all of these wireless networks have in common is that most of them transmit in the ISM frequency bands [12], where anyone is allowed to use radio equipment for transmitting (provided specific transmission power limits are not exceeded) without obtaining a license [13].

- Cellular telephones: 868 MHz band (868 – 868,6 MHz)
- Cellular telephones and remote control: 915 MHz band (902 – 928 MHz)
- IEEE 802.11 (b, g): 2400 MHz band (2400 – 2483,5 MHz)

- IEEE 802.11a: 5800 MHz band (5725 – 5850 GHz)

Table 2-1.- Frequency allocations [11]

	Europe	**USA**	**Japan**
WWAN Licensed	**Cellular:** 453 – 457 MHz, 463 – 467 MHz	**Cellular:** 824 – 849 MHz, 869 – 894 MHz	**Cellular:** 810 – 826 MHz, 940 – 956 MHz, 1429 – 1465 MHz, 1477 – 1513 MHz
	PCS[3]**:** 890 – 915 MHz, 935 – 960 MHz, 1710 – 1785 MHz, 1805 – 1880 MHz	**PCS:** 1850 – 1910 MHz, 1930 – 1990 MHz	**3G:** 1918,1 – 1980 MHz, 2110 – 2170 MHz
	3G: 1920 - 1996 MHz, 2110 - 2186 MHz		
WMAN	**IEEE 802.16**	**IEEE 802.16**	**IEEE 802.16**
Licensed	3,4 – 3,6 GHz	2,5 – 2,6 GHz, 2,7 – 2,9 GHz	4,8 – 5 GHz
Unlicensed	Same as WLAN	Same as WLAN	Same as WLAN
WLAN Unlicensed	**IEEE 802.11** 2400 – 2483 MHz 5,7 – 5,825 GHz HIPERLAN 1 5176 – 5270 MHz	**IEEE 802.11** 2400 – 2483 MHz (b, g) 5,7 – 5,825 GHz (a)	**IEEE 802.11** 2471 – 2497 MHz (b, g) 5,7 – 5,825 GHz (a)
WPAN Unlicensed	**IEEE 802.15** 2400 – 2483 MHz	**IEEE 802.15** 2400 – 2483 MHz	**IEEE 802.15** 2471 – 2497 MHz

2.1 Wireless Personal Area Networks (WPAN)

WPANs are used to transmit information in short distances, and they are typically applied for networking of portable and mobile computing devices, such as PCs, PDAs, cell phones, printers, speakers, microphones, keyboards, smart sensors, etc.

A WPAN is formed by a group of mobile nodes. Each of the nodes has equal functionality, because in these networks there is no client-server relation. The connection between the devices form a peer network [14].

Although there are a wide variety of technologies for WPANs, this work focuses on Bluetooth and ZigBee technologies, which are the most encountered ones among WPAN technologies.

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[3] Personal Communication Service or PCS.

2.1.1 Bluetooth

Bluetooth is a short distance radio-based network technology used to transmit voice and data. It was originally developed for cable replacement in Personal Area Networking (PAN) to operate all over the world, and, at the moment, it is the most popular technology designed for short range [15].

Bluetooth is an inexpensive personal area Ad Hoc[4] network operating in unlicensed bands and owned by the user [15]. Its aims are so-called *Ad Hoc piconets*, which are local area networks with a very limited coverage and without the need for an infrastructure. This technology allows connecting different small devices in close proximity without expensive wiring and without the need for a wireless infrastructure. Its commercial representation is a low-cost single-chip, based on radio wireless network technology [12].

Piconets are established dynamically and automatically and each Bluetooth device can enter and leave the network within the radio proximity [13]. A piconet is defined by a master device, which controls the hopping pattern and, also, controls the transmission within its piconet [16]. All devices using the same hopping sequence with the same phase form a *Bluetooth piconet*, which means that each piconet has a unique hopping pattern [12].

Bluetooth technology permits a device to belong to more than one piconet, which can be the master of only one piconet, i.e., a device can be the master of one piconet and slave of another piconet or a slave in different piconets (see Figure 2-3) [16]. A Master (M) terminal can handle seven simultaneous and up to 200 actives Slaves (S) in a piconet. The reason for the limit of eight active devices is the 3-bit address used in Bluetooth. If access is not available, a terminal can enter in Standby mode (SB) waiting to join the piconet later, i.e., SB devices do not participate in the piconet. A device can also be in a Parked mode (P), in a low power connection, i.e., P devices cannot actively participate in the piconet, because they do not have a connection. In the P mode, the terminal releases its MAC[5] address, while in the SB state it keeps its MAC address [15]. If a parked device wants to communicate and there are already seven active slaves, one slave has to switch to park mode to allow the parked device to switch to active mode [10].

If an S device belongs to more than one piconet, it acts as a bridging device, and the union of those piconets by the bridging device forms a Scatternet. Multiple piconets in the same geographic space interfere with each other, for that reason, Frequency-Hopping

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[4] "Ad Hoc" is actually a Latin phrase that means "for this purpose." It is often used to describe solutions that are developed on-the-fly for a specific purpose. In computer networking, an ad hoc network refers to a network connection established for a single session and does not require a router or a wireless base station [68].

[5] Media Access Control or MAC

Spread Spectrum (FHSS) scheme is used so that multiple piconets can coexist in same space [16].

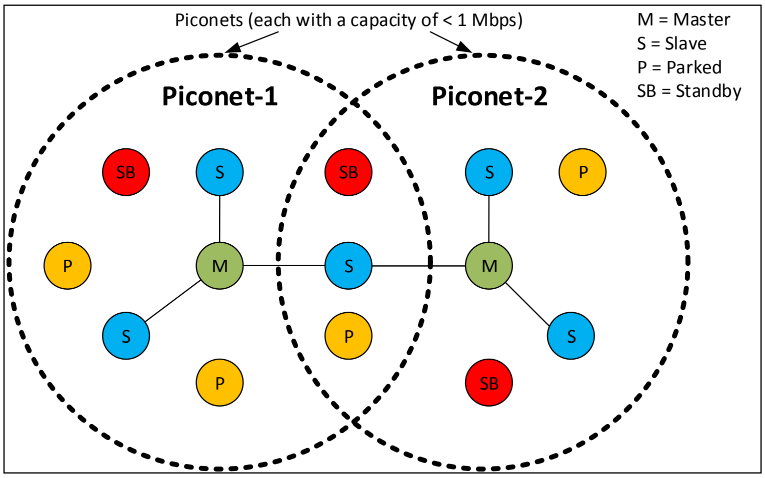

Figure 2-3.- Bluetooth scatternet [10]

The connection type in a Bluetooth piconet is based on FHSS scheme with a fast hopping rate of 1600 hops per second and each hop carrier has an equal probability to be selected (on average). Bluetooth uses 79 hop carriers equally spaced with 1 MHz [10].

Figure 2-4 describes the FHSS scheme, the vertical axis represents 6 hop carriers distributed among the frequency band. At the beginning, the slave has to tune at 2,405 – 2,406 GHz band in order to establish the connection with the piconet master and start the communication during 625 µs. After this time, the slave has to change to 2,402 – 2,403 GHz band in order to continue the communication with the master. After each 625 µs, the slave needs to synchronize and follow the hopping pattern established by the master.

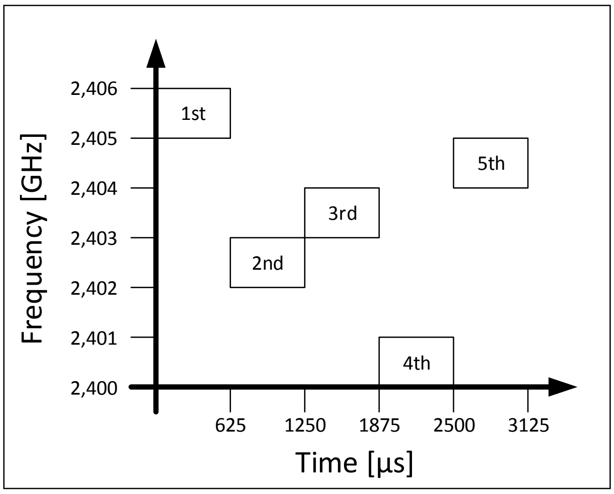

Figure 2-4.- The hopping sequence mechanism in Bluetooth

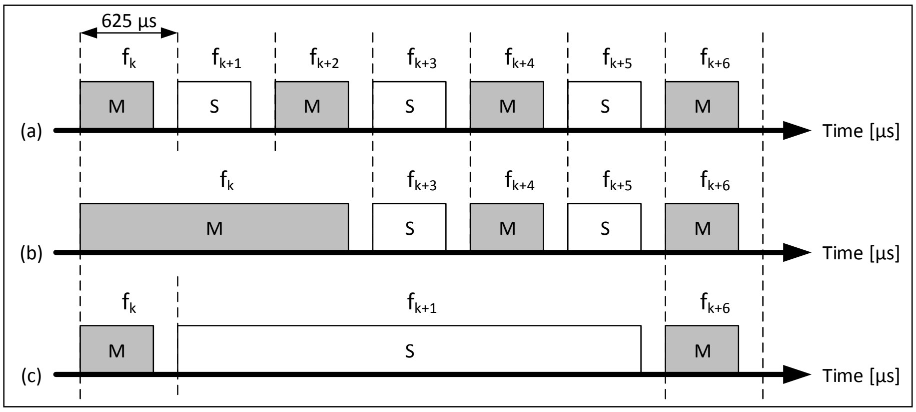

Figure 2-5.- Frequency selection during data transmission: (a) 1-slot packet, (b) asymmetric 3-slots packet, and (c) asymmetric 5-slots packet [10]. M and S represent the Master and Slave devices, meanwhile f_k represents the frequency hop during a slot.

Once the connection is established, the Time-Division Duplex scheme (TDD) along with the Time Division Multiple Access (TDMA) packet scheduling are used for separation of the transmission directions. The time between two hops is called a slot, which is an interval of 625 µs [10]. Each slot uses a different frequency and one packet can be transmitted per slot. Subsequent slots are alternatively used for transmitting and receiving. There is strict alternation of slots between the master and the slaves, where a master can send packets to a slave only in even slots and slave can send packets to the master only in the odd slots (see Figure 2-5).

Bluetooth applies FH-CDMA [6] for separation of piconets and mitigate the interference. On the average, all piconets can share a total of 80 MHz bandwidth available. Adding more piconets leads to performance degradation from a single piconet, because more and more collisions may occur. A collision occurs if two or more piconets use the same carrier frequency at the same time and this will probably happen when the hopping sequences are not coordinated [10].

Bluetooth transceivers use Gaussian FSK[7] for modulation and are available in three classes [10]:

- Class 1: 100 mW (20 dBm) with a typical range of 100 m without obstacles. Power control is mandatory.
- Class 2: 2,5 mW (4 dBm) with a typical range of 10 m without obstacles. Power control is optional.
- Class 3: 1 mW (0 dBm)

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[6] Frequency-Hopping Code Division Multiple Access or FH-CDMA

[7] Frequency-Shift Keying or FSK

In summary, Table 2-2 describes all the radio and baseband parameters of Bluetooth technology.

Table 2-2.- Bluetooth radio and baseband parameters [13]

Topology	Up to 7 simultaneous links
Modulation	Gaussian filtered FSK
RF bandwidth	220 kHz (-3 dB), 1 MHz (-20 dB)
RF band	2,4 GHz ISM frequency band
RF carriers	79 (23 as reduced option)
Carrier spacing	1 MHz
Access method	FHSS – TDD – TDMA
Frequency hop rate	1600 hops/s

2.1.2 ZigBee

ZigBee is a low-rate and low-power wireless technology (LR-WPAN[8]) capable of operating in short-range distances, and targeted towards automation and remote control applications. Based in the IEEE 802.15.4 standard, this technology is expected to provide low cost and low power connectivity for equipment that, contrary to Bluetooth that is intended for frequent recharging, need battery life from several months to several years. Moreover, ZigBee devices are actively limited to a data transfer rates of 250 Kbps, compared to Bluetooth, which has data rates of 1Mbps.

In addition, ZigBee wireless devices are designed to transmit 10 – 75 meters within the ISM worldwide bands, depending on the channel conditions and the power output consumption allowed for a given application [17].

Table 2-3.- Channel allocation in different countries and data rates [18]

Frequency Band	Band	Geographic Region	Data rate	Channels
868 MHz	ISM	Europe	20 Kbps	1
915 MHz	ISM	USA	40 Kbps	10
2400 MHz	ISM	Worldwide	250 Kbps	16

As shown in Figure 2-6, there are different shapes of networks that can range from a centralized star or a tree-based architecture to a complete mesh network. The network must be in one of the two networking topologies specified in IEEE 802.15.4: star and peer-to-peer.

[8] Low-Rate Wireless Personal Area Network or LR-WPAN

In the *star topology*, every device in the network can communicate only with the principal controller of a personal area network (PAN), known as PAN coordinator. Moreover, in a *peer-to-peer topology*, each device can communicate directly with any other device if the devices are placed close enough together to establish a successful communication link. A peer-to-peer network can take different shapes by defining restrictions on the devices that can communicate with each other. If there is no restriction, the peer-to-peer network is known as a *mesh topology*, otherwise, it is known as *tree topology*, where a ZigBee coordinator (PAN coordinator) establishes the initial network. ZigBee routers form the branches and relay the messages and ZigBee end devices act as leaves of the tree and do not participate in message routing [19].

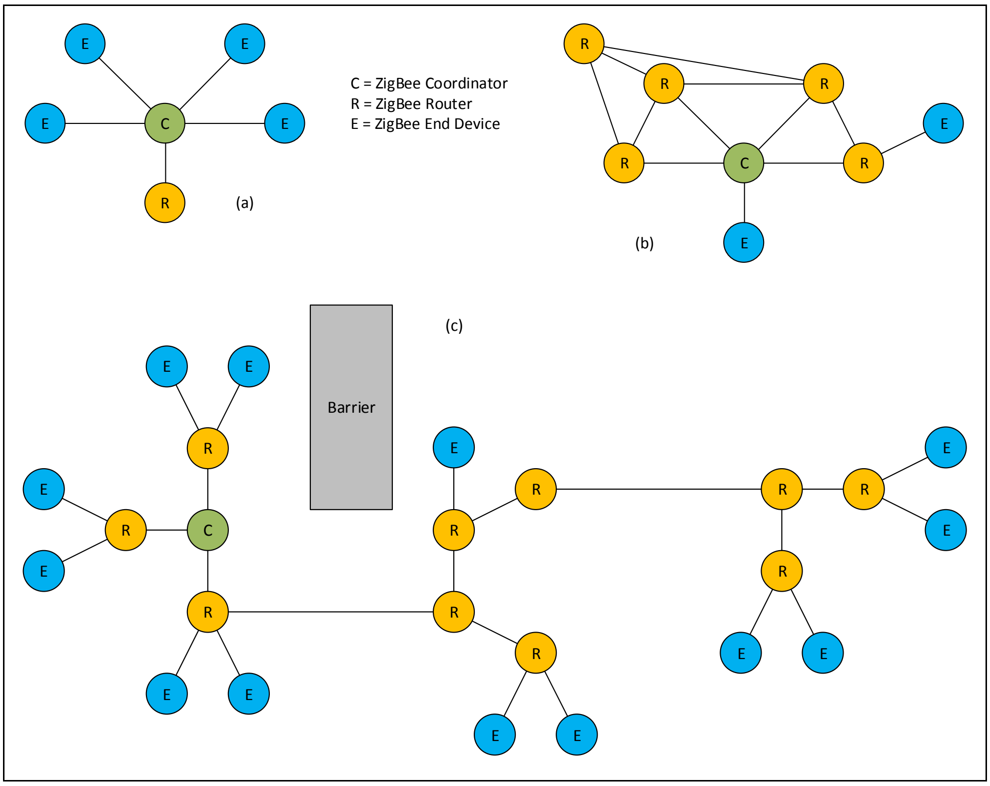

Figure 2-6.- ZigBee network topology: (a) star topology, (b) mesh topology, and (c) tree topology [19]

In addition, ZigBee routers can grow the network beyond the initial network established by the ZigBee coordinator [19], which acts as intermediate nodes relaying data from other devices. Router can connect to an already existing network, also capable of accepting connections from other devices [20].

Regardless of its topology, the network is always created by a PAN coordinator and there is only one PAN coordinator in the entire network. A coordinator is usually connected to a main supply, because it may need to have long active periods, moreover, all other devices are normally battery powered. The PAN coordinator controls the network, which allocates a unique address (16-bit or 64-bit) to each device in the network and selects a unique PAN identifier for the network. This PAN identifier allows the devices within a network to use the 16-bit short-addressing method and still be able to communicate with other devices across independent networks. Also, the coordinator is responsible of initiating the network and selecting the network parameters such as radio frequency channel, routing the messages throughout the network, and terminating the network [19].

On the other hand, the End Devices can be low-power/battery-powered devices, which can collect information from sensors and switches. They have sufficient functionality to talk to their parents (either the coordinator or a router) and cannot relay data from other devices. This reduced functionality can lead to reduce both economic costs and energy consumption. These devices do not have to be in the online mode the whole time, while the devices belonging to the other two categories have to, this means reducing the power consumption and increasing their battery life [20].

ZigBee is based on the IEEE 802.15.4 standard, which defines three modulation types: Binary Phase Shift Keying (BPSK), Amplitude Shift Keying (ASK), and Offset Quadrature Phase Shift Keying (O-QPSK). In BPSK and O-QPSK, the information is in the phase of the signal, however, in ASK the information is in the amplitude of the signal. Moreover, to mitigate the multipath drawbacks, the standard allows the use of Direct Sequence Spread Spectrum (DSSS) techniques [19]. The Table 2-4 provides further details about the modulations and frequency bands.

Table 2-4.- IEEE 802.15.4 data rates and frequencies of operation [19]

Frequency [MHz]	Bandwidth [MHz]	Symbol rate		Data characteristics		
		Chip rate [Kchip/s]	Modulation	Bit rate [Kbps]	Symbol rate [Ksymbol/s]	Spreading Method
868	868 – 868,6	300	BPSK	20	20	Binary DSSS
915	902 – 928	600	BPSK	40	40	Binary DSSS
2450	2400 – 2483,5	2000	O-QPSK	250	62,5	16-ary Orthogonal

On the other hand, there are two existing methods for channel access: contention based and contention free. In *contention-based* channel access, all the devices that want to transmit in the same frequency channel use the Carrier Sense Multiple Access with Collision Avoidance mechanism (CSMA-CA), which means that if a device wants to transmit, first it performs a clear channel assessment (CCA) to verify that the channel is not used by any other device. There are two ways to declare a frequency channel clear or busy: carrier sense (CS) or energy detection (ED) [19].

At the beginning of the transmission task, the device works as a receiver to detect and estimate the signal energy level in the desired channel (ED). In ED, the receiver only estimates the energy level and if there is a signal already in the band of interest, ED does not determine the type of the signal, which could be IEEE 802.15.4 signal or not. However, in CS, the type of the occupying signal is determined and if this signal is an IEEE 802.15.4 signal, the device will consider the channel to be busy even if the signal energy is below a user-defined threshold [19].

If the channel is being used, the device backs off for a random period of time and tries again. The random back-off and retry are repeated until either the channel becomes clear or the device reaches its user-defined maximum number of retries [19].

Moreover, in the *contention-free* method, the PAN coordinator dedicates a specific time slot to a particular device. This is called a guaranteed time slot (GTS), which the bandwidth for each node operating in this method is guaranteed and they will start transmitting during that GTS without using the CSMA-CA mechanism [19].

In summary, the Table 2-5 presents all the radio and baseband parameters of the ZigBee technology.

Table 2-5.- ZigBee radio and baseband parameters [13]

Topology	Ad Hoc (central PAN coordinator)
Modulation	Offset QPSK
RF band	2,4 GHz ISM frequency band
RF channels	16 channels with 5 MHz spacing
Spreading	DSSS (32 chips/4 bits)
Chip rate	2 Mchip/s
Access method	CSMA-CA

2.2 Wireless Local Area Networks (WLAN)

A WLAN is a wireless network in which a number of devices (mainly computers but also printers, servers, etc.) communicate with each other in limited geographical areas without having to be physically connected to each other. The great advantage of this technology is that it offers mobility to the user and requires only a simple installation.

The first WLAN standard was created by the IEEE (Institute of Electrical and Electronics Engineers) organization in 1997 and, this standard is known as IEEE 802.11. This standard only specifies physical layer characteristics and MAC layer. Since its inception, several international organizations have developed a broad activity in the standardization of WLAN standard and they have generated a wide range of new standards. In the United States most of the activity is performed by the IEEE with the IEEE 802.11 standard and its variants, such as IEEE 802.11b/a/g/n, etc. Meanwhile, in Europe most of the standardization activity is performed by the ETSI (European Telecommunications Standards Institute) with its activities in the HiperLAN standard and its variants, such as HiperLAN/1 and HiperLAN/2. Table 2-6 shows the technical characteristics of some WLAN technologies.

Table 2-6.- WLAN technologies [21], [9], [22], [18], [23]

Standard	Max Rate	Spectrum	Standard Approved	Spreading
IEEE 802.11 Legacy	1 - 2 Mbps	2,4 GHz	June 1997	FHSS or DSSS
IEEE 802.11b	11 Mbps	2,4 GHz	July 1999	DSSS or CCK
IEEE 802.11a	54 Mbps	5 GHz	July 1999	OFDM
IEEE 802.11g	20 - 54 Mbps	2,4 GHz	June 2003	DSSS and OFDM
IEEE 802.11n	108 - 600 Mbps	2,4 GHz and 5 GHz	September 2009	OFDM

Apart from the standard bodies, the main players of the wireless industry met within the Wi-Fi [9] Alliance, previously called Wireless Ethernet Compatibility Alliance (WECA). The mission of the Wi-Fi Alliance is to certify the interworking and the compatibility between IEEE 802.11 network equipment and also to promote this standard. The Wi-Fi Alliance regroups manufacturers of semiconductors for WLANs, hardware suppliers and software providers. Among them we can find companies like Cisco-Aironet, APPLE, Breezecom, Compaq, Dell, Fujitsu, IBM, Intersil, Nokia, Samsung, Symbol Technologies, Wayport and Zoom [18].

Wi-Fi products are identified as 802.11, and are then further identified by a lower case letter that identifies which specific technology is in operation, such as 802.11a. Each certification set is defined by a set of features that relate to performance, frequency and bandwidth. Each generation also furthers security enhancements and may include other features that manufacturers may decide to implement [22].

Wi-Fi CERTIFIED[10] products are tested to ensure that they work with previous generations of Wi-Fi products that operate in the same frequency band. For example, the Wi-Fi CERTIFIED 802.11g designation indicates a product has been certified to meet the standards for 802.11g, and will operate with devices Wi-Fi CERTIFIED for 802.11b or 802.11n (that support 2.4 GHz). This means that as you add new devices to your existing Wi-Fi network, you can be confident that they will work well together [22].

The most remarkable characteristics of the IEEE 802.11 systems and their evolution can be summarized as follows [18]:

- WLAN/1G: First generation (IEEE 802.11)

[9] Wireless Fidelity or Wi-Fi

[10] The Wi-Fi CERTIFIED™ program was launched in March 2000. It provides a widely-recognized designation of interoperability and quality, and it helps to ensure that Wi-Fi enabled products deliver the best user experience. The Wi-Fi Alliance has completed more than 5000 product certifications to date, encouraging the expanded use of Wi-Fi products and services in new and established markets [22].

  - Connectivity of PC terminals (between them or to a fixed LAN)
  - Bridge-based APs
  - Roaming
  - Coexistence with other networks (e.g. WLAN and Ethernet LAN) which means bridging. Note that there is a small problem in the IEEE 802.11 in general with respect to bridging where it does not fulfill completely the bridging rules and is hence non-conformant to the 802 paradigms.
- WLAN/2G: Second generation (IEEE 802.11b)
  - More effective management of WLAN
  - Interworking and interoperability
  - Migration starting from the first generation
- WLAN/3G: Third generation (802.11a/g)
  - High throughput
  - Design of networks more open and integrated
  - Conformity to the IEEE 802.11a/g standard
  - Minimization of antenna sizes
  - Improvement of receiver's sensitivities
- WLAN/4G: Fourth generation (IEEE 802.11n)
  - Very high throughput
  - Long distances at high data rates (equivalent to IEEE 802.11b at 500 Mbps)
  - Use of robust technologies, e.g., multiple-input multiple-output (MIMO) and space time coding

Although there is a wide variety of technologies for IEEE 802.11, this work focuses on IEEE 802.11b/a/g/n technologies, which are the most encountered ones among WLAN technologies.

2.2.1 IEEE 802.11

802.11 is a member of the IEEE 802 family, which is a series of specifications for local area network (LAN) technologies. Figure 2-7 shows the relationship between the various components of the 802 family and their place in the OSI model [9].

Individual specifications in the 802 series are identified by a second number. 802.3 is the specification for a Carrier Sense Multiple Access network with Collision Detection (CSMA-CD), which is related to (and often mistakenly called) Ethernet, and 802.5 is the Token Ring specification. Therefore, other specifications describe other parts of the 802 protocol stack. 802.2 specifies a common link layer, the Logical Link Control (LLC), which can be used by any lower-layer LAN technology. Management features for 802 networks are specified in 802.1 [9].

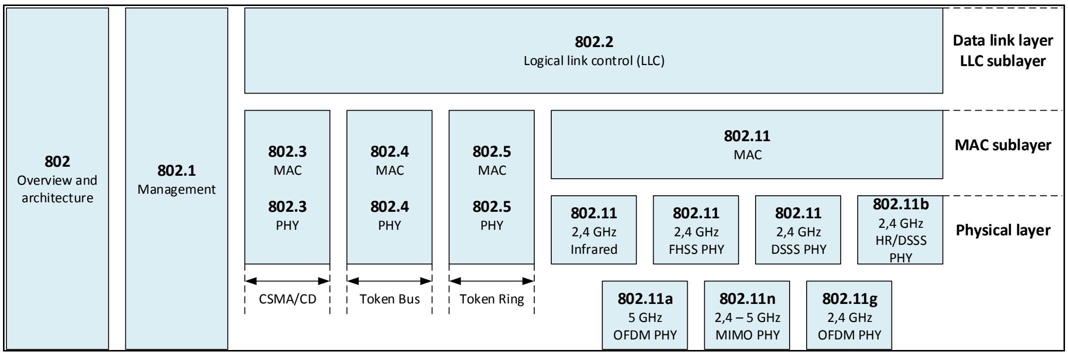

Figure 2-7.- The IEEE 802 family and its relation to the OSI model [9], [18]

802.11 is just another link layer that can use the 802.2/LLC encapsulation. The base of 802.11 specification includes the 802.11 MAC and two physical layers: a FHSS physical layer and a DSSS link layer. However, later revisions to 802.11 added additional physical layers, such as 802.11b and 802.11a. 802.11b specifies a high-rate direct-sequence layer (HR-DSSS), meanwhile 802.11a describes a physical layer based on orthogonal frequency division multiplexing (OFDM) [9].

The IEEE 802.11 standard considers four physical components, which are presented in Figure 2-8 [9]:

- The distribution system is the logical component of 802.11 used to forward frames to their destination.
- Access point (AP) or sometimes called wireless relay, which functions as a bridge and a relay point between the fixed network and the wireless network.
- To move frames from station to station, the standard uses a wireless medium.
- A wireless client station, in general a PC equipped with a wireless network interface card, known as a station.

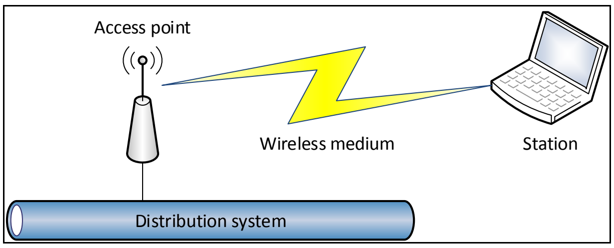

Figure 2-8.- Components of 802.11 LANs [9]

2.2.1.1 Network modes

The basic building block of an 802.11 network is the basic service set (BSS), which is a group of stations that communicate with each other. Communication can be performed in any area, so-called the basic service area. When a station is in the basic service area, it can communicate with the other members of the BSS. The IEEE 802.11 standard's model defines three modes, two of them are illustrated in Figure 2-9 and Figure 2-10 [9]. The third type defines a hybrid configuration combining infrastructure and ad hoc modes [18].

- Independent BSS or ad hoc mode
- Infrastructure BSS or infrastructure mode
- Mesh mode.

The ad hoc mode (Figure 2-9) simply represents a group of IEEE 802.11 wireless stations that communicate directly with each other without having a connection with an AP or a connection to a fixed network through the distribution system. This configuration is sometimes referred to as a peer-to-peer configuration. Each station can establish a communication with any other station in the cell which is called an independent cell Independent Basic Service Set (IBSS). This mode allows to create quickly and simply a wireless network where there is no fixed infrastructure or where such an infrastructure is not necessary for the required services (hotel room, conference centers or airport), or finally when the access to the fixed network is prohibited or difficult to create [18].

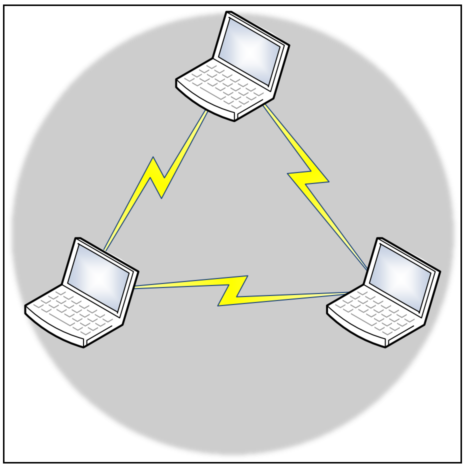

Figure 2-9.- Independent BSS or ad hoc mode [9]

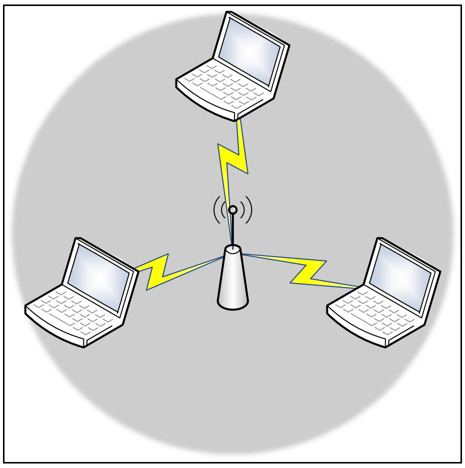

Figure 2-10.- Infrastructure BSS or infrastructure mode [9]

Infrastructure BSS networks (Figure 2-10) are distinguished by the use of an AP. APs are used for all communication in infrastructure networks, including communication between mobile nodes in the same service area. If one mobile station in an infrastructure BSS needs to communicate with a second mobile station, the communication must take two hops. First, the originating mobile station transfers the frame to the AP. Second, the AP transfers the frame to the destination station. Therefore, the network traffic can be divided into two directions: uplink (into the backbone) and downlink (from the backbone), which implies that the multi-hop transmission takes more transmission capacity than a directed frame from the sender to the receiver [9].

To provide for an extended coverage area, multiple BSSs are used where the APs are connected through a backbone or distribution system. The whole interconnected WLAN including at least two different BSSs (with respect to their APs) and the distribution system, is seen as a single logical IEEE 802 network to the LLC level and is called an Extended Service Set (ESS) [18]. In Figure 2-11, the ESS is the union of the four BSSs. In real-world deployments, the degree of overlap between the BSSs would probably be much greater than the overlap in Figure 2-11, which can be translated into a continuous coverage within the extended service area [9].

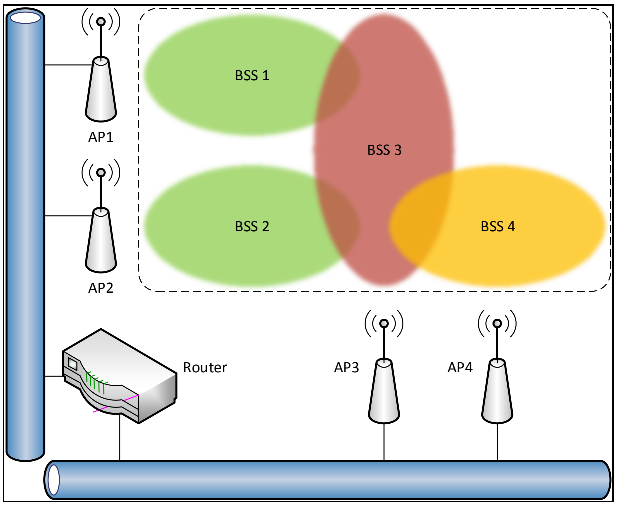

Figure 2-11.- Extended service set [9]

2.2.1.2 Shared media access

Access to the wireless medium is controlled by coordination functions. Ethernet-like CSMA-CA access is provided by the distributed coordination function (DCF). If contention-free service is required, it can be provided by the point coordination function (PCF), which is built on top of the DCF. Contention-free services are provided only in infrastructure networks [9].

The DCF is the basis of the standard CSMA-CA access mechanism. Similar to Ethernet, it first checks to see that the radio link is clear before transmitting. To avoid collisions, stations use a random backoff time after each frame, and the first transmitter to accomplish the backoff time is able to use the channel. In some circumstances, the DCF may use the CTS[11]/RTS[12] clearing technique to further reduce the possibility of collisions [9].

[11] Clear to Send or CTS

[12] Request to Send or RTS

Point coordination provides contention-free services. Special stations called point coordinators are used to ensure that the medium is provided without contention. Point coordinators reside in access points, i.e., the PCF is restricted to infrastructure networks. To gain priority over standard contention-based services, the PCF allows stations to transmit frames after a shorter interval. The PCF is not widely implemented in current market products [9].

In order to supervise the network activity, the MAC sublayer works in collaboration with the physical layer. The physical layer uses CCA algorithm to evaluate the availability of the channel. To know if the channel is free, the physical layer measures the power received by antenna called received signal strength indicator (RSSI). The physical layer thus determines that the channel is free by comparing the RSSI value with a fixed threshold and transmits thereafter to the MAC layer an indicator of free channel [18].

CSMA/CA protocol is based on [18]:

- Sensing the medium thanks to CS procedure (CS carrier sense)
- Using interframe space (IFS) timers
- Using positive acknowledgements and the collision avoidance approach
- Executing backoff algorithm
- Using multiple access

IEEE 802.11 standard defines four types of IFS timers (spaces between successive frames) classified by ascending order, which are used to define different priorities (Figure 2-12) [18]:

- Short interframe space (SIFS) is used to separate the transmissions belonging to the same dialogue (data frames and acknowledgements). It is the smallest gap between two frames. There is always, at most, only one station authorized to transmit at any given time, taking thus priority over all other stations. This value is fixed by the physical layer and is calculated in order that the transmitting station will be able to switch back to receive mode to be able to decode the incoming packet. A high priority SIFS is then used to transmit frames like ACK[13], CTS and response to a polling.
- Point coordination IFS (PIFS) is used by the AP (called coordinator in this case) to gain the access to the medium before any other station. It reflects an average priority to transmit the time-bounded traffic.
- Distributed IFS (DIFS) is the IFS of weaker priority than the two previous; it is used in the case of data asynchronous transmission.

[13] Acknowledgement or ACK

- Extended IFS (EIFS) is the longest IFS. It is used by a station receiving a packet which is corrupted by collisions to wait longer than the usual DIFS in order to avoid future collisions.

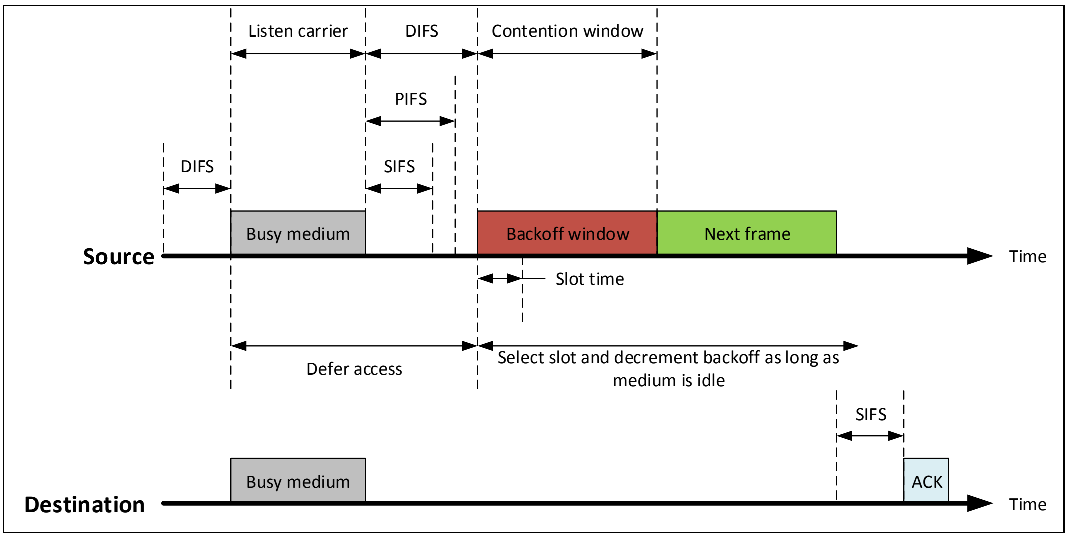

Figure 2-12.- CSMA-CA basic global mechanism for asynchronous data transmission [18]

When several stations wish to transmit simultaneously, the station wishing to emit the urgent frames as the acknowledgements will be able to send them in first. Then other priority frames will be transmitted considered to be like those related to the administration tasks or the traffic which has delay constraints. Lastly, the least important information concerning the asynchronous traffic will be transmitted after a longer latency [18].

Medium listening is fulfilled thanks to carrier sensing function in order to determine if the medium is available. Two types of carrier sensing functions in 802.11 manage this process: the physical carrier-sensing (PCS) and virtual carrier-sensing (VCS) functions. If either carrier-sensing function indicates that the medium is busy, the MAC reports this to higher layers [9]. PCS detects the presence of other stations by analyzing all the frames on the wireless medium and by detecting the activity on the medium thanks to the relative energy of its signal compared to the other stations. However, VCS is a procedure for listening at the MAC layer in the case of a reservation of the medium [18].

Figure 2-13 shows a transmission between two stations and the NAV setting of their neighbors. A station wanting to send frames, begins by initially transmitting a RTS control packet, which contains the source, the destination and duration of the transmission (i.e. total duration of the transmission of the packet and its ACK). The destination station answers (if the medium is free) with a CTS control packet, containing the same duration information. All stations receiving either the frame containing the request for reservation of channel RTS, or the frame of response of reservation CTS, set to 1 their VCS indicator called network allocation vector (NAV), for the given duration, and use this information together with the PCS when sensing the medium. If the NAV reaches 0, the VCS function indicates that the medium is idle. However, if the source does not receive the CTS packet, it assumes that a collision occurred and will retransmit the RTS packet after a random waiting period. If the recipient receives the CTS packet correctly, the source emits an acknowledgement to announce to the recipient that the packet CTS was received. Then the communication will be able to take place [18].

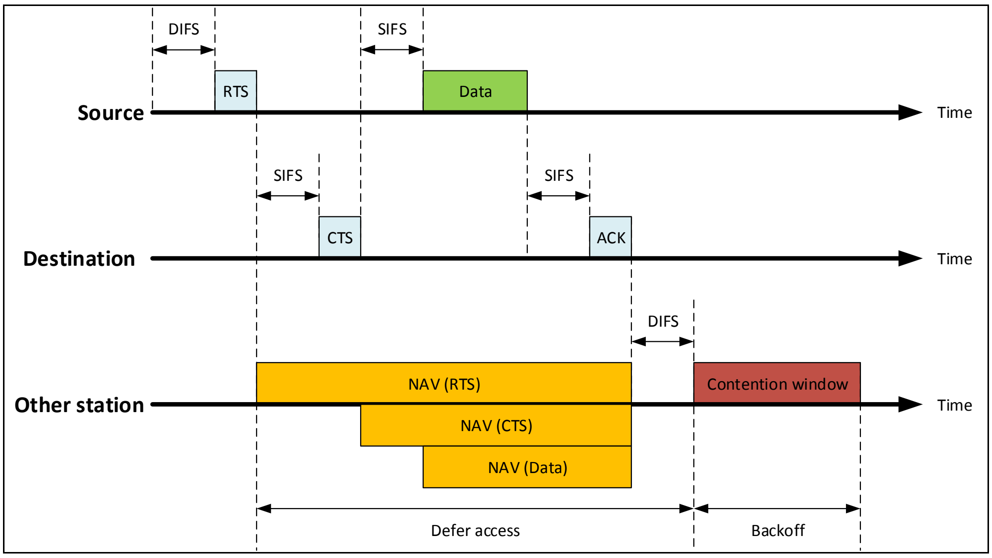

Figure 2-13.- CSMA-CA with RTS-CTS [18]

2.2.1.3 Physical layers variances

Three physical layers (PHY) were standardized in the initial revision of 802.11, which was published in 1997 [18]:

- A radio PHY using an FHSS technique operating in the 2,4 GHz ISM band
- A radio PHY using a DSSS technique operating in the 2,4 GHz ISM band
- A PHY for the infrared (IR) transmission, which is not widely used, operate in baseband at wavelength between 850 and 950 nm

The use of spread spectrum techniques increase the performances by minimizing the harmful effects of the multipath propagation, interferences and noise. In 1999, two further physical layers based on radio technology were developed [18]:

- Complementary codes keying (CCK) modulation in the case of the IEEE 802.11b system; the associated PHY is called HR-DSSS
- OFDM modulation in the case of IEEE 802.11a and 802.11g systems
- MIMO techniques in IEEE 802.11n

The physical layer is structured in two sublayers [18]:

- The convergence sublayer or Physical Layer Convergence Sublayer Procedure (PLCP). The purpose of this layer is to adapt to the lower sublayer which is dependent on the medium (OFDM, IR, DSSS or FHSS) inserting headers required for synchronization or identification of the used modulation on the medium. Also, it allows choosing the best antenna to capture the signal.
- The sublayer dependent on the transmission medium itself is primarily to code and transmit the bits sent by the convergence layer on the medium. This layer is called physical medium dependent (PMD).

2.2.2 IEEE 802.11b

The revision of the original 802.11b standard was ratified in 1999. 802.11b, which includes that the maximum transmission speed is 11 Mbps and using the same access method, CSMA-CA defined in the original standard. 802.11b operates in the 2.4 GHz band due to the space occupied by the codification of CSMA-CA protocol, in practice, the maximum transmission rate with this standard is about 5,9 Mbps over TCP and 7.1 Mbps over UDP.

2.2.3 IEEE 802.11a

The last correction of the IEEE 802.11a standard was ratified in 1999. This standard is based on the original standard, but in this case it operates in 5 GHz band and uses 52 subcarriers OFDM (Orthogonal Frequency-Division Multiplexing - Multiplexing Orthogonal Frequency Division). The maximum speed that IEEE 802.11a can reach is 54 Mbps, which becomes in practice a very useful standard for wireless networks with actual speeds about 20 Mbps. Also 802.11a has 12 non-overlapping channels, 8 for wireless network connections and 4 for point to point connections. A disadvantage of this standard is that it cannot interoperate with 802.11b standard equipment, unless the equipment implements both standards.

Because the 2.4 GHz band is widely used by cordless phones and microwave ovens among other devices, the use of 5 GHz band is an advantage, since it produces less interference. However, the use of this band also has its drawbacks, because the 802.11a equipment require LOS conditions, leading to the need for the installation of a greater number of access points, also this drawback implies that 802.11a devices have less coverage than 802.11b because its waves are more readily absorbed.

2.2.4 IEEE 802.11g

The third standard modulation was ratified in June 2003. 802.11g is the evolution of the 802.11b standard, it uses the 2,4 GHz band (similar than IEEE 802.11b) ant it operates at a theoretical maximum speed of 54 Mbps. Its actual average value is 22.0 Mbps, similar to the 802.11a standard. IEEE 802.11g is compatible with the standard by using the same frequencies. The need to create a compatibility between IEEE 802.11a and IEEE 802.11b force to establish this new standard. However, network devices based on 802.11g standard and devices based on 802.11b standard, reduce significantly the transmission rate, and the speed rate will be fixed by the 802.11b standard.

Devices based on 802.11g standard appeared in the market very quickly, even though the ratification was in June 20th 2003. This fact implied an advantage to the manufacturers to use the 802.11b equipment in order to implement new devices based on 802.11g.

2.2.5 IEEE 802.11n

In January 2004, the IEEE announced a working group to develop a new revision of the 802.11 standard. The real transmission rate may reach 600 Mbps, which means that the theoretical transmission rates would be even higher, and they could be reached 10 times faster than a network based on 802.11a and 802.11g standards, and about 40 times faster than a network connection based on 802.11b standard. Also, it is expected that the network coverage will be greater with this new standard, thanks to the MIMO (Multiple-Input Multiple-Output) technology, which allows multiple channels simultaneously to send and receive data through the incorporation of multiple antennas. The IEEE 802.11n standard has been finally approved in September 2009.

The characteristic which differentiate this standard from the others is that 802.11n can work in two frequency bands: 2,4 GHz (802.11b and 802.11g) and 5 GHz (802.11a). As a result, 802.11n is compatible with all previous versions of Wi-Fi devices. In addition, it is useful for 802.11n to work in the 5 GHz band, as it is less congested.

2.3 Wireless Metropolitan Area Networks (WMAN)

A metropolitan area network is the union of many interconnected LANs which is known as Wireless Local Loop (WLL). WMANs are based on the standard IEEE 802.16, which is known as WiMAX (Worldwide Interoperability for Microwave Access), and their characteristic is the capability to cover areas up to 50 km. The functionality of these networks is in the same manner as cellular communications, with the exception that the user terminal is not a mobile device, and the receiving antenna is in a fixed location, typically on the rooftops of buildings.

The tendency to MBWA communications together with the wide deployment of fixed asymmetric digital subscriber line (ADSL) wired lines, wireless systems evolved to support higher speeds. In this way, two types of line-of-sight (LOS) systems were developed [24]:

- Local Multipoint Distribution Systems (LMDS)
- Multichannel multipoint distribution service (MMDS)

LDMS allows, within limited coverage, transmit information at high speed from one point (typically the BS) to many points (customers) and vice versa. Also, it uses high frequency bands (24 or 39 GHz) whose use is regulated and requires payment of a license, for that reason their services were mainly targeted at business users in the late 1990's. However, LOS requirements involved installing antennas on rooftops, moreover, the short range of the technology stopped the growth of this technology by changing to other ones [24].

The most remarkable disadvantages are:

- The bandwidth is shared by users, so the benefits decrease as the number of users increases
- LOS conditions between the antennas to establish the radio link

The operation of MMDS is similar to the above, both having the same drawbacks. This technology was mainly used to provide TV broadcasting in zones that were not cabled. In this case the growth of satellite TV induced a redefinition of the target, and the system was used to serve Internet access. The main differences are [24]:

- MMDS uses a different frequency band, also regulated, typically between 2 and 3 GHz, which do not require LOS conditions
- The distance between the BS and clients can be more than 10 km, while in LMDS typically not exceed 5 km

The next generation of broadband wireless systems overcame the LOS problem, which tends to a cellular architecture [24]. This fact sets WiMAX as main alternative allowing non-line-of-sight (NLOS) links between BS and customer. Along with these widely developed technologies, many manufacturers have developed their own systems, which do not allow them to interoperate. Hence the need for the standardization of broadband wireless access networks.

2.3.1 WiMAX

WiMAX is a standard for wireless data transmission designed for use in the metropolitan area networks (MAN). Since January 2003, the IEEE approved the 802.16a standard, base current 802.16-2004 standard on which WiMAX is based, it has adapted to the 802.16e version, approved in December 2005, which provides mobility.

The standard IEEE 802.16 was created with the aim of finding an interoperable solution for the emerging wireless broadband. This standard was initially focused on developing a LOS broadband system, to operate in the 10 GHz to 66 GHz band, but afterwards the initial expectations of WiMAX are restricted to rural sites, with few accesses, i.e., all those areas where ADSL and the cable is out of reach [24].

The operation of WiMAX may be similar to Wi-Fi but with higher speeds, longer distances and for a greater number of users. WiMAX could address the lack of broadband access to suburban and rural areas that cable and phone companies still do not offer.

WiMAX Forum [25] is a non-profit organization formed in 2003 by component and equipment suppliers. Its objective is to propose and promote interoperability between products fulfilling IEEE 802.16 and HiperMAN (established by ETSI) standards, and thus accelerate the global deployment of broadband wireless solutions to be standardized. For that reason, WiMAX Forum has created the WiMAX certificate, which all broadband products compatible with the 802.16 standard must meet.

2.3.1.1 Network modes

The IEEE 802.16 standard's model defines three modes of interconnection: point-to-point, point-multipoint and mesh [18].

Point-to-point (Figure 2-14) and point-multipoint (Figure 2-15) connections are typically used in a fixed infrastructure, based on fixed IEEE 802.16 equipment, and both deployments can span tens of kilometers [18]. In a point-multipoint connection, the standard defines the elements BS and subscriber station (SS). In this network mode, the BS performs the same function as an AP in a Wi-Fi network, i.e., the BS acts as an interface between the SS and the core network. The SS allows the access to the network to users, after the connection between the BS and SS has been established.

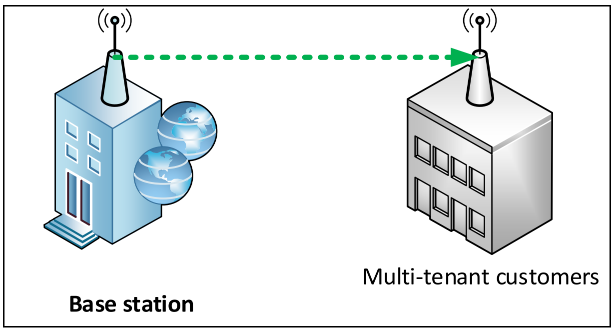

Figure 2-14.- Point-to-point connection [26]

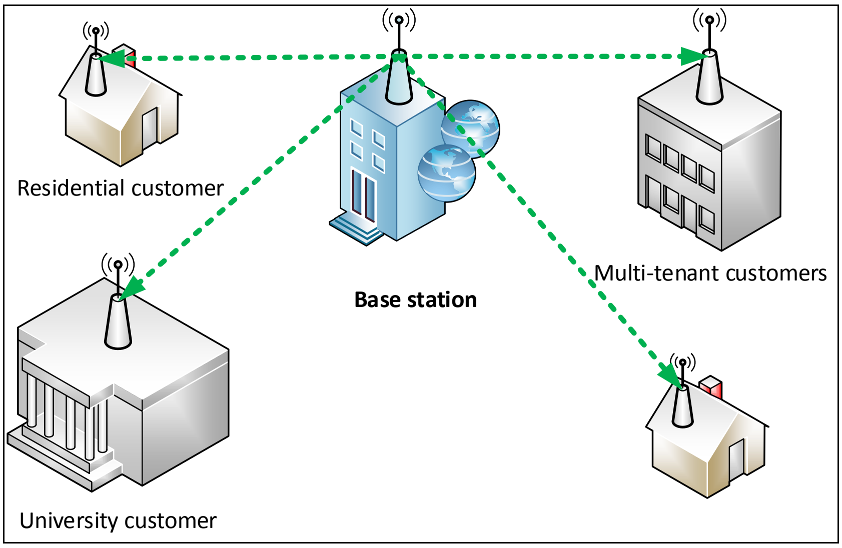

Figure 2-15.- Point-multipoint connection [26]

As an alternative to point-multipoint connections, the standard specifies the mesh interconnection (Figure 2-16), where each SS can connect to one or more SS in order to reach the connection with the BS. This is a multi-hop network, which allows a substantial increase of coverage without the need of increasing the number of BSs deployed. This fact implies a reduction of money investment.

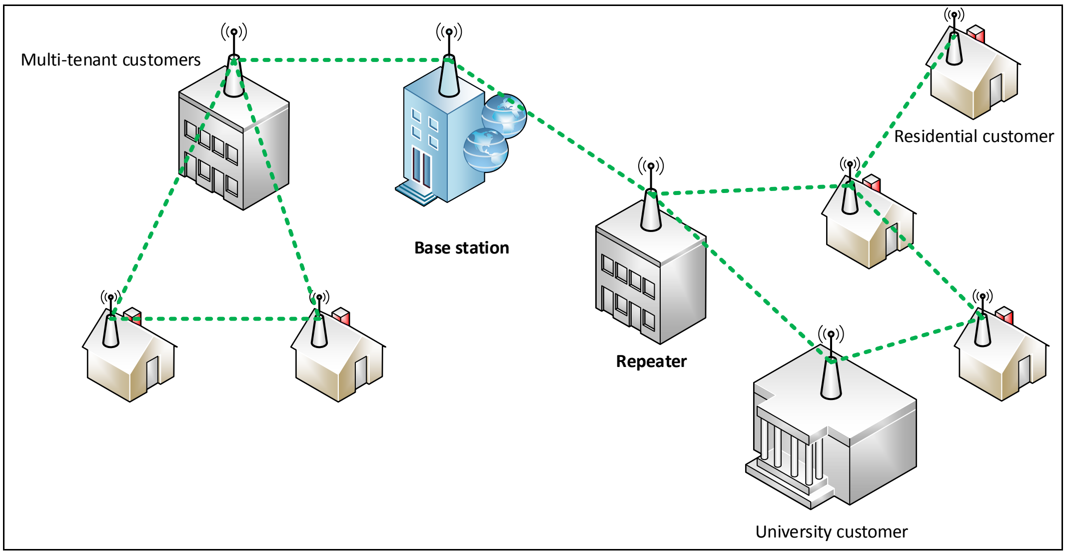

Figure 2-16.- Mesh connection [26]

2.3.1.2 Network elements

As was mentioned previously, WiMAX is targeted to rural areas in the beginning of development especially when local loops are not available. It is in that case financially much more efficient and effective. Normally, the BS resides in a central point accessible to the Internet and the outside world by satellite links or any other. They connect to remote transceivers called customer premises equipment (CPE), which are for the time being located on top of the buildings and there should be a second technology that concentrates traffic from the whole building to that CPE. The BS performs the control and scheduling tasks, also incorporates transport mechanism to establish the connection with the core network. There is a third element called "repeater" with the role of relaying circuits and switching frequencies for optimization problems. Practically there might be no difference among the three elements. However, for economic and performance purposes, a BS is designed with much more processing power, memory, etc., than the CPE or the repeater [18].

Contrary to the IEEE 802.11, IEEE 802.16 concentrates its protocols on QoS[14] characteristics, however both standards are related in the fact that they can use the same frequency. IEEE 802.16 is already to some extent an affordable technology, but it is more expensive than Wi-Fi [18].

2.3.1.3 Shared media access

IEEE 802.16 is again part of the IEEE 802 group and hence should conform to the bridging concepts. The addressing is based on MAC addresses and the BS is seen as a bridge, which has to perform the routing functions, for that reason it should implement all data link layer functionalities too [18].

As Figure 2-17 describes, the layers are divided into a physical and data link layer. In the data link layer, several sublayers are defined [18]:

- The first sublayer is called the service-specific convergent sublayer (SSCS) and is the adaptation of IEEE 802.16 for the transport IP, Ethernet and ATM[15]. The CS is capable to interact with both systems, ATM or IP, thanks to the Service Access Point (SAP) functionality. In practice it is only IP that is generalized in the available products.

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[14] Quality of Service or QoS, is a broad concept and refers to the network ability of assigning different priority to diverse multimedia applications, clients, or their data flows, as well as to guarantee certain levels of performance to a particular data flow. QoS metrics may include received throughput, data packet delay, jitter, bit error rate, packet drop probability, and others [27].

[15] Asynchronous Transfer Mode or ATM, is a telecommunication technology proposed by ITU-T in 1988 as the telecommunication standard for the Broadband Integrated Services Digital Network [69].

- The MAC sublayer is based on a connection-oriented principle. It is very close to the ATM transport protocol. The connection is using a context that describes the mapping between the incoming data flows and the underlying QoS.
- Security sublayer implements all the required elements of privacy due to the PHY layer. Examples are the key exchange and encryption/decryption processes. It is interfaced to the PHY layer through the PHY SAP.

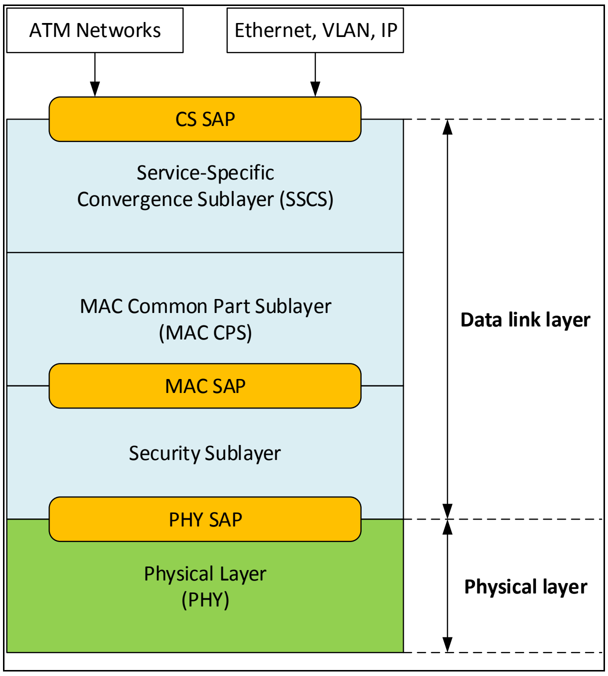

Figure 2-17.- Data link and physical layer structure [26]

On the other hand, the PHY specifies the characteristics of the different modes of operation: WirelessMAN SC, WirelessMAN SCa, WirelessMAN OFDM, WirelessMAN OFDMA and WirelessHUMAN [18]. The remarkable characteristics of each operation mode are described in Table 2-7.

Table 2-7.- PHY operation modes [18]

Operation Mode	Frequency Range	Scheduling
WirelessMAN SC	10 - 66 GHz	TDD/FDD
WirelessMAN Sca	2 - 11 GHz licensed bands	TDD/FDD
WirelessMAN OFDM	2 - 11 GHz licensed bands	TDD
WirelessMAN OFDMA	2 - 11 GHz licensed bands	TDD/FDD
WirelessHUMAN	2 - 11 GHz unlicensed bands	TDD

QoS is an essential brick of the standard and each IEEE 802.16 connection is associated to a specific QoS. Management messages dynamic service addition (DSA) and dynamic service change (DSC) are used for that purpose. IEEE 802.16 is equally suitable for both high data rate (VoIP, audio, and video) and low data rate (web browsing) applications. The protocol also supports bursty data flows and delay-sensitive traffic. In order to ensure that the diverse QoS requirements of all these applications are satisfied, the standard defines five classes of service [18] [27]:

- Unsolicited Grant Service (UGS) supports real-time, fixed size packets at fixed intervals (typically VoIP). The BS establishes fixed intervals for each data flow without the need to negotiate bandwidth.
- Real-time Polling Service (rtPS) supports real-time data with variable-sized packets issued at periodic intervals, such as video traffic (MPEG). The BS establishes the time in the upstream channel periodically, with the aim that the terminals can make requests for bandwidth. In request, the data volume to be transmitted is indicated.
- Extended Real-Time Polling Service (ertPS) is used for real-time data sources with variable bit-rate, which may require more strict delay and throughput guarantees (VoIP traffic with silence suppression). It is a hybrid system between UGS and rtPS. The BS assigns periodically part of the channel to the terminals in order to allow their transmissions. The terminals communicate to the BS the size changes over the allocated bandwidth.
- Non-real-time Polling Service (nrtPS) is used for non-delay-sensitive applications. They have variable-size packets with a minimum required data rate. The BS performs a request to each terminal aperiodically in order to know in advance the volume of data to be transmitted. The time between requests is established by the BS.
- Best Effort (BE). The terminals send requests and wait for the BS to allow them to transmit.

2.3.1.4 Physical layers variances

The physical layer is a heritage of several evolutions of the standard, as was presented in Table 2-7. The scheduling of connections is performed using time division duplex (TDD) to share uplink and downlink, but also frequency division duplex (FDD), orthogonal frequency division multiple access (OFDMA) and directive antenna that restrict their beams to a specific end point. The space domain is also managed through MIMO techniques that appeared in the late editions of the standard [18].

- WirelessMAN SC is the single carrier (SC) version made for LOS conditions in the frequency band 10 – 66 GHz, and it is aimed for applications with configuration flexibility. In order to establish the connection between the transmitting and receiving antennas, both must have been in LOS between them, this fact implies that the receiving antenna should be located in high places.

- WirelessMAN SCa is also the SC for frequencies below 11 GHz. It is capable to support LOS and NLOS operations including: adaptive modulation, channel estimation and equalization, multiple encoding schemes, adaptive antenna systems, transmit diversity techniques, power control and ARQ (Automatic Repeat Request).
- WirelessMAN OFDM is focused for NLOS operations in frequency bands below 11 GHz, and it is based on OFDM. Also, this version supports mesh network topologies, which is a great tool for optimizing system coverage.
- WirelessMAN OFDMA supports NLOS operation in frequency bands below 11 GHz, and is based on OFDMA. This is an extension of the OFDM technique to allow multiple users to share the channel.
- WirelessHUMAN includes specific features to work in unlicensed bands, being so-called High Speed Unlicensed Metropolitan Area Network (HUMAN). This version specifies the operation in the 5 to 6 GHz band using a flexible scheme based pipeline which includes channels of 10 and 20 MHz with 5 MHz of spacing.

2.4 Summary

All the wireless network technologies described in the previous sections integrate different types of scheduling and spreading, also different techniques to access the radio channels. These differences allow to designers to select the suitable technology depending on the application. Figure 2-18 classifies the wireless technologies as a function of their estimated position resolution.

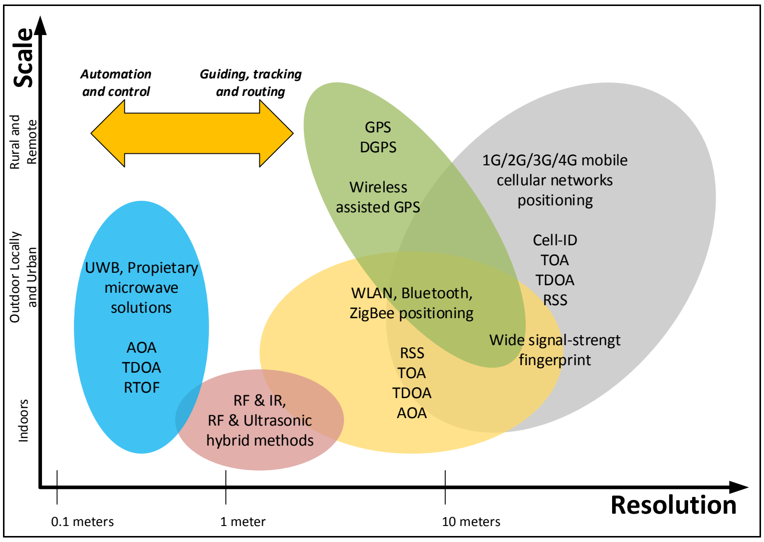

Figure 2-18.- Outline of current wireless-based positioning systems [28]

3 Non-Cooperative localization methods in wireless networks

The objective of any localization algorithm is to provide the absolute location of the MS with respect to its environment, however, most positioning technique relies on reference points for localization. In a network, there are two types of nodes [8], [29]:

- AP or anchor nodes, whose positions are known.
- MS or Non-located nodes, whose positions have to be estimated.

Non-cooperative methods refer to those algorithms that allow a non-located node to establish communication only with anchor nodes, and the position of the non-located node is estimated using the information transmitted by the anchors. Therefore, the accuracy of the position estimated is dependent on the density of anchors inside the network and the channel conditions, such as, multipath conditions illustrated in Figure 3-1 (LOS and NLOS propagations) and shadowing [8]. Those facts are a restrictive imposition limit for the use of non-cooperative methods in large-scale networks, however, in small-scale networks, where multipath conditions have a small impact, the non-cooperation between MSs becomes a great option [8].

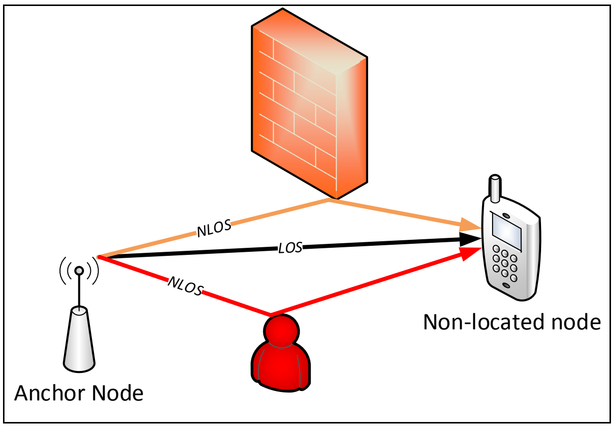

Figure 3-1.- Signal propagation in indoor environments [30]

Non-cooperative positioning is primarily considered for application scenarios such as cellular and Wi-Fi networks, where the MSs are typically connected to the BSs and APs respectively. Due to the lack of cooperation with other MSs, the amount of redundant information is smaller [31]. Figure 3-2 and Figure 3-3 illustrate the non-cooperative and cooperative positioning schemes, the difference between both schemes comes from the mutual information shared between the previously located MS and the recently non-located MS.

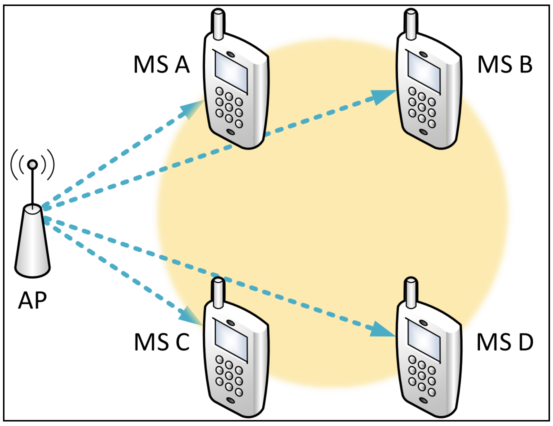

Figure 3-2.- Non-cooperative scheme

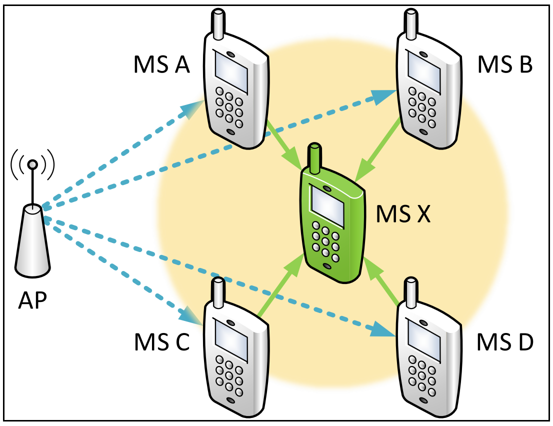

Figure 3-3.- Cooperative scheme

In WLAN location-based systems, there are three different classes of methods for positioning MS:

- Time based localization
    - Time of Arrival (TOA) [32] [33]
    - Time difference of Arrival (TDOA) [34] [35] [36]
    - Round-Trip Time of Flight (RTOF) [37] [38]
- Angle based localization: Angle of Arrival (AOA) [34] [39]
- Received signal strength based localization (RSS)
    - Cell identifier (Cell-ID) [40]
    - Fingerprinting [41] [42]
    - Pathloss [43] [44]

3.1 Time based localization

Time based localization is focused on measuring the reception time of the signal transmitted by the BS. This time measurement defines the propagation time of the signal, which is linearly dependent with the speed of propagation of a radio signal. WLAN signals typically employ OFDM technique, thus the TOA/TDOA type of localization is yet not well studied and that some of the LTE-based localization methods could apply also to most WLANs, because they have common OFDM technology.

3.1.1 Time of Arrival (TOA)

By definition, the TOA is the time it takes for a signal to go from the transmitter to the receiver. The time measures should be taken in three or more different APs which must be perfectly synchronized. The synchronization requirement is hard to be fulfilled in WLAN environments, and this technique is rarely addressed in WLAN positioning literature. To carry out these measurements, the MS must also be synchronized with the BS, because the signal emitted by the MS must include the exact time that the signal has been generated. Once the APs have received the signal, these measurements are sent to a central server, which is connected to the network and is responsible for estimating the MS position applying trilateration (see Figure 3-4). However, reflections and NLOS conditions distort the TOA of the signals [2].

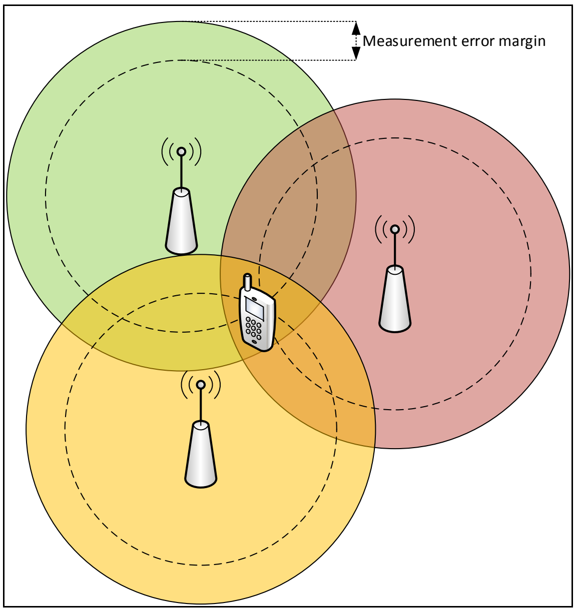

Figure 3-4.- TOA based localization method

3.1.2 Time Difference of Arrival (TDOA)

TDOA uses the difference between the arrival times of the signals at the MS coming from two different APs. Also known as hyperbolic multilateration, TDOA is the basis for many radio-navigation systems, including GPS. The difference between the arrival times at the MS define a hyperbola in the plane and the intersection of two or more hyperbolas can provide the location of the MS. This measurement provides us an improvement in the position accuracy, because the estimation only depends on the location of the anchor nodes and the synchronization between them, and the MS does not need to be synchronized with the APs [2] (see Figure 3-5). As synchronization degrades, the TDOA measurements become less accurate.

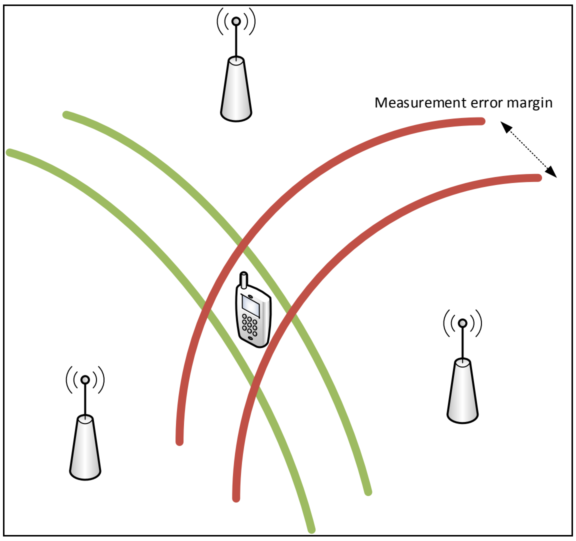

Figure 3-5.- TDOA based localization method

3.1.3 Round-Trip Time of Flight (RTOF)

To estimate the distance between two devices, a packet is transmitted between the devices (see Figure 3-6). The time required for the packet to travel from one device to the other and back is called the round trip time (RTT). The distance the packet traveled can be obtained by multiplying the RTT with the speed of light. In order to get the precise RTT, the measurement should ideally be done at the physical layer, however, not all the available WLAN devices in the market support direct access to the PHY. For that reason, the RTT is measured in the MAC layer [37].

The potential error sources for RTOF-based systems are: the uncertainties in determining the exact time of arrival of the reflected signal, inaccuracies in the timing circuitry used to measure the RTOF and the interaction of the incident wave with the target surface.

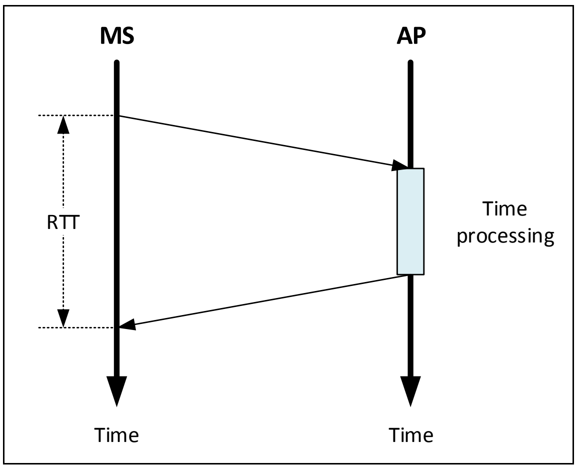

Figure 3-6.- RTOF based localization method [37]

3.2 Angle based localization

AOA differs from the other localization methods because it is based on measuring the angle of arrival of the radio signal generated by the MS. In order to acquire the angle, it is necessary to deploy a set of APs in the scenario. The accuracy provided by this measurement is up to centenary of meters, but this feature depends on the reflections and non- NLOS conditions, which distort the direction of arrival of the signals, deteriorating the accuracy of AOA positioning [2] (see Figure 3-7). Another drawback of this method is that directional antennas are required in the non-located node.

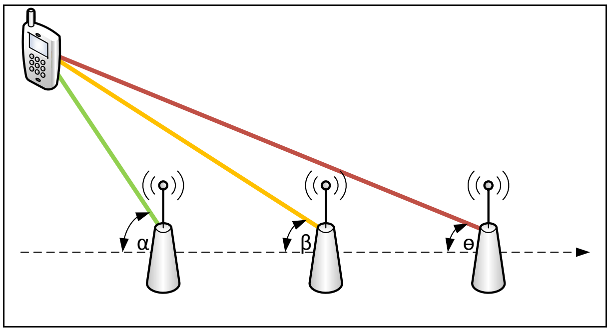

Figure 3-7.- AOA based localization method

3.3 Received Signal Strength based localization (RSS)

RSS based positioning is a technique that uses the power of the received signal to estimate the distance between receiver and transmitter. The MS location is estimated using models that relate the strength of the received radio signal either to the distance between the MS and the signal emitter or to the MS location directly [2]. RSS techniques are widely used in WLAN localization.

There are three different approaches of estimating the location via RSS which depend on which one is the transmitter and which one is the receiver. Considering the mobile station as the transmitter and the different base stations as the receiver, in which case the configuration is known as multilateral system, the base stations are responsible for estimating the position of the mobile device. If, however, the BSs are considered as the transmitters and the MS as the receiver, the MS is responsible for estimating the location. This configuration is known as unilateral system.

RSS based positioning methods can be divided into three main categories: cell identifier based, fingerprinting based “FP” [42] [41], and pathloss-based “PL” [43] [44]. Currently, the RSS is considered to be more easily available than AOA or TOA, as the RSS can be passively listened from the APs of the infrastructure WLAN, with no additional cost associated with infrastructure deployments and being based on software-based solutions at the receiver side [2], [45]. This method differs from others by the fact that synchronization is not required in estimating the distance.

RSS-based localization solutions, excluding cell-ID method, involve two stages [45]:

1. *Training/Offline phase*: the information about the indoor environment is collected, typically in the shape of measurement points coordinates and received signal strengths. The measurement points are also called fingerprints, and the information stored by each fingerprint can be their 3D coordinates or their received power, or both. The coordinates need to be measured with the help of indoor maps in an off-line initial phase.
2. *Estimation/Online phase*: this involves real-time processing, where the position of the non-located node is estimated based on the data stored in the training phase and on the current received signal strength from various heard APs.

3.3.1 Cell-ID based localization

Cell-ID localization is based on the fact that wireless networks are deployed in a cellular fashion, i.e., the wireless networks are divided into cells, and each cell is composed by one AP or BS which covers a small portion of the whole network coverage, thereby handling only a reduced amount of users.

The main idea of the Cell-ID localization, which in fact is called AP-ID in WLAN positioning, is that the MS finds the AP with the strongest signal, consequently, consults a database, which contains the information of all the APs, and finds the location identifier of the AP consulted (see Figure 3-8). Even in its simplicity, it presents several drawbacks that constrain its use, one of them being the fact that the accuracy depends on the cell size. If the cell size increases, the accuracy decreases.

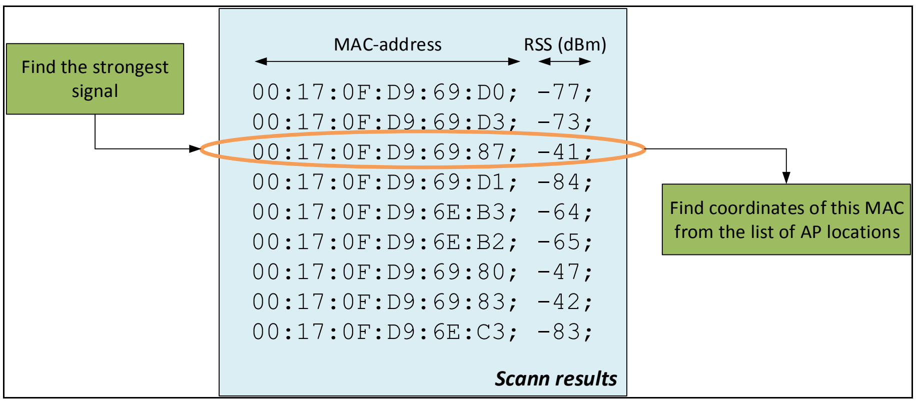

Figure 3-8.- Cell-ID based localization method [2]

3.3.2 Fingerprinting based localization (FP)

The principle of fingerprinting is based on the comparison between the off-line data base and the on-line captured data (see Figure 3-9 and Figure 3-10). For each location (x_i, y_i, z_i), a typical signal pattern $RSS_{i,ap}\ \forall \begin{cases} i = 1, \dots, N_{FP} \\ ap = 1, \dots, N_{ap} \end{cases}$ is extracted from the off-line collected data and saved to the fingerprint database with the coordinates of the location (Figure 3-9). In estimation phase, the current set of RSS measurements from the APs in the coverage area are compared to the patterns stored in database. The unknown MS position (x_{MS}, y_{MS}, z_{MS}) is estimated via pattern matching between the stored signal patterns and the measured signal vector (Figure 3-10) [2], [45]. This method can be used in either unilateral or multilateral systems.

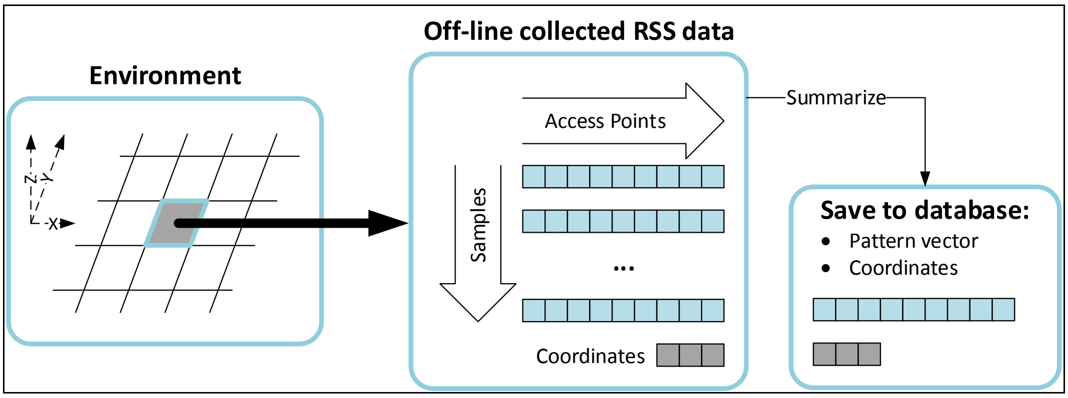

Figure 3-9.- Fingerprinting based localization method, training phase: generating fingerprint database [2]

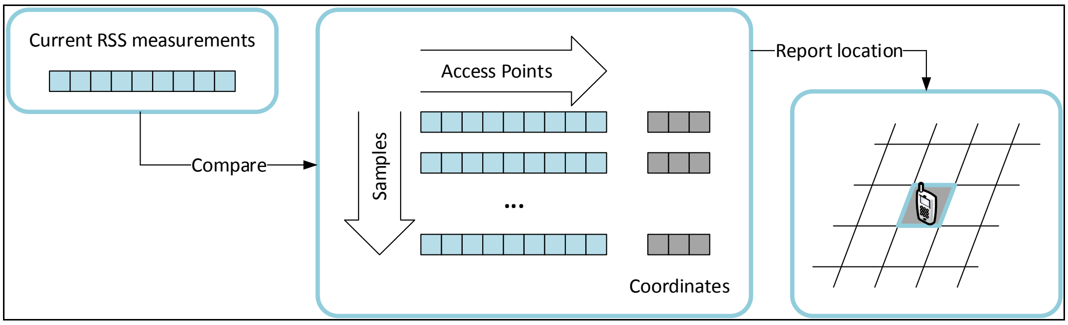

Figure 3-10.- Fingerprinting based localization method, estimation phase: positioning using fingerprints [2]

Compared to other RSS-based methods, fingerprinting algorithms are considered to be more robust against signal propagation errors such as multipath or attenuations generated by walls and other structures. Fingerprinting actually makes use of these location dependent error characteristics of radio signals to estimate the unknown MS position. A known disadvantage of fingerprinting approaches is the need of large databases in order to store the measured information, which is a laborious and time consuming task [2].

3.3.2.1 Training/Offline phase

In order to reduce the size of the database, which implies that the memory usage has to be reduced and the data collected from each fingerprint has to be summarized, a central tendency analysis has to be performed. This means selecting only one value which is the "most representative" or represents the "general tendency" of all values if several RSS values are measured in the same point. The measures of central tendency to be applied are: arithmetic mean, median, maximum value and mode. Figure 3-11, Figure 3-12 and Figure 3-13 show the impact of the data samples captured for each location in order to reduce the effect of noise and to achieve better accuracy.

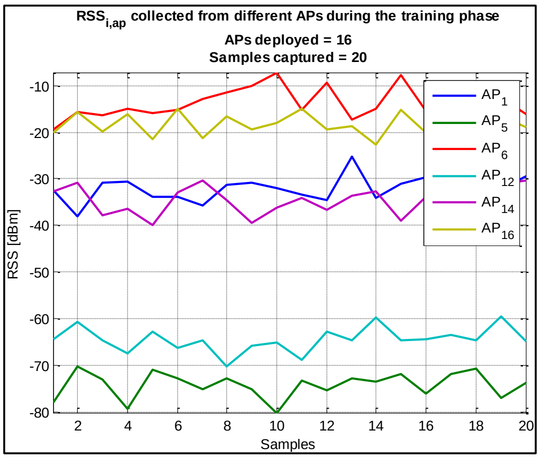

Figure 3-11.- RSS simulated of measured data at i-th fingerprint from different APs during the training phase

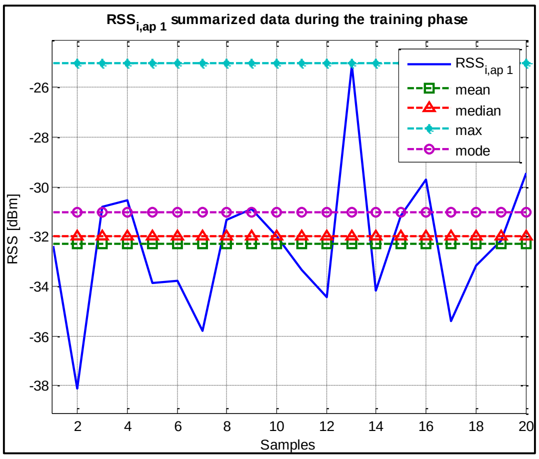

Figure 3-12.- $RSS_{i,ap\ 1}$ summarized data during the training phase

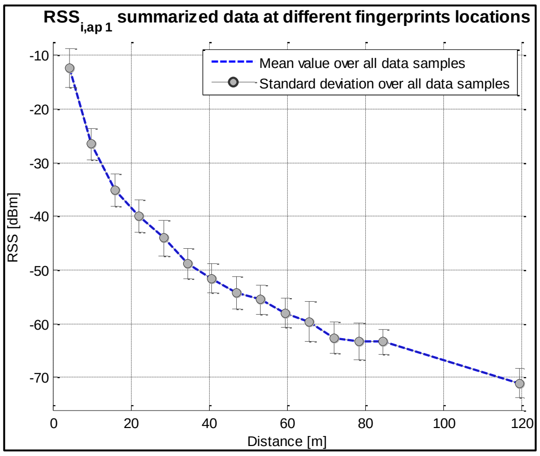

Figure 3-13.- $RSS_{i,ap\ 1}$ summarized data at different fingerprints locations during the training phase

3.3.2.2 Estimation/Online phase

Since the number of APs can be significant, there can be tens of APs measured per each RSS sample result. Thus choosing all the APs that the MS can "hear" may not be the optimal solution, because of the restrictions for database size and especially for the amount of data to be transferred from the MS [46]. In [46] it is shown that restricting the use of APs in the estimation phase may increase the positioning performance, and this restriction can be achieved estimating the average value of all the RSS measured from all the APs present in the scenario and using it as a threshold to select the "strongest" APs that user can hear.

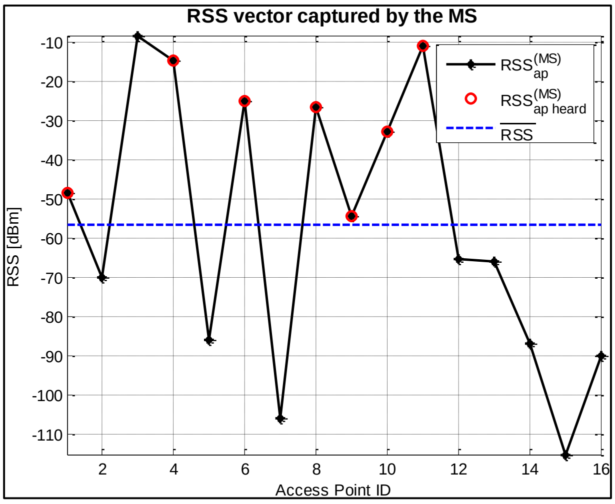

Figure 3-14.- RSS selection criterion performed by the MS

$$RSS_{ap_{heard}}^{(MS)}\ \forall\ ap_{heard}\ \in\ \mathcal{A}_{heard} \tag{3.1}$$

$$\overline{RSS} = \frac{1}{N_{AP}} \sum_{ap=1}^{N_{AP}} RSS_{ap}^{(MS)} \quad \forall \quad ap = 1, \dots, N_{AP} \tag{3.2}$$

Where: $RSS_{ap_{heard}}^{(MS)}$ The received signal strengths measured at the ap_{heard}-*th* AP "heard" in the unknown location at the mobile

$\mathcal{A}_{heard}$ Sub-set of all the AP in the scenario (i.e., what user hears at a certain point), which is composed by all the APs, whose $RSS_{ap} \geq \overline{RSS}$. The sub-set has N_{heard} elements

$RSS_{ap}^{(MS)}$ The received signal strengths measured at the *ap-th* AP in the unknown location at the mobile

N_{AP}	Number of APs deployed
$\overline{RSS}$	Average value of all $RSS_{ap}^{(MS)}$ measured at the *ap-th* AP in the unknown location at the mobile

Reducing the number of APs at each unknown MS location implies that the amount of data to be processed is reduced, and consequently the computational load is optimized. Once the amount of data has been optimized in the receiver and on the transmitter side, the new RSS vector of the MS is compared to the optimized fingerprints database, defining their difference as cost function which has to be minimized. This minimization will generate as a result the Euclidean distance, which defines the estimated position coordinates $(\hat{x}_{MS}, \hat{y}_{MS}, \hat{z}_{MS})$. Several cost functions are possible; one example is the Euclidian distance between the measured RSS and the RSS in the database, as below:

$$\hat{\imath} = \underset{i}{\operatorname{argmin}} \left\{ \frac{1}{N_{heard}} \sum_{ap=1}^{N_{heard}} \left| RSS_{ap_{heard}}^{(MS)} - RSS_{i,ap_{heard}} \right|^2 \right\} \quad \forall \begin{cases} i = 1, \dots, N_{FP} \\ ap \in \mathcal{A}_{heard} \end{cases} \tag{3.3}$$

Where:	$RSS_{i,ap_{heard}}$	The received signal strengths collected at the fingerprint *i-th* during the training phase
	N_{FP}	Number of fingerprints collected
	N_{heard}	Number of heard APs

As the equation (3.3) describes, in the fingerprinting approaches the positions of the APs are typically not known and not needed in the estimation process [45]. Other cost functions are possible, such as Gaussian likelihoods, Log-Likelihoods or rank-based, which are described in [47] and [41]

If no averaging over nearest neighbor (NN) points is used, the fingerprint with smallest Euclidean distance is selected, and the location of this point is returned as MS location. When the NN averaging is used, N_{neigh} fingerprints $\hat{\imath}$ with smallest Euclidean distances are selected, and the position of the MS is calculated as an average over corresponding locations [46].

3.3.3 Pathloss-based localization (PL)

Pathloss propagation models are used to translate RSS measurements to distances between the MS and APs. The MS needs to measure the RSS from at least three different APs, and the position of the MS is estimated using trilateration/multilateration (see Figure 3-15). As in cell-ID based methods, the MS needs prior information about the MAC addresses and locations of APs to apply trilateration/multilateration [2] or it needs to first estimate the AP location.

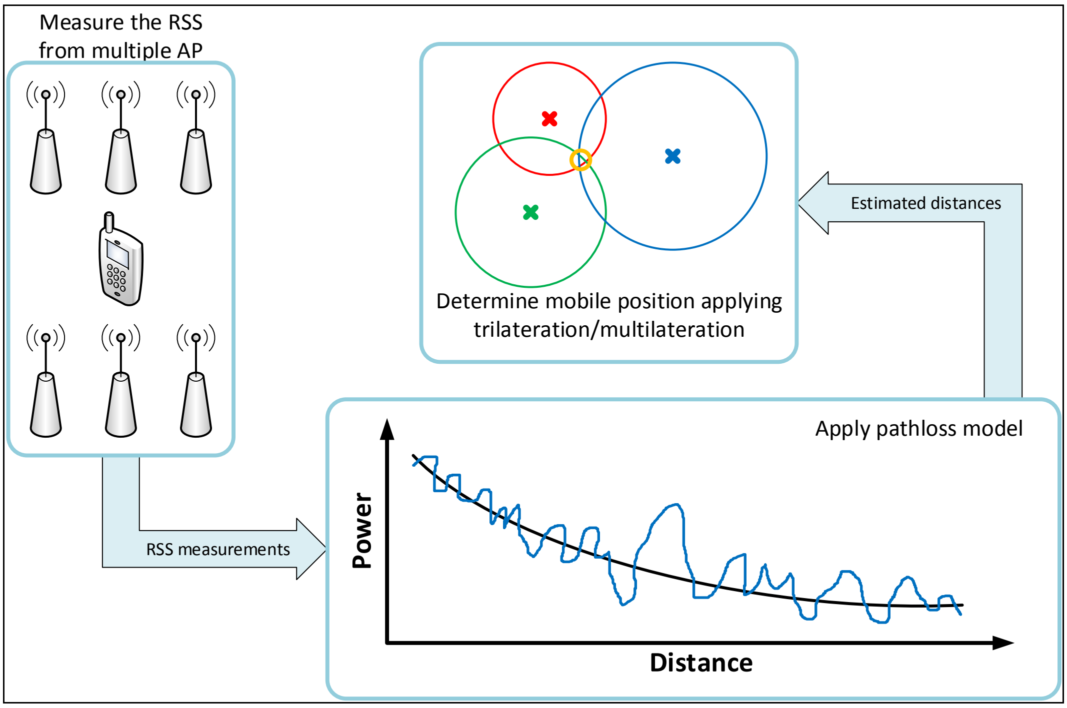

Figure 3-15.- Pathloss-based localization method [48]

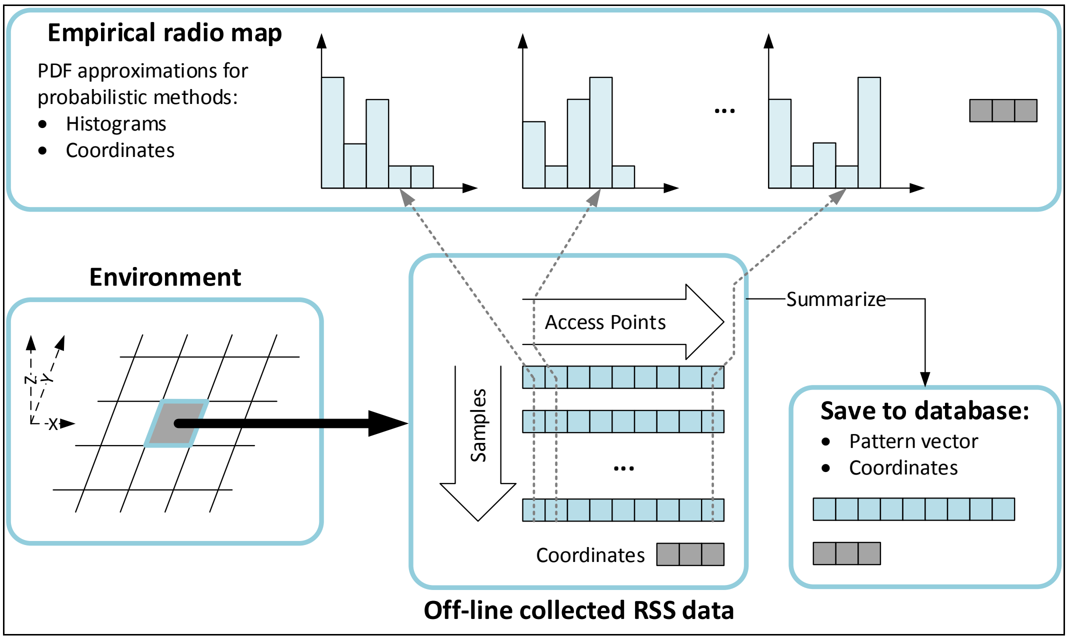

Figure 3-16.- Probabilistic/Pathloss-based localization method, training phase: empirical radio map [48]

Additionally, instead of trilateration methods, it also is possible to use cost functions similarly with FP case. In this case the measured RSS value is compared to a recreated RSS value based on the path-loss model and on a grid created at the receiver side.

In indoor environments, multipath and attenuation caused by walls, other structures, and even people complicate the modeling of signal propagation. Because of this, the positioning errors in pathloss-based positioning are typically larger than in fingerprinting [2].

In order to reduce the impact of the environmental effects, [43] and [45] describe a method for dynamic estimation of the model parameters for each AP using learning data collected at known positions. This method is known as Probabilistic/Pathloss method, which describes an empirical radio map with an associated PDF[16] to describe the propagation of the radio signals in the environment (see Figure 3-16). The number of required pathloss parameters is kept small in order to keep down the computational complexity and the amount of information required in the estimation phase [43]. Instead of the original fingerprints, this method stores a few parameters per AP [45]. Alternatively, the path loss parameters can be estimated via deconvolution approaches, such as LS and MMSE, as shown in [45].

3.3.3.1 Training/Offline phase

In the training phase, the pathloss model parameters for each AP are estimated within the given database (x_i, y_i, z_i) and $P_{RX_{i,ap}}$. A pathloss model is a model for signal attenuation in space and involves two modeling parameters per AP [43]. Let's assume that each AP can be characterized by a vector Θ_{AP} with M parameters [45], according to the following model:

$$\begin{cases} P_{RX_{i,ap}} = f\left(d_{i,ap}, \Theta_{AP}\right) \\ \Theta_{AP} = \left[P_{TX_{ap}} \quad n_{ap}\right] \end{cases} \tag{3.4}$$

$$\begin{cases} P_{RX_{i,ap}} = RSS_{i,ap} = P_{TX_{ap}} - 10 n_{ap} \log_{10} d_{i,ap} + \eta_{i,ap} \\ d_{i,ap} = \sqrt{\left(x_i - x_{ap}\right)^2 + \left(y_i - y_{ap}\right)^2 + \left(z_i - z_{ap}\right)^2} \end{cases} \tag{3.5}$$

Where:

$P_{RX_{i,ap}}$	The received signal strengths collected and summarized from the *ap-th* AP at the fingerprint *i-th* during the training phase
$d_{i,ap}$	The distance between the *ap-th* AP and the *i-th* measurement point

[16] Probability Density Function or PDF

$P_{TX_{ap}}$	The *ap-th* AP transmit power
n_{ap}	The path-loss coefficient of the *ap-th* AP
$\eta_{i,ap}$	The noise factor, typically assumed Gaussian distributed, of zero mean and standard deviation σ_{ap}. In the absence of prior information on σ_{ap}, it will be assumed constant over all APs and equal to σ.

The noise is typically due to shadowing, fading and measurement errors. In some cases, there is no additional prior information that describes this parameter, which implies that the noise variance σ^2 may be assumed constant per building.

The equation (3.5) can be written in matricial form as [45]:

$$\mathbf{P}_{\boldsymbol{RX_{ap}}} = \mathbf{H_{ap}}\boldsymbol{\Theta}_{\mathbf{ap}}^{\mathbf{T}} + \mathbf{n} \tag{3.6}$$

$$\begin{cases} \boldsymbol{\Theta}_{\mathbf{ap}} = \left[P_{TX_{ap}} \quad n_{ap}\right]^T \\ \mathbf{P}_{\boldsymbol{RX_{ap}}} = [RSS_{1,ap} \quad RSS_{2,ap} \quad \dots \quad RSS_{N_{FP},ap}]^T \end{cases} \tag{3.7}$$

$$\mathbf{H_{ap}} = \begin{bmatrix} 1 & -10\log_{10} d_{1,ap} \\ 1 & -10\log_{10} d_{2,ap} \\ \dots & \dots \\ 1 & -10\log_{10} d_{N_{FP},ap} \end{bmatrix} \tag{3.8}$$

Where:	$\boldsymbol{\Theta}_{\mathbf{ap}}^{\mathbf{T}}$	The unknown parameters per AP
	$\mathbf{P}_{\boldsymbol{RX_{ap}}}$	The vector with the summarized $RSS_{i,ap}$ from the *ap-th* AP at the *i-th* fingerprint.
	$\mathbf{n}$	Gaussian distributed $N_{FP} \times 1$ vector

It is a hard task to obtain prior information to describe the noise characteristics associated with the environment, for that reason it is necessary to estimate the noise variance from the non-summarized RSS measurements in order to build an accurate pathloss model which includes the effect of the noise in the model. Figure 3-17 shows the estimation performance applying a dispersion analysis to the non-summarized off-line database at different noise levels.

In some cases, the information related with AP location is not known. Thus, in order to increase the independence of this information, [45] proposes a solution to estimate the AP location using the off-line measurements collected. Based on the RSS vector of *ap-th* AP ($\mathbf{P}_{\boldsymbol{RX_{ap}}}$), it is defined as the estimated position of the *ap-th* AP $\left(\hat{x}_{ap}, \hat{y}_{ap}, \hat{z}_{ap}\right)$ the strongest "heard" fingerprint, i.e., the fingerprint location with the maximum RSS measurement.

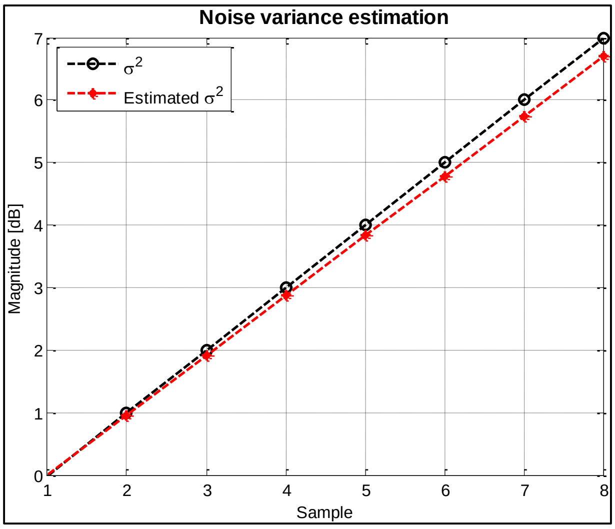

Figure 3-17.- Noise variance estimation

Figure 3-18 shows the estimated AP location after applying the strongest fingerprint criterion to the summarized fingerprint database. The simulation set up conditions, for Figure 3-17 and Figure 3-18, are:

- 10000 m^2 of area
- 16 APs
- 256 fingerprints
- 20 samples captured per RSS and summarized applying the arithmetic mean estimator
- 3 dB noise variance

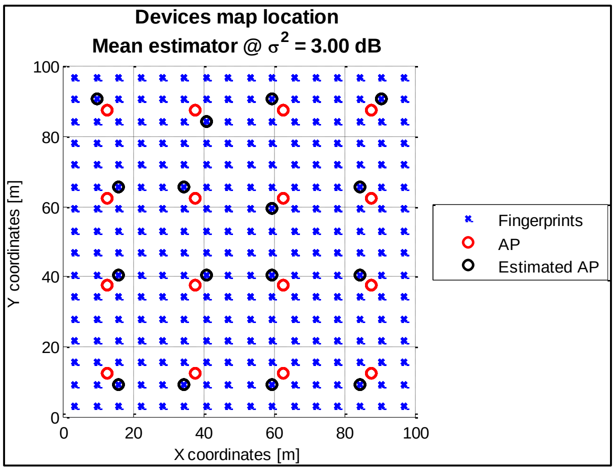

Figure 3-18.- Estimated AP location based on the strongest fingerprint

Once $(\hat{x}_{ap}, \hat{y}_{ap}, \hat{z}_{ap})$ have been estimated, which implies that $\hat{d}_{i,ap}$ has been estimated, the matrix $\mathbf{H_{ap}}$ can be computed and used in the equation (3.6) in order to estimate the $\boldsymbol{\Theta}_{\mathbf{ap}}^{\mathbf{T}}$ via the deconvolution method Least Squares (LS) [45]. Figure 3-19 shows the estimated AP parameters, applied to all the different central tendency measurements, via LS method. The simulation set up conditions are the same as in the Figure 3-18. Alternatively, MMSE[17] and POCS[18] estimators can also be used, as shown in [45], but the comparative analysis showed little difference in the performance of various deconvolution methods.

$$\widehat{\boldsymbol{\Theta}}_{\mathbf{ap}}^{\mathbf{T}} = \left(\mathbf{H}_{\mathbf{ap}}^{\mathbf{T}}\, \mathbf{H}_{\mathbf{ap}}\right)^{-\mathbf{1}} \mathbf{H}_{\mathbf{ap}}^{\mathbf{T}}\, \mathbf{P}_{\boldsymbol{RX_{ap}}} \tag{3.9}$$

Where: $\widehat{\boldsymbol{\Theta}}_{\mathbf{ap}}^{\mathbf{T}}$ The estimated parameters per AP

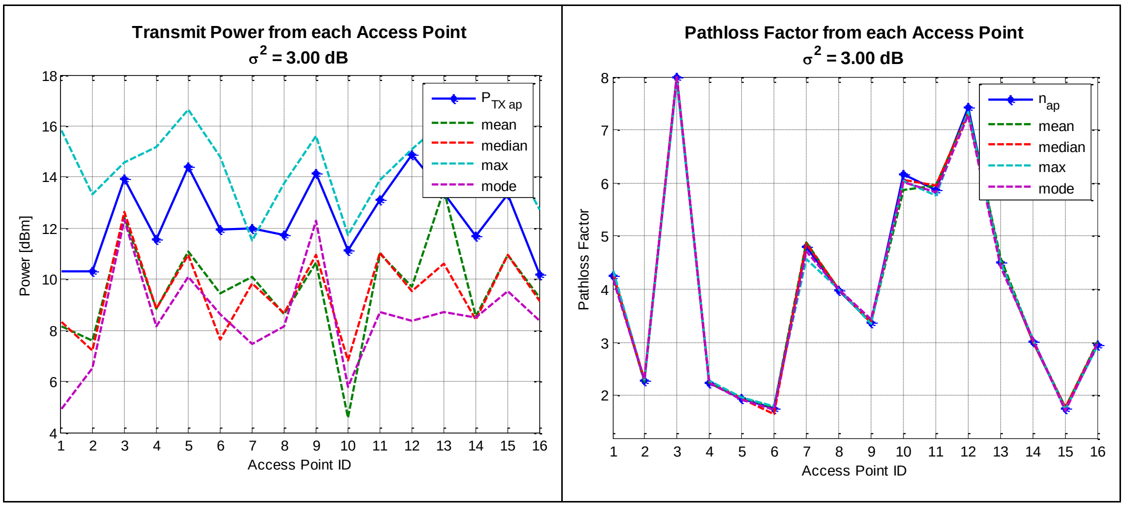

Figure 3-19.- Estimated AP parameters via LS method

3.3.3.2 Estimation/Online phase

Once the database size is reduced to $\{\hat{x}_{ap}, \hat{y}_{ap}, \hat{z}_{ap}, \hat{\Theta}_{ap}\}$ and given the measured RSS at the mobile $RSS_{ap_{heard}}^{(MS)}$, a PDF, defined as a Gaussian Log-likelihood function, can be related to each fingerprint point and each AP. However, other cost functions are possible, such as based on Gaussian likelihoods or Log-likelihoods or Rank-based [41].

$$p(i, ap_{heard}) = -\frac{1}{2}\log_{10}(2\pi\,\hat{\sigma}^2) - \frac{\left[RSS_{ap_{heard}}^{(MS)} - \hat{P}_{TX_{ap_{heard}}} + 10\hat{n}_{ap_{heard}}\log_{10}\hat{d}_{i,ap_{heard}}\right]^2}{2\,\hat{\sigma}^2} \tag{3.10}$$

---

[17] Minimum Mean Square Error or MMSE

[18] Projection Onto Convex Sets or POCS

Where: $\hat{\sigma}^2$ The estimated noise variance related to the $RSS_{i,ap}$ measurements

The problem of estimating the unknown MS location $(\hat{x}_{MS}, \hat{y}_{MS}, \hat{z}_{MS})$ is reduced by estimating the fingerprint $\hat{\imath}$ which maximizes the PDF described in the equation (3.10).

$$\hat{\imath} = \underset{i}{\operatorname{argmax}} \left\{ \frac{1}{N_{heard}} \sum_{ap=1}^{N_{heard}} |p(i, ap_{heard})|^2 \right\} \qquad (3.11)$$

$$\forall \begin{cases} i = 1, \dots, N_{FP} \\ ap \in \mathcal{A}_{heard} \end{cases}$$

Where: $p(i, ap_{heard})$ The Gaussian Log-Likelihood function related to each fingerprint point and for each AP

N_{FP} Number on fingerprints collected

N_{heard} The result of the equations (3.1) and (3.2) which establish the number of heard APs

As was described in section 3.3.2.2, also averaging over N_{neigh} points can be used in here and the position of the MS is calculated as an average over corresponding locations.

4 Cooperative localization methods in wireless networks

Cooperative positioning refers to a localization system where all nodes cooperate with each other in order to infer their locations by communicating and exchanging location-related information (Figure 4-1). The concept of cooperative positioning is mostly applied nowadays to ad hoc and wireless sensor network (WSN) application scenarios, where in fact, nodes can communicate either via a direct link or through multi-hop connections [31]. Recently, the cooperation concept has been introduced to heterogeneous communication systems, as described in [44], [49] and [50]. However, techniques proposed for WSN cannot be straightforwardly extended to mobile communication networks, because these networks usually operate in a very complex and adverse wireless environment due to factors such as multipath conditions and shadowing. Hence, the heterogeneity of today's wireless communication networks can be seen as an additional problem to be addressed [51].

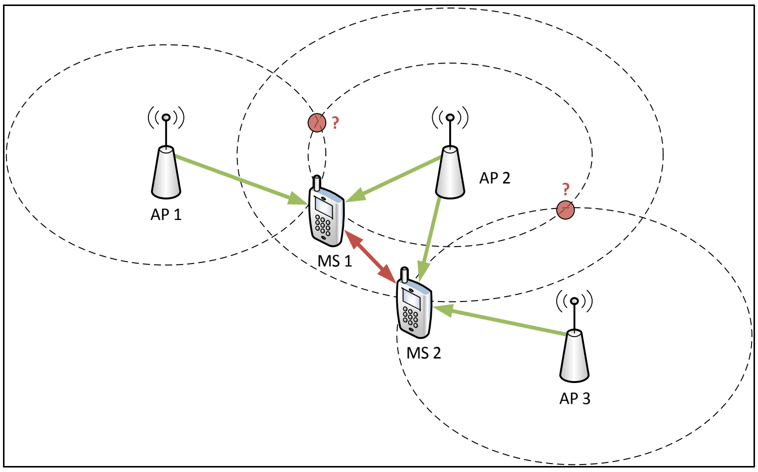

Figure 4-1.- The benefit of cooperative localization [52]

As [1] describes, the exploitation of spatial proximity estimated within a group of neighboring MS has the strong potential to enhance the location estimation accuracy, where by sharing radio signals better performances are achieved over the stand-alone cellular one [2]. However, even with this benefit, cooperative algorithms can be more sophisticated than those used for non-cooperative positioning. In fact, these methods must handle a larger number of variables, a more complicated cost function, and multiple minima due to the partial network connectivity [31].

Figure 4-1 addresses the benefit of cooperative localization using only distance estimates with respect to the APs, because of the fact that the MSs are unable to determine their respective positions without ambiguity. As it is described in the figure, MS 1 cannot reach the communication with AP 3, and MS 2 cannot communicate with AP 1. When MS 1 and MS 2 establish the communication between them, and range directly (as depicted by the red arrow), both devices can cooperate to unambiguously determine their positions [52].

From algorithmic point of view, there are two classes of cooperative algorithms: centralized algorithms [1] [53] and distributed algorithms [52] [54], however, from the statistical point of view, cooperative algorithms can be classified as Bayesian [8] [52] and non-Bayesian [8] [52]. Figure 4-2 describes this classification in detail.

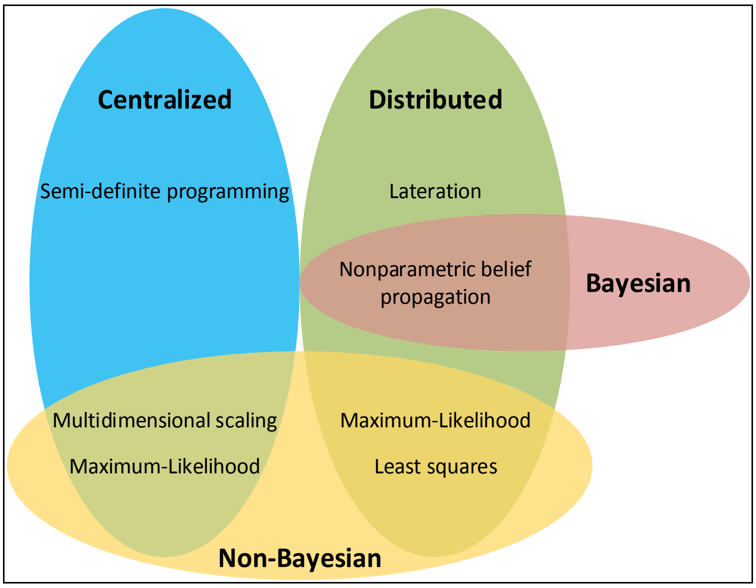

Figure 4-2.- Cooperative algorithms classification [8], [52], [55]

4.1 Centralized cooperative approach

In the centralized cooperative approach it is assumed that all information, i.e., the measurements collected by the MSs, is provided to one central entity, which could be a location server connected to the network. There, the measurements are jointly processed and the position for each MS in the network is determined. As all measurements are processed jointly in this approach, it is the optimum procedure from a position estimation accuracy point of view. Moreover, the MSs are less restricted in terms of complexity, which implies that a more complex algorithm could be implemented and which would be executed in the location server [51].

However, all measurements have to be collected at a central entity in advance, and hence the traffic is increased. Also, this fact implies that most of the computational load will be performed in the location server, hence, the higher cost for this device. Furthermore, centralization of all the information reduces the scalability of the algorithm [8].

Figure 4-3 describes the concept of centralized cooperative algorithm procedure. Once the training phase has been performed, the MSs initiate to collect the on-line data from all the APs (as depicted by the red and green thin arrows located on the left side of the figure) to send them afterward to the location server by the nearest APs (as depicted by the wider red and green arrows located on the up and down side of the figure). The location server will process the on-line and off-line data applying a RSS-based localization method. Once the server has obtained the corresponding cost function of each MS and jointly processed them, a multilateration will be applied based on the estimated distances MS-AP (as depicted by the wider red and green arrows located on the right-middle part of the figure), in order to estimate the position of each MS (as depicted by the wider red and green arrows located on the left-middle part of the figure). It has to be pointed out that multilateration is not the only possible solution, in addition least squares and minimizing or maximizing cost functions can be used.

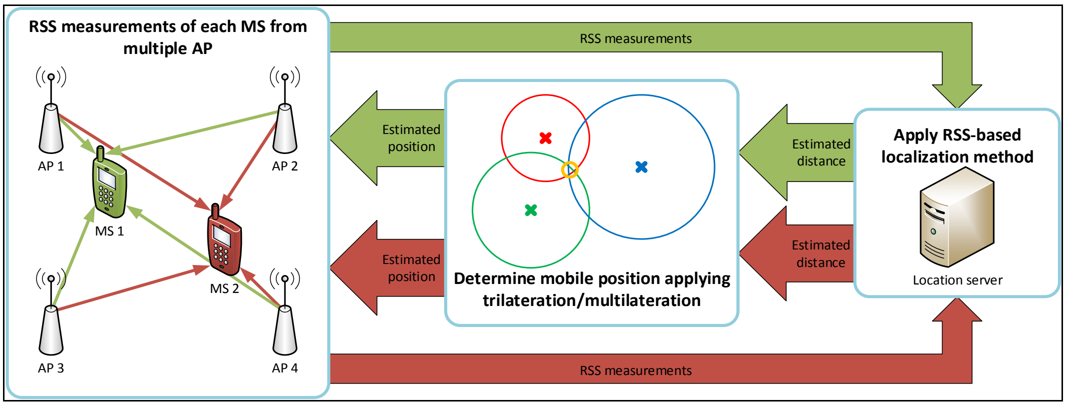

Figure 4-3.- Message flow for centralized cooperative algorithm

4.1.1 Semi-Definite Programming (SDP)

The Semi-Definite Programming is a subfield of convex optimization. SDP consists of minimizing a linear function subject to the constraint that an affine combination of symmetric matrices is positive semi-definite. This is a non-linear constraint but convex, for that reason SDP is considered as a convex optimization problem. However, the localization problem is a non-convex problem, hence, the basic idea of a SDP algorithm is to transform the non-convex quadratic distance constraints into a linear constraint by simplifying the quadratic term in the formulation [8]. Nevertheless, the algebraic degree of SDP addresses the computational complexity at a fundamental level. SDP is essentially to solve a class of univariate polynomial equations whose degrees are the algebraic degree. Normally, the algebraic degree is usually very big, even for some small problems [56].

When the number of devices increases, the solution of a large SDP becomes more complex. This problem can be solved by dividing the network into clusters, reducing the complexity of the entire network and achieving a reduction in terms of computation time [8].

Simulation results from different approaches and different scenarios are presented in [57], [58], [59] and [60].

4.1.2 Multidimensional Scaling (MDS)

Multidimensional scaling is a procedure for fitting a set of points in a space so that the distances between points correspond as closely as possible to a given set of dissimilarities between a set of objects [61]. The data for MDS analyses are called proximities which indicate the overall similarity or dissimilarity of the objects under investigation [62]. Often, the similarities or dissimilarities values are arranged in a rectangular matrix.

There are two major groups of methods for deriving proximities: direct and indirect methods. The set of objects might assign a numerical (dis)similarity value to each pair of points, or provide a ranking of the pairs with respect to their (dis)similarity. Both approaches are direct methods of collecting proximity data. Indirect methods for proximity data do not require that an object assigns a numerical value to the elements of the proximity matrix directly. Rather, the proximity matrix is derived from other measures, e. g. from confusion data or from correlation matrices [62].

Adapting to a localization algorithm, the objects are the MSs and the dissimilarities are the distance estimates. MDS can reconstruct the relative positions of the points based on the mutual distance between MS. The last step of a MDS algorithm is transforming the relative map into an absolute map based on the knowledge of the absolute position of some APs [8].

In the same way as SDP, when the number of devices becomes larger, the applicability of this method is limited. As [63] addresses, this problem can be mitigated applying map-stitching techniques, typically used in WSN.

Although MDS is originally a centralized algorithm, distributed solutions have been developed in [64].

4.1.3 Maximum-Likelihood Estimation (MLE)

Maximum-Likelihood Estimation is a popular statistical method used for fitting a statistical model to data and providing estimates for model's parameters. One of its advantages is its asymptotic efficiency. However, MLE has two major drawbacks, one of them is the fact it is very sensitive to model perturbations, i.e., if the data measurements deviate from the statistical model assumed the estimated results could not be optimal. [8] The other drawback is that MLE is a biased estimator, for that reason in [65] presents an Optimization to Maximum Likelihood (OML) algorithm, which minimizes the sum-of-squares bias.

4.2 Distributed cooperative approach

As to cope with scalability in dense large-scale networks using restricted infrastructure, the distributed cooperative approach can also be favored as an alternative to centralized methods. Also, these algorithms are usually considered more efficient in terms of computational cost. Here, the MSs have only the information available that they obtain from their neighbors via P2P[19] or ad hoc links, and the measurements with the APs (see Figure 4-4). The fact that the MSs have all the measurements means that they themselves are responsible of estimating their own position [8], [51]. Hence, the position estimation complexity is distributed among the MSs compared to the centralized approach [51].

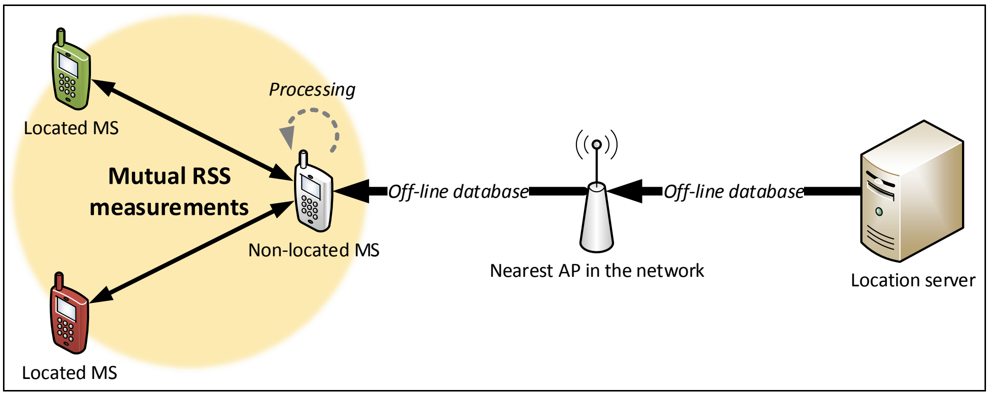

Figure 4-4.- Message flow for distributed cooperative algorithm

[19] Peer to Peer or P2P. In a P2P network, the "peers" are computer systems which are connected to each other via the Internet. Files can be shared directly between systems on the network without the need of a central server, i.e., each computer on a P2P network becomes a file server as well as a client [70].

On the other hand, distributed algorithms have lower accuracy compared to those achieved with a centralized algorithm, due to the fact that calculus is done at the MSs, where computational restrictions are present in order to avoid notorious battery consumptions [8].

Three distributed methods are present in distributed algorithms: lateration, Bayesian and non-Bayesian. Bayesian approaches consider MS coordinates (x_{MS}, y_{MS}, z_{MS}) as a realization of a random variable with a priori PDF, while non-Bayesian and lateration approaches consider (x_{MS}, y_{MS}, z_{MS}) as a deterministic variable [8].

4.2.1 Lateration

Lateration is based based on triangulation concept, but in this case the alteration methods use the distances between the MSs and APs instead of using angles. This method is known as trilateration if three nodes are used or multilateration when more than three nodes are used [8].

Trilateration is classified as a distributed localization algorithm, which is range based, i.e. it uses distance estimation to compute the position of MSs in a network with the help of the received information from the APs, e.g.: RSS [66]. Using the estimated distances obtained from neighbor MSs, non-located MS obtains their location estimating the intersection point of the circles centered at the APs with the radius equal to estimated distance (Figure 3-4). Hence, this technique is significantly affected by the presence of errors in the RSS measurements.

4.2.2 Nonparametric Belief Propagation (NBP)

The belief propagation (BP) is a popular technique for estimating the marginal probabilities of each of the variables. BP follows a message-passing formulation, in which at each iteration every variable passes a message to its neighboring factors, and factors to their neighboring variables. When the variables take a finite number of values, the messages may be represented as vectors [67].

Non-parametric belief propagation (NBP), also known as Sum-Product Algorithm (SPA) [52], is an inference algorithm for graphical models containing continuous, possibly non-Gaussian random variables. NBP extends the popular class of particle filtering algorithms[20], which assume variables are related by a Markov chain, to general graphs. Such sample-based representations are particularly useful in high-dimensional

[20] Particle filtering, also known as Sequential Monte Carlo (SMC) methodology, generate discrete random measures that can be naturally used to approximate integrals with respect to the posterior distribution given the data (including, e.g., its mean) [71].

spaces, where discretization becomes computationally difficult. In NBP, messages are represented by collections of weighted samples, smoothed by a Gaussian shape i.e., Gaussian mixtures [67].

4.2.3 Non-Bayesian Estimators

Based on [52] and [55], MLE and least squares estimation (LSE) are classified as a non-Bayesian estimators and the basic idea of both estimators is to minimize a cost function. First of all, the MSs broadcast their own coordinates to their neighbors, then each MS estimates the mutual distance to each MS using, e.g., the RSS from the APs. Finally, the MSs recalculate their own position using the RSS and the mutual distance between MSs. All these steps are repeated until the algorithm converges [8].

The drawback of this method is the possibility that the algorithm does not converge to a global minimum, which is caused by the bad selection of a starting point and which affects the global accuracy of the algorithm, for that reason the initial point has to be selected carefully when the algorithm is designed [8].

LSE only minimize the norm of the difference between the RSS and the distance estimation, however, MLE exploits the knowledge of the noise statistics of the RSS measurements [55].

4.3 Proposed cooperative approach

The cooperative approach proposed in this thesis, to corroborate the position enhancement by the cooperative methods, is classified as a distributed algorithm, which will be based on RSS based localization methods, such as FP and PL.

As was explained in section 3.3, the RSS based positioning involves two stages: the training phase and the estimation phase. In order to create the corresponding training database, the off-line measurements are required. With the database and the on-line measurements, the cost function of the RSS positioning method adopted (FP or PL) can be defined. Afterwards the joint cost function of all the MSs can be optimized.

Figure 4-5 describes more exhaustively the concept of proposed cooperative algorithm procedure. Once the training phase has been performed and the off-line data has been collected (as depicted by the wider light blue arrow located on the left side of the figure), the MSs begin to collect the on-line data from all the APs (as depicted by the red and green thin arrows located on the left side of the figure) and subsequently send them to the location server by the nearest APs (as depicted by the wider red and green arrows located on the down-left side of the figure). The location server will process the on-line and off-line data applying a RSS-based localization method, such as FP or PL.

Once the server has obtained the corresponding cost function of each MS and jointly processed (as depicted by the wider red and green arrows located on the up-right side of the figure), a multilateration will be applied based on the estimated distances MS-AP (as depicted by the wider red and green arrows located on the right side of the figure), in order to estimate the positions of each MS. The combination of the cost function of each MS allows us to estimate the mutual distance between MSs (as depicted by the wider yellow arrow located on the down-right side of the figure), which will be mapped on the scenario (as depicted by the thin yellow arrow located on the down-left side of the figure).

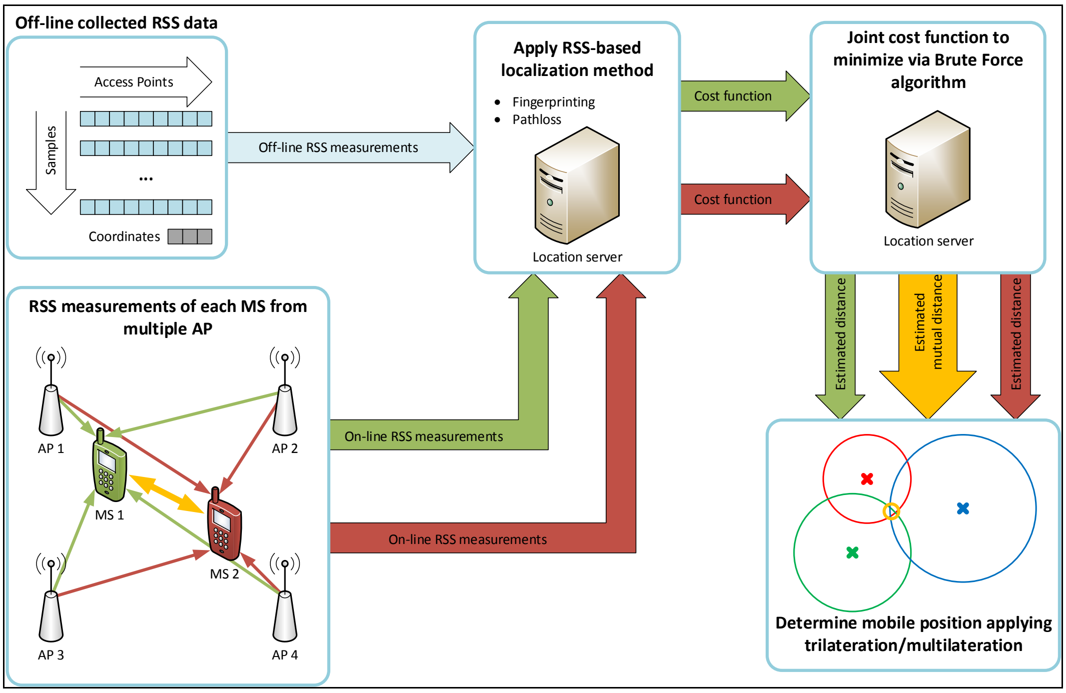

Figure 4-5.- Proposed cooperative algorithm

Let's assume that there are two non-located nodes which are described by their respective cost functions $cost_{MS\,1}(i)$ and $cost_{MS\,2}(j)$ which represents the likelihood functions (computed either via FP or via PL), where *MS 1* and *MS 2* are the two mobiles, and *i* and *j* are the indices of the fingerprint database. Assuming that the distance between the two mobiles is known, noted as $d_{true}(MS\,1, MS\,2)$, the optimization problem becomes:

$$(\hat{\imath},\hat{\jmath}) = \underset{i,j}{\operatorname{argmax}}\{cost_{MS1}(i) + cost_{MS2}(j)\}$$
$$\text{under the constraint: } d(i,j) = d_{true}(MS\,1, MS\,2) \tag{4.1}$$

Where: $d(i,j)$ The distance between the *i-th* fingerprint and the *j-th* fingerprint. In the absence of knowledge of the true distance, $d(i,j) = d_{true}(MS\,1, MS\,2) + n_{MS\,1,MS\,2}$, where $d(i,j)$ can be previously estimated also through RSS measurements from one MS to another.

This is a constraint maximization problem that can be solved either via Lagrange multiplier or by maximizing the equivalent problem:

$$(\hat{\imath}, \hat{\jmath}) = \underset{i,j}{\operatorname{argmax}} \left\{ cost_{MS\,1}(i) + cost_{MS\,2}(j) - \sqrt{|d(i,j) - d_{true}(MS\,1, MS\,2)|} \right\} \quad (4.2)$$

Equation (4.2) describes that, via testing all the fingerprint combinations, there are a pair or pairs which maximize the joint cost function. This exhaustive searching is known as Brute Force algorithm.

Figure 4-6 and Figure 4-7 show examples of the waveforms for $cost_{MS\,1}(i)$ and $cost_{MS\,2}(j)$ overall all the fingerprints, and the linear combination of both, respectively.

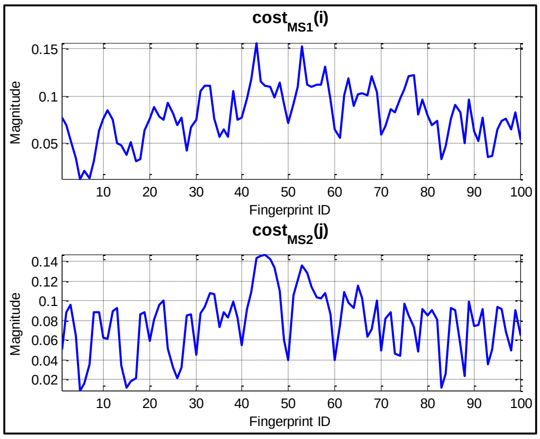

Figure 4-6.- cost$_{MS\,1}$(i) and cost$_{MS\,2}$(j)

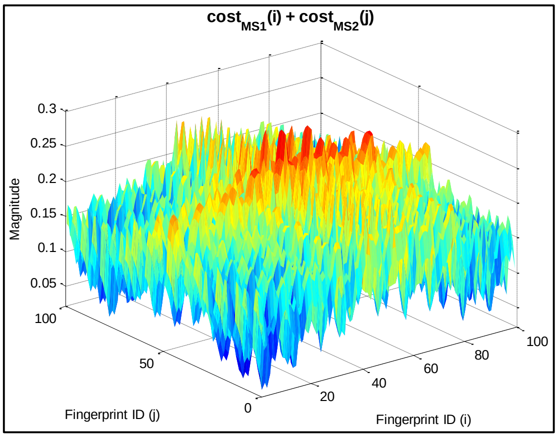

Figure 4-7.- Linear combination of cost$_{MS\,1}$(i) and cost$_{MS\,2}$(j)

5 Investigated approaches and comparative results

This section analyzes the results of computer simulations and experiments that have been performed by developing proof of concepts of both methods:

- Non-cooperative methods framework based on simulation results implemented in Matlab
  - FP approach
  - PL approach
- Proposed cooperative approach based on simulation results implemented in Matlab
- Proposed cooperative approach based on experimental results, using real devices in a WLAN, from different buildings. Those buildings are located in Tampere – Finland, such as Tietotalo, Duo, Sahkotalo, Koskikeskus and Hermia.
  - Proposed cooperative approach

The average location accuracy is evaluated quantifying the Root Mean Squared Error (RMSE) of the distance error, i.e., quantifying the difference between the true MS location and the estimated one based on the distance error, noted as ε.

$$\varepsilon = \sqrt{(x_{MS} - \hat{x}_{MS})^2 + (y_{MS} - \hat{y}_{MS})^2} \tag{5.1}$$

Where: (x_{MS}, y_{MS}) The real location coordinates of the MS

$(\hat{x}_{MS}, \hat{y}_{MS})$ The estimated coordinates of the MS

Assuming that each MS performs a trajectory in a determined scenario, the RMSE is quantified over all the samples acquired over the path described by the MS (or MS tracking points N_{TP}). To observe the performance of the algorithms under study, the RMSE has to be evaluated for different levels of noise variance present in the scenario.

$$RMSE = \sqrt{\frac{1}{N_{TP}} \sum_{n=1}^{N_{TP}} \{\varepsilon_n\}^2} \tag{5.2}$$

Where: ε_n The distance error of the *n-th* tracking point

As was described in Chapter 3, the solution of each algorithm will be the NN value or an average of NN. For that reason, the purpose of the RMSE merit figure is to allow the comparison between both solutions for different levels of noise power. Also, this merit figure allows us to perform the comparison between non-cooperative and cooperative methods.

On the other hand, in the case of non-cooperative methods, in order to compare the RMSE enhancement of all the approaches described before, a Monte Carlo[21] technique has to be applied to compute an averaged RMSE ($\overline{RMSE}$) and observe the tendency of this merit figure for different levels of noise power as well. For a given number of Monte Carlo iteration or realization (N_R), the averaged RMSE value of each non-cooperative approach at each noise level is defined as:

$$\overline{RMSE} = \sqrt{\frac{1}{N_R}\sum_{i=1}^{N_R}\left\{\frac{1}{N_{TP}}\sum_{n=1}^{N_{TP}}\left\{\varepsilon_n^i\right\}^2\right\}} \tag{5.3}$$

Where: ε_n^i The distance error of the *n-th* tracking point at the *i-th* Monte Carlo realization

For each non-cooperative and cooperative approach, a simulator has been created. If the simulator conditions are not specified, its default values are:

- 10000 m^2 of area
- 16 APs
  - Transmit power: $10\ dB\ \le P_{TX} \le 15dB$
  - Pathloss exponent: $1{,}2 \le n \le 8$
- 256 fingerprints
- 20 samples captured per RSS and summarized applying the arithmetic mean estimator
- 3 MSs which perform a straight line trajectory with 50 tracking points
- 20 samples of shadowing standard deviation: $0dB \le \sigma^2 \le 7dB$

The next sections address the simulated approaches in this thesis. At the beginning of each section, the simulator will be described using a block diagram in order to facilitate its comprehension.

[21] The Monte Carlo method is defined as representing the solution of a problem as a parameter of a hypothetical population, and using a random sequence of numbers to construct a sample of the population, from which statistical estimates of the parameter can be obtained. Monte Carlo method can be applied to a given problem that does not depend on the stochastic nature of the system being studied, but only on our ability to formulate the problem in such a way that random numbers may be used to obtain the solution [72].

5.1 Non-cooperative methods

5.1.1 Fingerprinting approach

Once the building parameters are established (Figure 5-1), the simulator defines the corresponding parameters of each AP, such as location, transmit power and pathloss exponent. Consequently, the fingerprint database can be defined based on the APs and building parameters. The simulator quantifies the RSS between fingerprints and APs in order to estimate the shadowing standard deviation present in the scenario, after this RSS measurements will be summarized applying a central tendency estimator, such as: arithmetic mean, median, maximum value and mode.

The next step of the simulator is to define the trajectory of each MS in order to estimate their position applying the Euclidean distance criterion based on the fingerprint database and RSS measurements between MSs and APs. Finally, with the estimated positions and the real positions, the RMSE can be quantified.

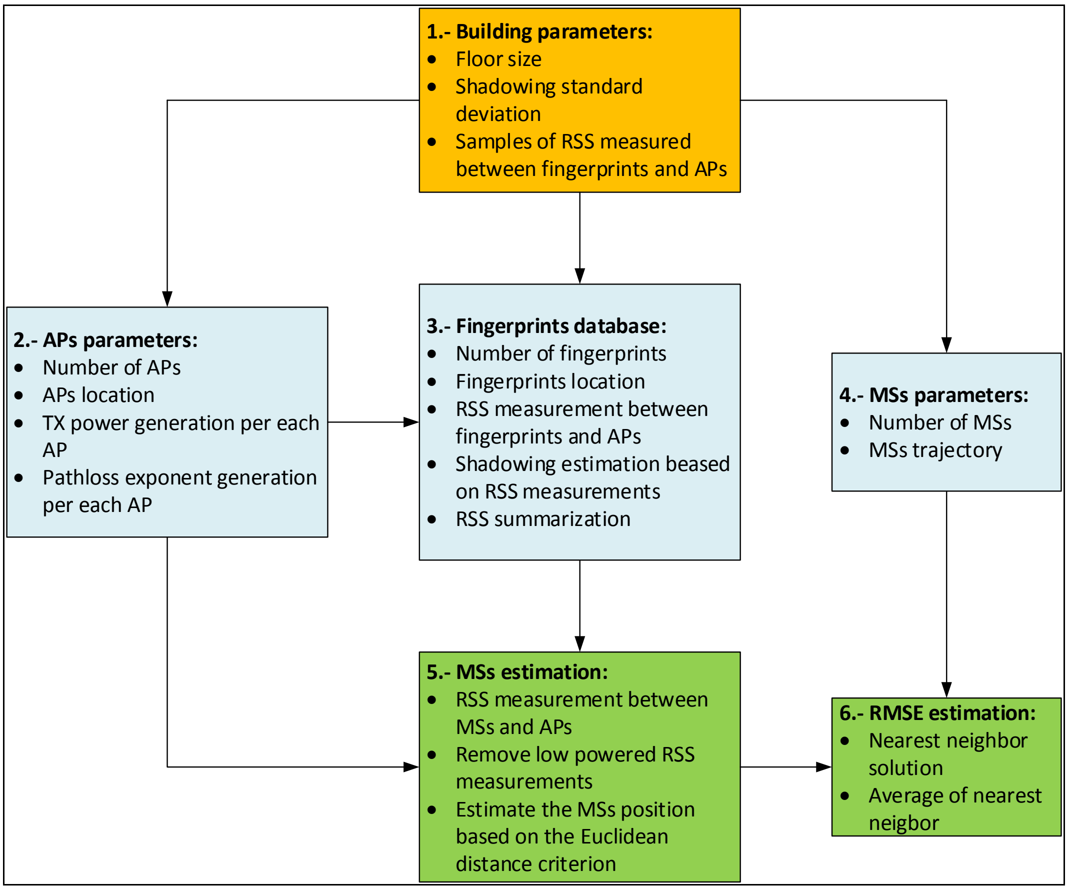

Figure 5-1.- Fingerprinting approach simulator

5.1.1.1 Transmit power and pathloss exponent from each AP

Figure 5-2 is describes the modeled transmit power and pathloss exponent associated with each AP present in simulator scenario.

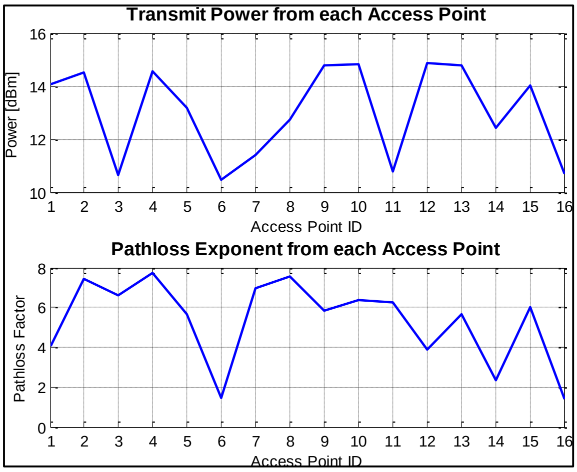

Figure 5-2.- P_{TX} and n from each AP

5.1.1.2 Shadowing estimation

Figure 5-3 shows the difference between the shadowing standard deviation established by the simulator and its estimated value. The difference between them is due to the number of samples acquired for each RSS measurement between fingerprints and APs. If the number of samples increases, the uncertainty of the estimated value decreases.

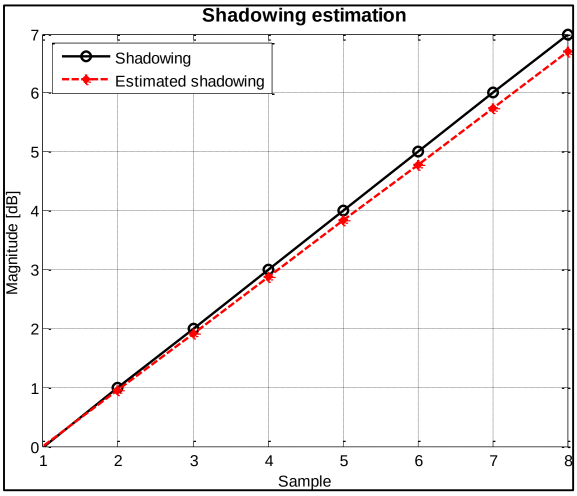

Figure 5-3.- Shadowing estimation

5.1.1.3 Device map location

As was described before, the simulator generates for each MS a straight line trajectory, which will be estimated via FP approach. Figure 5-4, Figure 5-5 and Figure 5-6 represent NN and average of four NN estimated locations of each MS.

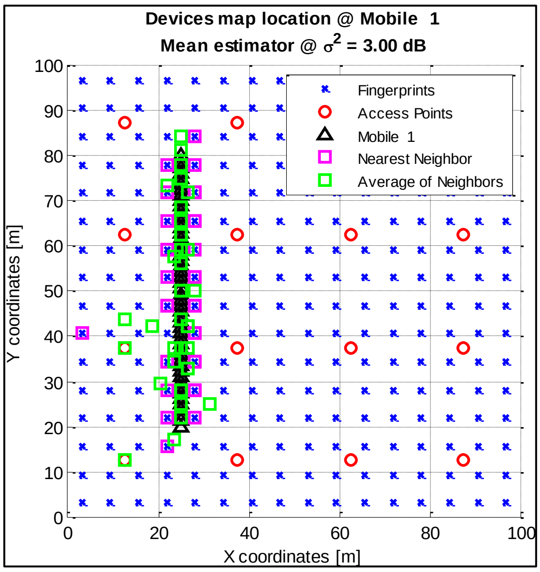

Figure 5-4.- MS 1 estimated location

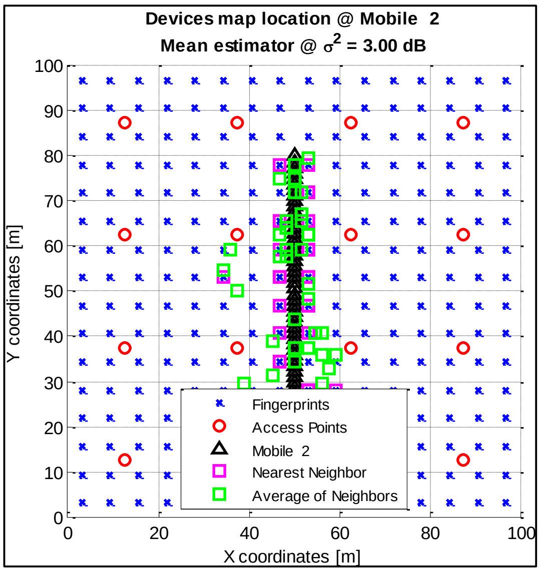

Figure 5-5.- MS 2 estimated location

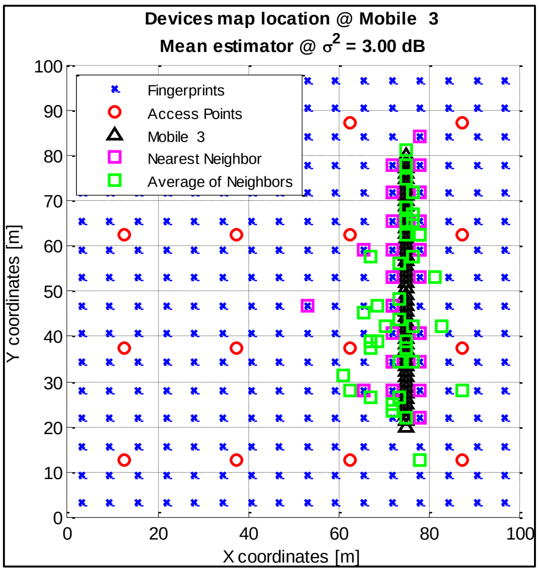

Figure 5-6.- MS 3 estimated location

5.1.1.4 RMSE estimation

The position accuracy for each MS in term of distance error between the estimated and the true point is shown in Figure 5-7, Figure 5-8 and Figure 5-9. Those figures describe the performance obtained, in terms of RMSE, of all the central tendency estimators described in section 5.1.1. It is possible to realize that the estimators which present a better performance are the arithmetic mean and median, for that reason and also of its simplicity, the arithmetic mean estimator will be applied in the proposed cooperative approach.

From those figures it is possible to realize that the RMSE is proportional to the noise power present in the environment.

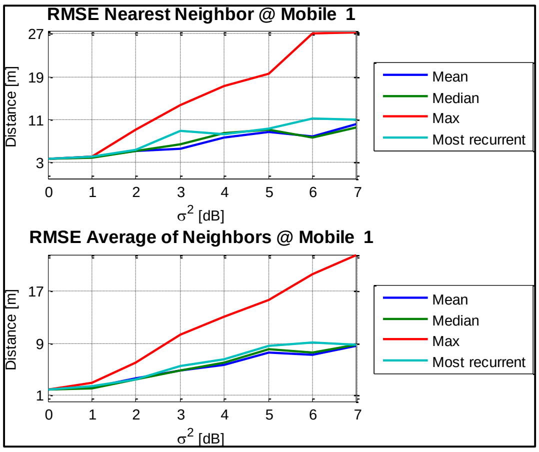

Figure 5-7.- RMSE of the MS 1 estimated position

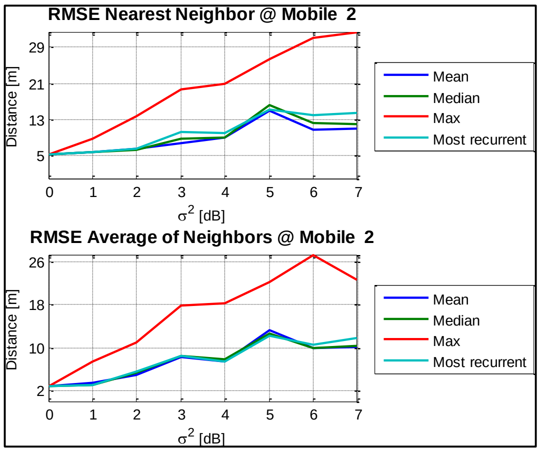

Figure 5-8.- RMSE of the MS 2 estimated position

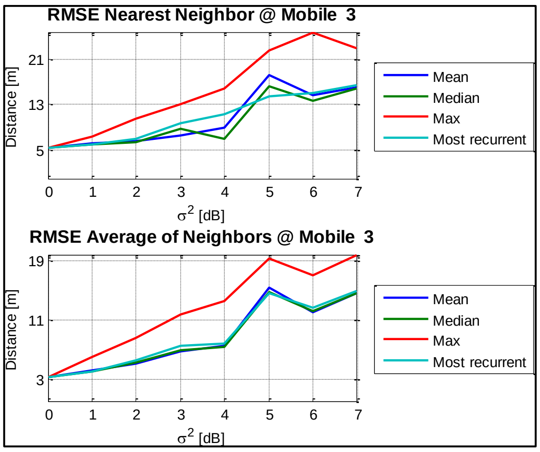

Figure 5-9.- RMSE of the MS 3 estimated position

5.1.1.5 Fingerprinting power maps

The fingerprint database allows us to map all the RSS measurements captured during the offline phase (Figure 5-10). This power map describes the coverage capability of each AP.

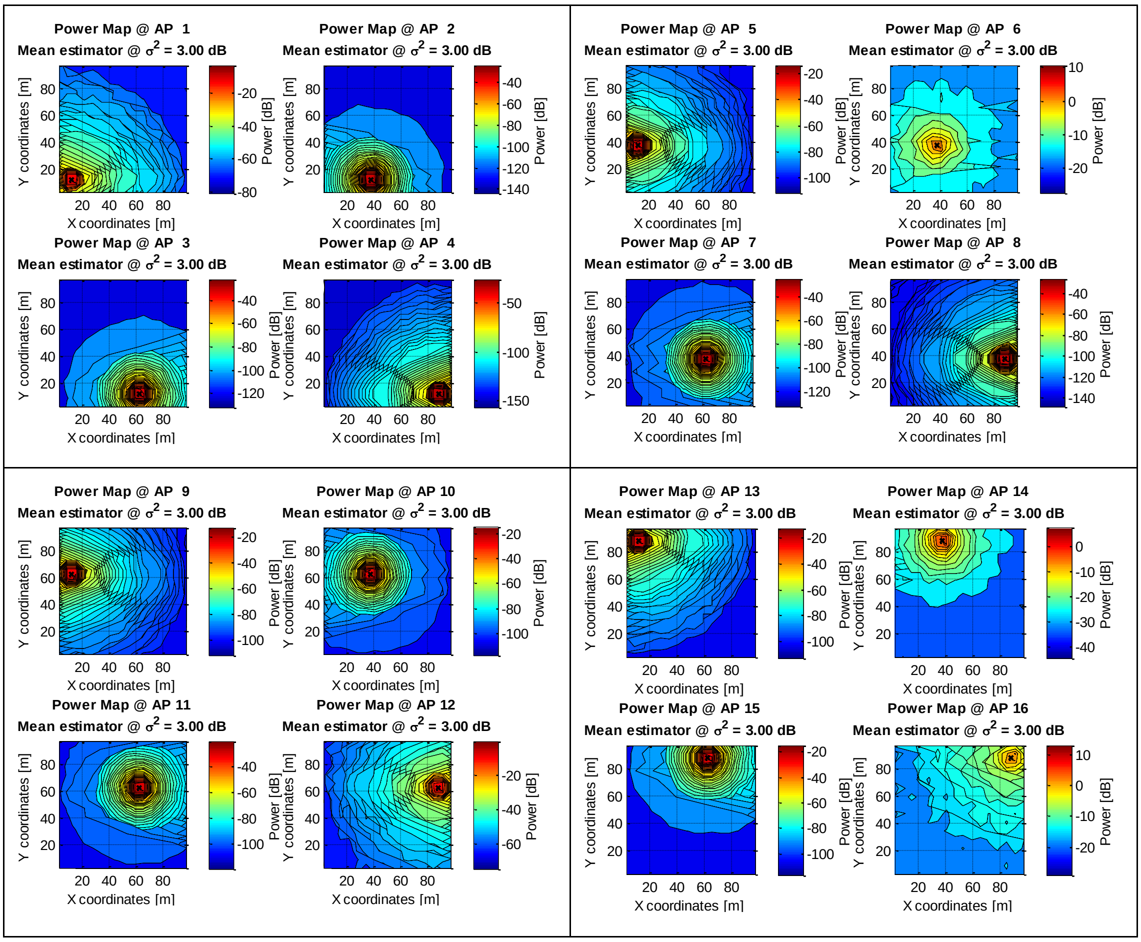

Figure 5-10.- Fingerprinting power maps

5.1.2 Pathloss approach

The difference between the fingerprinting approach (Figure 5-1) and the pathloss approach (Figure 5-11) is the fact that, the latter estimates the AP location, transmit power and pathloss exponents, as was described in section 3.3.3.1. The AP locations are estimated based on the fingerprint location with the maximum RSS measurement, meanwhile the transmit power and the pathloss exponent are estimated via LS.

On the other hand, the MS position is estimated applying the Maximum Likelihood criterion based on the PDFs which describe the propagation of the radio signals in the scenario and which were defined during the online phase.

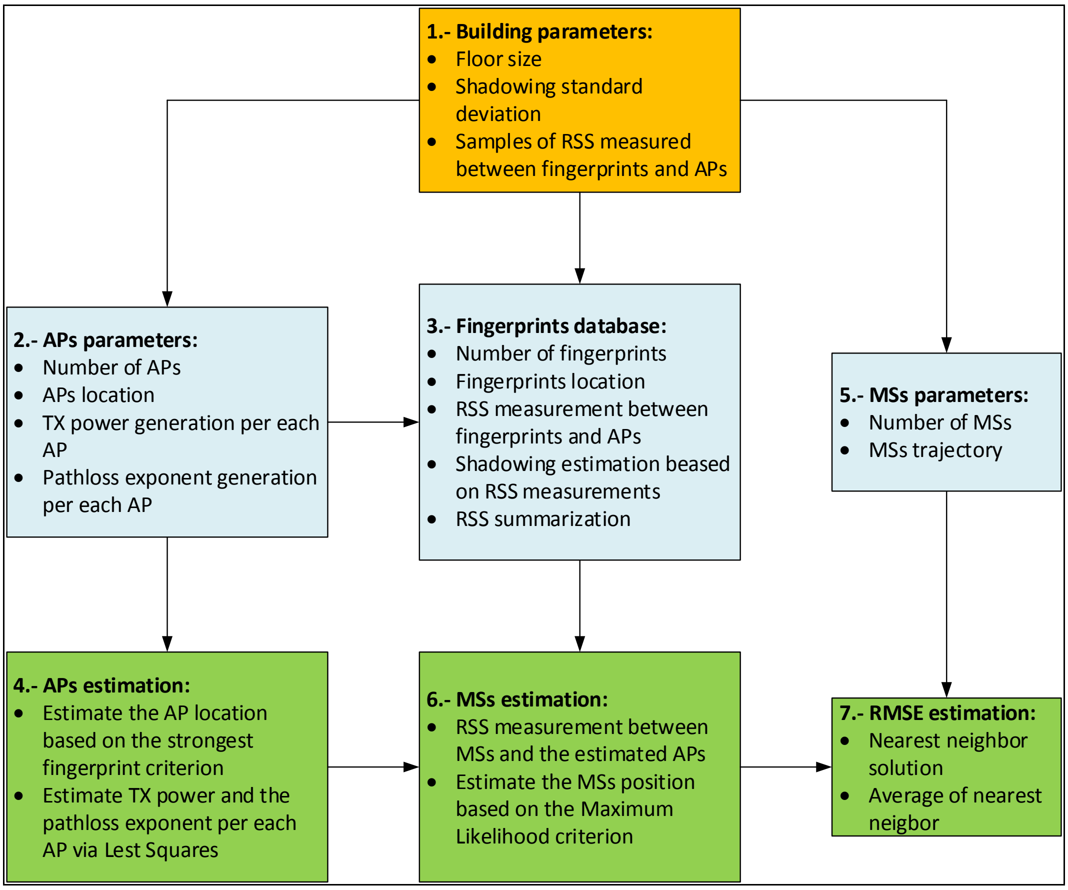

Figure 5-11.- Pathloss approach simulator

5.1.2.1 Transmit power and pathloss exponent estimation from each AP

With the database collected during the offline phase, the transmit power and pathloss exponent can be estimated. Figure 5-12 shows the accuracy of all the central tendency estimators applied to summarize the offline database.

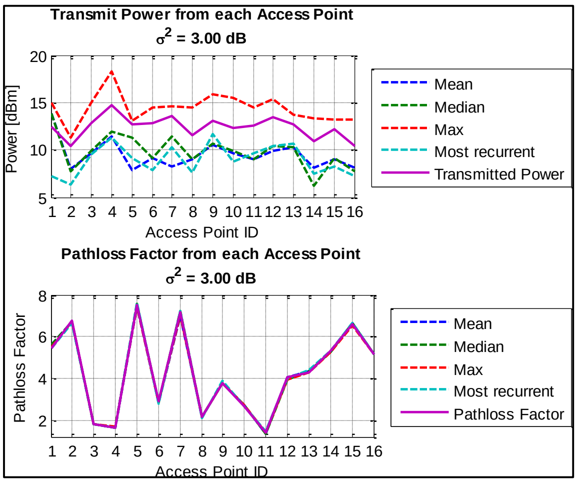

Figure 5-12.- P_{TX} and n estimation from each AP

5.1.2.2 Shadowing estimation

In the same way as in section 5.1.1.2, Figure 5-3 shows the difference between the shadowing standard deviation established by the simulator and its estimated value.

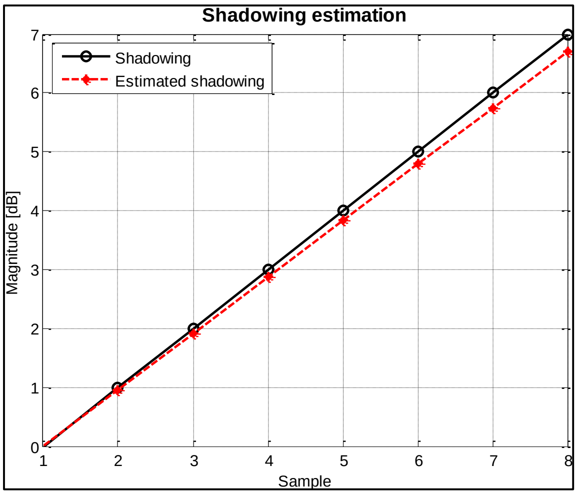

Figure 5-13.- Shadowing estimation

5.1.2.3 Device map location

Figure 5-14, Figure 5-15 and Figure 5-16 represent nearest neighbor and average of nearest neighbor estimated location of each MS, also the estimated position of each AP.

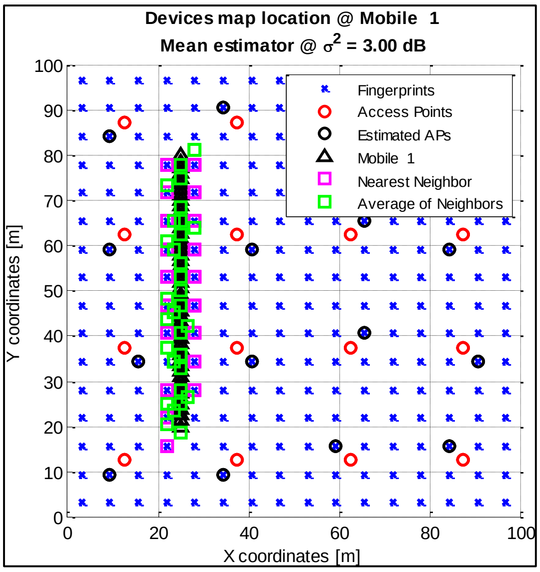

Figure 5-14.- MS 1 estimated location

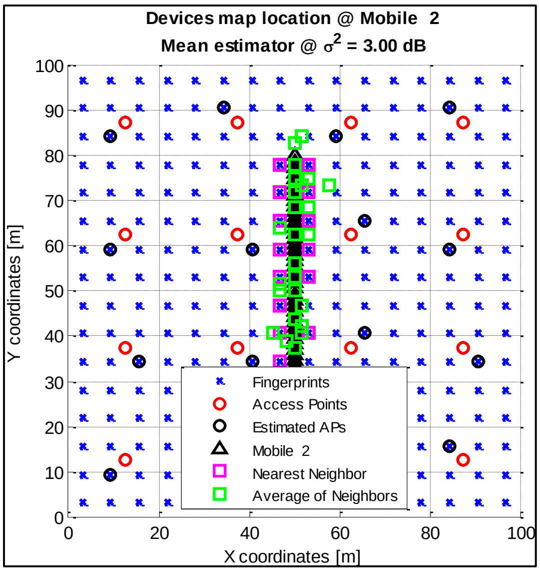

Figure 5-15.- MS 2 estimated location

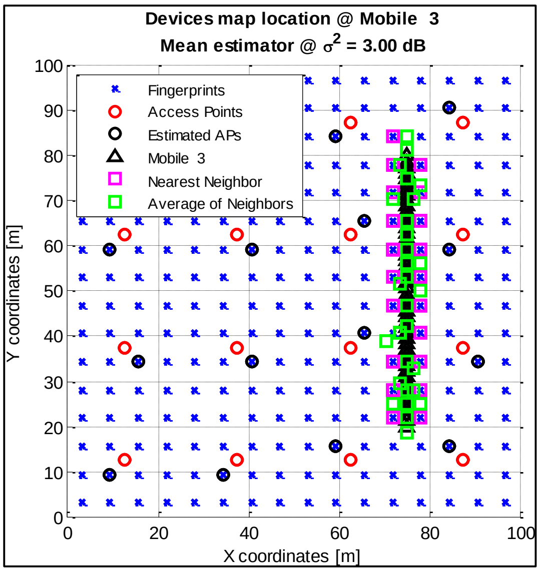

Figure 5-16.- MS 3 estimated location

5.1.2.4 RMSE estimation

In the same way as in section 5.1.1.4, the position accuracy for each MS is shown in Figure 5-17, Figure 5-18 and Figure 5-19. Those figures describe the performance obtained, in terms of RMSE, of all the central tendency estimators applied on the off-line database. Also, the estimators which present a better performance are the arithmetic mean and median.

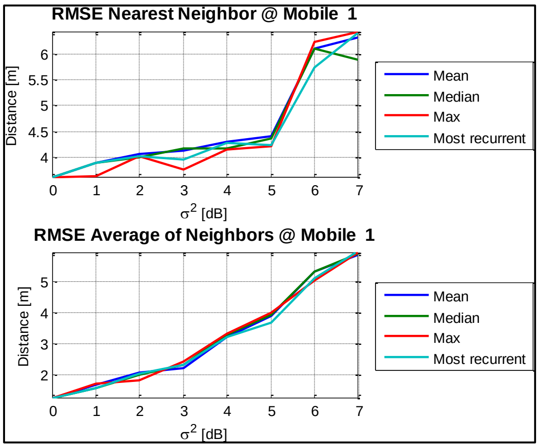

Figure 5-17.- RMSE of the MS 1 estimated position

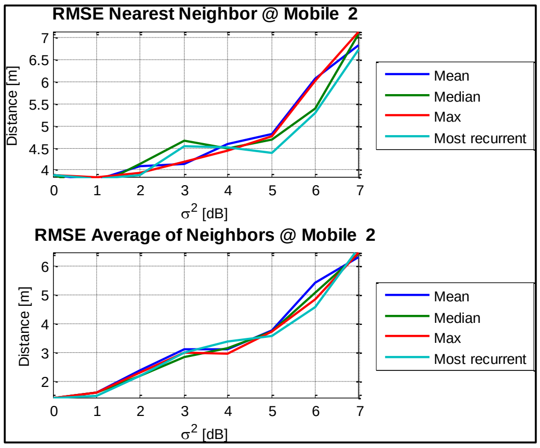

Figure 5-18.- RMSE of the MS 2 estimated position

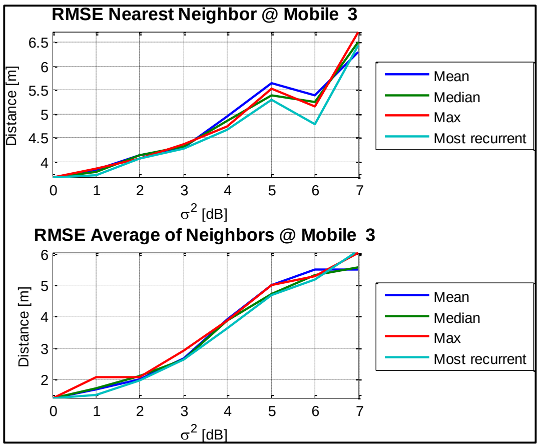

Figure 5-19.- RMSE of the MS 3 estimated position

5.1.2.5 Empirical radio map

Figure 5-20, Figure 5-21 and Figure 5-22 show the associated PDF to each MS. The red areas represent the zones with high probability for the MS to be located and the black triangle represents the real position of the MS for a given tracking point.

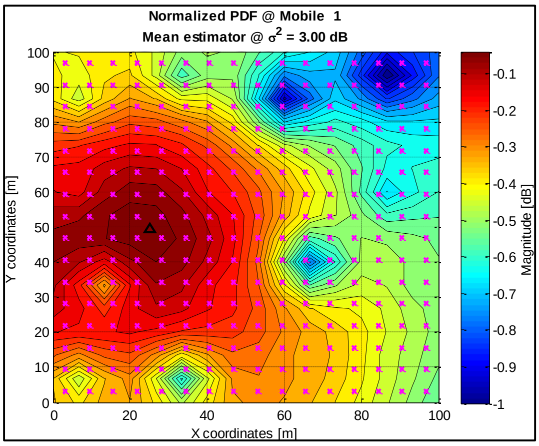

Figure 5-20.- PDF associated to one tracking point of the MS 1

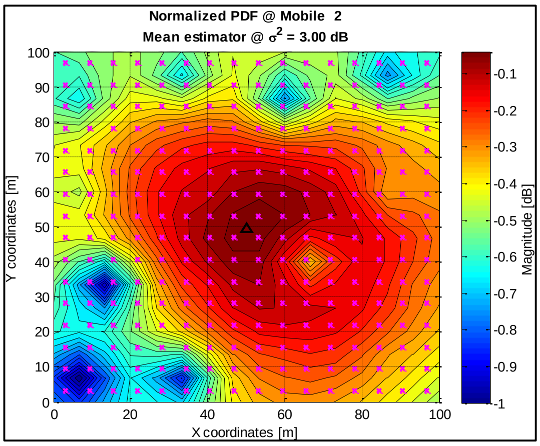

Figure 5-21.- PDF associated to one tracking point of the MS 2

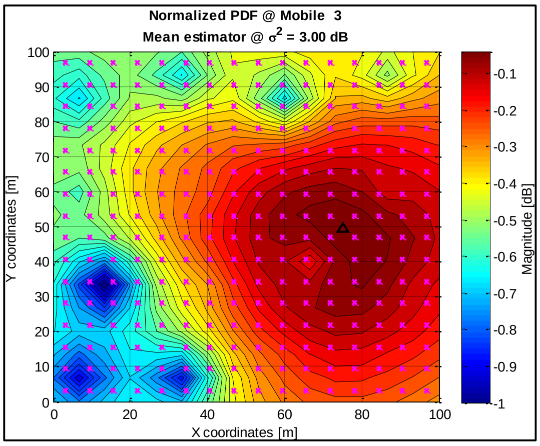

Figure 5-22.- PDF associated to one tracking point of the MS 3

5.1.3 Comparison between both approaches via Monte Carlo simulation

The purpose of this simulation is to compare the position accuracy of both approaches, FP (Figure 5-1) and PL (Figure 5-11), in terms of averaged RMSE. For this scenario, the random variable will be noise samples in the RSS measurements between fingerprints and APs. The main difference between Figure 5-1 and Figure 5-11 with Figure 5-23 is that in the last one, the MS position is estimated with both approaches (FP and PL) in the same Monte Carlo realization with the same random data in order to compare the position accuracy obtained from each approach. After the Monte Carlo realizations have been completed, the averaged RMSE will be quantified.

With the aim to compare both approaches, an additional approach has been implemented, which will be used as a reference. This approach is an ideal case of the PL approach, but in this case the PDF is defined based on the real AP parameters: transmit power, pathloss exponent and location.

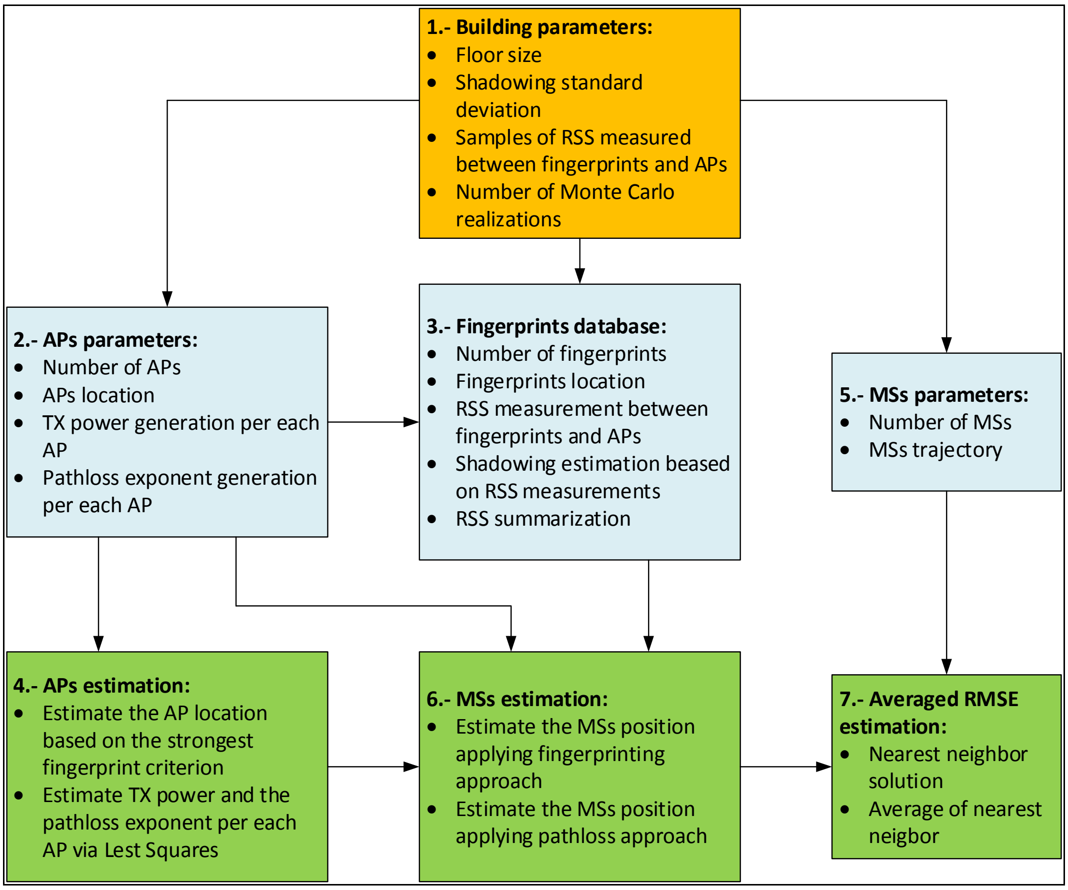

Figure 5-23.- Monte Carlo simulator

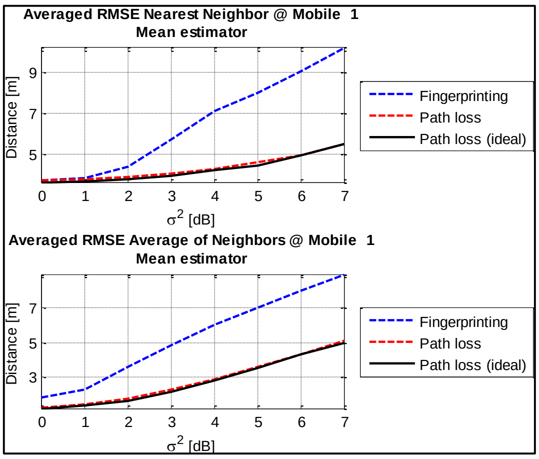

Figure 5-24.- Averaged RMSE of the MS 1 estimated position

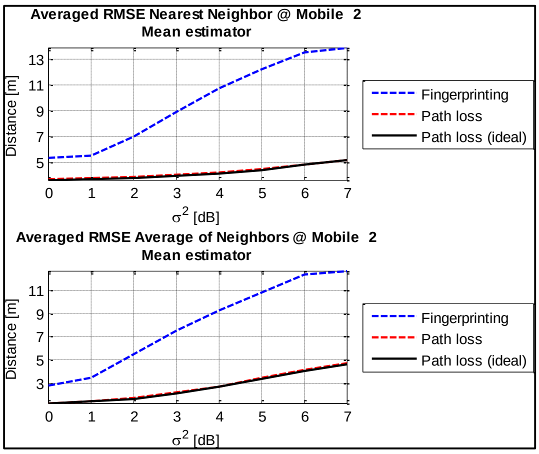

Figure 5-25.- Averaged RMSE of the MS 2 estimated position

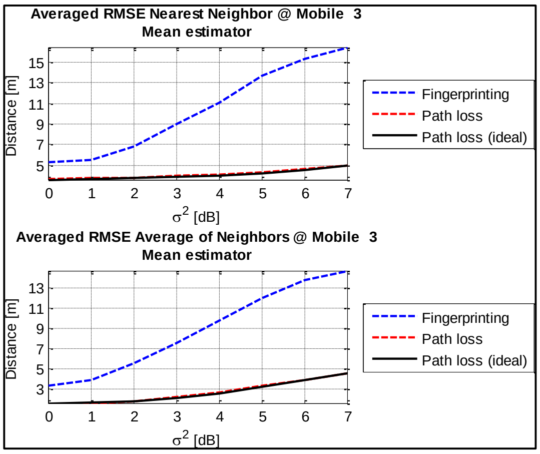

Figure 5-26.- Averaged RMSE of the MS 3 estimated position

From Figure 5-24, Figure 5-25 and Figure 5-26 it is possible to appreciate that the PL approach is substantially better than FP approach, because PL approach requires the shadowing standard deviation of the offline data base to define a PDF to the radio signal. The implication of the shadowing during the online phase increases the position accuracy, because the effect of this variable is used to estimate the optimal solution for the position problem.

Table 5-1 describes in more detail the simulation results of the averaged RMSE values for all the MSs, where the better performance of the PL approach is shown.

Table 5-1.- Averaged RMSE simulation results

	Nearest Neighbor								
MS 1	Shadowing [dB]	0	1	2	3	4	5	6	7
	FP [m]	3,737	3,826	4,416	5,709	7,104	7,991	9,035	10,189
	PL [m]	3,713	3,790	3,909	4,048	4,266	4,618	4,962	5,501
	Ideal PL [m]	3,646	3,690	3,806	3,973	4,215	4,464	4,935	5,499
MS 2	Shadowing [dB]	0	1	2	3	4	5	6	7
	FP [m]	5,301	5,498	6,957	8,924	10,786	12,247	13,558	13,957
	PL [m]	3,654	3,749	3,866	4,025	4,180	4,410	4,822	5,135
	Ideal PL [m]	3,612	3,672	3,778	3,904	4,098	4,342	4,760	5,120
MS 3	Shadowing [dB]	0	1	2	3	4	5	6	7
	FP [m]	5,338	5,499	6,774	9,001	11,093	13,695	15,267	16,464
	PL [m]	3,692	3,748	3,810	3,943	4,054	4,318	4,631	5,018
	Ideal PL [m]	3,608	3,655	3,737	3,828	3,999	4,184	4,513	4,985
	Average of Nearest Neighbor								
MS 1	Shadowing [dB]	0	1	2	3	4	5	6	7
	FP [m]	1,804	2,302	3,579	4,813	6,029	6,993	8,000	8,942
	PL [m]	1,266	1,406	1,789	2,266	2,896	3,622	4,343	5,117
	Ideal PL [m]	1,205	1,363	1,661	2,178	2,836	3,529	4,301	5,000
MS 2	Shadowing [dB]	0	1	2	3	4	5	6	7
	FP [m]	2,794	3,427	5,512	7,508	9,288	10,806	12,364	12,673
	PL [m]	1,266	1,408	1,744	2,171	2,724	3,456	4,087	4,717
	Ideal PL [m]	1,284	1,411	1,655	2,078	2,677	3,314	4,069	4,634
MS 3	Shadowing [dB]	0	1	2	3	4	5	6	7
	FP [m]	3,308	3,880	5,515	7,520	9,747	11,984	13,783	14,719
	PL [m]	1,360	1,469	1,735	2,121	2,619	3,248	3,879	4,539
	Ideal PL [m]	1,560	1,592	1,744	2,114	2,523	3,132	3,793	4,466

5.2 Cooperative method

For the cooperative method, the proposed cooperative approach described in section 4.3 was simulated and both localization algorithms, FP and PL were implemented in order to minimize the cooperative cost function based on the linear combination of all the MSs present in the scenario.

The main difference between the Figure 5-27 and the previous simulators (Figure 5-1, Figure 5-11 and Figure 5-23) is that, this simulator estimates the MS position via both methods, cooperative and non-cooperative, in order to compare the position accuracy obtained from both methods in terms of RMSE.

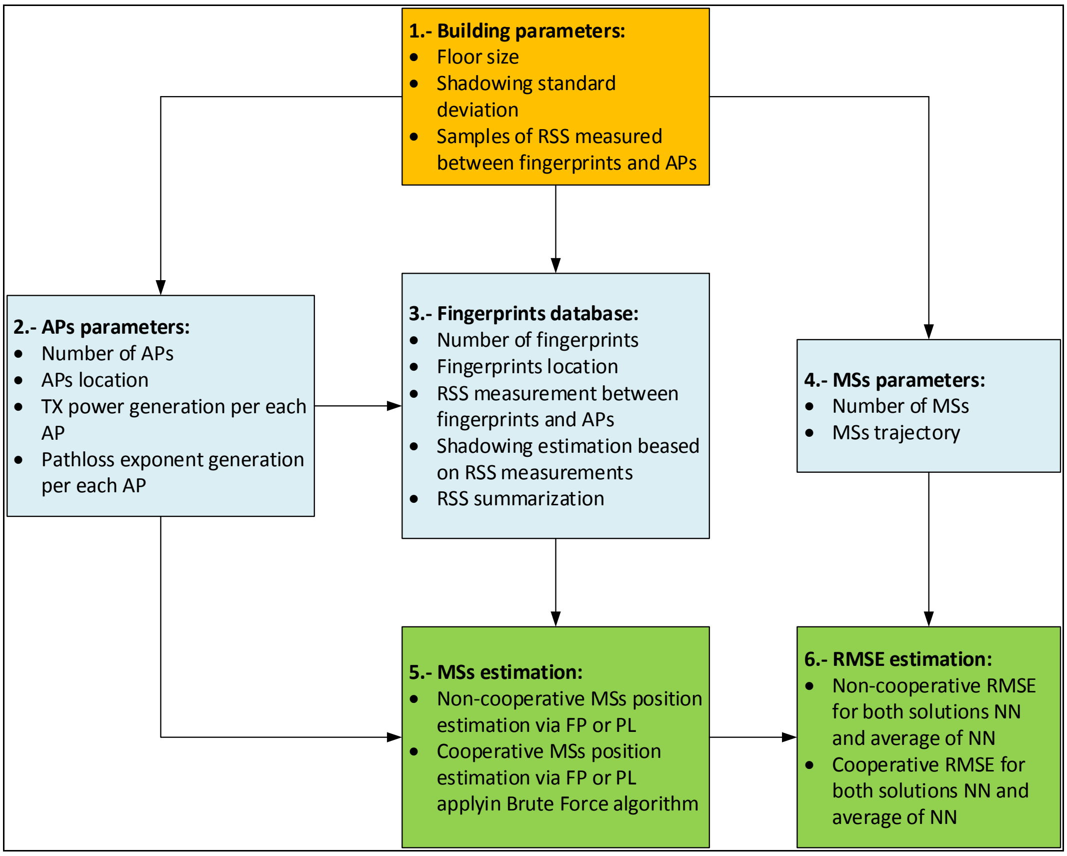

Figure 5-27.- Proposed cooperative approach simulator

As it was described at the begining of Chapter 3, the accuracy of the position estimated is dependent on the density of anchors inside the network and the channel conditions. For that reason, a simulation with low density of APs has been performed for both apporaches, FP and PL, in order to compare the performance between them.

It has to be pointed out that, the current simulator scenario differs from the previous scenarios in the following parameters:

- 4 APs
- 64 fingerprints
- Shadowing standard deviation: $0dB \leq \sigma^2 \leq 100dB$

5.2.1 Fingerprinting approach

Figure 5-29 addresses the fact that the MSs located in the middle of the scenario (e.g., MS 2) are capable to "hear" a greater number of APs than the MSs located in the limits of the scenario (Figure 5-28 and Figure 5-30) which can only "hear" the nearest APs. The performance of the cooperative position estimation, for a given scenario, is proportional to the number of "hearable" APs. It is possible to realize from the Figure 5-29 the impact of the number of hearable APs and the cooperation between MSs to increase the position accuracy at the MS 2.

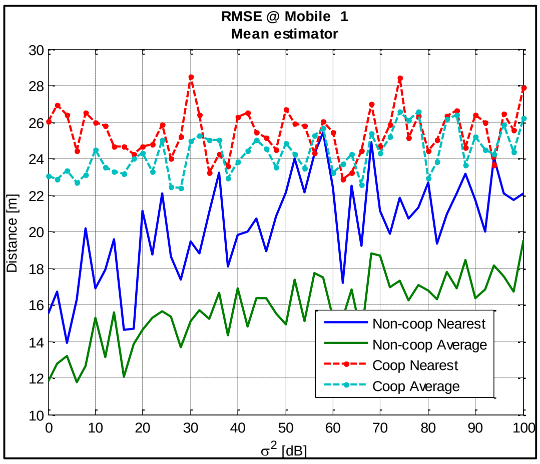

Figure 5-28.- RMSE comparison in the MS 1 via FP

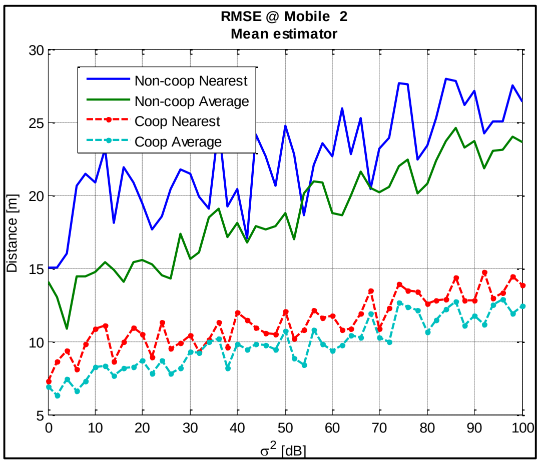

Figure 5-29.- RMSE comparison in the MS 2 via FP

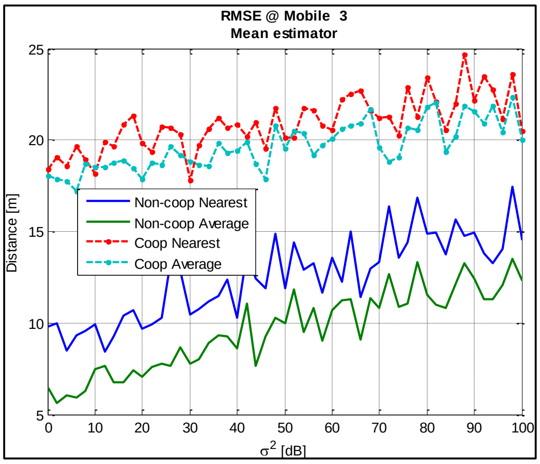

Figure 5-30.- RMSE comparison in the MS 3 via FP

5.2.2 Pathloss approach

In the same way as FP approach, the MSs located in the middle of the scenario, such as MS 2(Figure 5-32), are able to “hear” a higher number of APs than MS 1 (Figure 5-31) and MS 3 (Figure 5-33), which has an impact in the position accuracy.

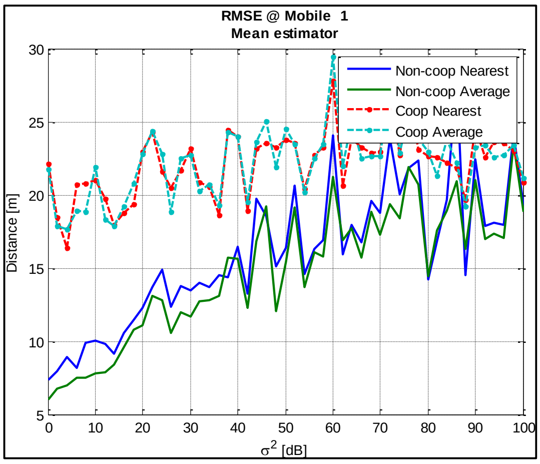

Figure 5-31.- RMSE comparison in the MS 1 via PL

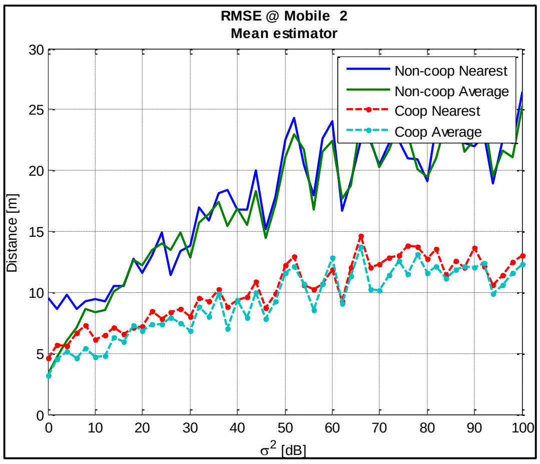

Figure 5-32.- RMSE comparison in the MS 2 via PL

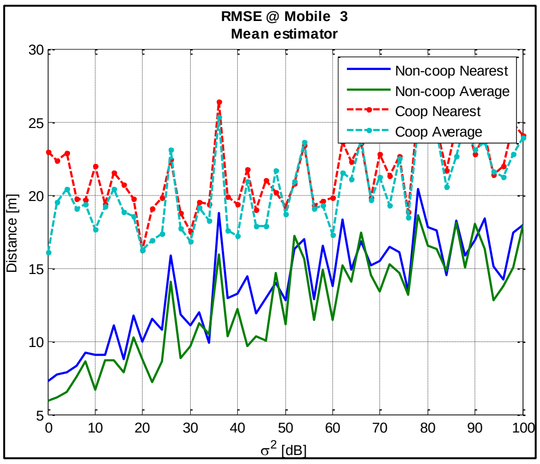

Figure 5-33.- RMSE comparison in the MS 3 via PL

5.2.3 Experimental results

To test the algorithm’s performance, some real-field measurements have been used. Those measurements were provided by the Positioning Research Group from Tampere University of Technology.

Figure 5-34, Figure 5-35, Figure 5-36, Figure 5-37 and Figure 5-38 compare the cooperative and non-cooperative distance estimation between MSs. For both methods, cooperative and non-cooperative, a FP approach has been applied to perform the comparison, and from those figures it is possible to corroborate that the proposed cooperative approach is capable of providing a good position accuracy, in terms of RMSE. In all the building datasets, the RMSE for both methods has been quantified in order to highlight the position accuracy enhancement for a cooperative scheme.

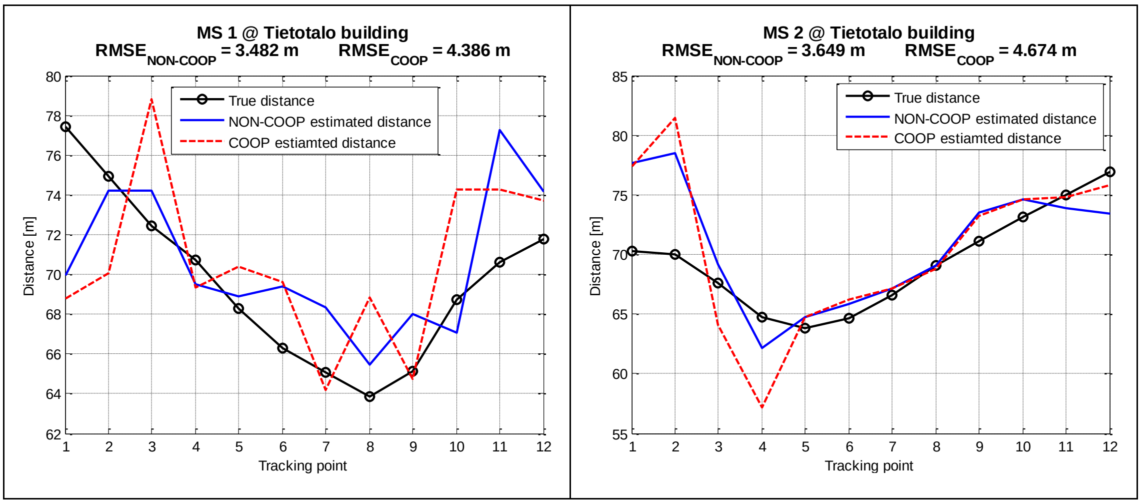

Figure 5-34.- Distance estimation of both MSs at Tietotalo building

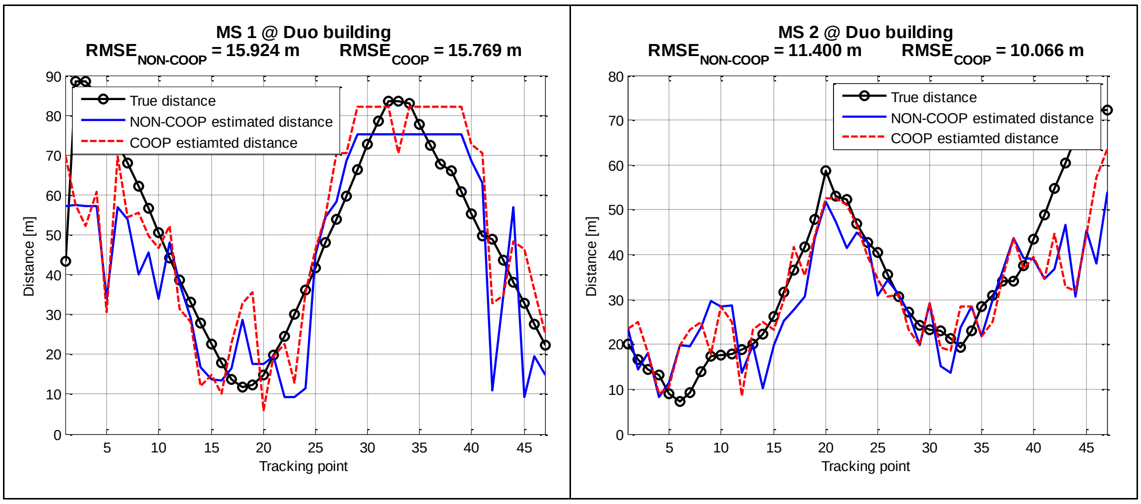

Figure 5-35.- Distance estimation of both MSs at Duo building

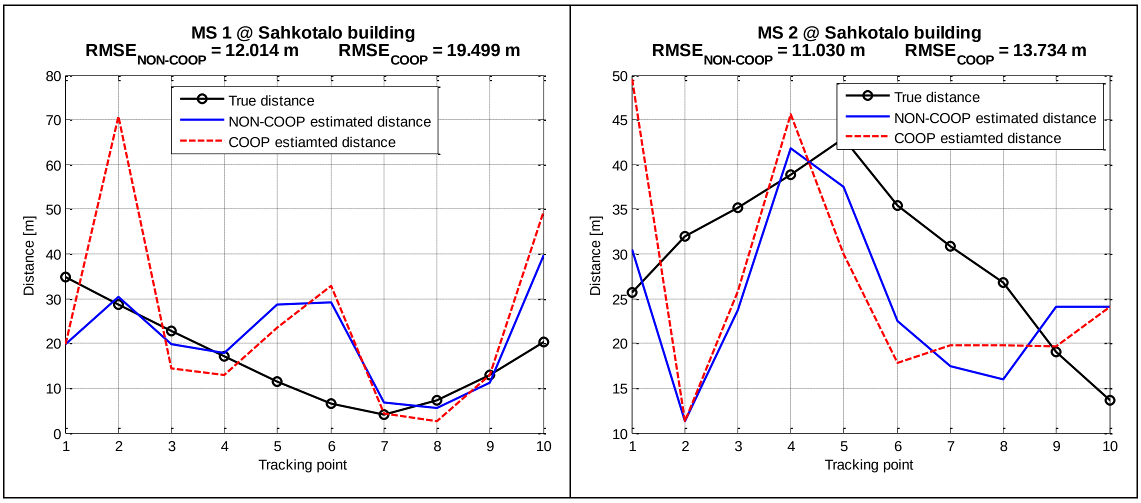

Figure 5-36.- Distance estimation of both MSs at Sahkotalo building

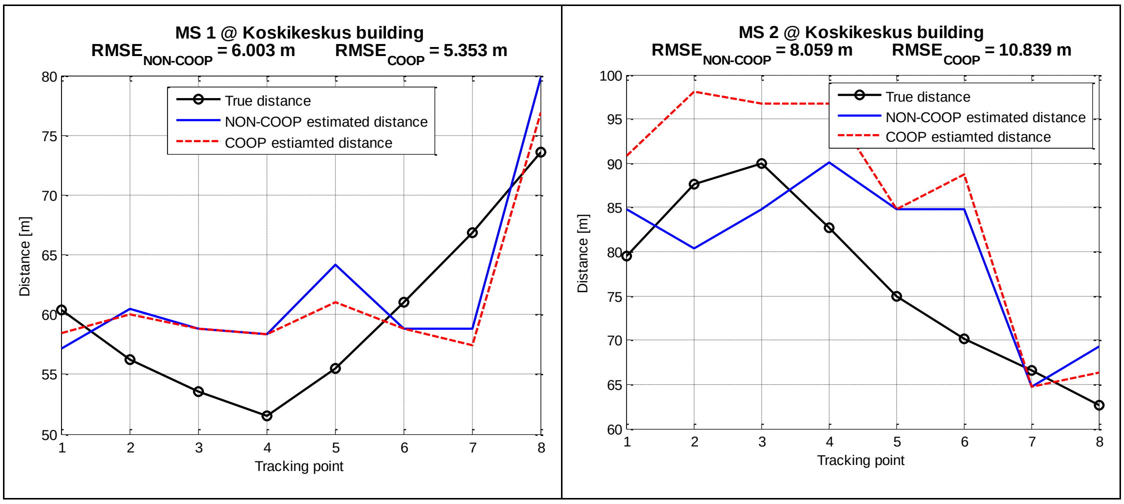

Figure 5-37.- Distance estimation of both MSs at Koskikeskus building

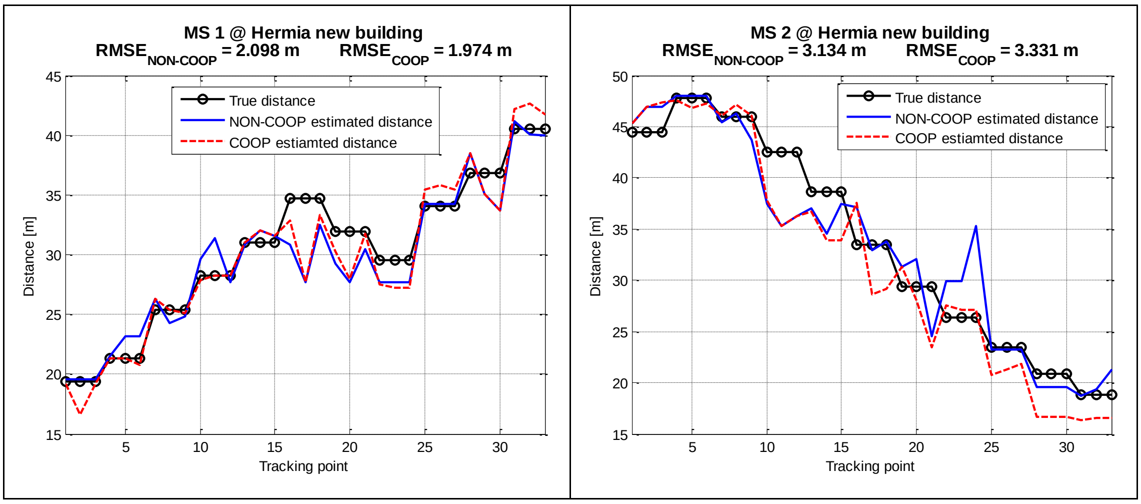

Figure 5-38.- Distance estimation of both MSs at Hermia new building

6 Conclusions and open directions

In a broad sense, the aim of the thesis has been to study distance-based positioning techniques for WLANs. We assumed the RSS simulation measurements with unknown statistics from the network devices as information sources, and these measurements were used in cooperative and non-cooperative algorithms to estimate the MS positions.

The thesis comprises several theoretical contributions from the current open literature which were presented and described in Chapters 3 and 4, and amongst all of them, we highlight the studies of cooperative networks. Specifically, the position accuracy shown in Chapter 5 revealed important insights into the nature of "heard" AP's uncertainty and the effect of cooperation between MSs. Those factors have a great impact in the position accuracy in terms of RMSE and they are dependent of the APs coverage capability. Also, as shown in the results, FP and PL approaches have notorious differences in terms of RMSE, and this is due to the implication of the shadowing during the online phase, which increases the position accuracy. Thanks to the measured data from real devices, it was possible to address the performance of both methods, cooperative and non-cooperative. Each algorithm can be more or less useful depending on the scenario in which applied. For example, in some buildings, such as: Duo, Koskikeskus and Hermia, the RMSE can achieve a lower value.

Regarding the proposed cooperative approach, it has to be said that the algorithm is robust, since it always provides reasonable results, even in very demanding conditions, but its accuracy is very poor at the MSs located in the limits of the scenario, in comparison with the non-cooperative approaches in a low density APs presence. Even though the MSs located in the middle of the scenario can overcome this problem and present an enhanced position accuracy substantially better than non-cooperative approaches.

Indoor positioning in wireless networks is a very interesting field of research nowadays, and many research efforts focus on it. The work done in this thesis is only a small part of what can be done. An open issue is to use a more complex cost function in the proposed cooperative approach in order to increase the position accuracy, also change the Brute Force algorithm by Lagrange multiplier with the aim of providing a more efficient software solution. Additionally, there are many unsolved challenges still in indoor positioning, such as regarding hybridization of several localization sources, security and privacy of the achieved solutions and complexity and battery consumption of cooperative WLAN localization approaches.

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APPENDIX I: Cooperative and non-cooperative localization via FP approach

```
%% Main_2D_WLAN_model_COOP_fingerprinting_V2
% Project:          Cooperative indoor positioning
% Author:           Tery Caisaguano Vasquez - 230078
% Advisers:         Elena-Simona Lohan
%                   Francescantonio Della Rosa
% File:             Main_2D_WLAN_model_COOP_fingerprinting_V2
% Version:          2.0
% Description:      Create a 2D model for non-cooperative position estimation.
%                   The model tracks the mobiles positions based on
%                   fingerprinting database and RSS measurements from each
%                   AP, and appliying the RMSE algorithm to find out the
%                   mobile position. In this model the AP position, TX
%                   power and "n" are not estimated.

%% Clearing MATLAB interface
clear all; close all; format long e; clc;

%% Setup MATLAB figure's configuration
drawnow; set(0, 'defaultlinelinewidth', 2); set(0, 'defaultaxesfontsize', 10);

%% Building parameters
% Floor dimension in meters: 100m x 100m
floor_x_size = 100;
floor_y_size = 100;

% Shadowing standard deviation in dB
sigma2_samples = 51;
sigma2 = linspace(0, 100, sigma2_samples);
sigma2_index = 19;

noise_samples = 20;

% Path loss exponent
n_min = 1.2;
n_max = 8;

% Labels in device map location plot
labels = false;

%% APs parameters
% Total number of APs
AP_num = (2)^2;

% Transmit power limits uniform distributed in dB
TX_power_min = 10;
TX_power_max = 15;

[AP.x_coord, AP.y_coord] = COOP_device_grid(floor_x_size, floor_y_size,
AP_num);
AP.TX_power = TX_power_min + ((TX_power_max - TX_power_min) * rand(1,
AP_num));
AP.n = n_min + ((n_max - n_min) * rand(1, AP_num));

%% Fingerprints parameters
% Total numer of fingerprints (measurements) in the floor
fingerprints_num = (8)^2;

fingerprints = cell(1, sigma2_samples);
```

```
[y, x] = meshgrid([1:fingerprints_num]', [1:fingerprints_num]');
x = x(:);
y = y(:);
for i = 1:sigma2_samples
    [fingerprints{i}.x_coord, fingerprints{i}.y_coord] =
COOP_device_grid(floor_x_size, floor_y_size, fingerprints_num);

    fingerprints{i}.shadow =
COOP_fingerprints_shadow_generation(sigma2(sigma2_index), AP_num,
fingerprints_num, noise_samples);

    % Fingerprints distance for each AP
    fingerprints{i}.distance = COOP_distance(AP, fingerprints{i});

    % Fingerprints received power estimation using Log-distance path loss
model
    fingerprints{i}.RX_power = COOP_RX_power_3D(AP_num, fingerprints_num,
noise_samples, AP, fingerprints{i});

    % Fingerprints received power statistics
    fingerprints{i}.statistics_RX_power =
COOP_RX_power_statistics(fingerprints{i}.RX_power);

    % Fingerprints mutual distance
    fingerprints{i}.mutual_ID = [x, y];

    x_coord = fingerprints{i}.x_coord(fingerprints{i}.mutual_ID(:,1)) -
fingerprints{i}.x_coord(fingerprints{i}.mutual_ID(:,2));
    y_coord = fingerprints{i}.y_coord(fingerprints{i}.mutual_ID(:,1)) -
fingerprints{i}.y_coord(fingerprints{i}.mutual_ID(:,2));
    fingerprints{i}.mutual_distance = sqrt(x_coord.^2 + y_coord.^2)';
end;
clear x y x_coord y_coord;

% Shadowing estimation
[shadowing, noise_matrix] = COOP_shadowing_estimation(fingerprints, AP_num,
fingerprints_num, sigma2_samples);

%% Mobile parameters
% Total number of mobile devices
mobile_num = 3;

% Total number of position samples
mobile_position_samples_num = 50;
mobile_position_index = mobile_position_samples_num/2;

mobile = COOP_mobile_data_structure_and_path(AP_num,
mobile_position_samples_num, mobile_num, sigma2_samples);

for i = 1:mobile_num
    for j = 1:sigma2_samples
        mobile{i,j}.shadow = COOP_mobile_shadow_generation(sigma2(j), AP_num,
mobile_position_samples_num);

        % Mobile distance for each AP
        mobile{i,j}.distance = COOP_distance(AP, mobile{i,j});
    end;
end;

%% Mobile position estimation
mobile_estimation = cell(mobile_num, sigma2_samples);

% Non-cooperative tracking
for i = 1:mobile_num
    for j = 1:sigma2_samples
        mobile_estimation{i,j} = COOP_tracking_mobile(AP_num,
mobile_position_samples_num,...
```

```
                                                          AP, fingerprints{j},
mobile{i,j}, shadowing(j));
    end;
end;

% Non-cooperative Root Mean Square Error of the estimated mobile position
RMSE = COOP_RMSE(mobile_num, sigma2_samples, mobile_estimation, mobile);

% Cooperative tracking
ME = cell(1, mobile_num);
M = cell(1, mobile_num);

for j = 1:sigma2_samples
    for i = 1:mobile_num
        ME{i} = mobile_estimation{i,j};
        M{i} = mobile{i,j};
    end;

    for current_mobile = 1:mobile_num
        [mobile_estimation{current_mobile,j}.cooperative_cost,...
         mobile_estimation{current_mobile,j}.cooperative_nearest_finger] =
COOP_cooperative_positioning(ME, M, fingerprints{j},...

mobile_position_samples_num, fingerprints_num, current_mobile,...

shadowing(j));
    end;
end;
clear ME M;

% Cooperative Root Mean Square Error of the estimated mobile position
cooperative_RMSE = COOP_cooperative_RMSE(mobile_num, sigma2_samples,
mobile_position_samples_num, mobile_estimation, mobile, fingerprints);

%% APs characteristics
figure (1);

subplot(211); plot(linspace(1, AP_num, AP_num), AP.TX_power); grid on;
xlabel('Access Point ID'); xlim([1 AP_num]);
ylabel('Power [dBm]');
title('Transmit Power from each Access Point', 'FontWeight', 'bold',
'FontSize', 12);
set(gca, 'XTick', linspace(1, AP_num, AP_num));

subplot(212); plot(linspace(1, AP_num, AP_num), AP.n); grid on;
xlabel('Access Point ID'); xlim([1 AP_num]);
ylabel('Pathloss Factor');
title('Pathloss Factor from each Access Point', 'FontWeight', 'bold',
'FontSize', 12);
set(gca, 'XTick', linspace(1, AP_num, AP_num));

%% Shadowing
figure (2);
plot(linspace(1, length(sigma2), length(sigma2)), sigma2, 'k',...
     linspace(1, length(sigma2), length(sigma2)), shadowing, 'r--');
xlabel('Sample'); xlim([1 length(sigma2)]);
ylabel('Magnitude [dB]'); ylim([min(sigma2) max(sigma2)]);
title('Shadowing estimation', 'FontWeight', 'bold', 'FontSize', 12); grid on;
legend('Shadowing', 'Estimated shadowing', 'Location', 'NorthWest');

%% Device map
for i = 1:mobile_num
    COOP_print_device_map(AP, fingerprints{sigma2_index},
mobile_estimation{i,sigma2_index}, mobile{i,sigma2_index}, i,...
                          sigma2(sigma2_index), mobile_position_samples_num,
floor_x_size, floor_y_size, labels)
end;
```

```
%% Non-cooperative RMSE for each mobile estimation
for i = 1:mobile_num

    figure (5 + i);

    subplot(211);
    plot(sigma2, RMSE.nearest_neighbor.mean(i,:),...
         sigma2, RMSE.nearest_neighbor.median(i,:),...
         sigma2, RMSE.nearest_neighbor.max(i,:),...
         sigma2, RMSE.nearest_neighbor.mode(i,:));
    set(gca, 'YTick',
[floor(min(RMSE.nearest_neighbor.max(i,:))):8:ceil(max(RMSE.nearest_neighbor.m
ax(i,:)))]); grid on;
    xlabel('\sigma^2 [dB]'); xlim([min(sigma2) max(sigma2)]);
    ylabel('Distance [m]'); ylim([0 max(RMSE.nearest_neighbor.max(i,:))]);
    buffer_text = sprintf('Non-cooperative RMSE Nearest Neighbor @ Mobile
%2d', i);
    title(buffer_text, 'FontWeight', 'bold', 'FontSize', 10);
    legend('Mean', 'Median', 'Max', 'Most recurrent', 'Location',
'EastOutside');

    subplot(212);
    plot(sigma2, RMSE.average.mean(i,:),...
         sigma2, RMSE.average.median(i,:),...
         sigma2, RMSE.average.max(i,:),...
         sigma2, RMSE.average.mode(i,:));
    set(gca, 'YTick',
[floor(min(RMSE.average.max(i,:))):8:ceil(max(RMSE.average.max(i,:)))]); grid
on;
    xlabel('\sigma^2 [dB]'); xlim([min(sigma2) max(sigma2)]);
    ylabel('Distance [m]'); ylim([0 max(RMSE.average.max(i,:))]);
    buffer_text = sprintf('Non-cooperative RMSE Average of Neighbors @ Mobile
%2d', i);
    title(buffer_text, 'FontWeight', 'bold', 'FontSize', 10);
    legend('Mean', 'Median', 'Max', 'Most recurrent', 'Location',
'EastOutside');

end;

%% Power maps for each AP
COOP_print_power_maps(AP, fingerprints{sigma2_index}, AP_num,
sigma2(sigma2_index));

%% Non-cooperative and Cooperative RMSE comparison
for i = 1:mobile_num
    figure (15 + i);

    plot(sigma2, RMSE.nearest_neighbor.mean(i,:),'-',...
         sigma2, RMSE.average.mean(i,:),'-',...
         sigma2, cooperative_RMSE.nearest_neighbor.mean(i,:),'.--',...
         sigma2, cooperative_RMSE.average.mean(i,:),'.--');
    xlabel('\sigma^2 [dB]'); xlim([min(sigma2) max(sigma2)]);
    ylabel('Distance [m]');
    buffer_text_line1 = sprintf('RMSE @ Mobile %2d', i);
    buffer_text_line2 = sprintf('Mean estimator');
    title({[buffer_text_line1], [buffer_text_line2]}, 'FontWeight', 'bold',
'FontSize', 10);
    legend('Non-coop Nearest', 'Non-coop Average', 'Coop Nearest', 'Coop
Average', 'Location', 'Best'); grid on;
end;
```

```
function shadow = COOP_fingerprints_shadow_generation(sigma2, TX_num,
RX_num, noise_samples)

    shadow = zeros(TX_num, RX_num, noise_samples);

    for i = 1:noise_samples
        for j = 1:RX_num
            shadow(:,j,i) = randn(1, TX_num);
            shadow(:,j,i) = sqrt(sigma2) * (shadow(:,j,i) -
mean(shadow(:,j,i))) / std(shadow(:,j,i));
        end;
    end;

end


function RX_power = COOP_RX_power_3D(TX_num, RX_num, noise_samples,
TX_device, RX_device)

    %% Received power estimation using Log-distance path loss model
    RX_power = zeros(TX_num, RX_num, noise_samples);
    for i = 1:TX_num
        for j = 1:RX_num
            for k = 1:noise_samples
                RX_power(i,j,k) = TX_device.TX_power(i) - (10 * TX_device.n(i)
* log10(RX_device.distance(i,j))) + RX_device.shadow(i,j,k);
            end;
        end;
    end;

end


function [shadowing, noise_matrix] =
COOP_shadowing_estimation(fingerprints, AP_num, fingerprints_num,
sigma2_samples)

    shadowing = zeros(1, sigma2_samples);
    noise_matrix = zeros(AP_num, fingerprints_num, sigma2_samples);

    for sigma2 = 1:sigma2_samples
        noise_matrix(:,:,sigma2) = std(fingerprints{sigma2}.RX_power, 0, 3);
        shadowing(sigma2) = (mean(mean(noise_matrix(:,:,sigma2), 2)))^2;
    end;

end


function shadow = COOP_mobile_shadow_generation(sigma2, TX_num,
RX_num)

    shadow = zeros(TX_num, RX_num);

    for i = 1:RX_num
        shadow(:,i) = randn(1, TX_num);
        shadow(:,i) = sqrt(sigma2) * (shadow(:,i) - mean(shadow(:,i))) /
std(shadow(:,i));
    end;

end
```

```
function mobile_estimation = COOP_tracking_mobile(AP_num,
mobile_position_samples_num,...
                                                     AP, fingerprints,
mobile, shadowing)

    % Mobile received power estimation for each AP
    mobile_estimation.RX_power = COOP_RX_power_2D(AP_num,
mobile_position_samples_num, AP, mobile);

    % Average of 4 nearest neighbor
    [mobile_estimation.avg_x_coord.mean,...
     mobile_estimation.avg_y_coord.mean,...
     mobile_estimation.MSE_mobile.mean,...
     mobile_estimation.nearest_finger.mean] = COOP_position
(mobile_estimation.RX_power,...

fingerprints.statistics_RX_power.mean,...

fingerprints.x_coord,...

fingerprints.y_coord,...
                                                            shadowing);

    [mobile_estimation.avg_x_coord.median,...
     mobile_estimation.avg_y_coord.median,...
     mobile_estimation.MSE_mobile.median,...
     mobile_estimation.nearest_finger.median] = COOP_position
(mobile_estimation.RX_power,...

fingerprints.statistics_RX_power.median,...

fingerprints.x_coord,...

fingerprints.y_coord,...
                                                              shadowing);

    [mobile_estimation.avg_x_coord.max,...
     mobile_estimation.avg_y_coord.max,...
     mobile_estimation.MSE_mobile.max,...
     mobile_estimation.nearest_finger.max] = COOP_position
(mobile_estimation.RX_power,...

fingerprints.statistics_RX_power.max,...

fingerprints.x_coord,...

fingerprints.y_coord,...
                                                           shadowing);

    [mobile_estimation.avg_x_coord.mode,...
     mobile_estimation.avg_y_coord.mode,...
     mobile_estimation.MSE_mobile.mode,...
     mobile_estimation.nearest_finger.mode] = COOP_position
(mobile_estimation.RX_power,...

fingerprints.statistics_RX_power.mode,...

fingerprints.x_coord,...

fingerprints.y_coord,...
                                                            shadowing);

    % Nearest Neighbor
    mobile_estimation.nearest_x_coord.mean =
fingerprints.x_coord(mobile_estimation.nearest_finger.mean(:,1)');
```

```
    mobile_estimation.nearest_y_coord.mean =
fingerprints.y_coord(mobile_estimation.nearest_finger.mean(:,1)');

    mobile_estimation.nearest_x_coord.median =
fingerprints.x_coord(mobile_estimation.nearest_finger.median(:,1)');
    mobile_estimation.nearest_y_coord.median =
fingerprints.y_coord(mobile_estimation.nearest_finger.median(:,1)');

    mobile_estimation.nearest_x_coord.max =
fingerprints.x_coord(mobile_estimation.nearest_finger.max(:,1)');
    mobile_estimation.nearest_y_coord.max =
fingerprints.y_coord(mobile_estimation.nearest_finger.max(:,1)');

    mobile_estimation.nearest_x_coord.mode =
fingerprints.x_coord(mobile_estimation.nearest_finger.mode(:,1)');
    mobile_estimation.nearest_y_coord.mode =
fingerprints.y_coord(mobile_estimation.nearest_finger.mode(:,1)');

end


function [mobile_RX_power, threshold_mobile, total_heared_APs] =
COOP_remove_low_powered_AP_signals(mobile_RX_power)

    %% Initializing variables
    total_heared_APs = zeros(1, size(mobile_RX_power, 1));

    %% Defining received power thresholds
    threshold_mobile = mean(mobile_RX_power, 1);

    %% Removing low powered measurements
    for i = 1:length(threshold_mobile)
        removed_APs = mobile_RX_power(:, i) < threshold_mobile(i);
        mobile_RX_power(removed_APs, i) = NaN;
        total_heared_APs(i) = length(find(removed_APs == 0));
    end;

end


function [avg_x_coord,...
          avg_y_coord,...
          MSE_mobile,...
          nearest_finger] = COOP_position (mobile_RX_power,...
                                           fingerprints_RX_power,...
                                           fingerprints_x_coord,...
                                           fingerprints_y_coord,...
                                           shadowing)

    %% Removing low powered singals
    [mobile_RX_power, ~, total_heared_APs] =
COOP_remove_low_powered_AP_signals(mobile_RX_power);

    %% Defining number of elements
    AP_num = size(mobile_RX_power, 1);
    mobile_position_samples_num = size(mobile_RX_power, 2);
    fingerprints_num = size(fingerprints_RX_power, 2);

    %% Nearest fingerprint estimation
    p = 2;
    cost = zeros(mobile_position_samples_num, AP_num, fingerprints_num);

    for i = 1:mobile_position_samples_num
        for j = 1:AP_num
```

```
            if (isnan(mobile_RX_power(j,i)) == 0)
                for k = 1:fingerprints_num
                    if (shadowing < 0.5)
                        cost(i,j,k) = (mobile_RX_power(j,i) - 
fingerprints_RX_power(j,k))^p;
                    else
                        cost(i,j,k) = (1 / (sqrt(2 * pi * shadowing^2))) * 
exp(-(mobile_RX_power(j,i) - fingerprints_RX_power(j,k))^p / (2 * 
shadowing^2));
                    end;
                end;
            end;
        end;
    end;

    MSE_mobile = zeros(mobile_position_samples_num, fingerprints_num);
    for i = 1:mobile_position_samples_num
        MSE_mobile(i,:) = (sum(cost(i,:,:))).^(1/p) / total_heared_APs(i);
    end;

    if (shadowing < 0.5)
        [~, index_mse] = sort(MSE_mobile, 2, 'ascend');
    else
        [~, index_mse] = sort(MSE_mobile, 2, 'descend');
    end;

    %% Nearest Neighbor
    nearest_finger = index_mse;

    %% Average of 4 Nearest Neighbor
    avg_x_coord = zeros(1, mobile_position_samples_num);
    avg_y_coord = zeros(1, mobile_position_samples_num);
    for i = 1:mobile_position_samples_num
        avg_x_coord(i) = sum(fingerprints_x_coord(index_mse(i,1:4))) / 
length(index_mse(i,1:4));
        avg_y_coord(i) = sum(fingerprints_y_coord(index_mse(i,1:4))) / 
length(index_mse(i,1:4));
    end;

end


function  [cooperative_cost, cooperative_nearest_finger] = 
COOP_cooperative_positioning(mobile_estimation, mobile, 
fingerprints,...

mobile_position_samples_num, fingerprints_num, current_mobile,...

shadowing)

    %% Defining data structure
    cooperative = struct('mean', [],...
                         'median', [],...
                         'max', [],...
                         'mode', []);

    cooperative_cost = cooperative;
    cooperative_cost.mean = cell(1, 
length(mobile{current_mobile}.mobile_pairs));

    cooperative_nearest_finger = cooperative;
    cooperative_nearest_finger.mean = cell(1, 
length(mobile{current_mobile}.mobile_pairs));

    %% Cooperative cost function to be maximized
```

```
    distance_difference = zeros(fingerprints_num^2,
mobile_position_samples_num);
    cost = zeros(fingerprints_num^2, mobile_position_samples_num);

    for m = 1:length(mobile{current_mobile}.mobile_pairs)

        % Joint cost function
        joint_cost = mobile_estimation{current_mobile}.MSE_mobile.mean' +
mobile_estimation{mobile{current_mobile}.mobile_pairs(m)}.MSE_mobile.mean';

        % Distance difference criteria
        for p = 1:mobile_position_samples_num
            distance_difference(:,p) = sqrt(abs(fingerprints.mutual_distance -
(ones(fingerprints_num^2,1) * mobile{current_mobile}.mutual_distance(m,p))));
        end;

        % Cooperative cost function
        for fp = 1:fingerprints_num
            cost((((fp - 1) * fingerprints_num) + 1:fingerprints_num * fp),:)
= joint_cost - distance_difference((((fp - 1) * fingerprints_num) +
1:fingerprints_num * fp),:);
        end;

        % Maximization of the cooperative function
        cooperative_nearest_finger.mean{m} =
zeros(fingerprints_num^2,mobile_position_samples_num,2);
        for p = 1:mobile_position_samples_num

            if (shadowing < 0.5)
                [sorted_cost, index_cost] = sort(cost(:,p), 'ascend');
            else
                [sorted_cost, index_cost] = sort(cost(:,p), 'descend');
            end

            cooperative_cost.mean{m}(:,p) = sorted_cost;

            cooperative_nearest_finger.mean{m}(:,p,1) =
fingerprints.mutual_ID(index_cost,1);
            cooperative_nearest_finger.mean{m}(:,p,2) =
fingerprints.mutual_ID(index_cost,2);
        end;

    end;

end
```

APPENDIX II: Cooperative and non-cooperative localization via PL approach

```
%% Main_2D_WLAN_model_COOP_path_loss_and_AP_estimation_V2
% Project:            Cooperative indoor positioning
% Author:             Tery Caisaguano Vasquez - 230078
% Advisers:           Elena-Simona Lohan
%                     Francescantonio Della Rosa
% File:               Main_2D_WLAN_model_COOP_path_loss_and_AP_estimation_V2
% Version:            2.0
% Description:        Create a 2D model for non-cooperative position estimation.
%                     The model tracks the mobiles positions based on
%                     fingerprinting database and RSS measurements from each
%                     AP. Path Loss modelling is implemented to apply the ML
%                     algorithm to find out the mobile position. Also, the
%                     model estimates the AP position, TX power, shadowing
%                     standard deviation and "n" using the LS algoritm. Those
%                     estimated parameters are used for the mobile tracking.

%% Clearing MATLAB interface
clear all; close all; format long e; clc;

%% Setup MATLAB figure's configuration
drawnow; set(0, 'defaultlinelinewidth', 2); set(0, 'defaultaxesfontsize', 10);

%% Building parameters
% Floor dimension in meters: 100m x 100m
floor_x_size = 100;
floor_y_size = 100;

% Shadowing standard deviation in dB
sigma2_samples = 51;
sigma2 = linspace(0, 100, sigma2_samples);
sigma2_index = 19;

noise_samples = 20;

% Path loss exponent
n_min = 1.2;
n_max = 8;

% Labels in device map location plot
labels = false;

%% APs parameters
% Total number of APs
AP_num = (2)^2;

% Transmit power limits uniform distributed in dB
TX_power_min = 10;
TX_power_max = 15;

[AP.x_coord, AP.y_coord] = COOP_device_grid(floor_x_size, floor_y_size,
AP_num);
AP.TX_power = TX_power_min + ((TX_power_max - TX_power_min) * rand(1,
AP_num));
AP.n = n_min + ((n_max - n_min) * rand(1, AP_num));

%% Fingerprints parameters
% Total numer of fingerprints (measurements) in the floor
fingerprints_num = (8)^2;
```

```
fingerprints = cell(1, sigma2_samples);
[y, x] = meshgrid([1:fingerprints_num]', [1:fingerprints_num]');
x = x(:);
y = y(:);
for i = 1:sigma2_samples
    [fingerprints{i}.x_coord, fingerprints{i}.y_coord] =
COOP_device_grid(floor_x_size, floor_y_size, fingerprints_num);

    fingerprints{i}.shadow =
COOP_fingerprints_shadow_generation(sigma2(sigma2_index), AP_num,
fingerprints_num, noise_samples);

    % Fingerprints distance for each AP
    fingerprints{i}.distance = COOP_distance(AP, fingerprints{i});

    % Fingerprints received power estimation using Log-distance path loss
model
    fingerprints{i}.RX_power = COOP_RX_power_3D(AP_num, fingerprints_num,
noise_samples, AP, fingerprints{i});

    % Fingerprints received power statistics
    fingerprints{i}.statistics_RX_power =
COOP_RX_power_statistics(fingerprints{i}.RX_power);

    % Fingerprints mutual distance
    fingerprints{i}.mutual_ID = [x, y];

    x_coord = fingerprints{i}.x_coord(fingerprints{i}.mutual_ID(:,1)) -
fingerprints{i}.x_coord(fingerprints{i}.mutual_ID(:,2));
    y_coord = fingerprints{i}.y_coord(fingerprints{i}.mutual_ID(:,1)) -
fingerprints{i}.y_coord(fingerprints{i}.mutual_ID(:,2));
    fingerprints{i}.mutual_distance = sqrt(x_coord.^2 + y_coord.^2)';
end;
clear x y x_coord y_coord;

% Shadowing estimation
[shadowing, noise_matrix] = COOP_shadowing_estimation(fingerprints, AP_num,
fingerprints_num, sigma2_samples);

%% APs parameteres estimation
AP_estimation = cell(1, sigma2_samples);
for i = 1:sigma2_samples
    % Strongest fingerprint criterion
    [AP_estimation{i}.x_coord, AP_estimation{i}.y_coord,
AP_estimation{i}.distance] = COOP_strongest_fingerprint(fingerprints{i},...

fingerprints_num,...

AP_num,...

floor_x_size,...

floor_y_size);

    % Transmit power and path loss coefficient estimation
    [AP_estimation{i}.TX_power, AP_estimation{i}.n] =
COOP_TX_power_and_path_loss_estimation(fingerprints{i},...

AP_estimation{i},...

noise_matrix(:,:,i),...

fingerprints_num,...

AP_num);
end;
```

```
%% Mobile parameters
% Total number of mobile devices
mobile_num = 3;

% Total number of position samples
mobile_position_samples_num = 50;
mobile_position_index = mobile_position_samples_num/2;

mobile = COOP_data_structure_and_mobiles_path(AP_num,
mobile_position_samples_num, mobile_num, sigma2_samples);

for i = 1:mobile_num
    for j = 1:sigma2_samples
        mobile{i,j}.shadow = COOP_mobile_shadow_generation(sigma2(j), AP_num,
mobile_position_samples_num);

        % Mobile distance for each AP
        mobile{i,j}.distance = COOP_distance_data_structure(AP_estimation{j},
mobile{i,j});
    end;
end;

%% Mobile position estimation
mobile_estimation = cell(mobile_num, sigma2_samples);

% Non-cooperative tracking
for i = 1:mobile_num
    for j = 1:sigma2_samples
        mobile_estimation{i,j} = COOP_tracking_mobile(AP_num,
mobile_position_samples_num,...
                                                     AP_estimation{j},
fingerprints{j}, mobile{i,j}, shadowing(j));
    end;
end;

% Non-cooperative Root Mean Square Error of the estimated mobile position
RMSE = COOP_RMSE(mobile_num, sigma2_samples, mobile_estimation, mobile);

% Cooperative tracking
ME = cell(1, mobile_num);
M = cell(1, mobile_num);

for j = 1:sigma2_samples
    for i = 1:mobile_num
        ME{i} = mobile_estimation{i,j};
        M{i} = mobile{i,j};
    end;

    for current_mobile = 1:mobile_num
        [mobile_estimation{current_mobile,j}.cooperative_cost,...
         mobile_estimation{current_mobile,j}.cooperative_nearest_finger] =
COOP_cooperative_positioning(ME, M, fingerprints{j},...

mobile_position_samples_num, fingerprints_num, current_mobile);
    end;
end;

% Cooperative Root Mean Square Error of the estimated mobile position
cooperative_RMSE = COOP_cooperative_RMSE(mobile_num, sigma2_samples,
mobile_position_samples_num, mobile_estimation, mobile, fingerprints);

%% APs characteristics
AP_ID = linspace(1, AP_num, AP_num);

figure (1);
```

```
subplot(211);
plot(AP_ID, AP_estimation{sigma2_index}.TX_power.mean, '--',...
     AP_ID, AP_estimation{sigma2_index}.TX_power.median, '--',...
     AP_ID, AP_estimation{sigma2_index}.TX_power.max, '--',...
     AP_ID, AP_estimation{sigma2_index}.TX_power.mode, '--',...
     AP_ID, AP.TX_power);
xlabel('Access Point ID'); xlim([1 AP_num]);
ylabel('Power [dBm]');
buffer_text_line1 = sprintf('Transmit Power for each Access Point');
buffer_text_line2 = sprintf('\\sigma^2 = %1.2f dB', sigma2(sigma2_index));
title({[buffer_text_line1], [buffer_text_line2]}, 'FontWeight', 'bold',
'FontSize', 10);
set(gca, 'XTick', AP_ID); grid on;
legend('Mean', 'Median', 'Max', 'Most recurrent', 'Transmitted Power',
'Location', 'EastOutside');

subplot(212);
plot(AP_ID, AP_estimation{sigma2_index}.n.mean, '--',...
     AP_ID, AP_estimation{sigma2_index}.n.median, '--',...
     AP_ID, AP_estimation{sigma2_index}.n.max, '--',...
     AP_ID, AP_estimation{sigma2_index}.n.mode, '--',...
     AP_ID, AP.n);
xlabel('Access Point ID'); xlim([1 AP_num]);
ylabel('Pathloss Factor'); ylim([n_min n_max]);
buffer_text_line1 = sprintf('Pathloss Factor for each Access Point');
buffer_text_line2 = sprintf('\\sigma^2 = %1.2f dB', sigma2(sigma2_index));
title({[buffer_text_line1], [buffer_text_line2]}, 'FontWeight', 'bold',
'FontSize', 10);
set(gca, 'XTick', AP_ID); grid on;
legend('Mean', 'Median', 'Max', 'Most recurrent', 'Pathloss Factor',
'Location', 'EastOutside');

clear AP_ID;

%% Shadowing
figure (2);
plot(linspace(1, length(sigma2), length(sigma2)), sigma2, 'k',...
     linspace(1, length(sigma2), length(sigma2)), shadowing, 'r--');
xlabel('Sample'); xlim([1 length(sigma2)]);
ylabel('Magnitude [dB]'); ylim([min(sigma2) max(sigma2)]);
title('Shadowing estimation', 'FontWeight', 'bold', 'FontSize', 12); grid on;
legend('Shadowing', 'Estimated shadowing', 'Location', 'NorthWest');

%% Device map
for i = 1:mobile_num
    COOP_print_device_map(AP, AP_estimation{sigma2_index},
fingerprints{sigma2_index}, mobile_estimation{i,sigma2_index},
mobile{i,sigma2_index}, i,...
                          sigma2(sigma2_index), mobile_position_samples_num,
fingerprints_num, AP_num,...
                          floor_x_size, floor_y_size, labels);
end;

%% Non-cooperative RMSE for each mobile estimation
for i = 1:mobile_num

    figure (5 + i);

    subplot(211);
    plot(sigma2, RMSE.nearest_neighbor.mean(i,:),...
         sigma2, RMSE.nearest_neighbor.median(i,:),...
         sigma2, RMSE.nearest_neighbor.max(i,:),...
         sigma2, RMSE.nearest_neighbor.mode(i,:));
    set(gca, 'YTick',
[floor(min(RMSE.nearest_neighbor.max(i,:))):0.5:ceil(max(RMSE.nearest_neighbor
.max(i,:)))]); grid on;
    xlabel('\sigma^2 [dB]'); xlim([min(sigma2) max(sigma2)]);
```

```
    ylabel('Distance [m]'); ylim([min(RMSE.nearest_neighbor.max(i,:))
max(RMSE.nearest_neighbor.max(i,:))]);
    buffer_text = sprintf('Non-cooperative RMSE Nearest Neighbor @ Mobile
%2d', i);
    title(buffer_text, 'FontWeight', 'bold', 'FontSize', 10);
    legend('Mean', 'Median', 'Max', 'Most recurrent', 'Location',
'EastOutside');

    subplot(212);
    plot(sigma2, RMSE.average.mean(i,:),...
         sigma2, RMSE.average.median(i,:),...
         sigma2, RMSE.average.max(i,:),...
         sigma2, RMSE.average.mode(i,:));
    set(gca, 'YTick',
[floor(min(RMSE.average.max(i,:))):1:ceil(max(RMSE.average.max(i,:)))]); grid
on;
    xlabel('\sigma^2 [dB]'); xlim([min(sigma2) max(sigma2)]);
    ylabel('Distance [m]'); ylim([min(RMSE.average.max(i,:))
max(RMSE.average.max(i,:))]);
    buffer_text = sprintf('Non-cooperative RMSE Average of Neighbors @ Mobile
%2d', i);
    title(buffer_text, 'FontWeight', 'bold', 'FontSize', 10);
    legend('Mean', 'Median', 'Max', 'Most recurrent', 'Location',
'EastOutside');

end;

%% Non-cooperative Cost function
PDF = cell(1, mobile_num);
for i = 1:mobile_num
    PDF{i} = COOP_print_cost_function(mobile_estimation{i,sigma2_index},
mobile{i,sigma2_index},...
                                      fingerprints{sigma2_index},
fingerprints_num,...
                                      floor_x_size, floor_y_size,
sigma2(sigma2_index),...
                                      i, mobile_position_index);
end;

%% Non-cooperative and Cooperative RMSE comparison
for i = 1:mobile_num
    figure (14 + i);

    plot(sigma2, RMSE.nearest_neighbor.mean(i,:),'-',...
         sigma2, RMSE.average.mean(i,:),'-',...
         sigma2, cooperative_RMSE.nearest_neighbor.mean(i,:),'.--',...
         sigma2, cooperative_RMSE.average.mean(i,:),'.--');
    xlabel('\sigma^2 [dB]'); xlim([min(sigma2) max(sigma2)]);
    ylabel('Distance [m]');
    buffer_text_line1 = sprintf('RMSE @ Mobile %2d', i);
    buffer_text_line2 = sprintf('Mean estimator');
    title({[buffer_text_line1], [buffer_text_line2]}, 'FontWeight', 'bold',
'FontSize', 10);
    legend('Non-coop Nearest', 'Non-coop Average', 'Coop Nearest', 'Coop
Average'); grid on;
end;


function shadow = COOP_fingerprints_shadow_generation(sigma2, TX_num,
RX_num, noise_samples)

    shadow = zeros(TX_num, RX_num, noise_samples);

    for i = 1:noise_samples
        for j = 1:RX_num
            shadow(:,j,i) = randn(1, TX_num);
```

```
            shadow(:,j,i) = sqrt(sigma2) * (shadow(:,j,i) -
mean(shadow(:,j,i))) / std(shadow(:,j,i));
        end;
    end;

end


function RX_power = COOP_RX_power_3D(TX_num, RX_num, noise_samples,
TX_device, RX_device)

    %% Received power estimation using Log-distance path loss model
    RX_power = zeros(TX_num, RX_num, noise_samples);
    for i = 1:TX_num
        for j = 1:RX_num
            for k = 1:noise_samples
                RX_power(i,j,k) = TX_device.TX_power(i) - (10 * TX_device.n(i)
* log10(RX_device.distance(i,j))) + RX_device.shadow(i,j,k);
            end;
        end;
    end;

end


function [shadowing, noise_matrix] =
COOP_shadowing_estimation(fingerprints, AP_num, fingerprints_num,
sigma2_samples)

    shadowing = zeros(1, sigma2_samples);
    noise_matrix = zeros(AP_num, fingerprints_num, sigma2_samples);

    for sigma2 = 1:sigma2_samples
        noise_matrix(:,:,sigma2) = std(fingerprints{sigma2}.RX_power, 0, 3);
        shadowing(sigma2) = (mean(mean(noise_matrix(:,:,sigma2), 2)))^2;
    end;

end


function shadow = COOP_mobile_shadow_generation(sigma2, TX_num,
RX_num)

    shadow = zeros(TX_num, RX_num);

    for i = 1:RX_num
        shadow(:,i) = randn(1, TX_num);
        shadow(:,i) = sqrt(sigma2) * (shadow(:,i) - mean(shadow(:,i))) /
std(shadow(:,i));
    end;

end


function mobile_estimation = COOP_tracking_mobile(AP_num,
mobile_position_samples_num,...
                                                AP, fingerprints,
mobile, shadowing)

    %% Mobile received power estimation for each AP
    mobile_estimation.RX_power = COOP_RX_power_2D(AP_num,
mobile_position_samples_num, AP, mobile);
```

```
    % Average of 4 nearest neighbor
    [mobile_estimation.avg_x_coord.mean,...
     mobile_estimation.avg_y_coord.mean,...
     mobile_estimation.PDF_mobile.mean,...
     mobile_estimation.nearest_finger.mean] = COOP_position_probability
(mobile_estimation.RX_power.mean,...

fingerprints,...

AP.TX_power.mean,...

AP.n.mean,...

AP.distance.mean,...

shadowing);

    [mobile_estimation.avg_x_coord.median,...
     mobile_estimation.avg_y_coord.median,...
     mobile_estimation.PDF_mobile.median,...
     mobile_estimation.nearest_finger.median] = COOP_position_probability
(mobile_estimation.RX_power.median,...

fingerprints,...

AP.TX_power.median,...

AP.n.median,...

AP.distance.median,...

shadowing);

    [mobile_estimation.avg_x_coord.max,...
     mobile_estimation.avg_y_coord.max,...
     mobile_estimation.PDF_mobile.max,...
     mobile_estimation.nearest_finger.max] = COOP_position_probability
(mobile_estimation.RX_power.max,...

fingerprints,...

AP.TX_power.max,...

AP.n.max,...

AP.distance.max,...

shadowing);

    [mobile_estimation.avg_x_coord.mode,...
     mobile_estimation.avg_y_coord.mode,...
     mobile_estimation.PDF_mobile.mode,...
     mobile_estimation.nearest_finger.mode] = COOP_position_probability
(mobile_estimation.RX_power.mode,...

fingerprints,...

AP.TX_power.mode,...

AP.n.mode,...

AP.distance.mode,...

shadowing);

    % Nearest Neighbor
```

```
    mobile_estimation.nearest_x_coord.mean =
fingerprints.x_coord(mobile_estimation.nearest_finger.mean(:,1)');
    mobile_estimation.nearest_y_coord.mean =
fingerprints.y_coord(mobile_estimation.nearest_finger.mean(:,1)');

    mobile_estimation.nearest_x_coord.median =
fingerprints.x_coord(mobile_estimation.nearest_finger.median(:,1)');
    mobile_estimation.nearest_y_coord.median =
fingerprints.y_coord(mobile_estimation.nearest_finger.median(:,1)');

    mobile_estimation.nearest_x_coord.max =
fingerprints.x_coord(mobile_estimation.nearest_finger.max(:,1)');
    mobile_estimation.nearest_y_coord.max =
fingerprints.y_coord(mobile_estimation.nearest_finger.max(:,1)');

    mobile_estimation.nearest_x_coord.mode =
fingerprints.x_coord(mobile_estimation.nearest_finger.mode(:,1)');
    mobile_estimation.nearest_y_coord.mode =
fingerprints.y_coord(mobile_estimation.nearest_finger.mode(:,1)');

end


function [avg_x_coord,...
          avg_y_coord,...
          PDF_mobile,...
          nearest_finger] = COOP_position_probability
(mobile_RX_power,...

fingerprints,...
                                                           AP_TX_power,...
                                                           AP_n,...
                                                           AP_distance,...
                                                           shadowing)

    %% Defining number of elements
    AP_num = size(mobile_RX_power, 1);
    mobile_position_samples_num = size(mobile_RX_power, 2);
    fingerprints_num = size(fingerprints.RX_power, 2);

    %% PDF to each fingerprint and for each AP in the grid
    p = 2;
    probability = zeros(mobile_position_samples_num, AP_num,
fingerprints_num);

    for i = 1:mobile_position_samples_num
        for j = 1:AP_num
            for k = 1:fingerprints_num
                probability(i,j,k) = - ((1 / 2) * log10(2 * pi * shadowing)) -
(mobile_RX_power(j,i) - AP_TX_power(j) + (10 * AP_n(j) *
log10(AP_distance(j,k))))^p / (2 * shadowing);
            end;
        end;
    end;

    PDF_mobile = zeros(mobile_position_samples_num, fingerprints_num);
    for i = 1:mobile_position_samples_num
        PDF_mobile(i,:) = sum(probability(i,:,:)) / AP_num;
    end;

    [~, index_pdf] = sort(PDF_mobile, 2, 'descend');

    %% Nearest Neighbor
    nearest_finger = index_pdf;
```

```
    %% Average of 4 Nearest Neighbor
    avg_x_coord = zeros(1, mobile_position_samples_num);
    avg_y_coord = zeros(1, mobile_position_samples_num);
    for i = 1:mobile_position_samples_num
        avg_x_coord(i) = sum(fingerprints.x_coord(index_pdf(i,1:4))) /
length(index_pdf(i,1:4));
        avg_y_coord(i) = sum(fingerprints.y_coord(index_pdf(i,1:4))) /
length(index_pdf(i,1:4));
    end;

end
```

```
function  [cooperative_cost, cooperative_nearest_finger] =
COOP_cooperative_positioning(mobile_estimation, mobile,
fingerprints,...

mobile_position_samples_num, fingerprints_num, current_mobile)

    %% Defining data structure
    cooperative = struct('mean', [],...
                         'median', [],...
                         'max', [],...
                         'mode', []);

    cooperative_cost = cooperative;
    cooperative_cost.mean = cell(1,
length(mobile{current_mobile}.mobile_pairs));

    cooperative_nearest_finger = cooperative;
    cooperative_nearest_finger.mean = cell(1,
length(mobile{current_mobile}.mobile_pairs));

    %% Cooperative cost function to be maximized
    distance_difference = zeros(fingerprints_num^2,
mobile_position_samples_num);
    cost = zeros(fingerprints_num^2, mobile_position_samples_num);

    for m = 1:length(mobile{current_mobile}.mobile_pairs)

        % Joint cost function
        joint_cost = mobile_estimation{current_mobile}.PDF_mobile.mean' +
mobile_estimation{mobile{current_mobile}.mobile_pairs(m)}.PDF_mobile.mean';

        % Distance difference criteria
        for p = 1:mobile_position_samples_num
            distance_difference(:,p) = sqrt(abs(fingerprints.mutual_distance -
(ones(fingerprints_num^2,1) * mobile{current_mobile}.mutual_distance(m,p))));
        end;

         % Cooperative cost function
        for fp = 1:fingerprints_num
            cost((((fp - 1) * fingerprints_num) + 1:fingerprints_num * fp),:)
= joint_cost - distance_difference((((fp - 1) * fingerprints_num) +
1:fingerprints_num * fp),:);
        end;

        % Maximization of the cooperative function
        cooperative_nearest_finger.mean{m} =
zeros(fingerprints_num^2,mobile_position_samples_num,2);
        for p = 1:mobile_position_samples_num
            [sorted_cost, index_cost] = sort(cost(:,p), 'descend');

            cooperative_cost.mean{m}(:,p) = sorted_cost;
```

```
            cooperative_nearest_finger.mean{m}(:,p,1) =
fingerprints.mutual_ID(index_cost,1);
            cooperative_nearest_finger.mean{m}(:,p,2) =
fingerprints.mutual_ID(index_cost,2);
        end;
    end;

end
```