Bayesian Algorithms for Mobile Terminal Positioning in Outdoor Wireless Environments

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Abstract

The ability to reliably and cheaply localize mobile terminals will allow users to understand and utilize the what, where and when of the surrounding physical world. Therefore, mobile terminal location information will open novel application opportunities in many areas.

The mobile terminal positioning problem is categorized into three different types according to the availability of (1) initial accurate location information and (2) motion measurement data. *Location estimation* refers to the mobile positioning problem when both the initial location and motion measurement data are not available. If both are available, the positioning problem is referred to as *position tracking*. When only motion measurements are available the problem is known as *global localization*. These positioning problems were solved within the Bayesian filtering framework in order to work under a common theoretical context. Filter derivation and implementation algorithms are provided with emphasis on the radio mapping approach. The radio maps of the experimental area have been created by a 3D deterministic radio propagation tool with a grid resolution of 5 m. Real-world experiments were conducted in a GSM network, deployed in a semi-urban environment, in order to investigate the performance of the different positioning algorithms.

A method is proposed to compute the Cramér-Rao lower bound (CRLB) in order to asses the performance of the received signal strength (RSS) based location estimation algorithm (database correlation method). The fingerprinting databases are usually constructed using complex 3D radio propagation prediction tools. Thus, the RSS-location mapping function is neither continuous nor differentiable everywhere as required by the Cramér-Rao bound calculations. The key approach is reconstructing the fingerprinting database using an empirical path loss formula that sufficiently characterizes the wireless propagation environment of the test area. The Cramér-Rao lower bound is derived and calculated for the reconstructed database in the experimental area. Furthermore, the posterior Cramér-Rao lower bound (PCRLB) is derived and computed in order to asses the performance of the position tracking algorithm.

Keywords: Mobile location estimation, received signal strength (RSS) fingerprinting, database correlation, Bayesian filtering, nonlinear filtering, inertial measurement unit (IMU), position tracking, global localization, Cramér-Rao lower bound (CRLB), posterior Cramér-Rao lower bound (PCRLB), sensor fusion, data fusion.

Kurzfassung

Die Fähigkeit, zuverlässige und kostengünstige Lokalisierung von mobilen Endgeräten, wird dem Nutzer zu verstehen und zu nutzen, was, wo und wann der umgebenden physikalischen Welt. Deshalb, öffnen Standortinformationen von mobilen Endgeräten neue Anwendungsmöglichkeiten in vielen Bereichen.

Das Positionierungsproblem von mobilen Endgeräten ist in drei verschiedene Typen kategorisiert, abhängig von (1) der Verfügbarkeit der ersten genauen Informationen über den Ort und (2) der Bewegungsmessdaten. *Location Estimation (Standortschätzung)* bezieht sich auf das mobile Positionierungsproblem, wenn sowohl die erste Position und die Bewegungsmessdaten nicht verfügbar sind. Wenn beide verfügbar sind, das Positionierungsproblem wird *Position Tracking (Positionsverfolgung)* benannt. Wenn nur Bewegungsmessungen zur Verfügung stehen, das Problem ist bekannt als *Global Localization (globale Lokalisation)*. Diese Positionierungsprobleme wurden gelöst innerhalb des Bayes-Filter-Frameworks, um Arbeiten im Rahmen eines gemeinsamen theoretischen Kontexts zu ermöglichen. Filterableitung und Durchführungsalgorithmen werden geliefert, wobei der Schwerpunkt auf dem Radio-Mapping-Ansatz liegt. Die Radio-Karten des experimentellen Bereichs wurden durch ein 3D-deterministischen Wellenausbreitungstool mit einer Rasterauflösung von 5 m erstellt. Reale Experimente wurden in einem GSM-Netz, eingesetzt in einem semi-urbanen Umfeld, durchgeführt, um die Leistung der unterschiedlichen Positionierungsalgorithmen zu untersuchen.

Eine Methode wird vorgeschlagen, zur Berechnung der Cramér-Rao untere Schranke (CRLB), um die Leistung der empfangenen Signalstärke (RSS) basierender Location Estimation Algorithmus (Datenbankkorrelationsmethode) zu prüfen. Die

Fingerabdruck-Datenbanken der Signalstärke werden in der Regel mithilfe komplexer 3D-Wellenausbreitungstool konstruiert. Deswegen, ist der RSS-Ort-Abbildungsfunktion weder kontinuierlich noch differenzierbar überall wie von der Cramér-Rao-Schranke-Berechnungen benötigt. Der Schlüssel ist eine Rekonstruktion der Fingerabdruck-Datenbank mit einer empirischen Pfadverlustformel, die die drahtlose Wellenausbreitungsumwelt des Test-Bereiches genügend charakterisiert. Die Cramér-Rao untere Schranke ist abgeleitet und berechnet für die rekonstruierte Datenbank in den experimentellen Bereich. Auch die Posterior Cramér-Rao untere Schranke (PCRLB) ist abgeleitet und berechnet, um die Leistung des Position Tracking Algorithmus zu prüfen.

Schlagwörter: Mobilgerätstandortschätzung, empfangene Signalstärke (RSS)-Fingerabdrucklokalisierung, Datenbankkorrelation, Bayes'sche Filterung, nichtlineare Filterung, Trägheitsmesseinheit (IMU), Positionsverfolgung, globale Lokalisation, Cramér-Rao untere Schranke (CRLB), Posterior Cramér-Rao untere Schranke (PCRLB), Sensorfusion, Datenfusion.

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List of Acronyms

2D	two-dimensional
3D	three-dimensional
A-GPS	Assisted-GPS
AOA	angle of arrival
AP	access point
ASF	additional secondary phase factor
BS	base station
CDB	cell database
CDF	cumulative distribution function
CDMA	code-division multiple access
CGI	cell global identity
CIR	channel impulse response
COO	cell of origin
CRB	Cramér-Rao bound
CRLB	Cramér-Rao lower bound
CTADB	cell TA database
DBF	discrete Bayesian filter
DBN	dynamic Bayes network
DCM	database correlation method
DGPS	differential GPS
DOA	direction of arrival
DR	dead reckoning
DTV	digital TV
ECEF	earth-centric earth-fixed
EGNOS	European geostationary navigation overlay service

EIRP	effective isotropic radiated power
EOTD	enhanced observed time difference
ESS	Ekahau Site Survey
EU	European Union
FCC	Federal Communications Commission
FI	Fisher information
FIM	Fisher information matrix
FOC	full operational capability
GBAS	ground-based augmentation systems
GIS	geographical information system
GL	global localization
GLONASS	GLObal NAvigation Satellite System (GLObalnaya NAvigationnaya Sputnikovaya Sistema)
GNSS	global navigation satellite system
GPS	global positioning system
GSM	Global System for Mobile communications (originally: Groupe Spécial Mobile)
HMM	hidden Markov model
IMU	inertial measurement unit
INS	inertial navigation system
IRNSS	Indian regional navigational satellite system
KF	Kalman filter or filtering
KLI	Kullback-Leibler information
KNN	k-nearest neighbour
LAAS	local-area augmentation system
LAC	location area code
LBS	location-based services
LE	location estimation
LMS	least mean square
LMU	location measurement unit
LOB	line of bearing
LOP	line of position
LORAN	LOng-RAnge Navigation
LOS	line of sight
LS	least squares
MAP	maximum a posteriori
ML	maximum likelihood

MLE	maximum likelihood estimate or estimator
MMSE	minimum mean square error
MSE	mean square error
MT	mobile terminal
MVU	minimum variance unbiased
NLOS	non-line-of-sight
NMR	network measurement report
NN	nearest neighbour
NPF	nonparametric filter
OTDOA	observed TDOA
PCRLB	posterior Cramér-Rao lower bound
pdf	probability density function
PF	particle filter or filtering
PRN	pseudorandom noise
PT	position tracking
QZSS	quasi-zenith satellite system
RBF	recursive Bayesian filter
RF	radio frequency
RMSE	root mean square error
RSE	root square error
RSS	received signal strength
RSSI	received signal strength indicator
RTT	round trip time
RxLev	received signal level
SAR	search and rescue
SBAS	satellite-based augmentation system
SD	standard deviation
SMS	short message service
SoL	safety-of-life
TA	timing advance
TAE	trimmed average estimate or estimator
TD	time difference
TDOA	time difference of arrival
TOA	time of arrival
UMTS	universal mobile telecommunications system
UTDOA	uplink TDOA
WAAS	wide-area augmentation system

WAE	weighted average estimate or estimator
WLAN	wireless local-area network
WPS	Wi-Fi positioning system
w.r.t.	with respect to
WWII	World War II

List of Symbols

$\lvert \cdot \rvert$	Absolute value
$\lVert \cdot \rVert$	Euclidean norm of a vector or value
$\lVert \cdot \rVert^2$	l_2 norm of a vector or value
∇	First derivative operator
∇^2	Second derivative operator (elements $\frac{\partial^2}{\partial s^2}$)
$a_{0:t}$	MT actions (movements) from time 0 up to time t
a_t	MT action at time t
ASF_i	Additional secondary phase factor of LORAN transmitter i
$Bel(s_t)$	Posterior belief over the state at time t
$Bel^-(s_t)$	Posterior belief just after executing the action a_t and before incorporating the network measurement o_t
c	Electromagnetic signal propagation speed, or common attenuation factor due to the MT's RF properties
$\hat{c}$	Estimate of the common attenuation factor
C_e	Positive definite covariance matrix of the error vector e
COV	Covariance matrix
d	Distance between the BS transmitter and the MS receiver, or Propagation delays due to atmospheric conditions
d_t	MT travelled distance at time t
D	Observed Doppler shift
D_{t+1}^{TA}	TA distance measurement of the serving BS at time $t+1$

$DB_{cell-ID}$	Database that contains location information and expected RxLev values of the areas covered by the main BS cell antenna at time t
DB_{res}	Database resolution
e_i	Unpredicted measurement error on channel i
$E[\cdot]$	Expectation or expected value or vector
f	Frequency
$f(s_t)$	State transition function at time t
F_t	Jacobian matrix of $f(s_t)$
FIM^{-1}	Inverse of the Fisher information matrix
h_{BS}	Height of the BS antenna
h_{MS}	Height of the MS antenna
$h(s_{t+1})$	Measurement function at time $t+1$
H_{t+1}	Jacobian matrix of $h(s_{t+1})$
i	Location candidate index
I	Identity matrix
$I(s)$	Fisher information for the data o
k	Number of the best weighted candidates
l	Number of observed neighbour BSs that coincide with the list of the predicted six strongest neighbour BSs at $s_t^{(i)}$
L	Path loss
L^{3D-DB}	Path loss of the 3D-DB
m	World (environment) model
m_t	World model at time t
M	Number of observed BSs or control channels
n	Number of MT state or position candidates
N	Integer number of cycles between the satellite and the receiver
$o_{0:t}$	Network observations (measurements) from time 0 up to time t
o_i	Measurement on channel i
o_t	Network observation at time t
$P_i(s)$	Average predicted RSS at location s from the i-th BS
P_r	Average received signal level at any location
$p(o_t \mid s_t, m)$	Network observation or measurement model

$p(s_t \mid s_{t-1}, a_{t-1}, m)$	MT motion model or transition probability density
Q	Covariance matrix of the process noise
r_i	Distance between the *i*-th BS and the MT
r_{ij}	Distance difference at the *i*-th and *j*-th BSs
R	Pseudorange to a satellite, or Residue, or covariance matrix of the measurement error
R_E	Radius of the sphere
R_{true}	True range to a satellite
$RxLev_{DB_j}$	Database RxLev prediction value of the *j*-th observed BS at $s_t^{(i)}$
$RxLev_t^{(j)}$	Measured received signal level from the *j*-th observed BS
$s^{(i)}$	*i*-th MT state or position candidate
$\hat{s}$	Estimate of s
s_t	State at time t
$\hat{s}_t$	Final MT location estimate at time t
$\hat{s}_t^{MAP}$	MAP estimate at time t
$\hat{s}_t^{MLE}$	MLE at time t
$\hat{s}_t^{WAE}$	WAE at time t
$\hat{s}_t^{TAE}$	TAE at time t
t, T	Time
t_i	TOA of the MT signal at the *i*-th BS
$t_{i_{LORAN}}$	Nominal emission time at LORAN transmitter i
t_{MT}	Time instant at which the MT signal is transmitted
Δt	Bias of receiver and satellite clocks
TD_{ij}	TD observation of LORAN transmitters i and j
TOA_i	*i*-th TOA measurement
$Tr()$	Trace of a matrix
$trans_{t-1}$	Translation in a 2D Cartesian coordinate system at time $t-1$
Var	Variance
$w^{(i)}$	Weight of $s^{(i)}$
$w_{MM}^{(i)}$	Weight of $s^{(i)}$ according to the measurement model

$w_{ND}^{(i)}$	Weight of $s^{(i)}$ according to the neighbourhood degree
$w_{SN}^{(i)}$	Weight of $s^{(i)}$ according to the strongest neighbour
x_i	*i*-th BS x-coordinate
x_{MT}	MT x-coordinate
x_r	Receiver geocentric x-coordinate
x_s	Satellite geocentric x-coordinate
x_t	MT x-coordinate at time t
y_i	*i*-th BS y-coordinate
y_{MT}	MT y-coordinate
y_r	Receiver geocentric y-coordinate
y_s	Satellite geocentric y-coordinate
y_t	MT y-coordinate at time t
z_r	Receiver geocentric z-coordinate
z_s	Satellite geocentric z-coordinate
α	Threshold value
α_{SN}	Constant bonus value
δ_r , δ_R	Receiver clock error
ϕ_i	AOA of the transmitted signal from the MT at the *i*-th BS
ϕ_t	MT orientation at time t
Φ	Carrier phase pseudorange
η	Normalization factor (constant)
λ	Carrier phase wavelength
θ_{t-1}	Orientation in a 2D Cartesian coordinate system at time $t-1$
ρ	Distance between the satellite at the transmission time and the receiver at reception time
ρ_i	Spatial distance between the ECEF coordinates of the receiver and LORAN transmitter i
$\sigma_{D^{TA}}$	Standard deviation of the TA measurement error
σ_{orient}	Standard deviation of orientation measurement error
σ_{RxLev}	Standard deviation of the RxLev measurement error

σ_{trans}	Standard deviation of the translation measurement error
$\sigma_d{}^2$	Variance of the MT translation measurement error
$\sigma_s{}^2$	Variance of the location estimator error
σ_x^2	Variance of the MT x-translation measurement error
σ_y^2	Variance of the MT y-translation measurement error
σ_ϕ^2	Variance of the MT orientation measurement error

Chapter 1

Introduction

1.1 Motivation

Mobile terminal (MT) positioning is a key problem in wireless environments. It is the most fundamental problem to providing customers with tailored and location-aware services. MT positioning is defined as the determination of the MT position using location-dependent parameters in a specific coordinate system. It is also termed *radiolocation* and *wireless geolocation*. The key driver for developing MT geolocation technologies in the USA was E-911. In the EU, it was commercial services in the first place, and later E-112 that utilizes the same techniques. Emergency call location has become a requirement in fixed and cellular networks in the USA in 1996 [FCC1996], [FCC2001] and in the EU in 2003 [EU2003]. Phase II of the Federal Communications Commission (FCC) E-911 mandate has set requirements on the location accuracy for the 67% and the 95% of all emergency calls using both network-based and mobile-based solutions as given in TABLE 1.1.

TABLE 1.1: Phase II of the FCC's E911 program requirement on location accuracy.

	Network-based	**Mobile-based**
67%	100 m	50 m
95%	300 m	150 m

Positioning of a MT is considered more critical because MT users and hence MT originated emergency calls are continually increasing. It is estimated that about 50% of all emergency calls in the EU are MT originated, and the expected tendency is rising [EU2003]. In the USA, it was estimated that one third of the daily E-911 calls, about 170,000, originate from MTs [FCC1996], [NJ1997].

The first application of MT geolocation dates back to World War II (WWII), when it was critical to locate military personnel rapidly and precisely in emergency situations [Pah2005]. Furthermore, non-military interest in this field dates back to about 40 years ago [Fig1969], [Ott1977]. While emergency call location could be considered the most important of location-based services (LBS) due to its urgency for life and property safety, commercial LBS are believed to make increasing revenues for network operators who could provide customers with attractive and tailored services [Ran2000]. Therefore, a lot of research is being carried out in this area. Examples of location-based services and applications include:

- Emergency response, i.e. E-911, E-112 and search and rescue (SAR)
- People tracking and navigation
- Environmental monitoring
- Health care
- Ubiquitous computing
- Location-specific advertising
- Mobile marketing
- Location-sensitive billing
- Enquiry and information services
- Mobile gaming
- Asset tracking
- Fleet management and logistics
- Fraud protection
- Mobile yellow pages
- Tourist and travel information
- Wireless system design and management
- Intelligent transportation systems
- Traffic telematics
- Toll systems
- Homeland security

Positioning Systems are usually categorized according to the application environment into *indoor*, *outdoor*, or hybrid *indoor/outdoor*, or according to the place where location calculations are performed into *network-based* or *mobile-based*. If the measurements are carried out by the MT and sent to the network for position calculations, the resulting hybrid approach is termed *mobile-assisted network-based*. The reverse configuration is referred to as *network-assisted mobile-based*, where necessary data for location calculations are sent from the network to the MT. The main approaches of positioning are *global* or *satellite-based* techniques, and *local* or *terrestrial-based* methods. Terrestrial-based methods have two variants: *Geometric* techniques, and *mapping* approaches. These methods differ relatively in terms of accuracy, coverage, cost, MT power consumption, and wireless system impact as shown in TABLE 1.2.

TABLE 1.2: Basic aspects of the different positioning techniques.

	Accuracy	**Coverage**		**Cost**	**Terminal Power consumption**	**Wireless System impact**
		Outdoor	**Indoor**			
Global or Satellite-based Methods	High (~15m)	Yes	None or very poor	Medium	High	Low or Medium
Terrestrial Geometric Techniques	Medium (~100m)	Yes	Yes	Medium	Low	Medium
Terrestrial Mapping Approaches	Low (100m-several km’s)	Yes	Yes	Low	Low	Low

1.2 Synopsis of Related Work

The importance of MT geolocation to the research community has been confirmed by the appearance of several special issues on the topic in well-known journals and magazines, see [Tek1998], [Ant2004], [Dog2005], [Kai2006], [Sav2007], [Lin2007], [Fra2008], [Bar2008], and [Lab2008]. A lot of PhD theses have also been conducted in the field, e.g. [Ken1996], [Hal2002], [Nyp2004], [You2004c], [Pri2005], [Wal2005], [Zhu2006], [Zim2006], and [Sir2007]. Examples of patent applications include [Son1991], [Mal1997], [Wax1998], [Mes1998], [Rao2000], and [Per2000]. Review and/or survey literature on wireless geolocation technology are provided in many books, e.g. [Caf1999], [Jag2003], [Kar2004], [Küp2005], and [Kol2006], book chapters, e.g. [Stü1999], [Pah2002, Ch. 14], [Stü2002], [Wec2003], [Pah2005, Ch. 13], and [Caf2005], and articles, see [Rit1977], [Rot1977], [Rap1996], [Stü1998], [Caf1998a], [Caf1998b], [Dra1998], [Zha2000], [Zha2002], [Sun2005], [Say2005], and [Gus2005].

The concept of using previously measured signal strength contours for positioning was first documented in [Fig1969]. The effect of fast fading was avoided by taking the median of the sample measurements over a sufficiently long time window.

A Kalman filter (KF) based on a locally linear MT motion model was suggested in [Hel1999] to help reduce the location error by filtering the initial location estimation. This has improved the linear regression smoothing procedure presented in [Hel1997]. The work in [Hel1999] has been extended by different assumptions on the motion model or by including human control factors, see [McG2002], [McG2003], and [Lee2003].

RADAR [Bah2000a], [Bah2000b] is an in-building location-aware tracking system based on the IEEE 802.11 network. Positioning is performed either by received signal strength (RSS) fingerprinting or by a mathematical model of the indoor RF propagation within WLAN infrastructures. The accuracy is within 2 m to 3 m with 50% probability. Similar approaches have also been presented in [Pra2002]. Including probabilistic schemes is presented in the Ekahau system [Roo2002a], [Roo2002b], the Nibble system in [Cas2000], [Cas2001] which uses the signal to noise ration (SNR) as the location-dependent parameter, and in [Wal2005] and the Horus system in [You2002], [You2003a], [You2003b], [You2004a], [You2004b], [You2004c] which uses the RSS as the location-sensitive parameter.

The system in [Hil1997] takes advantage of the multipath phenomenon by using pattern recognition as its fundamental means for MT positioning. It identifies a radio frequency (RF) signature based on multipath phase, amplitude, delay, direction, and polarization characteristics of a cellular telephone call. A single base station (BS) is required for the position estimation process.

MIT Cricket [Pri2000], [Pri2001], [Smi2004], [Pri2005] is an indoor positioning system for pervasive and sensor-based environments. Accuracy achieved ranges between 1 m to 3 m. Cricket location-aware applications enable users to discover resources in their physical proximity with the help of wall- and ceiling-mounted active beacons. Beacons of the Cricket system, which advertise location information, do not need any infrastructure for communications among themselves [Kol2006]. Passive positioning of users is achieved by a combination of radio frequency (RF) and ultrasound signals.

Different correlation methods have been suggested for the RSS database correlation approach. In [Lai2001], the correlation criterion is based on the least mean square (LMS) approach. The criterion presented in [Zim2004] is made exponentially based on the normal distribution. The hidden Markov model (HMM) has been utilized by the RSS database correlation method in [Ken1994], [Man1999]. The utilization of particle filtering (PF) has been presented in [Pes2006]. Database correlation of the channel impulse response (CIR) has been carried out using the Kalman filter (KF) with the Box-Cox metric [Nyp2002a] and the HMM [Nyp2002b].

A location estimation method based on a statistical signal strength model is presented in [Ton2001]. The utilization of propagation models used to predict signal strength has been made. The described approach was called the *statistical modeling approach*.

The Ekahau system [Roo2002a], [Roo2002b] utilizes a wireless local-area network (WLAN) to track tags equipped with WLAN access cards [Kol2006]. The system works by measuring the RSS and comparing it with an RSS radio map of the environment. The achieved accuracy is between 1 m and 3 m. Site survey and calibration of the radio map requires up to 1 h/1200 m^2. Ekahau provides an off-site planning tool, the Ekahau Planner, and an on-site verification and network optimization tool, the Ekahau Site Survey (ESS), in order to benefit from the combination of both tools.
Rosum’s technology [Rab2002], [Rab2003], [Rab2005], [Spi2004] uses high-power, high-bandwidth, unmodified analog and digital broadcast TV signals in order to determine a receiver’s position in indoor and outdoor environments [Kol2006]. The

timing of the TV signal is measured by synchronization information contained in all standard TV signals. The receiver's location is determined by a distance measuring technique called *multilateration*, using signals from three or more TV transmitting towers with well-known fixed coordinates. Due to the planar geometry of the TV stations, TV-based location systems do not provide accurate vertical information. This limitation can be overcome by employing pseudo-TV transmitters in order to augment the local TV signals. Rosum's TV/GPS hybrid positioning system provides a seamless indoor/outdoor positioning with an accuracy of 50 m RMS using the TV signals only.

Place Lab [Sch2003], [LaM2005], [Hig2006] and Skyhook's Wi-Fi Positioning System (WPS) use the map-based pinpointing approach [Kol2006]. The basic idea is having a kind of an *address book* containing wireless access points (APs), each associated with its unique ID and physical location, as landmarks. Any Wi-Fi capable device would be able to locate itself by matching broadcasted IDs to the entries in the address book or database. Both systems are accurate to about 20 m to 40 m and can be used outdoors as well as indoors. In less populated areas Place Lab uses the GSM and fixed Bluetooth devices, as well as 802.11 APs, in order to construct the wireless map of the environment. Once a year, the database is updated by performing street drives.

A GSM-based indoor fingerprinting localization system for large multi-floor buildings has been presented in [Ots2005a], [Ots2005b]. A wide fingerprint is used, along with the traditional six strongest neighbour cells, which includes signal strength records from extra cells that are strong enough to be detected but too week for efficient communication. Achieved median accuracy is reported to be 5 m.

A mobile location scheme based on the ratios of distances between MT and BSs derived from the differences of signal attenuations is introduced in [Lin2005]. No hardware modifications are required for the existing wireless infrastructure, and no perfect path loss and shadowing models are needed.

AeroScout's Wi-Fi positioning systems [Kol2006] utilize the wireless infrastructure to locate any standard 802.1b and g MT using both TDOA and RSSI techniques. The RSSI technique is used for tight indoor environments and the TDOA algorithm is used for outdoors, and large, open, indoor environments.

1.3 Thesis Objectives and Contributions

The main objective of the thesis is to provide a systematic and unified approach to the mobile terminal positioning problem in wireless environments capable of utilizing different sources of information. Accordingly, the following research questions have arisen:

1. Which theoretical framework can efficiently combine different information and measurement data?
2. How to classify the positioning problems when different combinations of information and measurements are available?
3. Which preprocessing steps are required in order to get the best of the available radio profile maps?
4. How to overcome difficulties that can prevent the Cramér-Rao lower bound (CRLB) analysis?
5. Does the resolution of radio mapping significantly affect the positioning accuracy of the location estimation algorithm?

The Bayesian filtering framework is the answer to the first question. This is a convenient mathematical formulation that allows utilizing different sources of measurements and information as discussed in chapter 4.

Three different combinations of information and measurements are defined in chapter 4. Consequently, the MT positioning problem has been categorized into three classes, *location estimation*, *position tracking*, and *global localization*, according to the presence of initial accurate information and the availability of motion measurements. Implementable algorithms to solve the resulted three positioning problems have been developed, see chapter 4, and their performances have been evaluated, see chapter 6. The developed position tracking algorithm is a practical alternative to the Kalman-like nonlinear filters. However, such filtering techniques require quite an accurate initial position estimate in order to maintain good convergence. If such information is difficult or impossible to obtain, as is the case in many practical applications, then the global localization algorithm comes into play.

The location estimation algorithm, which is equivalent to the database correlation method, is based solely on the world model and the online network measurements.

Necessary preprocessing steps to extract as much information as possible in order to enhance the correlation procedure and increase positioning accuracy are explained in chapter 3.

Chapter 5 shows how inherent difficulties that prevent performance assessment of the location estimation algorithm based on the CRLB analysis are overcome. The theoretical approach used to assess the position tracking filter is also provided.

Impact of the radio mapping resolution on the location estimation accuracy has been extensively studied and the results are presented in chapter 6.

The journal paper [Kha2008a] contains solely the global localization (or positioning) algorithm (or filter). Mathematical foundations of the three positioning algorithms along with performance evaluation in terms of the root square error (RSE) and success rate are published in [Kha2008b]. The journal paper [Kha2008b] also investigates the influence of different grid resolutions on the accuracy of the location estimation algorithm, and includes further preprocessing of the wireless world model to discriminate between different land features. Parts of the position tracking and global localization results are published in the three conference/workshop papers [Kha2007a], [Kha2007b], and [Kha2007c]. A preliminary version of the location estimation algorithm without any preprocessing of the wireless world model is published in [Kha2006a]. Versions with preprocessing steps are published in [Kha2006c] and [Kha2006d]. Comparison of the results in [Kha2006a] and [Kha2006c] are presented in [Kha2006b].

1.4 Thesis Outline

The rest of the thesis is structured as follows. An overview of the fundamental positioning systems is given in chapter 2. Chapter 3 discusses the mapping-based positioning approach and the preprocessing steps applied to the utilized wireless world model. The Bayesian filtering formulation for mobile terminal positioning and the developed algorithms for the different positioning problems are introduced and discussed in chapter 4. Chapter 5 describes and explains the theoretical approach used to asses the developed algorithms. Performance evaluation of the different positioning filters are presented and discussed in chapter 6. Chapter 7 concludes the thesis work and gives some outlook comments for possible extensions and future work.

Chapter 2

Positioning Systems

This chapter discusses the fundamental aspects of the basic positioning systems. Satellite-based positioning systems are introduced in section 2.1. An overview of ground-based or terrestrial positioning systems is presented in section 2.2. Section 2.3 includes two similar examples on augmentation systems for enhancing positioning solutions. The inertial navigation system is briefly described in section 2.4. The chapter is completed by giving few examples on hybrid positioning systems in section 2.5.

2.1 Satellite-Based Systems

Satellite-based positioning methods are global techniques that provide timing, position, and velocity information in a quick, accurate, continuous, and inexpensive manner on the globe where the satellite signals can be received, i.e. they are mainly employed for outdoor applications. The current generation of satellite-based location systems are usually referred to as global navigation satellite system (GNSS). The satellite-based approach is the most accurate MT positioning technique, and it was only made accessible for commercial applications in the nineties. Also, the European Union (EU) is most likely to follow the US and Japan in requiring high positioning accuracy of mobile emergency calls when the Galileo system will be fully operational [Ber2006]. However, the benefits of satellite-based positioning could be limited where location information is still needed due to signal blocking or degraded accuracy caused by multipath propagation. In such cases, other positioning methods should be triggered in order to backup the failed or degraded satellite signals.

2.1.1 Global Positioning System

The global positioning system (GPS) is operated and maintained by the US Department of Defence (DoD) with the basic mission of providing passive, real-time, 3D positioning, navigation and velocity data for land, air, and sea-based strategic and tactical forces operating anywhere in the world [US2003]. However, civil positioning has become the most predominant, although secondary, application. The nominal constellation of the system consists of 24 satellites in high-altitude orbits with 4 satellites in each of the 6 evenly spaced orbital planes inclined at 55° to the equator, in order to make distance measurements between any receiver antenna and 4 to 10 satellites in view possible. The average life of a GPS satellite is approximately 8 years. Full operational military capability of the GPS constellation was declared in 1995. The GPS satellites transmit two coded carrier signals: The L1 for public use and the L2 for military and authorized users. The 3D position is determined from the adjusted intersections of the range vectors, which is equivalent to the trilateration method used in terrestrial applications. The GPS positioning principle is based on time of arrival (TOA) measurements and the ephemeris[1] data.

GPS satellites transmit ranging code and navigation data by using code-division multiple access (CDMA) on two carrier frequencies, L1 (1575.42 MHz) and L2 (1227.60 MHz). The carrier frequencies are modulated by spread-spectrum signals to carry information to the receivers. Three pseudorandom noise (PRN) ranging codes are associated with each satellite. The C/A code modulates the L1 carrier phase, and the P code modulates both L1 and L2 carrier phases.

The two basic operating modes for positioning are *absolute point positioning* and *differential positioning*[2]. Most commercial hand-held GPS receivers provide 3D real-time absolute positioning with accuracies in the range of 10 m to 30 m. Differential positioning provides accuracies at the meter level for code phase observations and at the centimeter level for carrier phase tracking.

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[1] A tabular statement of the positions of a celestial body, i.e. satellite, at regular intervals.
[2] See section 2.3.1.

Thorough description of GPS techniques and applications is given in the GPS *blue books* [Par1996a], [Par1996b], and the GPS *red books* [ION1980], [ION1984], [ION1986], and [ION1994].

Absolute Point Positioning

Only a single passive receiver is involved in the distance or range measurements to the GPS satellites. The 3D point position determination is achieved using trilateration resulting in a 3D coordinate relative to the geocentric reference system. Theoretically, at least 3 satellites are required for the computation. In practice, at least 4 satellite ranges are required in order to resolve timing differences. Using more satellite ranges provides redundancy and hence more accuracy in the position calculation. Pseudoranges[3], i.e. approximate ranges, which are derived from the broadcast satellite signal, are based on code or carrier phase measurements. Doppler observable were one of the first solutions for GPS positioning as with the TRANSIT[4] system. Usually, point positioning with code pseudoranges is performed when using a single receiver.

The pseudoranges are determined in the GPS receiver by precisely measuring the time it takes a coded signal to travel from the satellites to the receiver antenna by the help of precisely synchronized atomic clocks in the satellites. Using the code measurements, the pseudorange to a selected satellite is denoted R and is given by

$$R = R_{true} + c \cdot \Delta t + d \qquad (2.1)$$

Where R_{true} is the unknown true range to the satellite, c is the signal propagation speed, Δt is the bias of receiver and satellite clocks, and d is the propagation delays due to atmospheric conditions, and can be usually estimated from atmospheric models. The true range R_{true} is written as

$$R_{true} = \sqrt{(x_s - x_r)^2 + (y_s - y_r)^2 + (z_s - z_r)^2} \qquad (2.2)$$

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[3] In case the position and bias errors are uncorrelated, *pseudorange* and *range* measurements are equivalent.
[4] TRANSIT was the first satellite navigation system, and was primarily used by the US Navy to provide accurate location information to ballistic missile submarines. TRANSIT was also used as a general navigation system by the US Navy, as well as in the field of hydrographic and geodetic surveying.

Where x_s, y_s, z_s are the known satellite geocentric coordinates from the ephemeris data, and x_r, y_r, z_r are the unknown geocentric coordinates of the receiver. Rearranging (2.1) to get R_{true} explicitly and substituting the result into (2.2), we get

$$R - c \cdot \Delta t - d = \sqrt{(x_s - x_r)^2 + (y_s - y_r)^2 + (z_s - z_r)^2} \tag{2.3}$$

In Equation (2.3) we have four unknowns, namely x_r, y_r, z_r and Δt. Therefore, at least four pseudorange measurements are needed in order to yield a receiver's 3D position fix. Position determination using the previous procedure is referred to as *circular multilateration.*

Carrier phase differences are based on a comparison between received satellite signals and signals generated by the receiver. The phase pseudorange Φ is modeled by

$$\lambda \cdot \Phi = \rho + c \cdot \delta_r + \lambda \cdot N \tag{2.4}$$

Where λ is the carrier wavelength, ρ is the distance between the satellite at the transmission time t and the receiver at reception time $t + \Delta t$, δ_r is the receiver clock error, and N is the integer number of cycles between the satellite and the receiver which is initially unknown. Most applications do not need carrier phase measurements. They are only used in case of increased accuracy requirements, e.g. relative positioning.

Derivation of (2.4) w.r.t. time [Hof2003], yields the expression for the observed Doppler shift D scaled to range rate as

$$D = \lambda \cdot \dot{\Phi} = \dot{\rho} + c \cdot \dot{\delta}_r \tag{2.5}$$

The Doppler shift is measured in the carrier tracking loop of a GPS receiver, and can be used to estimate the receiver's velocity if the satellite velocity is known.

Errors and Impairments

Aside from satellite and receiver clock errors, further error sources are grouped into three classes: Satellite, propagation, and receiver errors. Satellite errors are due to, e.g. orbital errors. Signal propagation errors include ionospheric and tropspheric refraction. Receiver errors are caused mainly by multipath signal propagation and variation of the antenna phase center. The main impairments of the stand-alone mobile-based GPS solution are the short battery life and the need of clear view to at least 4 satellites, which cannot always be guaranteed in urban areas. Another drawback of any satellite-based positioning system is the short life span of the satellites, i.e. it is necessary to permanently replace them.

GPS Modernization

The key feature in the GPS modernization concept, announced in Jan. 1999, is the implementation of new signal structures in future satellites. In order to make the system more independent, the capability to transmit data between satellites is planned to be included. Civilian users will not only access the C/A-code on the L1 carrier, but also a C/A-code on the L2 carrier known as L2c. This will provide them with dual-frequency operation to correct ionospheric errors. New military codes or M-codes will be implemented on the L1 and L2 carriers to provide more security, increased jamming resistance, and enhanced acquisition options. The L2c signal and the M-code implementations are planned for full operational capability (FOC) in 2010. Also a new frequency called L5 will be provided for use in safety-of-life (SoL) and critical applications, e.g. civil aviation applications. The FOC of the L5 signal is planned for 2014 [FRP2001].

2.1.2 GLONASS

GLONASS (GLObal NAvigation Satellite System)[1] is the Russian counterpart to the GPS. The development of the system began in 1976 with the goal towards global coverage by the year 1991. However, the satellite constellation was completed in 1995. The system fell down due to the collapse of the Russian economy. In 2001, it was decided to restore the system. The introduction of the Indian government as a system

[1] GLObalnaya NAvigationnaya Sputnikovaya Sistema.

partner has accelerated the restoration efforts with the goal towards global coverage by 2009.

The full functional constellation consists of 24 satellites, 21 operating and 3 on-orbit backups, deployed in 3 orbital planes separated by 120° with each plane containing 8 equally spaced satellites. If the constellation is fully populated, a minimum of 5 satellites are in view from any point at any time. At peak efficiency the GLONASS provides, with a probability of 99.7%, horizontal positioning accuracy within 57-70 m, vertical positioning accuracy within 70 m, velocity vector measuring within 15 cm/s accuracy, and time transfer within 1 µs [Mil2000].

2.1.3 Other Satellite-Based Systems

EGNOS

EGNOS (European Geostationary Navigation Overlay Service) is Europe's first activity in the field of GNSS and is a precursor to Galileo. The system consists of 3 geostationary satellites and a network of ground stations. The goal of EGNOS is to augment both GPS and GLONASS and makes them suitable for safety critical applications by transmitting a signal containing information on the reliability and accuracy of the positioning signals sent out by the GPS and GLONASS, in order to allow users in Europe and beyond to determine their position to within 2 m accuracy. This approach is also known as *satellite-based augmentation system (SBAS)*.

Galileo

The EU decided in 1998 to design a GNSS for civilian use called *Galileo*. Full compatibility with the GPS system is one key goal of the Galileo project. Galileo will provide five levels of services [Kap2006], namely: *open* service with no direct charges, *commercial* service combining value-added data to a high accuracy positioning service, *safety-of-life (SOL)* service for safety critical applications, *public regulated* service for government-authorized users requiring higher levels of protection, e.g. increased robustness against jamming or interference, and *search and rescue (SAR)* service. Galileo will offer more accuracy and faster position fixing than GPS and greater penetration capacities in urban areas and canyons, indoors, and under tree coverage.

BeiDou

BeiDou is a Chinese multistage regional satellite navigation program designed to provide its navigation and communication services to Chinese military and civil users [Kap2006]. The system requires two-way range or TOA measurements. Position calculations for all subscribers are carried out at an operations center. The current constellation consists of 3 satellites that provide limited coverage in and around China. BeiDou can also be used to augment the GPS and GLONASS systems [Rab2006]. Under the BeiDou-2 program it is planned to deploy 14-30 satellites.

QZSS

The Japanese government and industry are developing a regional satellite navigation system known as the quasi-zenith satellite system (QZSS) in order to meet commercial demands [Rab2006]. The constellation will consist of 3 highly inclined geosynchronous orbits, each containing one satellite, to serve Japan and all of Asia with positioning, velocity, and timing services. QZSS will also provide broadcast and communication services in the S-band to Japan [Rab2006]. The first satellite is expected to be launched in 2008, and the other two in 2009. QZSS will use the GPS L1, L2, and L5 signals to ensure operability with the GPS system. The future constellation of the QZSS system will contain 7 satellites.

IRNSS

The Indian Regional Navigational Satellite System (IRNSS) is to be constructed and controlled by the Indian government. The constellation would consist of 7 satellites and would provide an absolute positioning accuracy of better than 20 m in and around India.

2.2 Terrestrial Systems

The terrestrial or land-based methods that will be discussed in this section are also called *local*, *regional*, or *area-based* systems, because they rely on transmitting sources that cover only a restricted area. Coverage also depends on the geometry of the transmitting stations and the transmitting power.

2.2.1 LORAN-C

LORAN is an acronym for the US system LOng-RAnge Navigation developed during World War II (WWII) at the Radiation Laboratory of the Massachusetts Institute of Technology (MIT)[2]. It was a development of the British GEE radio navigation system. LORAN-C is the enhanced version of the original LORAN-A, and became in first operation in 1958. Other configurations like LORAN-B, LORAN-D, or LORAN-F are no longer in use [Hof2003]. Chayka (English: seagull) system is the Russian counterpart to LORAN-C.

LORAN-C is a low-frequency radio transmitter system working in the 90-110 kHz band with a carrier of 100 kHz corresponding to a wavelength of 3 km [Hof2003]. Therefore, LORAN-C signals are not easily blocked or reflected by man-made constructions, unlike GNSS signals which have poor penetration characteristics. It is a hyperbolic[3] system based on time difference measurements of radio signals received from 3 or more synchronized stations of a chain in order to provide position fixing to maritime, air, and – to a limited extent – land applications. All transmitters of a chain use the same frequency. The transmission power of the LORAN-C signals is very high and varies between 250 kW and 12 kW. Thus, the signals have a long range propagation capability. Therefore, the LORAN-C signals are less vulnerable to interferences and less influenced by obstructions.

The time difference (TD) between the times of arrival (TOA) of two transmitted radio signals is measured by the LORAN-C receiver for at least 2 pairs of transmitting stations. Using the time differences, the speed of radio wave propagation and considering the earth curvature, a line of position (LOP) can be calculated for each pair of transmitting stations. The intersection of the hyperbolic LOPs provides the position fix of the receiver. The i-th TOA measurement is given as

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[2] The LORAN system was originally known as LRN for *Loomis radio navigation*, after millionaire and physicist Alfred Lee Loomis, who invented LORAN and played a crucial role in military research and development during WWII.

[3] The hyperbolic positioning is a typical positioning approach, where 3 transmitters are required in order to determine a 2D position. A hyperbola is a line on which all receiving points have a constant difference in distance from two fixed and synchronized transmitting points called the *foci*. The receiver's 2D position is thus defined by the intersection of two hyperbolic lines. Because of the geometry of the terrestrial transmitters relative to any receiver close to the earth surface, hyperbolic approaches do not generally provide accurate estimates of height.

$$\mathrm{TOA}_i = t_{i_{LORAN}} + \frac{2R_E}{c} \arcsin \frac{\rho_i}{2R_E} + \delta_R + \mathrm{ASF}_i \tag{2.6}$$

Where $t_{i_{LORAN}}$ is the nominal emission time at transmitter i, which is known from the chain characteristics, R_E is the radius of the sphere, c is the speed of signal propagation, ρ_i is the spatial distance between the earth-centric earth-fixed (ECEF) coordinates of the receiver and transmitter i, δ_R is the receiver clock bias, and ASF_i is the *additional secondary phase factor*, which is the signal delay over land masses, of transmitter i. The TD observation equation is obtained by differencing two TOA measurements i and j as

$$\mathrm{TD}_{ij} = \mathrm{TOA}_j - \mathrm{TOA}_i \tag{2.7}$$

Or

$$\mathrm{TD}_{ij} = t_{j_{LORAN}} - t_{i_{LORAN}} + \frac{2R_E}{c}(\arcsin \frac{\rho_j}{2R_E} - \arcsin \frac{\rho_i}{2R_E}) + \mathrm{ASF}_j - \mathrm{ASF}_i \tag{2.8}$$

A minimum of 2 TD measurements derived from 3 TOA measurements are necessary to determine the 2D position of the receiver. This method is termed *hyperbolic trilateration*, because three range measurements are required for a 2D position fix. For the 3D case the method is referred to as *hyperbolic multilateration*.

The absolute accuracy of LORAN-C is poor and is in the range of about 460 m [Hof2003] with an availability of 99.6%. However, the strong signals used by LORAN-C are difficult to jam. US and European governments have agreed to maintain and upgrade their LORAN systems.

2.2.2 Cellular and Wireless Communication Networks

The techniques presented in this section are network-based unless otherwise is mentioned. However, most of these techniques can be implemented at the MT as well. It will be assumed that the MT and the base stations (BSs) are located on a relatively flat plane, i.e. the goal is to determine the 2D geolocation of the MT. The mathematical expressions describing these techniques are given without considering measurement errors.

Cell-ID

Cell-ID[4] (cell identifier), also known as cell of origin (COO) or cell global identity (CGI), can be considered the simplest and most cost-effective, although the less accurate, positioning method in cellular networks. The cell-ID method is based on cell and sector information. Cell size varies up to 3 km in urban areas and from 3 km to 20 km in suburban and rural areas. Thus, the location estimation accuracy depends heavily on the cell (sector) size. However, this method does not need any modifications to the MT or the network infrastructure. Accuracy improvement can be achieved by using timing advance (TA) information in GSM networks, i.e. cell-ID+TA, or round trip time (RTT) in UMTS networks, i.e. cell-ID+RTT. The resulting technique is referred to as *enhanced cell-ID*.

Time of Arrival

The time of arrival (TOA) method combines the measurements of the TOA of the MT signal when arriving at different BSs. Thus, the distance r_i between the *i*-th BS and the MT is given by

$$r_i = (t_i - t_{MT}) \cdot c \tag{2.9}$$

Where t_{MT} is the time instant at which the MT signal is transmitted, t_i is the TOA of the MT signal at the *i*-th BS, and c is the wireless signal propagation speed. The distance r_i can also be expressed as a function of the MT and the *i*-th BS coordinates as

$$r_i^2 = (x_i - x_{MT})^2 + (y_i - y_{MT})^2 \tag{2.10}$$

Where x_{MT}, y_{MT} and x_i, y_i are the unknown MT and the known *i*-th BS 2D coordinates in a Cartesian coordinate system respectively. Substituting (2.9) into (2.10), we get

[4] This method is referred to as *proximity sensing* in indoor wireless geolocation systems.

$$(t_i - t_{MT})^2 \cdot c^2 = (x_i - x_{MT})^2 + (y_i - y_{MT})^2 \qquad (2.11)$$

In order to determine the 2D geolocation of the MT, at least 3 TOA measurements at 3 different BSs are required. And the task is to solve a system of 3 equations of the type given in (2.11). If more than 3 TOA measurements are available, the task would be to solve an overdetermined system of equations, which should deliver more accurate MT location estimates.

The TOA method requires accurate synchronization between the MT and the BSs clocks, which is not a mandate in many current wireless system standards. However, a few microseconds drift in the MT clock generates a major error in the geolocation estimation of the TOA method. Other important sources of error are multipath propagation and the case of non-line-of-sight (NLOS) conditions. Typical positioning errors caused by NLOS propagation in TOA-based techniques for GSM have been measured [Sil1996]. The reported average errors are in the range of 400 m to 700 m.

Time Difference of Arrival

To help avoid the MT clock synchronization errors, the time difference of arrival (TDOA) is introduced. TDOA is the difference between the TOAs of the MT signal at 2 BSs. Only synchronization between the involved BSs is required. The TDOA measurement defines a hyperbolic locus on which the MT lies. At least 2 TDOA measurements are needed to determine the MT 2D position. In some situations, it is possible that two hyperbolas intersect in 2 points. Therefore, a third TDOA, or any a priori information, would be required in order to resolve the resulting ambiguity. The distance difference r_{ij} at the *i*-th and *j*-th BSs is defined as

$$r_{ij} = r_i - r_j = (t_i - t_{MT}) \cdot c - (t_j - t_{MT}) \cdot c = (t_i - t_j) \cdot c \qquad (2.12)$$

In GSM networks, this technique is termed *enhanced observed time difference (EOTD)* for the mobile-based solution, and *Uplink TDOA (UTDOA)* for the network-based implementation. In UMTS systems, the TDOA positioning solution is referred to as *Observed TDOA (OTDOA)*. A 1µs error in the BSs clocks is equivalent to a 300 m error. Therefore, location measurement units (LMUs) should be deployed to provide local calibration. At least one LMU would be required for a sectorized cell. It is estimated that up to 50,000 LMUs would be needed to cover the whole USA [Ful2002].

Angle of Arrival

Using an antenna array installed at the BS, the angle of arrival (AOA), also called direction of arrival (DOA) or angulation, of the MT signal can be determined by measuring the phase difference between the antenna array elements or by measuring the power spectral density across the antenna array, which is known as *beamforming*. In order to yield a 2D MT position, at least two AOA measurements are required at two different BSs. Each AOA measurement produces a straight line locus or a line of bearing (LOB) from the MT to the BS. The intersection of two lines gives the desired MT position fix. Utilizing the cell sector information, e.g. in GSM networks, can be considered a sort of coarse AOA estimation. The AOA of the transmitted signal from the MT at the *i*-th BS is denoted ϕ_i and given by

$$\tan\phi_i = \frac{y_{MT} - y_i}{x_{MT} - x_i} \tag{2.13}$$

Where ϕ_i is the angle between the LOB from the *i*-th BS to the MT and the *x*-axis.

AOA location estimation requires a lower number of BSs than the TOA and TDOA methods. Moreover, the AOA technique does not need BS or MT clock synchronization. Antenna array structures are not currently installed in 2G cellular systems. In 3G cellular systems such as UMTS, the use of antenna arrays is planned.

Regular sources of error in AOA measurements include noise and interference. Multipath propagation, NLOS effects, and error in the angular orientation of the installed antenna arrays corrupt AOA measurements. The conduction of test measurements helps to calibrate the angular orientation of the antenna array.

The accuracy of the AOA method decreases with increasing distance between the MS and BS due to fundamental limitations of the devices used to measure the arrival angles as well as changing scattering characteristics. For macrocells, scattering objects are primarily within a small distance of the MS, since the BSs are usually elevated well above the local terrain. Consequently, the signals arrive with a relatively narrow AOA spread at the BSs. For microcells, where BSs are placed below rooftop level, the BSs will often be surrounded by local scatterers and the signals arrive at the BSs with a large AOA spread. Therefore, AOA is useful for macrocells and impractical for microcells.

Received Signal Strength Based Range Estimation

The range information can also be derived from the received signal strength (RSS) by utilizing a path loss or attenuation formula, which is a function of the distance between the MT and the BS. However, RSS measurements are very inaccurate compared to time-based measurements. Transmitted power adjustments in, e.g. CDMA systems, have to be reported in order to facilitate the application of path loss models, which is a complex process. Path loss models are more applicable in indoor environments, where time measurements are hard to carry out due to the extremely short distances between the MT and BSs.

Mapping-Based Positioning

The mapping-based method, also known as database correlation method (DCM), is one way to improve the positioning accuracy of enhanced cell-ID techniques and is widely used in both indoor and outdoor environments. These schemes usually work in two stages. The first stage is the offline environment mapping of a location-sensitive parameter at reference positions. The location determination is the task of the second phase, in which the online location-sensitive parameter measurements are being correlated to the environment map or database in order to deduce a location estimate of the MT. The mapping-based approach is usually implemented as a terminal-assisted network-based solution. Refer to chapter 3 for more details.

TOA, TDOA, AOA, and RSS ranging methods are sometimes referred to as *geometric techniques*. Most of the current positioning solutions are based on the low-cost cell-ID techniques, due to their simplicity. The majority of network operators do not deploy more accurate methods, e.g. EOTD or A-GPS[5], unless they are enforced by law, e.g. E-911 mandate.

2.2.3 Television Networks

TV signals are 10,000 stronger than GPS signals [Kol2006]. Therefore, TV-based positioning is much easier and quicker than GPS positioning. Thus, TV-based positioning has better accuracy, acquisition time, and reliability than GPS positioning. MTs can be localized by the synchronization signals of TV. TV towers are globally

[5] See section 2.5.1.

deployed, especially in urban centers, and they transmit analog and digital commercial broadcast signals. Every tower often broadcasts multiple channels and utilizes frequencies that easily penetrate buildings and man-made structures. TV-based positioning can be used where GPS and other methods fail. This technique does not require any modifications to the TV broadcast stations.

2.2.4 FM and AM Radio

FM radio signals can be used for positioning mobile users [Cis1994]. Computing the location of a device based on signal strengths from FM radio stations has been suggested in [Kru2003]. Results showed the ability to correctly infer the device’s location about 80% of the time with accuracy down to a suburb level. AM broadcast signals have also been used for radiolocation applications, see [Hal2001], [Hal2002].

2.2.5 Pseudolites

Pseudolites or pseudo satellites are devices that generate GNSS-like navigation signals. However, the pseudolite concept is older than the GPS system. Pseudolites mounted on high mesas at a desert test range were used to test the GPS concept [Hen1979]. Pseudolites have been used to complement the GPS satellites since the earliest days of the GPS system. In order to speed up the initial tests of GPS, pseudolites were used as direct replacements for satellites which had not been yet launched [Cob1997]. GPS Pseudolites have been deployed for indoor use [Kol2006]. They are generally utilized in ground-based augmentation systems. As in any GNSS, at least four pseudolites have to be available for positioning and navigation, unless additional information sources, e.g. altitude sensors, are employed.

2.3 Augmentation Systems

Methods introduced in this section are based only on ground installations, which are also referred to as *ground-based augmentation systems (GBAS).*

DGPS

Differential GPS (DGPS) positioning process is based on using at least 2 receivers. Both receivers are simultaneously measuring code phase pseudoranges and/or carrier phases from at least 4 common GPS satellites, where the position fix of one receiver, called *reference station*, is known, and the position of the second receiver, usually moving, is unknown. The known position of the reference station is used to derive corrections to the GPS measurements and to the position fix calculated by using these measurements. The correction data is then transmitted to the second receiver to allow more accurate positioning than the aforementioned absolute point positioning. A network of reference stations forms a *local-area augmentation system (LAAS)* and a network of LAASs forms a *wide-area augmentation system (WAAS).*

DLORAN-C

The basic idea of differential LORAN-C (DLORAN-C) is the same as with DGPS. A reference station derives and transmits the correction data, i.e. the difference between the nominal values and the actual measurements. The user receiver applies these corrections to the measurements in order to reduce the ASF effect. Thus, an absolute accuracy in the range of 10 m can be achieved.

2.4 Inertial Systems

An inertial navigation system (INS) provides position fixes by a dead reckoning[6] (DR) algorithm. DR is the calculation of the current position by utilizing the knowledge about the previous position. This is achieved by applying to it (the previous position) the course and distance travelled since. A DR system consists of an inertial measurement unit (IMU) or several IMUs. An IMU usually contains accelerometer(s) in order to compute the travelled distance, after double integration of the measured acceleration w.r.t. time, and gyroscope(s) and/or compasses for heading or direction/orientation determination. Odometers, which are usually installed in land vehicles, can also deliver information about the travelled distance by counting wheel turns. INS is usually used in combination with GPS in order to compensate for GPS signal outages. The resulting integration is designated as GPS/INS.

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[6] Originally it is called *deduced reckoning* or *ded reckoning*. However, the term has been interpolated into dead reckoning.

2.5 Hybrid Systems

Assisted-GPS

Integration of GPS into cellular networks will support GPS positioning by additional DGPS reference stations as integral part of the cellular infrastructure and by additional signalling between BSs and MTs [Küp2005]. This configuration is known as *assisted-GPS* or *A-GPS* and is specified for almost all cellular systems.

Compared with standard GPS, A-GPS provides improved positioning accuracy, reduction of position acquisition time, and consequently, less power consumption of the GPS receiver installed in MTs. Also it offers an increased sensitivity, and then increased availability of the location service, especially in dense urban areas and indoor environments. Compared with network-based TOA and TDOA, A-GPS provides much better positioning accuracy, and higher cost efficiency due to the avoidance of implementing synchronization instruments at each BS. However, the extra signalling needed from the GPS reference stations increases the wireless system impact.

It is not required to install a reference station at every BS. One reference station would be enough for an area of about 200 km radius. The constellation of DGPS reference stations within a cellular network is also known as *wide-area DGPS*.

TV/GPS

Rosum’s TV/GPS integrated positioning system is an all-environment solution based on existing standards for digital TV (DTV) synchronization signals. The mean positioning error in tests ranges from 3.2 m to 23.3 m. TV/GPS based positioning is a feasible technique for seamless indoor/outdoor positioning capability [Rab2005].

Map-Aided Positioning

Map-aided positioning is carried out with the help of map information in order to correct for errors by utilizing map-matching algorithms. The map used in positioning serves as an artificial sensor and its geometric data are considered as artificial signals.

Chapter 3

Mapping-Based Positioning

The fingerprinting technique or mapping-based positioning method is discussed in section 3.1. Basics of radio propagation modeling necessary for wireless environment mapping are introduced in section 3.2. Section 3.3 describes briefly the main matching methods used for fingerprinting. The utilized RSS maps of our experimental area and preprocessing steps carried out to increase the usability of theses maps are presented in section 3.4.

3.1 Wireless Mapping and Fingerprinting for MT Positioning

The *mapping technique* is also referred to as *database correlation* or *comparison*, *location pattern matching* or *recognition*, *location fingerprinting*, or *location table look-up*. Mapping approaches determine the behaviour of a signal or location-sensitive parameter at every reference location in the area of interest. These methods are one way to enhance the accuracy of cell-ID and enhanced cell-ID techniques introduced in the previous chapter. In these methods, a database or map of location-dependent parameters is constructed using radio wave propagation prediction tools [Schm2003], [Zim2004], [Kha2006a], field measurements [Lai2001], [Nyp2004], or a combination of both [Zhu2006]. Later a moving MT collects measurements to be compared with the entries of the database in order to yield location estimates. Location-dependent parameters usually used for mapping include received signal strength levels (RxLev) from surrounding BSs [Lai2001], [Schm2003], [Zim2004], [Zhu2006], [Kha2006a] and the channel impulse response (CIR) [Aho2003], [Nyp2004], [Lay2006], which is the multipath propagation delay profile of the wireless environment. In GSM systems, the bandwidth is too small, unlike the UMTS system, for accurate positioning based on correlation of CIR only [Nyp2004]. Also the geometric time-based (TOA, TDOA, EOTD) and angle-based (AOA) methods could be used as location signatures either stand-alone (less accurate) or combined with other location parameters. To the best of our knowledge they are not widely used. However, in [Kel2000] a network-based fingerprint method composed of TOA and AOA has been proposed for wireless location finding in urban environments, and was found that AOA is more significant than TOA for location discrimination.

Propagation prediction tools are advantageous in terms of cost and map construction time. These tools vary in terms of accuracy according to the degree of geographical information precision integrated in the calculations, thus are divided into deterministic (3D), semi-deterministic (2~2.5D), or simple empirical formulas. Field measurements provide more realistic databases but at higher costs and longer construction time that render wide deployment impractical. Nevertheless, field measurements in some parts of the deployment environment do help to show the performance upper limit of location estimation algorithms using the mapping approach.

The essential location-sensitive parameters defined in GSM standard are location area code (LAC), cell-ID of the serving BS antenna, timing advance (TA)[1], and the measured signal strengths of the serving and up to six neighbouring cells. These parameters are known at the MT and the network during the dedicated mode. In the idle mode only the LAC is known at the network. Therefore, the other parameters, i.e. cell-IDs and signal strengths, measured by the MT have to be transmitted to the location server, e.g. via SMS, in order to use them in location calculation during the idle mode.

Mapping methods often utilize prediction data of RxLev and/or CIR produced during network planning. In the online positioning phase they use only the network available measurements and thus they don't require any expensive hardware installations at BSs or in MTs. Also they have short deployment time and cover current and legacy handsets. This is advantageous in terms of cost, coverage, and system impact compared

[1] The TA value results from the measured round trip propagation delay. It indicates the number of bits the MT has to consider, i.e. how early to start transmission, in order to be synchronized with the TDMA frame (time between two measurements). TA values determine the MT location within a circular ring of about 554 m [Wal2000].

to the other approaches, see chapter 2. Therefore, they seem to be the first alternative to take into consideration, especially for European network operators, since EU mobile location requirement still does not specify any accuracy levels unlike the US FCC mandate. However, mapping-based solutions require continuous update in order to adapt to changes in the environment structure and in the wireless network infrastructure, and to consider the time-varying nature of wireless channels. As already mentioned, this approach is usually implemented as a *mobile-assisted network-based* solution, which is very advantageous in GSM networks, where the MT, in the busy mode, transmits permanently RSS values of neighbouring BSs to the network for handover decisions. Thus, MTs require no or minor modifications. However, the GSM RSS fingerprinting solution is currently not subject to standardization.

The location accuracy of mapping approaches ranges between about 100 m and several kilometers depending on cell size, accuracy of reference maps, mapping resolution, propagation conditions, accuracy of observed measurements, and significance degree of the mapped location-dependent parameter. While CIR maps generally achieve more accurate estimates than RxLev mapping in urban and dense urban environments, they tend to have comparable performance in suburban and rural areas. Therefore, mapping techniques do not fulfil the FCC accuracy requirements in all situations. However, mapping methods are advantageous, because no line of sight (LOS) conditions are needed, knowledge about the location of the involved BSs are not needed during the online positioning phase, it can work even with one BS, its implementation costs are pretty low, and in combination with other methods, e.g. GPS, can exploit the cell-ID information for 3D positioning to resolve the altitude ambiguity and give accurate height estimates. Moreover, mapping techniques will still be needed also when more accurate technologies are fully available. They will achieve positioning for applications with low accuracy requirements; they will be deployed in areas of the network where more accurate methods are not supported; and finally, they will work as backup in case the accurate techniques fail for any reason. Therefore, improving positioning accuracy of mapping approaches is an active research topic.

3.2 Synopsis of Radio Propagation Modeling

Prediction models used to describe radio wave propagation are used during network planning for feasibility and interference studies, and for initial deployment. Basic understanding of these models is of great importance for their employment in positioning systems within wireless communication networks, since these models are functions of the distance to the BSs.

Radio wave propagation, in mobile communication environments, is generally influenced by three phenomena or mechanisms: *path loss* or *attenuation*, *shadowing* or *slow fading*, and *multipath* or *fast fading* [Stü1996]. For the practical utilization of propagation models in positioning systems, it is required to digitize the propagation environment and store the result in a database. This step is followed by the development and/or definition of mathematical approximation techniques that sufficiently describe the physical propagation mechanisms. The preceding process outputs deterministic and empirical models for implementation in different environments or cell types.

3.2.1 Radio Channel Model Components

Path Loss

Path loss is a large-scale signal fading component of the radio channel model. It is the loss of received power at the MT and is completely characterized by the distance between the MT and the BS, the operating frequency, the antenna height, and the surrounding terrain properties.

Shadowing

Shadowing, also shadow fading, is a medium-scale slow varying component of the radio channel model. Shadowing is a lognormally distributed random process caused by terrain configurations between the BS and the MT. Shadowing occurs when an obstacle blocks the signal path to the MT.

Multipath

Multipath fading is a small-scale fast varying component of the radio channel model with a Rician or Rayleigh distribution, depending on the presence or absence of the LOS situation respectively. Multipath is generated due to the constructive and destructive superposition of many reflected, diffracted, and scattered plane waves arriving at the MT with different time delays, phase shifts, and attenuations. Reflection and diffraction occur if the wavelength of the signal is much shorter than the size of the obstacle. Reflected signals suffer additional attenuation depending on the angle of incidence and the surface properties of the obstacle. Diffraction is caused by obstacle irregularities, e.g. corners or edges, bending the transmitted signal. Scattering occurs when the size of the obstacle is the same as or is less than the wavelength of the signal. As such, several copies of the signal are generated, each being much weaker than the original signal and further propagating in different directions.

3.3 Methods of Fingerprint Matching

The most straightforward algorithm to estimate the MT location is calculating the Euclidean distance or the root mean square error (RMSE) in signal space between the measured parameters or parameter vector and each fingerprint in the database. This algorithm is also referred to as *nearest neighbour* or *NN algorithm*, or the *maximum likelihood estimator (MLE)*, see section 4.2.2. A variant of the NN algorithm is searching for the *k* location candidates with the minimum RMSE in signal space and estimating the MT location by averaging the coordinates of these *k* locations. This procedure is known as the *k-nearest neighbour* or *KNN algorithm*. KNN algorithm is also termed *trimmed average estimation (TAE)*, see section 4.2.2. When the MT location is determined by the weighted averaging of the involved location candidates, the algorithm is called *weighted average estimation (WAE)*, see section 4.2.2.

If motion information is available, the Bayesian filtering technique provides a powerful tool to manage the situation by probabilistic data fusion. Refer to chapter 4 for the formal treatment of these matching methods.

3.4 Predicted Signal Strength Map of the Experimental Area

The utilized RSS maps or databases of the semi-urban test area of about 9 km^2 around the campus of Leibniz University of Hannover, Germany, have been constructed using a 3D deterministic radio propagation prediction model, described in [Kür2002]. These RSS maps are represented by 2D raster arrays with a uniform grid spacing of 5 m. Each 2D array corresponds to a GSM cell antenna working at 1800 MHz, see Figure 3.1. The experimental area contains 6 BSs, each with 3 sectors, and 4 indoor antennas, so that the total number of considered cells equals 22. The databases are a by-product of the network planning stage and contain location dependent parameter values (signal strength) in a working E-Plus GSM network at reference locations. The provided cell information in the interest area include antenna geographical location, antenna height, azimuth and tilt, effective isotropic radiated power (EIRP), channel numbers, cell identifiers, etc. Figure 3.2 illustrates the geometry of the involved BSs and distances from the area-centric BS to the rest.

The MT acquires information about its environment (or world) through the network measurements. However, the MT wireless environment is a stochastic system. Therefore, the network signal strength measurements are often noisy and deviate from the predicted RSS values, which are in turn not precise.

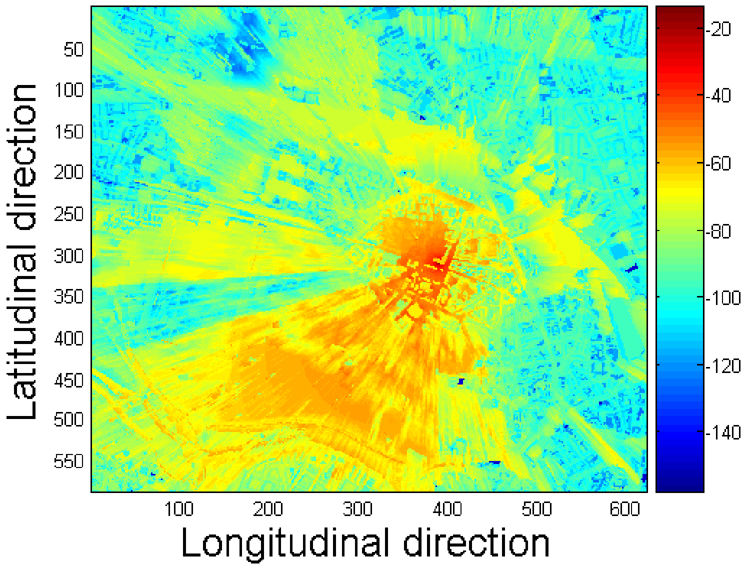

Figure 3.1: Map of RxLev (dBm) generated by the radio wave propagation prediction tool for a base station antenna. The simulation is performed over an area of approx. 9 km^2 divided into pixels (621 x 588 pixels in the longitudinal and latitudinal directions respectively) with a resolution of 5 m.

In order to enhance the prior information to be fused into the location estimation algorithm, as much information as possible could be extracted from the prediction databases. This would enhance the correlation process of measurements with knowledge about the MT world. Achieving this needs reorganization, partitioning, and clustering of the initial prediction databases. The previous steps are referred to as *database preprocessing* or *off-line phase* of the database correlation method.

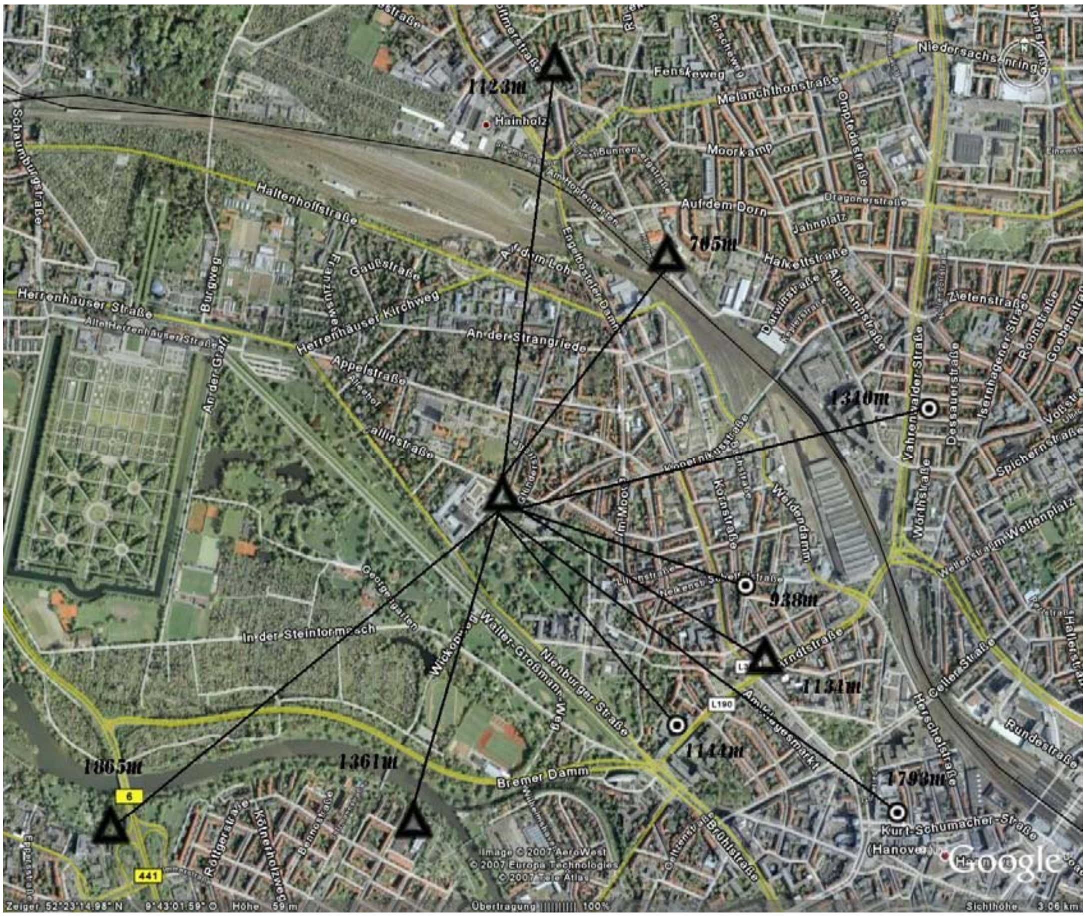

Figure 3.2: Geometry of the base stations in the experimental area generated by Google Earth. Base stations and indoor antennas are represented by triangles and circled dots respectively.

3.4.1 Primary Database Preprocessing

The localization algorithm can take advantage if the locations that are served by every cell antenna are determined. In this case, it is guaranteed that no position outside the coverage area of the BS cell antenna would be returned by the algorithm when the deviation between predicted and measured signal power levels are large or when the situation is highly ambiguous due to an increased number of possible location candidates. Thus, every cell antenna of the test area has acquired a separate database, called *cell database (CDB)*, which contains only the locations served by it. Each database entry consists of location ID, location coordinates, predicted RSS from serving cell, predicted RSS values and IDs of the strongest neighbour cells, and distance to the serving cell antenna. Figure 3.3 shows example results of this preprocessing step. Here, the BS has three sector cell antennas. The locations served by each cell antenna are depicted by different colors. The black dot represents the location of the BS.

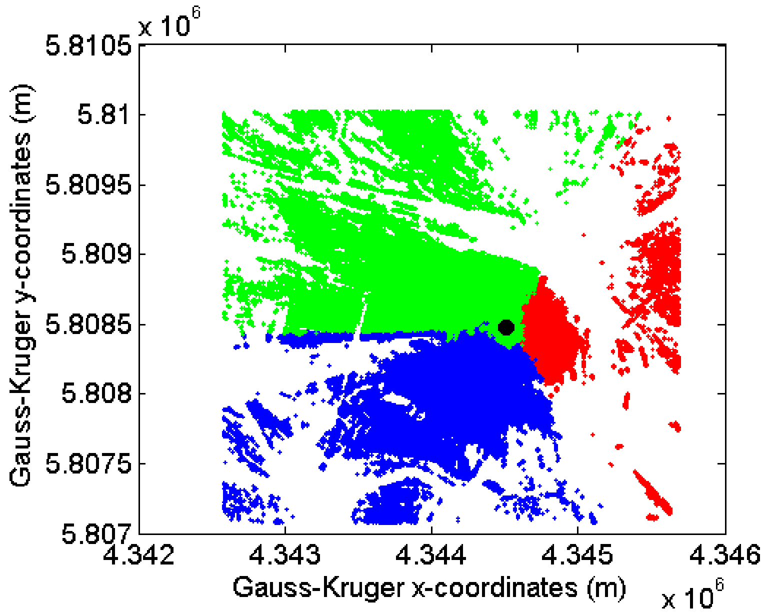

Figure 3.3: Results of the first preprocessing step for three sector cells.

Furthermore, every CDB has been divided into sub-databases according to all possible TA values (with an assumed error of $\pm\frac{1}{2}$ bits); each called *cell TA database (CTADB)* and labelled with a stamp indicating its TA value, see Figure 3.4. The location algorithm will process only the CTADB matching the TA measurement, thus, reducing the online computational burdens to a minimum.

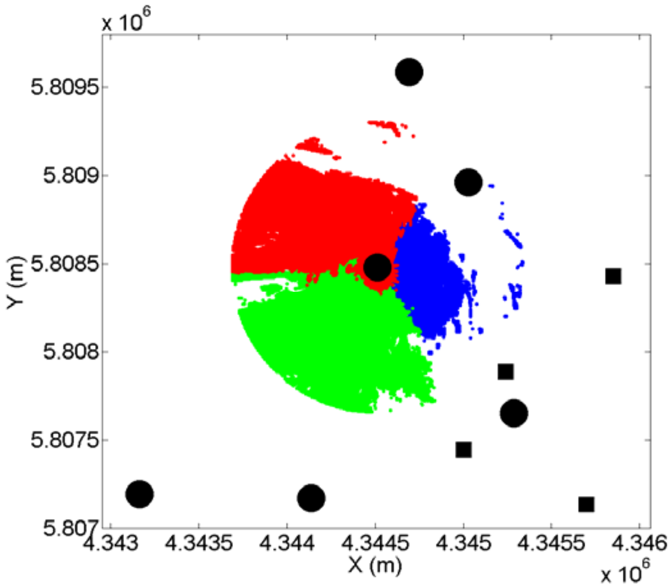

Figure 3.4: Locations served by the same sector cell antennas of Figure 3.3 up to distances corresponding to TA = 0. The other sector cell and indoor antennas' locations of the test area are depicted in black circles and squares respectively.

3.4.2 Secondary Database Preprocessing

GIS (Geographical Information System) data, with very high resolution of 30 cm, was used to assist in discriminating between the different environmental features, e.g. indoor, outdoor, water, green, etc. Moreover, the GIS data resolution was adapted to the 5 m resolution of the original radio propagation prediction maps, before the CTADBs were further divided according to the different environmental features. This is also very helpful for the computational efficiency of the localization algorithms.

Figure 3.5 shows outdoor pedestrian locations served by their main sector cell antennas for TA = 0. Databases as depicted in Figure 3.5 were the ones used in the proposed positioning algorithms presented in chapter 4. Moreover, these databases have been re-sampled to 10 m, 15 m … and 50 m resolutions in order to investigate the impact of grid spacing on the location accuracy of the *location estimation* algorithm.

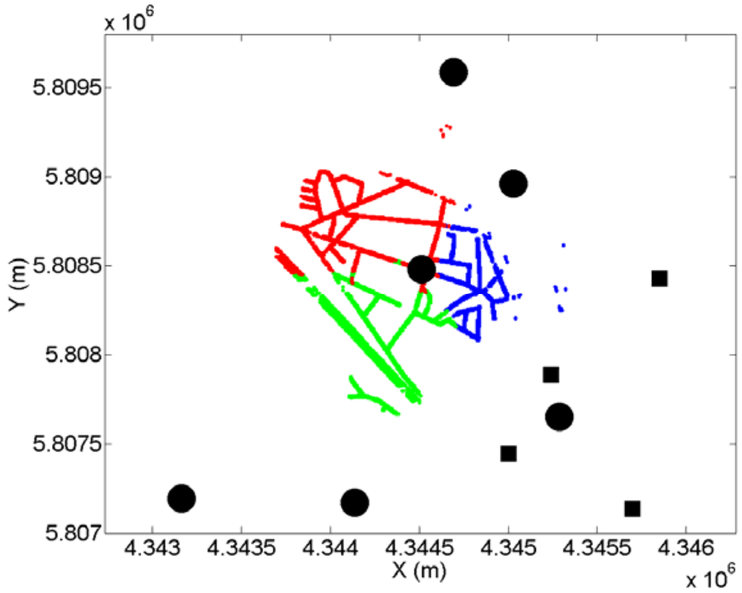

Figure 3.5: Outdoor pedestrian locations served by sector cell antennas up to distances corresponding to TA = 0.

Chapter 4

Bayesian Filtering Algorithms for Mobile Terminal Positioning

This chapter describes and formalizes the mobile terminal (MT) positioning problem within the Bayesian filtering framework which makes the flexibility and power of the developed algorithms clear and readable. Section 4.1 is dedicated to the theoretical background of the recursive Bayesian filter. The proof of the recursive Bayesian filtering formulation is included together with a listing of the basic algorithm. The implementation approach of the theoretical Bayesian filter, namely the discrete Bayesian filter, and a discussion on point estimation methods are presented in section 4.2. Categorization of the MT positioning problem into three types is provided in section 4.3, which also introduces implementable algorithms of the different types of the MT positioning problem. Before delving into details, a brief discussion on *estimation* is given in the following few paragraphs.

Estimation can be briefly defined as the process of extracting information from data[1]. The extracted information in turn can be estimates of parameters (or system states), and data is usually measurements (related somehow to the estimated parameters) corrupted by noise or measurement errors. System states and measurement data are categorized according to whether they are *static* or *dynamic*, *continuous* or *discrete*, and *linear* or *non-linear* [Gel1974]. The principal task of estimation methods is to compute parameter

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[1] The problem of predicting a discrete random variable from another random variable is called *classification*, *discrimination*, or *pattern recognition*.

values from measurements, taking into account prior knowledge of parameters and measurement errors.

The estimation problems are divided into three categories [Gel1974]. The problem is defined as *filtering* if the last measurement point coincides with the time at which an estimate is required. When the time of the desired estimate falls within the span of available measurement data, the problem is referred to as *smoothing*. If the time of estimate occurs after the last available measurement data, the problem is known as *prediction*.

The main approaches to stochastic parameter (or state) estimation are the *maximum likelihood (ML)*, or *Fisher* method[2] [Fis1912], [Fis1922], and the *maximum a posteriori (MAP)* or *Bayesian* method [Bay1763], [Jaz1970], [Rob2001]. The Fisher method is concerned with fixed and unknown parameters or constants. These parameters (together with measurements or observations) are treated as random unknowns or stochastic variables in the Bayesian paradigm where their initial or prior distributions are assumed to be known. However, ML and MAP may generate same estimates under certain circumstances. Here only the Bayesian filtering technique will be further discussed focusing on nonlinear recursive[3] state estimation for dynamical systems in the discrete-time case. Surveys on nonlinear recursive estimation can be found in [Sor1988], [Kul1996]. Information on linear recursive estimation is provided in [Kai2000], [And1979].

4.1 Recursive Bayesian Filtering

The recursive Bayesian filter (RBF) [Jaz1970] is a probabilistic framework for state estimation. It estimates the posterior belief or distribution of the MT position given its prior belief, motion or action information, wireless network measurements, and the model of the environment or world. The prior belief is a probability distribution over all possible positions before taking the MT actions and network measurements into account. The posterior belief is the conditional distribution of these probable positions after incorporating the MT motion information and network measurements. The world model is a radio profile map containing, at every location reference, single predicted received signal strength (RSS) value from each BS in the environment. Reaching the

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[2] See [Ald1997] for a historical perspective.
[3] See [Ber1985], [Box1992], [Con2003] for treatment of the non-recursive case.

final formulation of the RBF requires utilization of the *Bayes' rule*, the *Markov property* or *assumption*, and the theorem of *total probability*.

Definition 4.1 (Probabilistic Inference)
Let A denote a random variable and a denote a specific value that A might take. Random variables can take on multiple values according to specific probabilistic laws. Calculating these laws for random variables which are derived from other random variables using measurement data is termed *probabilistic inference*[4]. Thus, probability theory, which is the formal language of uncertainty, is the basis of probabilistic inference.

Remarks
(1) The basic problem in probability theory is calculating the properties of data generated by a process. Probabilistic or statistical inference is the inverse of probability. Thus, its basic problem is: given the data, what can we say (infer) about the process that generated that data.

(2) Probabilistic inference is sometimes called *machine learning*, *data mining*, or *data analysis* depending on the context [Was2004].

(3) Estimation, classification, and clustering[5] are special cases of probabilistic inference.

Definition 4.2 (Conditional Probability)
Often we have the case that knowledge or information about random variables is included in other random variables. In other words, we would be interested to compute the probability that A will take the value a knowing that the random variable B took the value b. This can be formally expressed as

$$p(a \mid b) = p(A = a \mid B = b) \tag{4.1}$$

Expression (4.1) is called *conditional probability* and is defined as

$$p(a \mid b) = \frac{p(a,b)}{p(b)} \tag{4.2}$$

[4] Probabilistic inference and estimation are referred to as *learning* in the computer science community.
[5] Classification and clustering are known in computer science as *supervised learning* and *unsupervised learning* respectively.

Where $p(b) > 0$. If A and B are independent, we get

$$p(a \mid b) = \frac{p(a)\, p(b)}{p(b)} = p(a) \tag{4.3}$$

Thus knowing the value of B does not help in inferring the value of A. Such a situation is called *conditional independence* which has a fundamental role in the following discussion.

Theorem 4.1 (Bayes' Rule)

The Bayes' rule is a formula for calculating the conditional probability giving more insight to the state estimation problem at hand. Equation (4.2) is written using Bayes' rule as

$$p(a \mid b) = \frac{p(b \mid a)\, p(a)}{p(b)} \tag{4.4}$$

The conditional probability $p(a \mid b)$ is referred to as *posterior probability*, while $p(a)$ is referred to as *prior probability*, which is the *subjective* initial degree of belief[6]. In the absence of prior knowledge, a uniform prior distribution should be chosen for discrete-valued random variables. The inverse conditional probability $p(b \mid a)$ is called *measurement likelihood* or *measurement model*, where b is the measurement data. As $p(b)$ is independent of a, it is often referred to as the *normalizer* η, and hence (4.4) can be written as

$$p(a \mid b) = \eta \; p(b \mid a)\, p(a) \tag{4.5}$$

Proof

Exchanging the positions of a and b in (4.2), and considering the fact that $p(a,b) = p(b,a)$, we have

$$p(a,b) = p(b \mid a)\, p(a) \tag{4.6}$$

[6] The prior probability distribution function assumed in any problem is often a subjective assessment of that problem. It helps to integrate knowledge gained through previous experiences or information that is analytically difficult or impossible to model.

Inserting (4.6) back into (4.2) completes the proof.

Remarks

(1) There is usually some prior knowledge about any process being studied. Throwing this knowledge away is nothing but waste of information. The Fisher or frequentist approach use only measurement data to know about the process at hand, hence the *objectivity* property of the approach. On the other, the Bayesian methods utilize both sources of information, i.e., prior knowledge and measurement data, and combine them using Bayes' rule.

(2) Bayes' rule is the only tool used by the Bayesian techniques in all situations. In contrast, frequentist methods require many different tools in order to do their job.

(3) Bayesian methods always marginalize[7] nuisance parameters[8] out of the joint posterior distribution. In other words, the Bayesian approach gets rid of nuisance parameters by integrating them out. This is an efficient straightforward way of dealing with nuisance parameters. Frequentist techniques do not have any general procedure to deal with them and they have no alternative but to estimate the nuisance parameters. Therefore, the Bayesian approach does not suffer from the problem of the frequentist approach in which nuisance parameters may invalidate an estimator [Kay1993].

(4) It is important however to mention that Bayesian and frequentist techniques are generally dealing with different problems. Bayesian approaches are used to formally combine prior belief with measurement data. Frequentist methods construct procedures with guaranteed long run performance, e.g. confidence intervals.

(5) Probabilities in Bayesian inference are only a measure of our state of knowledge about the world, not a measure of the world itself.

Definition 4.3 (Markov Property)

The random process a_t, where $t \in I$, is called *Markov* or *Markovian*, iff

$$p(a_t \mid a_\tau, \tau \le T) = p(a_t \mid a_T) \qquad \forall T \le t \tag{4.7}$$

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[7] See Appendix 4.A for the definition of marginalization.

[8] A nuisance parameter is one which we do not want to make inference about. Also we do not want that parameter to interfere with the inferences we are making about the parameters of interest.

Informally stated, if the present state is known, past and future are conditionally independent. In other words, the state at time T fully describes and characterizes the past up to time T, i.e., once at a given state, the probability law of the process in the future does not depend on how the process arrived at that given state [Jaz1970]. The Markov property is also referred to as the *generalized causality principle*[9] and it is a basic assumption necessary in the study of stochastic dynamical systems. The right-hand side of (4.7) is called the *transition probability density* of the Markov process[10]. The Markov chain is a special case of the Markov process where the system occupies a finite number of states.

Remark

Because the future is independent of the past for a known present, the position prediction of a MT will not depend on the past MT positions if the current position is known. However, given a map of the environment and considering constraints, e.g., maximum pedestrian speed, the Markov property can be violated in many situations. Practical implementations therefore should be tolerant in such cases in order to make value of useful knowledge not modeled or to prevent total fall down when system model does not precisely map reality. Thus, positioning algorithms should implement a flexible formulation of the Markov principle. They should be able to decide if past positions are essential for the prediction of the future position.

Theorem 4.2 (Total Probability Theorem)

Let $b_{i=1\dots n}$ be mutually exclusive, i.e., $p(b_i, b_j) = 0 \quad \forall i \neq j$ and exhaustive, i.e., $\sum_{i=1}^{n} p(b_i) = 1$. Following Definition 4.2 (Conditional Probability) and the axioms of probability measures, the *total probability theorem* states that

$$p(a) = \int p(a,b)db = \int p(a \mid b)\, p(b)db \qquad \text{(Continuous form)} \tag{4.8}$$

$$p(a) = \sum_{i=1}^{n} p(a,b_i) = \sum_{i=1}^{n} p(a \mid b_i)\, p(b_i) \qquad \text{(Discrete form)} \tag{4.9}$$

[9] The future can be predicted from knowledge of the present.

[10] The Markov process is named after the Russian mathematician Andrei Andreyevich Markov (1856-1922) who introduced the concept for discrete parameter systems with a finite number of states in 1907.

The total probability theorem is mainly employed in obtaining state estimates in the presence of model and/or measurement uncertainties.

Theorem 4.3 (Recursive Bayesian Filter)
Let the posterior belief distribution be expressed as

$$Bel(s_t) = p(s_t \mid o_{0:t}, a_{0:t}, m) \tag{4.10}$$

Where $Bel(s_t)$ is the posterior belief over the state (or position) of the MT at time t, s_t is the state at time t, $o_{0:t}$ and $a_{0:t}$ are the network measurement data (network observations or perceptions) and the actions (or movements) performed by the MT from time 0 up to time t respectively, and m is the world (or environment) model.

The *recursive Bayesian filter* equation is given as

$$Bel(s_t) = \eta \;\; p(o_t \mid s_t, m) \int p(s_t \mid s_{t-1}, a_t, m) \;\; Bel(s_{t-1}) \;\; ds_{t-1} \tag{4.11}$$

Proof
Applying Theorem 4.1 (Bayes' Rule) to (4.10) we get

$$Bel(s_t) = \frac{p(o_t \mid s_t, o_{0:t-1}, a_{0:t}, m) \;\; P(s_t \mid o_{0:t-1}, a_{0:t}, m)}{p(o_t \mid o_{0:t-1}, a_{0:t}, m)} \tag{4.12}$$

Here, actions and network measurements are assumed to occur in an alternative sequence, although in reality they take place concurrently. They are separated only for convenience and clarity of the mathematical treatment.

Employing Definition 4.3 (Markov Property) to the first term in the nominator in (4.12), and noting that the denominator, denoted η, is a constant probability relative to s_t, i.e., is a normalizing factor, (4.12) is rewritten as

$$Bel(s_t) = \eta \;\; p(o_t \mid s_t, m) \;\; p(s_t \mid o_{0:t-1}, a_{0:t}, m) \tag{4.13}$$

In order to ensure that $Bel(s_t)$ represents a valid probability distribution, η will help keeping the resulting product in (4.13) always sum up to 1.

Expanding the right most term in (4.13) using Theorem 4.2 (Total Probability Theorem) will result in

$$Bel(s_t) = \eta\ \ p(o_t \mid s_t, m) \int p(s_t \mid s_{t-1}, o_{0:t-1}, a_{0:t}, m)\ \ p(s_{t-1} \mid o_{0:t-1}, a_{0:t}, m)\ ds_{t-1} \tag{4.14}$$

Applying Definition 4.3 (Markov Property) to the first term in the integration and noting that the second term is simply $Bel(s_{t-1})$ will complete the proof.

Remarks

(1) Expression (4.11), also called the *Chapman-Kolmogorov* equation, is of great importance in the study of discrete stochastic dynamical systems (stochastic difference equations). It is usually computed in two steps termed *prediction* and *update*. The prediction step is given as

$$Bel^{-}(s_t) = \int p(s_t \mid s_{t-1}, a_{t-1}, m)\ \ Bel(s_{t-1})\ ds_{t-1} \tag{4.15}$$

Where $Bel^{-}(s_t)$ is the posterior belief just after executing the action a_t and before incorporating the network measurement o_t, and $p(s_t \mid s_{t-1}, a_{t-1}, m)$ is the MT motion model, i.e., the transition probability density that tells us how the state evolves over time as a function of the MT movements. It is the kernel of (4.11). The update step is given as

$$Bel(s_t) = \eta\ \ p(o_t \mid s_t, m)\ \ Bel^{-}(s_t) \tag{4.16}$$

Where $p(o_t \mid s_t, m)$ is the network measurement model that specifies the probabilistic law according to which these measurements are generated from the state, i.e. measurements are simply noisy projections of the state.

(2) Both motion and network measurement models describe the dynamical stochastic system of the MT and its environment. The state at time t is stochastically dependent on the state at time $t-1$ and the action a_t. The network measurement depends stochastically on the state at time t. Such a temporal model is also known as *hidden*

Markov model (HMM) or *dynamic Bayes network (DBN)* [Thr2005]. TABLE 4.1 shows a single iteration of the RBF algorithm.

(3) The posterior inference modifies the prior belief by the information contained in the measurement data. Therefore, the posterior estimate is a compromise between the prior belief and the likelihood function (measurement model).

TABLE 4.1: The basic recursive Bayesian filter algorithm.

1: Algorithm **Basic_RBF**($Bel(s_{t-1}), a_{t-1}, o_t, m$)
2: *for all* s_t *do*
3: $Bel^{-}(s_t) = \int p(s_t \mid s_{t-1}, a_{t-1}, m)\ Bel(s_{t-1})\ ds_{t-1}$ // Prediction
4: $Bel(s_t) = \eta\ \ p(o_t \mid s_t, m)\ \ Bel^{-}(s_t)$ // Update
5: *endfor*
6: *return*($Bel(s_t)$)

4.2 Implementation Approach and Point Estimation

4.2.1 The Discrete Bayesian Filter

The multidimensional integrals involved in (4.11) permit analytical or closed-form solutions only in few special cases, e.g., the well studied case, when the dynamical model is *linear* and both measurement data errors and initial conditions are *Gaussian* or *normally distributed*. An analytical solution is already existing and is known as the *Kalman filter*. The Kalman filter (KF) provides the optimal solution to this case where all the involved densities are Gaussian and only linear operations are being performed. Thus, the state will also be Gaussian all the time. When the dynamical model is nonlinear or the measurement data noise is non-Gaussian, the recursive Bayesian filter equation of (4.11) has no analytical solution.

Nonparametric filters (NPF) [Thr2005] provide implementable algorithms for the RBF. They approximate posteriors by a finite number of parameters, each corresponding to a region in the state space, i.e., they do not rely on a fixed functional form of the posterior. Moreover, the number of the parameters used to approximate the posterior can be varied. The quality of approximation depends on the number of these parameters. As the number of parameters approaches infinity, NPF tends to converge uniformly to the correct posterior. The NPF approach discussed here approximates posteriors over finite spaces by decomposing the state space into finitely many regions and represents the cumulative posterior for each region by a single probability value. Such an approach is known as *discrete Bayesian filter (DBF)*. The DBF is also referred to as the *forward pass* of a *hidden Markov model*. Particle filters also can numerically approximate the posterior belief by using Monte Carlo techniques, i.e., random parameters that cover the state space are chosen to approximate posteriors. Thus, the particle filter is a special case of the discrete Bayesian filter.

The DBF approximates the belief $Bel(s)$ at any time by a set of n weighted candidates as

$$Bel(s) \approx \{s^{(i)}, w^{(i)}\}_{i=1:n} \tag{4.17}$$

Where $s^{(i)} = \{x^{(i)}, y^{(i)}\}$ is the i-th MT position (or state) candidate and $w^{(i)}$ is a *normalized* probability value (also called weight) that determines the importance of $s^{(i)}$. The sum of all weights equals 1 so that $Bel(s)$ represents a valid probability distribution. However, normalization is not a crucial issue for practical algorithm implementation.

4.2.2 Point Estimation Methods

The aim is not just to find the belief distribution of the MT state, but to provide a single best guess of the state referred to as *point estimate*. This point estimate is simply the final MT location estimate that is output by the employed algorithm. There are several ways to calculate point estimates, e.g. *maximum a posteriori (MAP), weighted average estimate (WAE),* and *trimmed average estimate (TAE).*

Definition 4.4 (Point Estimation)
Point estimation of a parameter is the process of taking the probability distribution function, that represents the knowledge about that parameter, as an input, and performing a data reduction procedure, i.e. information processing, in order to output a

single *optimal value* or *best guess* that is believed to summarize the information about that parameter. Methods that achieve this process are called *(point) estimators*.

Remarks
(1) It is important to state that information is generally subjective, i.e. the probability distribution function that represents the information about a given system parameter does not represent the real state of that parameter, but it represents all information that we believe, as observers, have collected about the parameter. On the contrary, information processing is an objective procedure.

(2) Sources of collected information include prior knowledge about the system, current measurement data, and data from the past.

Definition 4.5 (Maximum a Posteriori Estimator)
The maximum a posteriori (MAP) estimator is the maximum of the posterior belief distribution $Bel(s_t)$ and is expressed as

$$\hat{s}_t^{MAP} = \arg\max_s Bel(s_t) = \arg\max_s p(o_t, a_t \mid s_t) Bel(s_{t-1}) \tag{4.18}$$

Thus, the MAP estimator is simply the location candidate with the highest assigned weight.

Remarks
(1) Within this framework, the prior belief represents a degree of belief in a certain range of parameter values rather than representing the distribution of the parameter values. This is due to the fact that the measurement likelihood is expected to dominate the content of our knowledge about the system behaviour and the prior belief is locally uniform in the region where the likelihood function is appreciable.

(2) If the measurement likelihood function has only one peak, i.e. unimodal density function, then the MAP estimator selects the *mode (maximum point)* of the a posteriori distribution.

(3) If the measurement likelihood function is normally distributed, the *mode* and the *mean* coincide, i.e. the MAP estimator is equivalent to the *mean-square error estimate*.

Definition 4.6 (Maximum Likelihood Estimator)
The maximum likelihood estimator (MLE) is a special case of the MAP estimator, where the prior belief distribution $Bel(s_{t-1})$ is uniformly distributed, i.e. non-informative. Non-informative distributions are also called *diffuse* or *improper* distributions [Bar2001]. The MLE is written as

$$\hat{s}_t^{MLE} = \arg\max_s Bel(s_t) = \arg\max_s p(o_t, a_t \mid s_t) \tag{4.19}$$

Remarks
(1) The MLE is a *non-Bayesian* estimator. Therefore, the unknown parameters are treated as non-random variables. This helps to asses the MLE performance using the Cramér-Rao bound, which applies to non-random parameters, see Chapter 5.

(2) The MLE coincides with the MAP estimator only in case of complete prior ignorance, i.e. the a priori knowledge approaches zero. Thus, Bayesian and non-Bayesian approaches to estimation can be philosophically unified. In this case, maximizing $p(o_t, a_t \mid s_t)$ is equivalent to maximizing $p(s_t \mid o_t, a_t)$.

(3) When a linear model can describe the data, and the errors are normally distributed with zero means, the least squares (LS) solution to the problem is equivalent to the MLE.

Definition 4.7 (Weighted Average Estimator)
The weighted average estimator (WAE) of the posterior belief $Bel(s_t)$ is defined as

$$\hat{s}_t^{WAE} = \frac{1}{\sum_{i=1}^{n} w^{(i)}} \sum_{i=1}^{n} s_t^{(i)} \cdot w_t^{(i)} \tag{4.20}$$

Remarks
(1) The WAE is the *mean value* of the posterior belief distribution and it will only coincide with the MAP estimator in case of *unimodal* and *symmetric* distributions, which is not often the case in the context handled here.

(2) The WAE is equivalent to the *minimum mean square error (MMSE) estimate* as long as the weighting procedure minimizes a mean-square criterion, as in Expression (4.23).

Definition 4.8 (Trimmed Average Estimator)
Averaging only a number k of the best weighted candidates yields the trimmed average estimator (TAE) as

$$\hat{s}_t^{TAE} = \frac{1}{k}\sum_{i=1}^{k} s_t^{(i)} \tag{4.21}$$

Where $k < n$ and n is the total number of location candidates.

4.3 A Taxonomy of Positioning Problems

Estimation of the MT position in its environment involves using a map of a location-dependent parameter of the environment, network measurement data, and motion information. The estimation accuracy could even be enhanced by utilizing any prior knowledge of the MT location when available.

Motion information is generally the most difficult piece of information to extract. Without dedicated motion sensors, e.g., an inertial measurement unit (IMU), motion estimation is either impossible or very inaccurate due to the noisy signal behaviour used to derive the MT motion pattern. Accordingly, the MT positioning problem could be divided into *location estimation* and *tracking* based on the availability of motion measurements. Location estimation (LE) algorithms calculate the MT location without incorporating any motion information or any prior knowledge about the initial MT position. Tracking algorithms can be further categorized according to the availability of prior knowledge into *position tracking* and *global localization*. In position tracking (PT), the initial position of the MT is known, and the problem is to find adequate procedures in order to compensate incremental errors in the motion sensor measurements. In the more challenging global localization (GL) problem, the initial location of the MT is unknown, and consequently the MT position has to be determined from scratch. This positioning problem is more difficult because multiple and distinct hypotheses have to be handled. Properties of the three defined positioning problems are summarized in TABLE 4.2.

4.3.1 Location Estimation

As mentioned above the location estimation algorithm calculates the MT position without any prior information about the accurate initial location of the MT or any motion measurements from dedicated sensors. Thus line 3 in TABLE 4.1 could not be executed. Consequently, the algorithm computes only the output probability of the network measurements, which is merely a table-lookup procedure.

TABLE 4.2: Comparison of the three positioning problems.

	Prior knowledge available?	**Motion information available?**
Location Estimation	No	No
Position Tracking	Yes	Yes
Global Localization	No	Yes

TABLE 4.3 depicts a single iteration of the location estimation algorithm to estimate the MT state at time t. It is initialized (in line 2) by allocating memory space for the location belief $Bel(s_t)$ and the final MT location estimate $\hat{s}_t$. The inputs (lines 2 and 3) are the network measurements o_t and the world model m_t. Where $DB_{cell-ID}$ is the database that contains location information and expected RxLev (received signal level) values (of the main and neighbouring cell antennas) of the areas covered by the main (or serving) BS cell antenna at time t, and $RxLev_t^{(j)}$ is the measured received signal level from the *j*-th observed BS. The weight of the location candidate i is calculated (in line 5) as

$$w^{(i)} = w_{MM}^{(i)} + w_{ND}^{(i)} + w_{SN}^{(i)} \tag{4.22}$$

Where $w_{MM}^{(i)}$, $w_{ND}^{(i)}$, and $w_{SN}^{(i)}$ are the weights according to the *measurement model*, *neighbourhood degree*, and *strongest neighbour* respectively. They are calculated as

$$w_{MM}^{(i)} = p(o_t \mid s_t^{(i)}, m) = \prod_{j=1}^{M} \frac{1}{\sigma_{RxLev}\sqrt{2\pi}} e^{-\frac{(RxLev_t^{(j)} - RxLev_{DB_j})^2}{2\sigma_{RxLev}^2}} \tag{4.23}$$

Where M is the number of observed BSs (main and neighbouring), i.e. $M_{\max} = 7$ in typical GSM network measurements, σ_{RxLev} is the standard deviation of the measured RxLev, and $RxLev_{DB_j}$ is the database RxLev prediction value of the *j*-th observed BS at $s_t^{(i)}$.

$$w_{ND}^{(i)} = l \tag{4.24}$$

Where l is the number of observed neighbour BSs that coincide with the list of the predicted six strongest neighbour BSs at $s_t^{(i)}$, i.e. $l_{\max} = 6$.

$$w_{SN}^{(i)} = \alpha_{SN} \tag{4.25}$$

Where α_{SN} is a constant bonus value and equals 1. It is assigned if the strongest observed neighbour BS coincides with the predicted *first* or *second* strongest neighbour BS at $s_t^{(i)}$. Otherwise, $w_{SN}^{(i)} = 0$.

After weight calculation the location candidate is added to the belief (line 6) together with the assigned weight. This is done for all location candidates before sorting them (line 8) in a descending order w.r.t. their weights.

TABLE 4.3: The location estimation algorithm.

1: Algorithm **LocationEstimation**(o_t , m_t)
2: $Bel(s_t) = 0$, $\hat{s}_t = 0$, $m_t = DB_{cell-ID}$
3: $o_t = \{cell - ID_t, TA_t, RxLev_t^{(j)}\}$
4: $for\, i = 1 : n\, do$
5: Compute the weight $w_t^{(i)}$
6: $Bel(s_t) = Bel(s_t) \cup \{s_t^{(i)}, w_t^{(i)}\}$
7: $endfor$
8: $Bel(s_t) = sort(Bel(s_t))$ // Descending sort
9: Calculate $\hat{s}_t$
10: $return(\hat{s}_t)$

Remark

When using Expression (4.19) to calculate $\hat{s}$, line 9 in TABLE 4.2, many candidates may have the same weight. Thus, the returned location estimate will depend on the stability of the sorting scheme utilized. Stable sorting algorithms maintain the relative order of the location candidates, i.e. a location candidate with the highest weight that appeared first in the unsorted belief will also appear first in the sorted belief. This is very disadvantageous as an arbitrary candidate could be returned as the location estimate though other candidates, also assigned with the same highest weight, would be more accurate. However, the effect of this negative aspect could be reduced by computing $\hat{s}$ using Expressions (4.20) or (4.21).

4.3.2 Position Tracking

A single iteration of the position tracking algorithm is given in TABLE 4.4. The inputs are the initial position (line 2) $s_{t-1} = (x_{t-1}, y_{t-1})$, the IMU data (line 3) $a_{t-1} = (trans_{t-1}, \theta_{t-1})$, where $trans_{t-1}$ and θ_{t-1} are the translation (e.g. after twice integration of the IMU acceleration measurement) and orientation (IMU compass) in a 2D Cartesian coordinate system at time $t-1$ respectively, the network measurement o_t (line 4), and the corresponding world map m_t (line 5) where w_j is the weight of the *j*-th location candidate and initially set to zero. Note that the proposed algorithm updates only one position hypothesis, i.e., n in Expression (4.17) equals 1.

The position tracking algorithm propagates the known initial MT location s_{t-1} using IMU data in the prediction step (lines 6 and 7). The propagated location is then updated by matching it to the set of candidate locations (lines 8-10) that are covered by the current serving cell antenna, after descending sort of the candidates w.r.t weight (line 11), the new MT position (line 12) is simply the candidate of the minimum Euclidean distance to the location computed in the prediction step.

Remarks

(1) The proposed position tracking algorithm assumes that $trans_{t-1}$ is generally greater than or equal to the resolution of the underlying world map. If this is not the case, the algorithm could be modified so that lines 6 and 7 will only be executed when the travelled distance is greater than or equal to the world map resolution in order to allow position state transition.

(2) The developed position tracking algorithm is a nonlinear recursive filter. Its flexibility, ease of implementation, and computational cost effectiveness make it an attractive alternative to the Kalman-type nonlinear filters.

TABLE 4.4: The position tracking algorithm.

1: Algorithm **PositionTracking**($s_{t-1}, a_{t-1}, o_t, m_t$)	
2: $s_{t-1} = (x_{t-1}, y_{t-1})$	// Input
3: $a_{t-1} = (trans_{t-1}, \theta_{t-1})$	// …
4: $o_t = \{cell-ID_t, TA_t\}$	// …
5: $m_t = DB_{cell-ID_t} =< x_j, y_j, w_j >$	// …
6: $x_t^- = x_{t-1} + trans_{t-1} \cdot \cos\theta_{t-1}$	// Prediction
7: $y_t^- = y_{t-1} + trans_{t-1} \cdot \sin\theta_{t-1}$	// …
8: *for* $j = 1:n$ *do*	// Update
9: $w_j = \dfrac{1}{\sqrt{(x_t^- - x_j)^2 + (y_t^- - y_j)^2}}$	
10: *endfor*	
11: $m_t = sort(m_t)$	// Descending sort
12: $s_t = (x_t, y_t) = (x_1, y_1)$	
13: *return*(s_t)	

4.3.3 Global Localization

The global localization algorithm has no information about the accurate MT position at the beginning. Thus, it has to resolve the location ambiguity and converge to the true position of the MT by tracking all probable location candidates and determine their weights every time the algorithm is run. When this task is successfully fulfilled, the algorithm is allowed to run in the position tracking mode (line 30 in TABLE 4.5).

As depicted in TABLE 4.5, the global localization algorithm is initialized by setting the travelled distance as measured by the IMU ($trvld\_dist$) to 0, and $Mode$ also to 0, i.e., global localization mode (line 3). The inputs (lines 4-7) are the same as in TABLE 4.4 except (line 5) that the global localization algorithm tracks a number of hypothetical candidates, unlike the position tracking algorithm. The global localization mode will run as long as the number of location candidates n in the belief distribution $Bel(s_{t-1})$ is greater than a certain threshold α (line 9). During this mode, the prediction and update steps will only run if the MT's travelled distance is greater than or equal to the database (or map) resolution DB_{res} (line 11), in order to allow position state transition using the world model. The updated candidate will only be added to the new belief, if the location it is matched to is not greater than DB_{res} away (lines 19-21). Therefore, the number of location candidates n will decrease after every run of the algorithm until their total number is equal to or less than the threshold α. In this very event, the updated MT position is simply estimated as the average of the remaining candidates, and the algorithm is switched to the position tracking mode (lines 25-28). Note that the algorithm returns no position estimates in the global localization mode. First after switching to the position tracking mode, location estimates are returned at the end of every update run, see TABLE 4.4. For both the global localization and position tracking algorithms no RxLev values have been used. Only the cell-ID and TA measurement of the network measurement report (NMR) have been utilized, see line 4 in TABLE 4.4 and line 7 in TABLE 4.5 respectively.

Remark

The update step of the position tracking and global localization algorithms has different roles. In the position tracking algorithm, the position estimate is decided upon the result of the update step, where in the global localization algorithm, the update step works to reduce the size of the position belief and makes it converge to a single estimate before allowing the position tracking algorithm to run.

4.3.4 How Global Localization Works

Solving the global localization problem for an MT in a GSM network is described and illustrated in Figure 4.1. Location state space, MT location belief, ground truth, and position estimation (when available) are depicted in green, red, solid blue diamond, and black respectively. At start, the MT location is not known and the algorithm has to handle all probable locations. Therefore, the location belief covers the whole state space, see Figure 4.1-a. After approximately 27 m of motion, many location candidates have been found improbable and thus have fallen out of consideration, as in Figure 4.1-b. After another 38 m of movement, the location belief has concentrated on two parallel streets, see Figure 4.1-c. As the MT moved further, the location belief has almost converged to the true position as in Figure 4.1-d. Figure 4.1-e shows how the MT location ambiguity has been resolved after a total movement of about 145 m with a position estimation error of approximately 16 m.

Remark

If the competing parallel street was longer than the true street where the MT is located, the number of location candidates n may reach the threshold α before performing a turn. Thus, the position belief would converge to a false position due to the concentration of location candidates on the wrong street. However, in practical situations the true street may be known and can be input to the algorithm by modifying the initial prior belief.

TABLE 4.5: The global localization algorithm.

Algorithm **GlobalLocalization**($Bel(s_{t-1}), a_{t-1}, o_t, m_t$)
// Initialization, only at the first run of the algorithm
$trvld\_dist = 0$, $Mode = 0$
// Inputs
$Bel(s_{t-1}) = DB_{cell-ID_t} =< x_i, y_i >, i = 1...n$
$m_t = DB_{cell-ID_t} =< x_j, y_j, w_j >, j = 1...q, < w_j >= 0$
$o_t = \{cell - ID_t, TA_t\}$, $a_{t-1} = (trans_{t-1}, \theta_{t-1})$
if $Mode == 0$ // Global localization mode
if $n > \alpha$
$trvld\_dist = trvld\_dist + \sqrt{(trans_{t-1} \cdot \cos\theta_{t-1})^2 + (trans_{t-1} \cdot \sin\theta_{t-1})^2}$
if $trvld\_dist >= DB_{res}$
for $i = 1 : n$ *do*
$x_i^- = x_i + trvld\_dist \cdot \cos\theta_{t-1}$ // Prediction
$y_i^- = y_i + trvld\_dist \cdot \sin\theta_{t-1}$ // …
for $j = 1 : q$ *do*
$w_j = \dfrac{1}{\sqrt{(x_i^- - x_j)^2 + (y_i^- - y_j)^2}}$ // Update
endfor
$< w_j >= sort(< w_j >)$ // Descending sort
if $(\frac{1}{w_1} \le DB_{res})$
add (x_1, y_1) to $Bel(s_t)$
endif
endfor
$trvld\_dist = 0$
endif
else if $n \le \alpha$
$Mode = 1$
$s_t = (\frac{\sum_i x_i}{n}, \frac{\sum_i y_i}{n})$
endif
else if $Mode == 1$ // Position tracking mode
PositionTracking($s_{t-1}, a_{t-1}, o_t, m_t$) // Table 4.3
endif

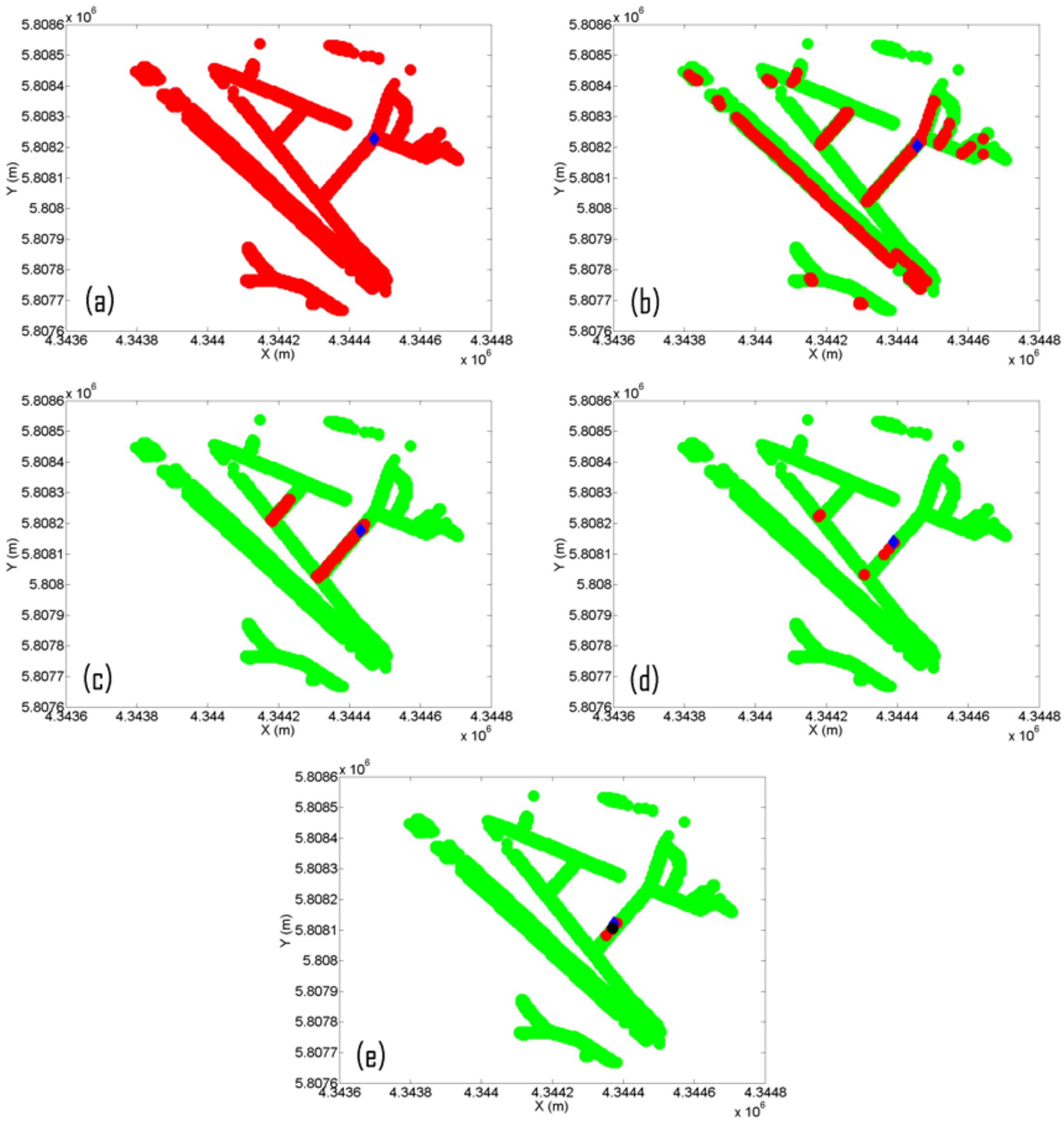

Figure 4.1: Global localization of a mobile terminal in a GSM environment.

APPENDIX

4.A Marginalization

Definition 4.A.1 (Marginalization)
The probability density function $p(X, Y, Z)$ contains information that determines how the values of the variables X, Y and Z can occur together. Marginalization is defined as the process to extract or derive information about X and Y, given all possible values of Z. Marginalization is mathematically expressed as

$$p(X, Y) = \int_Z p(X, Y, Z)dz \tag{4.26}$$

This is simply integrating $p(X, Y, Z)$ over all possible values of Z.

Chapter 5

Performance Bounds

Lower bounds give an indication of performance limitations. Therefore, they are used to determine whether imposed performance requirements are realistic or not. Performance evaluation of MT positioning algorithms, and in particular RSS-based techniques, is an interesting research topic. This is achieved by obtaining a lower bound on the covariance matrix of positioning errors. The Cramér-Rao lower bound (CRLB) is defined as the inverse of the Fisher information matrix (FIM) and provides an objective indication of the achievable accuracy of constant parameter estimation. The CRLB has been extended for random parameter estimation in [Tre1968]. Section 5.1 shows how to asses the performance of the database correlation method (DCM), i.e. the location estimation algorithm, using the CRLB. The performance evaluation of the position tracking algorithm requires the consideration of the dynamics involved in the problem. This is achieved by computing the posterior Cramér-Rao lower bound (PCRLB), which is presented in section 5.2.

5.1 Lower Bound for the Location Estimation Algorithm

The CRLB [Tre1968], [Kay1993], [Pap2002] and the Barankin lower bound [Bar1949] have been used in [Wei2003] and [Koo2004] respectively to compute achievable accuracies of RSS-based positioning methods. The work in [Wei2003] gives simulation results for a triangulation method based on a distance attenuation model of the signal strength. However, this approach is not suitable for the database correlation method if the RSS signatures are constructed by complex propagation prediction tools or by tedious survey measurements, because the RSS-location mapping function is not always continuous and differentiable everywhere in order to derive the CRLB. This disadvantage has been tackled in [Koo2004] by calculating the Barankin bound, which does not require the mapping function to be continuous and differentiable everywhere, for a database correlation method, in which the database was constructed by field RSS measurements. The difficulty in choosing the right points that contribute to the computation of the bound is the main problem of accuracy assessment using the Barankin bound.

The following subsections show how the RSS location mapping function is approximated by a suitable path loss empirical formula in order to derive the CRLB for investigating the DCM performance.

5.1.1 Propagation Modeling and Database Reconstruction

The original database of RSS-fingerprints, utilized in this work, is constructed by using a 3D deterministic radio propagation prediction model. Therefore, calculating the CRLB is infeasible due to the discontinuity of the RSS-location mapping function. However, this can be tackled by parameterization of the RSS-location relationship. The parameterization is achieved by employing a path loss model that can sufficiently characterize the wireless propagation environment of the experimental area.

The path loss model applied here is the well known COST-231-Hata model [COS1991], [COS1999], which extended the Hata model [Hat1980], which in turn is based on Okumura's correction functions [Oku1968], to cover the frequency band $1500\text{MHz} < f < 2000\text{MHz}$ by analyzing Okumura's curves in the upper frequency band. The COST231-Hata model for path loss L (dB) prediction is given as[1]

$$L = F + B \cdot \log d - E + G \tag{5.1}$$

Where

$$F = 46.3 + 33.9 \cdot \log f - 13.82 \cdot \log h_{BS} \tag{5.2}$$

[1] $\log = \log_{10}$ throughout this chapter.

$$B = 44.9 - 6.55 \cdot \log h_{BS} \tag{5.3}$$

$$E = (1.1 \cdot \log f - 0.7) \cdot h_{MS} - (1.56 \cdot \log f - 0.8) \tag{5.4}$$

$$G = \begin{cases} 0 \text{ dB for medium-sized city and suburban areas} \\ 3 \text{ dB for metropolitan centers} \end{cases} \tag{5.5}$$

And d is the distance between the BS transmitter and the MT receiver (in km), h_{BS} is the height of the BS antenna (in m), and h_{MS} is the height of the MT antenna (in m).

The COST231-Hata model predicts the path loss only in large and small macro cells (cell radius: 1 km – 30 km and 0.5 km – 3 km respectively), which is the common wireless layout in medium-small cities. The application range of the parameters is

f : 1500 – 2000 MHz
h_{BS} : 30 – 200 m
h_{MS} : 1 – 10 m

Substituting the known parameter values of f, h_{BS}, and h_{MS}, for a certain cell antenna of the experimental area, in Equations (5.2) – (5.4), then Expression (5.1) is rewritten as

$$L = a_1 + a_2 \cdot \log d \tag{5.6}$$

The parameter values used for the calculation were

$f = 1800$ MHz
$h_{BS} = 60$ m
$h_{MS} = 1.5$ m
$G = 0$ dB

Assuming isotropic antennas at the base and mobile stations, the average received signal level P_r at any location can be predicted as

$$P_r = EIRP - L \tag{5.7}$$

Where $EIRP$ is the effective isotropic radiated power. In order to reconstruct the RSS-signature database using the COST231-Hata model (COST-Hata DB), a_1 and a_2 in Expression (5.6) have to be computed using the existing database (3D-DB) built by the 3D deterministic radio propagation model. This is done by a least-squares procedure which will minimize

$$R = \sum_{i=1}^{n} (L_i - L_i^{3D-DB})^2 \tag{5.8}$$

Where n is the number of reference locations and L^{3D-DB} is the path loss of the 3D-DB, which is given as

$$L^{3D-DB} = EIRP - P_r^{3D-DB} \tag{5.9}$$

The resulting COST-Hata DB is used by an unbiased estimator to calculate the MT position. The corresponding CRLB is derived in Section 5.3.2.

5.1.2 Problem Formulation and Location Estimation

Each database location (entry) is defined by a 2D Cartesian coordinate $s = [x, y]^T$ associated with a column vector $P(s)$ of length M containing predicted RSS values from the M control channels. The measurement o_i on channel i is given by

$$o_i = c + P_i(s) + e_i \tag{5.10}$$

Where c is a common attenuation factor due to the MT's RF properties, $P_i(s)$ is the average predicted RSS at location s from the i-th BS, and e_i is an unpredicted measurement error. Thus, all measurements can be expressed in vector form as

$$\mathrm{o} = \mathrm{J}c + \mathrm{P(s)} + \mathrm{e} \tag{5.11}$$

Where all vectors are of length M and are defined as

$$\mathrm{o} = [o_1, ..., o_M]^T$$
$$\mathrm{J} = [1, ..., 1]^T$$
$$\mathrm{P(s)} = [P_1(s), ..., P_M(s)]^T$$
$$\mathrm{e} = [e_1, ..., e_M]^T$$

The least-squares location estimator is written as

$$\hat{s} = \min \| \mathrm{o} - \mathrm{P(s)} - \mathrm{Jc} \|^2 \tag{5.12}$$

Equation (5.12) is called the maximum likelihood estimator (MLE) if errors are assumed to be Gaussian with zero means. The factor c is estimated by

$$\hat{c} = (\mathrm{J}^T \mathrm{J})^{-1} \mathrm{J}^T (\mathrm{o} - \mathrm{P(s)}) = M^{-1} \mathrm{J}^T (\mathrm{o} - \mathrm{P(s)}) \tag{5.13}$$

Substituting (5.13) into Expression (5.12), we get

$$\hat{s} = \min \| \mathrm{B} \cdot (\mathrm{o} - \mathrm{P(s)}) \|^2 \tag{5.14}$$

Where $\mathrm{B} = \mathrm{I} - M^{-1}\mathrm{JJ}^T$ and I is the $M \times M$ identity matrix. Equation (5.14) is minimized by searching all candidate locations stored in the COST-Hata DB. Note that Expression (5.14) is equivalent to the MLE given in Equation (4.19).

5.1.3 Cramér-Rao Bound

5.1.3.1 Preliminaries

Definition 5.1 (Unbiased Estimator)
The estimator $\hat{s}$ is called an unbiased estimator for the non-random parameter s if

$$E[\hat{s}] = s, \qquad a < s < b \tag{5.15}$$

Where (a, b) denotes the range of possible values s can take.

It means that the expected value of an unbiased estimator is equal to the true value of the parameter being estimated.

Remarks

(1) The expectation in (5.15) is over the estimate which is a random variable as it is a function of the measurement.

(2) An unbiased estimator guarantees that on the average it will attain the true value, and it does not necessarily mean that it is a good estimator.

(3) A biased estimator will for some reason on average over- or underestimate the parameter being estimated, i.e. it is characterized by a systematic error.

(4) If $\hat{s}_1$ and $\hat{s}_2$ are both unbiased estimators for s, the one with lower error variance is preferable. The problem now is how to find an unbiased estimator with the lowest possible error variance and if it is possible to obtain an expression on the lower bound for the estimation error variance of all unbiased estimators.

(5) The extension of Definition 5.1 to the multi-parameter case is straightforward. $\hat{s}$ is said to be unbiased if

$$E[\hat{s}_i] = s_i, \qquad a_i < s_i < b_i, \quad i = 1,2,...,n \tag{5.16}$$

Where

$$s = [s_1\ s_2\ ...\ s_n]^T$$
$$\hat{s} = [\hat{s}_1\ \hat{s}_2\ ...\ \hat{s}_n]^T$$
$$E[\hat{s}_i] = [E[\hat{s}_1]\ E[\hat{s}_2] ...\ E[\hat{s}_n]]^T$$

(6) In the Bayesian case, where s is a random variable with a known prior probability density function, we have the unbiasedness property as

$$E[\hat{s}] = E[s] \tag{5.17}$$

Where the expectation on the right-hand side is with respect to the prior pdf.

Definition 5.2 (Mean Square Error)
A natural optimality criterion for estimators is the mean square error (MSE) which is defined as

$$MSE(\hat{s}) = E[(\hat{s} - s)^2] \tag{5.18}$$

MSE measures the average mean squared deviation of the estimate from the true value. Thus, the MSE of an unbiased estimator is simply the variance.

Remarks
(1) The adoption of the MSE criterion leads to unrealizable estimators, because the MSE is composed of the variance error and the bias [Kay1993]. A useful approach is to constrain the bias to be zero and find the *minimum variance unbiased* (MVU) estimator which minimizes the error variance.

(2) Generally, the MVU estimator does not always exist, and if it exists, we may not be able to find it. If the MVU estimator exists, it will only be produced by the maximum likelihood approach.

Definition 5.3 (l_2 Norm of a Vector)
The inner product of a vector with itself is given as

$$\langle a, a \rangle = \| a \|^2 \tag{5.19}$$

Which is the squared l_2 norm of this vector. This also applies for the inner product of two real *n*-vectors in a Euclidean space or for any other properly defined inner product. Thus, the l_2 norm is the *length* or *magnitude* of the vector.

Definition 5.4 (Schwarz Inequality)
The Schwarz inequality states the relationship between the magnitude of the inner product of two vectors and their l_2 norms as

$$| \langle a, b \rangle | \le \| a \| \| b \| \tag{5.20}$$

The generalization of (5.20) is the Schwarz inequality for real-valued functions or

$$|\langle f_1, f_2\rangle| = \int_{-\infty}^{\infty} f_1(o) f_2(o) do \leq \| f_1 \| \| f_2 \| \tag{5.21}$$

Where

$$\| f_i \| = \{\langle f_i, f_i\rangle\}^{1/2} = \{\int_{-\infty}^{\infty} f_i(o)^2 do\}^{1/2} \tag{5.22}$$

The equality in (5.21) holds iff

$$f_1(o) = cf_2(o), \qquad \forall o \tag{5.23}$$

Where c is some constant not dependent on o.

A theoretical lower bound on the minimum error variance (second order or mean squared error) or minimum error covariance matrix attainable by any unbiased estimator can be formulated by the Cramér-Rao lower bound (CRLB) [Tre1968], [Kay1993], [Pap2002]. The CRLB applies to non-random parameters[2] and uses the MLE, as described in 4.2.2 and 5.1.2. CRLB is the basic metric of accuracy for an estimate. This lower bound was given by Rao in [Rao1945]. It was also obtained independently by Cramér in [Cra1946a], hence the name of the bound. However, the Cramér-Rao inequality was first stated by Fisher [Fis1922] and proved by Dugué [Dug1937]. Historically, the Cramér-Rao inequality was apparently discovered, according to [Sto1996], for the single-parameter case in [Doo1936] and rediscovered in a more elegant manner in [Fré1943]. Generalizations of the Cramér-Rao inequality for the multi-parameter case were presented in [Dar1945], [Cra1946b], and [Rao1946]. The CRLB is a useful benchmarking tool to asses the performance of the proposed unbiased location estimator; see Expression (5.14) in Section 5.1.2. Therefore, the CRLB is a common ingredient in any wireless geolocation system feasibility study.

The key step for calculating the Cramér-Rao bound (CRB) for the multi-parameter case is the construction of the Fisher information matrix (FIM)[3] using the probability density function (pdf) of the wireless network measurements (or observations) given the MT

[2] The posterior Cramér-Rao bound [Tre1968] applies to random variables. Hybrid Cramér-Rao bounds, proposed in [Roc1987], apply to the joint estimation of non-random parameters and random variables.
[3] Also called the observability matrix.

location $p(o \mid s)$. Alternatively, the CRLB can be derived from information matrices of marginals of the joint probability density function. In this chapter, only the first approach is followed.

The term $p(o \mid s)$ is also called the measurement likelihood function where o is the network measurement and s is the MT location and is written as

$$p(o \mid s) = \frac{1}{(2\pi)^{\frac{M}{2}} \cdot \| C_e \|^{\frac{1}{2}}} \cdot \exp\{-\frac{e^T (C_e)^{-1} e}{2}\} \tag{5.24}$$

Where C_e is a positive definite covariance matrix of the error vector e. Substituting the minimized term in (5.14), which is an expression for the error e in (5.11), in Equation (5.24) we get

$$p(o \mid s) = \frac{1}{(2\pi)^{\frac{M}{2}} \cdot \| C_e \|^{\frac{1}{2}}} \cdot \exp\{-\frac{[\mathrm{B} \cdot (\mathrm{o} - \mathrm{P(s)})]^T (C_e)^{-1} [\mathrm{B} \cdot (\mathrm{o} - \mathrm{P(s)})]}{2}\} \tag{5.25}$$

Theorem 5.1 (Cramér-Rao Inequality)
If $\hat{s}$ is an unbiased estimator, then for the single-parameter case

$$\mathrm{Var}(\hat{\mathrm{s}}) \geq -E\{\nabla_s [\nabla_s (\ln p(o \mid s))]\}^{-1} \tag{5.26}$$

i.e.

$$\mathrm{Var}(\hat{\mathrm{s}}) \geq -E\{[\frac{\partial^2 \ln p(o \mid s)}{\partial s^2}]\}^{-1} \tag{5.27}$$

Or equivalently[4]

$$\mathrm{Var}(\hat{\mathrm{s}}) \geq \{E[(\frac{\partial \ln p(o \mid s)}{\partial s})^2]\}^{-1} \tag{5.28}$$

[4] See Appendix 5.A for the proof of the equivalence.

Assuming that the following regularity condition is satisfied:

$$E[\frac{\partial \ln p(o \mid s)}{\partial s}] = 0, \quad \forall s \tag{5.29}$$

The expectation in (5.27) is given by

$$E[\frac{\partial^2 \ln p(o \mid s)}{\partial s^2}] = \int \frac{\partial^2 \ln p(o \mid s)}{\partial s^2} p(o \mid s) ds \tag{5.30}$$

The *Fisher information* $I(s)$ for the data o is defined as

$$I(s) = -E[\frac{\partial^2 \ln p(o \mid s)}{\partial s^2}] \tag{5.31}$$

In other words, the CRLB on the error variance is the inverse of the Fisher information or

$$\mathrm{Var}(\hat{s}) \geq I(s)^{-1} \tag{5.32}$$

Expression (5.26) indicates that the more information, the lower the bound. Furthermore, Fisher information has the following properties, which are essential of an information measure: Nonnegative, and additive for independent measurement data.

For the multi-parameter case, e.g. 2D MT location estimator

$$COV(\hat{s}) \geq \mathrm{FIM}^{-1} \tag{5.33}$$

Where

$$COV(\hat{s}) = E[(\hat{s} - s)(\hat{s} - s)^T] \tag{5.34}$$

$$\mathrm{FIM}^{-1} = -E\{\nabla_s[\nabla_s(\ln p(o \mid s))]\}^{-1} \tag{5.35}$$

Proof

The first and second derivatives of $p(o\,|\,s)$ w.r.t. s exist and are absolutely integrable. From (5.17) we have

$$E[\hat{s}-s]=\int_{-\infty}^{\infty}[\hat{s}-s]p(o\,|\,s)do=0 \tag{5.36}$$

The derivation of (5.36) w.r.t. s yields

$$\begin{aligned}&\frac{d}{ds}\int_{-\infty}^{\infty}[\hat{s}-s]p(o\,|\,s)do\\&=\int_{-\infty}^{\infty}\frac{\partial}{\partial s}\{[\hat{s}-s]p(o\,|\,s)\}do=-\int_{-\infty}^{\infty}p(o\,|\,s)do+\int_{-\infty}^{\infty}[\hat{s}-s]\frac{\partial p(o\,|\,s)}{\partial s}do=0\end{aligned} \tag{5.37}$$

Utilizing the identity

$$\frac{\partial p(o\,|\,s)}{\partial s}=\frac{\partial \ln p(o\,|\,s)}{\partial s}\,p(o\,|\,s) \tag{5.38}$$

And noting that $\int_{-\infty}^{\infty}p(o\,|\,s)do=1$, from Equation (5.37) we get

$$\int_{-\infty}^{\infty}[\hat{s}-s]\frac{\partial \ln p(o\,|\,s)}{\partial s}p(o\,|\,s)do=1 \tag{5.39}$$

Expression (5.39) can be rewritten as

$$\int_{-\infty}^{\infty}\{[\hat{s}-s]\sqrt{p(o\,|\,s)}\}\{\frac{\partial \ln p(o\,|\,s)}{\partial s}\sqrt{p(o\,|\,s)}\}do=1 \tag{5.40}$$

The left-hand side of (5.40) is an inner product of two functions. Therefore, utilizing Expression (5.21) of the Schwarz inequality, will majorize the left-hand side of (5.40) as

$$\{\int_{-\infty}^{\infty}[\hat{s}-s]^2\, p(o\,|\,s)do\}^{1/2}\{\int_{-\infty}^{\infty}[\frac{\partial \ln p(o\,|\,s)}{\partial s}]^2\, p(o\,|\,s)do\}^{1/2} \geq 1 \tag{5.41}$$

Or

$$E\{[\hat{s}-s]^2\} \geq \{E[\frac{\partial \ln p(o\,|\,s)}{\partial s}]^2\}^{-1} \tag{5.42}$$

Where the equality holds iff

$$\frac{\partial \ln p(o\,|\,s)}{\partial s} = c(s)[\hat{s}-s]\,, \qquad \forall o \tag{5.43}$$

Expression (5.42) is equivalent to Equation (5.28), and thus the proof of the Cramér-Rao inequality for the single-parameter (non-random scalar parameter) case is completed. See [Kay 1993] pp. 70-72 or [Pap2002] pp. 343-345 for the proof of the multi-parameter (vector-valued parameters) case.

Remarks

(1) Expressions (5.26)-(5.28), (5.32), and (5.33) are called the *Cramér-Rao inequality* or *information inequality*. The right-hand side of these equations are known as the *Cramér-Rao lower bound (CRLB).*

(2) If an estimator achieves the bound, it is called an *efficient*[5] estimator, because it efficiently uses the data, or a *minimum variance bound* estimator. But an unbiased estimator which attains that minimum variance bound does not, in general, always exist. However, under certain regularity conditions, the MLE is the only estimator that may uniquely achieve the CRLB [Ken1961].

(3) The efficient estimator must be a MVU estimator. However, an MVU estimator is not necessarily efficient.

(4) If an unbiased estimator has the CRLB as its variance, it must be a *sufficient statistic*[6] for the parameter. A sufficient statistic for a parameter captures all the possible

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[5] All *existing* information has been *extracted*.
[6] The variance of an *efficient* estimator is a *sufficient* statistic.

information, about the parameter, that is included in the data. See Appendix 5.B for a mathematical definition of the sufficient statistic.

(5) The FIM is considered as a quantification of the maximum available or existing information about the parameters included in the measurement data; see Appendix 5.C for the definition of information.

(6) The FIM is calculated at the actual parameters' values. Thus, it is possible to compute the CRLB for real situations only if the actual states are known. However, the CRLB can be used to assess estimators in simulation studies where the true values of the state parameters are known.

5.1.3.2 Derivation of the CRLB for MT Location Estimation

Substituting Equation (5.25) into Equation (5.35), we obtain the FIM as

$$\mathrm{FIM} = -E\begin{bmatrix} \dfrac{\partial^2 \ln p(o\,|\,s)}{\partial x^2} & \dfrac{\partial^2 \ln p(o\,|\,s)}{\partial x \partial y} \\ \dfrac{\partial^2 \ln p(o\,|\,s)}{\partial y \partial x} & \dfrac{\partial^2 \ln p(o\,|\,s)}{\partial y^2} \end{bmatrix} = \begin{bmatrix} \mathrm{p_x}^T \mathrm{C}_r \mathrm{p_x} & \mathrm{p_x}^T \mathrm{C}_r \mathrm{p_y} \\ \mathrm{p_y}^T \mathrm{C}_r \mathrm{p_x} & \mathrm{p_y}^T \mathrm{C}_r \mathrm{p_y} \end{bmatrix} \tag{5.44}$$

Where

$$\mathrm{C}_r = \mathrm{B}^T \cdot C_e^{-1} \cdot \mathrm{B} \tag{5.45}$$

$$\mathrm{p_x} = \frac{\partial \mathrm{P(s)}}{\partial x} \tag{5.46}$$

$$\mathrm{p_y} = \frac{\partial \mathrm{P(s)}}{\partial y} \tag{5.47}$$

The CRLB is the inverse of the FIM or

$$COV_{CRLB} = \frac{\begin{bmatrix} \mathrm{p_x}^T C_r \mathrm{p_x} & -\mathrm{p_x}^T C_r \mathrm{p_y} \\ -\mathrm{p_y}^T C_r \mathrm{p_x} & \mathrm{p_y}^T C_r \mathrm{p_y} \end{bmatrix}}{(\mathrm{p_x}^T C_r \mathrm{p_x})(\mathrm{p_y}^T C_r \mathrm{p_y}) - (\mathrm{p_x}^T C_r \mathrm{p_y})^2} \tag{5.48}$$

Assuming errors are i.i.d. (independent and identically distributed); the covariance matrix C_e can be written as

$$C_e = \sigma^2 \cdot \mathrm{I} \tag{5.49}$$

Inserting Expression (5.49) into Expression (5.45) we get

$$\mathrm{C}_r = \frac{\mathrm{B}}{\sigma^2} \tag{5.50}$$

Thus, Equations (5.44) and (5.48) are rewritten respectively as

$$\mathrm{FIM} = \frac{1}{\sigma^2} \begin{bmatrix} \mathrm{p_x}^T \cdot \mathrm{B} \cdot \mathrm{p_x} & \mathrm{p_x}^T \cdot \mathrm{B} \cdot \mathrm{p_y} \\ \mathrm{p_y}^T \cdot \mathrm{B} \cdot \mathrm{p_x} & \mathrm{p_y}^T \cdot \mathrm{B} \cdot \mathrm{p_y} \end{bmatrix} \tag{5.51}$$

$$COV_{CRLB} = \sigma^2 \frac{\begin{bmatrix} \mathrm{p_x}^T \cdot \mathrm{B} \cdot \mathrm{p_x} & -\mathrm{p_x}^T \cdot \mathrm{B} \cdot \mathrm{p_y} \\ -\mathrm{p_y}^T \cdot \mathrm{B} \cdot \mathrm{p_x} & \mathrm{p_y}^T \cdot \mathrm{B} \cdot \mathrm{p_y} \end{bmatrix}}{(\mathrm{p_x}^T \cdot \mathrm{B} \cdot \mathrm{p_x})(\mathrm{p_y}^T \cdot \mathrm{B} \cdot \mathrm{p_y}) - (\mathrm{p_x}^T \cdot \mathrm{B} \cdot \mathrm{p_y})^2} \tag{5.52}$$

Recalling Equations (5.6) and (5.7), $P_i(s)$ is expressed as

$$P_i(s) = EIRP_i - a_1 - a_2 \cdot \log d_i = EIRP_i - a_1 - \frac{a_2}{2} \cdot \log[(x_i - x)^2 + (y_i - y)^2] \tag{5.53}$$

Inserting (5.53) into Equations (5.46) and (5.47), we get[7]

[7] See Appendix 5.D for a detailed derivation.

$$(\mathrm{p_x})_i = -a_2 \cdot \log e \cdot \frac{x_i - x}{(x_i - x)^2 + (y_i - y)^2} \tag{5.54}$$

$$(\mathrm{p_y})_i = -a_2 \cdot \log e \cdot \frac{y_i - y}{(x_i - x)^2 + (y_i - y)^2} \tag{5.55}$$

Assuming $\sigma_s{}^2 = \sigma_x{}^2 + \sigma_y{}^2$ where $\sigma_s{}^2$ is the variance of the location estimator error, we finally get

$$\sigma_s{}^2 \geq Tr(COV_{CRLB}) \tag{5.56}$$

5.1.4 Other Bounds

The Cramér-Rao bound will not be tight if an efficient estimator does not exist. In such situations, the variance of the MVU estimator will be larger than the CRB. Therefore, it is interesting to investigate techniques that may tighten the CRLB. A natural approach would be to further analyze the situation using higher-order derivatives[8] of the likelihood function, assuming that they exist. This improvement can be obtained by the Bhattacharyya bound [Bha1946-48], [Tre1966], which do better lower bounds than the Cramér-Rao inequality. Bhattacharyya bound is straightforward but computationally tedious [Tre1968].

Another alternative to the CRB is the aforementioned Barankin bound [Bar1949]. It has two major advantages over the CRB. It does not require the probability density function to be continuous or to be differentiable everywhere, and it provides the greatest lower bound. However, the Barankin bound is obtained by maximization over a function and the approach for finding this maximum is usually not straightforward [Tre1968].

[8] The CRB only makes use of the first-order derivative of the likelihood function.

5.2 Posterior Cramér-Rao Bound

The position tracking algorithm is a nonlinear recursive filter. In order to asses its performance we have to compute the FIM recursively. The resulting lower bound is known as the posterior[9] Cramér-Rao lower bound (PCRLB) [Tre1968], [Tic1998], [Sim2001], [Ber2001]. Unlike the CRLB for the deterministic (non-random or constant) parameters[10] introduced in the previous section, the estimator is not required to be unbiased[11] in order to compute the PCRLB. The only requirement is that both sides of the Cramér-Rao inequality must exist. Also it is supposed that the state transition pdf exists and is twice differentiable w.r.t. both its arguments. Similarly, it is supposed that the measurement pdf exists and is twice differentiable w.r.t. the state at the desired time index.

Pre-1989 attempts to formulate the CRLB for continuous- and discrete-time nonlinear filtering is presented in [Ker1989]. The modern discrete-time nonlinear filtering key reference for the recursive calculation of FIM is [Tic1998]. The recursive computations of the PCRLB for the discrete-time nonlinear prediction and smoothing are derived in [Sim2001].

Theorem 5.2 (Posterior Cramér-Rao lower bound)
The posterior Cramér-Rao lower bound is the inverse of the recursively computed Fisher information matrix. The recursive computation is given as

$$FIM_{t+1} = (Q + E[F_t \cdot FIM_t^{-1} \cdot F_t^T])^{-1} + E[H_{t+1}^T \cdot R^{-1} \cdot H_{t+1}] \tag{5.57}$$

Where F_t is the Jacobian matrix of the state transition function $f(s_t)$ evaluated at the true values of the state s_t, H_{t+1} is the Jacobian matrix of the measurement function $h(s_{t+1})$ evaluated also at the true values of the state s_{t+1}, Q is the covariance matrix of the process noise, and R is the covariance matrix of the measurement error. Note that the expectation $E[\cdot]$ is taken over the whole number of Monte Carlo trials.

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9 Also called *Bayesian CRLB*, *global CRLB*, or *Van Trees bound*.
10 Can also be termed as *parametric CRLB*.
11 The PCRLB also holds for estimators of unknown bias provided that the prior pdf tends to zero at infinity.

Proof

See [Tic1998] for an elegant and simple derivation, [Sim1999], [Sim2001], or [Ber1999]. The key assumption of the derivation of the CRLB for the filtering nonlinear state estimation is to regard the whole state history as an unknown vector.

The state transition matrix of the position tracking algorithm at time t is defined as

$$f(s_t) = \begin{bmatrix} x_t + d_t \cdot \cos\phi_t \\ y_t + d_t \cdot \sin\phi_t \\ d_t \\ \phi_t \end{bmatrix} \tag{5.58}$$

Where x_t, y_t, d_t, and ϕ_t are the MT x, y coordinates, travelled distance, and orientation respectively, that build the state at time t. Therefore, F_t is written as

$$F_t = \frac{\partial f(s_t)}{\partial s_t} = \begin{bmatrix} 1 & 0 & \cos\phi_t & -d_t \cdot \sin\phi_t \\ 0 & 1 & \sin\phi_t & d_t \cdot \cos\phi_t \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{5.59}$$

The measurement function $h(s_{t+1})$ contains only the TA measurement from the main or serving BS, which roughly estimates the distance between the MT and the serving BS. The definition of $h(s_{t+1})$ is given as

$$h(s_{t+1}) = \left\lfloor \sqrt{(x_{t+1} - x_{t+1}^{BS})^2 + (y_{t+1} - y_{t+1}^{BS})^2} \right\rfloor = \left[D_{t+1}^{TA} \right] \tag{5.60}$$

Where x_{t+1}, y_{t+1}, x_{t+1}^{BS}, y_{t+1}^{BS}, and D_{t+1}^{TA} are the MT x, y coordinates, serving BS x, y coordinates, and the TA distance measurement of the serving BS all at time $t+1$. Therefore, H_{t+1} is written as

$$H_{t+1} = \frac{\partial h(s_{t+1})}{\partial s_{t+1}} = \begin{bmatrix} \dfrac{x_{t+1} - x_{t+1}^{BS}}{D_{t+1}^{TA}} & \dfrac{y_{t+1} - y_{t+1}^{BS}}{D_{t+1}^{TA}} & 0 & 0 \end{bmatrix} \tag{5.61}$$

The covariance matrix of the process error Q is given as

$$Q = \begin{bmatrix} \sigma_x^2 & 0 & 0 & 0 \\ 0 & \sigma_y^2 & 0 & 0 \\ 0 & 0 & \sigma_d^2 & 0 \\ 0 & 0 & 0 & \sigma_\phi^2 \end{bmatrix} \tag{5.62}$$

Where σ_x^2, σ_y^2, σ_d^2, and σ_ϕ^2 are the error variances of the MT x, y, and total translation, and orientation respectively. Note that $\sigma_d^2 = \sigma_x^2 + \sigma_y^2$.

The measurement noise R is calculated as

$$R = \left[\sigma_{D^{TA}}^2\right] \tag{5.63}$$

Where $\sigma_{D^{TA}} \approx 277$ m assuming a TA measurement error of $\frac{1}{2}$ bit.

APPENDICES

5.A Proof of the Equivalence of Expressions (5.27) and (5.28)

This appendix will prove that the right-hand side of the inequalities (5.27) and (5.28) are two equivalent forms of the Fisher information.

We begin with considering the identity

$$\int_{-\infty}^{\infty} p(o \mid s)do = 1 \tag{5.64}$$

The derivation of (5.64) w.r.t. s yields

$$\int_{-\infty}^{\infty} \frac{\partial p(o \mid s)}{\partial s} do = 0 \tag{5.65}$$

Utilizing the identity (5.38), Expression (5.65) can be rewritten as

$$\int_{-\infty}^{\infty} \frac{\partial \ln p(o \mid s)}{\partial s} p(o \mid s)do = 0 \tag{5.66}$$

Deriving (5.66) w.r.t. s yields

$$\int_{-\infty}^{\infty} \frac{\partial^2 \ln p(o \mid s)}{\partial s^2} p(o \mid s)do + \int_{-\infty}^{\infty} [\frac{\partial \ln p(o \mid s)}{\partial s}]^2 \, p(o \mid s)do = 0 \tag{5.67}$$

This completes the proof. That is, the Fisher information expression with the second partial derivative of the log-likelihood function is equivalent to the Fisher information expression with the square of the first partial derivative.

5.B Sufficient Statistic

Definition 5.5 (Sufficient Statistic)
A statistic $T(O)$ is sufficient for s precisely if the *conditional probability distribution* of the data O, given the statistic $T(O)$, is *independent* of the parameter s. This is expressed as

$$p(O = o \mid T(O) = t, s) = p(O = o \mid T(O) = t) \tag{5.68}$$

Or in concise form as

$$p(o \mid t, s) = p(o \mid t) \tag{5.69}$$

5.C Definition of Information

The two most popular definitions of information are Fisher information (FI) and Kullback-Leibler information (KLI) [Sch1995]. Fisher information is a measure of how much information, about a parameter in a parametric family, is included in a data set assuming some smoothness conditions.

Kullback-Leibler information measures in the sense of likelihood how far apart two distributions are. In other words, if a measurement was generated from one distribution, the KLI tells how likely that it was not produced by the other distribution. KLI does not need any smoothness conditions on the densities. Furthermore, it is not affected by parameterization changes and it can be used even if the considered distributions are not all members of a parametric family. In general, KLI is not a metric as well as the Kullback-Leibler divergence which fails the triangle inequality.

5.D Derivation of Expressions (5.54) and (5.55)

Considering Equation (5.53), Expression (5.46) is rewritten as

$$(\mathrm{p}_{\mathrm{x}})_i = \frac{\partial(EIRP_i - a_1 - \frac{a_2}{2}\cdot\log[(x_i - x)^2 + (y_i - y)^2])}{\partial x} \tag{5.70}$$

Recall that

$$\frac{\partial}{\partial x}\log_a u = \frac{1}{\ln a}\cdot\frac{1}{u}\cdot\frac{du}{dx} \tag{5.71}$$

Applying the rule in (5.71) to (5.70), we get

$$(\mathrm{p}_{\mathrm{x}})_i = \frac{a_2}{2}\cdot\frac{1}{\ln 10}\cdot\frac{1}{u}.\frac{du}{dx} \tag{5.72}$$

Where

$$u = (x_i - x)^2 + (y_i - y)^2 \tag{5.73}$$

But

$$\frac{du}{dx} = -2(x_i - x) \tag{5.74}$$

And

$$\ln 10 = \frac{1}{\log e} \tag{5.75}$$

Substituting (5.74) and (5.75) into (5.72) yields (5.54). Expression (5.55) can be analogously obtained by partial derivation of Equation (5.53) w.r.t. y .

Chapter 6

Performance Evaluation

Performance evaluation of the location estimation, position tracking, and global localization algorithms, introduced in chapter 4, is the topic of this chapter. Section 6.1 describes the setup of the experimental measurements conducted. Positioning accuracy of the *location estimation* algorithm in terms of the *root square error (RSE)*, and the *maximum achievable accuracy* as suggested by the *CRLB*, explained in section 5.1, for mapping resolutions of 5 m up to 50 m in 5 m steps are discussed in section 6.2. Section 6.3 presents the positioning accuracy of the *position tracking* algorithm in terms of *reliability* or *success rate* and *RSE*, and the *maximum achievable accuracy* as proposed by the *PCRLB*, described in section 5.2, for the 5 m database resolution. Performance evaluation of the *global localization* algorithm in terms of *reliability* for a database resolution of 5 m is given in section 6.4.

6.1 Experimental Setup

Measurements have been carried out in an E-Plus GSM 1800 MHz network by a pedestrian along a route of about 1940 m long in a 9 km^2 semi-urban environment in Hannover, Germany, see Figure 6.1. There were six BSs, each with three sectors, and four indoor antennas in the test area. RxLev measurements of the serving BSs and up to 6 neighbouring stations along with GPS position fixes for ground truth have been logged into a file for later offline evaluation. Furthermore, the GPS positions have been used to generate IMU pseudo measurements to simulate real ones in order to investigate the feasibility of real IMU employment. Experimental results are based on a single Network Measurement Report (NMR) at 172 data points made during active calls. Each NMR contains cell-IDs and signal strength levels of the serving BS antenna and up to 6 neighbour BS antennas, and TA of the serving BS. Signal strength levels from the serving BS recorded during active calls are those of the traffic channel which undergoes power management. However, the position tracking and global localization algorithms depend only on the TA measurements that correspond to the serving BS wireless coverage, which can be sufficiently determined offline, taking account of power management effects. Thus, both algorithms are not affected by power management operations. For the location estimation algorithm, the network operator would need to keep prediction information for all possible ranges of the power management scheme in order to avoid the decrease in accuracy performance.

Figure 6.1: Path of the GSM measurements generated by Google Earth.

6.2 Location Estimation Results

6.2.1 Positioning Accuracy

The positioning accuracy of the location estimation algorithm in terms of the *RSE* has been investigated for the three presented point estimators and using different mapping resolutions. Figures 6.2-6.4 show the mean, 67th percentile, and 95th percentile positioning error respectively, of the different point estimators with varying world model resolution.

It can be seen that WAE and TAE always outperform the MAP estimator. This is logical as both WAE and TAE consider more location candidates of the posterior belief and not only one candidate as the MAP estimator does. Because in the context of mobile terminal positioning using RxLev mapping, multi-modal posterior belief distributions are generated; MAP estimation will choose only one peak of the posteriors which is not a suitable estimation decision. On the contrary, WAE and TAE consider more than the one peak and thus can better represent the multi-modal property of the posterior distributions.

Figure 6.3 also shows that TAE outperforms WAE at the 67th percentile positioning error for all mapping resolution. This might be due to the fact that WAE represents the whole posterior belief distribution, while TAE considers only the upper areas of the posteriors, i.e., location candidates of higher weight. In Figure 6.2 we can see that the TAE mean positioning error outperforms that of WAE only up to the resolution of 25 m. For the 30 m and 35 m resolutions both TAE and WAE perform almost the same. Starting from the 40 m resolution, the TAE further slightly outperforms the WAE. However, this does not imply the superiority of TAE for all cases. In Figure 6.4 at the 95th percentile positioning error, the TAE is slightly better than the WAE up to the 10 m resolution. From the 15 m resolution the WAE starts to perform obviously better than the TAE.

The explanation is that for lower mapping resolution, considering only upper areas of the posterior belief distributions to calculate a point estimate, as the TAE, will not correctly keep the information represented by the posterior distributions, and thus considering the whole distribution area, as the WAE, is more representative.

In Figures 6.2, 6.3, and 6.4, TAE was calculated by averaging the best 10% weighted location candidates, i.e. $k = 0.1 * n$ in Equation (4.21). The explanation in the previous paragraph can be confirmed if we look at the results obtained when k is increased up to $0.9 * n$.

Figures 6.5 and 6.6 show that increasing the number of location candidates to average ($k = 0.2 * n$ - $0.5 * n$) for TAE with decreasing mapping resolution enhances the performance of TAE at the mean and 67th percentile errors and always outperforms the WAE. We can notice the same tendency in Figure 6.7. However, k had to be over $0.2 * n$ in order to outperform the WAE at the 95th percentile positioning error with decreasing mapping resolution.

In Figure 6.8 we can see that for lower resolutions, increasing k over $0.7 * n$ does not enhance the TAE mean positioning error anymore. TAE will even perform worse than WAE for k over $0.8 * n$. Also at 67th percentile positioning error in Figure 6.9 no TAE accuracy enhancement was achieved by increasing k. However, at the 95th percentile in Figure 6.10 TAE performed better till k reached $0.7 * n$.

From the previous discussion we can conclude that TAE performs better with lower resolution mapping, i.e., up to 15 m, when k is increased up to $0.5 * n$.

We can also generally notice that for all point estimation methods, there is no significant decrease in the positioning accuracy with decreasing mapping resolution. Therefore, it was interesting to calculate how the run time of the location estimation algorithm changes with varying mapping resolution. Figure 6.11 depicts the average computation time needed for a single iteration on a standard PC with 2.2 GHz processor. At the 5 m resolution the execution time was only 23 msec. Computation time then drops down exponentially to under 3 msec as the mapping resolution decreases. However, execution time is linearly proportional to the number of location candidates.

These results can even suggest providing *mobile-based* implementation for the location estimation algorithm, which will supply customers with position information for low accuracy applications at very low costs. World models can initially be installed in the mobile terminals and updated as needed.

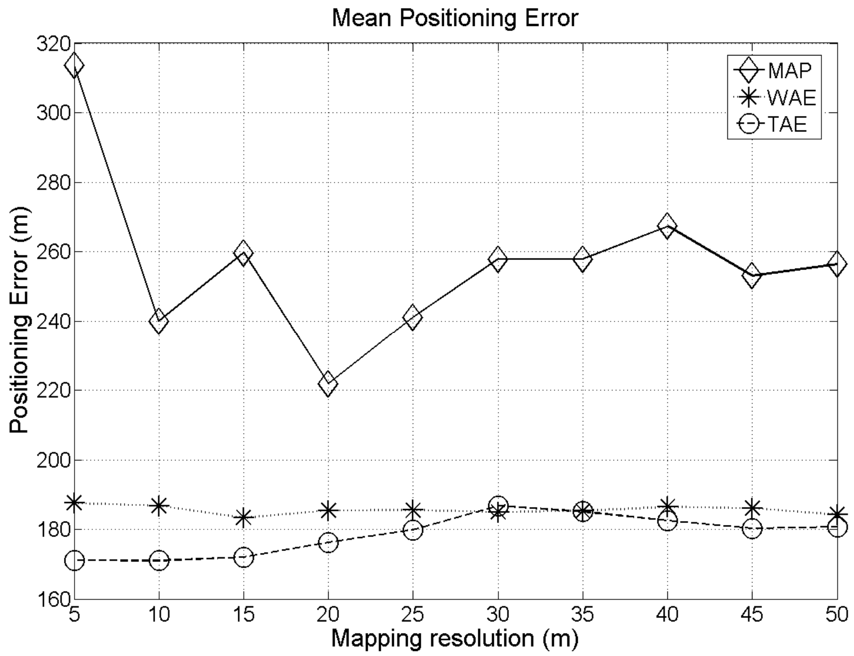

Figure 6.2: Mean positioning error of the location estimation algorithm at different mapping resolutions.

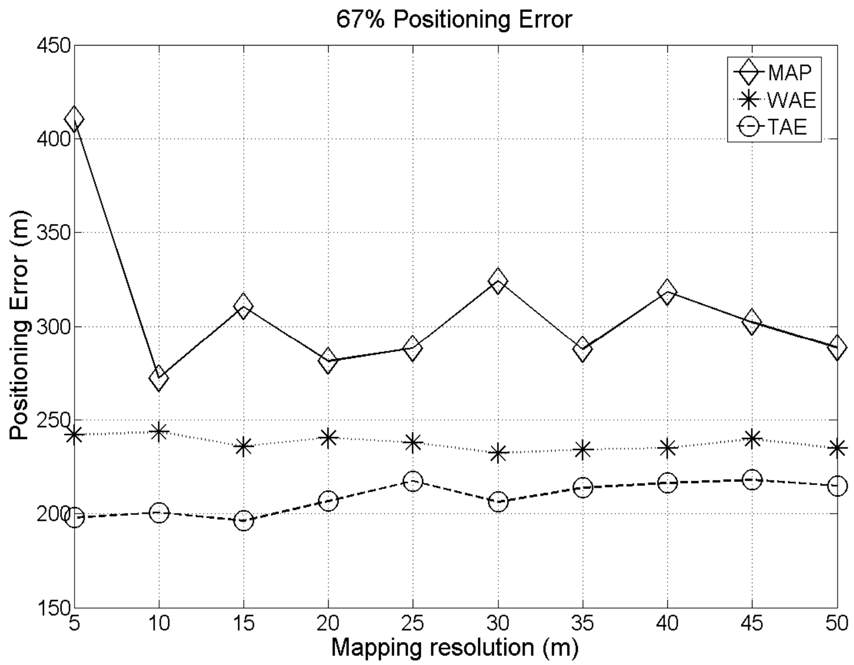

Figure 6.3: 67th percentile positioning error of the location estimation algorithm at different mapping resolutions.

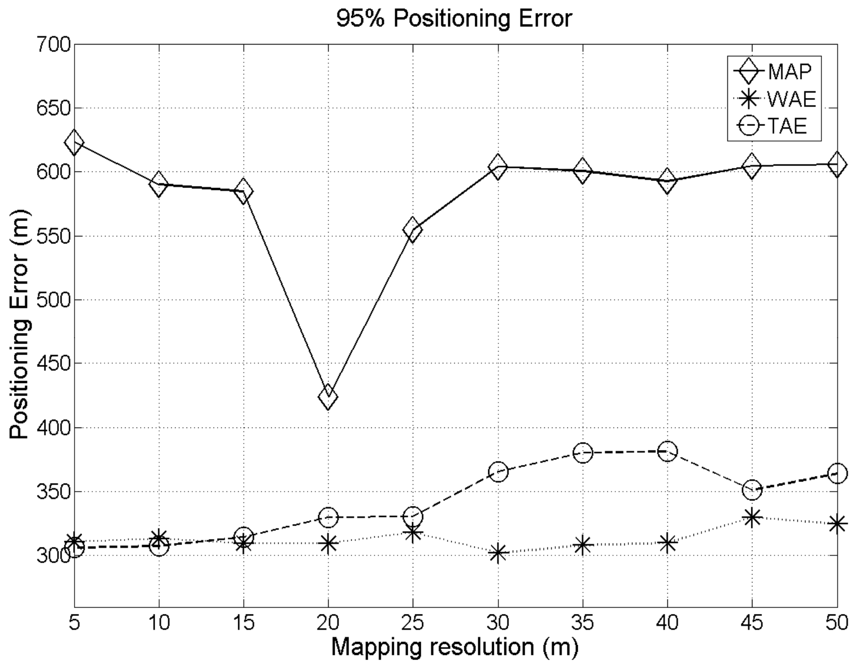

Figure 6.4: 95th percentile positioning error of the location estimation algorithm at different mapping resolutions.

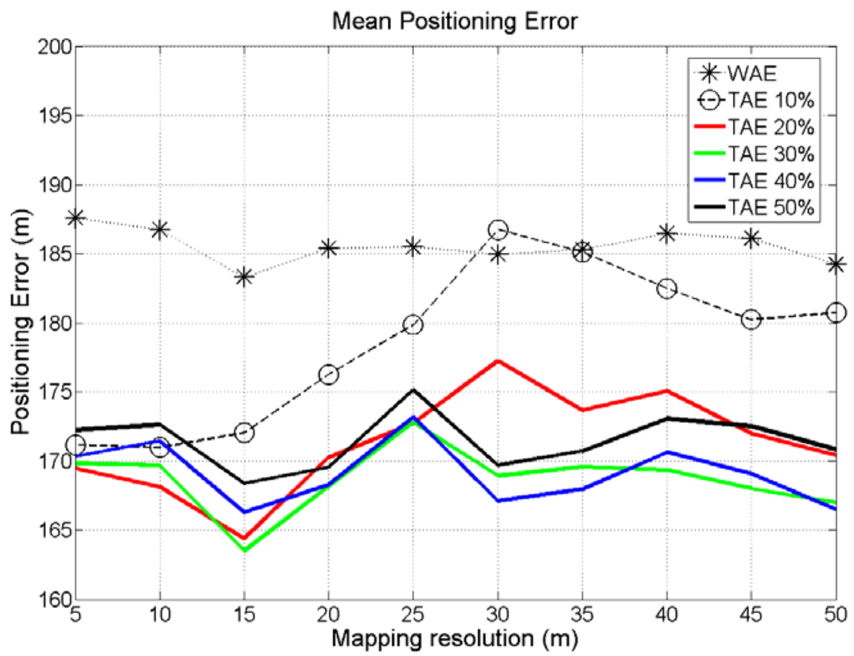

Figure 6.5: Mean positioning error of the location estimation algorithm using WAE and TAE, $(k = 0.1 * n - 0.5 * n)$.

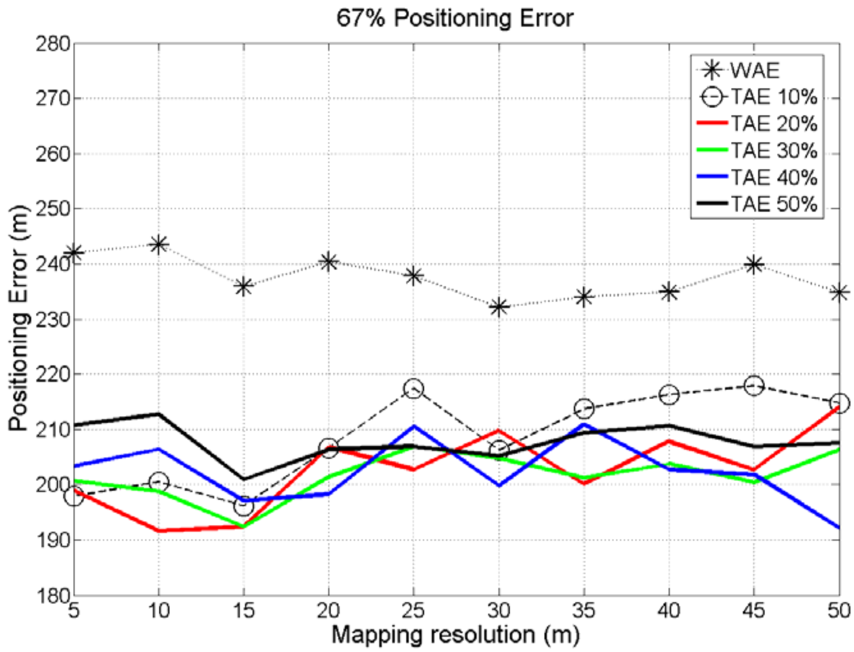

Figure 6.6: 67th percentile positioning error of the location estimation algorithm using WAE and TAE, ($k = 0.1*n - 0.5*n$).

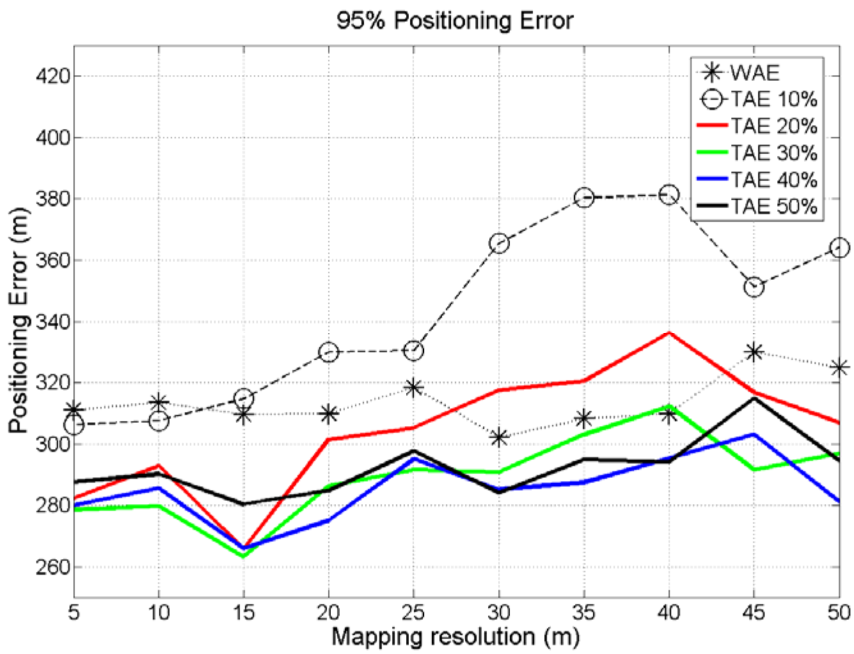

Figure 6.7: 95th percentile positioning error of the location estimation algorithm using WAE and TAE, ($k = 0.1*n - 0.5*n$).

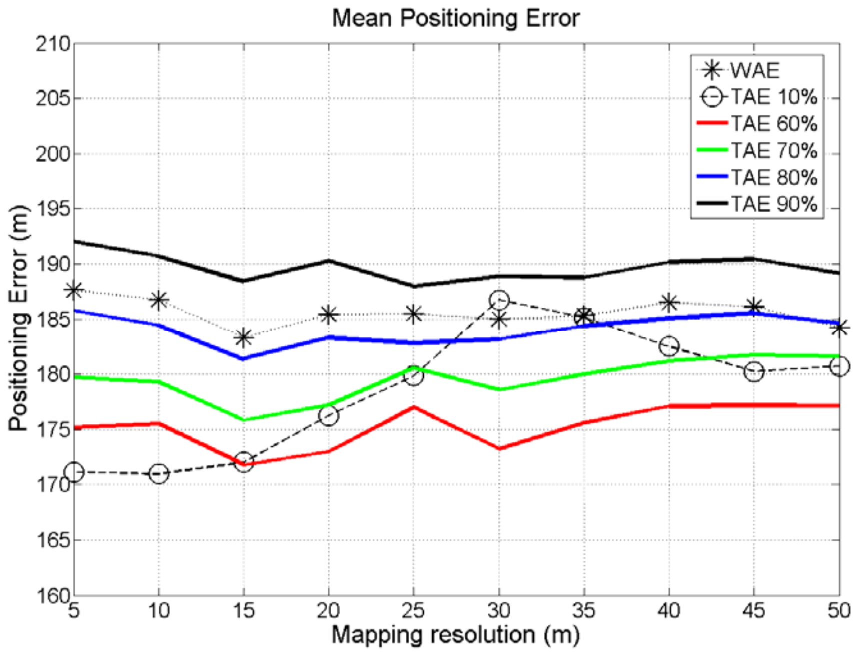

Figure 6.8: Mean positioning error of the location estimation algorithm using WAE and TAE, ($k = 0.6*n - 0.9*n$).

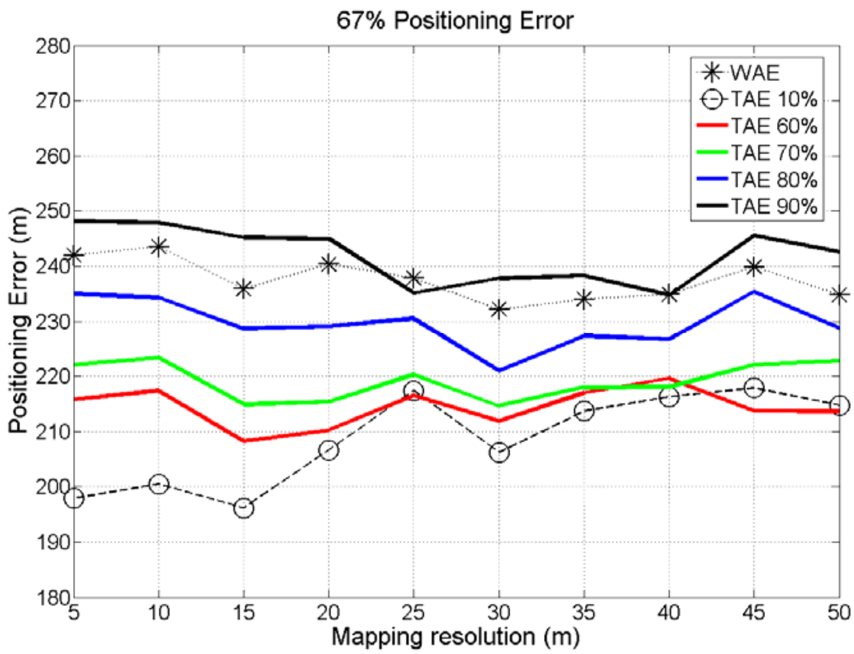

Figure 6.9: 67^{th} percentile positioning error of the location estimation algorithm using WAE and TAE, ($k = 0.6*n - 0.9*n$).

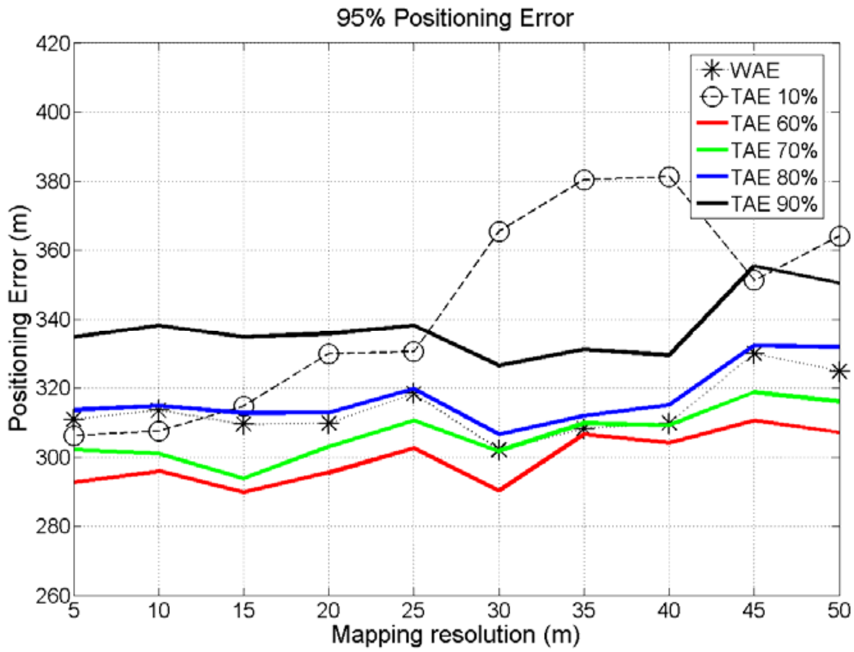

Figure 6.10: 95th percentile positioning error of the location estimation algorithm using WAE and TAE, ($k = 0.6 * n - 0.9 * n$).

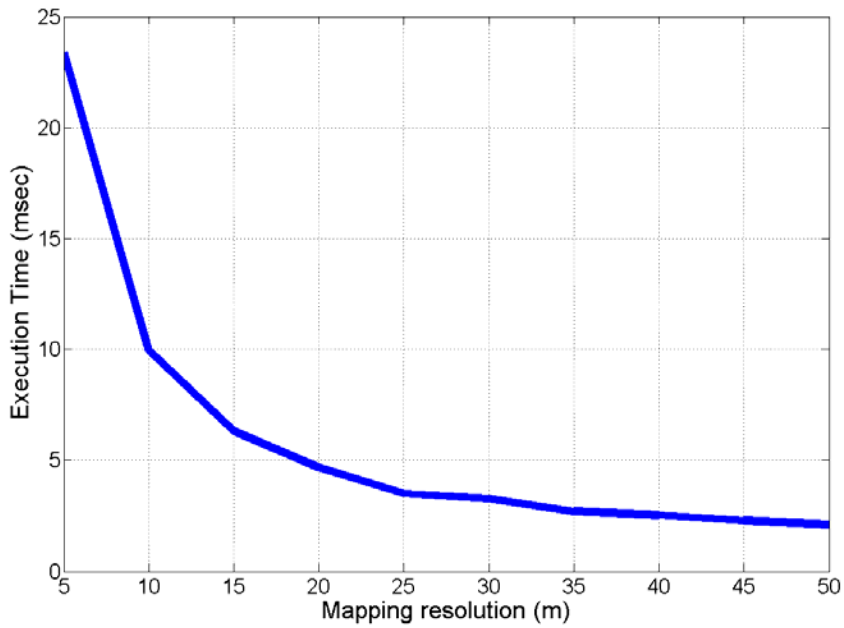

Figure 6.11: The average execution time needed for a single iteration of the location estimation algorithm using different mapping resolutions on a standard PC with 2.2 GHz processor.

6.2.2 CRLB

The CRLB depends mainly on the following factors [Wei2003], [Zhu2006]:

(1) BS geometry and the number of involved BSs. Ill-conditioned BS-MT layouts, e.g., insufficient number of BSs, and colinearity or coplanarity conditions [Qi2005] may cause the CRLB to suggest in some situations that the positioning error variance is infinite. Ideal BS configurations, e.g., all BSs are evenly distributed, are usually assumed when calculating the CRLB in simulation-based scenarios [Wei2003], [Zhu2006].

(2) BS separation distance and cell size. Increasing separation distances and cell sizes contribute to the generation of less accurate position estimates. Thus, FCC requirements could not always be fulfilled.

(3) Variance of the measurement error. Large variance leads to lower positioning accuracy.

(4) Number of measurement reports. Using more measurement reports in a single position estimation increases the accuracy. However, after exceeding a certain number of measurement reports, e.g., 10 reports, no noticeable improvement in the positioning accuracy could be achieved [Zhu2006]. Note that in real life using many measurement reports for position estimation is valid only for the stationary case. For moving MTs, generally one measurement report is available at each position.

(5) Measurement correlation. Correlated measurements reduce the amount of information included in all measurements. Usually for CRLB computation, measurements are assumed to be uncorrelated.

(6) Path loss exponent. High values indicate higher RSS signature uniqueness leading to less position estimation errors.

Due to the variance of measurement error assumed and the linear regression treatment (see section 5.1), the CRLB yields, in many cases, infinite positioning error variance because of the rank deficiency of the FIM. The employment of simple mapping functions that ignore useful information available in cellular networks which helps to enhance the positioning accuracy, e.g., TA (timing advance), cell identity of sector antennas, also contributes to the rank deficiency problem of the FIM. Such information is very complex or infeasible to model. Also knowledge about cell size and coverage could not be easily modelled for the CRLB computation. To overcome the problem one should consider only situations that certainly contribute to the CRLB calculation. In theses situations, the maximum error variance as given by the CRLB should not exceed certain constraints such as maximum cell size, sector information, and range information included in TA measurements. Moreover, reducing the assumed variance of measurement error helps in avoiding rank deficiency problems when calculating the CRLB.

Considering the above discussion, the CRLB could only be computed for 110 sample locations out of the total 172 data points. All computations are based on a single measurement report at each location sample, which is the case for moving MTs. Figure 6.12 illustrates the computed CRLB, MLE using the original 3D DB, and MLE using the reconstructed COST-Hata DB. It can be seen that the Cramér-Rao inequality holds except at lower cumulative distribution function (CDF) values (under 23% of all cases)[1]. The CRLB suggests that the 67th and 95th percentile positioning errors can not be better than 183 and 480 m respectively. Figure 6.12 also shows that the COST-Hata DB MLE performs slightly better than the 3D DB MLE at CDF values between 23% and 83%. Otherwise both achieve almost similar accuracy, which implies that the assumed empirical formula adequately characterizes the underlying wireless environment. The 67th and 95th percentile positioning errors of both MLEs are 292, 671 m, and 359, 667 m respectively.

Estimators that achieve or reach the CRLB are often referred to as *efficient* estimators. If an efficient estimator exists it will be a MLE. Suboptimal estimators that stay in the vicinity of the CRLB imply that these estimators are performing quite well. They can be called *subefficient* estimators. Staying away from the CRLB does not necessarily imply that the estimator under investigation is weak, because for the underlying estimation problem, an efficient or a subefficient estimator might not exist at all [Tre1968].

If the performance of an estimator falls below the CRLB, then such an estimator is referred to as *superefficient* estimator [Sto1996] w.r.t. the MLE,. The superefficiency stems from the fact that such estimators have a strictly lower asymptotic variance and

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[1] See the remark at the end of section 4.3.1.

therefore are statistically more efficient than efficient and subefficient estimators. Superefficient estimators are naturally *biased* estimators. Statistics provides two different implications for the expression *bias*. The bad implication refers to some undesired characteristic, and the good one refers to providing more useful and closer to the truth results, which could not be obtained while insisting on being unbiased.

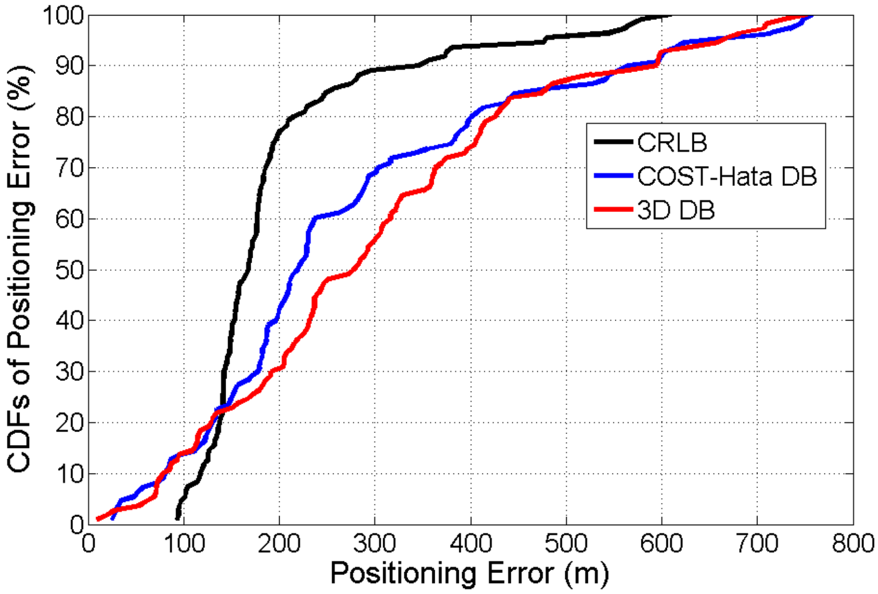

Figure 6.12: Positioning performance comparison of the Cramér-Rao lower bound (CRLB) and the maximum likelihood estimator (MLE) using both the original 3D and the reconstructed COST-Hata databases.

In Figure 6.13 we can see that both the WAE and TAE have similar performance. They perform clearly better than the MLE due to their bias that reduced the loss of information contained in the measurements. The WAE and the TAE perform better than the CRLB, i.e. superefficient, only at the 95th percentile positioning error. Figures 6.14 – 6.16 summarize the comparative performance of the CRLB, MLE, WAE, and TAE of the mean, 67%, and 95% positioning error respectively for mapping resolutions of 5 m up to 50 m. The superefficiency of WAE and TAE can be seen in the majority of cases of the mean positioning error of Figure 6.14 and in all cases of the 95th percentile positioning error in Figure 6.16. However, none of them could reach below the CRLB at the 67th percentile positioning error as seen in Figure 6.15. It is also shown in Figures 6.14 – 6.16 that the CRLB is almost the same irrespective of the mapping resolution, which means that no enhancement in the positioning accuracy could be obtained by varying the mapping resolution in the range between 5 m and 50 m. Also the performance of the MLE is always far away from the computed CRLB.

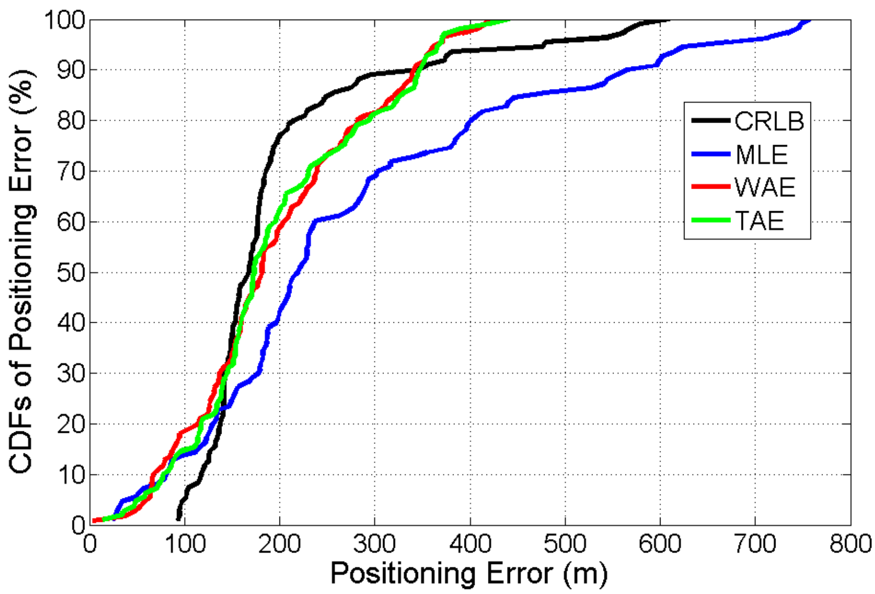

Figure 6.13: Positioning performance comparison of the Cramér-Rao lower bound (CRLB), the maximum likelihood estimator (MLE), the weighted average estimator (WAE), and the trimmed average estimator (TAE) using the reconstructed COST-Hata database.

Figure 6.14: Mean positioning error of the Cramér-Rao lower bound (CRLB), the maximum likelihood estimator (MLE), the weighted average estimator (WAE), and the trimmed average estimator (TAE) using the reconstructed COST-Hata database at different mapping resolutions.

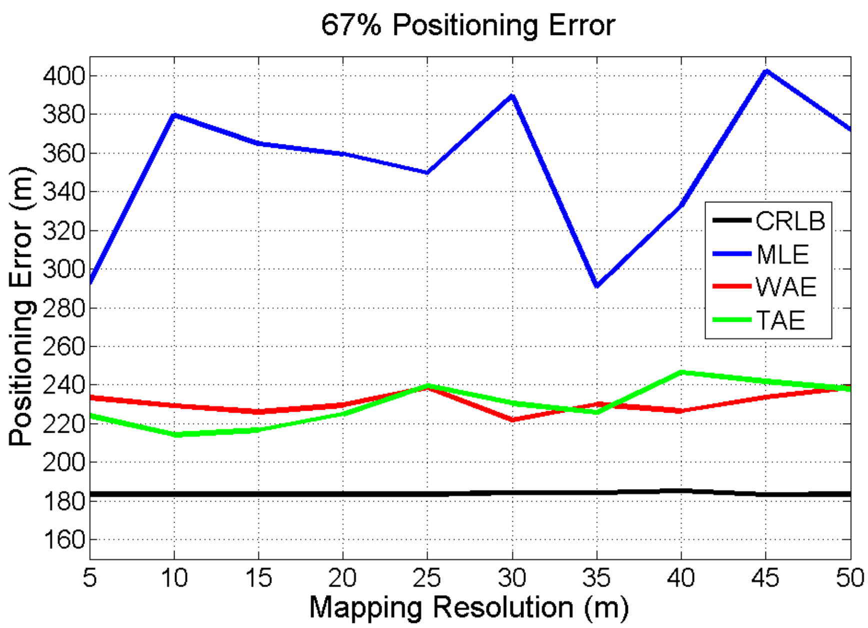

Figure 6.15: 67th percentile positioning errors of the Cramér-Rao lower bound (CRLB), the maximum likelihood estimator (MLE), the weighted average estimator (WAE), and the trimmed average estimator (TAE), using the reconstructed COST-Hata database at different mapping resolutions.

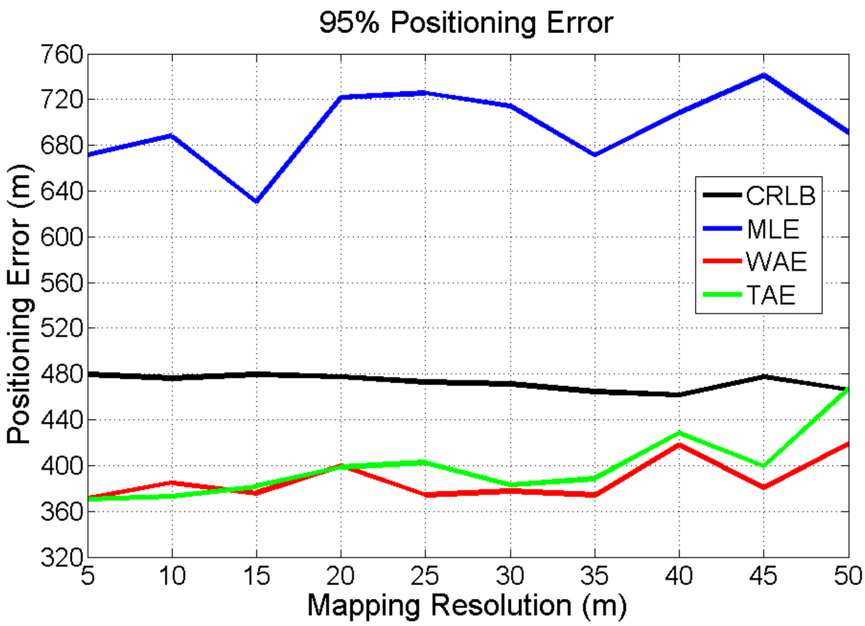

Figure 6.16: 95th percentile positioning errors of the Cramér-Rao lower bound (CRLB), the maximum likelihood estimator (MLE), the weighted average estimator (WAE), and the trimmed average estimator (TAE), using the reconstructed COST-Hata database at different mapping resolutions.

6.3 Position Tracking Results

6.3.1 Positioning Accuracy

Within position tracking experiments the initial location of the MT is known. We have investigated the performance of the tracking algorithm by varying the standard deviation of the translation measurement error (σ_{trans}) from 1% to 10% of the performed translation and the standard deviation of orientation measurement error (σ_{orient}) between 1° and 6°. The performance is evaluated in terms of *reliability* or *success rate* and the *RSE* in meters. We consider the MT position is reliably or successfully tracked if the final position estimation error over the whole experiment route of 1940 m is not greater than 50 m. All experiments have been repeated 100 times in order to get reasonable results. It can be seen in Figure 6.17, as expected, that the higher the σ_{trans} and/or the σ_{orient} are, the lower the reliability of the tracking algorithm along the test route. However, for σ_{trans} up to 4% and σ_{orient} up to 2°, reliability is over

90% of all repeats. With σ_{orient} up to 2° and σ_{trans} up to 10%, slightly less than 70% of the cases are successfully tracked. When σ_{orient} is increased up to 5°, reliability is at least about 60% of all repeats even with the worst case of σ_{trans}. For σ_{orient} equals 6°, the reliability drops below 60% as σ_{trans} is over 4%. Note that almost all algorithm failures are because of the underlying non-smoothed world model (maps). These utilized maps contain many location gaps and discontinuities that prohibit successful tracking.

Figure 6.18 shows that the mean positioning error for the different cases is between 15 m and 20 m. This is accurate enough for most positioning applications and confirms the suitability of IMU employment for reliable position tracking. The 67th percentile positioning error is always less than 20 m for all cases as illustrated in Figure 6.19. Figure 6.20 depicts the 95th percentile position tracking error which is almost always between 52 m and 56 m and less than 62 m in the worst cases.

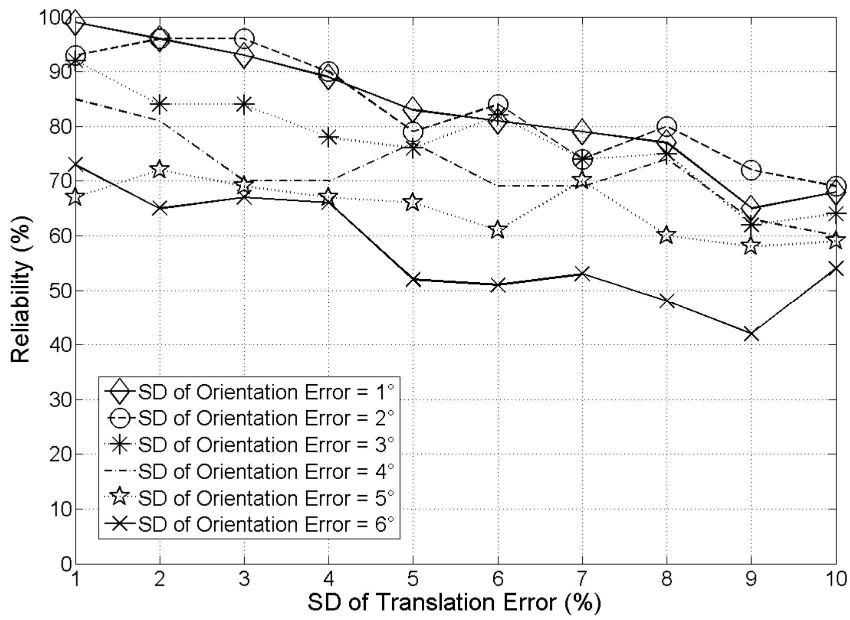

Figure 6.17: Reliability of position tracking with varying standard deviation (SD) of IMU translation and orientation.

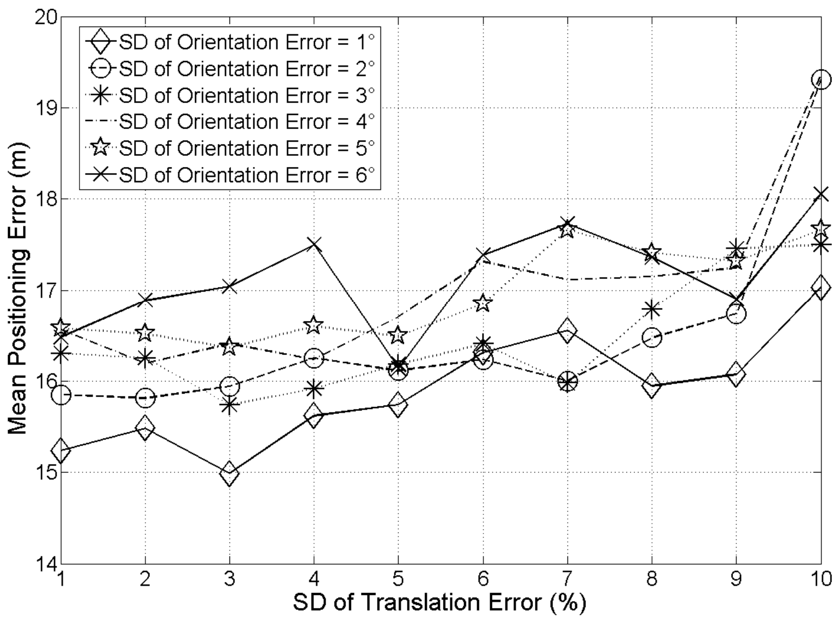

Figure 6.18: Mean position tracking error.

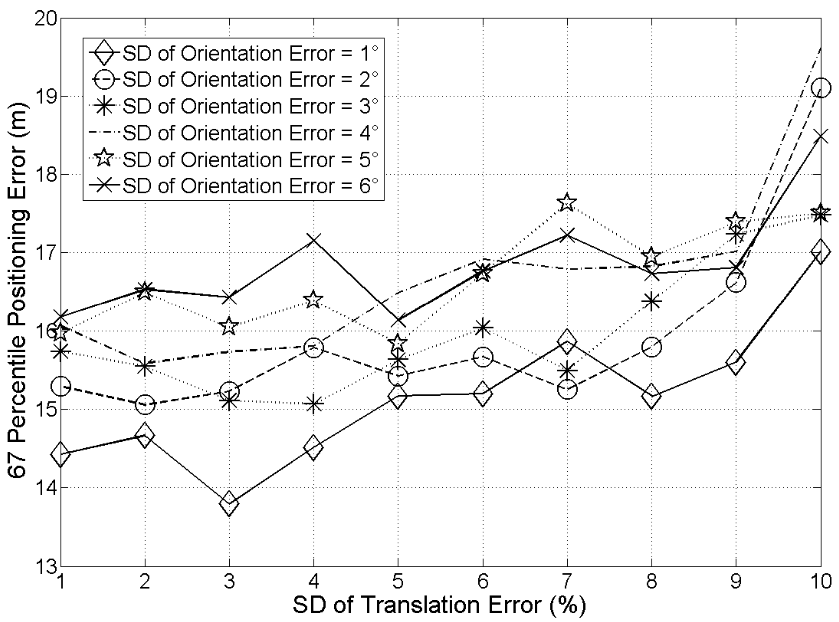

Figure 6.19: 67th percentile position tracking error.

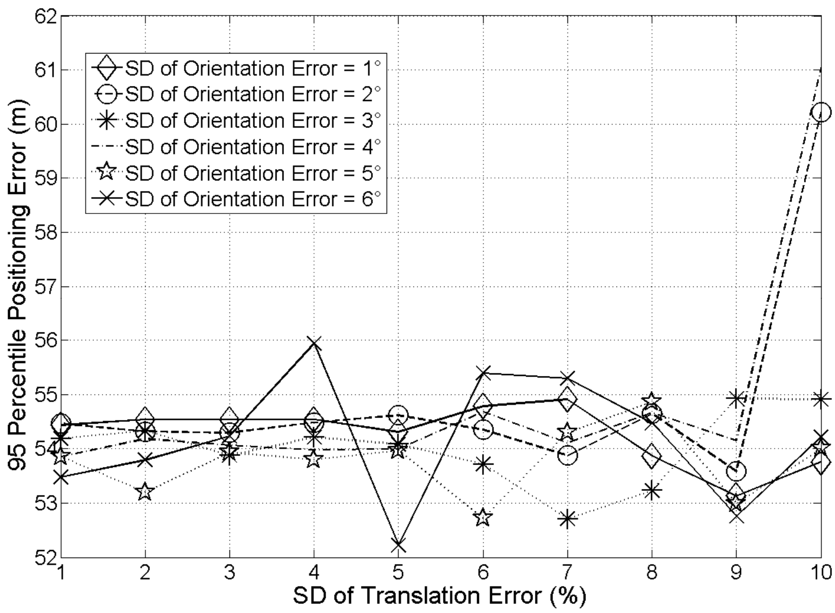

Figure 6.20: 95th percentile position tracking error.

6.3.2 PCRLB

The posterior Cramér-Rao lower bound (PCRLB) has been computed for all cases of σ_{trans} and σ_{orient}. The mean positioning error suggested by the PCRLB illustrated in Figure 6.21 is always less than 10 m for all values of σ_{trans} and σ_{orient} up to 4°. For values of σ_{orient} greater than 4°, the PCRLB is always less than 12 m. The mean positioning error of the position tracking algorithm is always in the vicinity of the PCRLB and is never more than 10 m away. Similar behaviour can be seen for the 67th and 95th percentile positioning errors depicted in Figure 6.22 and Figure 6.23 respectively. The 67th percentile positioning error of the PCRLB is almost always less than 8 m, and the 67th percentile positioning error of the position tracking algorithm stays in the vicinity of the PCRLB and is always less than 20 m. For the 95th percentile positioning error, the PCRLB is always less than 20 m and the accuracy of the position tracking algorithm is almost always less than 60 m. The similar performance of the PCRLB in all cases is due to the 5 m mapping resolution, which damps the differences of the produced positioning errors within the ranges assumed for σ_{trans} and σ_{orient}.

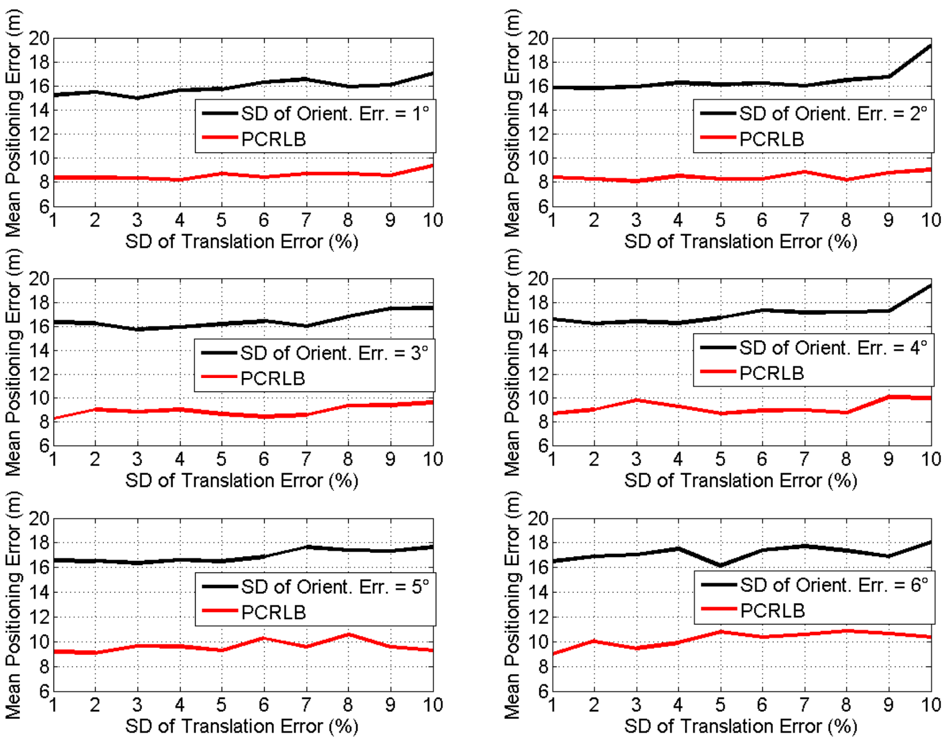

Figure 6.21: Mean positioning errors of the posterior Cramér-Rao lower bound (PCRLB) and the position tracking algorithm.

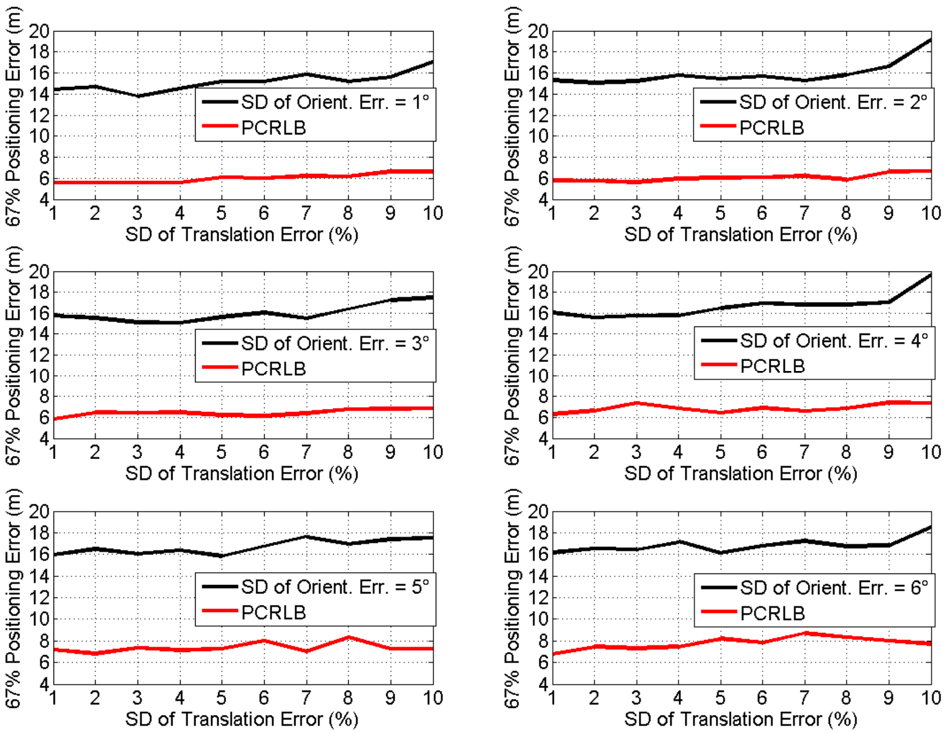

Figure 6.22: 67^{th} percentile positioning errors of the posterior Cramér-Rao lower bound (PCRLB) and the position tracking algorithm.

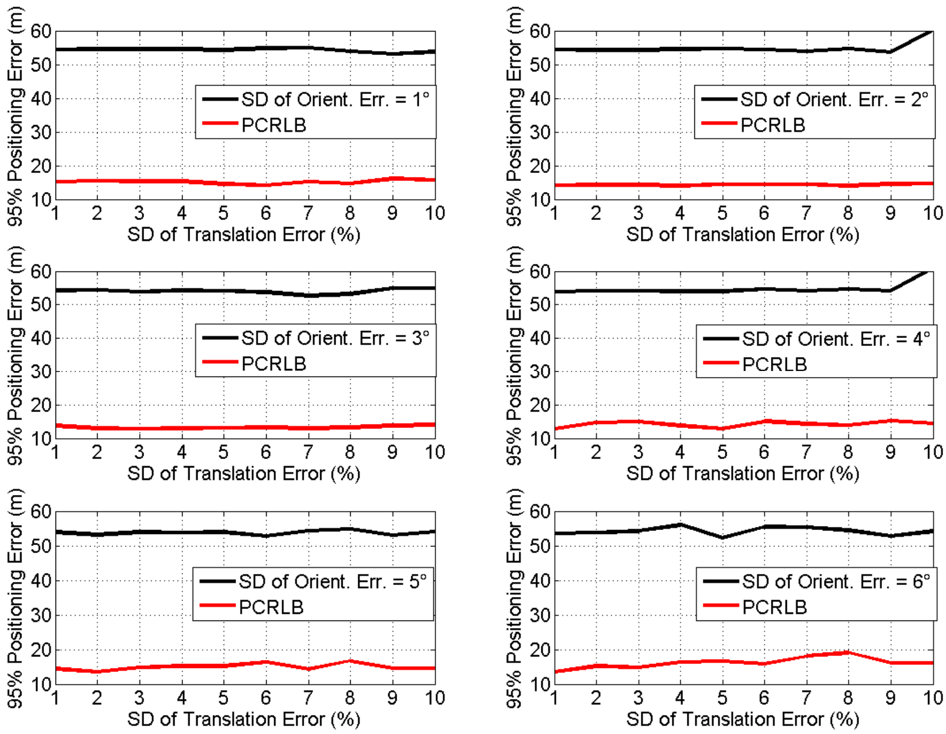

Figure 6.23: 95th percentile positioning errors of the posterior Cramér-Rao lower bound (PCRLB) and the position tracking algorithm.

6.4 Global Localization Results

In the global localization experiments, the *reliability* for the different values of σ_{trans} and σ_{orient} has been investigated. Global localization is considered reliable, i.e., successful, if the MT position estimation error just before switching to the position tracking mode (line 30 in TABLE 4.5) is not greater than 50 m in order to allow reliable position tracking as well. As shown in Figure 6.24, the global localization reliability is over 80% and 65% for σ_{orient} up to 3° and 6° respectively. The effect of σ_{trans} on the results is almost not significant, because of the 5 m map resolution that makes the update step insensitive to the range of translation errors assumed. Moreover, there is a slight tendency to increase the reliability of global localization with increasing σ_{trans} especially when σ_{orient} also increases, which seams counter intuitive. However, the fact is that large errors caused by high σ_{orient} values are compensated by increasing σ_{trans} and the given map resolution that prevents quick deviation from the true path. As was the case with position tracking, the non-smoothness or location discontinuities of the utilized maps played a significant role in reducing the success rate of the global localization algorithm.

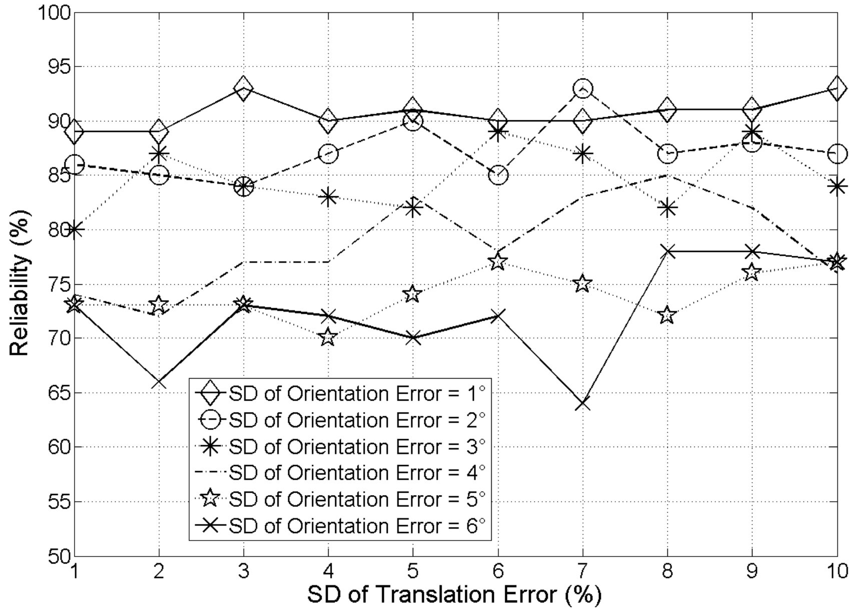

Figure 6.24: Reliability of global localization with varying standard deviation (SD) of IMU translation and orientation.

Chapter 7

Conclusions and Outlook

This thesis laid a theoretical foundation for using diverse sources of measurements and information to determine the position of a mobile terminal (MT) within wireless environments, based on the Bayesian filtering equation. Position information about mobile users is a fundamental element of any location-based service (LBS). The developed algorithms are widely applicable approaches that are neither restricted to any type of environment nor are tied to any particular technology. Research results were published in two journal and seven conference/workshop/symposium papers. The following five paragraphs are summarized answers to the five research questions formulated in section 1.3.

(1) A positioning algorithm based on the Bayesian filtering formulation has many attractive properties. Firstly, it is very fast and simple. Secondly, it is to a large extent modular. That is, when changing the problem one need only change the expressions for the prediction and update phases in the code. This enables the efficient employment and integration of further measurement data. Finally it provides a complete description of the posterior distribution not just a single point estimate.

(2) The mobile terminal positioning problem was first classified into three types according to the availability of (1) prior knowledge about the accurate initial position of the MT and (2) motion measurement data. When both sources of information are not available, the problem is termed *location estimation*. If both sources are available, the problem is known as *position tracking*. When only motion measurement data can be

obtained, the problem is referred to as *global localization*. These algorithms can be implemented either as *mobile-assisted network-based* or as *network-assisted mobile-based* to ensure security and privacy. Definitions of the last two problems, i.e. position tracking and global localization, follows the terminology used within the robotic research community.

(3) The wireless world model utilized and the preprocessing steps applied to it have been described. The locations that are served by every cell antenna in the experimental area were determined and grouped in separate databases according to all possible TA values and different land features.

(4) The measures needed in order to compute the Cramér-Rao lower bound (CRLB) for the location estimation algorithm have been discussed. The key approach was to parameterize the RSS-location mapping function by reconstructing the fingerprinting database using an empirical path loss formula that sufficiently characterizes the wireless propagation environment of the test area. Thus, the RSS-location mapping function became continuous and differentiable everywhere as required by the Cramér-Rao bound calculations.

(5) Experiments showed that mapping resolutions varied between 5 m to 50 m have almost no impact on the accuracy of the location estimation algorithm. Experimental results in a live GSM network deployed in a semi-urban environment showed that the FCC accuracy requirements for the location estimation case could not be achieved, also when using different mapping resolutions, except in only few cases at the 95th percentile positioning error, i.e. 300 m for the network-based solution. This has also been confirmed by the Cramér-Rao lower bound analysis. However, the execution time required for a single position calculation is pretty low.

In some cases, rank deficiency problems of the FIM cause the CRLB to suggest infinite positioning error variance. Therefore, calculations should consider non-modelled useful information and a proper choice of the RSS measurement error variance. Superefficiency, i.e. reaching below the CRLB, at the 95th percentile positioning error was observed for two *biased* estimators, namely the weighted average estimator (WAE) and the trimmed average estimator (TAE).

Performance analysis of the position tracking filter showed that a reliable and accurate MT positioning, compared to GPS, can be obtained and maintained by incorporating data from a simulated inertial measurement unit (IMU). Information obtained from an IMU allows further positioning with the help of suitable maps even if the contact to the wireless communication network is interrupted. The positioning error has always been in the vicinity of the posterior CRLB.

The absence of any prior knowledge, i.e. total ignorance, about the initial position of the mobile terminal was overcome by the global localization filter. The efficiency of the filter has been confirmed by its good success rate (convergence property).

Positioning methods within next generation mobile networks will be different from the classic ones, in order to utilize global navigation satellite systems, use different system measurements, e.g. WLAN, GSM, and UMTS, fuse IMU data which can be integrated in user terminals, and benefit from further sources of information. However, reliable positioning is only a single element of any successful LBS. Other elements that have to be considered are not always technical, but also social and ethical ones which may sometimes prove to be more challenging.

A modern positioning system has to prove a seamless behaviour in, e.g. outdoor/indoor transitions, and to have mechanisms for early detection of faults and failures in order to easily counteract and handle them. This can be partially achieved by an integrated IMU combined with a suitable map. Also a vision sensor can still provide and extract valuable information. A significant landmark offers so much more information than just the relative position to the MT. It gives strong evidence about the location. A speech input/output system can increase the interaction with the positioning algorithm. This speech system could decrease the time required to input instructions or useful restrictions. Thus, increasing the accuracy and decreasing the time needed to output a location estimate.

An objective performance comparison of different positioning algorithms and systems requires a standardized test environment (or benchmark), which is still not existed. It is only by building and testing real world systems that make new problems and issues arise, which in turn require research efforts to tackle. Another important point that should be taken into consideration is the need for really long term experiments in as many different environments as possible. The length of tests should be measured in days and weeks and not hours.

Developing theoretical performance bounds, taking false measurements or missed detections and different environment restrictions into account, is an interesting topic that needs more research efforts.

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