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**Radio Propagation Channel Modeling
for Mobile-to-Mobile Communications**

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Sciences and technology

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Dedication

To my beloved family

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Abstract

Mobile-to-Mobile (M2M) communication is a challenge, but fast growing since it has the potential to enhance the quality of data service with low energy consumption. This dual mobility generates non-stationary properties of the propagation channel, which requires precise modeling, for simulation network and system design.

This thesis aims for characterization and modeling M2M channels based on stochastic approaches. Some common M2M aspects like the non-stationarity and Doppler effects were also analyzed. In particular, we focus on examining the Body to Body (B2B) channels and the Vehicle to Pedestrian (V2P) channels based on measurements.

Therefore, a non-geometry based stochastic channel model (non-GSCM) was proposed for the measured channel transfer function of the B2B channels considering the antenna on-body position, i.e. head, belt and wrist, under the line of sight (LoS) and non line of sight (NLoS) conditions. The non-stationarity of the B2B channels was observed in function of the mutual body orientation and the relative Tx-Rx distance.

A GSCM was developed for the V2P Time-Varying Channel Impulse Response (TVCIR) considering the environment under investigation. Three propagation environments were measured: LoS, obstructed LoS by neighboring vehicles where the pedestrian was walking behind parked vehicles and the NLoS/LoS where the V2P link passes through three stages, i.e. the direct path blocked by wall separating terminals, a transition from NLoS to LoS and the

LoS situation. While the obstructed LoS scenarios can degrade the received signal power, the NLoS/LoS scenarios mostly occur in the safety critical scenarios such as crossing street intersections. The non-stationarity fading behavior were also observed here for the NLoS/LoS scenarios.

A general model for the auto-correlation fading (ACF) of the fading channel was derived assuming a typical M2M propagation scenario in the presence of moving scatterers. This model can well represent the ACFs of V2P and indoor M2M scenarios. Similarly, an analytical Doppler spectrum model for indoor M2M scenarios was developed and it allows to reproduce with good accuracy the Doppler properties of different indoor scenarios including LoS and NLoS environments. Finally, implementation techniques able to reproduce the fading characteristics of M2M channels including the Doppler characteristics were proposed and successfully compared to the measurement data.

Keywords: Mobile to Mobile, Channel model, Channel sounding, Stochastic channel model, Non stationary channels.

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List of acronyms

AIC	Akaike Information Criterion
AOA	Angle of Arrival
AOD	Angle of Departure
ACF	Auto-Correlation Function
AR	Auto-regressive
BS	Base Station
BAN	Body Area Network
B2B	Body to Body
CIR	Channel Impulse Response
CDF	Cumulative Distribution Function
CW	Continuous Wave
DSRC	Dedicated Short Range Communication
D2D	Device to Device
DPSS	Discrete Prolate Spheroidal (Slepian) Sequences
EM	Electromagnetic
FCC	Federal Communications Commission
F2F	Fixed to Fixed
F2M	Fixed to Mobile
FT	Fourier Transform
GSCM	Geometry based Stochastic Channel Model
GPS	Global Positioning System
IR	Impulse Response
IDFT	Inverse Discrete Fourier Transform
IFS	Isotropic Fixed Scatterers
IMS	Isotropic Moving Scatterers
I2I	Indoor to Indoor
I2O	Indoor to Outdoor
ISM	Industrial, Scientific and Medicals

ITS	Intelligent Transportation Systems
KS	Kolmogorov-Smirnov
KD	Kullback Divergence
LoS	Line of Sight
LSF	Local Scattering Function
MSE	Mean-Square-Error
MMSE	Minimum Mean-Square-Error
M2M	Mobile to Mobile
MPCs	Multi-path Components
MIMO	Multiple Input Multiple Output
non-GSCM	Non Geometry based Stochastic Channel Model
NIFS	Non-Isotropic Fixed scatterers
NIMS	Non-Isotropic Moving Scatterers
NLoS	Non Line of Sight
O2I	Outdoor to Indoor
O2O	Outdoor to Outdoor
PAC	Partial Auto-Correlation Function
PDP	Power Delay Profile
PSD	Power Spectral Density
pdf	Probability Density Function
PL	Path Loss
P2P	Pedestrian to Pedestrian
PIFA	Printed Planar Inverted-F Antenna
Rx	Receiver
RMS	Root Mean Square
RMSE	Root Mean Square Error
S11	Reflection Coefficients
SOTA	State-Of-The-Art
S21	Transmission Coefficients
TDL	Tapped Delay Line
TVCIR	Time Varying Channel Impulse Response
Tx	Transmitter
2D	Two Dimensional
UHF	Ultra High Frequency
UWB	Ultra Wide-Band
US	Uncorrelated Scatterers
VNA	Vector Network Analyzer
VHF	Very High Frequency
V2X	Vehicle to Everything

V2I	Vehicle to Infrastructure
V2P	Vehicle to Pedestrian
V2V	Vehicle to Vehicle
WSS	Wide Sense Stationary
WSSUS	Wide Sense Stationary-Uncorrelated Scatterers
WBAN	Wireless Body Area Network
WLAN	Wireless Local Area Network
WPAN	Wireless Personal Area Network

Notations

The mathematical notations and variables used in our work are summarized in the following table.

Set Theory

$\mathbb{R}$	Set of real numbers
$\mathbb{R}^{L \times N}$	Matrix of real numbers composed of L lines and N columns
$\in$	is an element of
$\mathbb{C}$	Set of complex numbers
$\mathbb{C}^{L \times N}$	Matrix of complex numbers composed of L lines and N columns

Mathematical Notations

$\delta(\dots)$	Dirac delta function
e^x	Exponential function
$\sqrt{x}$	Square root of x
$\sum_{n=1}^N$	Summation
$ x $	Absolute value of x
$(x)^n$	x raised to the n^{th} power
$\bar{x}$	Average value of x
$\dots/\dots$	Fraction
arg max	Arguments of the maxima
arg min	Arguments of the minimum
ln	Natural logarithm
$J_n(\cdot)$	Bessel function of order n
$I_0(\cdot)$	Modified Bessel function of the first kind with order zero

$A(i, j)$	i^{th} row and j^{th} column entry of matrix $\mathbf{A}$
$A(i, :)$	i^{th} row of matrix $\mathbf{A}$
$A(:, j)$	j^{th} column of matrix $\mathbf{A}$
$\mathbf{A}^T$	Transpose of matrix $\mathbf{A}$
$\mathbf{A}^H$	Hermitian transpose of matrix $\mathbf{A}$
$\log_{10}$	Logarithm function base 10
$\mathbb{E}[x]$	Expectation of a random variable x
$P(x)$	Probability of a random variable x
σ_x^2	Variance of a random variable x
$K(\cdot)$	Complete elliptic integral of the first kind

Variables

f_c	Center frequency
B	Bandwidth
τ_{excess}	Maximum excess delay
N_{ch}	Code length
ν_{cs}	Channel sampling rate
ν	Doppler frequency
ν_T	Maximum Doppler frequency due to Tx movement
ν_R	Maximum Doppler frequency due to Rx movement
ν_D	Maximum Doppler frequency due to Tx and Rx mobilities
t	Time
$h(t, \tau)$	Time varying channel impulse response
$h_p(t, \tau)$	p -th discrete scatterer contribution
P	Number of multi-path components (MPCs)
α_p	Complex amplitude of a MPCs
d_p	Relative distance for Tx to p -th scatterer and p -th to Rx
d_0	Direct relative distance between Tx and Rx
τ_p	Delay of the p -th discrete path
λ	Wavelength
a_p	Amplitude of the p -th discrete path
a_0	Amplitude of the first path
ϕ_p	Phase of the p -th discrete path
ϕ_0	Phase of the first path

φ^R	Angle of arrival
φ^T	Angle of departure
$\overline{PDP}$	time variant power delay profile averaged on the small-scale fading
N_λ	Window size of filter
t_j	j -th time instant
τ_l	Delay detected at iteration l
$\overline{PDP}(l)$	Average power delay profile at iteration l
$\bar{\alpha}_l$	The amplitude detected from $\sqrt{\overline{PDP}(t_j, \tau_l)}$
$W(\tau)$	Sounding pulse
$\mathbf{A}$	Matrix $\mathbf{A} \in \mathbb{R}^{L \times N}$ where L is the number of detected discrete (including the first path elements) and N is the time snapshot number
$\mathbf{T}$	Matrix $\mathbf{T} \in \mathbb{R}^{L \times N}$ where L is the number of detected discrete (including the first path elements) and N is the time snapshot number.
ϵ	Absolute error
$\tilde{\tau}$	Regression line to estimate delay time variation
N_d	Maximum number of used points to estimate $\tilde{\tau}(m)$
N_g	Maximum length of gap sequence allowed in a tracked path
$\mathbf{T}_f$	$\mathbf{T}_f \in \mathbb{R}^{P \times N}$ Matrix of delay for the tracked multipath components including first path component
$\mathbf{A}_f$	$\mathbf{A}_f \in \mathbb{C}^{P \times N}$ Matrix of complex amplitude for the tracked multipath components including first path component
$\sqrt{G_0}$	First path time variant power averaged on the small-scale fading
$\sqrt{G_p}$	Secondary multipath components time variant power averaged on the small-scale fading
g_0	Small-scale fading amplitude of the first path
g_p	Small-scale fading amplitude of secondary MPCs
PL	Path loss
PL_{ref}	Path loss of the first path at the reference distance d_{ref}
d_{ref}	Reference distance equal to 1 m

d_g	Path distance between transmitter reflected off the ground to the receiver
Γ_R	Fresnel reflection coefficient
θ	Angle between reflected path and ground plane
ϵ_g	Relative dielectric constant
β	Relative permittivity
σ	conductivity
$g_n(\varphi_n^T, \varphi_n^R)$	path complex amplitude caused by the interaction of the emitted signal with the nth scatterer
S	Large-scale fading
v_R	Rx velocity
v_T	Tx velocity
v_{S_n}	Velocity of the n-th scatterer
φ_v^S	Angle of n-th scatterer directional movement
ψ_n	Random phase shift of the nth path uniformly distributed within $[0, 2\pi]$
σ_S	Standard deviation of the large-scale fading
σ_F	Standard deviation of the Rice distribution
s_F	Non centrality parameter of the Rice distribution
K_F	Rice K-factor
$R(\Delta t)$	ACF
$S(\nu)$	Doppler spectrum
T_c	Coherence time
ν_{ds}	Doppler spread
T_{stat}	Stationarity time
PDP	Power delay profile

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Wireless communication is the oldest form of communications - smoke signals propagated along a LoS connection. However, the wireless communications, as we know it today, started with the work of Maxwell and Hertz, who gave the basis of the Electromagnetic (EM) transmission waves. In 1860, James Clerk Maxwell predicted the existence of EM waves. Heinrich Hertz succeeded in 1886 to transfer EM waves from a Transmitter (Tx) to a Receiver (Rx) and confirmed Maxwell's theory. In 1898, Guglielmo Marconi extended the work of Hertz to achieve long-distance communications. In 1901, he established a radio connection over the Atlantic for what he was awarded the Nobel Prize in 1909 and he is widely cited as the "inventor of wireless communications". After that, many of the basic research on wireless communications were conducted [8–10].

Nowadays, wireless technology has become a part of our daily life. Probably the most widespread use of wireless technology is the mobile phone because it allows people to communicate anywhere and at any time. The wireless access to the Internet is also nearly ubiquitous, both through Wi-Fi and 3G/4G mobile access. Ever increasing uses of the smart devices and demanding of new applications (road safety and home-care) and better quality of services have brought the evolution of wireless communication to the 5G network. Formerly, 2G to 4G systems were based on Base Sta-

tion (BS) centric approach, but the 5G systems will drop this assumption and move towards user-centric systems. A wide variety of new emerging applications is the major guiding force behind the development of 5G wireless systems [11]. One of the particular interest is the Mobile to Mobile (M2M) communications.

M2M communications occur when both Tx and Rx are moving in the environment. The major driving factors behind them are [12]:

- The consumer demand for better quality of services and new applications (road safety, home care).
- The government and military needs for robust communication systems in disaster recovery and battlefield scenarios where the fixed communications may not be able to handle the situation.

As a result, M2M communications are finding applications in many communication systems, e.g. the Vehicle to Everything (V2X) communications and the Device to Device (D2D) communications (cf. Figure 1).

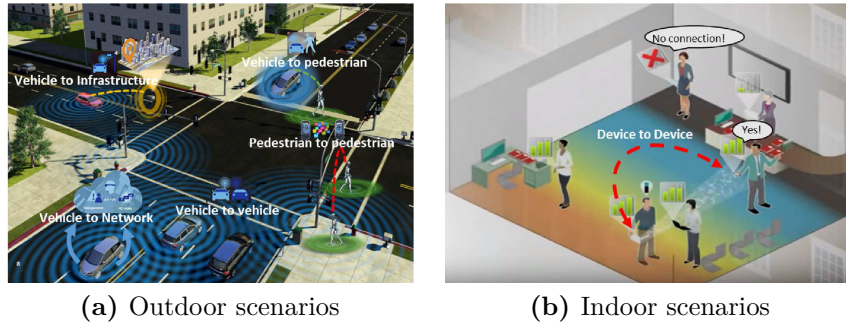


Figure 1: Some of M2M applications

The V2X communications are defined as a direct link between moving vehicles and a wide set of road infrastructure (road sensors) and passengers like vehicles, pedestrian, bicyclists etc. The Vehicle to Vehicle (V2V) communication systems, also known as inter-vehicle communication systems, have recently drawn great attention in order to improve the efficiency and safety of automobile traffic. Initiatives to create safer, comfortable and more efficient driving conditions have received strong support from both

governments and car manufacturers. The grand vision is that all future vehicles gather data and share information on traffic with each other, and with the road infrastructure, via direct wireless links [13]. An international standard, IEEE 802.11p, also known as Wireless Access in Vehicular Environments (WAVE), was recently published in [14] for both V2V and Vehicle to Infrastructure (V2I) traffic applications.

The D2D communications are defined as the information exchange via a direct link between mobile users [2]. It is aimed for short-range distances with lower power energy consumption. The use of mobile phones in D2D communications to supplement traditional cellular communications can extend the cellular coverage [15]. This will be achieved by using network users themselves as ad-hoc base stations to facilitate the routing of data traffic and to relay broadcasts. This can be done by defining the user mobility with the device-centric based 5G systems. The D2D system also provides an economical communication because it uses the same pre-existing cellular infrastructure [16].

A Particular subset of D2D communications is the Body to Body (B2B) communications. The B2B communications occur when the antennas are mounted close or on multiple human subjects free to move in the environment (cf. Figure 2). It finds applications in Pedestrian to Pedestrian (P2P) communications, paramedics, fire fighters, health care, sports and military [17].

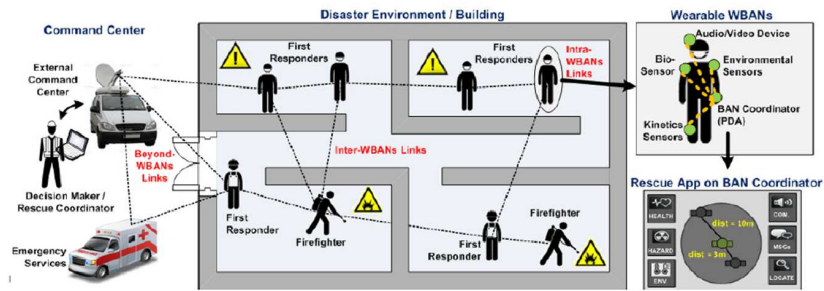


Figure 2: Rescue and Critical Operations Scenario in Disaster Environments [1].

The reliability of M2M applications highly depends on the quality of the communication link, which rely upon the properties of

the propagation channel. The wireless communication channel is defined as the medium over which the signal is transmitted from the Tx to the Rx. It poses a severe challenge on the wireless communication since it can corrupt the transmitted signal in a random way [18]. The channel properties determine the performance of the wireless communication systems and it can be used in the system design phase. Therefore, the simulation and performance evaluation of wireless communication systems require a deep understanding of its underlying propagation channel.

In the past, most of research efforts were devoted to the cellular channel (a static BS to a mobile vehicle). However, the characteristics of M2M propagation channels are significantly different from those channels, and thus new models are required. In the terrestrial M2M communications, both the Tx and Rx are in motion, close proximity and at relatively low elevation implying that the M2M channels are more dynamic and non-stationary. Consequently, M2M channels are susceptible to shadowing events caused by obstacles in the local environment intersecting the direct link between terminals, such as vehicles and buildings (outdoors), internal walls and furniture (indoor) and moving subjects (both indoors and outdoors).

Thesis Contributions

This thesis aims for measurement based characterization and modeling of M2M channels. The goal is to establish a general stochastic approach capable of appropriately modeling the M2M fading characteristics including the Doppler properties together with the non-stationarity aspect. In particular, we focus on examining the B2B and Vehicle to Pedestrian (V2P) channels. Therefore, the analysis was done in three steps: first performing the measurements and collecting the data, second study the channel characteristic by means of PL, large-scale fading and small-scale fading, third analyzing the time-varying channel using the Auto-Correlation Function (ACF) and Doppler spectrum metrics. The contribution of this thesis can be summarized in the following points:

1. Channel sounding of M2M communications: Two types of M2M channels were measured, i.e. the narrow-band indoor B2B channels and the wideband V2P channels, to exploit

the indoor and outdoor scenarios. Different mobility patterns were considered and various environment conditions were investigated.

2. Stochastic models: a Non Geometry based Stochastic Channel Model (non-GSCM) was developed in order to model the B2B channel transfer function while a Geometry based Stochastic Channel Model (GSCM) was proposed to model the V2P Time Varying Channel Impulse Response (TVCIR). The GSCM consists of first path component and secondary MPCs. These contributions and the non-GSCM were depicted as a combination of PL, large- and small-scale fading. Depending on the environment under consideration and antenna position, the model parameters were given.
3. non-stationarity channel aspect: while the GSCM can inherently model the non-stationarity behavior of the channel, the B2B fading and PL characteristics were analyzed in function of body orientation and Tx-Rx distance. Moreover, some non-stationarity tests developed for on-body channels [19] and V2V channels [20] were used to study the B2B fading channel, in terms of distribution and Doppler spectrum.
4. A general ACF model: the ACF model developed in [21] for M2M channel in the presence of moving scatterers under the assumption of isotropic scatterers was extended in order to account a general scattering environment. This model was then successfully compared to the measurement results both for V2P channels and indoor M2M channels.
5. Doppler spectrum model: similarly, a general analytical Doppler spectrum model based on a physical interpretation that is able to depict the Doppler properties of indoor M2M channels was proposed and successfully compared to the measurement data.
6. Channel implementation techniques: ACF and Doppler filter based implementation techniques were presented and they can produce stochastic processes that have the correlation (Doppler) properties and statistic distribution similar to the measurement data.
7. Auto-regressive (AR) model: AR model is an another method

proposed to model the time-varying B2B channels by means of generating correlated large- and small-scale fading.

Thesis Outline

The remainder of the thesis is organized as follows:

Chapter 1: A survey on Mobile-to-Mobile propagation channels: measurements and models

Chapter 1 presents the fundamentals of the propagation channel by first describing the channel from a system theoretic point of view. We review the characterization and modeling of propagation channels in general. A survey on the propagation channel measurements and modeling both for the V2V and B2B channels was then provided. Extensive references were given. A key characteristic of M2M channel is the non-stationarity fading behavior which can harmfully affect the communication channels. Therefore, some methods used to study the non-stationarity of V2V were presented.

Chapter 2: Narrow-band Mobile to Mobile Channels

Chapter 2 presents the narrow-band indoor B2B channel models based on measurement performed at 2.48 GHz. Different antenna on-body position and different mobility patterns were measured considering the LoS and NLoS scenarios. The outcome of the measurement is the time-varying channel transfer function.

The measurements were then modeled based on a statistical approach that consists of three components: PL, large-scale fading and small-scale fading. Considering the antenna on-body position and for each of the environment under investigations, the PL parameters and the dynamic channel component distributions were derived.

The second order statistics, i.e. ACF and Doppler spectrum, of the channel transfer function, large- and small-scale fading were also studied considering the environment under investigation and the mobility patterns where the antennas were placed on the heads of moving subjects. These specific scenarios were adopted due to the limited effects of body shadowing seen with the head position

so we can extend our evaluation from B2B scenarios specifically toward more general indoor M2M scenarios.

The ACF model for M2M channels in the presence of moving scatterers presented in [21] was extended in order to take into account a general scattering environment. This model was exploited to depict the measurement resulting in indoor M2M scenarios. An analytical Doppler spectrum model was also proposed for indoor M2M scenarios and compared to the measurements.

Finally, the non-stationarity behavior of the small-scale fading channel was assessed based on methods proposed in [19] for on-body channels and [20] for V2V channels.

Chapter 3: Wideband Mobile to Mobile Channels

Chapter 3 presents a GSCM based on V2P channel measurements carried out at 3.8 GHz. Several propagation conditions and different mobility patterns were investigated. The model is similar to the one proposed in [22] and it consists of the first path component and secondary discrete MPCs. In order to track the time evolution of the first path and the secondary MPCs, a detection procedure and a tracking algorithm were implemented. The time variant contributions stemming from each component was then modeled as a combination of PL, large- and small-scale fading. Depending on the environment under consideration, the model parameters were given.

Finally, the ACF and the Doppler spectrum were studied considering the scenario where Tx and Rx are in LoS and they were moving towards each other. They were modeled with the ACF model proposed in the previous chapter.

Chapter 4: Channel Model Implementation

Chapter 4 presents channel model implementation techniques that can preserve the channel correlation and Doppler properties. The goal is to successfully implement the proposed models of B2B and V2P channels with fading characteristics including the Doppler and correlation characteristics.

Therefore, the ACF and Doppler spectrum implementation techniques were proposed. These methods can generate large- and

small-scale fading with the same measurement distribution and correlation (Doppler) properties. A comparison of Doppler spectrum or ACF and fading statistical distribution between the measurement and simulation data was presented.

Finally, the AR model was also introduced to model the measured large- and small-scale fading of B2B channels, in terms of distribution and correlation (Doppler) properties.

Chapter 1

A Survey on Mobile-to-Mobile Propagation Channels: Measurements and Models

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In recent years, M2M communications have attracted much attention in response to a better quality of data service with low energy consumption [15]. The M2M communications are defined as an exchange of information via a direct link between mobile users. It can be used for a short-range communication distance or as an underlay to the cellular network. Accordingly, the M2M systems are finding applications in mobile ad-hoc networks, Intelligent Transportation Systems (ITS), multi-user cooperative communication systems and data security etc. [15]. Figure 1.1 illustrates

everyday examples of M2M communications.

Although the M2M communication is a promising application for 5G network [11], many research challenges have to be studied before their wide deployment. One of the most important challenges is the characterization and modeling of M2M propagation channels. In fact, in order to test, design and optimize wireless communication systems, models for propagation channels are requested. These models reflect the propagation channel properties that can affect system performance [8, 9, 23, 24]. Therefore, much research attention was focused on M2M channel measurements, for understanding the underlying physical phenomenon in M2M propagation environments; and to develop meaningful yet easy-to-use M2M channel models, thus facilitating the analysis and design of M2M communication systems.

This chapter presents an overview of the state of the art on measurements and modeling of two types of M2M channels: V2V and B2B channels.

The remainder of this chapter is outlined as follows. Section 1.1 discusses the channel characterization and modeling in general. Section 1.2 and Section 1.3 present State-Of-The-Art (SOTA) concerning V2V and B2B channel characterization and modeling. Section 1.4 reports some techniques used in order to detect the "stationarity region" of the M2M channels. Finally, Conclusions are given in Section 1.5

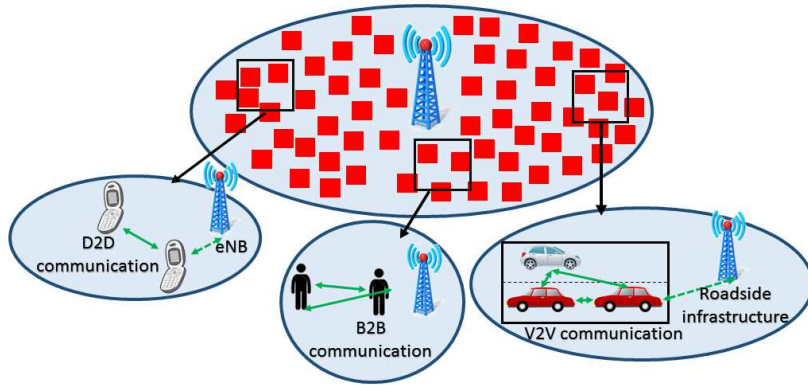


Figure 1.1: M2M communication systems [2]

1.1 Channel Modeling Fundamentals

1.1.1 Propagation principles

In mobile radio communications, the emitted EM waves reach the receiving antenna from many directions due to physical propagation mechanisms such as free-space propagation, reflection, diffraction, and scattering etc. [3, 9]. The free-space propagation occurs when a direct path, namely LoS path, exists between the Tx and the Rx [12]. The other three propagation mechanisms are created by obstacles in the channel, such as buildings, trees, mountains, etc. This effect is known as multi-path propagation. Figure 1.2 presents a typical scenario for the terrestrial mobile radio channel.

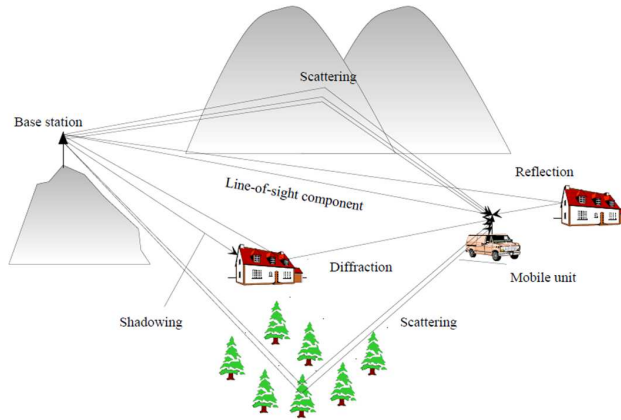


Figure 1.2: Typical mobile radio scenario propagation in a terrestrial environment [3].

The received signal is a superposition of an infinite number of attenuated, delayed, and phase-shifted replicas of the transmitted signal. This superposition can be constructive or destructive depending on the phase of each partial wave and it is defined for a given time instant as the Channel Impulse Response (CIR) of the channel. Moreover, the received signal can be affected by the Doppler phenomenon which introduces a frequency shift in each partial wave. Accordingly, the CIR will become time-variant and the propagation channel can be described by linear time-variant system [25].

In practice, it is difficult to characterize all these processes. Therefore, it is preferable to describe the channel statistically. This will be the subject of the following section.

1.1.2 Channel characterization

As mentioned above, the CIR consists of the superposition of MPCs each having a certain time-delay, amplitude and phase that vary over time. Therefore, the propagation channel can be completely characterized by the TVCIR as follows [26]:

$$h(t, \tau) = \sum_{p=1}^{P(t)} a_p(t) e^{i\phi_p(t)} \delta(\tau - \tau_p(t)) \quad (1.1)$$

where a_p , τ_p and $\phi_p(t)$ are the amplitude, delay and phase of the p^{th} path.

The phase $\phi_p(t)$ can be further expressed as follows:

$$\phi_p(t) = 2\pi f_c \tau_p(t) - \int_t 2\pi \nu_p(t) dt \quad (1.2)$$

where the first term $2\pi f_c \tau_p(t)$ depends on the delay and the second term $\int_t 2\pi \nu_p(t) dt$ is the Doppler shift of the p^{th} MPCs at time instant t .

The Fourier Transform (FT) of the TVCIR with respect to τ results in the time varying channel transfer function $H(t, f)$ [8]:

$$H(t, f) = \sum_{p=1}^{P(t)} a_p(t) e^{i\phi_p(t)} e^{i2\pi f \tau_p(t)} \quad (1.3)$$

Note that other system representations can be also derived both from these equations [27]. Likewise, the FT of the frequency response $H(t, f)$ with respect to t gives the Doppler variant transfer function also called Doppler spread function $B(\nu, f)$ while the FT of the TVCIR with also respect to t results in the delay Doppler function or the Doppler delay function also known as spreading function $D(\nu, \tau)$. The relationships between these functions are summarized in Figure 1.3.

To characterize the propagation channel in a stochastic manner, a multidimensional Probability Density Function (pdf) of the CIR

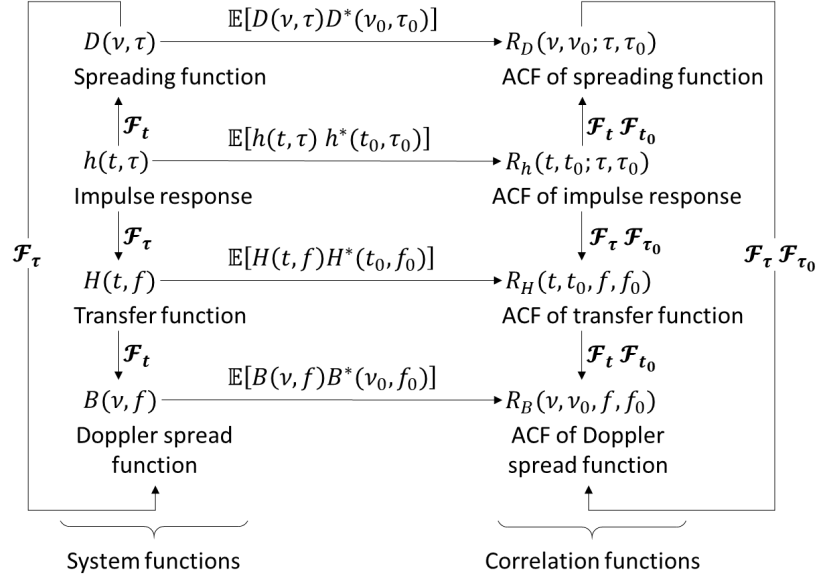


Figure 1.3: Relationships between system functions and correlation functions

is required, which is too much complicated in practice. Therefore, the study is limited to the second order statistic of the time variant system functions known as ACF. The ACFs of the channel are defined as follows [8]:

$$R_h(t, t_0; \tau, \tau_0) = \mathbb{E}[h(t, \tau)h^*(t_0, \tau_0)] \quad (1.4)$$

$$R_H(t, t_0; f, f_0) = \mathbb{E}[H(t, f)H^*(t_0, f_0)] \quad (1.5)$$

$$R_B(\nu, \nu_0; f, f_0) = \mathbb{E}[B(\nu, f)B^*(\nu_0, f_0)] \quad (1.6)$$

$$R_D(\nu, \nu_0; \tau, \tau_0) = \mathbb{E}[D(\nu, \tau)D^*(\nu_0, \tau_0)] \quad (1.7)$$

These ACFs are related with each other via a double FT as shown in Figure 1.3.

1.1.2.1 Wide-Sense-Stationary and non-Wide-Sense-Stationary Channels

Wide Sense Stationary (WSS) channel assumption implies that the ACF in time depend on the time difference $\Delta t = t - t_0$ and not

on the absolute time t [8]. The ACF of TVCIR becomes then:

$$R_h(t, t_0; \tau, \tau_0) = R_h(\Delta t; \tau, \tau_0) \quad (1.8)$$

The Uncorrelated Scatterers (US) assumption imposes that the second order statistic in frequency depends on the frequency difference $\Delta f = f - f_0$ and not on the absolute frequency f . Hence, the ACF of the time variant frequency response becomes:

$$R_H(t, t_0; f, f_0) = R_H(t, t_0; \Delta f) \quad (1.9)$$

A channel model that uses both assumptions is called a Wide Sense Stationary-Uncorrelated Scatterers (WSSUS) channel model. Combining these two assumptions, the ACFs previously presented become:

$$R_h(t, t_0; \tau, \tau_0) = R_h(\Delta t) \delta(\tau - \tau_0) \quad (1.10)$$

$$R_H(t, t_0; f, f_0) = R_H(\Delta t, \Delta f) \quad (1.11)$$

$$R_B(\nu, \nu_0; f, f_0) = R_B(\Delta f) \delta(\nu - \nu_0) \quad (1.12)$$

$$R_D(\nu, \nu_0; \tau, \tau_0) = R_D(\nu, \tau) \delta(\nu - \nu_0) \delta(\tau - \tau_0) \quad (1.13)$$

However, many practical channels such as M2M channels do not satisfy these assumptions, hence it has to be treated as non-WSSUS channels. In general, the characterization of non-WSSUS channels is more complex. In [20, 28], the V2V fading channel was considered as an ergodic process and the observations was divided in small regions within which the WSSUS properties hold. For each stationarity region, a Local Scattering Function (LSF) was estimated and used to characterize the non-stationary behavior of the V2V channels.

1.1.2.2 Statistical channel metrics

Power delay profile

The Power Delay Profile (PDP) measures the received power in function of delay τ and it can be calculated as the expectation of the squared magnitude of $h(t, \tau)$ over t under the WSSUS assumptions, as follows:

$$PDP(\tau) = \mathbb{E}_t [|h(t, \tau)|^2] \quad (1.14)$$

For a non-WSSUS channel, the PDP is a time variant and it was estimated using a time sliding windows where the WSSUS assumption holds.

Doppler spectrum

The Doppler Power Spectral Density (PSD) represents the energy distribution in function of the Doppler frequency. Its shape depends on the relative amplitudes and directions of the incoming waves [29]. For a WSSUS channel, the Doppler spectrum is calculated as:

$$S(\nu) = \mathbb{E}_\tau [|D(\nu, \tau)|^2] = \int_\tau R_D(\nu, \tau) d\tau = \int_{-\infty}^{\infty} R_H(\Delta t, 0) e^{-i2\pi\nu\Delta t} d\Delta t \quad (1.15)$$

As seen, it can be calculated as the FT of the ACF of the channel transfer function. Similarly, in the case of non-WSSUS channel, where the measurement data splits in small regions in which the WSSUS properties holds using a sliding windows, the Doppler spectrum can be then calculated for each region using (1.15).

Delay and Doppler spread

In a multi-path propagation environment, waves arrive from different directions, each has its own associated Doppler frequency and delay. Consequently, the the signal spreads both in delay and Doppler domains [29]. This phenomena are called Doppler and delay spreads.

The Doppler spread is defined as the range of frequencies over which the Doppler spectrum is essentially non-zero. Thus, it is calculated as the Root Mean Square (RMS) of the second central moment of the Doppler spectrum $S(\nu)$ [9, 30] as follows:

$$\nu_{ds} = \sqrt{\frac{\int_{-\infty}^{+\infty} (\nu - \bar{\nu})^2 |S(\nu)| d\nu}{\int_{-\infty}^{+\infty} |S(\nu)| d\nu}} \quad (1.16)$$

where: $\bar{\nu} = \int_{-\infty}^{+\infty} \nu |S(\nu)| d\nu / \int_{-\infty}^{+\infty} |S(\nu)| d\nu$ is the average Doppler spread.

The coherence time t_c is the time over which the channel is considered invariant over time. This can be assured when the normalized

time correlation function $R_H(\Delta t)$ is close to one. Therefore, it is determined at 0.9, 0.7, or 0.5 depending on the given case [9, 31].

Doppler spread and coherence time are parameters that describe the time varying nature of the channel caused by either the mobility of the Rx, Tx and scatterers in the environment. They measure the time varying channel in a small-scale region [9] and they are inversely proportional. If a base-band signal has a bandwidth greater than ν_{ds} or a symbol duration less than t_c , then the channel will be considered as slow fading channel, while in the inverse case, it will be appealed as fast fading channel.

Similarly, the Delay spread determine the range of delay over which the PDP is essentially non-zero. It can be calculated as the RMS of the second central moment of the PDP:

$$\tau_{RMS} = \sqrt{\frac{\int_{-\infty}^{+\infty} (\tau - \bar{\tau})^2 |PDP(\tau)| d\tau}{\int_{-\infty}^{+\infty} |PDP(\tau)| d\tau}} \quad (1.17)$$

The coherence bandwidth B_{coh} is a measure of the frequency selectivity of the channel and it is inversely proportional to the RMS delay spread. If the transmitted signal has a bandwidth greater than B_{coh} or a symbol duration less than τ_{RMS} , then the channel is seen as selective frequency channel, while in the inverse case, the channel is considered as non-selective frequency channel.

1.1.3 Channel modeling methods

In order to characterize the channel, three main modeling approaches were used: empirical, stochastic and deterministic [8, 32].

Empirical channel models are directly derived from extensive channel measurement campaigns for a typical scenario. A classical example of this method is the Okumura-Hata model that was developed to model the propagation losses in the channel [33]. The main advantage of such models is that the resulting channel characteristics are realistic and it can be stored and used directly in system simulations. However, this model does not include any physical interpretation and can only characterize a certain site-specific. In addition, if the channel characteristics change over time, then a large amount of measurement data is required.

Deterministic channel models compute the characteristics of the channel using the physical propagation of EM waves in a certain geographic place. Therefore, their accuracy is directly related to the accuracy of the scenario representation and their major drawback is the large computational effort required and the approximate nature of numerical computation methods, e.g. ray tracing.

Stochastic channel models describe the channel characteristics statistically. These models are not directly derived from measurements, but typical measurement scenarios are used to derive their parameters. They are, generally, employed to predict the pdf of the channel parameters over a larger area, rather than in a specific location. A classical example of this approach is the Rayleigh-fading channel model [34]. Moreover, the empirical and the stochastic approaches can be combined to achieve a reliable channel model, e.g. modeling the PL using Okumura-Hata model [33] and the large-scale fading with an appropriate stochastic model. Stochastic models can be further divided into two categories: GSCM and non-GSCM [35].

In the GSCM, the position of scatterers and the scattering properties are statistically defined. Consequently, for each propagation path, different channel properties, i.e. amplitude, delay and angular information, are assigned [35]. The great advantage of such models is their capability to adapt to different scenarios by changing the shape of the scattering region. Therefore, they can implicitly reproduce full channel characteristics. At this point, it is worth noting that it can describe the time-evolution of the channel by the motion of Tx, Rx and the scatterers which makes it useful for non-stationary channels.

In the non-GSCMs, paths from Tx to Rx are characterized by statistical parameters, without considering the geometry of the physical environment [35]. One of the most widely used is the Tapped Delay Line (TDL) model which is described by a finite number of delay taps that fade independently such as each tap consists of several MPCs.

1.1.4 Channel components

Classically, the channel power can be represented as a combination of three components: PL, large-scale fading and small-scale fading.

Starting with the free space propagation, it is well known that the transmitted EM wave will encounter the following PL:

$$PL_{fs} = \left(\frac{4\pi d}{\lambda} \right)^2 \quad (1.18)$$

where d is the distance between the Tx and Rx and λ is the wavelength. In general, the PL is defined as the attenuation with distance of the transmitted signal as it propagates from the Tx to the Rx. The PL helps in predicting the range of a radio system [29]. Commonly, this law (1.18) is approximated in dB with the following equation [23]:

$$PL[dB] = PL_{ref}[dB] + 10n \log_{10} \left(\frac{d}{d_{ref}} \right) \quad (1.19)$$

where PL_{ref} is the PL at reference distance d_{ref} and n is the PL exponent. The latter depends on the propagation environment. For instance, in free space, $n = 2$, while, in a simplified scenario where LoS and ground reflection are considered $n = 4$ [23]. The PL exponent is a measure of how fast the PL increases with distance. In general, it is empirically deduced from the measurements.

The PL model described in equation (1.19) assumes that the PL is constant at a given distance. In practice, different obstacles (building, trees) encountered along a path cause the variation of the received power at a given distance. This phenomenon is called shadowing or large-scale fading. Experimental results show that the large-scale fading can be modeled by a log-normal distribution in outdoor [36] and indoor [37] scenarios. Note that the large-scale fading plays an essential role in predicting the coverage reliability since its effects occur over large distances.

On a very short distance scale, the received signal may fluctuate significantly due to a small change in position over a short duration [24]. This phenomenon is called small-scale fading. It

is generated by the combination of different signals arriving from different directions with random amplitude and phase at the Rx antenna. Small-scale fading is modeled as a complex random process. Its envelope is generally described by two probability distributions: Rayleigh, when all the paths have the same average energy, and Rice, when there is a dominant path (generally, but not necessarily, LoS). The small-scale fading plays an important role in determining link level performance in terms of bit error rates and average fade durations. These dynamic effects are specified by the second-order fading statistic.

1.2 Vehicle-to-Vehicle Channels

1.2.1 V2V channel measurements

Channel measurements aim to understand the channel behavior and to develop realistic and trustworthy channel models. In fact, as stated in section 1.1.3, stochastic and empirical models have parameter values obtained from the measurement data, e.g. [38], while in the case of deterministic models, the parameters must be chosen carefully in order to represent the physical environment correctly [39]. Nevertheless, each model must be verified and validated by measurements.

Measuring the radio channel can be performed via a channel sounder. Channel sounding technique is based on sending a training signal known from the Tx that excites (i.e. sounds) the channel, while the Rx stores the received signal to estimate the radio channel [8,40]. The measurement equipment used for V2V channel measurements is pretty much similar to the one used for cellular channels. However, V2V channel measurements are more challenged than cellular or even V2I measurements. In V2V channels, both Tx and Rx are mobile and synchronization during the measurements is a challenge task.

Depending on the desired measurement requirements, scenarios and site locations must be chosen. This is a major step toward modeling the desired channel. In fact, different communication scenarios can lead to different channel statistics, thus different channel models [41]. Also, other conditions can affect the measurement data such as antenna height, velocity, frequency etc.

A number of real-life channel measurement campaigns have been conducted for vehicular communication systems, in many different propagation environments and with different measurement setups. This section gives a description of the carrier frequency, and antennas used to measure the V2V channels followed by a classification of the environments in which measurements take place.

1.2.1.1 Carrier frequency and measurement bandwidth

The channel characteristics depend on the frequency band, e.g. propagation loss and Doppler frequency shift. Today, the worldwide standardization associations have allocated the following frequency bands for ITS [42]:

- 5.850-5.925 GHz in North America,
- 5.875-5.905 GHz in Europe,
- 715-725 MHz and 5.770-5.850 GHz in Japan,

For that reason, several V2V measurement campaigns were conducted over the last few years at the 5 GHz band, e.g. [43–48] with the exceptions of some V2V measurements conducted at other frequency bands, e.g. the 2.4 GHz in [49, 50]. Some Multiple Input Multiple Output (MIMO) measurements were also conducted at 3.5 GHz in [51] and the 700 MHz was tested in [52]. Moreover, some measurements were performed with millimeter waves, e.g. the 60 GHz in [53] and the Ultra High Frequency (UHF), e.g. 900 MHz and 363.7 MHz, in [54, 55], respectively.

At this point, it is worth noting that different applications imply different bandwidths. Thus, the aforementioned measurements were performed with different bandwidths giving rise to different models. In [56, 57], several models were proposed for the 5 GHz with different bandwidth ((1-5-10-20-33.33-50) MHz).

Typically a wideband channel sounder was used to measure the TVCIR or the time-varying channel transfer function of V2V channels [45, 46, 56–61]. The radio channel is completely described by either one of these functions within the time span and bandwidth used for sounding. More details on its operating principles and the different existing types can be found in [8, 40]. However, some of the measurements were performed using narrow-band measurement

systems where a sine wave generator together with vector signal analyzer [4, 44, 62] or a spectrum analyzer in [63] at the Rx side were employed. Parameters like channel gain, fading and the Doppler frequency shift are then extracted.

Some MIMO measurements were carried out in order to exploit a higher throughput and reliability using MIMO channel sounders that are able to record quasi-simultaneously the CIR between each Rx and Tx e.g. [64–70]. At this point, it is worth noting that a 2x2 MIMO channel sounder based on pulse repetition sequences was built in [59] at 5.7 GHz with a bandwidth of 1 GHz using two parallel Tx and Rx chains and it was tested for different V2V scenarios [59, 71, 72].

The choice of the channel sounder depends on its capacities to measure the desired channel characteristics. A key factor in selecting a suitable channel sounder for a given measurement is the repetition time of the sounding pulse. In fact, the measured channel must be under-spread. In other words, the repetition time of the sounding pulse must be shorter than the coherence time of the channel, and longer than the maximum delay of the channel [40]. For example, the Vector Network Analyzer (VNA) which was widely used in indoor environments, and at low velocity, is not appropriate for V2V channels, due to the rapid change of the channel compared with its channel acquisition rate.

1.2.1.2 Antenna types and performance

The vehicle type and the antenna position play an important role in measurement planning. Antenna position must be selected according to the current applications. Nevertheless, antenna characteristics, e.g. radiation pattern, isolation and mismatch, are intuitively affected by the vehicular mounting position [73]. Note that a mutual coupling between the antenna and mounting tissues (shield) can occur impacting the communication performance. Moreover, the mounting tissues, i.e. metallic vehicle roof, vary from vehicle to another. In general, antenna calibration is measured after its installation in order to analyze its three-dimensional antenna pattern which nevertheless requires a considerable effort and time consuming in V2V scenario [74].

V2V communications are expected to operate in the horizontal plane. Due to the different use cases for ITS, the relative speed and moving direction between vehicles, an omnidirectional coverage for all azimuth angles is required with maximum gain in the horizontal plane. Therefore, the omnidirectional antennas were considered, at first, and the rooftop position was reported as the best position, e.g. [4, 43, 45, 48, 49, 56, 60, 70].

A small number of contributions have studied the V2V channels where the antennas were placed inside the car, e.g. [60, 61, 75], showing a higher PL (4-10 dB [75]) and stronger multi-path [56, 75]. Therefore, the packet error rate is quite sensitive to the exact antenna positions [76].

The height of vehicles was explored in [77] in order to enable more efficient V2V communication. It was shown that tall vehicles are significantly better relay candidates than short ones and they can be used as moving hotspots. Moreover, many antenna positions were studied in [78] using a 3D ray tracing simulator and considering two motorway scenarios. The antenna positions under investigations were the front and rear bumpers, left and right side of mirrors and under the car. It turns out that in the case of difficulties integration of roof position, the mirror sides can outperform (succeed) as a considerable alternative.

Multiple antenna techniques were considered for vehicular in order to mitigate interference and improve the link reliability [74, 79]. Measuring with multiple antenna elements allows to gain new insights into propagation effects and analyzing the impact of the antenna radiation pattern, as well as the performance of multi-antenna operation, e.g. [38, 41, 50, 51, 61, 67, 68, 80, 81].

1.2.1.3 Environments and conducting scenarios

The vehicular environments can be classified, based on their traffic density, into five categories: urban, suburban, highways, rural and tunnel environments (cf. Figure 1.4). It should be noted that the design of an environment type may vary from a country to country or even within the same country from a department to another. Therefore, the measurement location is well defined in most of the research activities.

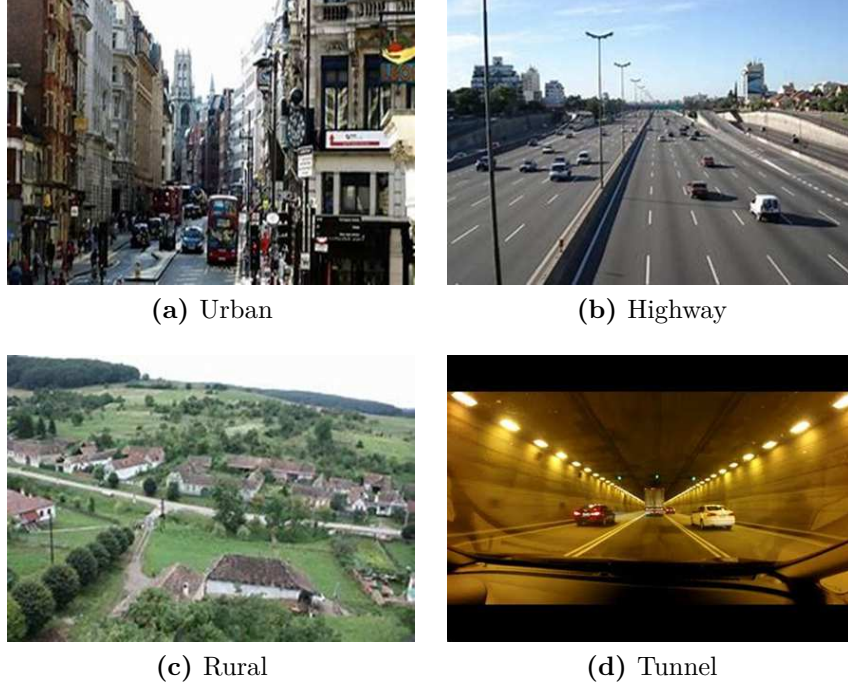


Figure 1.4: Typical types of V2V environments

V2V channel can pass from a LoS propagation to NLoS condition due to shadowing by obstacles as buildings or vehicles [70, 82], resulting in a non-stationary time-varying channel. Thus, understanding environment properties is a major task to properly model the V2V channel behavior. Also, the location can give some restrictions on terminal or obstacle speeds, the relative distance between terminals and traffic densities. These have a significant impact on the maximum Doppler spread, attenuation losses and the delay spread.

For example, in highways, the distance between terminals is normally greater than 1 km or between 300 m and 1 km and the speed is within range of 60-120 km/h. Subsequently, the maximum Doppler spread is expected to be large. At this point it is worth noting that most measurements have shown a maximum Doppler shift equal approximately to twice that of the maximum Doppler shift for a radio mobile scenario (i.e. $\nu_D = 2v/\lambda$ where v is the terminal speed) where the terminals were moving in opposite direction

with a quasi-equal speed; while in the same direction, a Doppler spectrum center at zero appears [61].

Nearby terminals can have a high probability of LoS propagation, thus low PL comparing to a large distance where some vehicles can play the role of obstacles giving rise to a NLoS scenario. Hence, regardless the type of scenarios, the relative distance between the terminals must be known at any instant of measurement so that the channel characteristics can be analyzed later from measurements. A Global Positioning System (GPS) and a recorded video were usually used for this sake in V2V measurements, e.g. [61, 81].

Consequently, writing down important notes: measurement parameters, starting and stopping times, incidents during measurements, terminal speed and so on are necessary in order to explore the measurement.

1.2.2 V2V channel characterization and modeling

Many research efforts have been devoted to characterize and model the V2V propagation channels for system simulations and testing. A key characteristic of V2V channels is the non-stationary behavior that complicates V2V channel characterization and imposes challenges for V2V channel modeling. In this section, a brief overview of V2V channel models are presented and they are classified as follows:

1. Measurement based modeling, when the measurement data are used for modeling purposes.
2. Non-measurement based modeling, when models are derived based on deterministic or stochastic geometrical assumptions by means of close expressions.

1.2.2.1 Measurement based modeling

The objective of channel measurements is to study the channel characteristics in order to design a realistic channel models for the communication systems. Therefore, several V2V channel measurement campaigns were performed over the years and the V2V channel statistics were studied based on the collected data. These

measurements were mainly performed to characterize the PL, Fading statistics, Doppler spectra, PDP, delay and Doppler spreads, considering the environment type (rural, highway, urban...).

In LoS scenarios, the PL exponent of the log-distance PL model was given to be between:

- 1.33-3.07 in the highway scenarios [38, 48, 63, 65, 81, 83]
- 1.79-3.18 in the rural scenarios [38, 45, 48, 83]
- 1.19-2.88 in the urban scenarios [38, 48, 83]
- 1.59-3.5 in the sub-urban scenarios [38, 44, 81]

It is worth mentioning that the value of PL exponent less than 2 is observed quite often for V2V LoS channels, indicating a power higher than what is received in free space propagation. In some studies, it was decided to use the dual-slope two rays PL model for urban and highway scenarios [44] and in [38] for rural scenarios. It was also considered for larger distance in [83] and a higher PL exponent was obtained for NLoS scenarios. A study on crowded highways has shown that the PL can experience larger variations [53]. In [84], an additional average attenuation of 10 dB in the received signal power was observed when the LoS path is obstructed by vehicles. Consequently, several factors, like differences in the environment, load traffic, antenna positions and pattern, etc. can lead to big variances into the PL modeling.

Along with the PL, the large- and small-scale fading were also reported. The Large-scale fading was generally characterized by a normal distribution in dB with zero mean [70, 85] while the small-fading was usually modeled either with Rayleigh, Ricean or double Rayleigh distribution [44, 56, 57, 63, 86–88]. A K-factor in the range of 2-11 was exhibited [54, 81]. In [44, 88], a slight transit from Rician to Rayleigh distribution was observed when the relative distance between terminals increases. The K-factor in function of time, frequency and space was reported in [43, 88]. In [89], the Rice distribution was employed for an inter-vehicle distance less than 100 m and the Rayleigh distribution for larger distance. This behavior was denoted by "severe fading" in [56, 57] and the small-scale fading was modeled by Weibull distribution. In fact, the major driving factors behind "severe fading" are the rapid transitions of MPCs

due to the high speed and low height of the Tx/Rx antennas as well as the rapid moving scatterers.

The joint Doppler-delay PSD was measured in [49, 61, 66, 87]. It was shown that Doppler properties can vary significantly with different time delays. In [4], three principle components of the Doppler spectrum were deduced from measurements as follows (cf. Figure 1.5):

- The LoS component
- The base of the spectrum given by the double ring model [90]
- The broadening due to the moving scatterers surrounding the terminals, such as pedestrian and moving vehicles

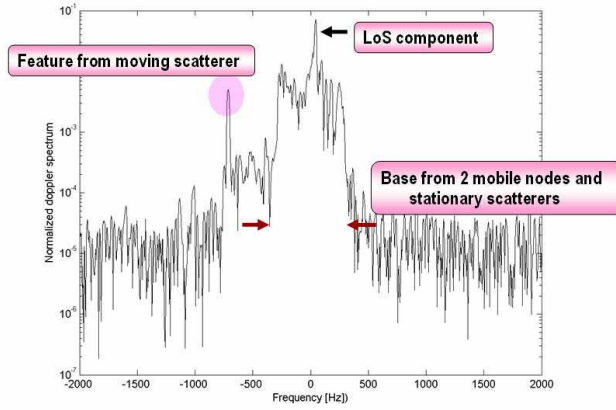


Figure 1.5: V2V Doppler components [4]

Doppler spreads and coherence times were reported in [44]. It was shown a linear dependence between the Doppler spread and the vehicle separation as well as the effective speed of terminals defined as the square root of the sum of squares of the terminal speeds. Moreover, a residual Doppler spread when the vehicles were stationary was shown and attributed to other motion in the environment. The Doppler spread was usually in the range of 26-550 Hz [71] although results close to 1000 Hz were reported for highway environments in [45]. At this point it is worth noting that the V2V links experience a Doppler spread larger than the one given in Fixed to Mobile (F2M) channels due to the mobility of both users and the surrounding objects. Moreover, a Doppler spectrum shapes

different from the traditional U-shaped Doppler spectrum of F2M channels are expected. The maximum Doppler shift was explained in function of the relative speed of the nodes in [44, 65].

Given that the V2V channels are characterized by a non-stationary fading behavior, the time-varying PDP was presented [67, 68, 91]. The distribution of the delay spread was often fitted by a log-normal distribution [56, 60]. A largest delay spread was found in the highway environment comparing to rural and urban environments [45, 46, 71, 81]. This is possibly due to the larger relative distance between vehicles, vehicle speeds and large far scatterers. Values of the delay spread can go from 10 ns for inter-vehicle distance of 10 m to 1 μ s in the urban dense area for inter-vehicle distance of 100 m [60, 66]. Finally, an order of 2-6 MHz was reported in [60] and 460 kHz in [46] for the coherence bandwidth.

GSCMs were proposed in [22, 92] where the properties of channel and the scatterers were extracted from measurement. The model consists of three components:

- LoS component
- Discrete components e.g., moving cars, building and road signs
- Diffuse components due to smaller objects located on the roadside

These models can easily handle the non-stationarity of V2V channels by prescribing the motion of the Tx, Rx, and mobile scatterers. Finally, the TDL channel model that consists of 6-12 taps was proposed in [58, 87] without considering the non-stationarity of V2V channels while a birth/death process was considered in [41, 56] to account the appearance and disappearance of taps, thus including the non-stationarity aspect of the channel.

1.2.2.2 Non-measurement based modeling

Some theoretical V2V channel models were also developed over the years where the channel measurement data were used only for validation purposes.

The simplest geometrical V2V channel model is the two-ring model [90] considering NLoS suburban scenarios. The LoS com-

ponent resulting in a Rician fading channel was derived in [93]. This model was extended to 3D model [94]. In [95], both single- and double-bounced rays were considered for narrow-band non-isotropic scattering MIMO V2V Ricean channels. This model is extended to a 3D wideband two-concentric-cylinder GSCM in [50]. A 2D non-isotropic scattering wide-band MIMO V2V GSCM based on the TDL structure was presented in [96]. It is a combination of a two-ring and an ellipse models in order to represent the LoS, single-, and double-bounced paths between terminals. The model can distinguish between the moving cars around the nodes and the stationary roadside environments, which are represented by a two ring model and an elliptic models, respectively. Moreover, a V2V channel model in the presence of moving scatterers was developed in [21] under the assumption of isotropic scatterers. However, all the aforementioned models were derived assuming a WSS channel, thus they can not reproduce the real physical V2V channels, but rather they are intended for comparison of different transmission schemes.

Other analytical models were developed, including the non-stationarity aspect of the channels. For example, in [97], the V2V two rings channel model was developed taking into account the variation of terminal velocities over time while the geometrical model of the street was considered in [98].

The ray-tracing method was adopted in [63, 99–102] for V2V channel characterization and modeling. An agreement between measured and simulated receive powers was within 3 dB standard deviation [102, 103]. However, the main drawback of ray tracing is its computational demands.

1.3 Body-to-Body Channels

While the V2V channels were largely addressed in the literature, a limited research effort was devoted to B2B channels. Similarly to the previous section, the limited contributions dedicated for characterizing and modeling the B2B channels where both Tx and Rx are in motion are presented here in this section. Note that similar channel behavior were observed in D2D channels, therefore, it will be included in the analysis.

1.3.1 B2B channel measurements

A small number of B2B channel measurements were performed for modeling purposes. Similar to Section 1.2.1, the impact of the measurement requirements, i.e. frequency bands, channel sounding techniques, antennas, environment and conducted scenarios, are reviewed here for B2B channels.

Most of the B2B measurements were performed at the Industrial, Scientific and Medicals (ISM) band, i.e. the 2.4 GHz and 5.8 GHz [5, 104–110] with few exceptions where the measurements were carried out at 1.8 GHz [75] and 868 MHz [111].

Measurement equipment varies from VNA [5, 109] to channel sounder [108], to ad-hoc sensor network sounding campaigns [104, 111].

Small antennas are required for B2B communication systems so that it can be integrated into the Wireless Body Area Network (WBAN) devices. Similarly, antennas are mounted on or close to the body depending on the current applications which can impact the antenna characteristics. Different antenna types were used, e.g. micro-strip antennas, printed dipole or loop antennas, printed monopoles or Printed Planar Inverted-F Antenna (PIFA) [112]. One or multiple antenna positions on the same subject were investigated at the same time, depending on the measurement setup capabilities. Positions like ear, hip and chest were investigated in [5], as shown in Figure 1.6, for two types of antennas with different radiation patterns, i.e. the planar monopole and the top loaded monopole antennas, in order to study the antenna impact on channel characteristics. It was shown that the channel gain strongly depends on the antenna type and on body position. In particular, normally polarized antennas yield to smaller attenuation in NLoS scenarios as compared to tangentially oriented ones due to the higher diffraction around the body. In [108], three subjects were simultaneously employed in the measurement and each one was equipped with four sensors. Five human subjects were used in [104] where maximum three subjects, depending on the scenario, were equipped with sensors, while the others were acting as dynamic scatterers.

Few MIMO measurements were performed [104, 108, 109]. In [108],

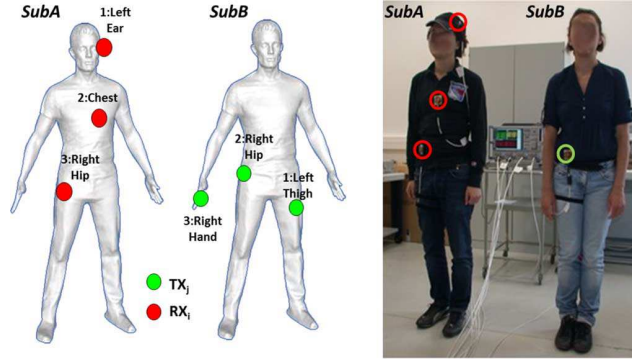


Figure 1.6: Antenna on-body positions for B2B channel investigations in [5]

the 4x32 MIMO channel matrix was investigated considering different antenna on-body positions for three human subjects. Four directional patch antennas were mounted there on Tx subject in different positions while four monopoles and PIFA antennas placed on each considered on-body position for the two Rx subjects, respectively.

Depending on the location of terminals, three types of B2B communication systems are given: Indoor to Indoor (I2I), Outdoor to Indoor (O2I) and Outdoor to Outdoor (O2O). The outdoor environments can be also classified, based on its vehicular and pedestrian traffic densities: urban, suburban, and rural environments; while the indoor premises can present an office, mall, hospital, airport etc.

As stated for vehicular channel, the relative distance between terminals must be known at any instant of measurement regardless of the measured scenarios. For that reason, a predefined grid was usually respected in B2B measurements [106]. In B2B scenarios, the channel can also experience a passage from LoS to NLoS due to the presence of the body blocking the direct communication [108].

Most of the B2B measurements were carried out with two human subjects instructed to perform controlled movements in order to study the LoS, NLoS conditions and the different types of body shadowing due to the body position, posture and movement. These scenarios can be summarized as follows:

- Random movements in a small area
- Straight line walking scenarios: parallel and opposite directions
- Rotation movements

Recently, the impact of vehicle sizes passing in the vicinity of a B2B link were investigated in [110,113] for different B2B scenarios.

Therefore, the same conclusion drawn in Section 1.2.1 for V2V channels is given here: measurement parameters, starting and stopping times, incidents during measurements, terminal speed and so on must be written down in order to explore the measurement.

1.3.2 B2B channel characterization and modeling

In B2B communications, the PL was found to be strongly dependent on the mutual body orientation [5,114]. Therefore, considering the antenna on-body position and the environment condition, the PL law was characterized in function of the relative distance between the terminals and the mutual body orientation. For different combinations of the on-body antenna positions, a range of 0.8 to 5 was depicted for the PL exponent considering the indoor scenarios in [5,108,115].

The small-scale fading distributions was generally modeled with Rice or Rayleigh distributions [108]. A K factor less than 1 was observed due to the presence of human bodies blocking the signal while a high K factor can be seen when the terminals are directly pointed to each other without any blockage. Moreover, K factor can also vary with the antenna on-body position [108,109]. In [104,113], the $\kappa - \mu$ distribution was used to model the distribution of small-scale fading B2B channels.

A maximum Doppler frequency of around 5 Hz and 6 Hz were reported in [104]. A coherence time for a correlation of 0.95 was found around 15 and 53 ms in [116] and a coherence bandwidth in the range of 6.6 and 30 MHz was found in [108], considering random body movements. The cross correlations of fading between antennas distributed or colocated on the human body were explored in [104,108]. In both papers, a low cross correlation between potential dual-branch diversity receivers was found, suggesting the

potential of successfully implementing a spatial diversity scheme. Moreover, it was shown that a diversity gain of 8.69 dB can be achieved using selection combination, maximal ratio or equal gain combining.

The maximum fading duration imposed by the passing vehicles in the vicinity of B2B links was given in [110].

Note that until now, no non-stationary (in the statistical sense) time-varying channel model was proposed for B2B channels.

1.4 Non-Stationary in Mobile-to-Mobile Channels

Different factors impose the non-stationarity of M2M channels, e.g. the variation of the scatterers in the environment, relative and absolute vehicle speed vectors etc. [72]. Therefore, the Doppler spectrum changes over time (non-WSS) and the contributions at different delays can be correlated (non-US) due to reflections on large objects, e.g. a guardrail on the road side. Some researches on statistics tests and metrics were started in order to detect the non-stationarity of the channel and to give some meaning stationarity time for the channel. Subsequently, the dependency on time and frequency is added to the stochastic analysis. So far, only the non-stationarity of V2V channels were explored in literature. In this section, we briefly present the methods that were used as well as the results extracted from the measurement data.

The spectral divergence metric was used in [117] in order to study the performance of the mismatch Wiener filter. The Wiener filter is a channel estimation filter which offers the best performance in terms of Mean-Square-Error (MSE) and recalculating the filter coefficients when the statistical properties of the channel change in time. However, by accepting an increase of MSE, one can use the same filter coefficients for several time regions, i.e. mismatch Wiener filter. Therefore, the method was based on defining a maximum allowed MSE increase and consequently finding out the range of spectral divergence values delivering it. This method was tested on the measurement results of [61].

The time frequency PDP and the time frequency Doppler spectra were presented in [20, 67, 69, 91, 118] for different V2V collision

avoidance applications. The methodology was based on estimating the LSF, which represent the time frequency scatterer correlation as defined in [28]. The time of stationarity was also estimated by analyzing the collinearity or the spectral divergence of the LSFs. The time-frequency-varying delay spread and Doppler spread distributions follow a bi-modal Gaussian mixture distribution. Moreover, it was found that the non-US behavior is due to the rich scattering presented in the environment. The dimensions of the minimum stationarity region was given to be on the order of 40 ms in time and 40 MHz in frequency.

The correlation matrix distance and the shadow fading correlation metric were performed to investigate the WSS assumption of 30x30 MIMO V2V channels [85, 119, 120]. A range of 10-40 m of stationary distance was obtained for an average velocity of 7.5 km/h. The shortest stationarity distances were found in the urban environment, mostly due to its high density of scatterers and the longest corresponds to the highway environment probably due to a few number of scatterers.

1.5 Summary

This chapter presents an overview of SOTA for V2V and B2B channel measurement and modeling. In general, the measurement equipments and the antenna position on the moving subjects affect the channel measurement performance. Moreover, the M2M channel characteristics depend on several factors like the conducted scenario, environment, antenna radiation pattern and position, frequency etc. Different modeling approaches, i.e. deterministic and stochastic, were investigated to reproduce the V2V channels while the B2B channel characteristics were only represented statistically. Hence, more study on B2B channel are requested in order to model the time-varying aspect of the channel in terms of Doppler spectrum, ACF and non-stationarity fading behavior.

Due to the non-stationarity behavior of the M2M channels, some techniques were proposed in order to determine the stationarity length of V2V channels. The major modeling methods proposed for V2V that can include this aspect are the GSCM and the TDL model with birth/death process.

Indeed, various V2V channel measurements were performed for ITS. However, other V2X scenarios need further attention, e.g. V2P, vehicle-to-train, P2P in the presence of moving and parked cars, for road safety purpose as well.

In order to fill the gap presented in the literature concerning the M2M channels, a time-varying B2B channel model and a wide-band V2P channel model based on measurements were presented in the following chapters.

Chapter 2

Narrow-band Mobile to Mobile Channels

Contents

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The limited contributions dedicated for B2B channel characterizations and modeling were presented in chapter 1. It was found that the human body itself plays an important role in impacting the channel characteristics. This effect can be linked to the mutual body orientation.

In this chapter, narrow-band indoor B2B measurement based channel models were presented. In particular, we focus on characterizing the B2B channel transfer function considering different antenna positions on the human body, e.g. head, belt and wrist.

Different mobility patterns and environment conditions were measured at 2.48 GHz. The goal of this work is to extend the current SOTA in B2B channel models and to establish a comprehensive stochastic channel model that can predict with accuracy the time-varying B2B channels by exploiting awareness of the mutual spatial position of the two terminals.

Therefore, a statistical approach was used and it consists of decomposing the measurement results into three major components: the channel gain, large-scale fading and small-scale fading. Considering the antenna on-body position and for each of the environment under investigations, the first statistical order of the channel dynamic components was derived. The second order statistic, i.e. ACF and Doppler spectrum, of the channel transfer function, large- and small-scale fading were also studied considering the antenna on-body position, the environment under investigation and the mobility patterns. Note that all these characteristics are important for describing the indoor B2B channel and in order to further develop or parametrize the channel models.

The ACF model for M2M channels in the presence of moving scatterers presented in [21] was extended in order to take into account a general scattering environment. This model was exploited to depict the measurement results given when the antennas were placed on the heads of moving subjects. Note that these types of scenarios can be further considered as indoor M2M scenarios, due to the negligible influence of body shadowing on the channel characteristics. A simple analytical Doppler spectrum model was also proposed for these types of channels (head to head channels $\equiv$ indoor M2M channels) and compared to the measurements.

Finally, the non-stationarity behavior of the small-scale fading was assessed based on methods proposed in [19] for on-body channels and [20] for V2V channels.

This chapter is organized as follows. Section 2.1 describes the measurement campaign. Section 2.2 presents the post-processing applied to the measurements in order to separate the channel components from each other. Then, the measurement results, by means of PL, small- and large-scale fading derived in LoS and NLoS conditions were given in section 2.3. The correlation and Doppler properties and modeling were exhibited in Section 2.4 and Section 2.5,

respectively. The non-stationarity behavior of small-scale fading was studied in Section 2.6. Finally, conclusions were drawn in Section 2.7

2.1 Channel Measurement Campaign

2.1.1 Measurement setup

A 4-port Rohde&Scharz VNA was employed to record the S-parameters. The time sweep mode was used which is a Continuous Wave (CW) mode where the main parameters to be set are the constant frequency and the length in time of the measurements. The frequency 2.48 GHz was chosen in order to avoid interferences by other networks around 2.4 GHz. A spectrum analyzer was employed to search for white spaces in the band of interest. The Tx power at antenna ports was set to 10 dBm. The time step was set to 4 ms providing 2501 points for each realization, considering a measurement time of 10 s. Table 2.1 reports the VNA set-up parameters.

Table 2.1: VNA setup parameters

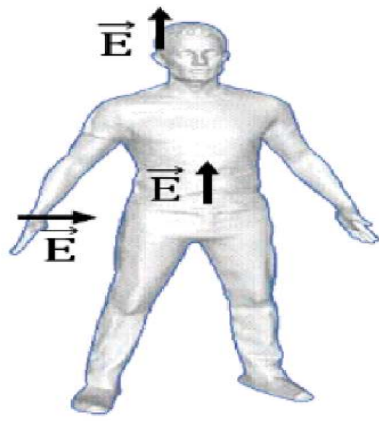
Frequency	2.48 GHz
Time step	4 ms
Tx power	10 dBm
Measurement time	10 s
Measurement points	2501
Dynamic range	110 dB

In all measurements all ports were employed, i.e. four antennas were used and mounted on four different subjects. This was oriented to study the communication between B2B coordinating sensors and to model the X2X channel, where X is the position of the node on the body.

Monopole antennas were used and three antenna on-body positions were considered, i.e. head (helmet), belt and wrist. Figure 2.1a visually describes these positions on the human body as follows:

1. Head position, where the antenna is vertically mounted on the right side of a helmet placed on the head of the subject.

2. Belt position, where the antenna is vertically placed on the lower front side of the subject torso.
3. Wrist position, where the antenna is horizontally placed on the right wrist of the subject.



(a) schematic representation



(b) Photo

Figure 2.1: Antenna on-body positions in all the three positions (head, belt, wrist) at the same time

Figure 2.1b presents how the antennas were attached to the body during measurements in all the three considered positions. As seen, for wrist position, the antenna was directed orthogonally with respect to the other cases. To verify radiation properties of the monopole antenna in proximity of the body, Reflection Coefficients (S_{11}) parameter was measured with a one-port setting VNA between 2 GHz and 3 GHz both for isolated and body-attached antennas (cf. Appendix A).

2.1.2 Measurement scenarios

The measurement environment was the offices of the LAP laboratory in MINATEC campus at CEA, Grenoble. The full campaign includes measurements performed in various indoor locations, e.g. single and multiple rooms, in order to take into account the LoS and NLoS conditions.

The single room environment is presented by room D423 (cf. Figure 2.2a). It is a classic large office of approximately 50 m^2 with desks, chairs, storage cabinets and bookshelves. The two adjacent rooms are represented as D423 and D420 (cf. Figure 2.2b). The second one is a smaller office room of approximately 30 m^2 with similar characteristics. During measurements, furniture was arranged at the sides of the room, leaving a large empty space in the center where the subjects were moving.

Several coordinated body movements were considered and recorded in several measurement runs, including static, rotation, random local movements around a fixed location or several straight line walking routes. Four people were involved and they were moving at a constant speed of approximately $0.5\text{--}0.6\text{ m/s}$. A sonorous synchronization was used in order to aid the subjects to move at a regular pace. Figure 2.2 presents the four human subject named here with the letters A, B, C and D and the six channel links measured in each run.

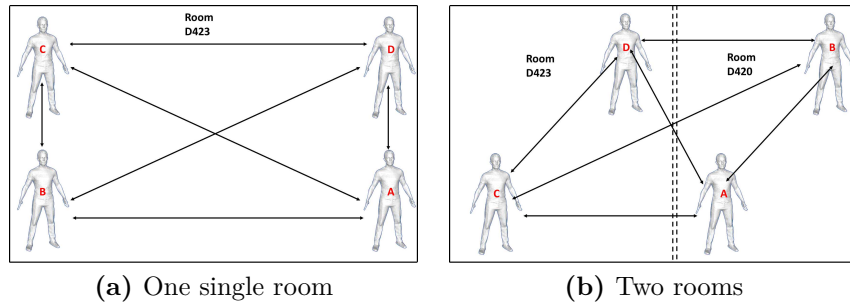


Figure 2.2: B2B communication links

2.1.2.1 Single room: Human body mobility description

Figure 2.3 shows the five measurement runs carried out in this first environment where each Body Area Network (BAN) has one antenna in the same on-body position, i.e. head, belt or wrist. The description of each run of measurements is the following:

1. Rotation around a fixed position in five steps (coordinated by sound) between 0° and 360° with a 90° step.
2. Random uncoordinated movements around fixed positions.
3. Straight line walking inside the room from one side to the other as depicted by arrows.
4. Straight line walking in the opposite sense with respect to run 3.
5. Walking towards the center of the room and, after turning, walking back to the original position.

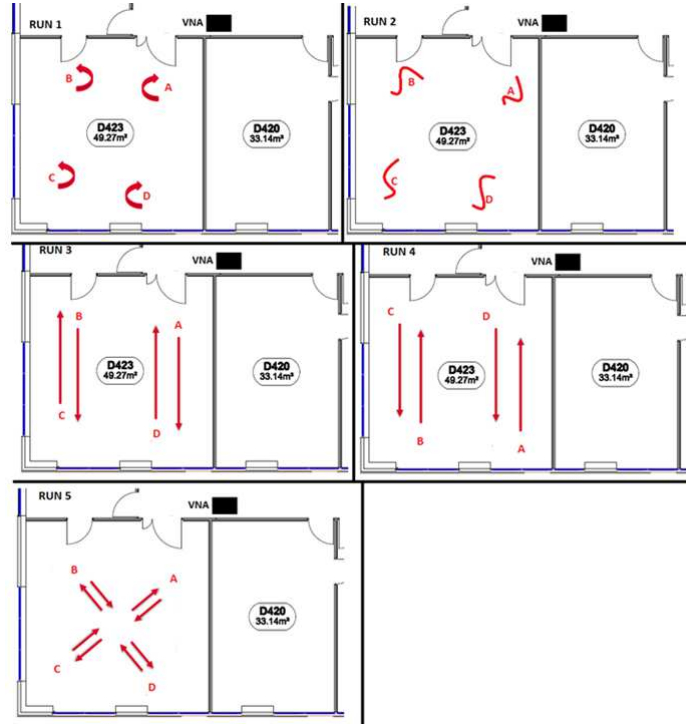


Figure 2.3: Plan of measurement runs in single room for "coordinators" scenarios

2.1.2.2 Two adjacent rooms: Human body mobility description

In the two adjacent room environment, two persons per office were considered. Figure 2.4 shows the seven runs with the different human body movements where each BAN has a single antenna alternated between the three on-body positions under consideration. A and B are in room 420, while C and D are in room 423. The description of each run of measurements is the following:

1. Random uncoordinated movements around fixed positions.
2. Straight line walking in opposite directions in both rooms.
3. Straight line walking in opposite directions in both rooms and in the opposite sense with respect to run 2.
4. Walking across the rooms in opposite directions.
5. Walking across the rooms in opposite directions and in the opposite sense with respect to run 4.
6. C walking towards the wall separating the rooms, D walking away from the same wall, while A and B are static facing that wall.
7. C walking towards the wall separating the rooms, D walking away from the same wall, while A and B are static facing away from that wall.

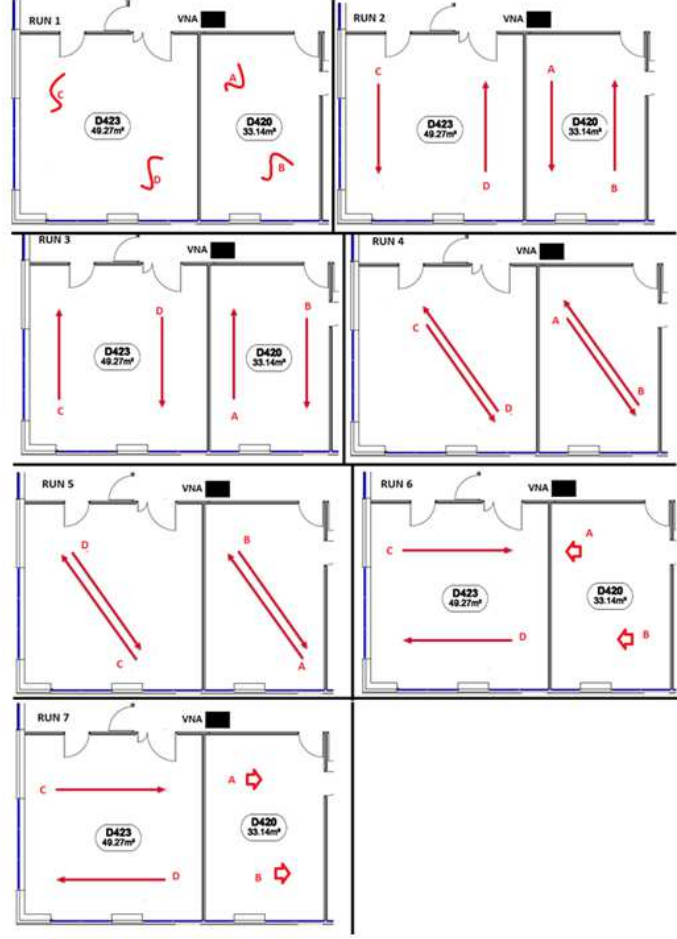


Figure 2.4: Plan of measurement runs in two rooms for "coordinators" scenarios

2.2 Channel Modeling Tools

2.2.1 Channel model definition

The outcome of the measurements is the S_{IJ} parameters where IJ represents the link between the two nodes I and J mounted on two different bodies. In other words, S_{IJ} corresponds to the narrow-band channel transfer function between the nodes I and J where I and J can be $\{A, B, C, D\}$.

In post-processing, it was decided to separate PL, mainly due to

distance between mobiles, from the large- and small-scale fading. Hence, the time-variant channel power can be expressed as (cf. Section 1.1.4):

$$H[dB] = -PL[dB] + 20 \log_{10} g[dB] + S[dB] \quad (2.1)$$

where PL is the distance dependent gain or PL, g is the small-scale fading envelope and S is the large-scale fading or shadowing.

PL in dB scale can be computed in the following way:

$$PL(d, \Omega) = -PL_{ref}(\Omega) + 10n(\Omega) \log_{10}(d/d_{ref}) \quad (2.2)$$

where n is the PL exponent that sets the rate at which the gain decreases with distance and PL_{ref} is the channel gain at the reference distance d_{ref} that is equal to 1m. Mutual body orientation Ω is defined as in Figure 2.5. This angle goes from 0° when the two BANs are straightly facing each other to 180° when they are back to back, passing by 90° when they are side by side. Note that both n and PL_{ref} were parametrized depending on the environment condition and antenna on-body position.

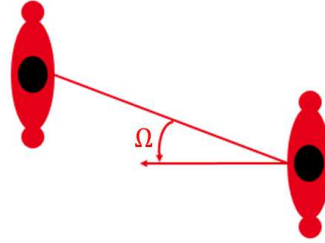


Figure 2.5: Visual definition of mutual body orientation angle Ω

Large-scale fading S is the part of the channel response that depends on slow change of the environment due to mobility as described in Section 1.1.4, e.g. an obstruction that shadows different rays of the multi-path propagation over time. Large-scale fading is classically characterized in dB scale with a zero-mean normal distribution [121]:

$$f(S[dB]) = \frac{1}{\sigma_S \sqrt{2\pi}} e^{-\left(\frac{S}{\sqrt{2}\sigma_S}\right)^2} \quad (2.3)$$

where σ_S is the standard deviation of the normal distribution.

On the other hand, small-scale fading $ge^{i\phi}$ is the time-varying part that depends on the constructive and destructive superposition of the different components of multi-path propagation that contributes to the rapid fluctuation over time (cf. Section 1.1.4). Small-scale fading amplitude is classically characterized through a Rice distribution [37]:

$$f(g) = \frac{g}{\sigma_F^2} e^{-\frac{g^2 + s_F^2}{2\sigma_F^2}} I_0\left(\frac{gs_F}{\sigma_F^2}\right) \quad (2.4)$$

where s_F is the non-centrality parameter, σ_F is the scale parameter and $I_0(\cdot)$ is the modified Bessel function of the first kind with order zero. The Rice K-factor is defined as $K_F = s_F^2/(2\sigma_F^2)$. It represents the power ratio between the dominant (coherent) path and the remaining MPCs. Therefore, the Rice parameters can give a hint on how the dominant power varies over distance and mutual body orientation.

At this point, it is worth noting that, in our model, shadowing effects caused by the bodies were mainly considered in the distance and orientation-dependent PL. Therefore, the large-scale fading only includes the slow effect caused by the environment on multi-path propagation, while the small-scale fading is the result of the constructive and destructive interferences caused by multi-path propagation for a given mutual body orientation. In other words, the body shadowing effects were incorporated into the model by describing the fading parameters as a function of the mutual body orientation.

2.2.2 Fading extraction

Small-scale fading was extracted by filtering the time domain measurements with a rectangular sliding window as follows:

$$g(t)e^{i\phi(t)} = \frac{h(t)}{\sqrt{\frac{1}{N_\lambda} \sum_{m=-N_\lambda/2}^{N_\lambda/2} |h(t - m\Delta t)|^2}} \quad (2.5)$$

where N_λ is the window size and Δt is time sampling rate which is equal to 4 ms.

The window size N_λ of 0.5 s (2.1λ) seems to offer the optimal separation between large- and small-scale fading. It was decided based

on the traveling distance considering a human speed of 0.5-0.6 m/s as well as the frequency use and the sampling rate. Nevertheless, to obtain a good filtering of the small-scale fading, the filter was applied twice to the measurements. An example of the filter response, which is the distant dependent gain and large-scale fading, is reported in Figure 2.6. Note that applying a longer time window filter instead of a second filtering would have affected too much the large-scale fading part.

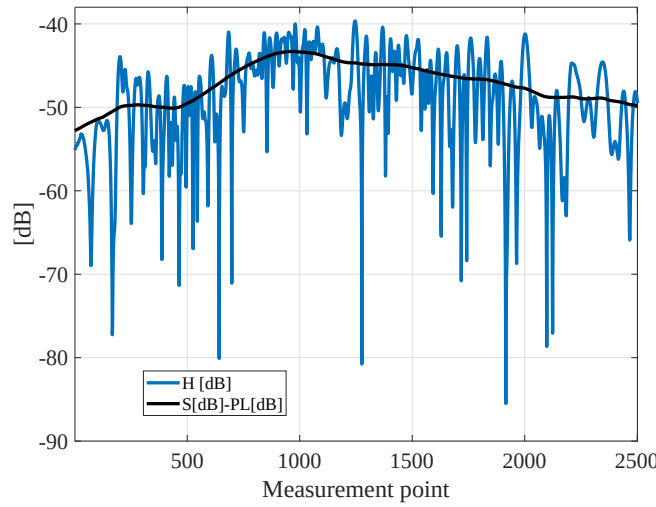


Figure 2.6: Channel response over time before and after filtering out small-scale fading

The following step is to separate the distance dependent gain from the large-scale fading. For each channel, the distance between the two terminals was computed knowing the initial and final positions of the routes and their trajectory, together with the time length of the measurements. Often, this initial distance calculation had to be corrected by visually inspecting the curves to secure a proper time-distance alignment. Once the distance alignment was completed, it is then possible to compute the gain in function of the distance and to subtract it in dB from the filtered measurement power response to obtain the large-scale fading.

2.3 Channel Modeling Results

In this section, the results of the measurement investigation are presented and the B2B channel statistics are reported. The approach was to provide results following the antenna on-body position scenarios and the environment under consideration. Some of these results were reported in [7, 122–124]. They were presented here in order to compare them with the results provided by the non-stationarity tests detailed in Section 2.6 and to validate that the B2B channels are non-stationary channels. Table 2.2 summarizes the model parameters and it is presented at the end of this section.

2.3.1 Path loss model

Figure 2.7 shows the distance dependence of the measurement data after filtering (what is left after extraction of the small-scale fading) for head to head links under LoS and NLoS conditions. The PL was fitted by the logarithmic PL model (2.2) in the least squares sense. The fitting procedure had led to an estimated PL exponent n and a reference channel gain PL_{ref} at 1 m equal to 1.28 and -41.5 dB, respectively for LoS whereas in NLoS they were best fitted with 0.94 and -46.9 dB, respectively. It is interesting to note that there is approximately 5 dB difference between PL_{ref} in single and double room. This is a classical value for attenuation from single wall in indoor empirical models.

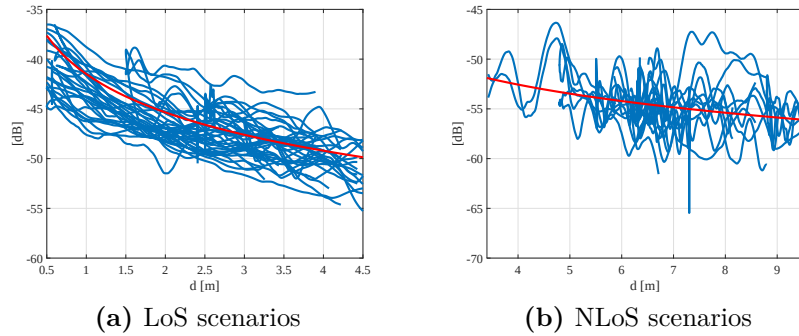


Figure 2.7: Distance dependent channel gain estimation and fitting for head to head links in LoS and NLoS scenarios

While the PL measured in head to head channels has shown an insignificant dependence on the reciprocal body orientation, the belt to belt links where the antennas were placed on the torso may suffer from significant body shadowing. For this reason, to accurately model the PL, it is important to take into consideration the reciprocal body orientation, i.e. antennas are body-shadowed or not.

Therefore, three mutual body orientation dependent zones were defined:

- LoS region, approximately for $0^\circ \leq \Omega \leq 80^\circ$, where the direct path between the terminals was not obstructed by the bodies.
- Shadowed region, approximately for $120^\circ \leq \Omega \leq 180^\circ$, where the two terminals were shadowed by the bodies.
- Transition region, that connects the two previous regions and it was characterized by a steep decrease (or increase) of the channel gain.

This behavior was particularly evident in LoS, an example is given in Figure 2.8 for a link where two people were walking in opposite directions in LoS.

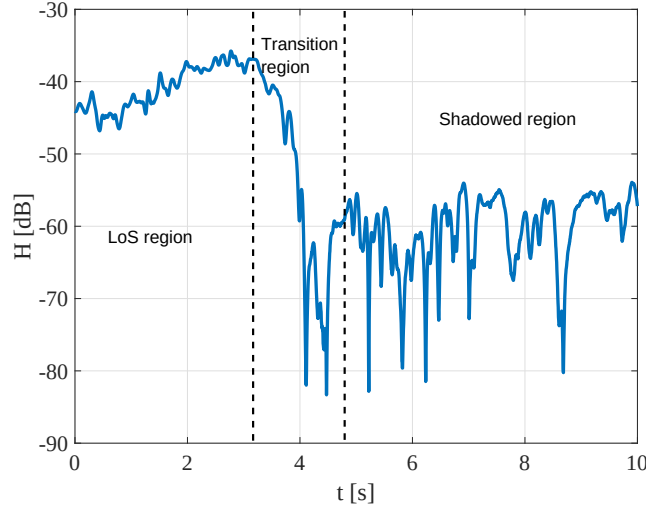


Figure 2.8: Example of channel with evident mutual body orientation regions

Figure 2.9 shows the results of Ω dependent fit of PL_{ref} and n for belt to belt LoS scenarios. As seen, similar tendencies are noticed in both curves. The PL_{ref} decreases with the increase of mutual orientation angle in the LoS and the transition region, while in the shadowed region, it increases slightly probably due to a larger multipath contributions in this region. The PL exponent n for $\Omega = 0^\circ$ is close to 2 which is usually obtained from free space propagation whereas in the shadowed region, it is close to 0 indicating that the channel gain in that zone is slightly dependent on the distance.

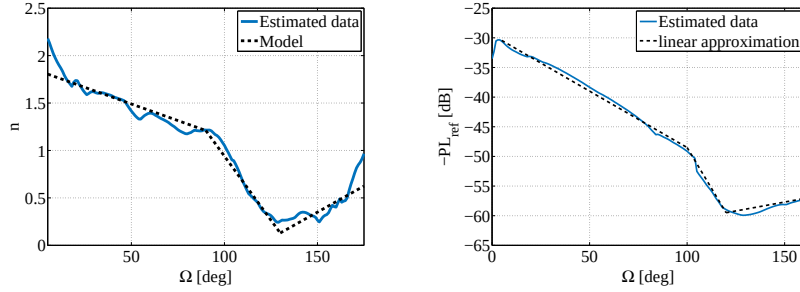


Figure 2.9: Plot of PL_{ref} and n dependence with respect to Ω in belt to belt single room scenarios

Therefore, the best fits for n and PL_{ref} were derived in function of the orientation angle as follows:

$$PL_{ref}(\Omega) = \begin{cases} -0.19\Omega - 29.5 & 0^\circ \leq \Omega \leq 100^\circ \\ -0.55\Omega + 6.5 & 100^\circ \leq \Omega \leq 120^\circ \\ 0.06\Omega - 66.7 & 120^\circ \leq \Omega \leq 180^\circ \end{cases} \quad (2.6)$$

$$n(\Omega) = \begin{cases} -0.007\Omega + 18.4 & 0^\circ \leq \Omega \leq 90^\circ \\ -0.027\Omega + 3.64 & 90^\circ \leq \Omega \leq 130^\circ \\ 0.011\Omega - 1.3 & 130^\circ \leq \Omega \leq 180^\circ \end{cases} \quad (2.7)$$

Figure 2.10 shows a good agreement between an example of measured belt to belt link and the proposed channel gain model considering the LoS condition.

For belt to belt NLoS scenarios, a fixed value of n was chosen, i.e. $n(\Omega) = 1.7$ while the PL_{ref} was best modeled in function of Ω as follows:

$$PL_{ref}(\Omega) = -0.065\Omega - 41 \quad (2.8)$$

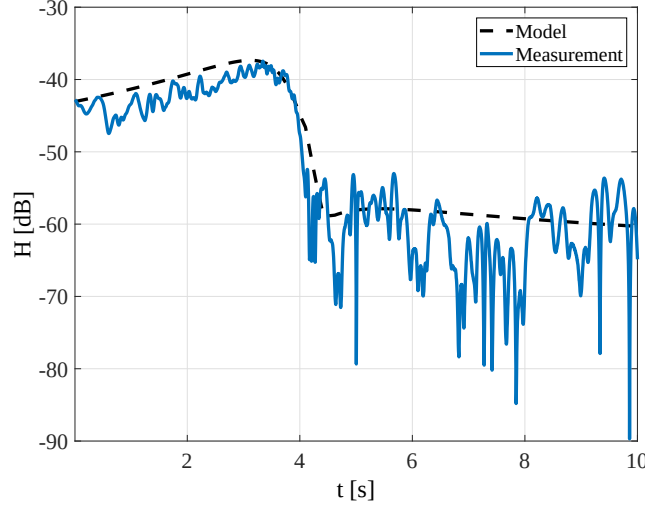


Figure 2.10: Comparison between measured channel and modeled channel gain for a given belt to belt single room link

The wrist to wrist channel losses may suffer not only from torso, but also from forearm/hand shadowing. Moreover, the orientation of the forearm itself may be different during the walking and it may change depending on each person, leading to channels showing different behavior. Therefore, in terms of characterization, the more evident difference with respect to the belt-to-belt channels is that Ω as defined in Figure 2.8 is not sufficient to describe mutual orientation issues. For a given Ω the two antennas may be either shadowed or not by the torsos, as visually shown in Figure 2.11 and this should be taken into account in the characterization.

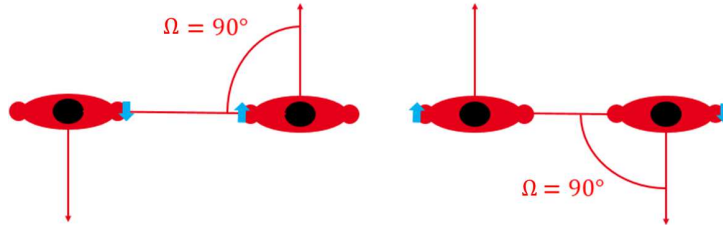


Figure 2.11: LoS and body shadowed positions for wrist to wrist channels and $\Omega = 90^\circ$

Therefore, the PL_{ref} behavior in LoS was first assessed according to the type of links, i.e. shadowed or not by the torso, and then it was modeled in function of Ω with Quadratic curves as follows:

$$PL_{ref}(\Omega) = \begin{cases} 0.00064\Omega^2 - 0.21\Omega - 43 & \text{Non shadowed} \\ 0.0091\Omega^2 - 0.4\Omega - 43 & \text{Shadowed} \end{cases} \quad (2.9)$$

Figure 2.12 presents the mutual orientation dependent PL_{ref} in the two different shadowing conditions as shown in Figure 2.11. As

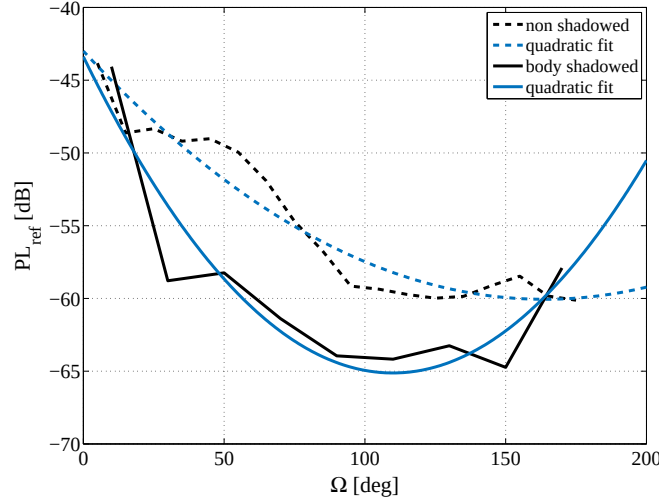


Figure 2.12: PL_{ref} dependence with mutual orientation angle in wrist to wrist LoS scenarios

noticed, there is a large difference for Ω around 90° , which corresponds to the highest shadowing condition while at the extremes, the two curves exhibits similar results as torso shadowing has limited impact when the two BANs are in front of each other, $\Omega = 0^\circ$, or their backs are facing, $\Omega = 180^\circ$. No evident Ω dependence in terms of n has shown for shadowed and non-shadowed regions, thus an average value of 1.1 was found in both cases.

Due to difficulties encountered to model the PL obtained from the wrist-to-wrist NLoS scenarios, a simple distance dependence PL model was considered and it was characterized by $PL_{ref} = -46.7$ dB and $n = 2.98$.

At this point, it is worth noting that the PL exponent, in most cases, is lower than the one associated with the free space propagation ($n = 2$), probably due to the scattering environment and the small relative distance measured between Tx and Rx. This result was also found in different indoor B2B channel contributions, e.g. [5, 125, 126].

2.3.2 Large-scale fading

The following step is to characterize the large-scale fading. Figure 2.13 shows the distribution of the aggregation of all large-scale fading contributions for head to head links in LoS and NLoS. It can be well modeled by a normal distribution (2.3) in dB with σ_S equal to 1.95 dB and 2.28 dB in LoS and NLoS, respectively.

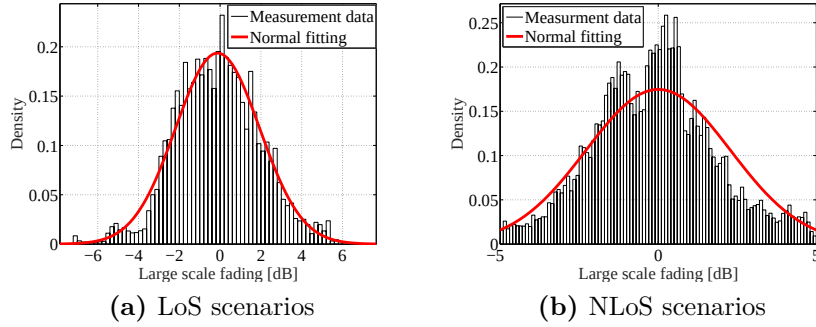


Figure 2.13: Normal fit of large-scale fading for head to head LoS and NLoS scenarios

Figure 2.14a presents the distribution of all large-scale fading contributions in dB in belt to belt LoS scenarios. Also in this case, there is sufficient agreement with a normal distribution, but the major difference with respect to head to head scenarios is that a larger standard deviation is obtained in this case, σ_S is 2.6 dB. Moreover, a study has been carried out to analyze the impact of the mutual body orientation on the large-scale fading parameter (cf. Figure 2.14b). As seen, σ_S gradually increases in the LoS zone until it reaches the transition zone, from where it remains fairly constant. This seems reasonable if we consider that the effects of the environment, on which large-scale fading depends, may have

a larger impact on channels where LoS is partially or completely shadowed. On the other hand, where the impact of the body is less relevant, i.e. for low values of Ω , σ_S assumes values closer to the one found in head to head channels.

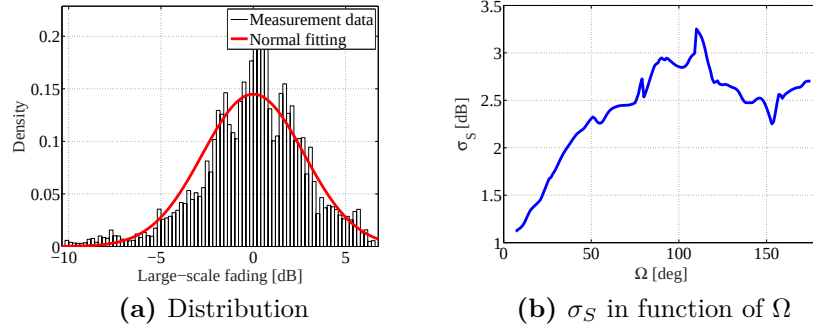


Figure 2.14: Normal fit of large-scale fading in dB for belt to belt LoS scenarios

Figure 2.15 shows the large-scale fading distribution of belt to belt links for NLoS scenarios. There is sufficient agreement with a normal distribution. σ_S is equal to 3.3dB, which is larger with respect to belt to belt LoS scenarios. The dependence of standard deviation on mutual body orientation was also analyzed, σ_S is generally comprised between 2.5 and 3.5dB, except for low and high values of σ_S . Note that those zones, i.e. small and large orientation angles, were the ones where the channel gain fit was more difficult and therefore it is reasonable that this reflected into a larger variability of large-scale fading.

Figure 2.16 shows the empirical data well fitted with normal distribution in wrist to wrist LoS and NLoS scenarios. Surprisingly, the standard deviation σ_S found in LoS scenarios is slightly larger than the one given in NLoS probably due the wide effect of shadowed and non shadowed regions in LoS with respect to the NLoS environments.

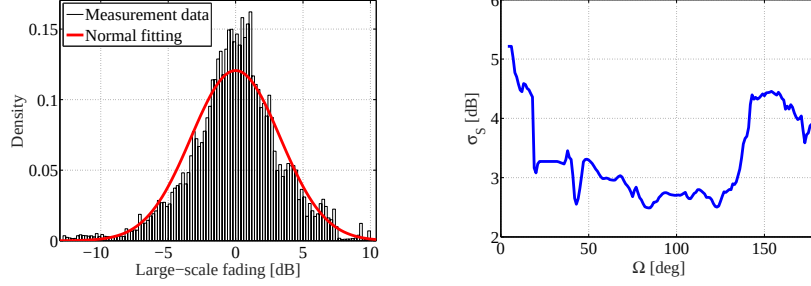


Figure 2.15: Normal fit of large-scale fading in dB for belt to belt NLoS scenarios.

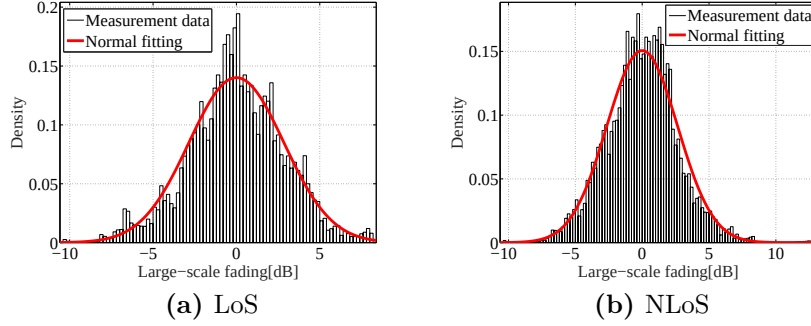


Figure 2.16: Normal fit of large-scale fading in dB for wrist to wrist scenarios

2.3.3 Small-scale fading

Figure 2.17 shows a good agreement between Rice distribution and the envelope of aggregation data extracted from all head to head links considering LoS and NLoS propagation conditions, respectively. The outcome of this fitting is a Rice noncentrality parameter s_F and the scale parameter σ_F . Their values are given in Table 2.2 for LoS and NLoS. The K-factor is equivalent to 3 dB and 2.25 dB in LoS and NLoS, respectively. As expected, the K-factor of NLoS is reasonably lower than the one given in LoS scenarios due to the less relevant dominant component when the two terminals are in two separated rooms.

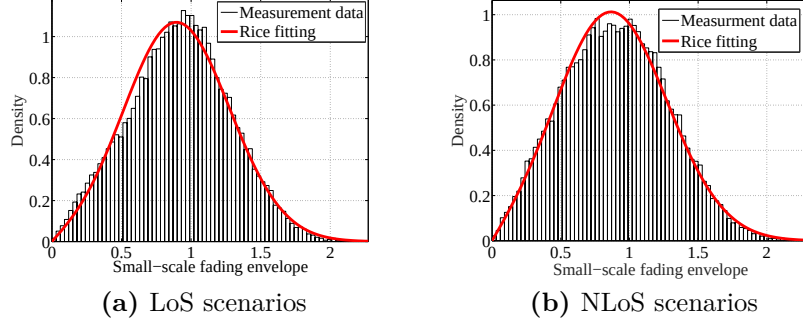


Figure 2.17: Small-scale fading distribution for head to head links in LoS and NLoS

At this point, it is worth noting that the Rice parameters have shown a distance dependence with inter-antenna distance considering the LoS scenarios (cf. Figure 2.18a). This dependence is approximately linear, with s_F decreasing and σ_F increasing when the distance increases as follows:

$$s_F = -0.036d + 0.9 \quad (2.10)$$

$$\sigma_F = 0.036d + 0.31 \quad (2.11)$$

This results in a decreasing K-factor as shown in Figure 2.18b which seems a reasonable behavior that can be heuristically explained by considering that, inside a room and with limited body shadowing, the LoS component becomes less dominant when the two terminals are further apart.

In a similar way as done for PL given by the belt to belt LoS scenarios, the behavior of small-scale fading with respect to mutual body orientation was investigated. In fact, it is reasonable to expect to find that Rice parameters depend on the mutual orientation angle, as shown in Figure 2.19a. Note that the three previously defined regions, i.e. LoS, transition and shadowed regions, can be possibly noticed and that each region shows different Rice parameters.

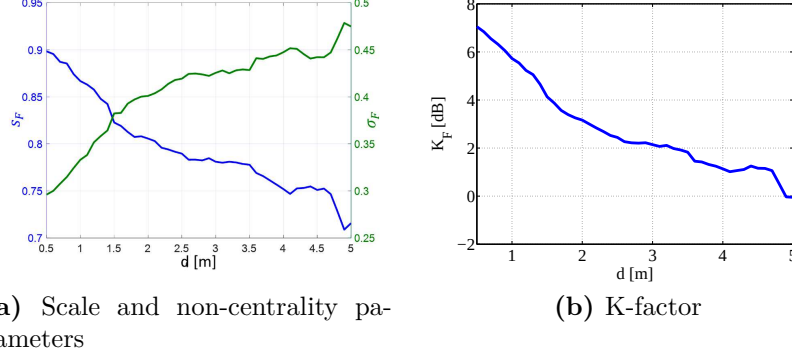


Figure 2.18: Rice parameters versus distance in head to head LoS scenarios

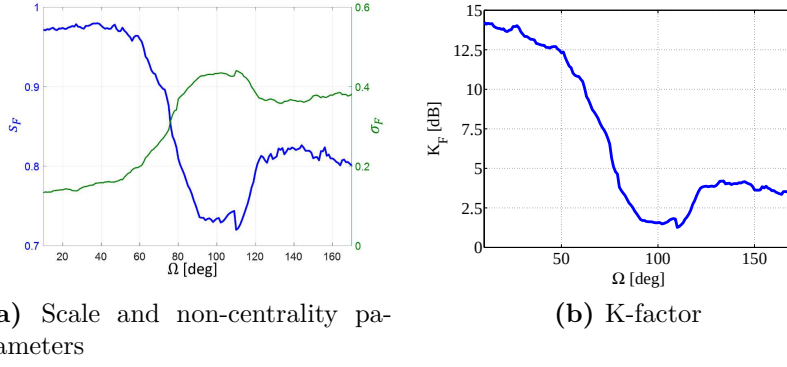


Figure 2.19: Rice parameters versus Ω in belt to belt LoS scenarios

Therefore, the Rice parameters can be expressed as follows:

$$s_F = \begin{cases} 0.97 & 0^\circ \leq \Omega < 50^\circ \\ -0.06\Omega + 1.27 & 50^\circ \leq \Omega < 90^\circ \\ 0.73 & 90^\circ \leq \Omega \leq 115^\circ \\ -0.06\Omega + 0.04 & 115^\circ \leq \Omega \leq 120^\circ \\ 0.81 & 120^\circ \leq \Omega \leq 180^\circ \end{cases} \quad (2.12)$$

$$\sigma_F = \begin{cases} 0.15 & 0^\circ \leq \Omega < 50^\circ \\ 0.007\Omega + 0.2 & 50^\circ \leq \Omega < 90^\circ \\ 0.43 & 90^\circ \leq \Omega \leq 115^\circ \\ -0.012\Omega + 1.8 & 115^\circ \leq \Omega \leq 120^\circ \\ 0.37 & 120^\circ \leq \Omega \leq 180^\circ \end{cases} \quad (2.13)$$

The Rice K-factor in function of the mutual orientation angle is presented in Figure 2.19b. As expected, the K-factor is high in the LoS region as there is a non-obstructed dominant path, and then, it rapidly decreases and it settles to values less than 3 dB in the transition and shadowed regions probably due to the reduction of the dominant power coupled with the significant scattered part of the body shadowing in these regions. Consequently, in order to model the small-scale fading in an accurate sense, the body orientation angle must be included in the Rice parameter descriptions.

Similarly, The Rice parameters have shown a mutual body orientation dependence in belt to belt NLoS scenarios (cf. Figure 2.20). As expected, the range of values is reduced compared to what was found in LoS scenarios, but the three regions are still visible.

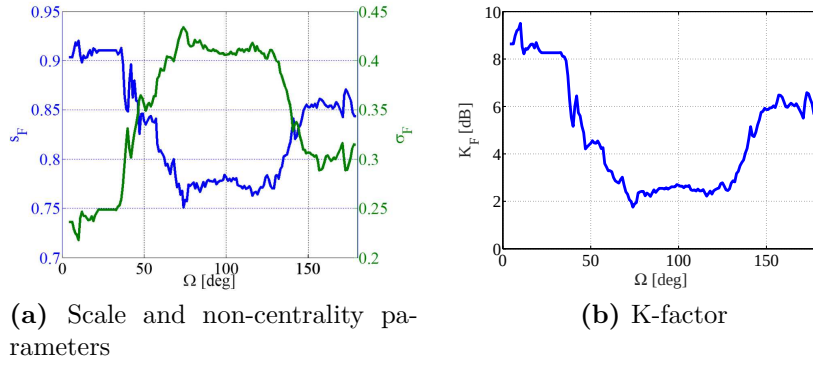


Figure 2.20: Rice parameters in function of body orientation angle in belt to belt NLoS scenarios

The Rice parameters of the small-scale fading obtained from wrist to wrist LoS scenarios have also shown a mutual body orientation dependence. Figure 2.21a presents the K-factor of shadowed and non-shadowed regions by the torso. As seen, a larger K-factor (between 4 dB and 8 dB) for $\Omega < 80^\circ$ in links non-shadowed by the torso while $K_F < 4$ dB was found for larger values of Ω probably due to forearm shadowing, and in torso shadowed links. It is interesting to note that the peak of K_F for channels on the same side of the torsos, is at $\Omega \approx 50^\circ$ and the curve is unsymmetrical with respect to $\Omega = 90^\circ$. This may not be only due to arm swinging and forearm orientation during walking, but also to the different

antenna orientation that, in the wrist case, is horizontal, as previously stated.

Figure 2.21b shows the mutual orientation dependence in K-factor for wrist to wrist NLoS scenarios. As seen, both behaviors, shadowed or non-shadowed regions, are qualitatively similar with insignificant difference for limited values of Ω .

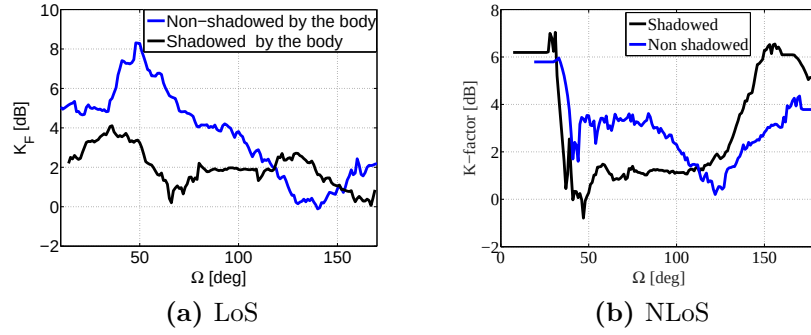


Figure 2.21: K-factor of wrist-to-wrist small-scale fading in function of Ω for torso shadowed channels (in black) and nonshadowed by the torso (in blue) in LoS and NLoS scenarios

Table 2.2: Model Parameters in LoS and NLoS scenarios

		Head to Head		Belt to Belt		Wrist to Wrist	
		LoS	NLoS	LoS	NLoS	LoS	NLoS
Path loss	n	1.28	0.94	eq. (2.7)	1.7	1.1	2.98
	PL_{ref} [dB]	-41.5	-46.9	eq. (2.6)	eq. (2.8)	eq. (2.9)	-46.7
large-scale fading	σ_S [dB]	1.95	2.28	2.6	3.3	2.85	2.64
small-scale fading	s_F	0.8	0.77	eq. (2.12)	0.8	0.76	0.78
	σ_F	0.4	0.42	eq. (2.13)	0.37	0.43	0.4

2.4 Time Correlation Function: Analysis and Modeling

The mobility of terminals and scatterers surrounding the terminals causes the temporal variations of the channel as described by the ACF or the Doppler spectrum. In other words, in order to model the M2M channel varying in time, the ACF or the Doppler spectrum must be represented by suitable models that can well depict the measurement data and reasonably explain the phenomenon.

In this section, the time correlation properties and modeling of head to head channels are reported.

2.4.1 Measurement results

As a first step, consider that the M2M channel given by one realization is a WSS channel and the ACF can be expressed in the following way [127]:

$$R(\Delta t) = \frac{\mathbb{E}[X(t) \cdot X^*(t + \Delta t)]}{\sqrt{\mathbb{E}[|X(t)|^2] \mathbb{E}[|X(t + \Delta t)|^2]}} \quad (2.14)$$

where $X(t)$ can represent here either the small or large-scale fading or the transfer function normalized with respect to its PL.

Hence, the ACF for each channel and for each specific acquisition was calculated. Figure 2.22 shows the comparison of small-scale fading ACFs for different realizations when Tx and Rx were in LoS and they were moving in the opposite direction. As seen, regardless the specific acquisition, the ACF patterns are qualitatively similar. It is thereby relevant to aggregate together all data samples of realizations with the same walking pattern.

Therefore, for a given scenario and similar mobility patterns, the M2M channel is considered for simplicity as a WSS channel and the ACF was calculated using equation (2.14).

It is important to note that the large-scale fading ACF was computed over its Gaussian values, i.e. in dB scale, while the channel transfer function and small-scale fading ACFs were computed over

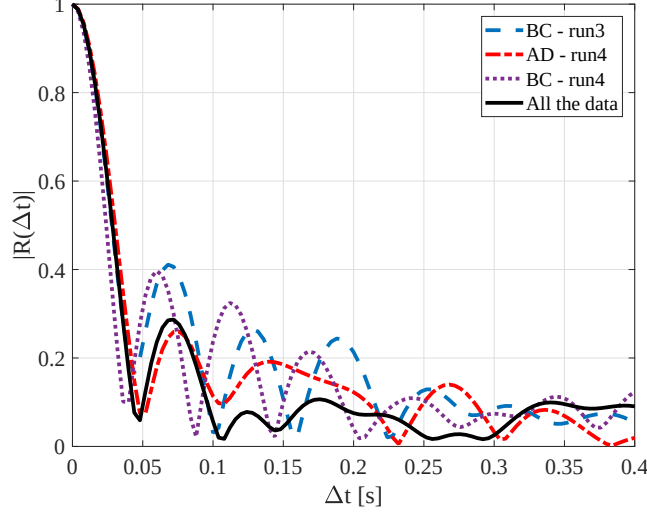


Figure 2.22: ACF of small-scale fading component for opposite walking scenario in LoS condition

complex values in order to study the impact of the phase information on one hand and to preserve the Gaussian properties given by the measured small-scale fading (complex Gaussian) on the other hand.

Figure 2.23, 2.24 and 2.25 present the ACFs of the normalized transfer function, the large-scale fading and the small-scale fading, respectively, considering different walking patterns in LoS and NLoS conditions. Table 2.3 presents the coherence time at 0.5 of the ACF for each walking scenario and dynamic channel component.

As expected, the large-scale fading presents the higher coherence time. Its ACF can be modeled, as a first approximation, by an exponential decay law [128]. Note that its shape does not strongly depend on the walking pattern. This is a consequence of the fact that large-scale fading is mainly due to furniture in the environment and shadowing by nearby bodies which results in longer coherence time compared to small-scale fading. Hence the correlation properties of large-scale fading are barely visible in the ACF of the channel transfer function.

The small-scale fading and channel transfer function ACFs present shapes that are significantly dependent on the type of movement.

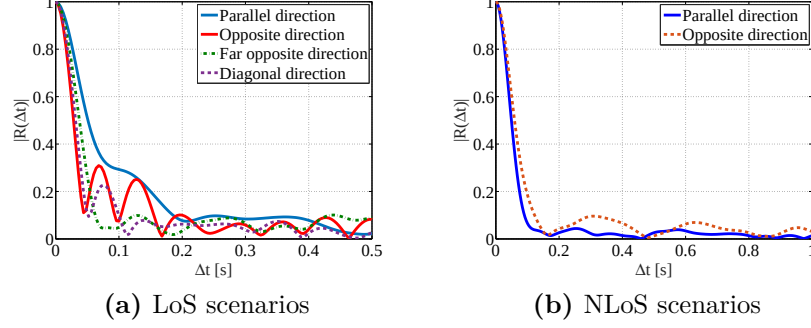


Figure 2.23: ACFs of channel transfer functions for different mobility patterns in LoS and NLoS conditions

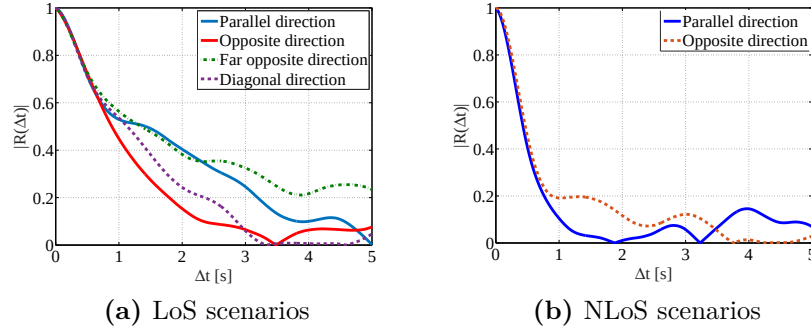


Figure 2.24: ACFs of large-scale fading for different mobility patterns considering LoS and NLoS conditions

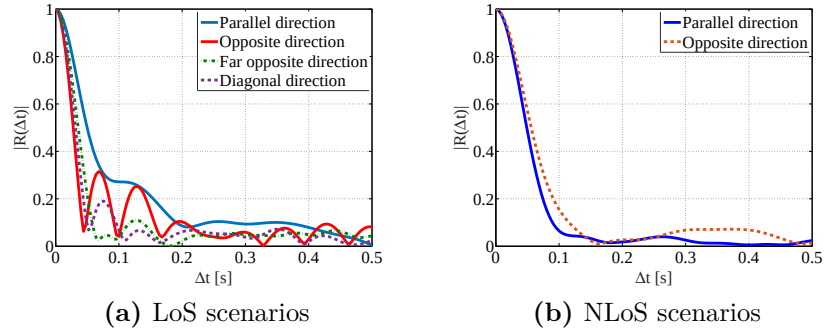


Figure 2.25: ACFs of small-scale fading for different mobility patterns in LoS condition

The measured coherence time varies between 28 ms and 59 ms (cf. Table 2.3). These results, when compared to the coherence time of the large-scale fading (typically higher than 400 ms), suggests that the similarities in terms of coherence time and shape mean that the ACF of the transfer function mainly depends on the one of small-scale fading. Moreover, the fast decorrelation of small-scale fading is due to the fast decorrelation of the phase information [129]. Therefore, in what follows, a time correlation function model for the M2M fading channels is developed and compared to the measurement data.

Table 2.3: Coherence Time and Doppler spread of M2M channels considering several mobility patterns and different environments

Walking pattern	Propagation condition	Doppler spread [Hz]	Coherence time [ms]		
			<i>Normalized transfer function</i>	<i>Small-scale fading</i>	<i>Large-scale fading</i>
Parallel direction	LoS	4.3	51	50	1 425
	NLoS	4.1	49.3	48.9	427
Opposite direction	LoS	6.66	28.2	27.8	887
	NLoS	3.18	59.1	55.9	463
Diagonal direction	LoS	6	31.4	31.2	1 132

2.4.2 M2M time correlation function model

In this section, an ACF model of M2M channels in the presence of moving scatterers is presented. This model is an extension of the one given in [21] for isotropic scatterers, in order to take into account a general scattering environment. This model can also account for different mobility patterns of the terminals and the scatterers.

Figure 2.26 presents a typical scenario for indoor M2M channel in the presence of moving scatterers. The Rx and Tx are presented by two human subjects that are moving with velocity v_R and v_T in the direction of φ_v^R and φ_v^T , respectively. Similarly, v_{S_n} and $\varphi_v^{S_n}$ indicate the velocity and the direction of motion, respectively, for the n^{th} moving scatterer.

For a general scattering environment, the attenuation factors due to the interaction of an emitted signal with the scatterers are a function of the emitted and received angles [130]. Thus, the normalized

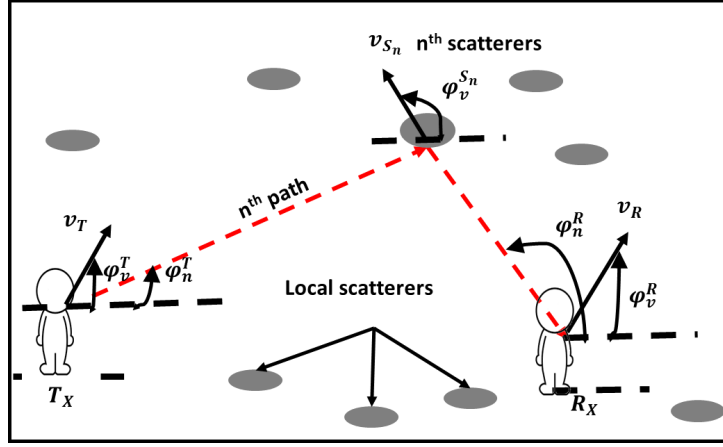


Figure 2.26: A typical propagation scenario of B2B with moving scatterers

fading channel transfer function can be written as:

$$g(t)e^{i\phi(t)} = \lim_{N \rightarrow +\infty} \sum_{n=1}^N g_n(\varphi_n^R, \varphi_n^T) e^{i2\pi\nu_n t + \psi_n} \quad (2.15)$$

where N is the number of scatterers, g_n is the n^{th} path amplitude resulting in the interaction of the transmitted signal with the n^{th} scatterer, φ_n^T and φ_n^R represent the n^{th} angles of departure (AOD) and arrival (AOA), respectively. The phase shift of the n^{th} path ψ_n is usually assumed to be uniformly distributed between 0 and 2π [34]. The Doppler frequency shift is represented by ν_n which can be expressed as [21]:

$$\nu_n = \frac{1}{\lambda} [v_T \cos(\varphi_v^T - \varphi_n^T) - v_{S_n} [\cos(\varphi_n^T - \varphi_v^{S_n}) + \cos(\varphi_v^{S_n} - \varphi_n^R)] + v_R \cos(\varphi_v^R - \varphi_n^R)] \quad (2.16)$$

where

- The first term $\frac{v_T}{\lambda} \cos(\varphi_v^T - \varphi_n^T)$ is the Doppler frequency shift due to Tx mobility.
- The second term $\frac{v_{S_n}}{\lambda} [\cos(\varphi_n^T - \varphi_v^{S_n}) + \cos(\varphi_v^{S_n} - \varphi_n^R)]$ is the Doppler frequency shift due to the mobility of the n^{th} scatterer.

- The third term $\frac{v_R}{\lambda} \cos(\varphi_v^R - \varphi_n^R)$ is the Doppler frequency shift due to Rx mobility.

Considering the speed vectors and attenuation factors constant over time, the channel can be seen then as a WSS channel. In addition, assuming that the phases of the paths, ψ_n , are independent and uniformly distributed between 0 and 2π , the ACF can be then expressed as [131]:

$$R(\Delta t) = \lim_{N \rightarrow \infty} \sum_{n=1}^N \mathbb{E} \left[|g_n(\varphi_n^T, \varphi_n^R)|^2 e^{i2\pi\nu_n \Delta t} \right] \quad (2.17)$$

For a continuous scatterer distribution, equation (2.17) is rewritten as follows:

$$R(\Delta t) = \int_0^\infty \int_0^{2\pi} \int_0^{2\pi} \int_0^{2\pi} |g(\varphi^T, \varphi^R)|^2 e^{i2\pi\nu \Delta t} p(\varphi^T, \varphi^R, \varphi_v^S, v_S) d\varphi^T d\varphi^R d\varphi_v^S dv_S \quad (2.18)$$

where $p(\varphi^T, \varphi^R, \varphi_v^S, v_S)$ is the joint distribution between the Angle of Arrival (AOA), the Angle of Departure (AOD), the velocity and moving direction of the scatterers. At this point, it is reasonable to say that φ_v^S and v_S are independent from φ^R and φ^T , hence:

$$p(\varphi_v^S, v_S, \varphi^T, \varphi^R) = p_{\varphi_v^S, v_S}(\varphi_v^S, v_S) p_{\varphi^T, \varphi^R}(\varphi^T, \varphi^R) \quad (2.19)$$

where $p_{\varphi_v^S, v_S}(\varphi_v^S, v_S)$ is the joint distribution of directions and velocities for the moving scatterers while $p_{\varphi^T, \varphi^R}(\varphi^T, \varphi^R)$ is the AOD and AOA joint distribution.

Therefore, equation (2.18) becomes:

$$R(\Delta t) = \int_0^\infty \int_0^{2\pi} \int_0^{2\pi} \int_0^{2\pi} |g(\varphi^T, \varphi^R)|^2 p_{\varphi^T, \varphi^R}(\varphi^T, \varphi^R) p_{\varphi_v^S, v_S}(\varphi_v^S, v_S) e^{i\frac{2\pi}{\lambda} [v_T \cos(\varphi_v^T - \varphi^T) - v_S [\cos(\varphi^T - \varphi_v^S) + \cos(\varphi_v^S - \varphi^R)] + v_R \cos(\varphi_v^R - \varphi^R)] \Delta t} d\varphi^T d\varphi^R d\varphi_v^S dv_S \quad (2.20)$$

where $|g(\varphi^T, \varphi^R)|^2 p_{\varphi^T, \varphi^R}(\varphi^T, \varphi^R)$ denotes the angular power distribution of the received signal.

Consequently, equation (2.20) represents a general ACF of M2M channels in the presence of moving scatterers considering a general scattering environment.

Under the isotropic scatterers' assumption, the model given in [21] is obtained. Moreover, this model can also include some analytical models found in literature. For instance, the analytical ACF of

M2M fading channels in the presence of fixed scatterers [90, 132], can be derived by taking $p_{\varphi_v^S, v_S}(\varphi_v^S, v_S) = \delta(v_S)/(2\pi)$, i.e. the scatterers move (vibrate) uniformly in all directions with a null velocity. For F2M fading channels with fixed scatterers [34, 133], the analytical time correlation function model can be obtained by considering $v_T = 0$ and $p_{\varphi_v^S, v_S}(\varphi_v^S, v_S) = \delta(v_S)/(2\pi)$, while for Fixed to Fixed (F2F) fading channels with moving scatterers [134, 135], it can be given by setting $v_T = v_R = 0$.

2.4.2.1 Application to indoor M2M channels

In this section, equation (2.20) was used in order to derive analytical models for the ACF of the small-scale fading given in parallel and opposite walking scenarios considering the LoS conditions. Then, a comparison between the model and the corresponding measurement data is presented showing the validity of the model. Note that these equations developed for special mobility patterns can also represent the ACFs in NLoS. However, for brevity, we only represent the results of LoS scenarios.

Same walking direction

Let us consider the parallel walking patterns where the Tx and Rx were moving simultaneously in the same direction, whereas two subjects (assumed as scatterers) were walking in the opposite direction. All four human subjects were moving at the same velocity v . Therefore, the scenario can be seen as an M2M communication system with moving and fixed scatterers taking the room as a reference system. In this scenario, the following relations hold true:

$$\left\{ \begin{array}{l} p_{v_S, \varphi_v^S}(v_S, \varphi_v^S) = a\delta(v_S - v)\delta(\varphi_v^S + \pi/2) + \\ \quad + (1 - a)\delta(v_S)/2\pi \\ v_T = v_R = v \\ \varphi_v^T = \varphi_v^R = \pi/2 \end{array} \right. \quad (2.21)$$

where a is the portion of scatterers (the two human subjects) moving at speed $v_s = v$ ($a = P(v_S = v)$).

Considering a uniform scatterer distribution, the joint probability distribution of AOA and AOD is then equal to $1/(4\pi^2)$, i.e. $p_{\varphi^T, \varphi^R}(\varphi^T, \varphi^R) = 1/(4\pi^2)$. Moreover, given that the path amplitudes are periodic with period of 2π , the angular power function can then be described by a double Fourier series:

$$|g(\varphi^T, \varphi^R)|^2 = \sum_{n=-\infty}^{+\infty} \sum_{m=-\infty}^{+\infty} \gamma_{nm} e^{i(n\varphi^T + m\varphi^R)} \quad (2.22)$$

where γ_{nm} are the coefficients of the double Fourier series of $|g(\varphi^T, \varphi^R)|^2$. Therefore, using (2.21), (2.22) and taking into account the following Bessel function property [136]:

$$e^{iz \cos \alpha} = \sum_{q=-\infty}^{+\infty} i^q J_q(z) e^{iq\alpha} \quad (2.23)$$

the time correlation function (2.20) becomes:

$$\begin{aligned} R(\Delta t) = & a \sum_{n=-\infty}^{+\infty} \sum_{m=-\infty}^{+\infty} (-1)^{(n+m)} \gamma_{nm} J_n(4\pi\nu_D \Delta t) J_m(4\pi\nu_D \Delta t) \\ & + (1-a) \sum_{n=-\infty}^{+\infty} \sum_{m=-\infty}^{+\infty} (-1)^{n+m} \gamma_{nm} J_n(2\pi\nu_D \Delta t) J_m(2\pi\nu_D \Delta t) \end{aligned} \quad (2.24)$$

where $\nu_D = v/\lambda$ is the maximum Doppler frequency shift due to the mobility of terminals which is, in our case, equal to 4.96 Hz ($v = 0.6$ m/s).

Equation (2.24) presents the time correlation function of small-scale fading for parallel walking scenario considering a uniform distribution of non-isotropic scattering patterns. For the isotropic scattering case, i.e. $\gamma_{nm} = 1$ for $n = m = 0$ and 0 elsewhere, equation (2.24) becomes:

$$R(\Delta t) = a J_0^2(4\pi\nu_D \Delta t) + (1-a) J_0^2(2\pi\nu_D \Delta t) \quad (2.25)$$

Figure 2.27 presents a comparison between the measured ACF of small-scale fading for parallel walking scenario and the curves given by the M2M-Non-Isotropic Moving Scatterers (NIMS) model (2.25) taking $a = 0.09$ and the M2M-Isotropic Moving Scatterers (IMS) model (2.24) where γ_{nm} coefficients are estimated up to the first or tenth orders using a non-linear least square fitting. Note that several upper bounds for Bessel function are given in [137] and can be used to truncate the infinite series in (2.24). The value of a in the equation (2.25) was chosen in

order to obtain a best fit between the measurement data and the model. The small value of a , which is the proportion of moving scatterers, shows that the fixed scatterers are predominant in the environment. This is in line with the experiment as they represent the whole scenario, with the exclusion of the two moving humans.

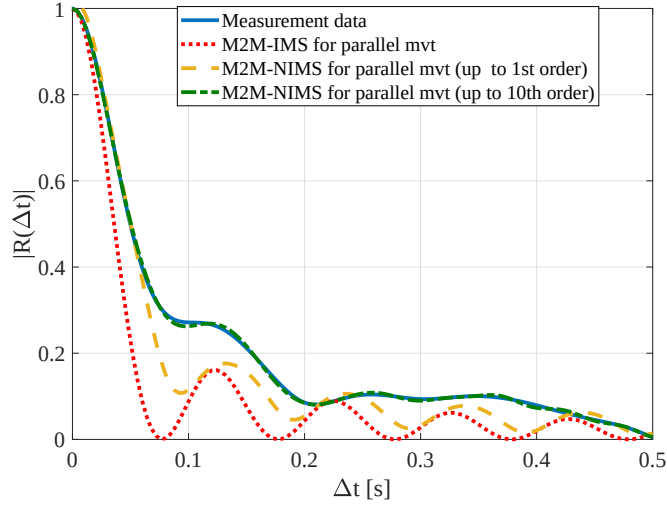


Figure 2.27: Time correlation function of measurement data vs. analytical formulas for parallel movements (mvt). (IMS:isotropic moving scatterers, NIMS: non-isotropic moving scatterer)

The coherence time of the measurement data at 0.5 is 50 ms which corresponds to that given by the non-isotropic scattering model (50.5 ms) while for isotropic scattering case, it is 36 ms. Consequently, the M2M-IMS model can roughly represent the temporal variation of the measured correlation function up to the coherence time, while the M2M-NIMS model can be considered as a more accurate time correlation function model. As expected, the accuracy of the fitting increases with the number of orders.

Opposite walking direction

In a similar way, let us consider the opposite walking realizations where the Rx and Tx were moving simultaneously towards each other and simultaneously with other human subjects (considered as moving scatterers). The scenario can be also described as an M2M communication link in the presence of moving scatterers, considering the room as

the reference system and the following hypothesis hold true:

$$\left\{ \begin{array}{l} p_{v_S, \varphi_v^S}(v_S, \varphi_v^S) = \delta(v_S - v)[b\delta(\varphi_v^S - \pi/2) \\ + c\delta(\varphi_v^S + \pi/2)] + (1 - b - c)\delta(v_S)/(2\pi) \\ \varphi_v^T = -\varphi_v^R = \pi/2 \\ v_R = v_T = v \end{array} \right. \quad (2.26)$$

where b and c are the proportions of moving scatterers with Tx and Rx directions of motion, respectively ($b = P(\varphi_v^S = \pi/2)$ and $c = P(\varphi_v^S = -\pi/2)$).

Accordingly, the time correlation function of this type of channels was developed using equation (2.20) assuming a uniform distribution of non-isotropic scattering patterns and using the properties cited in equations (2.22) and (2.23), as follows:

$$\begin{aligned} R(\Delta t) = & \sum_{n=-\infty}^{+\infty} (b\gamma_{0n} + (-1)^n c\gamma_{n0}) J_n(4\pi\nu_D \Delta t) \\ & + (1 - b - c) \sum_{n=-\infty}^{+\infty} \sum_{m=-\infty}^{+\infty} (-1)^n \gamma_{nm} J_n(2\pi\nu_D \Delta t) J_m(2\pi\nu_D \Delta t) \end{aligned} \quad (2.27)$$

while for an isotropic environment, (2.27) will become:

$$R(\Delta t) = (b + c)J_0(4\pi\nu_D \Delta t) + (1 - b - c)J_0^2(2\pi\nu_D \Delta t) \quad (2.28)$$

Figure 2.28 presents a comparison between the measured ACF of the small-scale fading for opposite walking scenario and the curves given by the M2M-NIMS model (2.28) taking $b + c = 0.09$ and the M2M-IMS model (2.27) where γ_{nm} coefficients are estimated up to the first or tenth orders using a non-linear least square fitting. A small value for $b + c$ in the equation (2.28) was chosen in order to be in line with the experiment conditions as there were few moving and many fixed scatterers.

The coherence time of the measurement data at 0.5 is 27.8 ms which corresponds to that given by the non-isotropic scatterers' model (28.3 ms) while for the case of isotropic scattering pattern, it is 34.5 ms. Consequently, the M2M-IMS model can roughly represent the temporal variation of the measured correlation function up to the coherence time, while the M2M-NIMS model of order 1 and 10 can fit the measurements up to 0.12 s and 0.5 s, respectively.

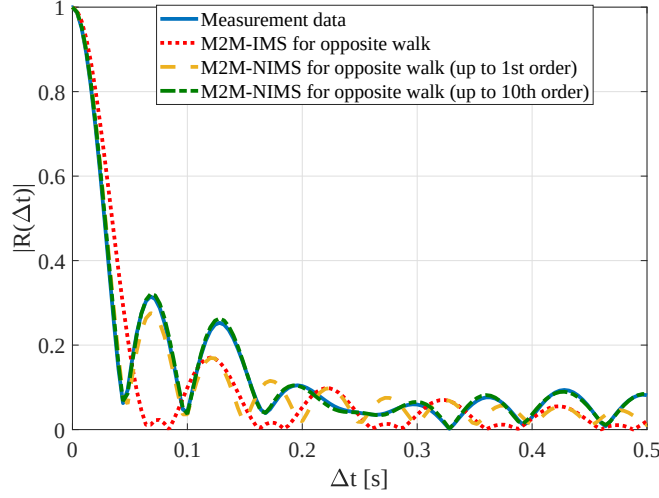


Figure 2.28: Time correlation function of measurement data vs. analytical formulas for opposite movements (IMS:isotropic moving scatterers, NIMS: non-isotropic moving scatterer)

2.5 Doppler Spectrum: Analysis and Modeling

Similarly, in this section, the Doppler spectrum properties and modeling of head to head channels are reported.

2.5.1 Measurement results

Doppler spectrum represents the distribution of energy with respect to Doppler frequency shift. Several methods were proposed in order to estimate the Doppler PSD [138]. The PSD of a realization was calculated as the FT of its ACF (cf. Section 1.1.2.2) such as:

$$S(\nu) = \int_{-\infty}^{+\infty} R(\Delta t) e^{-i2\pi\nu\Delta t} d\Delta t \quad (2.29)$$

where $R(\Delta t)$ is the ACF of the normalized channel transfer function.

In order to preserve the WSS property of the channel, The Doppler spectrum was then calculated by averaging the measured PSDs for a given walking pattern and scenario condition. The Doppler spread was computed as the RMS of the second central moment of the Doppler spectrum (cf. Section 1.1.2.2).

Doppler spectra of parallel and opposite walking movements in LoS and NLoS scenarios are presented in Figure 2.29. The Doppler frequency axis is normalized with respect to the maximum Doppler frequency due to the mobility of terminals ν_D (cf. Table 2.4). As seen, the Doppler spectrum properties show also a dependence on the mobility pattern; and for that reason, it must be characterized not only based on the propagation environment but also on the mobility pattern. In fact, the difference in Doppler spectrum shapes can be simply linked to a difference of relative speed between terminals: considering the LoS scenario (cf. Figure 2.29a), the parallel walking scenario has a null relative speed and it is indicated by the presence of peak around zero while the opposite direction holds a relative speed equal to twice the terminal speed manifested by peaks around ± 2 . Moreover, the angular distribution of AOA and AOD as well as the positions of moving objects (the two other subjects) can play a role in the distribution of power w.r.t. Doppler frequency shifts.

Table 2.3 presents the Doppler spread for different mobility patterns. At this point, it is worth mentioning that the Doppler spread of parallel movement is inline with those obtained in indoor fixed wireless communication with moving scatterers [139].

Table 2.4: Maximum Doppler Frequency

Walking pattern	Scenario	ν_D [Hz]
Parallel direction	LoS	4.133
	NLoS	4.96
Opposite direction	LoS	4.133
	NLoS	4.96

2.5.2 M2M analytical Doppler spectrum model

The Doppler spectrum model of M2M channels in the presence of moving scatterers can be obtained by taking the FT of the ACF model (2.20). However, a closed form expression for this Doppler spectrum is uneasy to derive. Moreover, the scatterer velocity v_S is supposed to be a random variable, thus, the maximum Doppler frequency ν_{max} obtained from (2.16) $\nu_{max} = \max(\nu_n) = (v_T + 2v_S + v_R)/\lambda$ is also a random variable. Nevertheless, considering a given scatterer position and velocity distributions, the Doppler spectrum of M2M channels can be written in

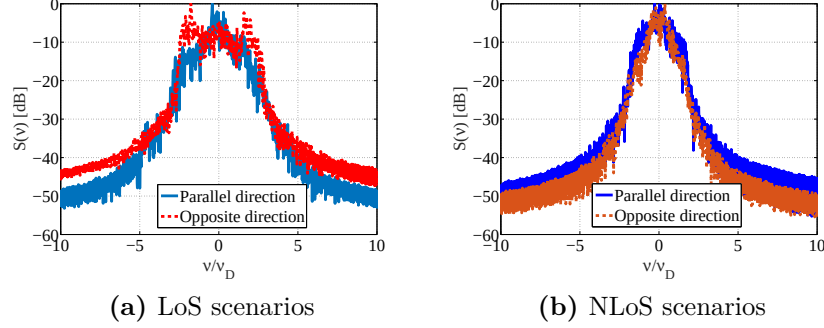


Figure 2.29: Doppler spectra in LoS and LoS scenarios: parallel movement and opposite movement

a closed form. In what follows, the Doppler spectrum of M2M channels for the parallel and opposite walking scenarios in LoS are derived.

For a non-isotropic scattering uniformly distributed in the environment, the Doppler spectrum of M2M channels where the terminals were moving in the same direction is derived as the FT of (2.24) and it can be expressed as follows:

$$\begin{aligned}
 S(\nu) = & a \sum_{n=-\infty}^{+\infty} \sum_{m=-\infty}^{+\infty} \sum_{p=-\infty}^{+\infty} \gamma_{nm} e^{ip\nu} J_n(2p\nu_D) J_m(2p\nu_D) \\
 & + (1-a) \sum_{n=-\infty}^{+\infty} \sum_{m=-\infty}^{+\infty} \sum_{p=-\infty}^{+\infty} \gamma_{nm} e^{ip\nu} J_n(p\nu_D) J_m(p\nu_D) \quad (2.30)
 \end{aligned}$$

The development of this formula is given in the appendix B. For isotropic scatterers, the Doppler PSD can be forwardly calculated from the FT of equation (2.25) and it is expressed in the following way:

$$S(\nu) = \begin{cases} \frac{a}{2\pi^2\nu_D} K \left[\sqrt{1 - \left(\frac{\nu}{4\nu_D}\right)^2} \right] + \frac{1-a}{\pi^2\nu_d} K \left[\sqrt{1 - \left(\frac{\nu}{2\nu_D}\right)^2} \right] & |\nu| < \nu_d \\ \frac{a}{2\pi^2\nu_D} K \left[\sqrt{1 - \left(\frac{\nu}{4\nu_D}\right)^2} \right] & \nu_D < |\nu| < 2\nu_d \\ 0 & \text{Elsewhere} \end{cases} \quad (2.31)$$

where $K[\cdot]$ is the complete elliptic integral of the first kind.

Similarly, the Doppler spectrum of the opposite walking scenario is

derived from (2.27) (cf. Appendix B and [140]) as follows:

$$\begin{aligned}
 S(\nu) = & (1 - b - c) \sum_{n=-\infty}^{+\infty} \sum_{m=-\infty}^{+\infty} \sum_{p=-\infty}^{+\infty} (-1)^m \gamma_{nm} e^{ip\nu} J_n(p\nu_D) J_m(p\nu_D) \\
 & + \frac{1}{4\pi\nu_D} \sum_{n=-\infty}^{+\infty} (d\gamma_{n0} - c\gamma_{0n})(i)^n F_n\left(\frac{\nu}{2\nu_D}\right)
 \end{aligned} \tag{2.32}$$

where $F_n(x) = 2 \frac{\cos(n \cos^{-1}(x))}{\sqrt{1-x^2}}$ for $|x| \leq 1$ and $F_n(x) = 0$ for $|x| > 1$.

For the isotropic scatterers uniformly distributed in the environment, this equation becomes:

$$S(\nu) = \begin{cases} \frac{(1-b-c)}{\pi^2\nu_D} K \left[\sqrt{1 - \left(\frac{\nu}{2\nu_D}\right)^2} \right] + \frac{b+c}{2\pi\nu_D \sqrt{1 - \left(\frac{\nu}{2\nu_D}\right)^2}} & |\nu| \leq 2\nu_D \\ 0 & \text{Elsewhere} \end{cases} \tag{2.33}$$

As seen, the Doppler spectrum can hardly be calculated from its analytical model given for non-isotropic scatterers uniformly distributed in the environment, thus it was forwardly estimated as the FT of the ACF calculated up to tenth order. Figure 2.30 compares the Doppler spectrum of measurement data obtained in opposite and parallel walking scenarios to its corresponding analytical formulas, respectively. The Doppler spread in parallel and opposite walking scenario are 4.24 Hz and 6.48 Hz, respectively, which well correspond to the one given by the non isotropic scattering models (4.68 Hz for parallel direction and 7 Hz for opposite direction).

Due to the fact that these models require an infinite number of Fourier coefficients, and to the current lack of analytical studies on Doppler spectrum for M2M channels, a simple analytical Doppler spectrum model that is able to retrieve the measured Doppler characteristics is proposed. Moreover, this model does not impose any constraints on the position

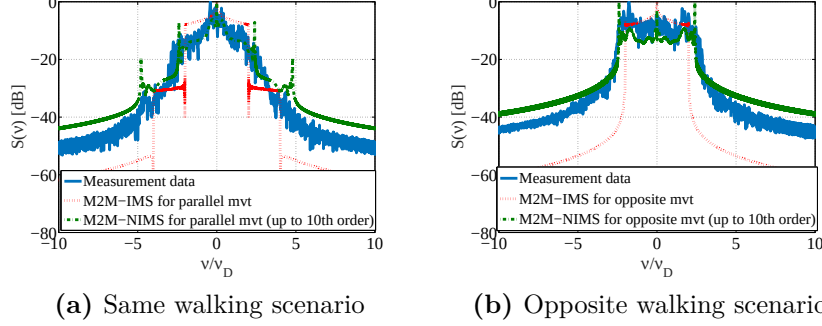


Figure 2.30: Doppler spectrum of measurement data vs. analytical formulas for parallel movements and opposite movements (mvt). (IMS:isotropic moving scatterers, NIMS: nonisotropic moving scatterer)

of the moving scatterers and it is presented as follows:

$$S(\nu) = \begin{cases} \frac{1-\beta_1-\beta_2}{\pi\nu_d^{TR} \sqrt{1-\left(\frac{\nu}{\nu_d^{TR}}\right)^2}} + \frac{\beta_2}{\beta_3\nu^2+1} + \beta_1 e^{-\left(\frac{\nu}{\bar{\nu}_d^{TS}}\right)^2}; & |\nu| \leq \nu_d^{TR} \\ \beta_1 e^{-\left(\frac{\nu}{\bar{\nu}_d^{TS}}\right)^2} + \frac{\beta_2}{\beta_3\nu^2+1}; & \text{Otherwise} \end{cases} \quad (2.34)$$

where β_i , $i = 1, 2, 3$, are parameters to be estimated from measurement data, $\bar{\nu}_d^{TS}$ is the average of maximum Doppler frequencies due to the mobility of scatterers seen by the Tx and ν_d^{TR} is the maximum Doppler frequency resulting from the relative mobility between terminals.

This model includes the effects of moving scatterers and Rx with respect to Tx. In fact, taking the Tx as the observational frame reference, M2M channels can be seen as F2M channels with moving scatterers. Therefore, the first term in the proposed model (2.34) represents Jakes spectrum and it is employed to depict the Doppler effects due to the mobility of Rx with respect to Tx. The second term is the analytical model proposed in [141] to model the impact of non-uniform moving scatterers. The third term is the Gauss model used to model the Doppler properties of diffuse scatterer channels [142], and it was here employed to represent the cap given by the measurement data.

2.5.2.1 Application to indoor M2M channels

In this section, the proposed model is compared to the measurement data considering different mobility patterns and propagation conditions.

Same walking direction

Considering the parallel walking movements, the terminals were moving simultaneously with the same velocity vector, i.e. in the same direction and at the same speed. This type of link can be described as a F2F link in the presence of moving scatterers, taking the terminals' point of view. This explains why the Doppler spectrum is centered around 0, as found for indoor fixed wireless communications surrounded by moving scatterers [37, 143, 144]. Therefore, from the Tx's point of view, the Rx is static, i.e. ν_d^{TR} is equal to 0 Hz, whereas the environment and the two other persons move at speed v and $2v$ respectively, where v is the node speed and it was approximately equal to 0.5 m/s in LoS scenarios and 0.6 m/s in NLoS scenarios. Thus, the average of maximum Doppler frequencies due to the moving scatterers with respect to Tx $\bar{\nu}_d^{TS}$ is equal to $3v/(2\lambda)$ (cf. Table 2.4).

Analytical Doppler spectrum models for moving scatterers in F2F channels considering a uniform and non-uniform scattering patterns were developed in [141] as follows:

$$S(\nu) = \frac{1}{\pi^2 \nu_d} K \left[\sqrt{1 - \left(\frac{\nu}{2\nu_d} \right)^2} \right] \quad (2.35)$$

$$S(\nu) = \frac{1}{b\nu^2 + 1} \quad (2.36)$$

where ν_d is the maximum Doppler frequencies due to the mobility of scatterers and b is a parameter to be estimated from the measurement data.

At this point, it is worth noting that equation 2.35 was also considered for M2M channels with fixed scatterers where Tx and Rx were moving with the same velocity.

Therefore, to support our proposed model, Figure 2.31 compares the Doppler spectrum of parallel walking movement measured in LoS condition to the analytical models given in literature for the moving scatterers in F2F channels [141] and the proposed model (2.34). The maximum Doppler frequency ν_d in equation (2.35) was calculated from the node speed 0.5 m/s, i.e. $\nu_d = 4.113$ Hz, while b in equation (2.36) was taking

equal to 0.5 in order to attain a suitable fitting for the main part of the measured power. The Doppler parameters in equation (2.34), β_i , were estimated using a nonlinear least square method [145, 146] (cf. Table 2.5). As seen, the proposed model fits better the measurement data compared to those proposed in literature. Similarly, the parallel walking scenarios in NLoS shows a good agreement between the proposed model and the measurement data (cf. Figure 2.31). Table 2.5 exhibits the Doppler parameters of equation (2.34), β_i , estimated using a nonlinear least square method; and Table 2.6 presents the Doppler spreads estimated from the proposed model that are in line with measured ones.

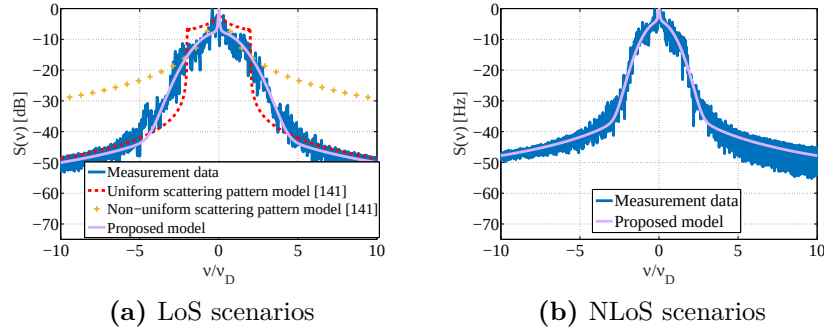


Figure 2.31: Same walking scenarios: measured Doppler spectra and proposed models in LoS and NLoS

Table 2.5: Values of β_i Parameters

Walking pattern	Scenario	β_1	β_2	β_3
Parallel direction	LoS	0.1667	0.8333	49.2138
	NLoS	0.3668	0.6332	15.5163
Opposite direction	LoS	0.03	0.01	0.5
	NLoS	0.2066	0.00023	0.00932

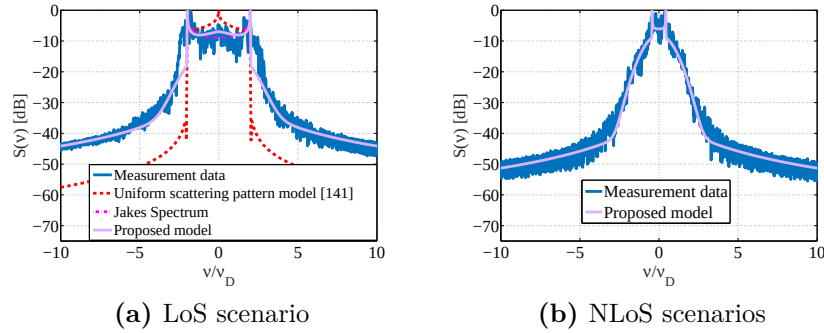
Opposite walking direction

Now, observing the Doppler spectrum of opposite walking movements, one can readily detect the presence of Jakes spectrum (cf. Figure 2.32).

Table 2.6: Doppler Spread

Walking pattern	Scenario	Measurement data	Proposed model
Parallel direction	LoS	4.3 Hz	4.49 Hz
	NLoS	4.1 Hz	3.6 Hz
Opposite direction	LoS	6.66 Hz	5.65 Hz
	NLoS	3.18 Hz	3.25 Hz

In fact, from the Tx's point of view, the link can be described as a F2M channel in the presence of local moving scatterers where the mobile terminal is moving with a velocity equal twice the human subject speed. This explains the presence of peaks in the Doppler spectrum around ± 2 in LoS (cf. Figure 2.32a). However, in NLoS, the two peaks are not around ± 2 (cf. Figure 2.32b) and this is due to the fact that the waves are traveling the wall so the wavelength varies which imposes a variation in the maximum Doppler frequency ($\nu_D = v/\lambda$). The Doppler frequency shifts ν_d^{TR} and $\bar{\nu}_d^{TS}$ are given in Table 2.4). Figure 2.32 and Table 2.6 show a good agreement between the measured Doppler spectra and the proposed model for LoS and NLoS scenarios.

**Figure 2.32:** Opposite walking scenario: Measured Doppler spectrum and proposed model for LoS and NLoS

2.6 Non-Stationarity Analysis

The non-stationary behavior of the B2B channels was revealed in Section 2.3 where the Rice parameters and the PL parameters were best described in function of Tx-Rx distance or mutual body orientations. Therefore, in this section, some of the stationarity test proposed in the

literature were used to study the non-stationarity of the B2B small-scale fading channels considering the head position.

2.6.1 Stationary stochastic process

A stochastic process $X(t)$, is a function of time whose values depend on the outcome of a random experiment A [147]. The individual record of a stochastic process is called a realization while, at a fixed time instant, t_0 , the stochastic process is a random variable. Thus, for each time instant t , $X(t)$ will have a probability distribution.

A stationary process is a process whose its statistical properties do not vary over time [147]. In other words, the random variable probability distribution of $\{X(t_1), X(t_2), \dots, X(t_n)\}$ is the same and their joint probability distribution remains invariant under a shift in time Δt , i.e.:

$$F_{X(t_1), X(t_2), \dots, X(t_n)}(x_1, x_2, \dots, x_n) = F_{X(t_1 + \Delta t), X(t_2 + \Delta t), \dots, X(t_n + \Delta t)}(x_1, x_2, \dots, x_n) \quad (2.37)$$

where $F(\cdot)$ is the joint distribution function of the set of random variables $\{X(t_1), X(t_2), \dots, X(t_n)\}$.

In this case, the stochastic process is said to be "completely stationary". However, the complete stationary is considered as severe requirement. Thus, a more relaxed notion was made which is a "stationary process up to order m ".

A stochastic process is said to be stationary up to order m , as stated in [147], if for any admissible $t_1, t_2, \dots, t_n$ and any Δt , all the joint moments up to order m of $\{X(t_1), X(t_2), \dots, X(t_n)\}$ exist and equal to the corresponding joint moments up to order m of $\{X(t_1 + \Delta t), X(t_2 + \Delta t), \dots, X(t_n + \Delta t)\}$, i.e.

$$\mathbb{E}[X(t_1)^{m_1} X(t_2)^{m_2} \dots X(t_n)^{m_n}] = \mathbb{E}[X(t_1 + \Delta t)^{m_1} X(t_2 + \Delta t)^{m_2} \dots X(t_n + \Delta t)^{m_n}] \quad (2.38)$$

where $m_1, m_2, \dots, m_n$ are positive integers satisfying $m_1 + m_2 + \dots + m_n \leq m$.

Note that, in this case, we do not impose for each time instant the probability distribution to be the same, but only the main characteristics (mean). Similarly, we focus only on one feature for the joint probability distribution which is the joint moments up to order m .

Likewise, a process is said stationary up to order 2, if it has constants mean and variance as well as if its ACF depends on the time difference

between two instants and not on the individual time points, i.e.:

$$\begin{aligned}\mathbb{E}[X(t)] &= \mu = \text{constant} \\ \mathbb{E}[X^2(t)] &= \mu' = \text{constant} \\ \mathbb{E}[X(t_1)X(t_2)] &= \text{function of } (\Delta t = t_2 - t_1) \text{ only} = R(\Delta t)\end{aligned}\tag{2.39}$$

At this point it is worth noting that if a Gaussian process is a stationary process up to order 2, then it is completely stationary [147]. The small-scale fading of the B2B channels was characterized as complex Gaussian stochastic process. Thus, in order to test its stationarity degree, its first and second order statistics were analyzed via stationarity tests provided by the literature.

2.6.2 First order statistic: Hypothesis test

The hypothesis test was proposed in [19] to assess the non-stationarity behavior of the first order statistic obtained from On-body channels where the Tx and Rx antennas were attached to a single body. This method is also employed here in order to highlight the results shown previously (cf. Section 2.3) which set forth a distance dependent small-scale fading behavior.

2.6.2.1 Statistical hypothesis test implementation

Assuming that the measured small-scale fading channel is stationary within a region of length L , the statistical hypothesis tests were applied in order to find a suitable value of L . The method, as shown in Figure 2.33, is based on decomposing the N time-samples (observations) of the small-scale fading channel into M non-overlapping blocks of length L such as

$$N = L \times M\tag{2.40}$$

However, there is a trade-off between the number of blocks and the length of each blocks. More observations within a block contribute to more accuracy in calculating the mean and variance of each block, while a large number of blocks will allow for a more robust results.

For similar mobility patterns and a given environment propagation condition, the statistical hypothesis test was implemented as follows:

1. Considering each realization $g(t)$, the N time-samples (observations) were decomposed into M blocks of length L

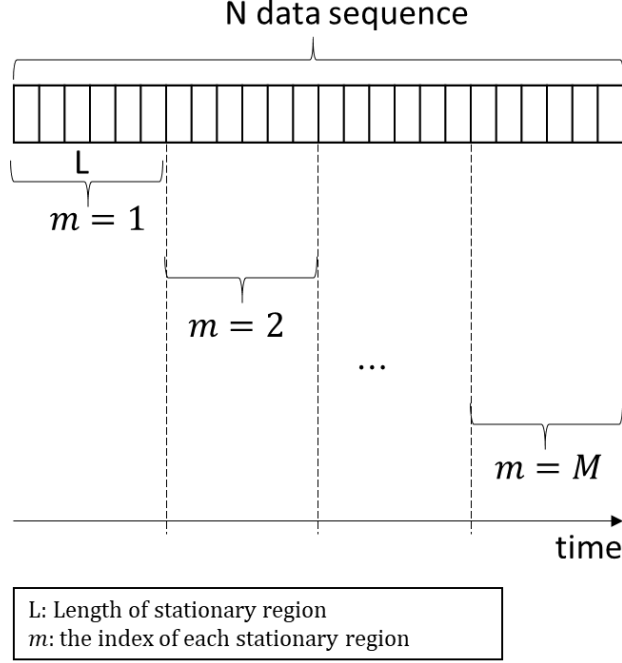


Figure 2.33: Schematic representation of the used stationarity regions for hypothesis tests

2. Three hypothesis tests, i.e. Kolmogorov-Smirnov (KS), Wilcoxon rank sum and Ansari-Bradley tests (cf. Appendix C and [148]) were employed on each two consecutive blocks in order to study the stationarity (similarity between two consecutive blocks), in terms of Cumulative Distribution Function (CDF), median and variance, respectively.
3. The probability of CDF, mean and variance stationarities are calculated as follows:

$$\begin{aligned}
 P(\% \text{CDF stationarity}) &= \frac{\sum_{p=1}^{M^*} \text{P values given by KS test} \geq a}{M^*} \\
 P(\% \text{mean stationarity}) &= \frac{\sum_{p=1}^{M^*} \text{P values given by Wilcoxon rank sum test} \geq a}{M^*} \\
 P(\% \text{variance stationarity}) &= \frac{\sum_{p=1}^{M^*} \text{P values given by Ansari Bradley test} \geq a}{M^*}
 \end{aligned} \tag{2.41}$$

where $M^* = (M - 1) \times N_g$ and N_g is the number of realizations. a denotes the significance level upon which a decision is made regarding the similarities between X and Y .

Typical values used for α were 0.05, 0.01 and 0.001. It determines the significant of type error I in the hypothesis test defined as refusing the idea of similarities between two sets of values X and Y when X and Y are in reality belong to the same distribution. Therefore, one wants to reduce this type of error in order to prevent as much as possible its occurrence. In our tests we set α to 0.01 for all hypothesis tests based on some tests as described in appendix C.

In order to perform a reliable and robust test, the minimum required length L was set to 100 (1.65λ), respectively, for all hypothesis tests. This value was derived from a study carried on to achieve a minimum power of test around 80% as explained in appendix C.

Note that the KS test represents the test where any change between two blocks is detected. Thus, it is considered as the severe test and it was used to determine the stationarity region while the other tests were employed to highlight more on the cause of the non-stationarity. Looking into (2.41), one can readily detect that a probability of 100% means that all two consecutive blocks are similar, 50% indicates only 50% of consecutive blocks are similar while 0% imposes that no consecutive blocks are similar. Thus, for stationarity probability of 0%, the stationarity region is given. However, the 0% is considered as severe requirement, thus a threshold of 20% was decided in order to determine the stationarity length, L_{stat} , i.e.

$$P(\% \text{CDF stationarity}) \approx 20\% \quad L = L_{stat} \quad (2.42)$$

2.6.2.2 Application on measurement data

Figure 2.34 and 2.35 present the stationarity test results in function of L that is set in function of λ for head to head LoS and NLoS scenarios, respectively considering different mobility patterns. As seen, the median test is most of the time above 60% while the KS and variance tests vary in a similar way indicating that the difference behavior of the KS test is probably due to the variance change.

Considering the parallel walking LoS scenario (cf. Figure 2.34a), the KS test is around 50%; when Tx was faraway from Rx and he was moving in the opposite direction of Rx under the LoS condition (far opposite direction), the KS test was around 40% which is smaller than the one given in parallel walking LoS scenario (cf. Figure 2.34b). In the case of Tx and Rx were close to each other and they were walking towards to each other (opposite or cross directions), the KS test decreases with the increases of L (cf. Figure 2.34c and 2.34d) revealing the non-stationarity

behavior of the small scale fading after 8λ for opposite direction and 10λ for cross direction. Therefore, the stationarity regions in these case is set to be around 8λ and 10λ .

These observations can be related to the variation of Tx-Rx distance in time as highlighted in Section 2.3.3 where it was found that the K-factor decreases with the increase of Tx-Rx distance in LoS due to the mitigation of the coherent power. In fact, in parallel walking scenario, the Tx-Rx distance is considered static over time, thus no variation in the small-scale parameter were expected. For far opposite direction, the Tx-Rx distance was varying slightly with time, hence the resulted KS test was smaller from the one given in parallel walking scenario. The large variation of Tx-Rx distance was seen in scenarios where the terminals were moving toward each others, e.g. opposite and crossing direction, this explains the detection of the non-stationarity behavior in KS test for those scenarios.

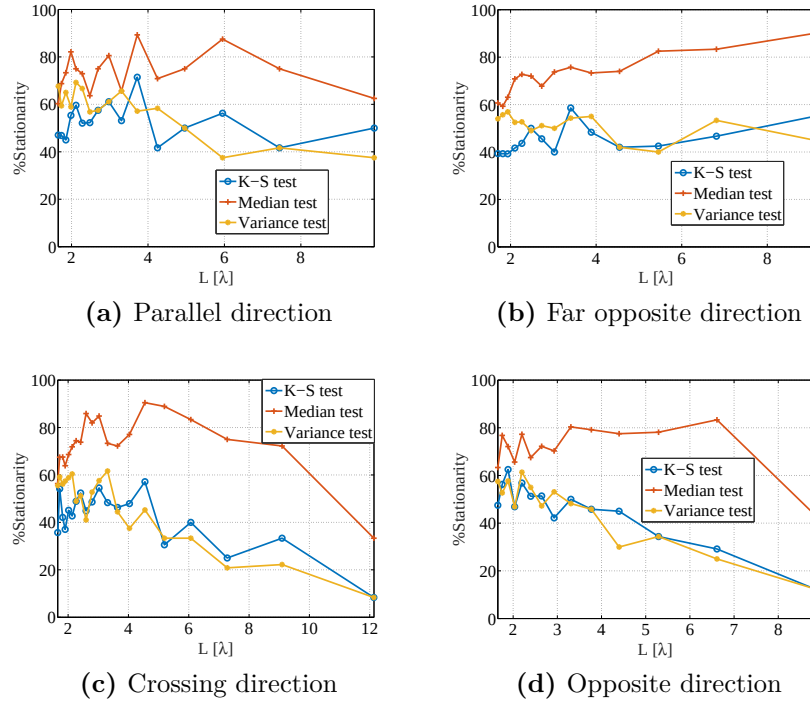


Figure 2.34: Stationarity test results of indoor head to head LoS scenarios

Similar to what was found in Section 2.3.3, the small-scale fading of

head to head NLoS scenarios can be considered stationary in the large sense and no distance dependance for the K-factor was found (cf. Figure 2.35). This can be related to the large effect of the MPCs presented in the environment and the less impact of the coherent component. Consequently, the hypothesis test and the distance dependance test (cf. Section 2.3.3) draw the same conclusion that the small-scale fading of head to head links are distance dependent for LoS scenarios and no distance dependent for NLoS scenarios due to the propagation environment.

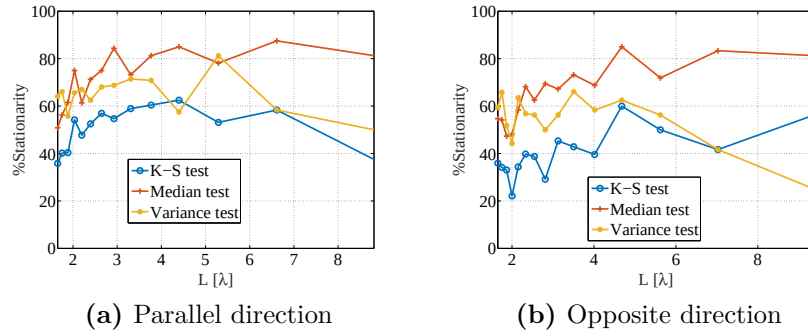


Figure 2.35: Stationarity test results of indoor head to head NLoS scenarios

2.6.3 Doppler spectrum: Collinearity metric

The method proposed in [20] to investigate the non-stationarity of the V2V scattering function was used here to analyze the non-stationarity behavior of the second order statistic, i.e. Doppler spectrum, for the small-scale fading obtained from head to head LoS and NLoS scenarios. This method considers the fading channel as ergodic process and splits the measurement in small regions, within which the WSSUS properties hold. The minimum stationarity region is defined as the smallest time-region where the WSSUS properties are true.

Therefore, the measurement data were split in K_t stationarity regions of dimension L using a sliding window. The time index of each stationarity region is denoted by $k_t \in \{1, \dots, K_t\}$ and it corresponds to its center. The relative time index within each stationarity region is denoted by the variable $l' \in \{-L/2, \dots, L/2 - 1\}$ and the relationship between the relative and absolute time index is given by $l = (L - L/2)k_t + l'$ where $L/2$ is the time shift between consecutive stationarity regions. Figure 2.36 exhibits the schematic representation of the time sliding

window used to determine the stationarity regions. Hence, within each stationarity region, the small-scale fading was assumed stationary and the local Doppler spectrum was calculated.

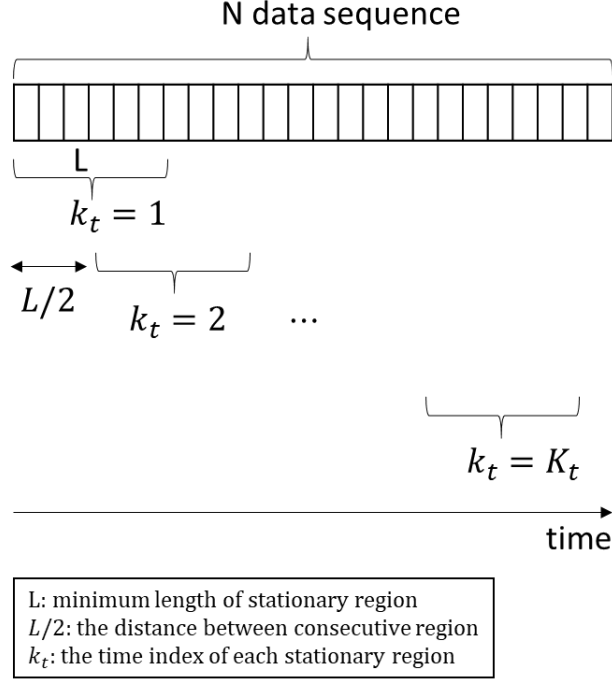


Figure 2.36: Schematic representation of the time sliding window used to determine the stationarity regions

Similar to [20], the Multitaper power spectral density estimate S^{MT} was used to calculate the Doppler spectrum. Its basic idea is to average independent Doppler spectra obtained from a signal multiplied by a family of mutually orthogonal tapers (windows) [149]. In other words, for a stationarity region k_t as defined in Figure 2.36, the Doppler spectrum was calculated as follows [149]:

$$S^{MT}(k_t, l' \Delta \nu) = \frac{1}{J} \sum_{p=0}^{J-1} \sum_{l'=-L/2}^{L/2-1} \Delta t \left| w_{p,l'} g(l' - k_t) e^{i\phi_{l'-k_t}} e^{-i2\pi \Delta \nu l' \Delta t} \right|^2 \quad (2.43)$$

where $\Delta \nu$ is the Doppler frequency sample and $w_{p,l}$ is the p^{th} taper of the Discrete Prolate Spheroidal (Slepian) Sequences (DPSS) defined as follows:

$$\sum_{l'=0}^{L-1} \frac{\sin(2\pi \frac{J}{L\Delta t} (l'-n))}{\pi(l'-n)} w_{p,l'} = \lambda_p^{ev} w_{p,n} \quad n = 0, 1, 2, \dots, L-1 \quad (2.44)$$

where λ_p^{ev} is the p^{th} eigenvalue.

The main motivation behind considering the multitaper method is that it reduces the noise variance of the Doppler spectrum given from the periodogram method by the number of tapers used [149]. In multitaper process, the entire signal is used in each modified periodogram and the orthogonality of the Slepian tapers decorrelates the different modified periodograms. Therefore, a smoother estimate of Doppler spectrum is obtained without averaging overlapping segments like Welch's method, which is incompetent, in our case, because we calculate the Doppler spectrum on small data blocks.

The number of tapers used is a key parameter determining the estimator performance. Accordingly, a Two Dimensional (2D) Wiener filter was employed in order to evaluate the performance of the multitaper estimator and to determine the number of tapers required " J ". In fact, the 2D Wiener filter coefficients can be simply estimated from the local measured Doppler spectrum as follows:

$$\hat{A}_{k_t} = \frac{\hat{S}_{F_{k_t}}^{MT}}{\hat{S}_{F_{k_t}+Noise}^{MT}} \quad (2.45)$$

where $\hat{S}_{F_{k_t}}^{MT}$ and $\hat{S}_{F_{k_t}+Noise}^{MT}$ are the local Doppler spectra of the measurement data and the same data corrupted with additive complex Gaussian noise for the stationarity region k_t , respectively. They were calculated using equation (2.43)

Classically, the 2D Wiener filter was used to estimate the Minimum Mean-Square-Error (MMSE) between a WSS process of interest and a given measurement data of another related process. However, here, it was only used to assess the MSE ε by comparing the outcome of the estimator (the small-scale fading given by the 2D Wiener filter) and the measured small-scale fading within the stationarity region under investigation. To do that, the stationarity region must be predefined, hence this method was used considering three different stationarity length, i.e. 4λ , 8λ and 10λ . These values are chosen based on the previous section where stationarity distances around 8λ and 10λ were found for the opposite and cross walking LoS scenarios.

Figure 2.37 sketches the schematic diagram implemented in order to determine the optimum number of tapers for a given stationarity region. the $ge^{i\phi} + Noise$ data are the measured small-scale fading corrupted with additive complex Gaussian noise that has zero mean and σ_{Noise}^2 variance. Different values for σ_{Noise}^2 , i.e. 0.4, 0.07 and 2.25, were considered in

order to analyze the dependency of the optimization result with respect to the amount of added noise. Those values were determined such as a difference of 0 dB, -15 dB and 15 dB are considered between the measured σ_F and the added noise. The Filter coefficients are calculated from equation (2.45) based on the local Doppler spectrum measured in the k_t stationarity region using the multi-taper process.

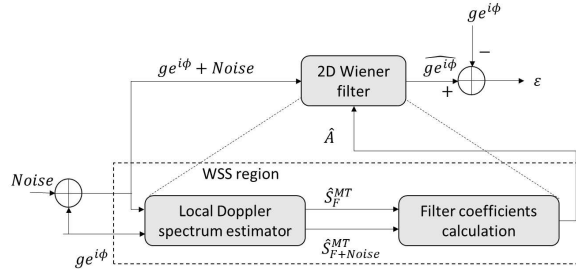


Figure 2.37: Wiener filter [6]

Similarly to [6], the MSE was computed over the total number of WSS region K_t as follows:

$$\varepsilon = \frac{1}{K_t} \sum_{k_t=1}^{K_t} \frac{\sum_{l=1}^L \left| (\widehat{g(l)e^{i\phi_l}})_{k_t} - (g(l)e^{i\phi_l})_{k_t} \right|^2}{\sum_{l=1}^L |(g(l)e^{i\phi_l})_{k_t}|^2} \quad (2.46)$$

where $(\widehat{g(l)e^{i\phi_l}})_{k_t}$ is the small-scale fading estimated from the Wiener filter (cf. Figure 2.37).

The optimum required parameters, i.e. number of tapers and stationarity window size, are those whom minimize the MSE ε , without involving high computational complexity in the estimation process.

Figure 2.38 and Figure 2.39 present the MSE results in function of J for LoS and NLoS considering different mobility patterns. As seen, in line with results presented in [6], we have also deduced here:

- Regardless the stationarity region length or the amount of noise added to the data, all the MSE curves decrease slowly with the increase of J after $J = 3$.
- The size of the considered stationarity region L does not have a strong impact on the MSE results .
- For a smaller amount of noise, a smaller MSE is obtained after $J = 3$.

Consequently, the optimal number of tapers was set to 5 and the minimum stationarity length was considered equal to 8λ .

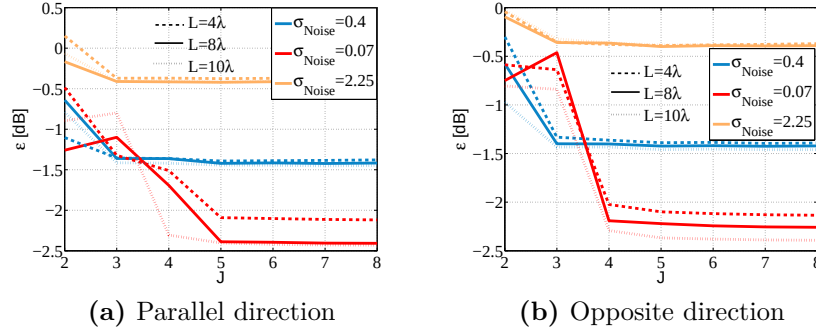


Figure 2.38: LoS scenarios: MSE in function of J

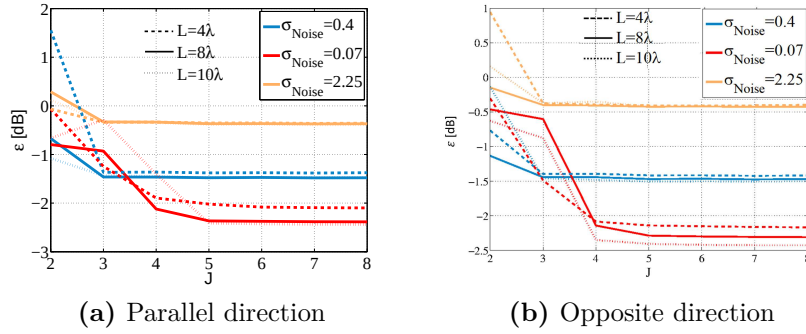


Figure 2.39: NLoS scenarios: MSE in function of J

2.6.3.1 Application to measurement data

After calculating the Doppler spectrum using the multitaper PSD with five tapers for each stationarity region k_t , the collinearity metric was used to assess the similarities between any two estimated Doppler spectra, hence to characterize the stationarity. The collinearity metric can be expressed as follows:

$$C(k_t, k_t + \Delta k_t) = \frac{\sum_{l'=-L/2}^{L/2-1} S^{MT}(k_t, l' \Delta \nu) S^{MT}(k_t + \Delta k_t, l' \Delta \nu)}{\sqrt{\sum_{l'=-L/2}^{L/2-1} |S^{MT}(k_t, l' \Delta \nu)|^2 \sum_{l'=-L/2}^{L/2-1} |S^{MT}(k_t + \Delta k_t, l' \Delta \nu)|^2}} \quad (2.47)$$

The collinearity metric is described as a bounded metric that gives values between 0 and 1. A collinearity close to 1 results from comparing very similar PSDs, whereas a collinearity close to 0 indicating the dissimilarities between the two compared Doppler PSDs. Therefore, an indicative threshold th was set in order to identify the degree of similarities between the Doppler spectra and to define the time stationarity region.

The minimum stationarity time T_{stat} is the minimum duration length of stationarity region and it is defined as follows:

$$T_{stat}(k_t) = L(k_t^{max} - k_t^{min})/2 + L \quad (2.48)$$

where

$$\begin{aligned} k_t^{min} &= \arg \max_{0 \leq k_s + \Delta k_s \leq k_s} (C(k_t, k_t + \Delta k_t) \geq th) \\ k_t^{max} &= \arg \min_{k_s + 1 \leq k_s + \Delta k_s \leq k_s} (C(k_t, k_t + \Delta k_t) \geq th) \end{aligned} \quad (2.49)$$

The probability of stationarity were calculated as follows:

$$P(\%Stationarity) = \frac{\sum_{n=1}^{C_2^{K_t}} \theta_n}{C_2^{K_t}} \quad (2.50)$$

where $C_2^{K_t}$ is a two combination of a set K_t which represents the total number of collinearity test and θ_n is defined as follows:

$$\theta_n = \begin{cases} 1 & C(k_t, k_t + \Delta k_t) \geq th \\ 0 & C(k_t, k_t + \Delta k_t) \leq th \end{cases} \quad (2.51)$$

Three threshold were considered, i.e. $th = \{0.9, 0.8, 0.7\}$. Figure 2.40 presents the collinearity test results given by the parallel walking LoS scenarios for the three considered thresholds. As expected, the large stationarity time is given by the less restrictive threshold. This can be also exhibited in Figure 2.41 where the time-varying stationarity time obtained from the parallel walking LoS scenarios under different considered thresholds are presented. The stationarity time indicates for how long the time-varying properties of the small-scale fading remains stationary in time. The minimum stationarity time is equal to 1.936 s for $th = 0.9$ and $th = 0.8$ while a minimum stationarity time of 5.808 s is obtained for $th = 0.7$. The probability of stationarity is presented in Table 2.7. As seen, the probability of stationarity is close to 50% for $th = 0.8$ which indicates that 50% of the estimated Doppler spectra are similar.

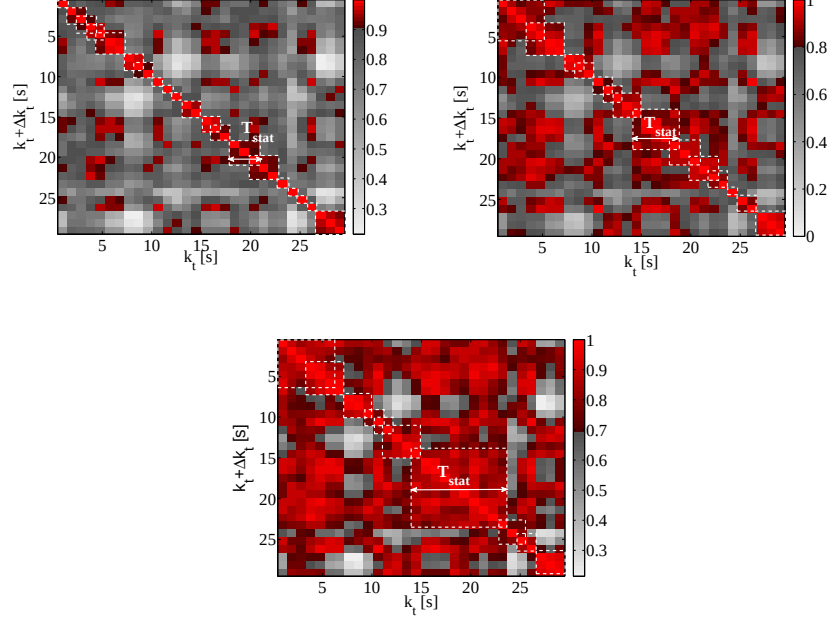


Figure 2.40: Parallel walking LoS scenarios: Collinearity test results

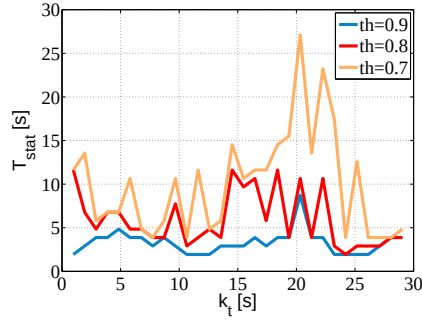


Figure 2.41: Stationarity time in function of k_t for parallel walking LoS scenarios

Figure 2.42 and Figure 2.43 present the collinearity results for opposite walking LoS scenarios. As expected, the stationarity time is smaller compared to the parallel walking LoS scenarios. Moreover, most of the stationarity times for the given stationarity regions are around 1.936 s (8λ) for $th = 0.9$ indicating dissimilarities between the Doppler spectra and the minimum time stationarity region is 8λ . At this point, it is worth noting that the probability of stationarity is always less than 50% even

for $th = 0.7$ (cf. Table 2.7) highlighting the non-stationarity behavior of the small-scale fading for this type of scenario.

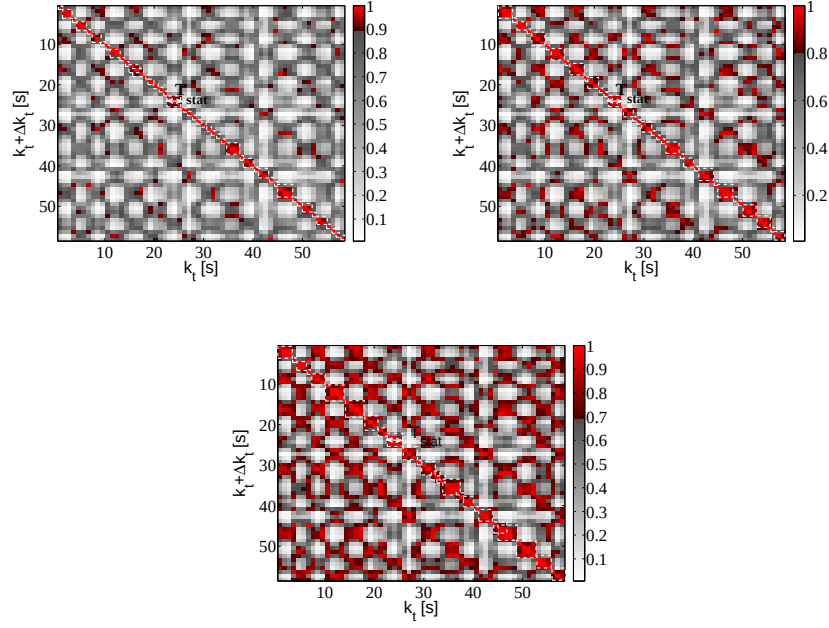


Figure 2.42: Opposite walking LoS scenarios: Collinearity test results

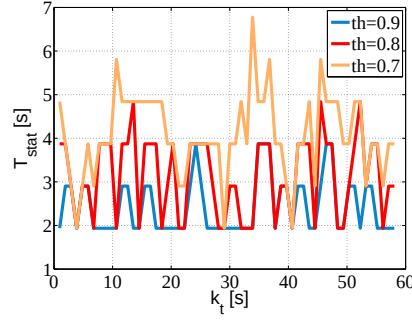


Figure 2.43: Stationarity time in function of k_t for opposite walking LoS scenarios

For brevity, Figure 2.44 shows the collinearity test results for parallel and opposite walking scenario under the NLoS condition considering $th = 0.8$. Similarly, the stationarity time of the opposite direction is

smaller than the one of parallel direction. Compared to the LoS, the NLoS results exhibit more stationarity behaviors, probably because of the fast variation of the dominant power exhibited in the LoS scenarios. This can be also deduced from Table 2.7 where the Probability of stationarity is equal to 63% and 46% for parallel and opposite walking NLoS scenarios, respectively. The time-varying stationarity time of parallel and opposite walking NLoS scenarios are shown in Figure 2.45.

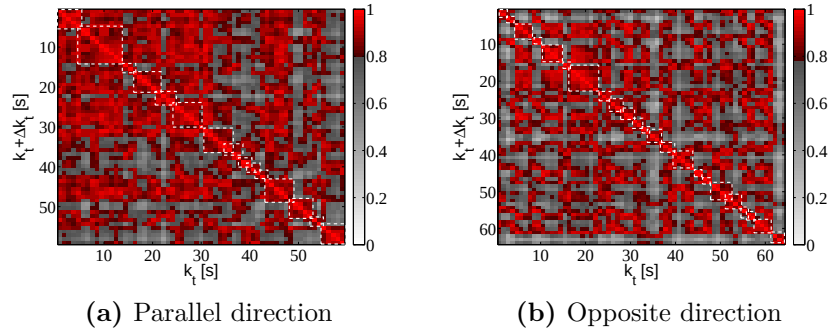


Figure 2.44: NLoS scenarios: Collinearity test results

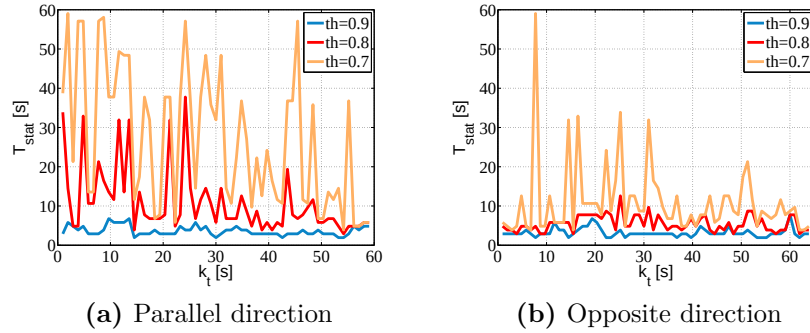


Figure 2.45: Stationarity time in function of k_t for NLoS scenarios

Consequently, Table 2.8 lists, for each scenario, the minimum and maximum of stationarity time T_{stat} , i.e. $\min T_{stat}$ and $\max T_{stat}$, and the mean $\mu_{T_{stat}}$ of T_{stat} , in second and in function of λ , for $th = 0.8$. As seen, the opposite walking LoS scenario reveals explicitly the non-stationarity behavior of the small scale fading. This is probably due to the fast variation of the coherent path in this case which can impact the

Doppler spectrum. For a given walking scenario, the small-scale fading obtained from LoS environment exhibits extra non-stationarity behavior compared to the one given by the NLoS environment.

Table 2.7: Probability of stationarity results for head to head scenarios

Walking patterns	Propagation condition	Probability of Stationarity[%]		
		$th = 0.9$	$th = 0.8$	$th = 0.7$
Parallel direction	LoS	17	46	73
	NLoS	22	63	87
Opposite direction	LoS	4	15	29
	NLoS	19	46	69

Table 2.8: Stationarity time results for head to head scenarios

Walking patterns	Propagation condition	$\min_{T_{stat}}$ [s]	$\max_{T_{stat}}$ [s]	$\mu_{T_{stat}}$ [s]
Parallel direction	LoS	1.9 (7.8 λ)	11.6 (48 λ)	5.9 (24.4 λ)
	NLoS	2.9 (12 λ)	37.7 (155.8 λ)	10.9 (45 λ)
Opposite direction	LoS	1.9 (7.8 λ)	4.8 (19.8 λ)	3.1 (12.8 λ)
	NLoS	2.9 (12 λ)	12.6 (52 λ)	5.5 (22.7 λ)

2.7 Conclusion

In this chapter, a measurement based stochastic channel model is proposed for indoor B2B channels. The model consists of three major components, i.e. the channel gain, large- and small-scale fading. Depending on the antenna on-body position and the propagation environment, the model parameters were given. The PL was described by a logarithmic PL model where its parameters were modeled in function of the mutual body orientation in order to account the spatial variation of the channel. The small-scale and the large-scale fading distributions were fitted with a normal and Rice distributions, respectively. The distribution parameters were also studied in function of distance and mutual body orientations. It was found that the large-scale fading distribution parameters are slightly influenced by the mutual body orientation while the small-scale fading parameters have exhibited a strong variation with respect to Tx-Rx distance and the mutual body orientation suggesting model that can describe a direct dependence between Rice parameters with mutual body positions in terms of distance and orientation. Moreover, we can expect that the general trends of channel components with respect to mutual body positions is consistent independently of the specific setup of our measurements, in terms of frequency and antenna used.

Due to the negligible influence of the body shadowing found in head to head scenarios, these scenarios were described as indoor M2M scenarios. Therefore, the correlation and Doppler properties of indoor M2M scenarios were explored for different mobility patterns under LoS and NLoS conditions. It was found that the ACF and Doppler spectrum must be analyzed considering the specific mobility pattern as well as the propagation condition. We pointed out that the small-scale fading has a predominant effect in the ACF of the channel over the large-scale fading. In fact, the fast decorrelation given by the ACF of the channel transfer function is due to the fast decorrelation of the complex small-scale fading ACF. Moreover, a general model for the time correlation function of M2M fading channels in the presence of moving scatterers was developed considering a general scattering environment. The model is an extension of [21] and a generalization of some classical channel models, e.g. F2M, F2F and M2M channels. This model was used to depict the small-scale fading ACF for parallel and opposite walking scenarios, considering a uniform distribution of non-isotropic scattering patterns. Due to its generality, this model will be also used in the next chapter to produce the ACF measured in V2P channels.

Owing to the complexity of the Doppler spectrum calculation based on the proposed model, a simple analytical Doppler spectrum model was developed. The proposed model is simple, only three parameters need to be estimated from the measurement data. Also, it allows to reproduce with good accuracy the Doppler properties of different indoor M2M scenarios including LoS and NLoS conditions, by means of a closed analytical formula. Due to the physical interpretation behind it, it can account other different indoor M2M scenarios, e.g. the cross walking scenarios.

The non-stationarity behavior of the indoor M2M small-scale fading were also studied based on methods proposed in literature for On-body channels [19] and V2V channels [20]. Therefore, the hypothesis tests and the collinearity metric were employed in order to assess the non-stationarity behavior of the first and second order statistics. Accordingly, we have found the same conclusion presented previously: the Rice parameters of the small-scale first depend on Tx-Rx distance considering the LoS conditions whereas non dependency was found for the NLoS environment. Based on the collinearity test, the Doppler spectrum has shown a time variation aspect in the opposite direction LoS scenarios which can be simply related to the rapid variation of the relative distance between terminals which impact the angle of LoS and the coherent power. At this point, it is worth mentioning that the minimum stationarity time

found for indoor M2M scenarios was around 1.9s which is quite larger than the time interval used for ACF modeling.

In a following step, we intend to successfully implement the model based on the scenario and the propagation condition with fading characteristics including the Doppler characteristics, as presented in Chapter 4.

In the next chapter, a wide-band V2P channel model based on the measurement campaign is presented.

Chapter 3

Wideband Mobile to Mobile Channels

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The V2X channels are defined as a direct link between moving vehicles and a wide set of road passengers like vehicles, pedestrian, bicyclists etc. While the V2V propagation was largely addressed in the literature (cf. Chapter 1), V2P channels have received a poor attention. Only [75] has reported the narrow-band V2P channel characteristics in suburban environments at 1.85 GHz considering a moving and stationary person while a stationary person were considered in [150, 151].

This chapter presents a GSCM based on a V2P channel measurement campaign carried out at 3.8 GHz. Several propagation conditions and different mobility patterns were investigated. The model is similar to the one proposed in [22] and it consists of first path and secondary discrete MPCs. In order to track the time evolution of the first path and the secondary MPCs, a detection procedure and a tracking algorithm

were implemented. A parametrization technique for the first path and secondary MPCs was also presented.

This chapter is organized as follows. The V2P channel measurement campaign is detailed in Section 3.1. Section 3.2 presents the proposed channel modeling approach, the secondary discrete multi-path detection procedure and the tracking algorithm. The parametrization technique for the secondary MPCs and the first path are described in Section 3.3. The time correlation function and the Doppler properties are studied in section 3.4 and 3.5, respectively. Finally, conclusions are given in Section 3.6.

3.1 Channel Measurement Campaign

3.1.1 Measurement setup

UCL-ULB channel sounder was used to record the TVCIR. It mainly consists of two units, a Tx unit and a Rx unit, as shown in Figure 3.1 (cf. Appendix A). The center frequency f_c was 3.8 GHz and the measurement bandwidth B was set to 200 MHz resulting in a high delay resolution of 5 ns. The choice of frequency and bandwidth was driven by the capacity of the channel sounder. Note that this band does not prevent the extension of this investigation to other frequencies, e.g. 5.9 GHz band which was dedicated to V2X communications, by simple scaling. The transmit power at antenna ports was 23 dBm. The code length N_{ch} was 4094 which corresponds to a maximum measurable excess delay τ_{excess} of 20.47 μ s giving rise to a maximum measurable path length of 6.141 km. To achieve a high Doppler resolution, a channel sampling rate ν_{cs} of 1062 Hz was considered which corresponds to a maximum relative speed of 150 km/h approximately. The main channel sounder parameters are summarized in Table 3.1. During measurements, the channel sounder stored the Tx location by a GPS together with the measured data stream (time-tagged).

Dipole antennas were used at Tx and Rx terminals. The antenna gain is 1.75 dBi. These antennas works in the range of 3.7 GHz to 3.9 GHz and it has a maximum radiation efficiency at 3.8 GHz (cf. Appendix A). Tx antenna was mounted on the roof of a car while the Rx antenna was placed on a cardboard tube carried by a human subject acting as a pedestrian (cf. Figure 3.2). This was done in order to avoid the impact of body shadowing on the measured V2P channels. Indeed, the body shadowing effect must be incorporated in the model to make it

more realistic, and this can further be done by adding an EM body interaction model [152].

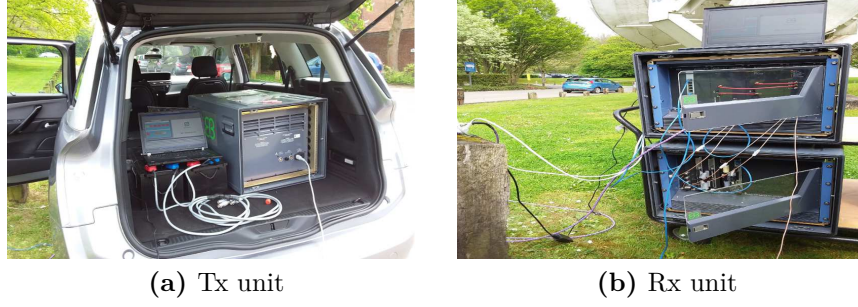


Figure 3.1: Channel sounder equipment

Table 3.1: Measurement setup parameters

Center frequency f_c	3.8 GHz
Bandwidth B	200 MHz
Delay resolution	5 ns
Transmit power	23 dBm
Maximum measurable excess delay, τ_{excess}	20.47 μ s
Channel sampling rate ν_{cs}	1062 Hz



Figure 3.2: Tx and Rx antenna positions

3.1.2 Measurement scenarios

Our V2P measurement campaign was carried out in two different site locations. Figure 3.3 presents satellite photographs of the measurement sites where the red lines indicate Tx path.

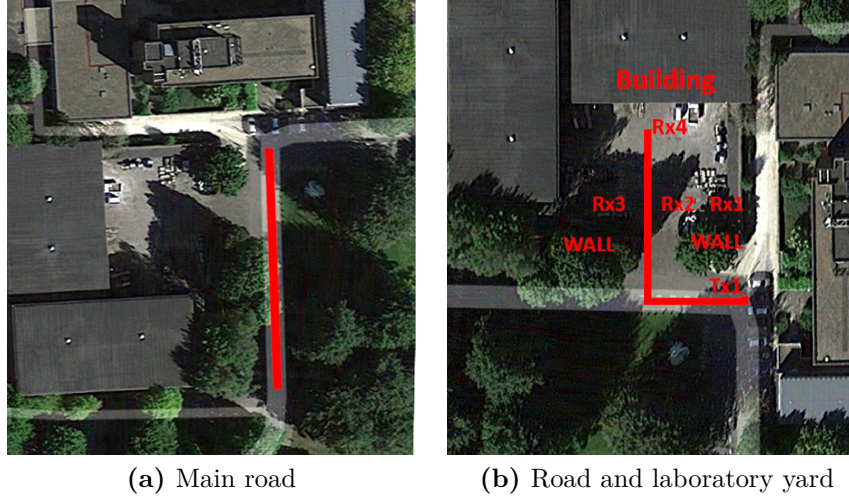


Figure 3.3: Measurement location

The first site is in the neighborhood of UCL campus, in Belgium. The avenue includes two lanes, one for each direction. On the side of road, there are fields of green grass and some trees. During the measurement, Tx vehicle was traveling the road while Rx subject was walking next to the road on grass (considered as a sidewalk). Two types of V2P measurements were carried out, respectively in LoS and NLoS. The NLoS condition is mainly considered when Rx subject was walking behind vehicles parked on the road (cf. Figure 3.4). Different mobility patterns were considered including parallel, opposite and orthogonal directions as shown in Figure 3.5 and 3.6.

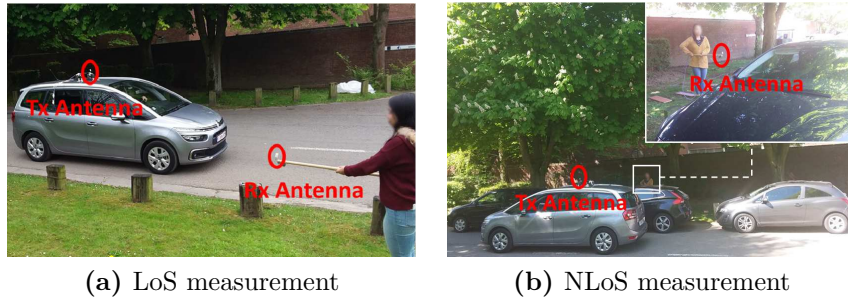


Figure 3.4: Example of LoS and NLoS Measurements

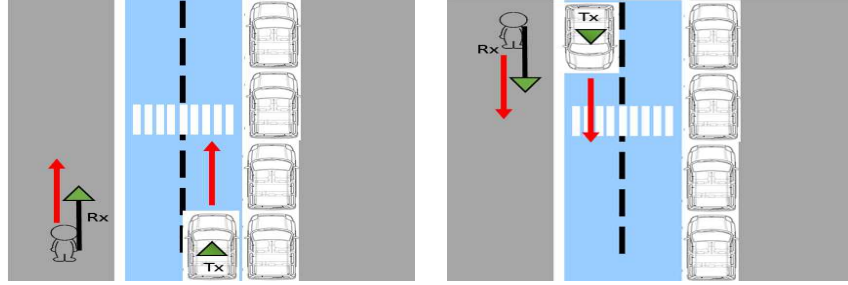
The second location, also on the UCL campus, consists of a main road

and a yard in front of a building. The yard was enclosed by walls separated by a car entrance. During measurement, Rx subject was walking inside the yard while Tx vehicle was moving from the main road to the yard or inside the yard depending on the scenario. Tx and Rx positions are marked in Figure 3.3. Four different scenarios were considered and they are described as follows (cf. Figure 3.7):

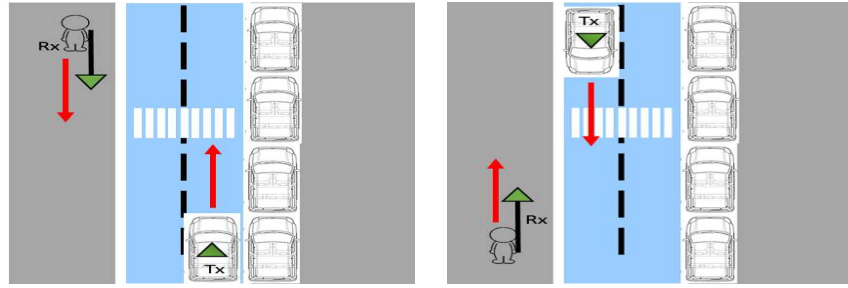
- Parallel direction then orthogonal direction 1: Tx and Rx start moving from Tx1 and Rx1, respectively and they meet at Rx2.
- Parallel direction then orthogonal direction 2: Tx vehicle drives from Tx1 to Rx4 while Rx subject walks from Rx1 to Rx3. At this point, it is worth noting that Tx and Rx meet at Rx2 without stopping and then the Rx subject continue crossing behind the mobile vehicle.
- Orthogonal direction then opposite direction: Rx subject walks from Rx4 to Rx2 while Tx vehicle moves from Tx1 to Rx4.
- Convoy direction: Tx and Rx terminals are both moving inside the yard behind each other starting from Rx4 and stopping at Rx2.

The vehicle speed was around 30 km/h except in the convoy direction scenario where the vehicle was moving behind the pedestrian, the vehicle speed was then around the usual walking pedestrian speed, i.e. 5 km/h. The distance between the Tx vehicle and the Rx pedestrian varied in the range of 2 m to 40 m depending on the measurement scenario.

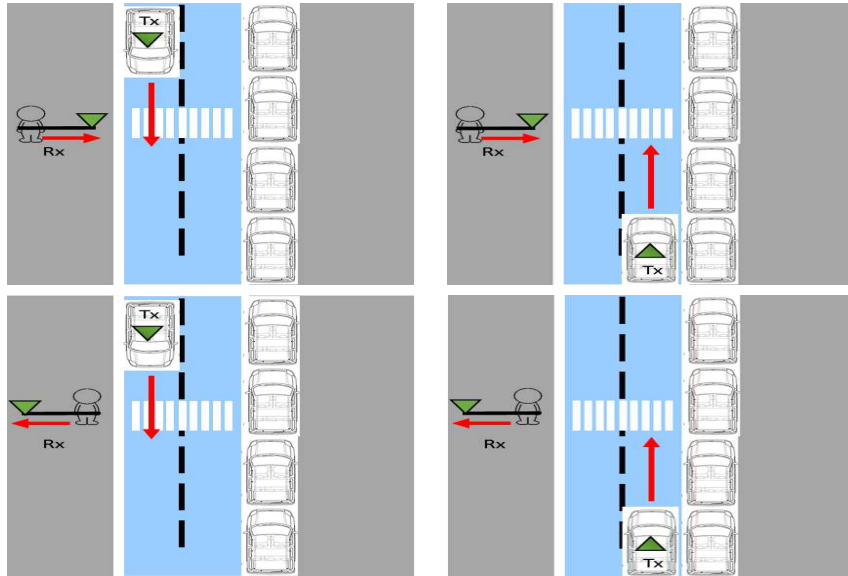
The measurement campaign was conducted during four days, and a total of 115 measurement runs were recorded. The recorded time was between 3 s and 20 s, approximately, depending on the measurement scenario. Four people were involved in the measurement campaign. In Tx vehicle, one person acted as a driver and a second colleague recorded the Tx GPS information and the car speed. The Rx antenna was carried by a human subject acted as a pedestrian while another person was responsible of controlling the channel sounder and writing the measurement protocol.



(a) Parallel direction

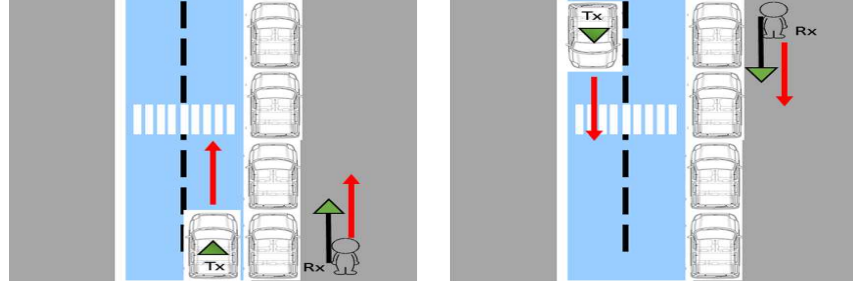


(b) Opposite direction

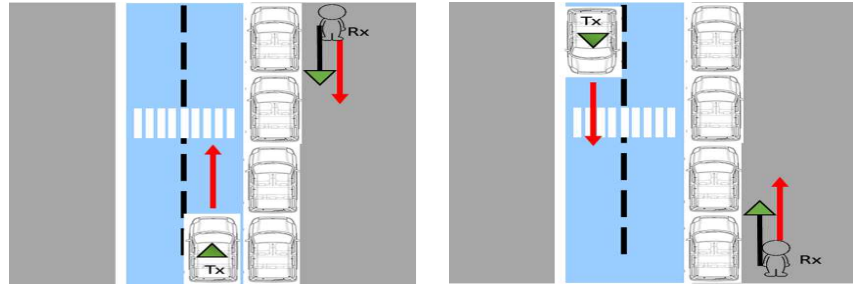


(c) Orthogonal direction

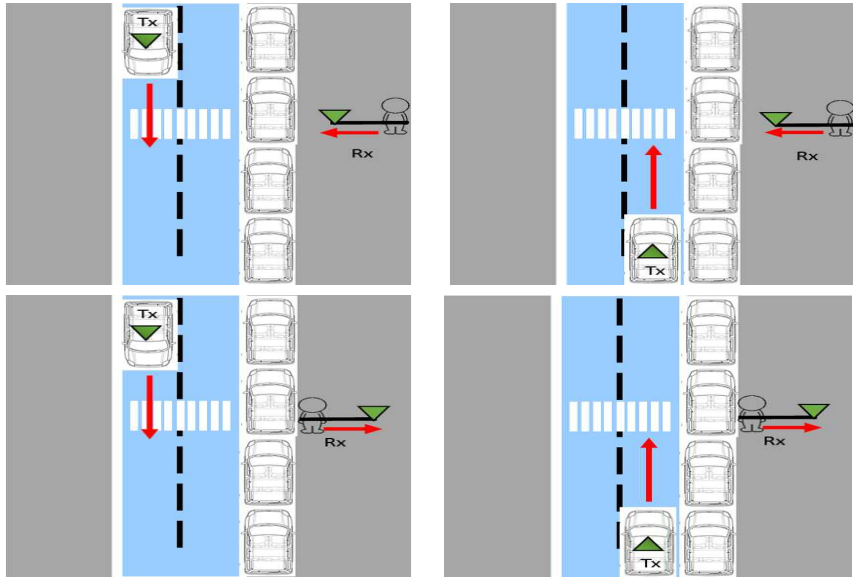
Figure 3.5: LoS measurement scenarios



(a) Parallel direction



(b) Opposite direction



(c) Orthogonal direction

Figure 3.6: NLoS measurement scenarios

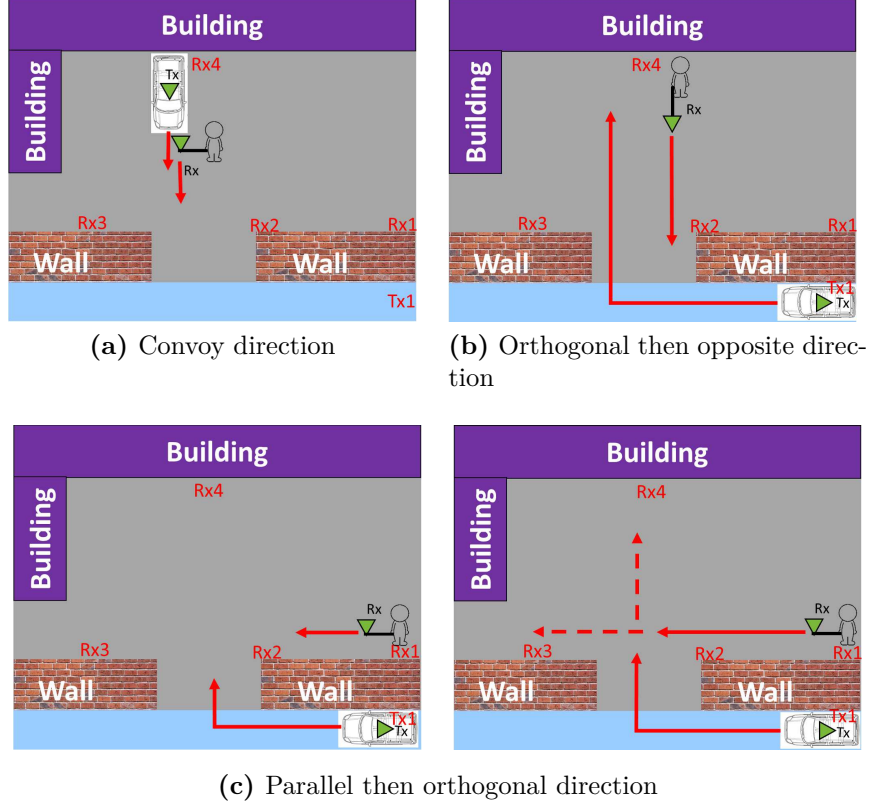


Figure 3.7: Second location: LoS and NLoS/LoS measurement scenarios

3.2 Channel Modeling Tools

In order to model the M2M channels, the non-stationarity of the channel, i.e. the change of channel statistics over time, must be included in the model. In our case, the non-stationarity is due to the dynamic change of the environments around the mobile terminals. A GSCM approach was proposed in [22, 92] in order to model the V2V channels. It is a combination of stochastic and deterministic (geometric) approaches. Its basic idea is to place scatterers around the terminals according to a statistical distribution, assign them different channel properties, and sum up their respective signal contributions at the receiver (cf. Section 1.1.3). Consequently, this approach can inherently model the non-stationary behavior of the channel since it can include the dynamic change of the scattering contributions.

Following their steps, a GSCM is proposed, here, in order to model the measurement results. A MPCs extraction method and a MPCs tracking algorithm are also proposed.

3.2.1 Geometry based stochastic channel model

In agreement with our measurement, the TVCIR can be divided into two major parts:

- The first path which mainly consists of the LoS and the ground reflection paths.
- The secondary multi-path stemming from specular reflection of scatterers.

Therefore, the TVCIR can be modeled as follows [22]:

$$h(t, \tau) = \sum_{p=0}^{P(t)} h_p(t, \tau_p) \quad (3.1)$$

where $P(t)$ is the time varying number of discrete scatterers and $p = 0$ represents the first path. The p-th discrete scatterer contribution can be further modeled as follows [153]:

$$h_p(t, \tau_p) = \alpha_p(d_p) \delta(\tau - \tau_p) \delta(\varphi_p^R - \varphi_p^R) \delta(\varphi_p^T - \varphi_p^T) \quad (3.2)$$

where $d_p = c \times \tau_p$, $\alpha_p(d_p) = a_p(d_p) e^{j\phi_p}$, τ_p , φ_p^R and φ_p^T are the time variant propagation distance, complex amplitude, the excess delay and the angles of arrival and departure of the p-th discrete path, respectively (cf. Figure 3.8). Note that all the discrete multi-path parameters in (3.2), $a_p e^{j\phi_p}$, τ_p , φ_p^R , φ_p^T are also time variant, although the time dependence is left out to simplify the notations.

3.2.2 Multi-path component detection

In order to extract the first path contribution and the discrete scatterer MPCs, a detection algorithm based on serial "search and subtract" of the contributions from the individual discrete scatterers is employed. This is similar to the CLEAN method [154, 155] and it can be summarized as follows:

- Find the strongest amplitude in the PDP

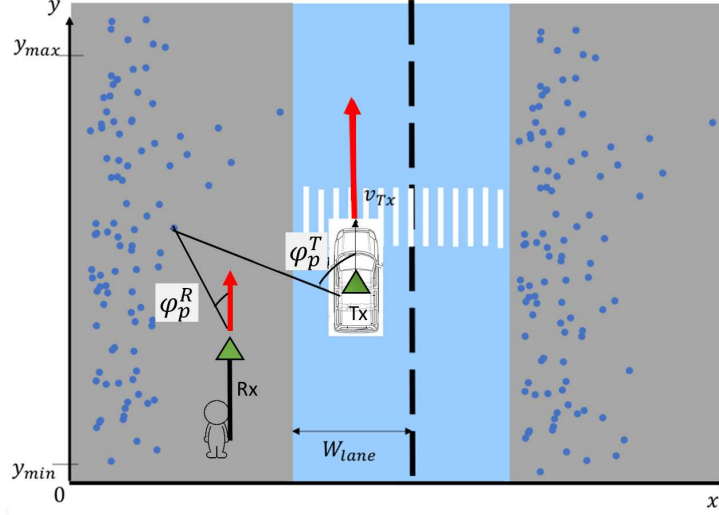


Figure 3.8: 2D Geometrical model for V2P channels

- Subtract this dominant amplitude from the PDP.
- Iterate until the maximum detected power is below a given threshold.

In order to reduce the chance of detecting noise peaks as MPCs, the measurement data was filtered with a 40λ sliding window assuming 30 km/h the Tx vehicle speed, (cf. Figure 3.9). This corresponds to a distance of approximately 3 m during 0.38 s. A careful selection of the window size is critical to avoid having noisy components appropriate to the small-scale fading components and to apply the average filter over uncorrelated data samples. In the literature, it was mostly considered in the range of 20λ and 40λ for UHF and Very High Frequency (VHF) [156].

Therefore, the PDP averaged over time is obtained as follows:

$$\overline{PDP}(t, \tau) = \frac{1}{N_\lambda} \sum_{m=-N_\lambda/2}^{N_\lambda/2} |h(t - m\Delta t, \tau)|^2 \quad (3.3)$$

where N_λ is the window size and Δt is the sampling time.

Starting by setting the iteration counter $l = 1$, the MPCs detection approach was applied as an iteration of four steps:

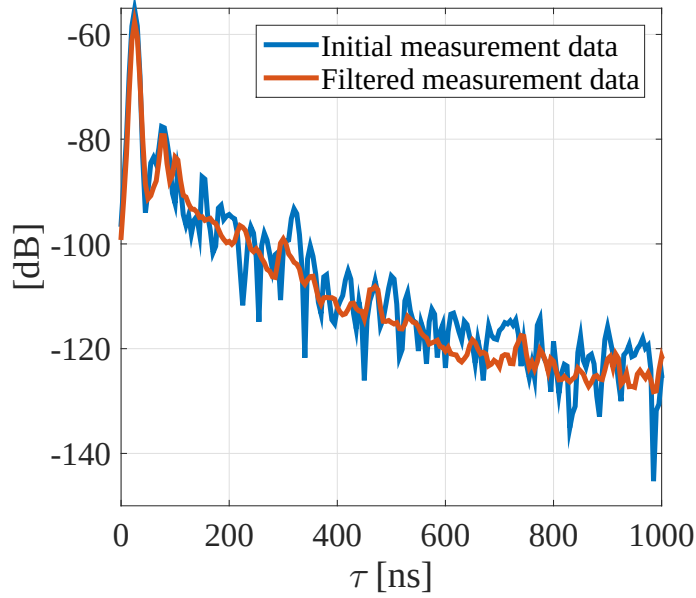


Figure 3.9: Example of the initial measurement data vs. the measurement data filtered with a 40λ sliding window

Step 1: Find for each time instant t_j , the delay that corresponds to the maximum power amplitude in $\overline{PDP}(l)$, i.e.

$$\tau_l = \arg \max_{\tau} \{ \overline{PDP} \} (l) \quad (3.4)$$

The corresponding amplitude is:

$$\bar{\alpha}_l = \sqrt{\overline{PDP}(t_j, \tau_l)} \quad (3.5)$$

Step 2: Subtract the strongest contribution detected from the $\overline{PDP}(l)$ as follows:

$$\overline{PDP}(l+1) = \overline{PDP}(l) - \overline{PDP}(l)(\tau_l) |W(\tau - \tau_l)|^2 \quad (3.6)$$

where $W(\tau)$ is the sounding pulse with duration of τ_{excess} .

In order to avoid the detection of a discrete contribution that is in the neighborhood of the detected scatterers, we block a number of points u around $\overline{PDP}(\tau_l)(l)$ by setting the appropriate PDP amplitude to 0 ($\overline{PDP}(l)\delta(\tau_l - u/(2B)) = \overline{PDP}(l)\delta(\tau_l + u/(2B)) = 0$). The number of blocked points must be small enough to not remove a possible discrete

contribution and long enough in order to avoid the detection of an erroneous discrete contribution. Therefore, it was determined with respect to the Impulse Response (IR) sounding pulse width (cf. Figure 3.10) and it was chosen equal to 6.

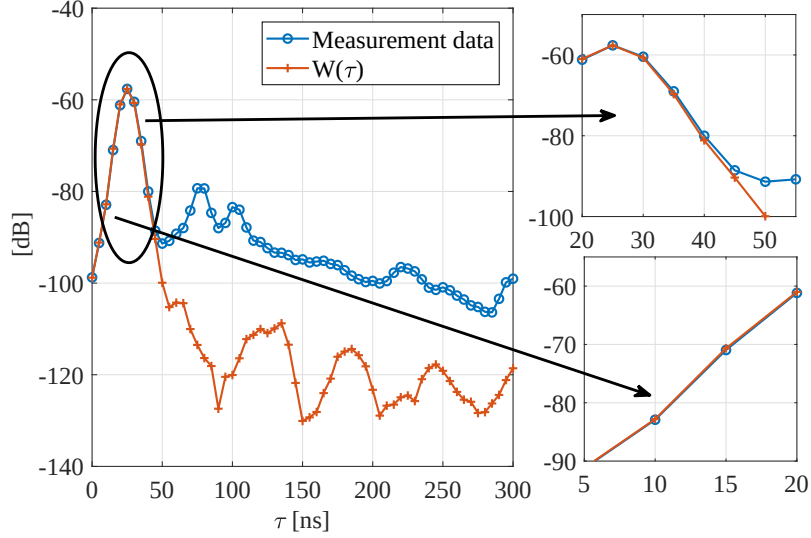


Figure 3.10: Detection method and the correction made after the peak detection

Step 3: Store the detected MPCs $\{\bar{\alpha}_l, \tau_l\}$ in two matrices $\mathbf{A}$ and $\mathbf{T}$, respectively, for further processing.

Step 4: Set $l = l+1$ and continue iterate until the remaining maximum power amplitude is at least 6 dB above the noise level.

The two resultant matrices $\mathbf{A} \in \mathbb{R}^{L \times N}$ and $\mathbf{T} \in \mathbb{R}^{L \times N}$ are as follows:

$$\mathbf{A} = \begin{bmatrix} \bar{\alpha}_{11} & \bar{\alpha}_{12} & \dots & \bar{\alpha}_{1N} \\ \bar{\alpha}_{21} & \bar{\alpha}_{22} & \dots & \bar{\alpha}_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ \bar{\alpha}_{L1} & \bar{\alpha}_{L2} & \dots & \bar{\alpha}_{LN} \end{bmatrix} \quad \mathbf{T} = \begin{bmatrix} \tau_{11} & \tau_{12} & \dots & \tau_{1N} \\ \tau_{21} & \tau_{22} & \dots & \tau_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ \tau_{L1} & \tau_{L2} & \dots & \tau_{LN} \end{bmatrix} \quad (3.7)$$

where L is the number of detected discrete MPCs (including the first path elements) and N is the time snapshot number.

Figure 3.11 presents the detected discrete contribution of one measured IR when Tx and Rx are in LoS and they are moving in the same direction.

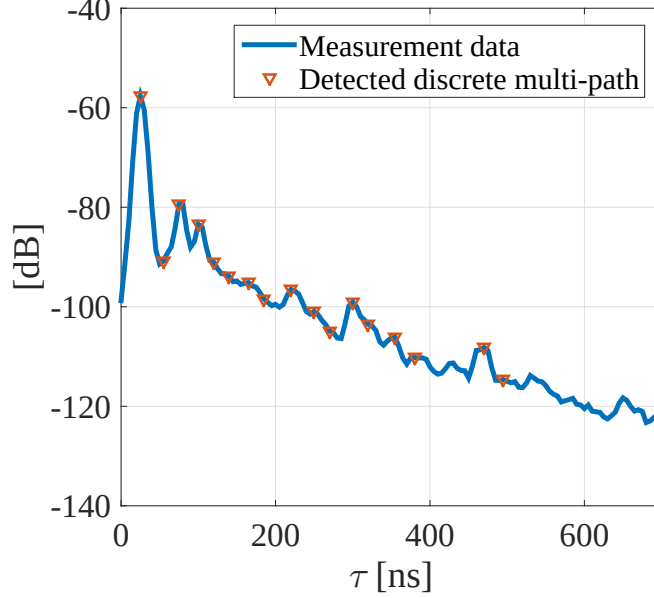


Figure 3.11: An example of the outcome of multi-path detection algorithm

3.2.3 Multi-path components tracking

To track the time evolution of the delay and magnitude for a reflected path, a tracking algorithm similar to the one proposed in [92] was employed using the following steps:

Step 1: Search the row k_m and the column l_m of the strongest element, i.e. the highest amplitude, in the matrix $\mathbf{A}$:

$$\{k_m, l_m\} = \arg \max_{k,l} |\mathbf{A}(k, l)| \quad (3.8)$$

The corresponding delay is then given by $\mathbf{T}(k_m, l_m)$.

Step 2: Search in the adjacent column (time samples) of $\mathbf{T}$, $l_m - 1$ and $l_m + 1$, for the closest delay component to $\mathbf{T}(k_m, l_m)$:

$$\begin{aligned} k_{m-} &= \arg \min_k |\mathbf{T}(:, l_m - 1) - \mathbf{T}(k_m, l_m)| \\ k_{m+} &= \arg \min_k |\mathbf{T}(:, l_m + 1) - \mathbf{T}(k_m, l_m)| \end{aligned} \quad (3.9)$$

The absolute error is then determined as follows:

$$\begin{aligned} \epsilon_{m-} &= |\mathbf{T}(k_{m-}, l_m - 1) - \mathbf{T}(k_m, l_m)| \\ \epsilon_{m+} &= |\mathbf{T}(k_{m+}, l_m + 1) - \mathbf{T}(k_m, l_m)| \end{aligned} \quad (3.10)$$

if neither ϵ_{m-} nor ϵ_{m+} are smaller than $1/B$, the components $\mathbf{T}(k_m, l_m)$ and $\mathbf{A}(k_m, l_m)$ are discarded by setting the components in $\{k_m, l_m\}$ to zero and return to step 1. Otherwise, create a vector $\mathbf{t}_f$ of N null elements then store $\mathbf{T}(k_m, l_m)$, $\mathbf{T}(k_{m-}, l_m - 1)$ and/or $\mathbf{T}(k_{m+}, l_m + 1)$ elements in $\mathbf{t}_f$ at the same column position as they were in the matrix $\mathbf{T}$, i.e. l_m , $l_m - 1$ and/or $l_m + 1$, respectively. For example, if we consider that both ϵ_{m-} and ϵ_{m+} are smaller than $1/B$, then the vector $\mathbf{t}_f$ becomes as follows:

$$\begin{aligned} \mathbf{t}_f &= \begin{bmatrix} 0 & 0 & \cdots & \mathbf{T}(k_{m-}, l_m - 1) & \mathbf{T}(k_m, l_m) & \mathbf{T}(k_{m+}, l_m + 1) & 0 & \cdots & 0 \end{bmatrix} \\ &= \begin{bmatrix} 0 & 0 & \cdots & \tau_{k_{m-}, l_m - 1} & \tau_{k_m, l_m} & \tau_{k_{m+}, l_m + 1} & 0 & \cdots & 0 \end{bmatrix} \end{aligned} \quad (3.11)$$

After that proceed to step 3.

Step 3: Estimate the time variation of the delay samples found so far by fitting a regression line to the non zero elements of the vector $\mathbf{t}_f$ as follows:

$$\tilde{\tau}(l) = a + bl \quad (3.12)$$

Then find $\mathbf{T}(k_{m--}, l_m - 2)$ and $\mathbf{T}(k_{m++}, l_m + 2)$ where

$$k_{m\pm\pm} = \arg \min_k |\mathbf{T}(:, l_m \pm 2) - \tilde{\tau}(l_m \pm 2)| \quad (3.13)$$

and determine the absolute error

$$\epsilon_{m\pm\pm} = |\mathbf{T}(k_{m\pm\pm}, l_m \pm 2) - \tilde{\tau}(l_m \pm 2)| \quad (3.14)$$

if ϵ_{m--} and/or ϵ_{m++} are smaller than $1/B$, store $\mathbf{T}(k_{m--}, l_m - 2)$ and/or $\mathbf{T}(k_{m++}, l_m + 2)$ in the vector $\mathbf{t}_f$ at the position $l_m - 2$ and/or $l_m + 2$, respectively.

Repeat this step taking the adjacent column, i.e. $\{l_m \pm 3\}$, and so on, until a temporal gaps, i.e. situations where the components of a path are missing in one or few consecutive time bins, is equal to N_g , then proceed to step 4.

Note that in order to well estimate the time variation of a path (the tracked curvature) depicted by equation (3.12), i.e. estimate a and b parameters, we use at most the last N_d elements (or the first N_d elements, depending on the direction) stored in the vector $\mathbf{t}_f$. In our case, N_d and N_g were set to 52.7λ and 5λ , respectively, considering the speed of Tx and Rx, the delay and time resolutions as well as the capability to correctly tracking a path using the proposed algorithm, accordingly.

Step 4: Store the tracked components, i.e. the vector $\mathbf{t}_f$, as a row in the matrix $\mathbf{T}_f$. While vector $\mathbf{t}_f$ corresponds to the time delay evolution

of one detected path, the rows of the matrix $\mathbf{T}_f$ are the detected MPCs including the first path elements. Remove the tracked components from $\mathbf{A}$ and $\mathbf{T}$ by setting the appropriate entries to 0. If there is some nonzero elements in matrices $\mathbf{A}$ and $\mathbf{T}$ return to step 1, otherwise proceed to step 5.

Step 5: To combine the elements of matrix $\mathbf{T}_f$ that are likely to belong to the same path, determine $\{l_{p,b}, m_{p,b}\}$ and $\{l_{q,e}, m_{q,e}\}$ as the start and end for each path p and find the path q that minimizes:

$$\xi = |\mathbf{T}_f(k_{p,b}, l_{p,b}) - \mathbf{T}_f(k_{q,e}, l_{q,e})| \quad (3.15)$$

if $\xi \leq 1/B$ and $l_{q,e} \leq l_{p,b} \leq 15\lambda + l_{q,e}$, in other words, if the path p starts after the path q and it is at most far away from the path q by $3N_g$, then combine these two paths and repeat step 5 until no combining paths are found. After that proceed to step 6.

Step 6: Measure the length, in terms of time bins, of the longest time appearance for each tracked path in $\mathbf{T}_f$. If the tracked paths have an appearance smaller than N_λ , the tracked path is discarded and remove it from the matrix $\mathbf{T}_f$. This was done in order to better model the tracked path as will be described in section 3.3. Finally, for each instant, find the complex values α_p from the TVCIR that correspond to the appropriate delay values in $\mathbf{T}_f$ and store them in the matrix $\mathbf{A}_f$.

Consequently the matrices $\mathbf{T}_f \in \mathbb{R}^{P \times N}$ and $\mathbf{A}_f \in \mathbb{C}^{P \times N}$ represent the evolution of the detected discrete MPCs (including the first path) in time and in magnitude, respectively.

Figure 3.12 shows a good agreement between the measured PDP and the tracking outcome when Tx and Rx were moving toward each other in LoS and NLoS conditions. The NLoS condition is considered here when Rx was moving behind parked vehicles.

3.3 Channel Model Results

Similar to [22, 92], the time variant complex amplitude of the p -th MPC presented in (3.2) was modeled as:

$$\alpha_p = \sqrt{G_p} g_p e^{j\phi_p} \quad (3.16)$$

where $\sqrt{G_p}$ and $g_p e^{j\phi_p}$ are the time variant power averaged on small-scale fading and the small-scale fading of the p -th MPC, respectively.

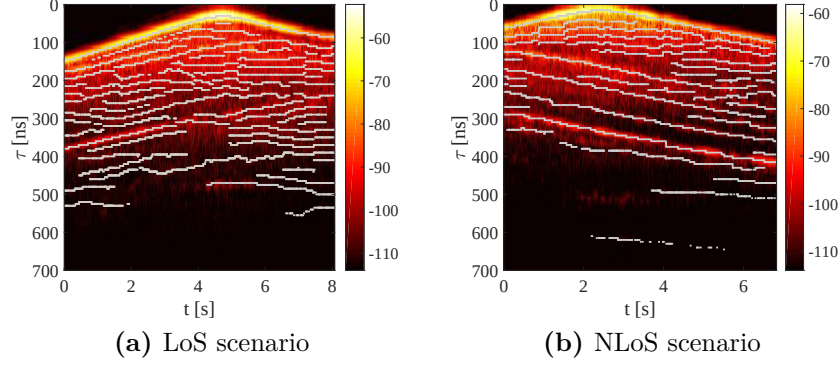


Figure 3.12: Outcome of MPC tracking algorithm when Tx and Rx are moving in the opposite direction under LoS and NLoS conditions

The first arriving path component mainly consists of the LoS and the ground reflection path. Hence, it exhibits fading characteristics and it was modeled in the same way by replacing the index p by 0 in (3.16).

The time variant power averaged on the small-scale fading $\sqrt{G_p}$ was modeled as follows:

$$10 \log_{10} G_p = -[PL_p + S_p] \quad (3.17)$$

where PL_p and S_p are the PL and the large-scale fading, respectively.

Depending on the environment propagation condition (i.e. LoS or NLoS), the measurement data were aggregated in order to extract the best fitting values of PL, large- and small-scale fading parameters. In this section, the PL, small- and large-scale fading models are presented for the first path component and secondary MPCs. Table 3.2 reports the model parameters at the end of the section.

3.3.1 Path loss model

3.3.1.1 First path component

For LoS scenarios, the PL was modeled with a two rays model defined as follows (cf. Figure 3.13):

$$PL_0 = \left[10 \log_{10} \left(\frac{\lambda}{4\pi} \right)^2 \left| \frac{e^{-\frac{2\pi i d_0}{\lambda}}}{d_0} + \Gamma_R \frac{e^{-\frac{2\pi i d_g}{\lambda}}}{d_g} \right|^2 \right] \quad (3.18)$$

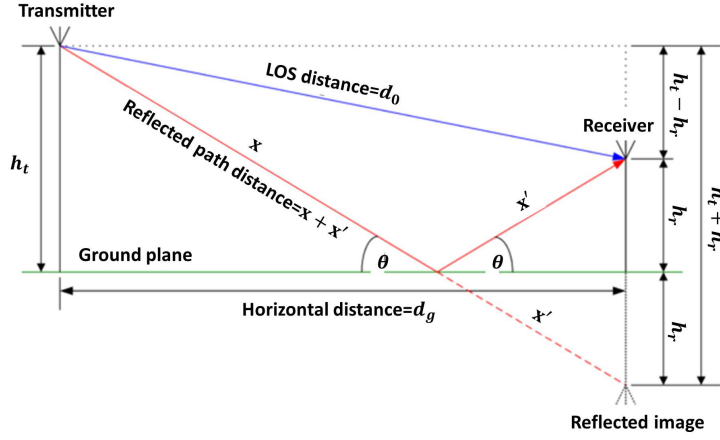


Figure 3.13: Two rays model

where d_0 is the LoS distance, d_g is the path distance between the transmitter reflected off the ground to the receiver and Γ_R is the Fresnel reflection coefficient given as:

$$\Gamma_R = \frac{\epsilon_g \sin \theta - \sqrt{\cos^2 \theta - \epsilon_g}}{\epsilon_g \sin \theta + \sqrt{\cos^2 \theta - \epsilon_g}} \quad (3.19)$$

where θ is the angle between the reflected path and ground plane and ϵ_g is the relative dielectric constant expressed as $\beta - j60\sigma\lambda$. β and σ are the relative permittivity and conductivity and they are set to 15 and 0.35 S/m [157], respectively.

Figure 3.14 presents an example of PL extracted from the first path component measured in LoS scenario and the proposed two rays model. As seen, the measured PL is in line with the two rays model. Note that the misalignment is due to the parameter estimations, i.e. dielectric constant, reflected and direct path distances. Moreover, we could use the logarithmic PL model for simplicity, however we prefer the two rays model because it can physically interpret the effective presence of the LoS and the ground reflection paths as it is in our case.

By filtering the amplitude $|\alpha_0(d_0)|^2$ with a rectangular sliding window of 40λ , the time variant power averaged over the small-scale fading was extracted in NLoS scenarios and NLoS/LoS scenarios (cf. Figure 3.6 and Figure 3.7). Then, the large-scale fading and the PL were separated by deriving a PL law.

The logarithmic PL model was used for the NLoS scenarios and it is

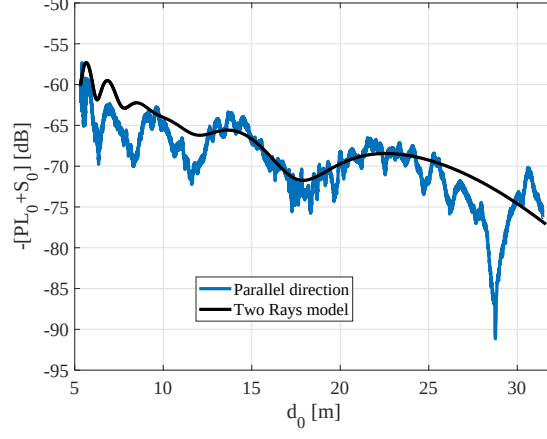


Figure 3.14: Example of PL modeling of the first path for LoS scenarios

expressed as follows:

$$PL_0 = PL_{0,ref} + 10n_0 \log_{10} \left(\frac{d_0}{d_{0,ref}} \right) \quad (3.20)$$

where $PL_{0,ref}$ and n_0 are the PL at reference distance $d_{0,ref}$ that is equal to 1 m and the PL exponent, respectively.

Figure 3.15 shows a good agreement between the proposed model and the measurement data.

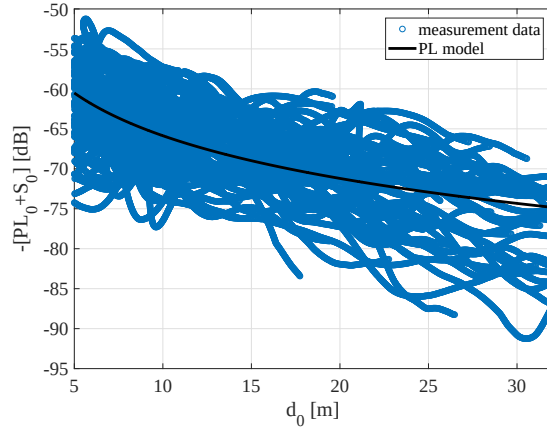


Figure 3.15: PL model of the First path component measured in NLoS scenarios

Due to the transition from NLoS to LoS in scenarios described in Figure 3.7b and 3.7c (cf. Figure 3.16), a PL model was developed as follows:

$$PL_0 = \begin{cases} PL_{0,ref}^{NLoS} + 10n_0^{NLoS} \log_{10} \frac{d_0}{d_{0,ref}} & d_{NLoS} \leq d_0 \\ PL_{0,ref}^{NLoS/LoS} + n_0^{NLoS/LoS} \times d_0 & d_{NLoS} \leq d_0 \leq d_{LoS} \\ PL_{0,ref}^{LoS} + 10n_0^{LoS} \log_{10} \frac{d_0}{d_{0,ref}} & d_0 \leq d_{LoS} \end{cases} \quad (3.21)$$

where $PL_{0,ref}^{NLoS}$, $PL_{0,ref}^{NLoS}$, n_0^{NLoS} , n_0^{LoS} are the PL at reference distance $d_{0,ref}$ and the PL exponents given when Tx and Rx are in NLoS and LoS, respectively. The reference distance $d_{0,ref}$ is equal to 1 m while d_{NLoS} and d_{LoS} represent the critical distance between terminals indicating the end of NLoS and LoS conditions, respectively. $PL_{0,ref}^{NLoS/LoS}$ and $n_0^{NLoS/LoS}$ are the parameters of the PL equation depicting the losses during the transition region (between the LoS and NLoS) when the direct link between Tx and Rx swaps from NLoS to LoS.

In other words, the proposed model (3.21) for the NLoS/LoS scenarios is a system of three equations in order to represent the following regions:

- LoS region, where Tx and Rx are in LoS.
- NLoS region, where Tx and Rx are in NLoS due to wall blocking the direct path.
- Transition region, that connects the two previous regions and it was characterized by a steep decrease (or increase) of the channel gain.

This model is similar to the one presented for belt to belt scenarios in Section 2.3.1 where also three mutual body orientations zones, i.e. LoS, transition and shadowed regions, were proposed to describe the orientation angle dependent-PL parameters.

In order to determine the critical distance d_{NLoS} and d_{LoS} , the GPS coordinate of a point, says "O", between the two walls as shown in Figure 3.16 was estimated using Google maps. Then, the distances from this point to Tx and Rx were calculated considering the Tx and Rx GPS coordinates. The Tx GPS was stored during measurement while the Rx GPS was estimated using Google map.

The distances from the point O to Tx and Rx are denoted by $\overline{OTx}$ and $\overline{ORx}$, respectively and their values were assigned with negative and positive signs depending on the Tx and Rx positions with respect to O as follows:

- If Tx is on the road, a negative sign is assigned to $\overline{OT_x}$.
- If Tx is inside the yard, a positive sign is assigned to $\overline{OT_x}$.
- If Rx is on the right side of O, a negative sign is assigned to $\overline{OR_x}$.
- If Rx is on the left side of O, a positive sign is assigned to $\overline{OR_x}$.

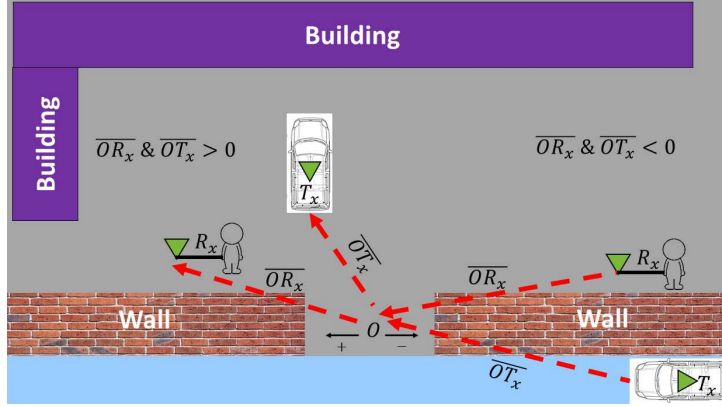


Figure 3.16: Method to separate LoS from NLoS in the NLoS/LoS scenarios

This method gives a general vision about the LoS and NLoS regions. If $\overline{OT_x}$ is negative, then Tx is on the road, thus Tx and Rx are in NLoS or in the transition region. $\overline{OR_x}$ becomes positive when Rx start to crossing to the next side of the yard, in this case Tx and Rx are positives.

Figure 3.17 presents a good agreement between the proposed model and the two NLoS/LoS measurement scenarios exhibited in Figure 3.7. At this point it is worth noting that the measurement was uncontrollable since Tx and Rx cannot see each other during the beginning of the measurements, therefore a transition region of one realization can belong to the LoS or NLoS regions for other realizations which explains the mixing regions (cf. Figure 3.17). For the orthogonal then opposite direction scenario, a transition region was not clearly noticed from the measurement data, so only the LoS and NLoS models were used (cf. Figure 3.17).

3.3.1.2 Secondary multi-path components

Similar to the previous section, the time average power is extracted by filtering the amplitude $|\alpha_p(d_p)|^2$ with a time domain rectangular sliding

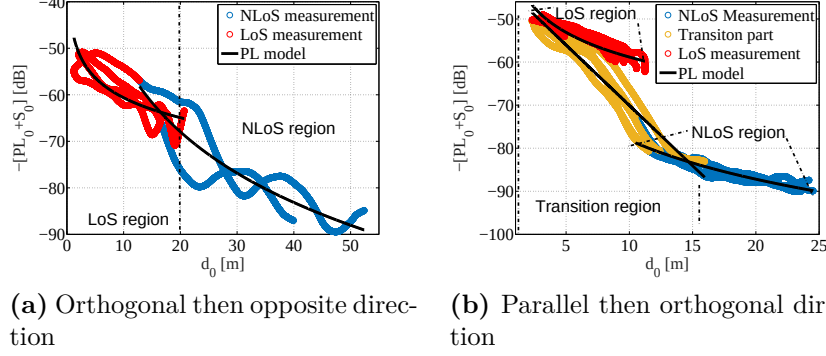


Figure 3.17: First path: PL model vs. measurement data considering the NLoS/LoS scenarios

window of 40λ [156]. The following step is to separate the large-scale fading and the PL by deriving the PL law as follows:

$$PL_p = PL_{p,ref} + 10n_p \log_{10}(d_p/d_{p,ref}) \quad (3.22)$$

where $PL_{p,ref}$ and n_p represent the PL at reference distance of $d_{p,ref}$ which is equal to 1 m and the PL exponent, respectively.

Depending on the scenario propagation condition, the measurement data are interpolated in order to extract the best fitting values of n_p and $PL_{0,p}$. Figure 3.18 present a good agreement between the measurement data and the proposed model for the different measured propagation conditions. Note that similarities in terms of n_p and $PL_{p,ref}$ for LoS and NLoS scenarios (cf. table 3.2) are expected since both measurements were done in the same location (cf. Table 3.2).

3.3.2 Large-scale fading

3.3.2.1 First path component

After subtracting the losses from the first path component using equation (3.18), (3.20) and (3.21) depending on the measurement propagation conditions and filtering out the small-scale fading, the large-scale fading is then characterized by a normal distribution in dB of zero mean (cf. eq. (2.3)) and an ACF described as follows:

$$R_{S,0}(\Delta t) = \sigma_{S,0}^2 e^{-\ln 2 \times \left(\frac{\Delta t}{t_{c,0}}\right)^2} \quad (3.23)$$

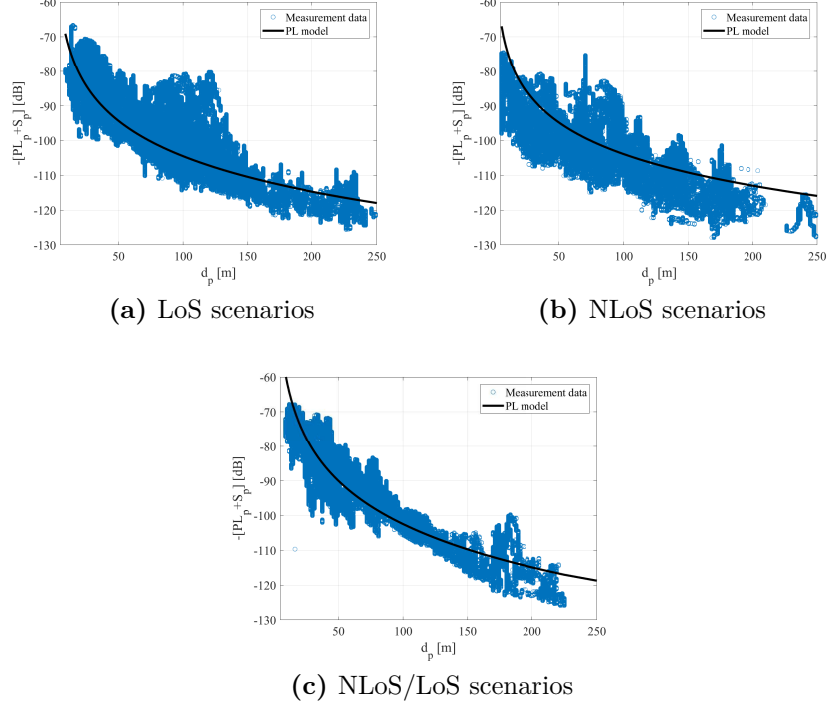


Figure 3.18: Secondary MPCs: PL model

where $\sigma_{S,0}$ and $t_{c,0}$ are the standard deviation and the coherence time at 0.5, respectively.

Figure 3.19 and Figure 3.20 present a good agreement between the large-scale fading distribution and ACF of the first path components with the proposed model, for the different propagation conditions. Note that the standard deviation of the large-scale fading given in LoS and NLoS scenarios are approximately the same, as expected.

3.3.2.2 Secondary multi-path components

The large-scale fading of the discrete scatterers was deduced after derived the PL law (3.22) and it was modeled by a normal distribution in dB of zero mean and an ACF described by an exponential decay law as follows:

$$R_{S,p}(\Delta t) = \sigma_{S,p}^2 e^{-\ln 2 \Delta t / (t_{c,p})} \quad (3.24)$$

where $\sigma_{S,p}$ and $t_{c,p}$ are the standard deviation and the coherence time at 0.5, respectively.

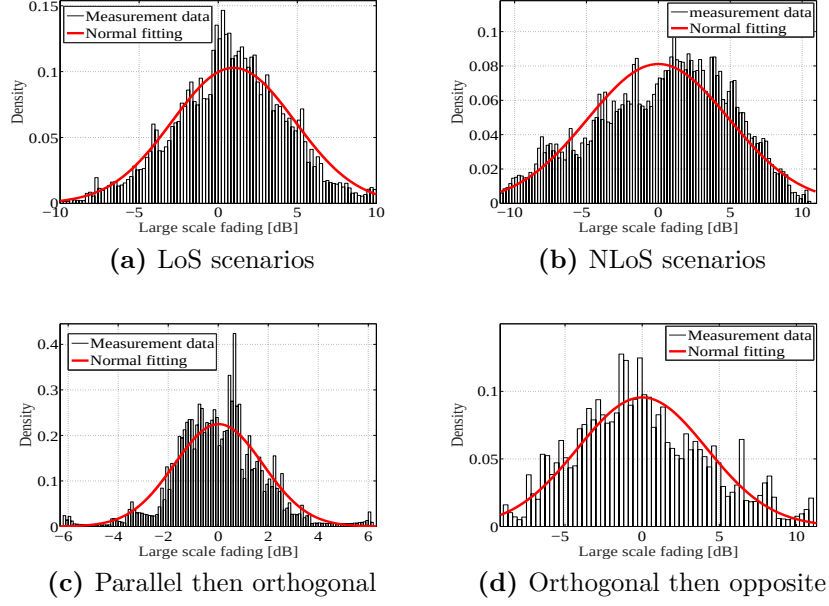


Figure 3.19: First path: large-scale fading distribution

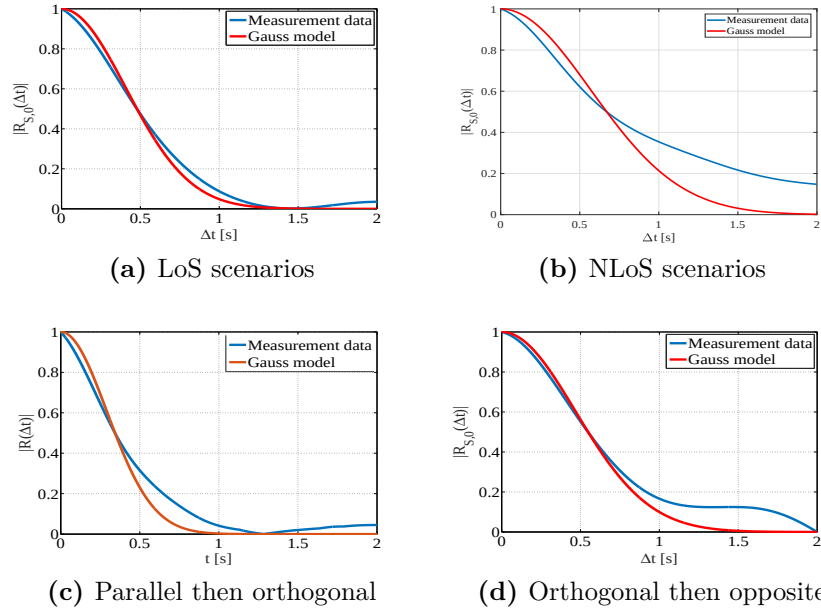


Figure 3.20: First path: ACF modeling for the large-scale fading

Figure 3.21 shows a good agreement between the measured large-scale fading and the proposed model regardless of the measurement environment. The standard deviation $\sigma_{S,p}$ measured in the three different conditions, are also approximately similar, as the measurement were conducted in places nearby so the same scatterer contributions are expected.

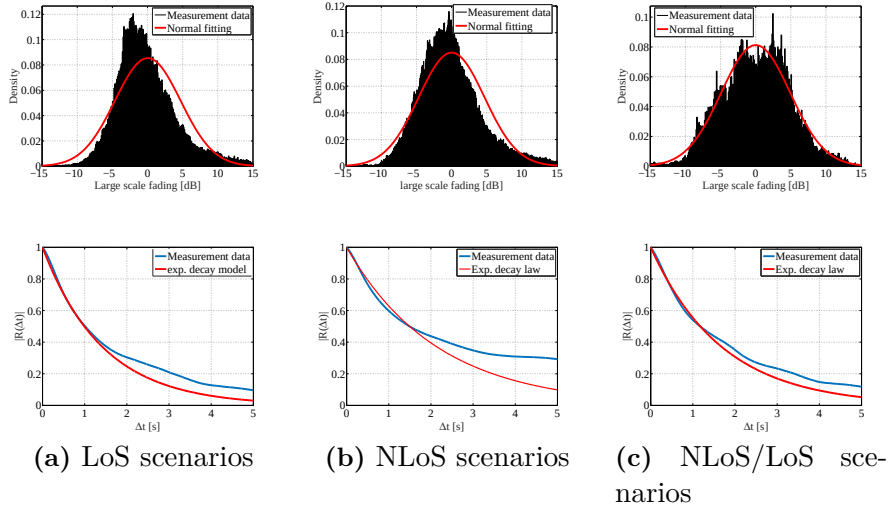


Figure 3.21: Secondary MPCs: Normal distribution and ACF model

3.3.3 Small-scale fading

The small-scale fading envelope corresponds to the filtered out signal when performing the 40λ sliding average window on power amplitude of discrete scatterers $|\alpha_p(d_p)|^2$ or first path contributions $|\alpha_0(d_0)|^2$. It was characterized for both by Rice distribution.

3.3.3.1 First path component

Considering the propagation condition, the first path small-scale fading was modeled with a Rice distribution that has a k-factor $K_{F,0}$ and a standard deviation $\sigma_{F,0}$ (cf. Figure 3.22).

Note that the standard deviation $\sigma_{F,0}$ given in NLoS scenarios is slightly larger than the one extracted from the LoS measurements due to the presence of parked vehicle shadowing the LoS path (cf. Table 3.2).

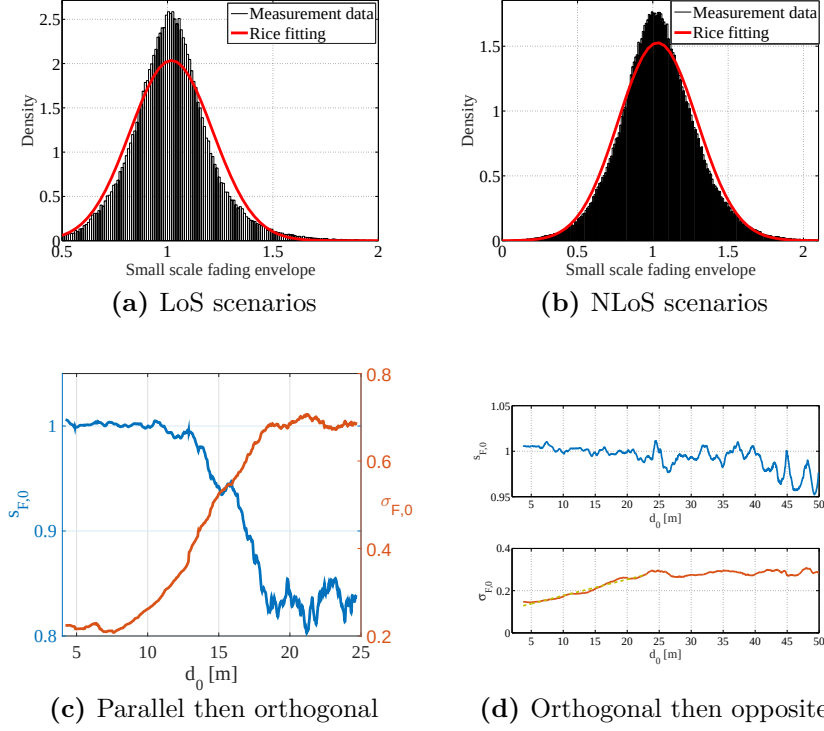


Figure 3.22: First path: small-scale fading distribution

In fact, as seen in Figure 3.23, the first path power fluctuates rapidly in the NLoS scenarios compared to the LoS scenarios. A deep fade of -90 dB occurred in NLoS and this can be due to the shadowing of vehicles while the minimum power obtained from the LoS scenarios is around -75 dB.

Similar to the previous chapter, the Rice parameters have also shown a slight variation with respect to the relative distance between terminals (cf. Figure 3.22c and 3.22d). However, here, the variation is due to the environment mutation from NLoS to LoS. Note that the three defined regions, i.e. LoS, NLoS and transition regions, can be also observed for the case of parallel the orthogonal walking scenarios. Moreover, the range of the non-centrality parameter $s_{F,0}$ and the scale parameter $\sigma_{F,0}$ is approximately close to the ones obtained for head to head scenarios (cf. Section 2.3.3).

Therefore, for the parallel then orthogonal walking directions, the non-centrality parameters $s_{F,0}$ and the standard deviation $\sigma_{F,0}$ are mod-

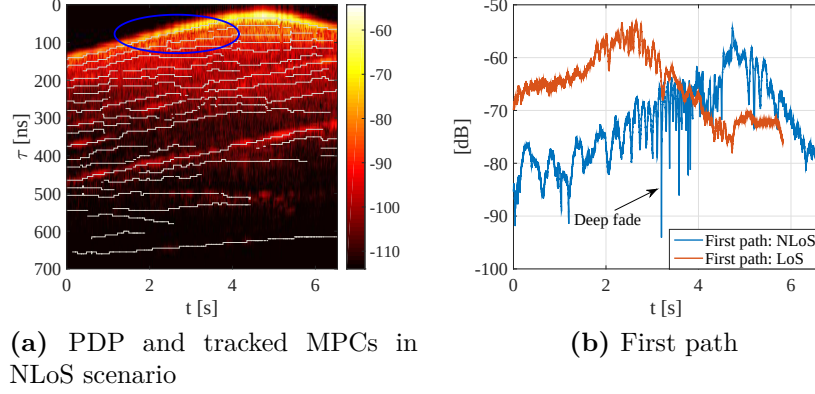


Figure 3.23: First path: NLoS vs. LoS

eled as follows:

$$s_{F,0} = \begin{cases} 1 & d_0 < 13.5 \\ -0.03d_0 + 1.4 & 13.5 \leq d_0 \leq 18.16 \\ 0.83 & d_0 \geq 18.16 \end{cases} \quad (3.25)$$

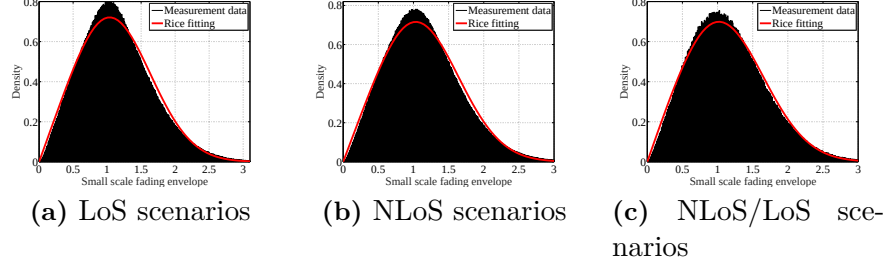
$$\sigma_{F,0} = \begin{cases} 0.22 & d_0 < 10 \\ 0.053d_0 - 0.29 & 10 \leq d_0 \leq 18.7 \\ 0.7 & d_0 \geq 18.7 \end{cases} \quad (3.26)$$

For the orthogonal then opposite walking scenarios, $s_{F,0}$ is always approximately equal to 1 while $\sigma_{F,0}$ increases slightly with distance until 20 m as follows:

$$\sigma_{F,0} = \begin{cases} 7.7 \times 10^{-3}d_0 + 0.1 & d_0 < 20 \\ 0.27 & d_0 \geq 20 \end{cases} \quad (3.27)$$

3.3.3.2 Secondary multi-path components

Figure 3.24 present a good agreement between the measured small-scale fading of the secondary MPCs and the Rice distribution for the different measurement scenarios. The Rice parameters are similar for all measurements, this can be reasonably explained by the fact that the measurements were conducted in the same location so similar discrete scatterer contributions were expected. The K-factors are close to 0 dB which results in a Rayleigh distribution. At this point, it is worth noting that there was no evident variation for the Rice parameters with respect to distance considering the NLoS/LoS scenarios.

**Figure 3.24:** Secondary MPCs: small-scale fading distributions**Table 3.2:** Parameters of the first path component and secondary MPCs in LoS, NLoS and NLoS/LoS scenarios

		LoS scenarios		NLoS scenarios		NLoS/LoS scenarios	
						PO scenario*	OO scenario*
First path	Path loss	n_0	-	1.78		3/2.8/1.9	5.2/-/1.3
		PL_0 [dB]	-	48		48/42/40	53/-/2.5
	Large-scale fading	$\sigma_{S,0}$ [dB]	3.87	4.92		1.77	4.176
		$t_{c,0}$ [s]	0.48	0.67		0.34	0.55
	Small-scale fading	$K_{F,0}$ [dB]	11.058	8.52		cf. (3.25)&(3.26)	cf.(3.27)
		$\sigma_{F,0}$	0.2	0.26		cf. (3.26)	cf. (3.27)
Secondary multi-path	Path loss	n_p	3.38	3			4.13
		PL_p [dB]	36.75	43.4			19.65
	Large-scale fading	$\sigma_{S,p}$ [dB]	4.67	4.68			4.91
		$t_{c,p}$ [s]	1	1.26			1.7
	Small-scale fading	$K_{F,p}$ [dB]	0.25	-0.2			-0.85
		$\sigma_{F,p}$	0.61	0.63			0.66

*PO scenario: parallel then orthogonal walking direction; OO scenario: Orthogonal then opposite walking direction.

3.4 Time Correlation Function Model

A general ACF model for M2M channels in the presence of moving scatterers was developed previously in Chapter 2 considering a general scattering environment. Therefore, based on this model (cf. equation (2.20)) and with the help of Bessel properties (cf. (2.23)) and path amplitude properties (cf. (2.22)), the ACF model of M2M channels in the presence of non-isotropic fixed scatterers uniformly distributed in the environment is obtained as follows:

$$R(\Delta t) = \sum_{q=-\infty}^{+\infty} \sum_{n=-\infty}^{+\infty} i^{(n+q)} \gamma_{qn} J_q(2\pi\nu_T \Delta t) J_n(2\pi\nu_R \Delta t) e^{iq\varphi_v^T} e^{in\varphi_v^R} \quad (3.28)$$

where γ_{qn} are the coefficients of the double Fourier series of the multi-path power function (cf. equation (2.22)), ν_T and ν_R are the maximum Doppler frequencies due to the mobility of Tx and Rx while φ_v^T and φ_v^R are the directions of Tx and Rx motions, respectively.

Considering the LoS scenarios where Tx and Rx were moving toward each other, the motion directions of Tx and Rx, in this case, are given as follows:

$$\varphi_v^T = -\varphi_v^R = \pi/2 \quad (3.29)$$

Therefore, substituting φ_v^T and φ_v^R by $+\pi/2$ and $-\pi/2$, respectively, in equation (3.28), the ACF model of M2M channels in the presence of Non-Isotropic Fixed scatterers (NIFS) (M2M-NIFS) for opposite movement is deduced as follows:

$$R(\Delta t) = \sum_{q=-\infty}^{+\infty} \sum_{n=-\infty}^{+\infty} (-1)^q \gamma_{qn} J_q(2\pi\nu_T \Delta t) J_n(2\pi\nu_R \Delta t) \quad (3.30)$$

Considering the isotropic scattering environment, i.e. isotropic scatterers uniformly distributed in the environment, this equation will be reduced to:

$$R(\Delta t) = J_0(2\pi\nu_T \Delta t) J_0(2\pi\nu_R \Delta t) \quad (3.31)$$

Equation (3.31) represents the ACF model of M2M channels in the presence of Isotropic Fixed Scatterers (IFS) (M2M-IFS).

Figure 3.25 presents a comparison between the ACF $R(\Delta t, \Delta \tau)$ where $\Delta \tau = 0$ obtained in opposite walking scenario when Tx and Rx are in LoS and the curves given by equations (3.31) (M2M-IFS) and (3.30) (M2M-NIFS for opposite movement) where γ_{qn} coefficients were estimated up to the tenth orders using a non-linear least square fitting. The maximum Doppler frequencies of Tx and Rx were derived for velocities of 30 km/h and 1.33m/s, respectively. The measured coherence time at 0.5 is 2.46 ms which well corresponds to that given by the M2M-NIFS model (2.46 ms) and the M2M-IFS case (2.26 ms). As seen, the M2M-IFS model can roughly represent the temporal variation of the measured correlation function up to 0.015 s, while the M2M-NIFS model can fit the measurements up to 0.1 s, thus it can be considered as a more accurate time correlation function model.

At this point, it is worth noting that the proposed ACF model for indoor M2M channels can well depict the M2M ACF measured in outdoor and so it can account different range of speeds (0.5m/s in indoor 30km/h in outdoor) and different type of environments. Indeed, the Fourier coefficients γ_{qn} change with the type of environment and the dimension required in order to model the ACF up to a certain time Δt depends on the Tx and Rx speeds (the tenth order had modeled the ACF of indoor M2M and outdoor V2P opposite movements up to 0.5 and 0.1 s, respectively).

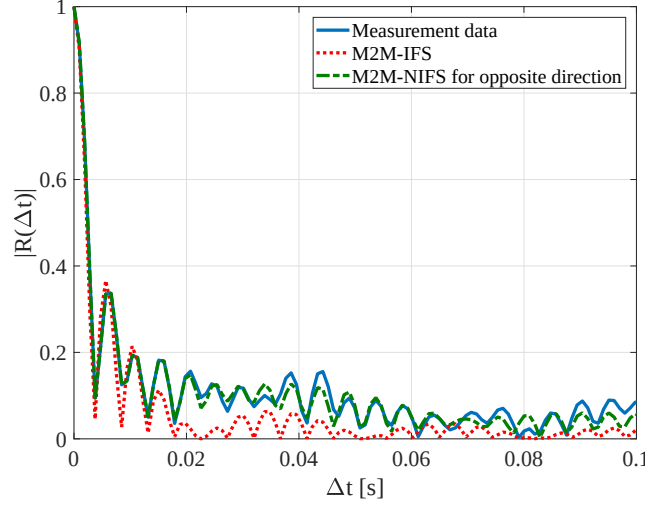


Figure 3.25: Time correlation function of measurement data vs. analytical formula for opposite movement in LoS.

3.5 Doppler Model

Figure 3.26 compares the Fourier transform of equation (3.31) and equation (3.30) given for tenth order to the Doppler spectrum measured in the case of opposite direction when both Tx and Rx are in LoS. The Doppler frequency axis is normalized with respect to the maximum Doppler frequency due to the mobility of terminals, i.e. $\nu_D = \nu_T + \nu_R$. The measured Doppler spectrum was calculated as the Fourier transform of the measured ACF within Δt interval of $[-0.1; 0.1]$.

As seen, the M2M-IFS model can well fit the measurement up to -10 dB while the M2M-NIFS model for opposite direction is in excellent agreement with the measurement data (cf. Figure 3.26). This conjectures that equation (3.30) calculated up to tenth order can well model the time correlation function up to 0.1s, thus a good fit is expected between the Doppler spectrum calculated from the measured ACF within the interval $[-0.1; 0.1]$ and the one given by (3.30) up to tenth order. Moreover, the Jakes spectrum, calculated for a maximum Doppler frequency $\nu_T + \nu_R$, is unable to depict the measurements.

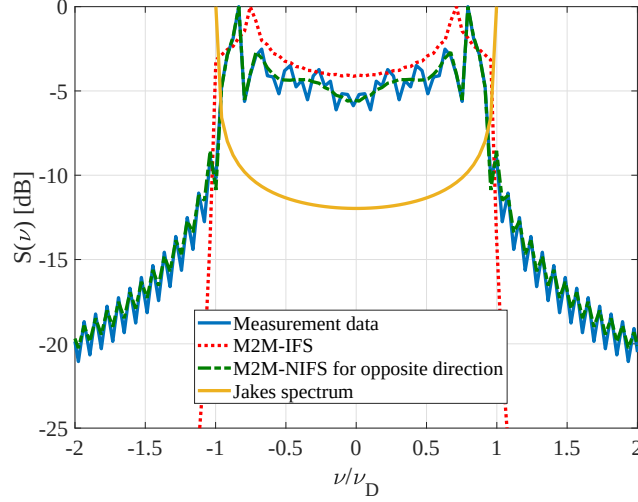


Figure 3.26: Doppler spectrum of measurement data vs. analytical formula for opposite movement in LoS

3.6 Conclusion

Due to the lack of V2P channel measurement, characterization and modeling, we present in this chapter, for the first time, wide-band measurement based V2P channel characterization and modeling. The full description of the measurement campaign was provided. The measurements were performed at 3.8 GHz and bandwidth of 200 MHz. The peculiarity of this frequency band is its proximity to the 3.5 GHz, which is considered for 5G network. Different mobility patterns were considered in various propagation environments, i.e. LoS, obstructed LoS by neighboring vehicles where the pedestrian was walking behind parked vehicles and the NLoS/LoS where the V2P link passes through three stages, i.e. the direct path blocked by wall separating terminals, a transition from NLoS to LoS and the LoS situation. While the obstructed LoS scenarios can degrade the received signal power, the NLoS/LoS scenarios occur mostly in the safety critical scenarios such as crossing street intersections.

A GSCM similar to the one proposed for V2V channels [22, 92] was proposed and it consists of two major components: the first path component and the secondary MPCs. Its peculiarity is related to its capability to model the non-stationarity channel aspect inherently. A detection and tracking algorithms were implemented in order to track the first

path component and the discrete scatterer MPCs in time. Similar to B2B channels, they were best fitted with a combination of PL, large-scale fading and small-scale fading. Depending on the measurement propagation condition (LoS, NLoS and NLoS/LoS), the parameter values were given. The small-scale fading was found to be described with a Rice distribution while the large-scale fading was characterized in dB by a normal distribution with zero mean. Depending on the measurement scenario, a PL model for the first path was proposed while a log distance model was always used for the MPCs. Therefore, a two rays model was implemented for the PL of the first path in LoS scenarios and a log distance model for the NLoS scenarios. In the NLoS/LoS scenarios, a model based on three equations was proposed in order to present the LoS, NLoS and the transition regions. Moreover, the Rice parameters for this type of scenarios were exhibited a variation in function of the Tx-Rx distance, highlighting the non-stationary behavior of the V2P fading channel. Note that this approach is similar to the one used to model the belt to belt channel presented in the previous Chapter, where the PL and the Rice parameters were modeled considering three propagation regions, i.e. LoS, shadowed and transition regions.

Finally, a general ACF for V2P channels was deduced from the model given in chapter 2, section 2.4.2. As example, we consider the opposite walking LoS scenario and we have proven that the analytical expression of the time correlation function proposed in this thesis is effective to reproduce the M2M channel characteristics regardless the scenario under consideration.

At this point, it is worth noting that another wide-band channel measurement campaign was carried out considering the P2P channels and it is described in Appendix D.

In a following step, we plan to successfully implement the model based on the scenario and the propagation condition with fading characteristics including the Doppler characteristics.

Chapter 4

Channel Model Implementation

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In order to explore the B2B and V2P communications in real-world scenarios, channel models were proposed for both in Chapter 2 and Chapter 3, respectively. These models were based on measurement campaigns carried out in different propagation environments (LoS and NLoS) and considering different mobility patterns. A combination of PL, small-scale fading and large-scale fading was proposed for the B2B channel transfer function and for the components of the V2P GSCM. Moreover, the correlation and Doppler properties were explored and modeled both for the small-scale fading and large-scale fading.

In this chapter, channel model implementation techniques that can preserve the channel correlation and Doppler properties are presented. The goal is to successfully implement the proposed models based on the scenario and the propagation condition with fading characteristics including the Doppler characteristics.

The chapter is organized as follows. Section 4.1 and Section 4.2

present ACF and Doppler spectrum based implementation techniques, respectively, that can generate a stochastic process that has the same first and second statistical orders of the measurement data. The generated data were then compared to the measurements. Section 4.3 introduces AR models that were developed to model the measured large- and small-scale fading. Classically, the AR process was used to model correlated fading channels. Therefore, it was analyzed here to assess its degree of modeling the correlation and Doppler properties of the B2B channels. Finally, conclusions are drawn in section 4.4

4.1 ACF Based Implementation

Here, we present the results of a channel model implementation including the time correlation properties obtained from measurements. Owing that the measured small- and large-scale fading can be described with complex and real Gaussian values, respectively, hence, the proposed method is based on generating correlated random normal variables, whose correlation characteristics were retrieved from the ACF models derived in the previous chapters.

4.1.1 Implementation technique

A classical way [127] to generate a correlated normal distributed random variable with a given correlation matrix $\mathbf{R}$ is done by finding a matrix $\mathbf{U}$ such that:

$$\mathbf{R} = \mathbf{U}\mathbf{U}^H \quad (4.1)$$

where $\mathbf{U}^H$ denotes the Hermitian transpose of $\mathbf{U}$.

The correlation matrix $\mathbf{R}$ is a positive definite symmetric Toeplitz matrix while the matrix $\mathbf{U}$ is the lower triangular matrix of $\mathbf{R}$. They are defined as follows:

$$\mathbf{R} = \begin{bmatrix} 1 & \rho_1 & \dots & \dots & \rho_N \\ \rho_1 & 1 & \dots & \dots & \rho_{N-1} \\ \vdots & \vdots & \ddots & \dots & \vdots \\ \rho_{N-1} & \rho_{N-2} & \dots & 1 & \rho_1 \\ \rho_N & \rho_{N-1} & \dots & \dots & 1 \end{bmatrix} \quad \mathbf{U} = \begin{bmatrix} u_{1,1} & 0 & 0 & \dots & 0 \\ u_{2,1} & u_{2,2} & 0 & \dots & 0 \\ \vdots & \vdots & \dots & \ddots & \vdots \\ u_{N-1,1} & u_{N-1,2} & \dots & \dots & 0 \\ u_{N,1} & u_{N,2} & \dots & \dots & u_{N,N} \end{bmatrix} \quad (4.2)$$

where $\rho_j = R(j)$ is the ACF at lags j .

The Cholesky factorization was used in order to decompose the correlation matrix $\mathbf{R}$ into a product of a lower triangular matrix $\mathbf{U}$ and its conjugate transpose [158].

Using the matrix $\mathbf{U}$, one can generate correlated random numbers $\mathbf{X}_c = [x_1^c \ x_2^c \ \dots \ x_N^c]^T$ from uncorrelated standard normal values $\mathbf{X} = [x_1 \ x_2 \ \dots \ x_N]^T$, where $[\cdot]^T$ denotes the transpose of matrix, as follows:

$$\mathbf{X}_c = \mathbf{U}\mathbf{X} \quad (4.3)$$

This method is straightforwardly applied for the large-scale fading, since it can be described as normal random variable in dB. Then, a vector of correlated large-scale fading, in dB, was obtained by taking into account the measured standard deviation σ_S as follows:

$$\mathbf{S} = \sigma_S \mathbf{X}_c \quad (4.4)$$

where $\mathbf{S} = [s_1 \ s_2 \ \dots \ s_N]^T$.

Small-scale fading implementation was obtained in a similar manner, by generating correlated and normal distributed complex values $\mathbf{X}_c$, instead of real values. Therefore, the small-scale fading envelope will result from the envelope of:

$$\mathbf{X}_F = \sigma_F \mathbf{X}_c + s_F \quad (4.5)$$

where $\mathbf{X}_F = [x_1^F \ x_2^F \ \dots \ x_N^F]^T$, σ_F and s_F are the measured standard deviation and the root mean square of the dominant component power as defined in [159], respectively.

At this point, it is worth mentioning that with a large number of data samples, the computational time of this method increases due to the intensive computation of the lower triangular matrix coefficients.

In what follows, this method was implemented in order to generate correlated small-scale and large-scale fading considering the indoor M2M measurements where the antennas were placed on the heads of subjects moving in one single room (LoS).

4.1.2 Example 1: Large-scale fading

In this section, the implementation technique based on correlation properties was applied in order to simulate correlated large-scale fading. The indoor M2M scenarios were considered (cf. Chapter 2). As shown in Section 2.4.1, the large-scale fading ACFs are independent of the mobility patterns and it can be described by an exponential decay law as follows:

$$R(\Delta t) = \exp \left(-\ln 2 \left(\frac{\Delta t}{t_c} \right) \right) \quad (4.6)$$

where t_c is the coherence time at 0.5.

Note that this model was also used to depict the ACF of the large-scale fading given by the secondary MPCs as presented in Section 3.3.2.2. Based on the proposed ACF model and the normal distribution parameters (cf. Table 4.1), the implementation technique was applied and correlated large-scale components were generated. Figure 4.1 and Table 4.1 compare the measurement results with those simulated. As seen, the amplitude characteristics are in excellent agreement with the measurement results while the ACF of the generated data is in line with the proposed model. The Root Mean Square Error (RMSE) between the measured and simulated ACFs is calculated up to the coherence time and it is equal to 0.015.

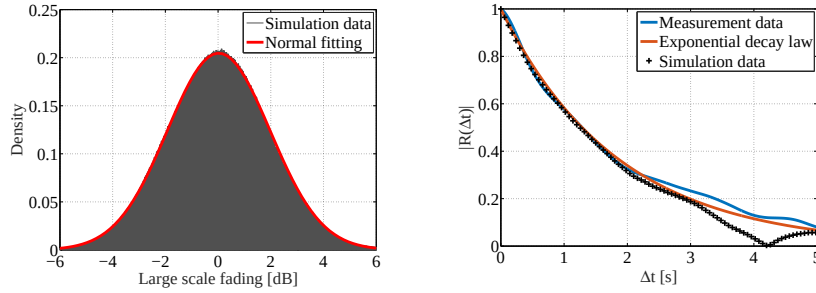


Figure 4.1: Generated large-scale fading: distribution and correlation properties

4.1.3 Example 2: Small-scale fading

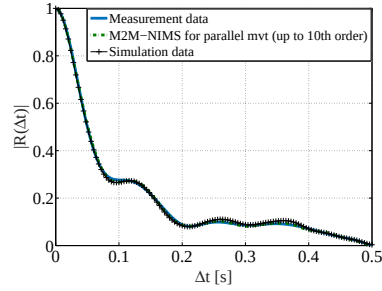
In this section, the ACF based implementation technique is performed in order to generate correlated small-scale fading complex components. Both the indoor M2M parallel and opposite walking LoS scenarios were considered (cf. Chapter 2). The small-scale fading ACFs given in equation (2.24) and (2.27) for parallel and opposite walking scenarios, respectively, were used as well as the measured Rice distribution parameters given in Table 4.1. At this point, in this simulation, we used the constant values of the Rice parameters deduced from measurement, for simple validation of the implementation method. However, this method can be employed considering a distance or mutual body orientation dependence, based on the measurement as it was performed in [124]. In this case, the non-stationary of the channel was incorporated by calculating

the ACF of each data sequence considered for a stationary distance and angle intervals.

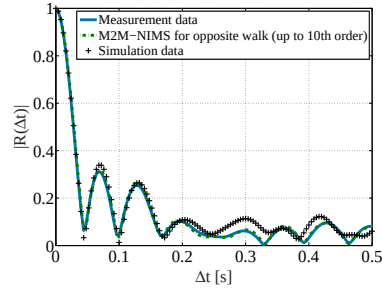
Figure 4.2 shows an excellent agreement between the measured ACF and the generated ACF for indoor parallel and opposite walking LoS scenarios. The coherence times obtained from the generated small-scale fading considering the indoor parallel and opposite walking LoS scenarios are 52 ms and 28 ms, respectively, which well represent the corresponding measured ones. The RMSE of ACFs was calculated up to 0.5 s and it is equal to 0.023 and 0.025 for parallel and opposite walking scenarios, respectively. A good match between the Rice parameters of the generated and measured data was found as shown in Table 4.1.

Table 4.1: First and second statistical orders' characteristics: measurements vs. data generated from ACF based implementation

Data	Type	Walking patterns	Standard deviation	Non centrality parameter	Coherence time [ms]	RMSE
large-scale fading	Measurement	-	1.95	-	1284	-
	Simulation	-	1.94	-	1248	0.015
small-scale fading	Measurement	Parallel	0.4	0.8	52	-
	Simulation	direction	0.4	0.8	52	0.023
	Measurement	Opposite	0.4	0.8	28	-
	Simulation	direction	0.4	0.8	28	0.025



(a) Parallel direction



(b) Opposite direction

Figure 4.2: ACF properties of the generated small-scale fading components from ACF based implementation

4.2 Doppler Spectrum Based Implementation

It was shown in Section 2.4.1, that the Doppler spectrum (or ACF) of the channel mainly depends on the one of small-scale fading. This

is intuitively evident since the small-scale fading is due to the rapid fluctuation of the received signal caused by the mobility of terminals and scatterers in the environment. Therefore, a channel implementation technique based on the Doppler model (2.34) is derived in order to generate small-scale fading that have the same Doppler properties of the channel transfer function. The generated data is then compared with the measurement data.

4.2.1 Implementation technique

In this section, a fading channel implementation based on the proposed Doppler model given in Section 2.5 is presented. The method is similar to Young and Baulieu technique proposed for mobile fading channel [160].

Figure 4.3 presents the block diagrams of the simulation method. Two identical independent Gaussian random variables $x(t)$ and $y(t)$ are used in order to generate the in- phase and quadrature components of the small-scale fading channel, each passing through the same filter, which has a transfer function equal to $\sqrt{|S(\nu)|}$. Then, the correlated data are transformed to the time domain using the Inverse Discrete Fourier Transform (IDFT). After that, the small-scale fading results from summing the correlated data, scaled by the measured standard deviation σ_F and shifted using the desired non-centrality parameter s_F .

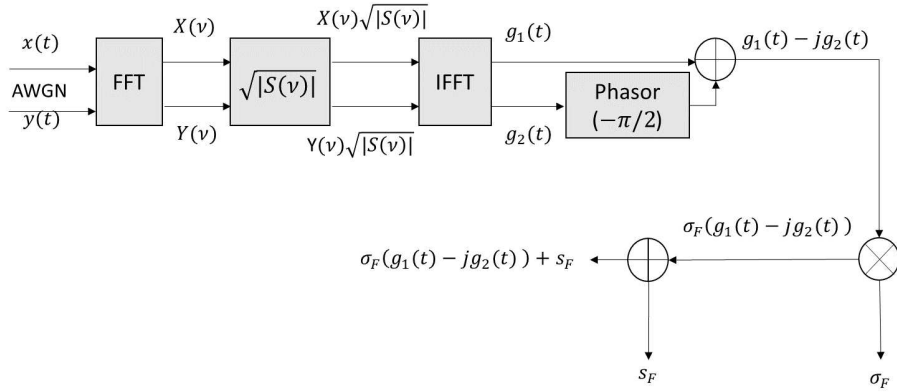


Figure 4.3: Block diagram to generate Rician correlated fading with Doppler filter

At this point, it is worth noting that taking the square root of the proposed Doppler spectrum model as the transfer function of the filter, one

can generate a small-scale fading that has the same Doppler spectrum of the channel. In what follows, this method was forwardly applied in order to generate small-scale fading that have the same measured Doppler properties given in parallel and opposite walking LoS scenarios for indoorM2M channels. Therefore, the measured Rice distribution in LoS and the proposed Doppler model (2.34) were considered.

4.2.2 Examples

Figure 4.4 and Table 4.2 show an excellent agreement of Rician distribution and Doppler spectrum between the measured small-scale fading obtained in opposite and parallel walking scenarios under the LoS condition and the data generated with the proposed method. Moreover, Figure 4.5 also shows a similarities between the ACFs of the generated and measured data for both scenarios. The RMSE of the ACFs was calculated up to 0.5s and it is equal to 0.066 and 0.067 for parallel and opposite walking LoS scenarios, respectively.

Table 4.2: First and second statistical orders' characteristics: measurements vs. data generated from Doppler spectrum based implementation

Walking patterns	Data types	σ_F	s_F	Doppler spread [Hz]	RMSE
Parallel direction	Measurement	0.4	0.8	4.133	-
	Simulation	0.4	0.78	4.48	0.06
Opposite direction	Measurement	0.4	0.8	6.66	-
	Simulation	0.4	0.75	6.29	0.067

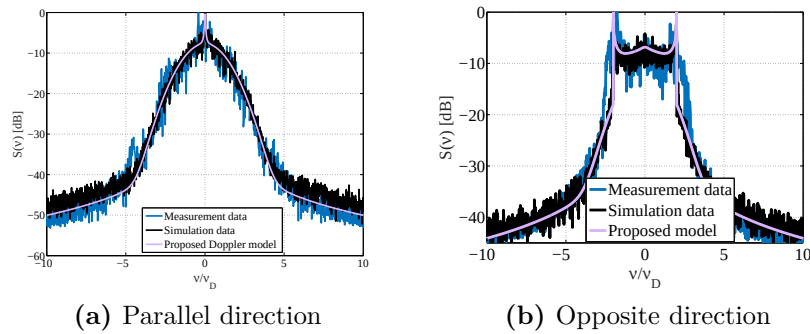


Figure 4.4: Doppler properties of the generated small-scale fading components from Doppler filter based implementation

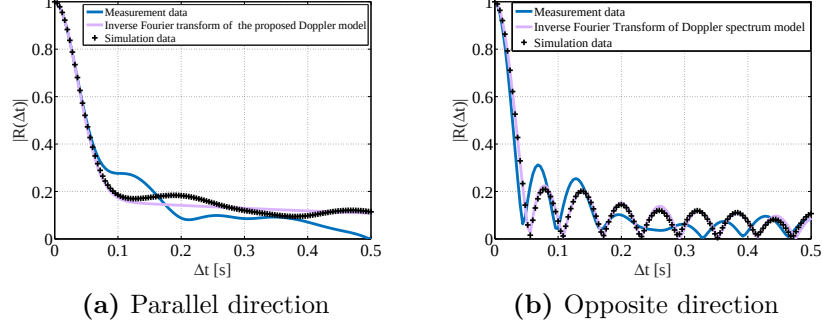


Figure 4.5: ACF properties of the generated small-scale fading components from Doppler filter based implementation

4.3 Auto-regressive Model

Classically, the AR process was used to model correlated fading channels [161]. In [162], it was proposed to model the time-varying On-Body channel transfer functions. In this section, AR models were derived to model the correlated small- and large-scale fading considering the head to head LoS scenarios (indoor M2M LoS scenarios).

4.3.1 Auto-regressive process: definition and parameter estimation

An AR process is a linear filter whose input is a white noise (complex white noise for complex values and real for real values) that has a zero mean and a variance equal to σ_ϵ^2 and its output is a stochastic process $Y(t)$ that has a zero mean and a variance equal to σ_Y^2 [163]. In other words, the AR process is an all-pole model and it is defined as follows [164]:

$$y^1(t) = - \sum_{k=1}^p z_k y^1(t-k) + \epsilon \quad (4.7)$$

where $y^1(t)$ is a realization of the stochastic process $Y(t)$, p is the order of the AR process, z_k , where $k = \{1, 2, \dots, p\}$, are the AR coefficients and ϵ is a white noise that has a zero mean and a variance equal to σ_ϵ^2 .

The corresponding Doppler power spectral density is calculated in the following way [164]:

$$S_Y(\nu) = \frac{\sigma_\epsilon^2 \Delta t}{|1 + \sum_{k=1}^p z_k \exp(-i2\pi\nu k \Delta t)|^2} \quad (4.8)$$

where Δt is the sampling rate and $1/2\Delta t \leq \nu \leq 1/2\Delta t$.

In order to calculate the AR parameters $(z_1, z_2 \dots z_p, \sigma_\epsilon^2)$, the Yule-Walker equations must be solved. These equations represent the relation between the AR parameters and the correlation coefficients ρ_i , in the following way [163, 164]:

$$\mathbf{R}_{yy} \cdot \mathbf{z} = -\boldsymbol{\rho} \quad (4.9)$$

And

$$\sigma_\epsilon^2 = \sigma_Y^2 \left(1 + \sum_{k=1}^p z_k \rho_{-k} \right) \quad (4.10)$$

where $\mathbf{R}_{yy} = \begin{pmatrix} 1 & \rho_1 & \dots & \rho_{p-1} \\ \rho_1 & 1 & \dots & \rho_{p-2} \\ \vdots & \vdots & \ddots & \vdots \\ \rho_{p-1} & \rho_{p-2} & \vdots & 1 \end{pmatrix}$ is the correlation matrix of Y , $\mathbf{z} = [z_1 \ z_2 \ \dots \ z_p]^T$ and $\boldsymbol{\rho} = [\rho_1 \ \rho_2 \ \dots \ \rho_p]^T$

In other words, knowing the order of the AR model p , one can calculate the AR parameters from $p+1$ equations using $p+1$ lags of the ACF. On the other hand, given the AR order and the AR parameters, one can calculate the correlation coefficients as follows [163, 164]:

$$\rho_k = C_1 b_1^k + C_2 b_2^k + \dots + C_p b_p^k = \sum_{i=1}^p C_i b_i^k \quad (4.11)$$

where C_i , for $i = 1, 2 \dots p$, are the constant values that are computed using the boundary conditions which are determined by $\rho_0, \rho_1 \dots \rho_{p-1}$ and b_i , are the roots of the following characteristic equation:

$$A(x) = 1 + z_1 x^{-1} + \dots + z_p x^{-p} \quad (4.12)$$

Owing that a computational effort is needed to compute the inverse of R_{yy} and to estimate the AR parameters, the properties of the correlation matrix, i.e. a positive definite Toeplitz symmetrical matrix, are used instead. In [164], some methods to solve the Yule-Walker equations are presented, such as Yule-Walker method, Least square method, Burg method, etc. In our case, the Burg's method was used.

Burg's method consists in the estimation of the reflection coefficients, i.e. measure of the correlation between two data points without taking the effects of the intermediate data points [163], from the sample data and then it uses the Levinson-Durbin algorithm [164, 165] to determine

the AR parameters. The reason of this choice derives from the fact that the Burg's method aims for the optimization of the white noise variance [165] and it can also guarantee that the roots of the characteristic equation, which are the poles of the transfer function of the AR model, to be in or on the unit circle. Therefore, the system is always stable with Burg's method.

The Akaike Information Criterion (AIC) is used to determine the AR order as follows:

$$AIC(p) = \ln(\sigma_\epsilon^2) + 2p/N \quad (4.13)$$

where N is the number of observations (data samples).

The order p is determined as the first local minimum of AIC. Note that the estimated polynomial of order p fits precisely to the data points that were used in the estimation process. Nevertheless, this estimated AR process could have a poor fit to the new data. Therefore, the question is to determine the best order of the AR process that can overcome the overfit and underfit issues.

Nowadays, there exists many criteria used to estimate the AR order and they are derived from several effects that can influence the estimation process such as the method of estimation, the number of observations etc. As mentioned in [164], it is difficult to find one reference criterion that takes into account all these effects. However, the asymptotic approximation method (AIC) gives an accurate selection of p if p is less than $N/10$ [164]. In addition, [166] recommended that the maximum model order should be less than $N/2$. At this point, it is worth noting that the AIC had a tendency for over fit, i.e. the model have too much parameters [167]. Therefore, another criterion is introduced as follows: "*if p is the order of the AR process, then the standard error of the estimated Partial Auto-Correlation Function (PAC) at lags $p + 1$ and higher must be less than $1/\sqrt{N}$* " [163]:

$$\hat{\sigma}[\hat{r}_k] = 1/\sqrt{N} \quad k \succ p \quad (4.14)$$

where $\hat{r}_k$ is the value of the PAC at lags k .

The PAC is calculated as the opposite of the reflection coefficient. It is composed from the last AR coefficient of order $k(z_k)$ where k goes from 1 to p . In fact, If a stochastic process is modeled by an AR process of order p , its PAC has then a cutoff at lags $p + 1$ and higher whereas its ACF at lags p tails off [163].

4.3.2 AR model: simulation

The methodology used to simulate the AR model can be summed up as follows:

1. The point intersection between the refraction coefficients amplitude in function of $k = 1, 2 \dots p_1$ where p_1 is given by the AIC and the standard error, i.e. $1/\sqrt{N}$ determines the optimal AR order p such as the PAC at lags $p + 1$ is less than $1/\sqrt{N}$.
2. Estimate the AR parameters using Burg's method [168].
3. Implement the AR filter function and generate multiple data samples.

4.3.3 AR Model: Application to Indoor M2M Channels

In this section, AR models based on the measurement data of head to head scenarios (cf. Chapter 2) are presented for the small- and large-scale fading.

4.3.3.1 Large-scale fading: AR model

Concatenating all the large-scale fading data samples given in LoS head to head scenarios, a significant discontinuity on the reassembling point, i.e. between the end of a realization and starting of the next realization, is appealed and it can induce a remarkable erroneous noise variance. Therefore, in order to limit the error due to concatenation, Chebyshev interpolation [169] is applied before finding the AR model parameters.

The AR order p determined via the AIC is 9. Figure 4.6 compares the PAC calculated up to order 40 with the standard error $\pm 1/\sqrt{N}$. As seen, the AR order 9 is a reasonable choice since the PACs at p biggest start to be within $\pm 1/\sqrt{N}$.

Using Burg's method, the AR parameters of order 9 were estimated (cf. Appendix E). The AR coefficients were implemented as filter coefficients and a data sequence that has a normal distribution with variance equal to the white noise variance was inserted as an input of the AR filter. The output of the AR filter is then a data sequence that has approximately the same first and second statistical orders of the measured large-scale fading.

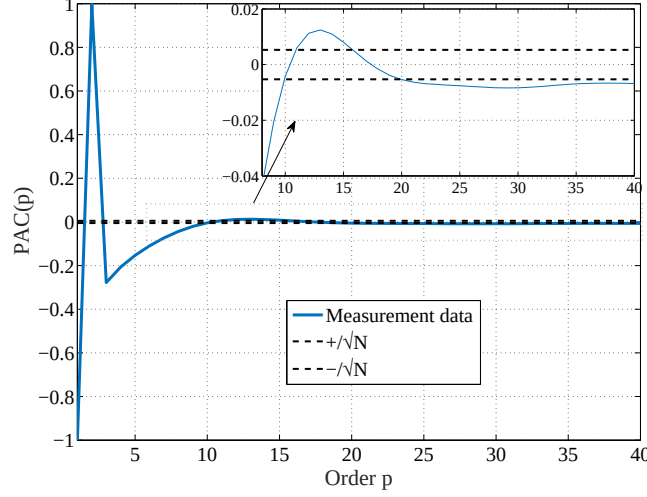


Figure 4.6: Partial autocorrelation function (PAC)

Figure 4.7 and Table 4.3 compare the large-scale fading properties measured in LoS to the data sequence generated using AR model. The RMSE was calculated up to the coherence time at 0.5. As seen, there is a good match between the normal distribution of the measured large-scale fading and the one given by the generated data. However, dissimilarities are noticed between the measured and generated ACF as well as the one given by the analytical equation (4.11). In fact, the AR model of order p can well depict the correlation properties up to $(p-1) \times \Delta t$ which is in our case equal to 32 ms. Nevertheless, the proposed AR model can well depict the ACFs up to 520 ms indicating that the AR order used may fit up to 130 samples. Therefore, in order to model the ACF up to the coherence time at 0.5, the AR order must be increased. As an example, we consider the AR order 322 which ensures the representation of the ACF up to the coherence time. Figure 4.8 shows that the ACF given by the large-scale fading AR process of order 322 matches the ACF of the measurement data up to the coherence time and more.

Consequently, the developed AR model has some limitations in modeling the second statistical order for large-scale fading depending on the AR order and how many parameters needed to model the ACF up to the coherence time.

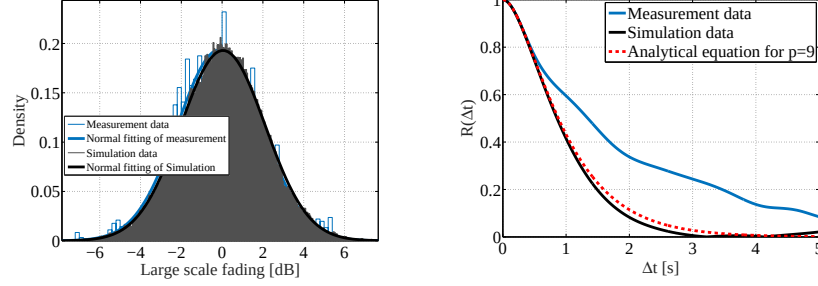


Figure 4.7: First and second statistical order properties of the large-scale fading: measurement vs. estimation using AR model

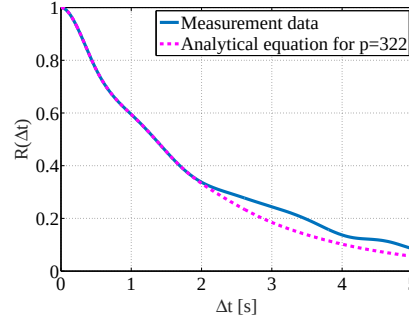


Figure 4.8: ACF of the large-scale fading: measurement data vs. AR process of order 322

4.3.3.2 Small-scale fading: AR model

Similarly, the AR model of the small-scale fading is presented in this section. The AR parameters were deduced from the experimental data taken from parallel and opposite walking realizations in head to head LoS scenarios. The AR order is determined using the two criteria presented previously (cf. Section 4.3.1) and it was found to be equal to 13 for both. Using Burg's method, the AR coefficients were estimated (cf. Appendix E). Then, a new data sequence is generated from the AR filter coefficients taking the complex white noise sequence as input.

Figure 4.9 and Table 4.3 show the Ricean distribution and the correlation properties of the measured and estimated fading envelope both for the parallel and opposite walking LoS scenarios. As seen, there is an excellent agreement between the Rice distribution and the ACFs of the estimated data and the measured data. The RMSE exhibits the degree

of similarities between the ACFs and it was calculated up to the 0.5 s. Therefore, the AR model can well model the first and second statistical orders of the measurement data regardless the measured scenarios. In fact, with an AR model of order 13, we can ensure to match the measured correlation properties up to 48 ms that is close or bigger than the measured coherence times (cf. Table 4.3). Nevertheless, looking into Figure 4.9, one can see that the proposed AR models can well represent the ACFs beyond 48 ms (around 100 ms and 120 ms). This can be simply explained by the fact that the AR order can well depict the measurement data beyond the data used to model the AR model. In fact, the small-scale fading decorrelates fast so a small AR order is expected. Therefore the considered AR order, i.e. 13, is considered as more than enough to represent the small-scale fading.

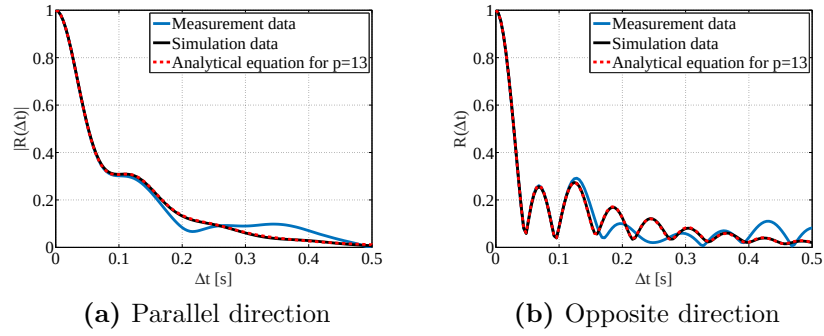


Figure 4.9: ACFs of the small-scale fading: measurement vs. simulation using AR model

Table 4.3: First and second statistical order properties of the large- and small-scale fadings: measurement vs. estimate using AR model

Data	Walking patterns	types	Standard deviation	Non centrality parameter	Coherence time [ms]	RMSE
large-scale fading	-	Measurement	1.95 dB	-	1284	-
	-	Simulation	1.95 dB	-	856	0.11
	-	Analytical formula for $p = 9$	-	-	877	0.11
small-scale fading	Parallel walking	Measurement	0.4	0.8	52	-
		Simulation	0.5	0.8	52	0.03
	LoS scenarios for $p = 13$	Analytical formula	-	-	52	0.03
	Opposite walking	Measurement	0.4	0.8	28	-
		Simulation	0.4	0.8	28	0.041
	LoS scenarios for $p = 13$	Analytical formula	-	-	28	0.03

4.4 Conclusion

In this chapter, channel model implementation techniques that preserve the correlation or Doppler properties were presented. The proposed time correlation function model and Doppler spectrum model described in Chapter 2 were used to generate large- and small-scale fading that have the same first and second statistical orders of the measured one. A good agreement between the measurement and the generated data was found.

The AR process was also proposed in order to model the correlated large- and small-scale fading. It was found that the AR model can well estimate the first statistical order for both the small- and large-scale fading. Due to the fast decorrelation of the small-scale fading, a small AR order is needed while a large order is requested to model the large correlation of the large-scale fading which increases the computational time and the complexity of the system. Nevertheless, in our case, the large-scale fading ACFs can be well represented by an exponential decay law or Gaussian model (cf. Chapter 2 and Chapter 3). Hence, the proposed ACF based implementation can be used instead.

In [124], both the ACF based implementation and the AR model were employed to model the correlated large- and small-scale fading of the measured B2B channels and a comparison between the measurement and the simulation data considering a combination of PL, correlated large- and small-scale fading was presented.

Note that these proposed implementation techniques are used to generate correlated Gaussian variables. If the ACF or the Doppler spectrum model is known and the variable can be assumed as a Gaussian random variable, one can simply use one of the three proposed implementation techniques in order to simulate the measurement data. At this point, it is worth noting that the ACF and Doppler based implementations are preferable since it preserves the physical interpretation of the desired generated phenomenon (variable).

Conclusions & Perspectives

The wireless propagation channel in general is a complicated process that can significantly impact the performance of the system, e.g. coverage, reliability and capability. To understand and to characterize the channel behavior with the help of measurements, several parameters need to be investigated. These channel properties are then reproduced via channel models aimed for network simulation and system testing. Such a measurement based characterization and modeling for time-varying Mobile to Mobile (M2M) channels was the topic of this thesis. In particular, we performed Body to Body (B2B) and Vehicle to Pedestrian (V2P) channel measurements for modeling purposes.

Chapter 1 presents an overview of State-Of-The-Art (SOTA) for Vehicle to Vehicle (V2V) and B2B channel measurement and modeling. The characteristics of these channels depend on several factors like the conducted scenario, environment, antenna radiation pattern and position etc. Due to the dynamic mobility of terminals, the environment changes rapidly giving rise to non-stationary channel. Therefore, M2M channel models that can include this aspect are needed. However, different V2V channel models considering or not the channel non-stationarity were developed while only the stochastic approach was adopted for B2B channels.

In order to fill the gap in B2B channel characterization and modeling, a narrow-band time-varying B2B channel model was proposed based on measurements in Chapter 2. The measurements were performed at 2.48 GHz for different antenna on-body positions, i.e. belt, wrist and head. Multiple mobility patterns were measured and various indoor locations, i.e. single and two rooms, were considered in order to take into account the Line of Sight (LoS) and Non Line of Sight (NLoS) scenarios.

The outcome of the measurement was the channel transfer function. A statistical approach was proposed and it consists of decomposing the

measurement results into three major components: Path Loss (PL), large- and small-scale fading. The PL was modeled with a log distance model, the large-scale fading distribution was fitted with a normal distribution with zero mean while a Rice distribution was found for the small-scale fading. For a given antenna on-body position and environment under consideration, the model parameters were given. While head position suffers from limited influence by the body, the belt position is strongly affected by body shadowing and finally wrist position is both affected by the arm movement and the orientation of the body. Therefore, the model parameters were investigated as a function of the relative distance between terminals for the antenna on head position and in function of the mutual body orientations for belt and wrist scenarios.

In order to reproduce the temporal variation of the B2B channels, the fading distributions and the PL model are not enough, the second order statistics of the channel, i.e Auto-Correlation Function (ACF) and Doppler spectrum, must be modeled. Therefore, ACFs of the channel transfer function, the large-scale and small-scale fading were presented for the head to head scenarios considering different mobility patterns under the LoS and NLoS conditions. The head to head scenarios were considered because its fading characteristics were the least impacted by the body shadowing, so we can extend our evaluations from B2B specifically towards a more general M2M scenarios. For a given propagation environment and similar mobility patterns, the ACF was calculated. This was done in order to be in a Wide Sense Stationary (WSS) condition. In other words, if the studied channel turns out to be non-stationary, it will be due to the terminals' movement and not because of the variation of the environment condition or the Transmitter (Tx)/Receiver (Rx) motion direction. Regardless the scenario under study, similarities in terms of coherence time and shape, were observed between the ACF of the transfer function and the small-scale fading implying that the ACF of the B2B channels mainly depends on the one of small-scale fading. Moreover, the dependance of the channel transfer function ACF on the type of mobility and the environment condition was detected.

Considering a general scattering environment, we derive a general ACF model of M2M scenarios where some scatterers surrounding the terminals are in motion. This model is an extension of [21] and a generalization of some classical channel models, e.g. Fixed to Mobile (F2M), Fixed to Fixed (F2F) and M2M channels. The goal is to successfully depict the correlation properties measured in M2M scenarios. Therefore, this model was used to describe the ACF up to lags 0.5 and 0.1 s for indoor M2M scenarios (cf. Chapter 2) and V2P scenarios (cf. Chap-

ter 3), respectively. A good match between the measurements and the model were found. A close form for the Doppler spectrum as the Fourier Transform (FT) of the derived ACF model is uneasy to express. Nevertheless, considering a specific type of scenario, a close expression can be derived. This was done for indoor M2M scenarios considering the parallel and opposite directions.

The Doppler spectra of the indoor M2M channel transfer function were also characterized for different mobility patterns and different environment conditions. Similarly, the Doppler spectrum was estimated considering a given mobility pattern and propagation condition. The same conclusion drawn above for the ACF were also given here: Doppler spectrum depends on the mobility patterns and the environment under consideration. An analytical Doppler spectrum model was then proposed and it allows to reproduce with good accuracy the Doppler properties of different indoor M2M scenarios including LoS and NLoS environments. The proposed model is simple, only three parameters need to be estimated from the measurement data. Due to the physical interpretation behind it, it can account other different indoor M2M scenarios, e.g. the cross walking scenarios.

To conclude the indoor M2M channel analysis, the non-stationarity channel behavior was verified based on some approaches proposed in the literature [19,20] considering a given mobility pattern. The Hypothesis test was used to study the temporal (distance) variation of the Rice parameters. Due to the time invariant distance between terminals in parallel walking scenario, the Rice parameters were static. In the case of opposite walking LoS scenario where the relative distance undergoes a dynamic change in time, the hypothesis test reveals the variation of the fading parameters with time (distance). This is similar to the result found when a distance sliding windows were performed on the measured small-scale fading to model the Rice parameters as a function of distance. Moreover, no evident dependence of the Rice parameters in function of the Tx-Rx distance for the opposite walking NLoS scenario. The time-varying Doppler spectra were also investigated using collinearity metrics. The method is based on splitting the measurement in small regions where the WSS properties hold. As expected, the smallest stationarity length was found for opposite walking LoS scenarios and it was around 3 s. At this point, it is important to note that this result asserts the relevance of modeling the indoor M2M ACF at lags 0.5 s with a WSS ACF model since the ACF is at least stationary up to lags 3 s that is quite larger than the coherence time or 0.5 s.

Another type of M2M channel that was poorly addressed in the literature is the V2P channels. Road safety has received significant attention in the recent years. While the V2V and Vehicle to Infrastructure (V2I) propagation was largely addressed in the literature, only one contribution was devoted for V2P channels. Chapter 3 details wide-band V2P measurements based channel characterizations and modeling. The measurements were performed at 3.8 GHz with a bandwidth of 200 MHz. At this point, it is worth mentioning that the frequency ranges around 3.5 GHz will be considered for 5G mobile networks worldwide. Different mobility patterns were investigated and three propagation environments were considered: LoS, obstructed LoS by neighboring vehicles where the pedestrian was walking behind parked vehicle and the NLoS/LoS where the V2P link passes through three stages, i.e. the direct path blocked by wall separating terminals, a transition from NLoS to LoS and the LoS situation. While the obstructed LoS scenarios can degrade the received signal power, the NLoS/LoS scenarios occur mostly in the safety critical scenarios such as crossing street intersections.

Consequently and for the first time, a Geometry based Stochastic Channel Model (GSCM) similar to the one proposed for V2V channels [22] was proposed to model the Time Varying Channel Impulse Response (TVCIR) of the V2P channels. Its peculiarity rely on modeling the non-stationary aspect of the channel implicitly. The model consists of first path and secondary Multi-path Components (MPCs). In order to track the time evolution of the first path and the secondary MPCs, a detection procedure and a tracking algorithm were implemented. They were fitted with a combination of PL, large-scale fading and small-scale fading. For a given environment (LoS, NLoS and NLoS/LoS), the channel parameters were characterized. Similar to B2B channels, the small-scale fading distribution was described with a Rice distribution while the large-scale fading distribution in dB was a normal distribution with zero mean. Depending on the measurement scenario, a PL model for the first path was proposed while a log distance model was used for the PL extracted from the MPCs. Therefore, a two rays model was proposed for the LoS scenarios and a log distance model for the NLoS scenarios. In the NLoS/LoS scenarios, a model based on three equations was proposed in order to present the LoS, NLoS and the transition region from NLoS to LoS. At this point, it is worth noting that the MPCs parameters are similar which is relevant because the measurement were carried out in the same place so similar scatterer contributions were expected. Moreover, the Rice parameters of the first path has shown distance variant in the NLoS/LoS scenarios probably due to the change in the environment

conditions (passage from NLoS to LoS) which can impact significantly the coherent power. Nevertheless, no evident distance variant was observed for these scenarios in the Rice parameters of the MPCs which can be explained by the fact that the scatterers presented in the environment give a share in characterizing the Rice parameter of MPCs.

Note that these two models, i.e. stochastic B2B channel model and V2P GSCM, can be used for PHY layer implementation and development of MAC and Network layer protocol for M2M communications.

In order to successfully implement the proposed models of B2B and V2P channels based on the scenario and the propagation condition with fading characteristics including the Doppler characteristics, two implementation techniques, i.e. ACF based implementation and Doppler filter implementation, were proposed in Chapter 4. A good match between the generated and the measured data, in terms of distribution and correlation (Doppler) properties, were given both for the small-scale fading and large-scale fading. Moreover, an Auto-regressive (AR) model was described showing its capability to model the B2B correlated fading channels. At this point it is worth noting that these proposed implementation techniques were used to generate correlated Gaussian variables. Therefore, if the ACF or the Doppler spectrum model is known and the variable can be assumed as a Gaussian random variable, one can simply use one of the three proposed implementation techniques in order to simulate the measurement data.

Outlook

The main contributions of this thesis are the M2M channel characterization and modeling in general and the V2P and B2B channel characterization and modeling, in particular. In this section, I would like to highlight on some future works that we intend to perform on the measurement in order to gain deeper understanding for the channel behavior and open new horizons in this field.

Concerning the B2B channels: the ACFs and Doppler spectra are characterized and modeled for different mobility patterns and environment conditions considering the indoor head to head scenarios considered as indoor M2M scenarios. Moreover, the non-stationarity of the small-scale fading was assessed for these types of scenarios. So, in the future, we are intending to use or extend the proposed ACF and Doppler spectrum model to model the ACF of the other B2B scenarios, i.e. belt to belt and wrist to wrist, on one hand and looking into the non-stationarity of these channels in terms of Doppler spectrum in function

of the mutual body orientation on the other hand. Note that the ACFs of belt to belt and wrist to wrist channels were characterized in [170] while the AR model and the ACF implementation technique were used to generate correlated large- and small-scale fading similar to the ones measured in belt to belt and wrist to wrist scenarios [124].

Concerning the V2P channels: a first wide-band channel model for the V2P channels was given here which is GSCM that consists of first path component and secondary MPCs. Each scatterer contribution was described as a combination of PL, large-scale fading and small-scale fading. The model parameters were given for each environment under investigation. Indeed the model represents the delay variation of the channel, however some study on the delay spread will be considered in the future work. In a following step, we plan to successfully implement the model based on the scenario and the propagation condition with fading characteristics including the Doppler and correlation characteristics and compare it to the measurement data. Therefore, some future works on characterizing and modeling the ACF and Doppler spectrum of the first path component and the secondary MPCs is essential so then each path can be generated based on the previously proposed implementation techniques. Probably, we can also use the AR process to model the time-varying MPCs for simplicity. If we consider the first path component as a summation of unresolvable path components, then its ACF can be modeled with the general developed ACF of M2M scenarios in the presence of moving scatterers. The ACF of opposite walking LoS V2P scenarios was characterized and modeled. Further study into the characterization and modeling of the ACF and Doppler spectra considering other V2P scenarios is favorable. Given that the V2P channels are non-stationary channel, some stationary test will be performed in order to parametrize the stationarity region. At this point it is worth reminding that more V2P measurements are needed in the near future considering different propagation environments, e.g. crowded city, or other safety critical scenarios such as crossing streets, or different frequencies or even performing some Multiple Input Multiple Output (MIMO) measurements.

Finally, we would like to point out that a wide-band Pedestrian to Pedestrian (P2P) channel measurement campaign was carried out and it is described in Appendix D. Therefore, the characterization and modeling of P2P channels is also planned and projected (noted) in our agenda.

List of Publications

Journal Papers

F. Mani, G. Makhoul, C. Oestges and R. D'Errico, "On the Generation of Correlated Short- and Long-Term Fading for Multiple BANs," in *IEEE Antennas and Wireless Propagation Letters*, vol. 16, pp. 1867-1870, 2017.

G. Makhoul, F. Mani, R. D'Errico and C. Oestges, "On the Modeling of Time Correlation Functions for Mobile-to-Mobile Fading Channels in Indoor Environments," in *IEEE Antennas and Wireless Propagation Letters*, vol. 16, pp. 549-552, 2017.

Conference Papers

G. Makhoul, F. Mani, R. D'Errico and C. Oestges, "Time correlation properties of dynamic mobile to mobile channels in indoor environments," 2016 *10th European Conference on Antennas and Propagation (EuCAP)*, Davos, 2016, pp. 1-5.

G. Makhoul, F. Mani, R. D'Errico and C. Oestges, "Doppler characteristics for indoor mobile-to-mobile channels," 2017 *11th European Conference on Antennas and Propagation (EuCAP)*, Paris, 2017, pp. 2468-2472.

G. Makhoul, F. Mani, R. D'Errico and C. Oestges, "Analyse et modélisation de la corrélation temporelle dans le canal mobile-à-mobile intra-bâtiment," 2017 *20ème Journées Nationales Microondes (JNM)*, Saint Malo

COST TDs

F. Mani, G. Makhoul, L. Minnighini and R. D'Errico, "Towards a Spatially Aware Stochastic Channel Model for Body to Body Communications in Indoor Environment", *European Cooperation in the Field of Scientific and Technical Research (EURO-COST)*, IC1004 TD(15)13007, 2015.

G. Makhoul, F. Mani, R. D'Errico and C. Oestges, "Time Correlation in Mobile to Mobile Indoor Channels," *European Cooperation in the Field of Scientific and Technical Research (EURO-COST)*, IC1004 TD(15)13007, June, 2016.

Appendix A

Measurement Equipment

Contents

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A.1 Impact of On-Body Antenna

Placing an antenna on the body may significantly affect its performance [5, 108]. Therefore, the reflection coefficient of the antenna, S11 parameter, was measured with a one-port setting VNA between 2 GHz and 3 GHz both for isolated antenna and when it was attached on the body. Figure A.1 shows the results for both the vertically and horizontally oriented cases. A shift in the resonance frequency was obtained for belt and wrist positions whereas no significant change is observed for the head position. Nevertheless, for all the cases, the S11 parameter at the measurement frequency is below -10 dB showing a good antenna matching. Moreover, the antenna radiation can be also influenced by the presence of the human body. Figure A.2 presents a comparison of the antenna gain pattern for theta polarization on the azimuthal plan when it is isolated and when it is placed in belt position on a torso standard CTIA phantom. These measurements were performed in an anechoic chamber. It results an increased gain in the forward direction and a 30 dB shadowing in the backward direction.

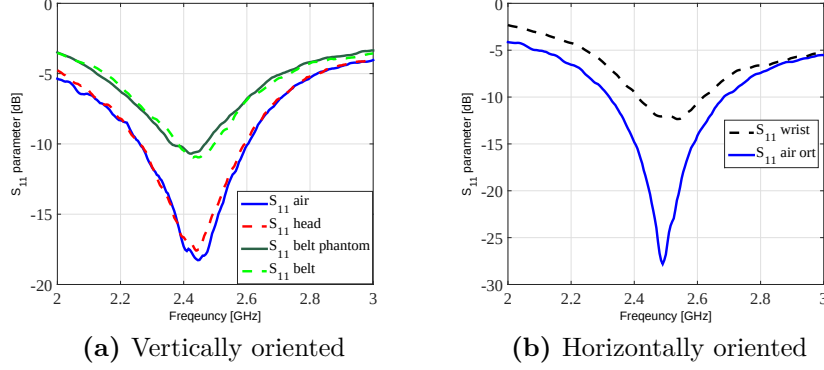


Figure A.1: Comparison of S_{11} parameters for isolated and on-body monopole antenna [7]

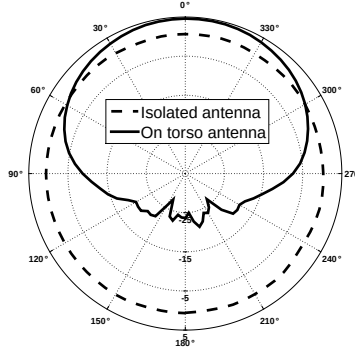


Figure A.2: Measured gain patten [dBi] in the isolated and on-torso cases [7]

A.2 Channel Sounder

UCL-ULB channel sounder is a channel sounder that records the time-varying channel impulse response (TVCIIR). It mainly consists of two units, a transmitter (Tx) unit and a receiver (Rx) unit, as shown in Figure A.3. The Rx unit is further connected to the Data Acquisition (DAQ) module. A remote user control which is the Real Time Control Software (RTCS), is used in order to change setting at the Tx or Rx unit. It is accessed through a control notebook connected to each unit with a Local Area Network (LAN) cable. The Tx and Rx units are synchronized via Rubidium clocks. In fact, a small frequency offset can lead to phase rotation (Doppler) and sliding in the delay domain. The

sounder can be synchronized in the following two steps:

1. The clock synchronization, where the relative phase rotation is minimized by tuning the Rubidium clocks
2. The time tag synchronization, where a common absolute time reference is allocated to both units.

A calibration measurement before the data acquisition is essential in order to compensate the system and cable losses. Actually, it was measured with an attenuator of -50 dB which was back-to-back connected to both units through RF cables. After successful synchronization and calibration measurement, two units can be moved to the measurement site. Inputs parameters or sounder settings can be adjusted with the help of "Setup Wizard" in the controlling notebook. The input parameters to be defined before measurements are: center frequency, bandwidth, transmit power, number of samples per chip, code length, channel sampling rate and number of Tx and Rx antennas. Table 3.1 presents an overview of the measurement configuration parameters.

The center frequency f_c was 3.8 GHz and the measurement bandwidth B was set to 200 MHz. The choice of frequency and bandwidth was limited by the efficient range of the channel sounder. The transmit power was 23 dBm. The number of samples per chip N_{sc} also called the chip rate was 2; it controls the delay resolution of the IR such that higher chip rate achieves better delay resolution $\Delta\tau$

$$\Delta\tau = \frac{1}{B/2 \times N_{sc}} \quad (\text{A.1})$$

The code length is constituted of several chips and it must be longer than the maximum measurable excess delay of the channel but shorter than the coherence time. Moreover, Long codes provide processing gain and improve the dynamic range. Therefore, in our measurement, the code length N_{ch} was set to 4094 giving a maximum measurable excess delay τ_{excess} of 20.47 μs (which corresponds to a maximum measurable path distance 6.141km) calculated in the following way:

$$\tau_{excess} = \frac{N_{ch} \times N_{sc}}{B/2} \quad (\text{A.2})$$

Finally, the channel sampling rate ν_{cs} is sampled according to Nyquist criterion, as follows:

$$\nu_{cs} = \frac{v_m + 2v_s}{\lambda} N_\lambda \quad (\text{A.3})$$

where v_m is the maximum speed of the mobile terminal, v_s is the maximum speed of the scatterers and N_λ is the number of wished channels per wavelength. To achieve a high Doppler resolution, a channel sampling rate of 1062 Hz is considered.

To ensure the channel sounding of non-WSSUS channels, the channel must be under-spread, i.e. the two-dimensional Nyquist criterion is fulfilled [28].

$$2\nu_{max}\tau_{max} \leq 1 \quad (\text{A.4})$$

where ν_{max} and τ_{max} are the maximum Doppler frequency and the maximum excess delay of the channel, respectively. In our measurements, the maximum delay and Doppler shift of the signal contributions are $20.47\mu\text{s}$ and 531 Hz, respectively. These channel parameters fulfill the two-dimensional Nyquist criterion (A.4). After the sounding signal (PN sequence) is designed in the delay domain, it is modulated, up-converted to the desired center frequency and periodically transmitted via the Tx unit. At the receiver side, the signal is Band Pass (BP)-filtered, down-converted and demodulated into I/Q format. Consequently, the output of the channel sounder is the discrete time-variant impulse response

$$h(m, u) = h(m\Delta t, u\Delta\tau) \quad (\text{A.5})$$

where m is the time index and u is the delay index.

Moreover, the channel sounder stored the location of Tx by Global Positioning System (GPS) together with the measured data stream (time-tagged), when GPS coverage is available.

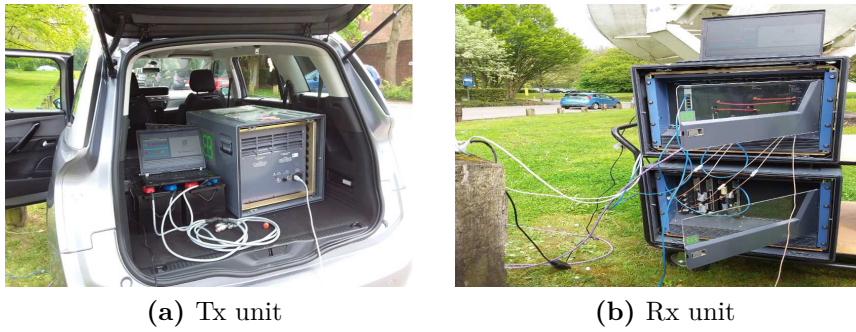


Figure A.3: Channel sounder equipment

A.3 Dipole Antennas

Node antennas are employed at Tx and Rx terminals. Figure A.4 shows the node antenna which is a highly efficient dipole antenna with an almost isotropic radiation pattern. The antenna gain is 1.75 dBi. These antennas use an optimized quarter wave current trap principle and they are protected from shock by a Rohacell jacketing. Moreover, they are equipped with SMA female connectors and have an input impedance of 50Ω . They can operate efficiently within a bandwidth of 3.7 GHz to 3.9 GHz and have a maximum radiation efficiency at 3.8 GHz as shown in figure A.5.

The Tx antenna was mounted on the roof of a car while the Rx antenna was placed on a cardboard tube carried by a human subject (cf. Figure 3.2). The total length of the cardboard tube is 100 cm and the distance between the antenna and the human subject was around 50 cm.

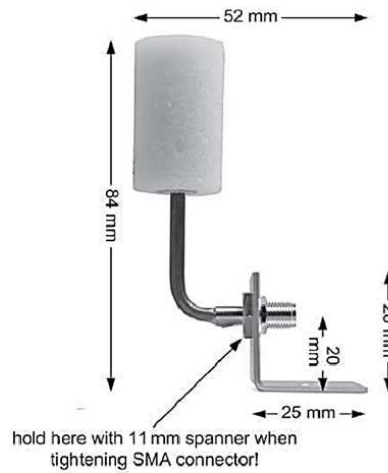


Figure A.4: Node antenna

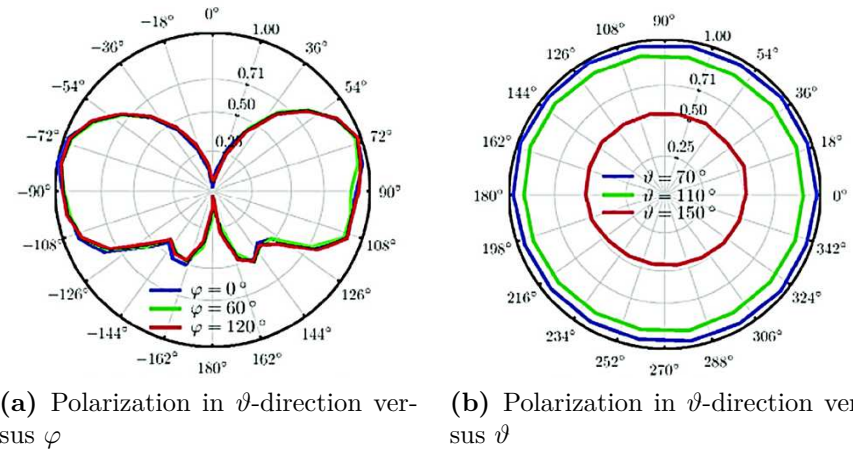


Figure A.5: Radiation pattern of the node antenna at 3.8 GHz

Appendix B

Doppler Spectrum Model Developement

The Doppler Spectrum is estimated by applying the FT on the ACF (2.24), hence:

$$S(\nu) = \int_{-\infty}^{+\infty} R(\Delta t) e^{-i2\pi\nu\Delta t} d\Delta t$$

$$\begin{aligned} S(\nu) = & a \sum_{n=-\infty}^{+\infty} \sum_{m=-\infty}^{+\infty} (-1)^{(n+m)} \gamma_{nm} \int_{-\infty}^{+\infty} J_n(4\pi\nu_D\Delta t) J_m(4\pi\nu_D\Delta t) e^{-i2\pi\nu\Delta t} d\Delta t \\ & + (1-a) \sum_{n=-\infty}^{+\infty} \sum_{m=-\infty}^{+\infty} (-1)^{(n+m)} \gamma_{nm} \int_{-\infty}^{+\infty} J_n(2\pi\nu_D\Delta t) J_m(2\pi\nu_D\Delta t) e^{-i2\pi\nu\Delta t} d\Delta t \end{aligned} \quad (\text{B.1})$$

Using the following properties:

$$J_n(x) = \frac{1}{2\pi} \int_{-\pi}^{+\pi} e^{i(n\tau - x \sin \tau)} d\tau \quad (\text{B.2})$$

$$\int_{-\infty}^{+\infty} e^{-i2\pi(\epsilon_2 - \epsilon_1)t} dt = \delta(\epsilon_2 - \epsilon_1) \quad (\text{B.3})$$

$$\delta(x - a) = \sum_{k=-\infty}^{+\infty} e^{ik(x-a)} \quad (\text{B.4})$$

, the (B.1) becomes:

$$\begin{aligned}
S(\nu) = & a \sum_{n=-\infty}^{+\infty} \sum_{m=-\infty}^{+\infty} (-1)^{(n+m)} \gamma_{nm} \int_{-\infty}^{+\infty} \frac{1}{2\pi} \int_{-\pi}^{+\pi} e^{i(n\tau_1 - 4\pi\nu_D \Delta t \sin \tau_1)} d\tau_1 \\
& \frac{1}{2\pi} \int_{-\pi}^{+\pi} e^{i(m\tau_2 - 4\pi\nu_D \Delta t \sin \tau_2)} d\tau_2 e^{-i2\pi\nu \Delta t} d\Delta t \\
+ (1-a) & \sum_{n=-\infty}^{+\infty} \sum_{m=-\infty}^{+\infty} (-1)^{(n+m)} \gamma_{nm} \int_{-\infty}^{+\infty} \frac{1}{2\pi} \int_{-\pi}^{+\pi} e^{i(n\tau_1 - 2\pi\nu_D \Delta t \sin \tau_1)} d\tau_1 \\
& \frac{1}{2\pi} \int_{-\pi}^{+\pi} e^{i(m\tau_2 - 2\pi\nu_D \Delta t \sin \tau_2)} d\tau_2 e^{-i2\pi\nu \Delta t} d\Delta t \quad (\text{B.5})
\end{aligned}$$

$$\begin{aligned}
S(\nu) = & a \sum_{n=-\infty}^{+\infty} \sum_{m=-\infty}^{+\infty} (-1)^{(n+m)} \gamma_{nm} \int_{-\infty}^{+\infty} e^{-i2\pi(\nu + 2\nu_D \sin \tau_1 + 2\nu_D \sin \tau_2) \Delta t} d\Delta t \\
& \frac{1}{2\pi} \int_{-\pi}^{+\pi} e^{in\tau_1} d\tau_1 \frac{1}{2\pi} \int_{-\pi}^{+\pi} e^{im\tau_2} d\tau_2 \\
+ (1-a) & \sum_{n=-\infty}^{+\infty} \sum_{m=-\infty}^{+\infty} (-1)^{(n+m)} \gamma_{nm} \int_{-\infty}^{+\infty} e^{-i2\pi(\nu + \nu_D \sin \tau_1 + \nu_D \sin \tau_2) \Delta t} d\Delta t \\
& \frac{1}{2\pi} \int_{-\pi}^{+\pi} e^{in\tau_1} d\tau_1 \frac{1}{2\pi} \int_{-\pi}^{+\pi} e^{im\tau_2} d\tau_2 \quad (\text{B.6})
\end{aligned}$$

$$\begin{aligned}
S(\nu) = & a \sum_{n=-\infty}^{+\infty} \sum_{m=-\infty}^{+\infty} (-1)^{(n+m)} \gamma_{nm} \frac{1}{2\pi} \int_{-\pi}^{+\pi} \delta(\nu + 2\nu_D \sin \tau_1 + 2\nu_D \sin \tau_2) e^{in\tau_1} d\tau_1 \\
& \frac{1}{2\pi} \int_{-\pi}^{+\pi} e^{im\tau_2} d\tau_2 \\
+ (1-a) & \sum_{n=-\infty}^{+\infty} \sum_{m=-\infty}^{+\infty} (-1)^{(n+m)} \gamma_{nm} \frac{1}{2\pi} \int_{-\pi}^{+\pi} \delta(\nu + \nu_D \sin \tau_1 - \nu_D \sin \tau_2) e^{in\tau_1} d\tau_1 \\
& \frac{1}{2\pi} \int_{-\pi}^{+\pi} e^{im\tau_2} d\tau_2 \quad (\text{B.7})
\end{aligned}$$

$$\begin{aligned}
S(\nu) = & a \sum_{n=-\infty}^{+\infty} \sum_{m=-\infty}^{+\infty} (-1)^{(n+m)} \gamma_{nm} \frac{1}{2\pi} \int_{-\pi}^{+\pi} \sum_{k=-\infty}^{+\infty} e^{ik(\nu + 2\nu_D \sin \tau_1 + 2\nu_D \sin \tau_2)} e^{in\tau_1} d\tau_1 \\
& \frac{1}{2\pi} \int_{-\pi}^{+\pi} e^{im\tau_2} d\tau_2 \\
+ (1-a) & \sum_{n=-\infty}^{+\infty} \sum_{m=-\infty}^{+\infty} (-1)^{(n+m)} \gamma_{nm} \frac{1}{2\pi} \int_{-\pi}^{+\pi} \sum_{k=-\infty}^{+\infty} e^{ik(\nu + \nu_D \sin \tau_1 + \nu_D \sin \tau_2)} e^{in\tau_1} d\tau_1 \\
& \frac{1}{2\pi} \int_{-\pi}^{+\pi} e^{im\tau_2} d\tau_2 \quad (\text{B.8})
\end{aligned}$$

$$\begin{aligned}
S(\nu) = & a \sum_{n=-\infty}^{+\infty} \sum_{m=-\infty}^{+\infty} (-1)^{(n+m)} \gamma_{nm} \frac{1}{2\pi} \int_{-\pi}^{+\pi} \sum_{k=-\infty}^{+\infty} e^{ik\nu} e^{i(n\tau_1 + 2k\nu_D \sin \tau_1)} d\tau_1 \\
& \frac{1}{2\pi} \int_{-\pi}^{+\pi} e^{i(m\tau_2 + 2k\nu_D \sin \tau_2)} d\tau_2 \\
+ (1-a) & \sum_{n=-\infty}^{+\infty} \sum_{m=-\infty}^{+\infty} (-1)^{(n+m)} \gamma_{nm} \sum_{k=-\infty}^{+\infty} e^{ik\nu} \frac{1}{2\pi} \int_{-\pi}^{+\pi} e^{i(n\tau_1 + k\nu_D \sin \tau_1)} d\tau_1 \\
& \frac{1}{2\pi} \int_{-\pi}^{+\pi} e^{i(m\tau_2 + k\nu_D \sin \tau_2)} d\tau_2 \quad (\text{B.9})
\end{aligned}$$

Finally, the Doppler spectrum is expressed as:

$$\begin{aligned}
S(\nu) = & a \sum_{n=-\infty}^{+\infty} \sum_{m=-\infty}^{+\infty} \sum_{k=-\infty}^{+\infty} \gamma_{nm} e^{ik\nu} J_n(2k\nu_D) J_m(2k\nu_D) \\
& + (1-a) \sum_{n=-\infty}^{+\infty} \sum_{m=-\infty}^{+\infty} \sum_{k=-\infty}^{+\infty} \gamma_{nm} e^{ik\nu} J_n(k\nu_D) J_m(k\nu_D) \quad (\text{B.10})
\end{aligned}$$

Appendix C

Non Stationarity Test

Contents

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C.1 Hypothesis Test: Definitions

A statistical hypothesis testing is a method which enables one to accept or reject an assertion about the probability function of random variable based on the measured data. The assertion under test is called the null hypothesis, H_0 . If the null hypothesis is rejected, then an alternative hypothesis, H_1 is accepted. The null hypothesis is usually based on the assumptions of equality, symmetries or independence, which one wants to prove by the experimental results. The alternative hypothesis is based on the assumptions of differences, asymmetries or dependence, which one will accept if the null hypothesis is rejected [171]. Classically, the easier assumption to deal with is given for the null hypothesis rather than the alternative hypothesis.

The decision of a test is based on the observed value of a test statistic that is a function of the measured data. Two types of regions are defined: the critical region and the acceptance region. The critical region or the rejection region is the subset of values assumed by the test statistic which, in accordance with the test, leads to the rejection of H_0 . In the

contrary case, the acceptance region is the subset values assumed by the test statistic leads to accept H_0 . The choice of the rejection region (or acceptance region) should be indicated before conducting the test.

Performing a test can lead to the correct decision or to a one of the two errors described as follows:

- Type I error: Rejecting H_0 when H_0 is true
- Type II error: Accepting H_0 when H_0 is false

Considering R_1 and R_2 are the rejection and acceptance regions, respectively, and the test statistic is denoted by T , thus the first and second type errors, a and b , respectively, can be expressed as follows

$$\begin{aligned} a &= P(T \in R_1 | H_0 \text{ is true}) \\ b &= P(T \notin R_1 | H_1 \text{ is true}) \end{aligned} \quad (\text{C.1})$$

a is often called the size of the test or the significance level [148]. It refers to a criterion of judgment upon which a decision is made regarding the value stated in a null hypothesis. In other words, if the P value calculated for the statistic test based on the measurement data is less (bigger) than a , then H_0 is rejected (accepted). P value is also called a probability value or the associated probability or the significance probability and it is defined as the probability of obtaining a sample outcome, given that the value stated in the null hypothesis is true.

The two sided statistic test was considered here and it is defined as follows:

$$H_0 \text{ is accepted iff } P \geq a/2 \text{ or } P \leq -a/2$$

The power of the test is the probability of correctly rejecting H_0 . It is calculated as follows:

$$P(H_1 \text{ is true} | H_1 \text{ is true}) = 1 - b \quad (\text{C.2})$$

Moreover, the power of test depends on the following four factors [148]

1. The degree of falness of H_0 , i.e. the amount of discrepancy between the assertions stated in H_0 and H_1
2. The size of test a
3. The number of measurement data involved in the test statistic, the sample size.

4. The critical region

Consequently, a hypothesis test is consistent for a specified alternative if the power of the test approaches 1 as the sample size approaches infinity. In fact, the main purpose of hypothesis test is to provide tests with largest power for a given level of significance.

Considering two independent blocks of measured small-scale fading, X and Y of length L , and using the following assumptions:

- The observation values of X , i.e. $\{x_1, x_2, \dots, x_L\}$, and Y , i.e. $\{y_1, y_2, \dots, y_L\}$, are mutually independent.
- X and Y are derived from a continuous distribution functions F_X and G_Y , respectively.

Three hypothesis testing were employed here, in order to study the stationarity properties of the small-scale fading channels and they are:

- Kolmogorov-Smirnov (KS) test studies the similarity of F_X and G_Y .
- Wilcoxon rank sum test studies the median homogeneity of X and Y .
- Ansari Bradley test studies the variance homogeneity of X and Y .

The KS test is mainly useful for general alternative hypothesis because it can detect any types of differences between the empirical distribution functions under test but it can not be relied upon efficient for detecting differences in variability, e.g. median or variance. Therefore, the other test were employed in order to identify the cause of accepting or rejecting the similarities between two blocks given by the KS test.

C.1.1 Kolmogorov-Smirnov Two-sample test

KS test compares two empirical distribution functions of X and Y . It tests the distance metric which is determined by the maximum absolute difference between the two empirical distribution functions.

The null and alternative hypothesis, H_0 and H_1 are defined as follows:

$$\begin{aligned} H_0 : & F_X(x) = G_Y(y) \quad \text{for all } x = y \\ H_1 : & F_X(x) \neq G_Y(y) \quad \text{for at least one of } x = y \end{aligned}$$

The empirical distribution functions of X and Y are calculated as follows:

$$\begin{aligned} F_X(x) &= \frac{\text{number of observations } X's \leq x}{L} \\ G_Y(y) &= \frac{\text{number of observations } Y's \leq y}{L} \end{aligned} \quad (\text{C.3})$$

Therefore, the statistic test of KS is calculated as follows:

$$D_L = L \max_{(-\infty < x, y < +\infty)} \{|F_X(x) - G_Y(y)|; \text{for } x = y\} \quad (\text{C.4})$$

Since $F_X(x)$ and $G_Y(y)$ are step functions changing only at the observed values of X and Y , thus the empirical distribution function can be rewritten using the order statistics of the observation X and Y data. Considering $z(1), z(2), \dots, z(2L)$ are the order statistics for the combined samples of X and Y , equation (C.4) become:

$$D_L = L \max_{j=1,2,\dots,2L} \{|F_X(z(j)) - G_Y(z(j))|\} \quad (\text{C.5})$$

Subsequently, for a given α significance level, H_0 is rejected if $D_L > D_\alpha$, where D_α is the upper α percentile for the null hypothesis distribution of D_L , i.e. $P(D_L \geq D_\alpha | H_0) \leq \alpha$. Thus, in order to implement the test, the cumulative distribution function of D_L must be calculated. Different methods were proposed considering a small sample sizes [148] and for large sample size, an asymptotic null distribution was derived as follows:

$$\lim_{L \rightarrow +\infty} P\left(\frac{D_L}{\sqrt{2L}} \leq d\right) = 1 - 2 \sum_{j=1}^{+\infty} (-1)^{j-1} e^{-2j^2 d^2} = Q(d) \quad (\text{C.6})$$

In this case, H_0 is rejected if $\frac{D_L}{\sqrt{2L}} \geq q_\alpha$; where $\alpha = Q(q_\alpha)$.

The KS test is mainly useful for general alternative hypothesis because it can detect any types of differences between the empirical distribution functions under test. It is used for a preliminary study of data samples and therefore can not be relied upon efficient for detecting differences in variability, e.g. median or variance.

C.1.2 Wilcoxon rank sum test

Wilcoxon rank sum test is a linear rank test primarily sensitive to differences in central tendency, i.e. median.

The null and alternative hypothesis, H_0 and H_1 are defined as follows:

$$\begin{aligned} H_0 : & F_X(x) = G_Y(y - \theta) \quad \theta = 0; \text{ for all } x = y \\ H_1 : & F_X(x) = G_Y(y - \theta) \quad \theta \neq 0; \text{ for at least one of } x = y \end{aligned}$$

The method is based on combining order arrangement of the two data samples, X and Y . The rank of an observation, x , is equal to the number of observations that are less or equal to x . Therefore, if the median of Y exceeds (is less than) the median of X , then the ranks of Y , in this case, will be larger (smaller) than the ranks of X . The Wilcoxon rank sum test statistic is then, applied as follows:

$$W_{2L} = \sum_{j=1}^{2L} jZ_j \quad (\text{C.7})$$

where i represents the ranks of data samples and Z_j is an indicator defined as:

$$Z_j = \begin{cases} 0 & j \in X \\ 1 & j \in Y \end{cases} \quad (\text{C.8})$$

Subsequently, at an α level of significance, H_0 is rejected if $W_{2L} \geq W_{\alpha/2}$ or if $W_{2L} \leq L(2L+1) - W_{\alpha/2}$. The constant $W_{\alpha/2}$ is estimated so that we have a probability of $\alpha/2$ in both tails of W_{2L} distribution.

If H_0 is true, the exact mean and variance of W_{2L} is expressed as follows [148]:

$$\begin{aligned} \mathbb{E}[W_{2L}] &= \frac{L(2L+1)}{2} \\ \text{Var}[W_{2L}] &= \frac{L^2}{12} \left[2L + 1 - \frac{\sum_{j=1}^{gr} (ti_j - 1)ti_j(ti_j + 1)}{2L(2L-1)} \right] \end{aligned} \quad (\text{C.9})$$

where gr denotes the number of tied groups and ti_j is the size of tied group j . Ties group is a group of x_i and/or y_i that have the same value (thus, the same rank). Therefore, the average of their associated integer scores (rank) is assigned for each. An untied observation is considered to be a tied "group" of size 1. In particular, if there are no tied observations, then $gr = 2L$, $ti_j = 1$ for $j = 1, \dots, 2L$, so the variance is reduced to $L^2(2L+1)/12$.

For a small number of observations L , the W_{2L} distribution under the null hypothesis is obtained by enumeration. For a large L , i.e. $2L \geq 12$, a normal approximation to the distribution of W_{2L} is used due to the

asymptotic normality of the general linear rank statistic [148]. Subsequently, H_0 is rejected if

$$\left| \frac{W_{2L} - \mathbb{E}[W_{2L}]}{\sqrt{\text{Var}[W_{2L}]}} \right| \geq z_{a/2} \quad (\text{C.10})$$

where $z_{a/2}$ is the value that has an $a/2$ area in the right tail of the standard normal distribution.

C.1.3 Ansari Bradley test

Ansari Bradley test is a distribution-free rank test for the dispersion problem. Dispersion measures the spread around the distribution central value.

The null and alternative hypothesis, H_0 and H_1 are defined as follows:

$$\begin{aligned} H_0 : F_X(x) &= G_Y(\theta y) \quad \theta = 1; \text{ for all } x = y \\ H_1 : F_X(x) &= G_Y(\theta y) \quad \theta \neq 1; \text{ for at least one of } x = y \end{aligned}$$

Based on these hypothesis definitions, one can readily detect that a location difference may contribute to a dispersion difference [148]. In fact,

$$\begin{aligned} \mathbb{E}[F_X] &= \theta \mathbb{E}[G_Y] \\ \text{Var}[F_X] &= \theta^2 \text{Var}[G_Y] \end{aligned} \quad (\text{C.11})$$

The test statistic is defined as follows:

$$A_{2L} = \frac{L(2L+1)}{2} - \sum_{j=1}^{2L} \left| j - \frac{2L+1}{2} \right| Z_j \quad (\text{C.12})$$

where Z_j is defined in (C.8).

Accordingly, a small value of A_{2L} suggests that X is more dispersive than Y . Similarly to wilcoxon rank sum test, the critical region and the P value can be determined by enumeration, considering a small number of observations, L [148]. For a large L , the normal approximation to the distribution A_{2L} can be employed. The exact mean and variance of A_{2L} , are calculated as follows [172]:

$$\begin{aligned} \mathbb{E}[A_{2L}] &= \frac{L(L+1)}{2} \\ \text{Var}[A_{2L}] &= \frac{L \left[2 \sum_{j=1}^{2L} t_j r_j^2 - L(L+1)^2 \right]}{4(2L-1)} \end{aligned} \quad (\text{C.13})$$

where gr denotes the number of tied groups, ti_j is the size of tied group j and r_j is the average score associated with the observations in tied group j .

Subsequently, at an a level of significance, H_0 is rejected if

$$\left| \frac{A_{2L} - \mathbb{E}[A_{2L}]}{\sqrt{\text{Var}[A_{2L}]}} \right| \geq z_{a/2} \quad (\text{C.14})$$

where $z_{a/2}$ is the value that has an $a/2$ area in the right tail of the standard normal distribution.

C.2 Determination of the Significance Level a

The significance level is the probability of rejecting H_0 when H_0 is true. It is denoted as the type error I. One wants to reduce this type of error in order to prevent as much as possible its occurrence. Usually, three values for the significance level were used, i.e. 0.001, 0.01 and 0.05.

In order to determine a properly for the KS test, the critical region q_a (C.6) was estimated for $a = \{0.05, 0.01, 0.001\}$ (cf. Table C.1). Figure C.1 presents the maximum empirical distance D_{max} in function of window length L . If the measured distance is bigger than $D_{max} = Q(a)\sqrt{2L}$, then H_0 is rejected. As seen, the 0.05 is the more sever criterion while the 0.001 is the more soft one.

Table C.1: KS test: Significance level and its corresponding critical region

Significance level	Critical region
a	q_a
0.05	1.358
0.01	1.628
0.001	1.948

The kullback divergence metric is defined as:

$$KD_{jk} = |(D_{max_{a_j}} - D_{max_{a_k}}) \log_{10}(\frac{D_{max_{a_j}}}{D_{max_{a_k}}})| \quad (\text{C.15})$$

where $D_{max_{a_j}}$ and $D_{max_{a_k}}$ the maximal accepted distance difference considering a_j and a_k as significance levels.

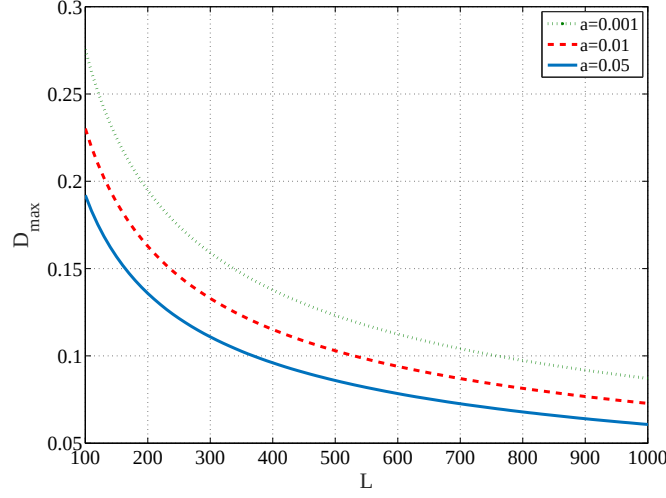


Figure C.1: KS test: maximum Distance difference in function of L for different significant level

This metric was used in order to depict the difference of D_{max} between the considered significance level (cf. Table C.2). As expected, the results of 0.01 are close to both 0.001 and 0.05 while a large difference is given between 0.05 and 0.001. Therefore, for KS test, the significance level a was set to 0.01.

Table C.2: KD of KS test

	0.001	0.01	0.05
0.001	0	0.64	2.36
0.01	0.64	0	0.54
0.05	2.36	0.54	0

Considering a large number for L , the null distribution of Wilcoxon rank sum and the Ansari-Bradley test can be approximated to normal standard distribution and the values of $z_{a/2}$ given by the $a/2$ area in the right tail of the standard normal distribution are given in table C.3. Figure C.2 and C.3 present the W_{2L} and A_{2L} considering different significance level. As expected, the 0.05 is the more severe one. Table C.4 and C.5 exhibit the Kullback Divergence (KD) values between different significance level for Wilcoxon and Ansari-Bradley tests. Accordingly, a

equal to 0.01 is also considered for the Wilcoxon rank sum and Ansari-Bradley tests.

Table C.3: $z_{a/2}$ for a given a

	0.001	0.01	0.05
$z_{a/2}$	3.29	2.58	1.96

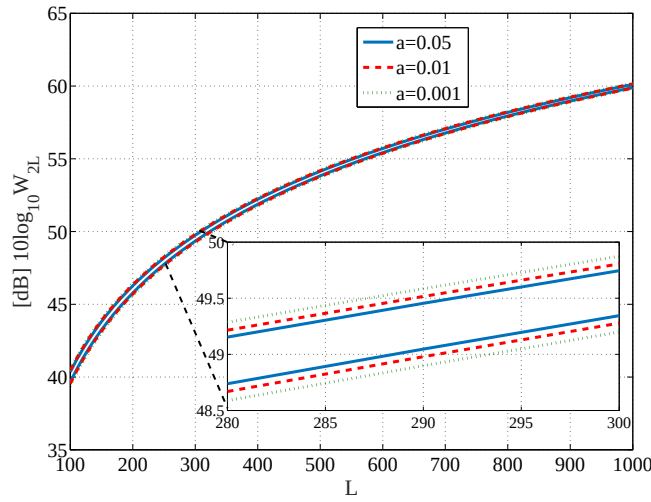


Figure C.2: Statistic test of Wilcoxon rank sum test W_{2L} in function of L

Table C.4: Kulback divergence of W_{2L} [dB]

	0.001	0.01	0.05
0.001	0	52.6	58
0.01	52.6	0	51.32
0.05	58	51.32	0

C.3 Determination of Minimum Length L_{min}

The minimum required length L_{min} is related to the power of the test. The power of the test is defined as H_1 is accepted given that H_1 is true

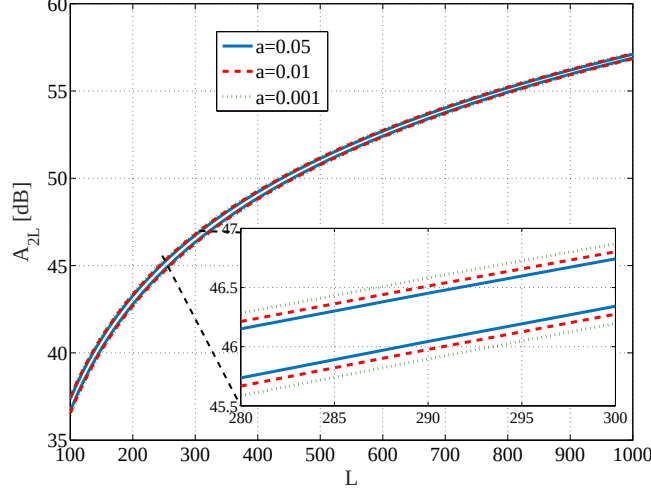


Figure C.3: Statistic test of Ansari-Bradley test A_2 in function of L

Table C.5: Kulback divergence on A_{2L} in dB

	0.001	0.01	0.05
0.001	0	46.67	55.12
0.01	46.67	0	48.48
0.05	55.12	48.48	0

and it can be expressed as function of to the type error II, as follows:

$$Power = 1 - b \quad (C.16)$$

Having a higher power test implies reducing the possibility of the type error II occurrence. Accordingly, the power of the test is related to the some criteria mentioned previously, i.e. significance level, critical region (alternative hypothesis):

$$Power = P(T > \text{critical region} | H_1 \text{ is true}) = P(T > z_{1-b} | H_1 \text{ is true}) \quad (C.17)$$

Subsequently, power calculations for any test require knowledge of the probability distribution of the test statistic under the alternative, but the alternatives in nonparametric problems are often extremely general.

Nevertheless, considering the KS test, the minimum required length can be simply determined for a given significance level and minim de-

tected distance from Figure C.1. Thus, considering the critical region is larger than 0.23 for $a = 0.01$, the minimum required length is then 100.

In [173], a method was proposed in order to determine an approximate total sample size L for the Wilcoxon rank sum test, considering an a -level one-sided test and an approximate power of $1 - b$ against an alternative value ϵ as follows

$$L = \frac{(z_a + z_b)^2}{6 \left(p' - \frac{1}{2}\right)^2} \quad (\text{C.18})$$

where $p' = P(X > Y)$.

Using the three following assumptions:

- power test : 80%
- $a = 0.01$
- H_1 Median difference Δ , then $p' = \varphi(2\Delta)$ (cf. Table C.6)

For two sided test, the z_a will be replaced by $z_a/2$ and the minimum required length, (C.18), is presented in Figure C.4 considering different value of Δ (cf. Table C.6). If the minimum required length is 100, then the maximum accepted median difference is 0.17. Moreover, if the length of block increases, then the power increases and the maximum accepted median difference decreases (cf. Figure C.5).

Table C.6: P' for a given Δ

Median difference Δ	Probability of X succeed Y p'
0.1	0.58
0.2	0.65
0.3	0.73
0.4	0.79
0.5	0.84
0.6	0.88
0.7	0.92
0.8	0.94
0.9	0.96
1	0.98

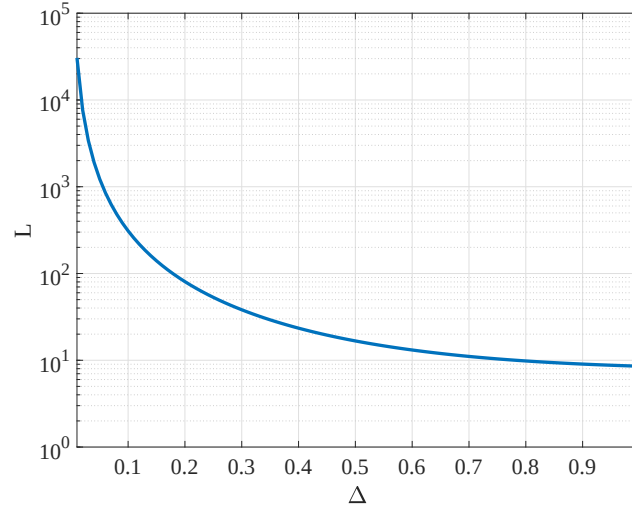


Figure C.4: Difference in Median in function of the minimum required length for a power of 80%

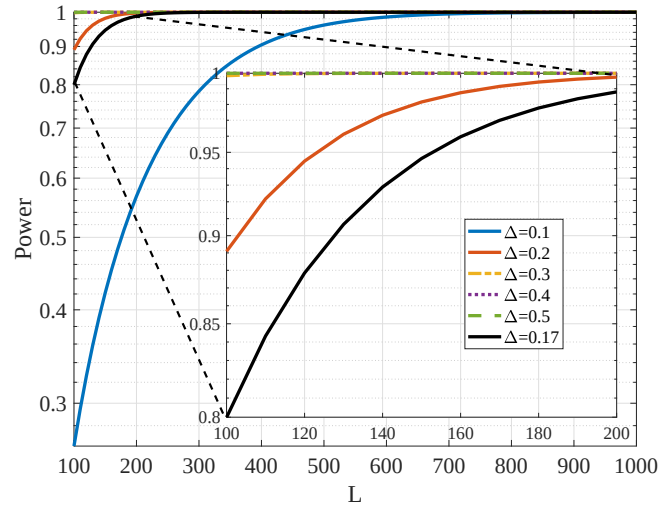


Figure C.5: Power of Wilcoxon rank sum test in function of length L for different given median difference

For Ansari-Bradley test, a simulation method based on Monte Carlo technique is used in order to determine the minimum required length for a given power. Repeated generating data sample from the alternate hypothesis and compared to the data sample generated under the null

hypothesis can provide a basis for power estimation. In other words, L data samples are generated considering the mean and sigma of the null hypothesis and compared to N realizations of length L generated under the alternate hypothesis. The Power of the test is then estimated as:

$$Power = \sum_i^N \frac{P_i}{N} \quad (C.19)$$

where

$$P_i = \begin{cases} 1 & \text{if } H_0 \text{ is rejected} \\ 0 & \text{if } H_0 \text{ is accepted} \end{cases}$$

Varying length of a realizations (alternate hypothesis), on can trace power in function of length (alternate hypothesis) for a given alternate hypothesis (length). 1 000 repeated realizations were considered. Figure C.6 traces the flow chart of Monte Carlo power simulation technique.

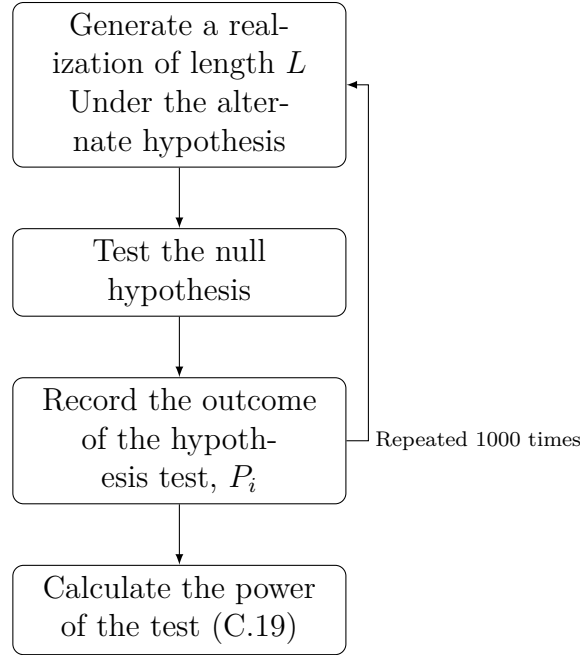


Figure C.6: Flow chart of Monte Carlo power estimation

Considering a Rice distribution with $s_F = 0.8$ and $\sigma_F = 0.4$ (the same as the measurement data in LOS condition) under the null hypothesis

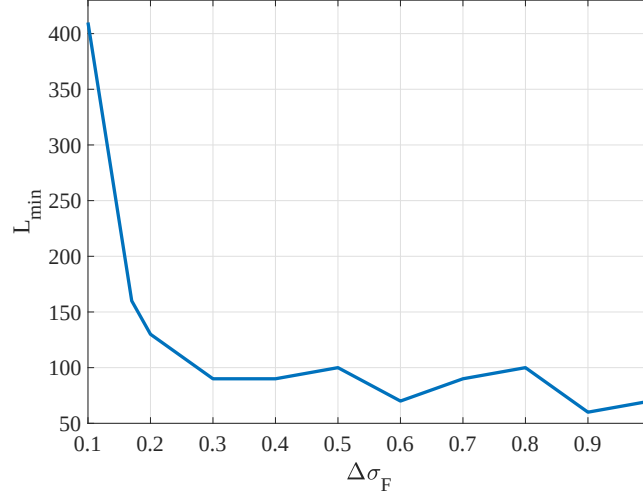


Figure C.7: Ansari Bradley test: the minimum required length in function of the critical variance difference

test, we imply the Ansari Bradley statistic test for an alternative hypothesis where $\Delta\sigma_F = |\sigma_F - \sigma_{F_1}| = \{0.1, 0.2, 0.3, 0.5, 0.6, 0.7, 0.8, 0.9, 1\}$. The minimum length L_{min} required for a test power of 80% is drawn in function of $\Delta\sigma_F$ in Figure C.7. As expected, L_{min} decreases with the increase of σ_F . For an accepted minimum variance difference of 0.2, L_{min} must be bigger or equal 130 approximately.

Appendix D

Pedestrian to Pedestrian Channel Measurement Campaign

Contents

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D.1 Measurement Setup

A pedestrian to pedestrian (P2P) was carried out using the UCL-ULB channel using the same set-up parameters of the V2P channel measurement (cf. Table 3.1). Dipole antennas were used at Tx and Rx terminals, each was placed on a cardboard tube carried by a human subject acting as pedestrian (cf. Figure D.1).

D.2 Measurement Scenarios

P2P measurement campaign was carried out in the same location of V2P measurement (cf. Figure D.2) and two types of P2P measurements were performed, respectively in line-of-sight (LoS) and non-line-of-sight (NLoS). The NLoS condition is mainly considered when Tx subject was walking behind vehicles parked on the road (cf. Figure D.3). Different mobility patterns were measured including parallel, opposite and



Figure D.1: Tx and Rx antenna positions

orthogonal directions as seen in Figure D.4 and D.5. Moreover, some measurements were performed next to a parked vehicle on the road while Tx and Rx subjects are crossing the road in the same and opposite directions (cf. Figure D.6 and Figure D.7) or when a car was traveling the road (cf. Figure D.8 and Figure D.9).

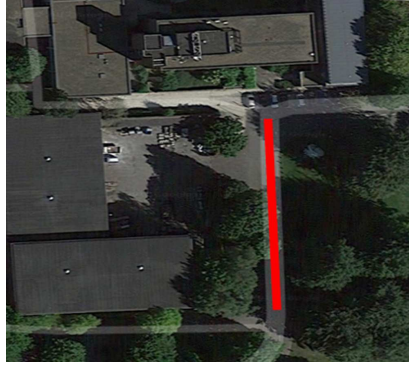


Figure D.2: P2P: Measurement location

Vehicle speed was around 30 km/h and the distance between the Tx vehicle and the Rx pedestrian varied in the range of 0.5 m to 10 m depending on the measurement scenario.

The measurement campaign was conducted during one day, and a total of 64 measurement runs were recorded. The recorded time was between 2 s and 10 s, approximately, depending on the measurement

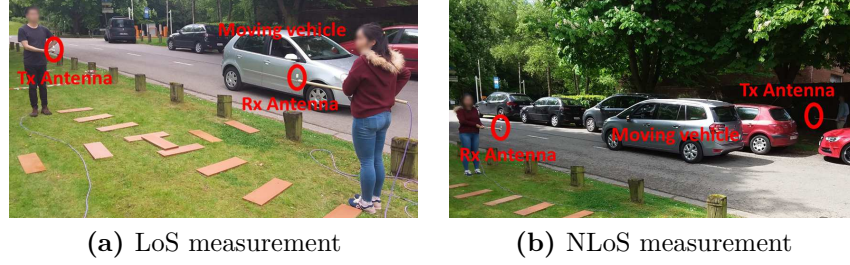


Figure D.3: Example of LoS and NLoS Measurements

scenario. Four people were involved in the measurement campaign. In Tx vehicle, one person acted as a driver, the Tx and Rx antennas were carried by two human subjects acted as pedestrians while another person was responsible of controlling the channel sounder and writing the measurement protocol.

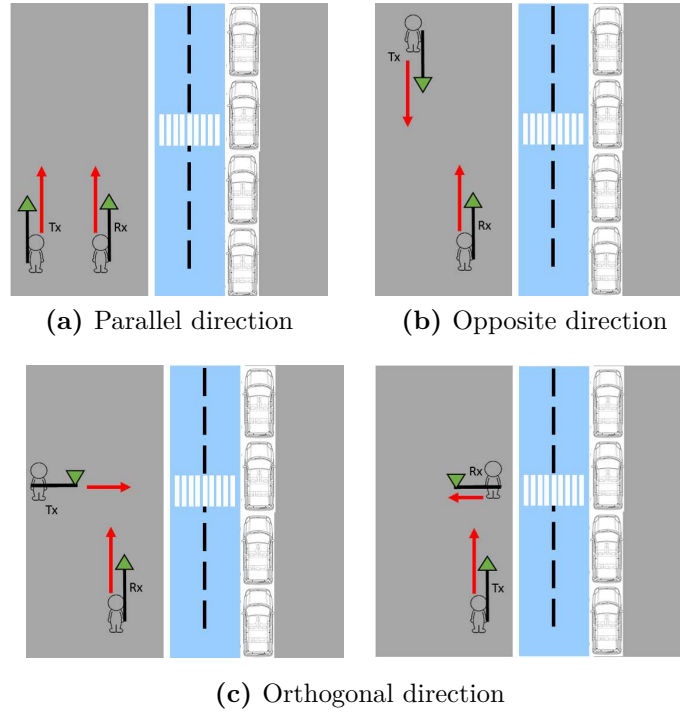
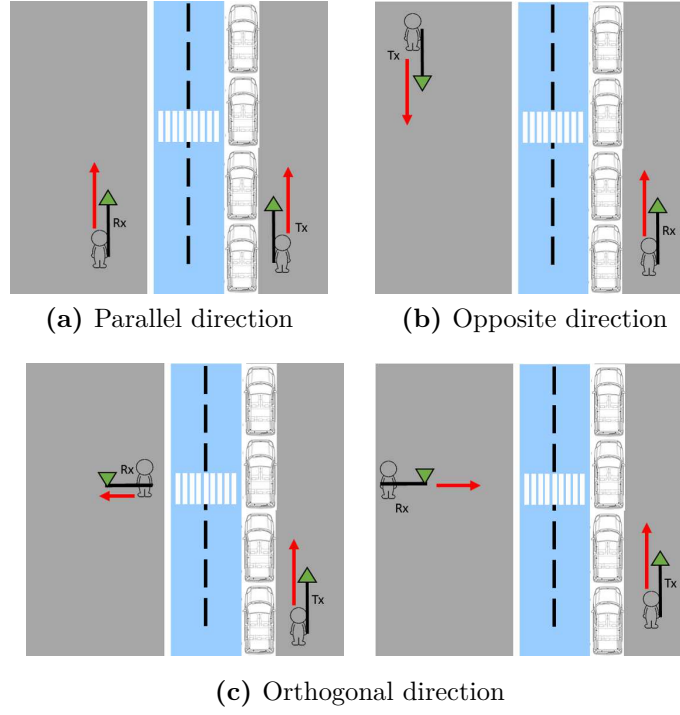
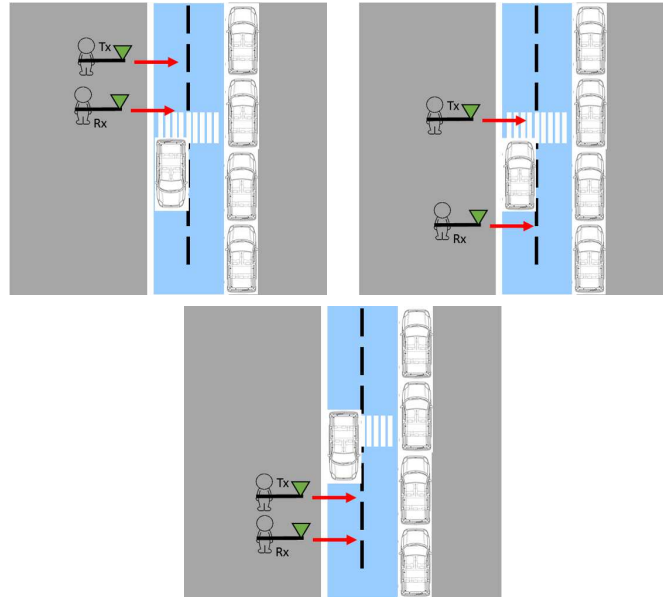


Figure D.4: P2P: LoS scenarios

**Figure D.5:** P2P: NLoS scenario**Figure D.6:** P2P parallel walking scenarios with fixed car

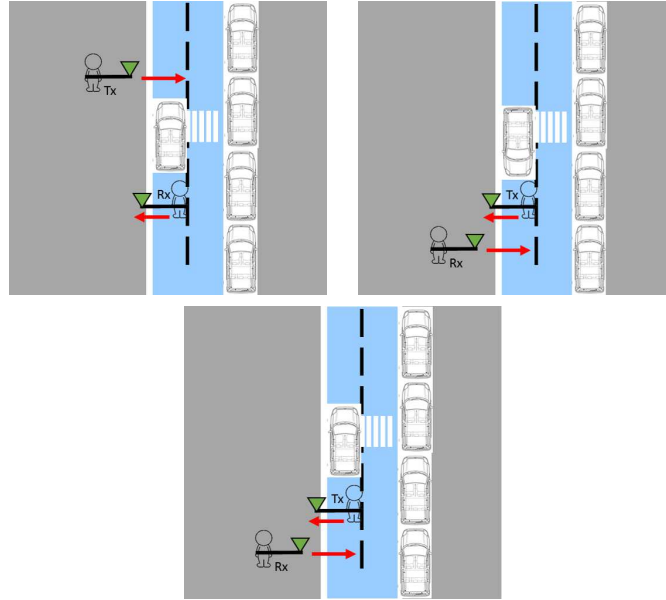
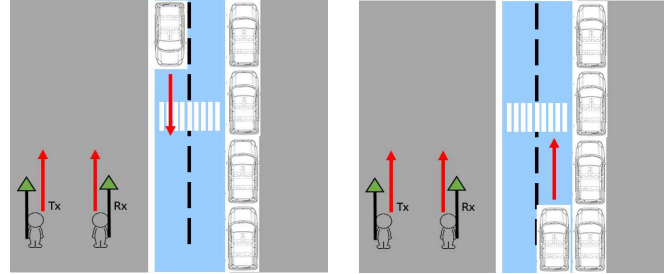
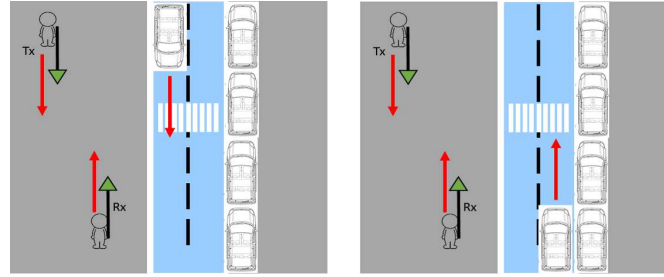


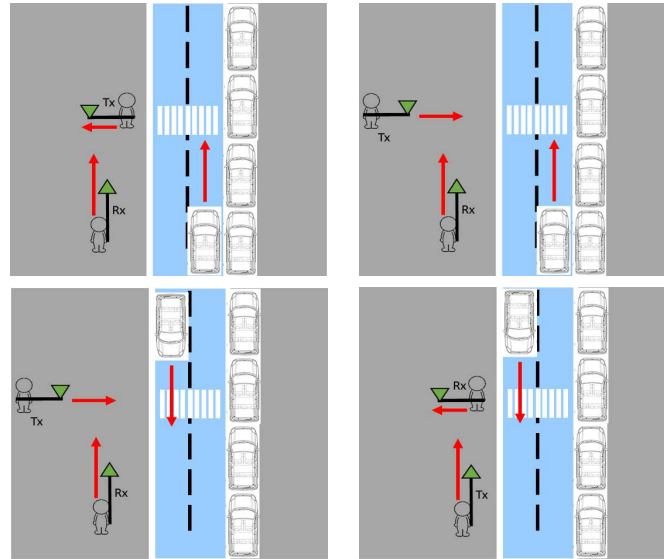
Figure D.7: P2P opposite walking scenarios with fixed car



(a) Parallel direction

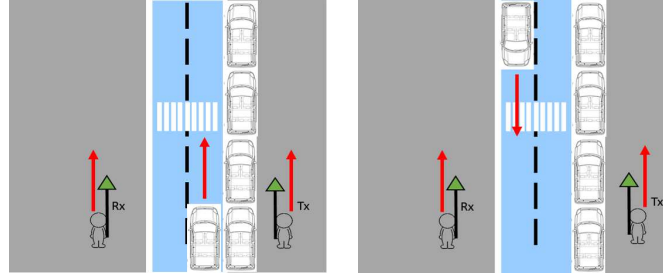


(b) Opposite direction

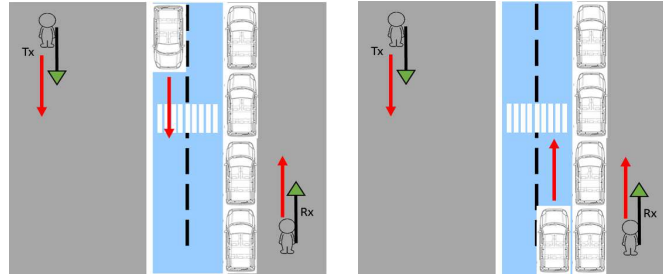


(c) Orthogonal direction

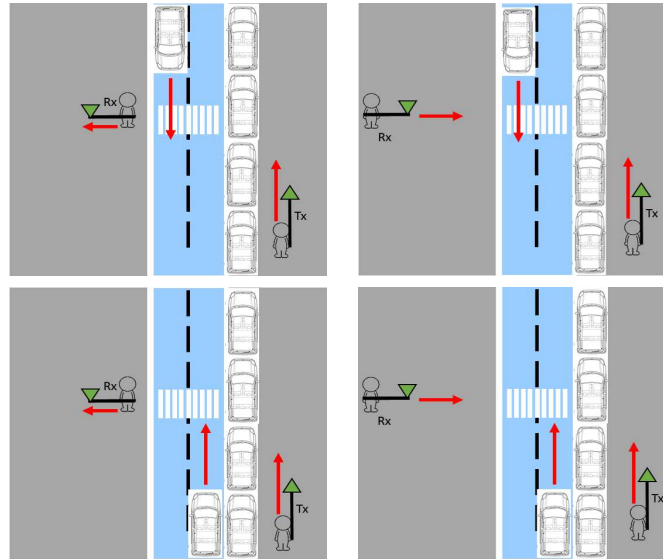
Figure D.8: P2P: LoS scenario in the presence of moving vehicle



(a) Parallel direction



(b) Opposite direction



(c) Orthogonal direction

Figure D.9: P2P: NLoS scenario in the presence of moving vehicle

Appendix E

Autoregressive Coefficients

Contents

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E.1 Autoregressive Coefficients for Large Scale Fading

Table E.1: AR parameters of order 8

a_1	-2.16
a_2	1.18
a_3	0.0032
a_4	0.001
a_5	-7.49×10^{-4}
a_6	-0.0023
a_7	-0.0034
a_8	8.61×10^{-4}
a_9	-0.021
σ_ϵ^2	7.52×10^{-7}

E.2 Autoregressive Coefficients for Small Scale Fading

Table E.2: Parallel walking LoS scenarios: AR parameters of order 16

a_1	-2.26+0.08i
a_2	0.082-0.09i
a_3	0.9-0.09i
a_4	0.14+0.04i
a_5	-0.77+0.11i
a_6	0.14+0.005i
a_7	-0.19-0.017i
a_8	0.16- 0.035i
a_9	0.22-0.052i
a_{10}	0.24+0.05i
a_{11}	0.14-0.03i
a_{12}	-0.11+0.06i
a_{13}	0.03-0.031i
σ_ϵ^2	8.8×10^{-5}

Table E.3: Opposite walking LoS scenarios: AR parameters of order 16

a_1	-2.4-0.009i
a_2	1.28+0.02i
a_3	0.53+0.005i
a_4	-0.13-0.043i
a_5	-0.38+0.027i
a_6	0.11+0.006i
a_7	-0.11+0.02i
a_8	0.06- 0.055i
a_9	0.07+0.032i
a_{10}	-0.1-0.0009i
a_{11}	0.13+0.003i
a_{12}	-0.11-0.012i
a_{13}	0.03+0.006i
σ_ϵ^2	9.27×10^{-5}

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