IN FACULTY OF ENGINEERING



Marwan Yusuf

Doctoral dissertation submitted to obtain the academic degree of Doctor of Electrical Engineering

Supervisors

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 Faculty of Engineering and Architecture, Ghent University
- ** Département Electronique, Electrotechnique, Automatique Faculté des Sciences et Technologies, Université de Lille, France

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Karıma

Acknowledgement

"A comic is worth a thousand words." Anonymous



WWW. PHDCOMICS. COM

Ghent, January 2022 Marwan Yusuf

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List of Acronyms

Α	
AR AGC APDP	autoregressive automatic gain control averaged power-delay profile
В	
BER BM	bit-error rate bi-directional measurement
C	
CCF CDF CIR CMD COTS CPR CSI CTF	channel correlation function cumulative distribution function channel impulse response correlation matrix distance commercial off-the-shelf co-polarization ratio channel state information channel transfer function
D	
DU DP DPSS	doubly-underspread dual-polarized discrete prolate spheroidal sequences
Ε	
EAF	expected ambiguity function
G	
G GBSM	gain geometry-based stochastic model
Н	
Н	horizontal

Ι	
IIR IoT IR ITS K	infinite-impulse response internet of things impulse radio intelligent transportation system
KS	Kolmogorov-Smirnov
L	-
LOS LRS LSF LT LTV	line of sight local region of stationarity local scattering function low-traffic linear time-variant
Μ	
MA MIMO MIMOSA ML mmWave MPC MT	moving-average multiple-input multiple-output multi-input multi-output system acquisition machine learning millimeter wave multipath component medium-traffic
0	
OFDM OM P	orthogonal frequency division multiplexing omni-directional measurement
PSM PDeP PDoP	parametric stochastic models power-delay profile power-Doppler profile
Q	
Q R	quality factor
RC RSSI RSU RT	reverberation chamber received signal strength indication roadside unit reverberation time

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Rx	receiver
S SAR SD SISO T	specific absorption rate spectral divergence single-input single-output
2LBT TDL TF TFYW Tx	two-level block-Toeplitz tapped-delay line time-frequency time-frequency Yule–Walker transmitter
U	
US UWB	uncorrelated scattering ultra wideband
V	
V V2I V2V	vertical vehicle-to-infrastructure vehicle-to-vehicle
W	
wss X	wide-sense stationary
XPD	cross-polarization discrimination

Nederlandse samenvatting

De vijfde generatie telecommunicatietechnologie (5G), in combinatie met andere technologieën zoals kunstmatige intelligentie en internet-of-things (IoT), zal de manier waarop we vandaag leven en met elkaar omgaan veranderen, zowel in de industrie als in de samenleving. 5G maakt een bredere netwerkdekking, betrouwbare netwerkverbindingen en snellere gegevensoverdracht mogelijk, en het langetermijnperspectief van 5G is enorm. Met de snelle toename van het aantal apparaten en machines dat verbonden is met het internet, is een nieuw tijdperk van informatie-gestuurde toepassingen en ecosystemen aangebroken. 5G zal deze groei mogelijk maken, en zal samen met de hoeveelheid gegevens die hierdoor wordt gegenereerd, het begin vormen van een tijdperk van "Massive IoT". In de komende jaren zal 5G zorgen voor een snellere netwerkverbinding via verbeterde mobiele breedbanddiensten, met name dankzij hoogfrequente of millimetergolfbanden (mmWave). Naast verbeteringen aan de bestaande functies van mobiele netwerken, ondersteunt 5G nieuwe functies voor kritieke toepassingen zoals externe bediening van infrastructuur, drones, robotica en voertuigen. Deze functies vereisen een stabiele verbinding met een extreem lage wacht- en reactietijd.

Om de efficiëntie van het radiospectrum dat door dergelijke technologieën wordt gebruikt, te vergroten, werken onderzoekers aan het nauwkeurig modelleren van het radiokanaal tussen de zend- en ontvangstantennes. Het radiokanaal is het medium waarin het draadloze signaal zich voortbeweegt en is verantwoordelijk voor de veranderingen van de kenmerken van het signaal dat bij de ontvanger aankomt. Het fenomeen van multipad-propagatie beschrijft de veelheid aan ontvangen signalen die het resultaat zijn van verschillende interacties met de fysieke objecten in de omgeving. Dergelijke interacties vinden plaats via verschillende propagatiemechanismen zoals reflectie, diffractie en verstrooiing. Kanaalmodellering heeft dus tot doel een wiskundige weergave te maken van de effecten die het communicatiekanaal heeft op de karakteristieken van de draadloze signalen, wat fading wordt genoemd. Met behulp van nauwkeurige kanaalmodellen is een realistische evaluatie van de prestaties mogelijk bij het ontwerp van communicatiesystemen, evenals het optimaliseren van linkprestaties en datasnelheden. In dit werk richten we ons enerzijds op kanaalmodellering voor communicatie tussen voertuigen, en anderzijds op kanaalmodellering voor binnen-toepassingen, zoals het waarnemen van mensen in een industriële ruimte.

Bij communicatie tussen voertuigen verandert de propagatieomgeving snel als gevolg van de mobiliteit van de voertuigen, de relatief lage positie van de antennes en het grote aantal objecten dat zich mogelijk rond de zender en ontvanger bevindt. Bijgevolg is het onderliggende fadingproces in deze kanalen selectief in zowel de tijd als frequentie, en de statistische eigenschappen ervan blijven niet constant (stationair) gedurende lange tijdsduur en over de volledige frequentiebandbreedte. Met andere woorden, de propagatiekanalen van voertuigen verschillen aanzienlijk van de bekende draadloze cellulaire netwerken, waardoor speciale meetcampagnes en realistische modellen van radiokanalen nodig zijn om hun potentieel volledig te benutten. Naast communicatie tussen voertuigen vormt ook draadloze communicatie in industriële binnen omgevingen een uitdaging. Terwijl typische binnen omgevingen (bv. woningen en kantoren) dispersieve fading ervaren, kunnen omgevingen met veel metalen voorwerpen dispersie hebben op hogere niveaus. Sterk reflecterende omgevingen worden gekenmerkt door een rijke elektromagnetische verstrooiing, tijds- en hoekspreiding, en kunnen kenmerken van een complexe caviteit vertonen. Het hoofddoel van dit werk is het modelleren van draadloze radiokanalen voor verschillende scenario's en toepassingen met betrekking tot toekomstige 5G-netwerken, die zullen helpen bij het ontwikkelen van efficiëntere en robuustere communicatie- en detectieoplossingen. Het eerste deel is gewijd aan het bestuderen van het gedrag van draadloze kanalen voor communicatie tussen voertuigen met een focus op stochastische modellering van propagatieparameters voor het niet-stationaire fadingproces. Het doel van het tweede deel is om het propagatiekanaal binnenshuis te onderzoeken in sterk reflecterende industriële scenario's. De reflecterende kenmerken van dergelijke omgevingen zijn gemodelleerd op basis van de theorie van elektromagnetische straling en worden gebruikt in toepassingen voor het waarnemen van mensen in een ruimte.

In Hoofdstuk 2 wordt het onderzoek naar het niet-stationaire fadingproces gepresenteerd op basis van voertuig-naar-infrastructuur (V2I) mobiele kanaalmetingen in een voorstedelijke omgeving. De stationariteit in de tijds- en frequentiedomeinen wordt bepaald door de geldigheid van respectievelijk de wide-sense stationaire (WSS) en ongecorreleerde verstrooiing (US) aannames. Het fading proces in kanalen voor communicatie tussen voertuigen is niet-stationair, d.w.z. niet-WSSUS. Een niet-stationair proces kan echter worden onderverdeeld in opeenvolgende stationariteitsgebieden met een eindige uitbreiding in tijd en frequentie, waarbij de WSSen US-aannames geldig zijn, waardoor de statistische momenten kunnen worden berekend. Daartoe wordt de niet-parametrische lokale verstrooiingsfunctieschatter gepresenteerd en gebruikt om de stationariteits-tijd te schatten. De niet-stationaire fadingparameters worden statistisch gemodelleerd voor verschillende polarisaties, en de toepassingsrelevantie in termen van kanaalcapaciteit en diversiteitstechnieken wordt besproken. Hoofdstuk 3 richt zich op het modelleren van het niet-stationaire mobiele kanaal in tunnels. Het maakt gebruik van de stationariteits-analyse die in Hoofdstuk 2 wordt gepresenteerd, naast een tweevoudig-gepolariseerde kanaalanalyse met meerdere ingangen en meerdere uitgangen. Op basis van V2I-metingen in rechthoekige en gewelfde tunnels wordt de impact van verkeersdichtheid en antennekarakteristieken (directiviteit en polarisatie) op de niet-stationaire fadingparameters onderzocht. Hoofdstuk 4 bespreekt de parametrische modellering van het niet-stationaire fadingkanaal via een vector tijd-frequentie auto-regressieve benadering. De benadering wordt toegepast om het gemeten propagatiekaneel in tunnels

uit Hoofdstuk 3 te simuleren. De stabiliteit van een dergelijk model wordt onderzocht en het model wordt gevalideerd door de parametrische en niet-parametrische spectra te vergelijken.

In reflecterende binnenomgevingen is diffuse verstrooiing een relevant propagatie mechanisme. Het omvat de dichte multipad-verstrooide velden alsook zwakke gereflecteerde componenten nadat alle mogelijke gereflecteerde paden uit de meetgegevens zijn verwijderd. De diffuse vermogensdichtheid kan tot 95% van het totale vermogen vertegenwoordigen in omgevingen met veel verstrooiing en kan worden gekarakteriseerd op basis van de ruimte-elektromagnetische (RE) theorie. Net als bij ruimte-akoestiek, beschouwt RE de binnenomgeving als een verlieslatende ruimte, waar alle effectieve verliezen kunnen worden beschreven door de exponentiële afname van de diffuse velden in de tijd. De vervaltijdconstante, ook wel de nagalmtijd (RT) genoemd, is een functie van het volume en het absorptieoppervlak van de kamer. Een algemene beschrijving van de RT is gebaseerd op de Sabine-nagalmtheorie. In Hoofdstuk 5 wordt de reflecterende binnenomgeving van industriële schepen gemodelleerd op basis van de RE-theorie. Er wordt een op RF gebaseerde methode voor het schatten van de bezetting geïntroduceerd die gebruik maakt van de RT-parameter. De methode is experimenteel gevalideerd in een benedendeks scheepscompartiment met behulp van radiokanaal meetapparatuur en commerciële kant-en-klare ultra-breedband apparatuur. Daarnaast wordt een op Doppler gebaseerde valdetectiemethode voorgesteld als een aanvullende techniek voor veiligheids-, bewakings- en waarschuwingssystemen. In Hoofdstuk 6 wordt aandacht besteed aan de frequentieafhankelijkheid van de RT tot 40 GHz. Binnenmetingen in een laboratoriumomgeving worden gebruikt om de RT, Q-factor en de gemiddelde absorptiecoëfficiënt van de kamer te modelleren. Het model is gevalideerd door vergelijking met gerapporteerde onderzoeken. Ten slotte besluit Hoofdstuk 7 dit boek met een samenvatting van het volbrachte werk en enkele mogelijkheden voor toekomstig onderzoek.

English Summary

The fifth generation of telecommunication technology (5G), in combination with other technologies like artificial intelligence, internet-of-things (IoT), and more will change the way we live and interact today, in industries as well as in societies. 5G has promised to provide wider network coverage, reliable network connections and faster data transfer. In contrast to mobile network technologies so far, the long-term perspective of 5G is tremendous. With the rapid increase in the number of connected devices and machines, a new era of information-driven applications and ecosystems has emerged. 5G will enable this growth along with the amount of data generated by it, introducing an era of Massive IoT. Over the next few years, 5G will provide faster network connection through enhanced mobile broadband services especially at high frequency or millimeter wave (mmWave) bands. Besides the improvements to the existing features of mobile networks, 5G will support mission critical control usage scenarios. These scenarios, such as remote control for critical infrastructure, drones, robots and vehicles, require a stable connection with an extremely low latency.

In order to increase the efficiency of the radio spectrum used by such technologies, researchers work to accurately model the radio channel between the transmitting and receiving antennas. The radio channel is the medium through which the wireless signal propagates, and is responsible for the changes of the characteristics of the signal arriving at the receiver. The phenomenon of multipath propagation describes the multitude of received signals resulting from several interactions with the physical objects in the environments. Such interactions happen through different propagation mechanisms like reflection, diffraction, and scattering. Thus, channel modelling aims to make a mathematical representation of the effects the communication channel has on the wireless signals characteristics, that is called fading. Using accurate channel models, realistic evaluation of the overall performance is possible in the design of communication systems, as well as optimizing link performances and data rates. In this work, we focus on channel modelling for vehicular communications and indoor applications such human sensing at mmWave for IoT.

In vehicular communications, the scattering environment changes rapidly due to the mobility of the vehicles, the relative low height of the antennas and the large number of scatterers potentially located around the transmitter and receiver. Consequently, the underlying fading process in these channels is time and frequency selective, and its statistical properties do not remain constant (stationary) for long time duration and frequency bandwidth. In other words, the vehicular propagation channels are significantly different from the well-known wireless cellular networks, such that dedicated measurement campaigns and realistic radio propagation channel models are required in order to fully exploit their potentials. On the other hand, wireless propagation in indoor industrial environments is challenging. While typical indoor environments (e.g. residential and office) experience dispersive fading, highly metallic environments can have dispersion at much higher levels. Highly reflective environments are characterized by rich electromagnetic scattering, time and angular dispersion, and can exhibit features of a complex reverberant cavity. The main aim of this work is the modelling of wireless radio channels for different scenarios and applications related to 5G future networks, that will help develop more efficient and robust communication and sensing solutions. The first part is dedicated to studying the behavior of wireless channels for vehicular communications with a focus on stochastic modelling of propagation parameters for the non-stationary fading process. The goal of the second part is to investigate the indoor propagation channel in highly reflective industrial scenarios. The reverberant characteristics of such environments are modelled based on the theory of room electromagnetics, and exploited for human sensing applications to highlight their importance and utility.

In Chapter 2, the investigation of the non-stationary fading process is presented based on vehicle-to-infrastructure (V2I) mobile channel measurements in a suburban environment. The stationarity in the time and frequency domains are defined by the validity of the wide-sense stationary (WSS) and uncorrelated scattering (US) assumptions, respectively. The fading process in vehicular channels is nonstationary, i.e., non-WSSUS. However, a nonstationary process can be divided into consecutive stationarity regions with finite extension in time and frequency where the WSS and US assumptions are valid, allowing to calculate its statistical moments. To that end, the non-parametric local scattering function estimator is presented and used to estimate the stationarity time based on the channel correlation function. The non-stationary fading parameters are statistically modelled for different polarizations, and application relevance in terms of channel capacity and diversity techniques is discussed. Chapter 3 focuses on modelling the non-stationary mobile channel in tunnels. It uses the stationarity analysis framework presented in Chapter 2 in addition to dual-polarized multiple-input multiple-output channel analysis. Based on V2I measurements in rectangular and arched tunnels, the impact of traffic density and antenna characteristics (directivity and polarization) on the non-stationary fading parameters are investigated. Chapter 4 discusses the parametric modelling of the non-stationary fading channel via a vector time-frequency autoregressive approach. The approach is applied to simulate the measured tunnel propagation channel from Chapter 3. Stability of such model is investigated and the model is validated by comparing the parametric and non-parametric spectra.

In reflective indoor environments, diffuse scattering is a relevant propagation mechanism. It includes the dense multipath scattered fields plus weak specular components after removing all possible specular paths from the measurement data. The diffuse power density may represent up to 95% of the total power in rich scattering environments and can be characterized based on the room electromagnetics

(RE) theory. Similar to room acoustics, RE views the indoor environment as a lossy cavity, where all the effective losses can be described by the exponentially decaying tail of the diffuse fields in time. The decay time constant, also known as the reverberation time (RT), is a function of the volume and the absorption area of the room. A general description of the RT is based on Sabine's reverberation theory. In Chapter 5, the indoor reverberant environment of industrial ships is modelled based on the RE theory. RF-based occupancy estimation method is introduced that makes use of the RT parameter. The method is experimentally validated in a belowdeck ship compartment using radio channel sounder equipment, and commercial off-the-shelf ultra-wideband devices. In addition, a Doppler-based fall detection method is proposed as a complementary technique for safety monitoring and alert systems. In Chapter 6, attention is paid to the frequency-dependency of the RT up to 40 GHz. Indoor measurements in a lab environment are utilized to model the RT, Q-factor, and the average absorption coefficient of the room. The model is validated by comparison to reported studies. Finally, Chapter 7 concludes this book with a summary of the accomplished work, and some opportunities for future research.

Introduction

1.1 Context and motivation

The recent years have seen a rapid increase in the number of wireless devices, including smart phones, tablets, gadgets, vehicles and even machines, resulting in a massive amount of accessible information. This opened the door for a new level of emerging applications and innovative use cases as shown in Figure 1.1, that are yet to be completely defined today. The new era of information led to the development of 5G [1]. The fifth generation (5G) of mobile networks promises to deliver a unifying connectivity that will take on a much larger role than previous generations. It is a new kind of network that will not only interconnect people, but also interconnect and control machines, objects, and devices. For the past four decades, mobile networks have evolved to connect people in new and better ways. Approximately, every 10 years a new generation of mobile technologies is introduced that delivers a big leap in performance, efficiency and capability. While the first four generations of mobile networks connected people by delivering better voice and faster data services, it is envisioned that 5G will do much more [2]. It is a platform for innovations that will redefine a wide range of industries by connecting virtually everyone and everything, from workers and patients to robots and crops, supporting the connectivity needs across a variety of world-changing use cases [3].

5G technology, along with technologies like Artificial Intelligence, Internet of Things (IoT), and more will change the way we live and interact today, in industries as well as in societies [4, 5]. It has promised to provide wider network



Figure 1.1: Illustration of 5G main features and future prospects (Source: Gigabyte - What is 5G?)

coverage, reliable network connections and faster data transfer [2]. In contrast to mobile network technologies so far, the long-term perspective of 5G is tremendous, as shown in Figure 1.1. Over the next few years, it will provide faster network connection through Enhanced Mobile Broadband services. The number of IoT devices is expected to grow by 145% to 75 billion devices until 2025 [6]. 5G will enable this growth along with the amount of data generated by it, introducing an era of Massive IoT. Besides the improvements to the existing features of mobile networks, 5G will be especially ground-breaking in terms of mission critical control usage scenarios. These scenarios, such as remote control for critical infrastructure, drones, robots and vehicles, require a stable connection with an extremely low latency.

5G is envisioned to support a multitude of service and devices, thus it needs to be adaptable to a huge variance of requirements around coverage, throughput, capacity, latency, reliability, etc. [2]. 5G must scale from supporting low data rate sensors at kbps to new immersive mobile experiences at multi-Gbps. In addition, 5G will make the best use of the spectrum available across regulatory types and spectrum bands. While previous generation networks primarily operated in licensed spectrum bands below 3 GHz, 5G will bring the next level of integration with support for licensed, unlicensed, and shared spectrum. Moreover, 5G will expand spectrum usage to low bands below 1 GHz, mid-bands between 1 GHz and 6 GHz, and high bands above 24 GHz. Making this 5G vision a reality will require a unified, more capable air interface design that will bring new levels of flexibility, scalability, and efficiency to meet the expanding connectivity needs in the next


Figure 1.2: Illustration of 5G radio access technologies (Source: Qualcomm 5G-NR)

decade and beyond [7]. One of the enabling technologies of 5G new radio (5G NR), shown in Figure 1.2, is millimeter wave (mmWave) communications. Benefiting from the very large bandwidth, mmWave communication is able to provide a data rate of several gigabits per second with ease. Higher frequency propagation introduces severe path loss. However, if we consider small cells of 100–200 m radius, the mmWave communication can achieve satisfactory performance. Another approach to overcome high path loss is beamforming, which can be achieved along with massive multiple-input multiple-output (MIMO) technologies. A high-gain steerable antenna array is able to transmit or receive signals in specific directions, get around obstructions, and compensate for severe path-loss. Besides, massive MIMO can greatly increase the capacity and reliability of the system with respect to the conventional MIMO [8].

5G should provide seamless coverage and high-quality connectivity between various devices and behave well under diverse network topologies, such as multi-hop networks, moving networks, device-to-device, vehicular communications, etc [9]. Furthermore, 5G systems should be adapted to a wide range of scenarios, such as indoor, urban, suburban, rural areas, etc. All the above-mentioned technologies set new requirements for 5G channel modelling [10]. Channel modelling is very important for algorithm and system design, such as channel estimation and compensation. It allows rapid and efficient testing and performance evaluation via simulation or emulation. In this work, we focus on **channel modelling** for **vehicular communications** and **mmWave and indoor applications** such as **human**



Figure 1.3: Overview of the state-of-the-art and challenges of channel modelling for 5G and beyond

sensing for IoT. The work combines efforts and findings from two separate research projects, thus the organization of this work into two parts. The first part deals with outdoor mobile channel modelling for vehicular applications, while the second part focuses on indoor channel modelling at mmWave and human sensing in industrial environments. Figure 1.3 gives an overview of the state-of-the-art and challenges of channel modelling for 5G and beyond [10]. The main areas to which our work contributes are highlighted in red. A new 5G channel model should support a wide frequency range (e.g., 350 MHz to 100 GHz). The model at higher frequency bands (e.g., above 6 GHz) should maintain compatibility with the model at lower frequency bands [10]. The parameters and statistics of the channel model should vary smoothly with the frequency. Channel parameters and statistics at adjacent frequencies should have strong correlations ensuring frequency dependency and consistency. In vehicular scenarios, both the transmitter and receiver are equipped with lower antennas and may interact with a larger number of scatterers. Channel models have to take into account the mobility of both ends, which significantly increases the modelling complexity. The relative speed between the two ends and rapid-changing environments introduce extra Doppler frequency shift and result in serious non-stationary channels. All of these make the vehicular channels differ greatly from conventional cellular channels [11].

1.2 Outdoor channel modelling for vehicular applications

Vehicular communications have recently attracted much interest due to the rapid development of wireless communication technologies. Through the integration of information and communication technologies, all road users can gather sensor data and share information about traffic and road state dynamics with each other and with the road infrastructure. This envisioned intelligent transportation system (ITS) will improve the safety and efficiency of transportation by enabling a wide range of applications [12]. Such systems require reliable low-latency vehicular-to-vehicular (V2V) and vehicular-to-infrastructure (V2I) communication links that provide robust connectivity at a fair data rate. An essential requirement for the development of such vehicular systems is the accurate modelling of the propagation channel in different scenarios and environments [13].

Some V2I propagation channels resemble existing cellular links, where one node is stationary, while the other node is mobile. In urban areas, the roadside unit (RSU) is placed at lamp post height, much lower than the rooftops of surrounding buildings, and typically at intersections. In other areas, the RSU is placed at 1-2 m height, making it similar to the V2V scenario from a propagation point of view [14]. The unique placement height and surroundings of the nodes for vehicular communication result in different dominant propagation mechanisms [14]. For example, propagation over rooftops is dominant in cellular communications, while scattering in the horizontal plane over short distances (<100m) is more important for vehicular communications with surrounding scatterers of higher density and mobility. One of the main challenges that strongly differs from cellular scenarios is the rapidly time-varying radio propagation channel for vehicular communications. Owing to the changing scattering environment and the mobility of the transmitter (Tx) or the receiver (Rx), the vehicular communication channel is characterized by a non-stationary fading process [15, 16]. One of the main challenges of V2I is the expected large Doppler shift of the line of sight (LOS) path when the vehicle passes by the RSU at high speed. This is due to the higher relative speed and smaller LOS angle of arrival/departure of Rx/Tx in the V2I case. Such fast Doppler shifts would increase the non-stationarity of the channel and cause serious performance degradation to the communication system, if not carefully addressed via Doppler planning and compensation [17].

1.2.1 Wireless channel models

In wireless propagation, the transmitted signal is modelled when arriving at the receiving antenna as a collection of plane waves, also called propagation paths or multipath components (MPCs). Each propagation path interacts with physical



Figure 1.4: multipath propagation

objects in the environment while traveling through the propagation medium or the radio channel. Multipath propagation is thus responsible for the changes of the characteristics of the signal due to a multitude of possible interactions with realistic objects via different propagation mechanisms. Figure 1.4 shows a schematic of multipath propagation in the V2I scenario. Main propagation phenomena include: reflection from a smooth specular surface like walls, vehicles, people, and ground, scattering of rough surfaces in a non-coherent (diffuse) manner when the surface's irregularities are comparable to the wavelength of the traveling signal e.g. trees foliage, and diffraction when the waves bend over edges into the shadowed regions due to interference following the Huygens-Fresnel principle [18].

A channel model can be considered as a mathematical representation of the radio channel impulse response (CIR). The generated CIRs are used for the purpose of system performance simulation. The exact CIR is the result of solving the Maxwell equations given a specific site and boundary conditions. However, it is not practical to solve them on a large scale, and an approximated solution should be obtained [13]. The wireless channel modelling approaches can be classified according to the accuracy of their approximation into deterministic versus stochastic models, shown in Figure 1.5. The most basic approach is the replay model, where the CIRs collected in measurement campaigns are used as the channel in system simulations. However, they are only valid for the very specific scenarios where the measurements were taken. Ray-tracing models are based on the ray theory of propagation, including interaction mechanisms such as shown in Figure 1.4. They require the full description of the environment, including terrain data, materials, and each object's geometry, location and scattering properties [13]. The time and



Figure 1.5: General classification of wireless channel models

computational demands of such models are often unrealistic owing to the very large number of scatterers and the lack of exact material parameters knowledge.

For stochastic models, the fundamental distinction is between physical and analytical models. Physical channel models characterize an environment by describing the physical parameters of the double-directional multipath propagation shown in Figure 1.4. Physical models, which can be MPC-based or cluster-based, are usually classified as geometry-based stochastic models (GBSM) and non-geometric stochastic models, also known as parametric stochastic models (PSM). The term GBSM refers to the fact that the modeled impulse response is related to the geometrical location of Tx/Rx and other interacting objects. The regular-shaped GBSM places the scattering points around the Tx and Rx in a shape of a circle or ellipse, while the irregular-shaped GBSM only places scattering points on physically realistic positions. Figure 1.6 shows an overview of the channel models commonly used for vehicular scenarios, including the GBSM. The channel model is derived as follows. Firstly, the GBSM gives a mathematical function of the CIR obtained from the electromagnetic properties of environment, and then utilizes the proposed stochastic distribution of the scatterers along with the geometrical knowledge to get the statistical properties of the parameters. The PSM, on the other hand, describes the statistical properties of the fading process based on the measured CIRs, without assuming an underlying geometry. The most commonly used type is the tappeddelay line (TDL), also shown in Figure 1.6. It is a wideband stochastic approach that models the time and frequency selectivity of the fading process via a finite number of delay taps, each following a given Doppler spectrum. The TDL model has been widely adopted due to its flexibility and low complexity compared to the



Figure 1.6: Overview of wireless channel models commonly used for vehicular scenarios: a) regular-shaped GBSM, b) irregular-shaped GBSM, c) ray-tracing, d) stochastic tapped delay line [13]

other approaches [13].

In contrast to physical models, analytical channel models characterize the CIR between the individual Tx and Rx antennas in a mathematical/analytical way without explicitly accounting for wave propagation. Analytical models are popular for synthesizing MIMO matrices in the context of system and algorithm development and verification. The most common type is the correlation-based models, such as the Kronecker model and the Weichselberger model, which characterize the MIMO channel matrix statistically in terms of the correlations between the matrix entries [19].

1.2.2 The WSSUS channel

In this work, we use the PSM to describe the wireless propagation in terms of the MPCs physical parameters. Various parameters can be associated with a propagation path such as: directional parameters like the angles of arrival and departure (AoA, AoD) which describe the spatial properties of the MPC, a delay parameter which quantifies the amount of time it takes to travel the path distance, and a complex amplitude parameter expressing the magnitude and phase of the MPC's electric field as seen at the receiving antenna. For the single-input single-output (SISO)

channel, the channel parameters are further simplified by modelling the MPC only through the time delay of arrival and the Doppler spectrum governing the time variation, irrespective of their AoDs and AoAs. This results in the TDL model shown in Figure 1.6. Hence, the wireless channel can be represented as a random linear time-variant (LTV) system in the form of

$$r(t) = \sum_{\tau} h(t,\tau) s(t-\tau).$$
 (1.1)

The received signal r(t) is related to the transmit signal s(t) via the 2-D CIR function $h(t, \tau)$ (neglecting noise and interference), where t is the time and τ is the delay. Theoretically, the CIR is a continuous function of both τ and t, but for a bandlimited system, the discrete form representation such as the TDL model is widely used to match the symbol period of a given system. The system can also be expressed in terms of frequency shifts by the spreading function $S_{\rm H}(\nu, \tau) = \prod_{t \to \nu} \{h(t, \tau)\}$ where \mathbb{F} is the Fourier transform and ν is the Doppler frequency.

For most wireless communication systems, statistical descriptions of individual system functions are sufficient, and these functions can be fully characterized by their autocorrelation functions, e.g. $E\{h(t', \tau)h^*(t, \tau')\}$ or $E\{S_H(\nu', \tau)S_H^*(\nu, \tau')\}$, where * is the complex conjugate. Generally, the autocorrelation functions depend on four variables. If the channel is wide-sense stationary (WSS), the autocorrelation function depends on the relative time difference only. That is to say, we can drop the time variables t and t' and use their difference Δt . The WSS assumption also implies uncorrelated Doppler shifts due to the time-frequency duality of the Fourier transform. Thus, the dependence on Doppler variables ν' and ν shall be replaced by a Dirac function $\delta(\nu - \nu')$. The uncorrelated Scattering (US) condition assumes that the channel can be represented by uncorrelated MPCs, i.e., both amplitudes and phases are uncorrelated for components with different delays. An US channel will be WSS in the frequency domain, again because of the time-frequency duality.

The CIR is a WSSUS random process when $h(t, \tau)$ is stationary with respect to t and mutually uncorrelated for different τ . Hence, the autocorrelation of the scattering function simplifies to

$$E\{S_{\rm H}(\nu',\tau)S_{\rm H}^*(\nu,\tau')\} = C_{\rm H}(\nu,\tau)\delta(\nu-\nu')\delta(\tau-\tau'), \qquad (1.2)$$

where $C_{\rm H}(\nu, \tau)$ is known as the scattering function, i.e., the power spectral density of the WSSUS process. For non-WSSUS channels, discussed in the following sections, this simplification is only valid within certain time and frequency intervals, known as the stationarity time and stationarity bandwidth, respectively [16]. The local scattering function (LSF) $C_{\rm H}(t, f; \nu, \tau)$ becomes time and frequency dependent, which then describes the power of MPCs with delay τ and Doppler shift ν occurring at time t and frequency f [16]. This is true for doubly-underspread channels, a condition satisfied by most practical wireless radio channels, as will be discussed later. It means that the amount of delay-Doppler correlation has to be smaller than the amount of delay-Doppler dispersion. In other words, only the neighboring MPCs are correlated [16].

1.2.3 Non-stationary fading channel

In the past, propagation channel models have adopted the WSSUS assumptions [20]. They imply that second-order channel statistics are independent of the absolute time and frequency, and hence, allow for a simplified statistical description of channels; this has formed the basis of many designs of wireless transceivers. However, the WSSUS assumptions are not always fulfilled in practice, particularly in vehicular scenarios, and thus must be accounted for [21]. The author in [22] has shown that, in both single and multi-carrier systems, the WSS assumption in V2V channels can lead to optimistic bit-error rate (BER) simulation results that are erroneous. In reality, power, delay and Doppler associated with reflected MPC drift with time (WSS-violation), and channels show correlated scattering due to several MPCs that are close in the delay-Doppler domain resulting from the same physical object, or delay/Doppler leakage due to bandwidth/time limitations at Tx or Rx (US-violation).

The non-stationarity can be characterized by assuming a local stationarity for a finite region in time and frequency. A definition of the stationarity time and stationarity bandwidth is proposed in [16], where the author provides a theoretical framework that extends the scattering function of the WSSUS to a time-frequency (TF) dependent local scattering function. The LSF can be estimated within this finite region where WSSUS assumptions approximately hold [23]. This stationarity region is computed from the channel correlation function (CCF), which extends the TF correlation function of the WSSUS [16, 20].

For WSSUS channels, the scattering function is the power spectrum of the channel transfer function (CTF) H(t, f), while for non-WSSUS channels, the scattering function is not defined [20]. In [16], the author introduces the TF-dependent LSF as an extension to the WSSUS scattering function. The CCF appropriate for the non-WSSUS case is also defined, which extends the TF correlation function of WSSUS channels. The LSF C_{TF} and CCF A_{TF} are given as

$$C_{\mathbf{TF}}(t, f, \tau, \upsilon) = \iint R_{\mathbf{TF}}(t, f, \Delta t, \Delta f) e^{-j2\pi(\upsilon\Delta t - \tau\Delta f)} d\Delta t d\Delta f \qquad (1.3)$$

and

$$A_{\mathbf{TF}}(\Delta t, \Delta f, \Delta \tau, \Delta \upsilon) = \iint R_{\mathbf{TF}}(t, f, \Delta t, \Delta f) e^{-j2\pi(t\Delta \upsilon - f\Delta \tau)} dt df \quad (1.4)$$

where $R_{\text{TF}}(t, f, \Delta t, \Delta f)$ is the autocorrelation of the CTF for time lag Δt and frequency lag Δf . It is shown in [16] that the LSF describes the mean power of

effective scatterers causing delay-Doppler shifts (τ, v) at time t, and frequency f. However, it does not characterize the scatterers correlation, thus the introduction of CCF. The following relation shows that the correlation of scatterers separated by the lags $(\Delta \tau, \Delta v, \Delta t, \Delta f)$ is measured by the integral CCF

$$A_{\mathbf{TF}}(\Delta t, \Delta f, \Delta \tau, \Delta v) = \iiint C_{\mathbf{TF}}(t, f, \tau, v)$$

$$\times e^{-j2\pi(t\Delta v - f\Delta \tau + \tau\Delta f - v\Delta t)} dt df d\tau dv$$
(1.5)

1.2.3.1 Measuring non-stationarity

In order to evaluate how much the non-stationary models truly reflect the varying nature of the vehicular channel, accurate characterization of the non-stationarity of the channel is required. For a non-stationary channel, the fading statistics change in time. Since communication algorithms often rely on the knowledge of secondorder statistics of the channel, appropriate measures of the similarity between channel statistics are required, so that the fading parameters can be accurately evaluated and the channel modelling becomes physically meaningful. For stochastic modelling [24], the WSS region is first estimated and the time-varying parameters (MPCs lifetime, birth, initial power, angle and delay as well as their dynamic evolution) are modeled in terms of the WSS regions, while the small-scale fading is characterized within each region. GSCM can incorporate non-stationarity via varying some channel parameters over time (e.g. number of delay taps and angles of propagation paths of regular-shaped GSCM in [25]), or via random mobility models that use dynamic motion (e.g. changes of speed and moving direction in [26]). The WSS region is then used as a measure of non-stationarity in order to validate such models, by showing that the resulting CTF has the same WSS region as found from realistic measurements [25]. Several measurement-based metrics have been proposed to measure the size of the WSS region.

A traditional measure of the change in channel statistics is the shadow fading correlation [27], where the decorrelation distance of shadowing can be considered as an equivalent stationarity distance as proposed in [28]. Correlation matrix distance (CMD) was proposed in [29, 30] to characterize the non-WSS behavior of MIMO channels. Spectral divergence (SD) measures the distance between strictly positive spectral densities and was applied to LSF measured at different times in [31]. However, since it is an unbounded pseudo-metric, it can only qualitatively assess the non-WSS nature of channels. A comparison of the above metrics was provided in [32], where it was suggested to use SD and shadowing metrics for a measurement system with a small electrical array aperture, e.g. 4×4 , and to use the CMD metric for arrays with large electrical apertures. Authors in [33, 34] defined a statistical test where the intervals of WSS are identified based on the evolutionary power-delay profile (PDeP) estimated at different time instances. Another approach is based on



Figure 1.7: Collinearity of LSFs over a 250 ms period and the local stationarity region (in red) at a certain instance t = 100 ms for a 0.9 threshold value

the collinearity between spectral densities [15, 35], which can be calculated as

$$CL(t_1, t_2) = \frac{c_{\rm H}(t_1)^{\rm T} c_{\rm H}(t_2)}{\|c_{\rm H}(t_1)\| \|c_{\rm H}(t_2)\|},$$
(1.6)

where $c_{\rm H}(t_1)$ is the power spectral density at time instance t_1 stacked in a vector form. Collinearity was calculated between consecutive PDePs in [36] and between LSFs in [35], and the support of the region where it exceeds a certain threshold was used as an estimate of the local region of stationarity (LRS). Figure 1.7 shows the collinearity of LSFs over a 250 ms period and the LRS at a certain instance t = 100 ms for a 0.9 threshold value.

While these metrics manage to capture the non-WSS behavior of the channel, they are mainly empirical measures; they lack a theoretical framework that can be used as an extension to the WSSUS in [20]. In addition, many of the existing works have limitations, e.g. dependency on the spatial structure of the MIMO channel which is not valid for single antenna systems, and measurements in cellular scenarios that are different from vehicular scenarios.

1.2.3.2 Doubly-underspread channels

The channel's non-stationarity in the TF domain corresponds to the delay-Doppler correlations in the dual domain (i.e. to the CCF spread in $(\Delta \tau, \Delta v)$ directions), as shown in (1.5). The CCF spread about the origin can be measured by the following

moment of the CCF

$$s_{\mathbf{TF}}^{(w)} = \frac{1}{\|A_{\mathbf{TF}}\|_1} \iiint |w| |A_{\mathbf{TF}}(\Delta t, \Delta f, \Delta \tau, \Delta \upsilon)| \, \mathrm{d}\Delta t \mathrm{d}\Delta f \mathrm{d}\Delta \tau \mathrm{d}\Delta \upsilon \quad (1.7)$$

where $||A_{TF}||_1$ is the first norm of the CCF across all four dimensions. Setting the weight factor w to Δv and $\Delta \tau$ results in the CCF moments $s_{TF}^{(\Delta v)}$ and $s_{TF}^{(\Delta \tau)}$, respectively. These moments quantify the Doppler and delay lag spans within which there are significant correlations. Hence, the stationarity region can be defined via a stationarity time and a stationarity bandwidth, respectively, as follows

$$T_s = \frac{1}{s_{\mathbf{TF}}^{(\Delta \upsilon)}}, \quad F_s = \frac{1}{s_{\mathbf{TF}}^{(\Delta \tau)}}.$$
(1.8)

According to [16], the channel can be approximated with good accuracy by a WSSUS channel within this region. Hence, the stationarity region can be used to meaningfully evaluate the fading parameters and their statistics.

The amount of delay and Doppler spread is determined by the extension of the TF-varying LSF in (τ, v) directions. Since the LSF only changes significantly from one stationarity region to another, we calculate the (local) TF-dependent RMS delay spread σ_{τ} and RMS doppler spread σ_{v} within each region as

$$\sigma_{\tau}^{2}(t,f) = \frac{1}{\rho_{\mathbf{TF}}^{2}(t,f)} \int (\tau - \overline{\tau})^{2} P_{\mathbf{TF}}(t,f,\tau) d\tau$$

$$\sigma_{\upsilon}^{2}(t,f) = \frac{1}{\rho_{\mathbf{TF}}^{2}(t,f)} \int (\upsilon - \overline{\upsilon})^{2} Q_{\mathbf{TF}}(t,f,\upsilon) d\upsilon$$
(1.9)

where $\rho_{\text{TF}}^2(t, f) = \int \int C_{\text{TF}}(t, f, \tau, v) d\tau dv = E\{|H(t, f)|^2\}$ is the local path gain, $P_{\text{TF}}(t, f, \tau) = \int C_{\text{TF}}(t, f, \tau, v) dv$ is the local PDeP, $Q_{\text{TF}}(t, f, v) = \int C_{\text{TF}}(t, f, \tau, v) d\tau$ is the local power-Doppler profile (PDoP), and $\overline{\tau}$ and \overline{v} are the local mean delay and Doppler, respectively.

A measure of the channel selectivity is the coherence region, which quantifies the time and frequency spans within which the CTF is considered constant, or at least strongly correlated. The coherence region is defined by a coherence time T_c and a coherence bandwidth F_c shown in Figure 1.8, that can be approximately related to the delay and Doppler spreads as follows [14, 37]:

$$T_c \approx \frac{1}{2\pi\sigma_v}, \quad F_c \approx \frac{1}{2\pi\sigma_\tau}.$$
 (1.10)

The relation between the stationarity region and coherence region is of great importance. According to [23], the LSF of non-WSSUS channels can be considered a TF-dependent delay-Doppler power spectrum only if the channel is both dispersionunderspread and correlation-underspread. These two underspreads constitute the



Figure 1.8: Illustration of the coherence region (T_c, F_c) and stationarity region (T_s, F_s) at a certain point (t,f) in the TF domain. The background represents the magnitude of the CTF in grayscale.

doubly-underspread (DU) property. A simple way of describing this property is using the following inequality

$$T_s F_s \gg T_c F_c \gg 1 \tag{1.11}$$

which states that: the CTF is slowly varying (dispersion-underspread), and the channel statistics variation is even slower (correlation-underspread). Thus, the stationarity region is much larger than the coherence region for DU channels. An illustration of a DU channel is shown in Figure 1.8 where the TF-selectivety of the CTF is shown in grayscale. The figure shows the large stationarity region that contains smaller coherence regions where the CTF is highly correlated. Further practical implications are discussed in Chapter 2.

1.2.4 Vehicular channel modelling in tunnels

1.2.4.1 Models for tunnel propagation

An essential requirement for the development of vehicular communication systems is the accurate modelling of the propagation channel in different scenarios and environments [13]. One of the unexplored scenarios that needs more attention is tunnels. Being a confined environment, propagation behavior in tunnels differs from other environments as it plays the role of an oversized waveguide [38] as shown in Figure 1.9. Deterministic channel models for tunnels include: waveguide models, ray tracing models and numerical methods for solving Maxwell's equations in tunnel environments [39]. These methods suffer from large computational complexity and incomplete description of the propagation environment (scatterers, mobility, traffic, etc.). In addition, the arbitrary shape of arched tunnels makes it hard to describe its internal surface by a canonical coordinate system and, consequently, no analytical formulation is currently available [40]. While various approximate approaches have been proposed, they are more complicated to implement and the computation time may not be acceptable for long-range communication [40, 41]. Another possibility is to make a drastic simplification of the tunnel shape, assuming its cross-section to be either rectangular or circular. Even though this simplification may give sufficient accuracy for an empty tunnel by using modal theory, when the antennas are situated very near the tunnel walls the prediction of the fading becomes less accurate [41].

On the other hand, empirical stochastic models that are obtained from measurements in real traffic conditions describe the specific environment with less computational cost [39]. As the propagation is influenced by many factors (e.g. tunnel geometry, obstacles, nodes setup, traffic), measurements in practical scenarios are required to characterize and model the propagation in tunnels. Several studies have been published based on propagation measurements in tunnels. Some of these studies investigate propagation in subway tunnels [42], where the geometry and traffic conditions are different from road tunnels. Others investigate road tunnels in terms of only path loss [43]. Authors in [44] study the field distribution in the transverse plane and the correlation in both transverse and longitudinal directions. These studies investigate propagation under no traffic conditions and do not include dispersion parameters like the delay spread. On the other hand, the work in [45] suggests that a single-slope model is more adequate for the path loss when there is traffic. Delay spread is measured in [46, 47] and compared to simulation results, but no statistical models are presented. In addition, the delay and Doppler spreads are evaluated in [48] for a V2V scenario in an empty tunnel, where a lognormal model is used to fit their statistical distributions.

1.2.4.2 Multiple antennas and polarization

Multiple antennas can be used at both the mobile unit and the fixed unit to exploit the spatial domain of the radio channel. This will increase the channel capacity and reliability in tunnels. In multipath environments, the condition of low correlation of paths between the Tx and Rx that leads to a good performance of MIMO systems is typically due to the rich scattering environment with distributed obstacles, giving rise to a wide angular spread of rays. However, the structure symmetry of tunnels does not allow for a large spread in the directions of rays. According to the modal theory [49], the superposition of the several hybrid modes supported by the structure is what gives rise to decorrelation among channels. In this case, the maximum degree of freedom of the channel is limited by the number of modes propagating in the tunnel [50]. Thus, the capacity enhancement brought about by MIMO



Figure 1.9: General transverse-electric (TE) and transverse-magnetic (TM) propagation modes in a waveguide structure (Source: radartutorial.eu - waveguides)

techniques in tunnels depends on the wavelength, excitation location, transverse dimensions and range of the tunnel, among others [40].

MIMO systems that exploit the polarization domain have recently gained increasing attention. Orthogonally polarized antennas often have high decorrelation; a major advantage for multiplexing systems. Making use of co-located dual-polarized (DP) antennas allows for compact antenna array design, which is essential for vehicular communications. The restrictions of equipment size, power, and cost can make it difficult, if not impossible, to physically mount the antennas of the vehicle far enough apart to achieve low correlation [51]. As the form factor of the antenna array becomes larger, this causes other challenges in engineering that may restrict MIMO technology (e.g. long cables or several distributed RF-chains). Moreover, such mounting choices are driven not only by performance and cost, but also by aesthetic design considerations [13]. Hence, DP antennas represent an attractive option for vehicular communications. However, when multi-polarized antennas are used, the choice of the polarization at the Tx and the Rx can result in substantially different propagation conditions. Depolarization mechanisms caused by scatterers and antenna design result in gain imbalance and correlation between channel matrix elements; a big disadvantage of DP MIMO. For an extensive literature overview of analytical and experimental studies related to DP channels, see [52-54] and references within. Nonetheless, very limited results on tunnels can be found [39]. It is thus important to explore the impact of antenna polarization on the propagation

characteristics in tunnels.

1.2.5 Simulating the non-stationary fading process

In the literature, various modelling approaches have been proposed to simulate a non-stationary fading channel:

- Different subsequent tap models depending on the delay spread and the BER statistics [21], which lack smooth transitions between the different models.
- "Birth/death" Markov process to account for the appearance and disappearance of delay taps [55], which doesn't account for the MPC drifting from one tap to another.
- Stochastic modelling of the evolution of dynamic scatterers and their delay and angular properties [24], which follows the birth/death approach but adds linear tracking of MPCs in delay and angle domains.
- Geometry-based channel modelling that includes inherently the non-stationary behavior of the channel via the dynamic nature of the scattering environment geometry [25, 26], which has large generation and computation costs.

Another approach to describe the random fading process is parametric modelling [56]. Such models involve a parametric representation of an innovations system driven by white innovations noise. The statistics of the output process are then characterized by the parameters of the innovations system. Sparse (parsimonious, low-dimensional, low-rank) representations of the LTV radio channel have been widely used [57]. We consider an autoregressive (AR) modelling approach for the accurate generation of non-stationary vector (multivariate) processes. This technique belongs to the class of parametric spectral estimation, and employs allpole infinite-impulse response (IIR) filtering to shape the spectrum of uncorrelated Gaussian variates. An AR model is preferred over moving-average (MA) or hybrid ARMA models, as the variations of the mobile channel response resemble a correlated series with low peaks and deep fades [58]. An AR model for wideband indoor radio propagation was first presented in [59] and later applied to UWB channel modelling in [60] for indoor scenarios. Parametric modelling in the frequency domain is also investigated in [61] for WSSUS wideband and UWB channels.

Most existing non-stationary models were extended from their stationary counterpart. A vector time-frequency (VTF) AR model that describes non-WSSUS multivariate processes has been proposed in [62]. The frequency shifts (Doppler shifts), in addition to time shifts, provide an intuitive and physically motivated way of capturing the spectral and temporal correlation of non-stationary vector processes without a severe loss in parsimony. The model is parsimonious for the practically relevant class of underspread vector processes (i.e., processes with rapidly decaying correlation in time and frequency). Based on a system of linear equations with a two-level block-Toeplitz (2LBT) structure, a VTFAR parameters estimator is also presented [62]. In our work, a framework is proposed for long-term vehicular channel simulation based on the VTFAR model for a sparse parametric description of non-stationary multivariate random processes.

1.3 Indoor channel modelling in metallic environments

With the rise of 5G technology, a fourth industrial revolution has emerged, known as Industry 4.0. Industry 4.0 takes the digital technology to a whole new level with the help of interconnectivity through the (industrial) IoT [63]. The IIoT is central to how cyber-physical systems and production processes will transform with the help of big data and analytics. Real-time data from sensors and other information sources helps industrial devices and infrastructures in their decision-making, in coming up with insights and specific actions. Machines are further enabled to automate tasks that previous industrial revolutions could not handle. Hence, the IIoT is crucial to use cases related to connected ecosystems e.g. smart factories. However, wireless propagation in indoor industrial environments, such as shown in Figure 1.10, is challenging. Highly reflective metallic environments are characterized by rich electromagnetic scattering, time and angular dispersion, and can exhibit features of a complex reverberant cavity. While typical indoor environments (e.g., residential and office) show RMS delay spreads of 15-100 ns at 2.4 GHz, highly reverberant environments can reach up to 1200 ns [64].

1.3.1 Reverberation and room electromagnetics

Diffuse scattering combined with the highly metallic surroundings gives rise to electromagnetic reverberation, making this type of radio channel highly suited for the application of the room electromagnetics theory. The room electromagnetics model describes the time-dispersion of signal power, which directly affects the signal quality. A lower signal quality may cause inter-symbol interference and negatively affect communication throughput. There are additional reasons why room electromagnetics is especially suited for radio channel modelling in enclosed metallic environments. Firstly, room electromagnetics provides an elegant way of calculating the signal loss through walls by modelling the two rooms that share the wall as a pair of lossy but coupled electromagnetic reverberation chambers [65]. This can be useful for calculating the signal penetration loss through imperfectly sealed doors. Secondly, the model can easily account for wireless signal absorption and shadowing by persons present in the environment by increasing the "absorption area" parameter contained within the model equations. This feature in particular



Figure 1.10: Rich scattering industrial indoor environments

will allow us to account for persons in the environment as will be discussed in the following section.

1.3.1.1 Room electromagnetics theory

In reflective indoor environments, diffuse scattering is a relevant propagation mechanism in terms of the contribution of the dense multipath components to the total power density. It includes the diffuse scattered fields plus weak specular components after removing all possible specular paths from the measurement data. The diffuse power density may represent up to 95% of the total power [66] in rich scattering environments and can be characterized based on the room electromagnetics theory [67]. Similar to room acoustics [68], room electromagnetics views the indoor environment as a lossy cavity, where all the effective losses can be described by the exponentially decaying tail of the diffuse fields in time. Figure 1.11 shows the theoretical power-delay profile with the LOS and dense MPCs. The decay time constant, also known as the reverberation time (RT), is a function of the volume and the absorption area of the room [65, 69]. A general description of the reverberation time is based on Sabine's reverberation theory [67, 70], which can be expressed as

$$\tau = \frac{4V}{\alpha \, cA} \tag{1.12}$$



Figure 1.11: Theoretical model of room electromagnetics including a LOS and an exponential tail with time constant τ

where V is the room volume, α is the average absorption coefficient of the room surfaces, A is the total surface area and c is the velocity of light.

Several studies were conducted based on room electromagnetics, e.g. [65, 69, 71]. They validate the use of the acoustic reverberation models in electromagnetics, and show that the reverberation is confined in the room where the Tx and Rx are located, and that the RT is location and antenna independent. The RT has previously been used to calculate the effective absorption coefficient as a single parameter that characterizes a room [67]. In addition, the mean received diffuse power can be determined everywhere by knowing RT and the volume of the room [69]. From the assumption of diffuse scattering, the RT allows the determination of the path loss and delay time parameters [71]. Specific absorption rate (SAR) as a basic restriction for RF human exposure is often found numerically from knowledge of the distribution of complex permittivity in the body, and experimental values are scarce. A measurement-based approach based on the RT is a suitable alternative for the assessment of the whole-body averaged SAR [65].

Nonetheless, reverberation models are derived based on several simplifications. Sabine's theory assumes homogeneous repartition of energy within the room, and consequently uniformly distributed absorption, and that the field is completely diffuse. Different approaches have been adopted to obtain more accurate approximations of the reverberation time. Among others, Eyring presented his paper that described the reverberation in highly absorbent enclosures based on the mean free path between reflections [72]. In other words, his approximation is that the number of reflections is constant over time. This approximation can be further improved by introducing a variance to the number of reflections at a given time [68]. In addition, the RT has normally been investigated at a single frequency [65, 67, 69]. Whilst the RT can be estimated using computational-based methods [73], excessive processing time and memory resources are needed especially at higher frequencies.

The measurement-based method in [74] has been used to address the frequency dependency of the RT in the 2-10 GHz band. It showed that the RT decreases for increasing frequency and validated the model by measurement and by comparison to reported results in the literature. At higher frequencies, other work [75] suggested that the indoor scenario ceases to reverberate due to severe path-loss, and the room electromagnetic theory is not applicable anymore at frequencies as high as 94 GHz.

1.3.1.2 Reverberation time and Q-factor

The RT can also be related to the quality factor (Q) of the room. Being regarded as lossy cavities, residential rooms generally have low Q values [76]. In contrast with indoor scenarios, Q is more frequently used to describe the capacity of reverberation chambers (RCs) to store electromagnetic energy. Several works have addressed the determination of Q in RCs [77]. Basically, Q can be obtained either from the power-ratio method (frequency domain) or the decay-time method (time domain). It was reported that the decay-time method produces better estimate of Q than the power-ratio method [77]. Hence, the RT used in the decay-time method is regarded as a very important parameter for the diffuse absorption [67]. From the theory of electromagnetic fields in cavities, Q is defined as the ratio of the energy stored to the energy dissipated in the cavity per cycle of duration 1/f [76]. This can be formulated as

$$Q_i = \frac{2\pi f E}{P_i},\tag{1.13}$$

where E, P_i and f are the energy stored, the power dissipated and the frequency, respectively. Four types of mechanisms contribute to the dissipation of power in cavities: (1) power lost in the walls of the cavity P_1 , (2) power absorbed by lossy objects inside the cavity P_2 , (3) power dissipated due to aperture leakage P_3 , and (4) dissipated power in the receiving antennas load P_4 . The overall Q can then be expressed as [76]

$$Q = \left[\sum_{i=1}^{4} 1/Q_i\right]^{-1}.$$
(1.14)

The first three types of losses exhibit nearly no frequency dependence, while the last type is inversely proportional to the frequency squared [76]. Consequently, at high frequencies, the losses in walls, apertures and objects dominate the power dissipation and Q_4 becomes large with little contribution to the overall Q. Alternatively, the decay-time method relates Q to the RT by the following expression [76]

$$Q = 2\pi f \tau \tag{1.15}$$

1.3.2 Human sensing in a reverberant ship environment

An increasingly common requirement of smart systems is to extract information about the people present in an environment in a device-free way, meaning that



Figure 1.12: Industrial ship environments

humans are not expected to carry any dedicated devices or passive tags. Humansensing is of high importance in the context of IoT: from building automation to surveillance and safety monitoring in the case of natural or man-made disasters. Hence, deploying wireless networks in confined, reflective spaces such as found in metallic warehouses, aircraft cabins, and below-deck ship compartments is essential to the envisioned Industry 4.0 and ITS. In particular, below-deck spaces in ships, such as shown in Figure 1.12, have been a primary focus of a number of studies, exploring the wireless RF propagation and communication performance [78–81]. Current shipboard monitoring systems use extensive lengths of cables to connect a massive number of sensors to control units. Wired installation during ships construction results in a high cost and weight. In addition, ships represent a harsh environment wherein wires are vulnerable to moisture, heat and hazardous elements, making maintenance a very difficult task. On the other hand, wireless communication is a serious challenge in such hostile environments [81].

1.3.2.1 Human sensing techniques

Human sensing is most commonly achieved by sensing a well-defined set of spatiotemporal properties, namely: presence, count, activity, and identity. At the lowest level, human sensing is equivalent to measuring, directly or indirectly, one or more of the ways humans impact their environments (i.e. human traits) from which the spatio-temporal properties can be inferred [82]. These physical traits can be static (e.g. weight, shape, scent, reflectivity, attenuation, emissivity, internal motion) or dynamic (e.g. gait, vibration, sound, external motion), each being the focus of a single or multiple sensing methods. With regard to human counting or occupancy detection, different types of sensing solutions are available today, each having its advantages as well as limitations [82]. Solutions vary in the targeting approach (e.g. counting people through doorways or within certain areas) or the sensing modality (visual, thermal, RF, etc.). Image-based solutions, for example, are prone to blind spots, sensitive to environmental condition like lighting, smoke etc., pose privacy issues and are computationally expensive due to the image processing, which is often based on machine learning algorithms. On the other hand, RF-based solutions have a great potential in overcoming many of those drawbacks [82]. Using RF signals such as Wi-Fi or Zigbee has the benefit of exploiting the deployed networks for sensing as well, without additional infrastructure. RF sensing is mainly based on received signal strength indication (RSSI) or channel state information (CSI). This limits the accuracy of such methods in hostile propagation environments, even with the use of probabilistic and machine learning algorithms [82]. Another limitation is that they usually require extensive training, which must be performed in the same targeted environment and for each number of the supported count range.

Another RF-based solution makes use of the ultra wideband (UWB) technology. UWB is a technology that can be used for both communication and sensing. The IEEE 802.15.4a is the international standard defining the UWB physical and MAC layers. This standard is designed to deliver very accurate measurements of the time of flight of the radio signal, leading to localization with centimeter accuracy. Moreover, it provides simultaneous two-way communications up to 27 Mbps and consumes low energy, making it a perfect fit for battery-powered devices [83]. In 2018, further security aspects are added to the physical layer, forming the 802.15.4z standard. On the other hand, UWB sensing is based on multi-target detection via radar transceivers [82]. An impulse radio (IR) UWB radar transmits a narrow impulse signal that occupies a wide bandwidth in the frequency domain, with fine resolution and high penetration. The radar then receives and analyses the backscattered signal to infer the number of people and distances within the radar range. While it has the best performace among the RF solutions, its need for a dedicated radar sensor adds to the mentioned limitations [82].



Figure 1.13: Impact of the number of people on the power decay rate

1.3.2.2 Room electromagnetics for occupancy estimation

A sensing solution that performs well in certain indoor scenarios, like in a lab or office environment, can not guarantee the same performance in industrial environments. The authors in [84], for example, used the IR UWB radar for people counting in two environments: an indoor room and an elevator with metal structure, and noticed a performance degradation in the elevator compared to the room. As aforementioned, highly reflective environments cause rich multipath scattering. Reflections from targeted humans can easily be buried in the scattered multipath components that can contribute up to 95% of the total power density [66]. Nonetheless, the method proposed in this work exploits the diffuse multipath scattering in such reflective environment to estimate the number of people indoors. The main difference is that, as the environment becomes more reverberant, our technique's performance improves, while other RF techniques' performance deteriorates.

Room Electromagnetics relates the RT to the absorption inside the room. The presence of people in the room will alter the total absorption area, and hence, the RT of the room. Figure 1.13 shows the decrease in the RT as the number of people increases within a room. The inverse relation between the number of people and the RT has been recorded in reverberation chambers using human phantoms [85] and inside cars with real humans [86]. In this work, we exploit this relation to detect the presence and number of people inside ship compartments. This should work in the whole room where the reverberating field fills up. Wherever the person is in the room (e.g. behind a pipe), he will perturb the reverberating field, and this will show up in the RT. The PDeP is calculated based on the CIR, a quantity most wideband communication systems measure via e.g. pilot symbols [87]. This gives



Figure 1.14: Human sensing for occupancy and fall detection using RF signalling between Tx and Rx

our solution the capability to be integrated in communication networks such as UWB systems [83].

1.3.2.3 Doppler analysis for fall detection

Operation onboard ships for example sometimes requires crew members to work alone in isolated rooms. With the lack of reliable communication below-deck, a person falling on the ground can become a serious situation if not detected in time. A complementary feature to occupancy sensing that detects if a person alone has fallen from a standing position is highly desirable. Figure 1.14 shows a schematic of an RF system that can be used for occupancy sensing and fall detection. RF-based fall detection in the literature is mainly based on Doppler radar sensors that scan the environment at rates higher than 1 KHz [88]. Other solutions that use Wi-Fi signals are also available [89, 90]. They use machine learning by extracting features from the CSI that are unique for the fall compared to other normal activities. However, all these studies focus on residential environments, which are far less hostile than industrial ones. In residential environments, it is much easier to extract information from the phase or Doppler domain for velocity or micro-Doppler signature analysis [88]. An example of how the environment can impact the detection performance can be found in [90], where the fall detection precision of a one-class support-vector machine classifier drops from 96% in an anechoic chamber, to 83% in a dormitory room. Hence, this work explores the possibility of fall detection in harsh environments using Doppler analysis of the

CIRs available in wideband communication systems at a much lower rate than radar solutions.

1.4 Measurement equipment

1.4.1 Radio channel sounding

In this work, we focus on stochastic empirical modelling, meaning that we will derive the stochastic models (i.e. the fading parameters) through experimental results based on a channel sounding measurement campaign in a certain environment. This measurement procedure excites the wireless channel at the transmitter then captures the received signal through the use of special measurement equipment such as a channel sounder. In other words, channel sounding is the process of determining the CIR of a transmission radio channel. The concept originated from classic acoustic measuring methods for determining distance. The CIR provides complex, comprehensive information on the impact of the channel of interest on a radio signal, including the magnitude and phase of the signal. As shown in Figure 1.4, signal echoes caused by reflections, distortions due to diffraction and scattering effects, shadow effects caused by buildings and trees, and even weather-related effects such as rain and snow have an influence on the radio channel, which is called fading. In a SISO system, multipath fading can degrade the signal quality. On the other hand, with the development of MIMO systems, it can enhance channel capacity and improve QoS. In order to model the fading process, channel sounding is used to capture the multidimensional spatial-temporal channel characteristics and estimate the fading parameters.

1.4.2 MIMOSA channel sounder

Channel measurements are performed with the Multi-input Multi-output System Acquisition (MIMOSA) radio channel sounder [91]. Table 1.1 summarizes the main specifications of MIMOSA. It uses a carrier frequency of 1.35 GHz. This carrier frequency lies conveniently within the operating band of the LTE-V standard [92] radio interface that supports V2I communications (named Uu-interface), which operates in the licensed 2 GHz band (880-2690 MHz). Orthogonal frequency division multiplexing (OFDM) is used to encode up to 8 parallel transmit channels, and by connecting each to a two-port RF switch with 50 dB isolation, a total of 16×16 channels are measured at the cost of channel acquisition time. Therefore, 2 OFDM symbols are successively sent, the first one for one polarization and the other one for the orthogonal polarization. At Rx, the signals measured at the two outputs of each bi-polarized patch antenna are simultaneously stored. With a symbol duration of ≈ 82 µs and by taking the duration of the preamble and of the

Parameter	Setting
center frequency	1.35 GHz
bandwidth	80 MHz
Tx and Rx polarization	H/V
OFDM subcarriers per channel	819
OFDM symbol duration T_S	81.92 μs
cyclic prefix duration T_{CP}	$0 \le T_{CP} \le T_S$
full channel acquisition time	$2(T_S + T_{CP}) \le 327.68 \ \mu s$

Table 1.1: MIMOSA Channel Sounder Specifications

cyclic prefix into account, the acquisition time of a full polarimetric channel matrix (deduced from the reception of 2 successive symbols) is about 300 µs.

The total number of subcarriers of the OFDM scheme is 8192 occupying a total bandwidth of 100 MHz. However, a 200 Msamples/s analog-to-digital converter (A/D) is used at Rx such that the transmitting band has been reduced to 80 MHz. This is performed by suppressing the subcarriers situated at the lower and higher frequency band of the spectrum. The subcarriers can be allocated either to only one antenna or distributed among all Tx antennas. As an example with 8 Tx antennas, Figure 1.15 shows the distribution of the 1024 subcarriers per antenna, their spacing being equal to 97.66 kHz. The channel sounder is fully parallel; the data for all transmit antennas are simultaneously modulated onto subcarriers using interleaved frequency division multiplexing.

1.4.3 Hardware and antenna features

The Tx chain is presented in Figure 1.16. It consists of the following parts: 1) "time and position records information such as the GPS position and 3D position of the antenna array (yaw, pitch, roll). 2) "signal manager" is a computer embedded into a chassis that includes the FPGA-based digital processing cards to generate and send the signals. The baseband Tx module consists of four FPGA-400 MHz cards, each including two 500 Msample/s 16-bit digital-to-analog (D/A) converters and 1 GB RAM. 3) "RF module" where the baseband signals are mixed at 1.3 GHz and the different stages are all synchronized with the 10 MHz local oscillator. The RF signals are sent to each antenna after being processed in the RF filters and mixers with output power values between 0.01 W to 1 W per RF chain (maximum power of 8 W for the 8 outputs). Figure 1.17 presents the Tx unit of the sounder.

Similarly, the Rx chain is composed of several parts illustrated in Figure 1.18. The RF module transposes the received signals to baseband. The AGC adjusts the signal strength to optimize the signals at the input of the analog-to-digital converter



Figure 1.15: Subcarriers allocation for 8 Tx antennas [91]



Figure 1.16: schematic of the MIMOSA channel sounder Tx chain

(A/D). The digital signals are then processed by the digital processing unit to compute in real-time the complex CTF H(f). The signal processing module includes 2 FPGA cards with eight 200 MSample/s converters, each FPGA simultaneously processing 4 dual-port antennas. In the FPGAs, an OFDM symbol synchronization algorithm is applied to the received preamble and FFTs are performed in parallel. All modules are synchronized to a 10 MHz rubidium clock. The data is sent to an embedded PC either for display or record on a 300 GB hard drive. The GPS position and 3D antenna array orientation are tagged along the data. The receiver has 16 inputs such that the processing is performed in parallel. The bandwidth is 100 MHz and the automatic gain control (AGC) dynamic is 64 dB with 0.5 dB step. Figure 1.19 shows pictures of the Rx unit. With such architecture, no post-processing is needed and the binary-format files containing the MIMO channel matrices can be directly used for extracting the channel characteristics. Each



Figure 1.17: MIMOSA channel sounder Tx hardware parts



Figure 1.18: schematic of the MIMOSA channel sounder Rx chain



Figure 1.19: MIMOSA channel sounder Rx hardware parts

channel coefficient is corrected by the AGC gain and by the correction factors of the Tx-Rx chains measured during a calibration procedure.

The channel sounder is equipped with different types of antennas. A dualpolarized patch antenna of horizontal (H) and vertical (V) polarization is used for directional propagation modelling. The peak gain is 7.4 dBi and the HPBW is 120°. The elementary dual-polarized patch antenna was designed with CST Microwave Studio software. The length and width of the ground plane is 103 mm, the dimension of the metallic patch being about 1.4 times smaller. The measured bandwidth, for a $|S_{11}|$ of -10 dB, is 75 MHz, whereas the port isolation and cross polarization are larger than 30 dB and 25 dB across the whole frequency band, respectively. For the omni-directional propagation modelling, a wideband antenna is used from Cobham Antenna Systems, model XPO2V-0.8-6.0/1441. It features vertical polarisation, 0.8 - 6 GHz bandwidth, and 2 dBi gain. Figure 1.20 shows the different types of antennas mounted on the top of the measurement van carrying the MIMOSA Rx.

1.5 Outline and contributions

The main aim of this work is the modelling of wireless radio channels for different scenarios and applications related to 5G future networks, that will help develop more efficient and robust communication and sensing solutions. The first part of this dissertation (Chapter 2-4) is dedicated to studying the behavior of wireless channels for vehicular communications with a focus on stochastic modelling of propagation parameters for the non-stationary fading process. The goal of the second part (Chapter 5 and 6) is to investigate the indoor propagation channel



Figure 1.20: omni-directional and patch antennas used for measurements with MIMOSA

in highly reflective industrial scenarios. The reverberant characteristics of such environments are modelled based on the theory of room electromagnetics, and exploited for human sensing applications to highlight their importance and utility.

In Chapter 2, the investigation of the non-stationary fading process is presented based on V2I mobile channel measurements in a sub-urban environment. The nonparametric LSF estimator is presented and used to estimate the stationarity time based on the CCF. The non-stationary fading parameters are statistically modelled for different polarizations, and application relevance in terms of channel capacity and diversity techniques is discussed.

Chapter 3 focuses on modelling the non-stationary mobile channel in tunnels. It uses the stationarity analysis framework presented in Chapter 2 in addition to DP MIMO channel analysis. Based on V2I measurements in rectangular and arched tunnels, the impact of traffic density and antenna characteristics (directivity and polarization) on the non-stationary fading parameters are investigated.

Chapter 4 discusses the parametric modelling of the non-stationary fading channel via a VTFAR approach. The approach is applied to simulate the measured tunnel propagation channel from Chapter 3. Stability of such model is investigated and the model is validated by comparing the parametric and non-parametric spectra.

In Chapter 5, the indoor reverberant environment of industrial ships is modelled based on the room electromagnetics theory. RF-based occupancy estimation method is introduced that makes use of the reverberation time parameter. The method is experimentally validated in a below-deck ship compartment using radio channel sounder equipment, and COTS UWB devices. In addition, a Doppler-based fall detection method is proposed as a complementary technique for safety monitoring and alert systems.

In Chapter 6, attention is paid to the frequency-dependency of the reverberation time up to 40 GHz. Indoor measurements in a lab environment is utilized to model

the RT, Q-factor, and the average absorption coefficient of the room. The model is validated by comparison to previous reported studies.

Finally, Chapter 7 concludes this book with a summary of the accomplished work, and proposes some directions for future research.

1.6 Publications

1.6.1 A1 International Journals

(publications in journals listed in the ISI Web of Science)

1.6.1.1 As first author

- [MY1] M. Yusuf, E. Tanghe, F. Challita, P. Laly, D. P. Gaillot, M. Liénard, L. Martens, W. Joseph, "Stationarity Analysis of V2I Radio Channel in a Suburban Environment", *IEEE Transactions on Vehicular Technology*, 2019.
- [MY2] M. Yusuf, E. Tanghe, M. -T. Martinez-Ingles, J. Pascual-Garcia, J. -M. Molina-Garcia-Pardo, L. Martens, W. Joseph, "Frequency-Dependence Characterization of Electromagnetic Reverberation in Indoor Scenarios Based on 1–40 GHz Channel Measurements", *IEEE Antennas and Wireless Propagation Letters*, 2019.
- [MY3] M. Yusuf, E. Tanghe, P. Laly, F. Challita, B. Lannoo, R. Halili, R. Berkvens, M. Weyn, L. Martens, D. P. Gaillot, M. Lienard, W. Joseph, "Experimental Study on the Impact of Antenna Characteristics on Non-Stationary V2I Channel Parameters in Tunnels", *IEEE Transactions on Vehicular Technology*, 2020.
- [MY4] M. Yusuf, E. Tanghe, B. De Beelde, P. Laly, M. Ridolfi, E. De Poorter, L. Martens, D. P. Gaillot, M. Lienard, W. Joseph, "Human Sensing in Reverberant Environments: RF-Based Occupancy and Fall Detection in Ships", *IEEE Transactions on Vehicular Technology*, 2021.
- [MY5] M. Yusuf, E. Tanghe, F. Challita, P. Laly, D. P. Gaillot, M. Liénard, L. Martens, W. Joseph, "Autoregressive Modeling Approach for Non-stationary Vehicular Channel Simulation", *IEEE Transactions on Vehicular Technology*, 2021.

1.6.1.2 As co-author

[MY6] F. Challita, P. Laly, M. Yusuf, E. Tanghe, W. Joseph, P. Degauque, M. Liénard, D. P. Gaillot, "Channel Correlation-Based Approach for Feedback

Overhead Reduction in Massive MIMO", *IEEE Antennas and Wireless Propa*gation Letters, 2019.

- [MY7] F. Challita, P. Laly, M. Yusuf, E. Tanghe, W. Joseph, M. Liénard, D. P. Gaillot, P. Degauque "Massive MIMO Communication Strategy Using Polarization Diversity for Industrial Scenarios", *IEEE Antennas and Wireless Propagation Letters*, 2020.
- [MY8] B. De Beelde, E. Tanghe, M. Yusuf, D. Plets, W. Joseph, "Radio Channel Modeling in a Ship Hull: Path Loss at 868 MHz and 2.4, 5.25, and 60 GHz", *IEEE Antennas and Wireless Propagation Letters*, 2021.
- [MY9] B. De Beelde, A. Lopez, D. Plets, M. Yusuf, E. Tanghe, W. Joseph, "Directive mmWave radio channel modeling in a ship hull", *International Journal of Microwave and Wireless Technologies*, 2021.

1.6.2 C1 International conferences

1.6.2.1 As first author

- [MY10] M. Yusuf, E. Tanghe, L. Martens, P. Laly, D. P. Gaillot, M. Liénard, P. Degauque, W. Joseph, "Experimental Investigation of V2I Radio Channel in an Arched Tunnel", *13th European Conference on Antennas and Propagation (EuCAP)*, Krakow, Poland, 31 March-5 April 2019.
- [MY11] M. Yusuf, E. Tanghe, F. Challita, P. Laly, D. P. Gaillot, M. Liénard, B. Lannoo, R. Berkvens, M. Weyn, L. Martens, W. Joseph, "Experimental Characterization of V2I Radio Channel in a Suburban Environment", *13th European Conference on Antennas and Propagation (EuCAP)*, Krakow, Poland, 31 March-5 April 2019.
- [MY12] M. Yusuf, B. D. Beelde, E. Tanghe, E. D. Poorter, L. Martens, P. Laly, D. P. Gaillot, M. Liénard, W. Joseph, "Estimation of the Number of Persons in a Reverberant Environment Using Bistatic Radar", *14th European Conference* on Antennas and Propagation (EuCAP), online, 15-20 March 2020.
- [MY13] M. Yusuf, E. Tanghe, L. Martens, W. Joseph, F. Challita, P. Laly, D. P. Gaillot, M. Liénard, "Experimental Characterization of Non-Stationary V2I Radio Channel in Tunnels", *IEEE 91st Vehicular Technology Conference* (VTC2020-Spring), online, 25-28 May 2020.

1.6.2.2 As co-author

[MY14] F. Challita, P. Laly, M. Liénard, D. P. Gaillot, E. Tanghe, M. Yusuf, W. Joseph "Impact of Polarization Diversity in Massive MIMO for Industry 4.0",

European Conference on Networks and Communications (EuCNC), Valencia, Spain, 18-21 June 2019.

[MY15] B. De Beelde, E. Tanghe, M. Yusuf, D. Plets, E. De Poorter, W. Joseph, "60 GHz Path Loss Modelling Inside Ships", 14th European Conference on Antennas and Propagation (EuCAP), online, 15-20 March 2020.

1.6.3 Patents

[MY16] M. Yusuf, E. Tanghe, L. Martens, W. Joseph, "People Detection", European Patent Publication No. WO2021180879, European Patent Office, 2020.

1.6.4 Awards

[MY17] Best paper award: M. Yusuf, B. De Beelde, E. Tanghe, P. Laly, D. P. Gaillot, M. Lienard, Eli De Poorter, L. Martens, Wout Joseph, "Fall Detection of a Person in a Reverberant Environment Using Bistatic Radar", URSI Benelux Forum, December 2019.

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Part I

Outdoor Channel Modelling for Vehicular Communications

2

Mobile channel modelling in a sub-urban environment

In this chapter, we investigate the V2I channel measured in a suburban environment using the local scattering function (LSF) framework discussed in Section 1.2. We investigate the stationarity region in time based on the channel correlation function (CCF), and compare it to the empirical measure of collinearity. To completely characterize such doubly dispersive channels, the values of the coherence region are obtained and used to investigate system design relevance, e.g., the effect of non-stationarity on the assumption of ergodic capacity and effective diversity [1].

Based on the LSF, power profiles of the delay (PDeP) and Doppler (PDoP) can be estimated, and subsequent analysis of the corresponding second central moments can be performed. The RMS delay and Doppler spreads are evaluated in [2] for several V2V scenarios, where a bimodal Gaussian mixture is used to model their statistical distribution. Other studies show that the distributions of the spreads follow a lognormal model [3–5]. However, these studies do not take channel polarization into consideration. We statistically model the delay and Doppler spreads of the channel across stationarity regions for horizontal and vertical polarization. In addition, the small-scale fading of the wideband channel taps is modelled.

The chapter is structured as follows. We describe the characterization of the stationarity region and omni-directional propagation modelling in Section 2.1. The directional dual-polarized propagation modelling is presented in Section 2.2. We draw conclusions in Section 2.3.



Figure 2.1: Tx as a roadside unit (left) and the omnidirectional antenna used at both Tx and Rx (right)

2.1 Omni-directional propagation modelling

2.1.1 Measurements setup and scenario

Channel measurements are performed with the MIMOSA radio channel sounder presented in Section 1.4. It uses B = 50 MHz of transmission bandwidth for this measurement campaign with a single wideband omni-directional antenna at both the transmitter (Tx) and the receiver (Rx). Measurements have been carried out at the campus of the university of Lille in France. Figure 2.1 shows the Tx as the roadside unit. The environment can be categorized as suburban: the road is narrow with one lane in each direction, and buildings and vegetation are set back 5-8 m from the curb. In order to follow the V2I scenario, the Tx is placed on the curb with the antenna at 2.5 m height. The Rx antenna is mounted on the rooftop of the van carrying the Rx inside. The van moves along the road at 40 km/h speed, crossing Tx position during a total route of 500 m shown in Figure 2.2. The radio channel is sampled with a snapshot repetition time $t_s = 975.3 \ \mu s$. With this parameters setting, we capture a total number of snapshots X = 49536 snapshots, each with Y = 512 samples in frequency domain, and we achieve a maximum Doppler shift of $1/2t_s = 512$ Hz and a minimum resolvable delay resolution of 20 ns.



Figure 2.2: Top view of measurement route at the university of Lille campus. Tx location is marked with a yellow pin and Rx van moves from point B to A (Map data ©2018 Google).

2.1.2 Non-parametric local scattering function estimation

Due to the high mobility of Tx, Rx and scatterers in vehicular communications, the environment is rapidly changing, and the observed fading process is non-stationary. The channel sounder provides a sampled measurement of the continuous channel transfer function (CTF) H(t, f) that is time-varying and frequency selective. We consider the discrete CTF to be

$$H[m,q] = H(t_s m, f_s q) \tag{2.1}$$

where the frequency resolution $f_s = B/Y$, the time index $m \in \{0, ..., X - 1\}$ and the frequency index $q \in \{0, ..., Y - 1\}$

Since the environment changes with a finite rate, we can approximate the fading process to be locally stationary for a region with finite extent in time and frequency. This allows us to locally estimate the power spectral density of the non- wide-sense stationary uncorrelated scattering (WSSUS) fading process, in order to describe its TF-varying statistical behavior. This local region is defined by M samples in time and N samples in frequency. Using a sliding window over the recorded CTF, we estimate a discrete version of the TF-dependent LSF in (1.3). As aforementioned, the observed fading process in vehicular channels shows a much stronger violation of the WSS assumption than the US assumption. Hence, in this work, we focus on



Figure 2.3: Illustration of the windowing used for the LSF estimation applied to the discrete CTF H[m,q]

the time variation of the non-stationary fading channel and we assume the channel to be stationary over the whole bandwidth, i.e. N = Y. This is in correspondence with previous studies suggesting the stationarity bandwidth to have much larger values in similar scenarios [6].

Estimating the power spectrum of a process requires statistically independent realizations of the same process, which is very difficult to obtain using measurements. When tapering the measurement data using multiple orthogonal windows, we obtain multiple independent spectral estimates from the same measurement by estimating the spectrum of each individual taper. The total estimated power spectrum is thus calculated by averaging over all tapered spectra.

For the TF-sampled CTF H[m, q], we use the discrete version of the LSF multitaper-based estimator proposed in [7, 8]. The applied orthogonal 2-D tapering windows are computed from K and L orthogonal tapers in time and frequency domains, respectively. We estimate the LSF for consecutive regions in time using a sliding window with the size of $M \times N$ samples in TF domain. The time index of each region $r_t \in \{0, ..., \frac{X-M}{\Delta_t} - 1\}$ corresponds to its center, while Δ_t denotes the sliding time shift between consecutive estimation regions as shown in Figure 2.3. The LSF estimate is formulated as

$$\hat{C}[r_t, n, p] = \frac{1}{KL} \sum_{w=0}^{KL-1} \left| H^{(G_w)}[r_t, n, p] \right|^2$$
(2.2)

where $n \in \{0, ..., N-1\}$ denotes the delay index and $p \in \{-M/2, ..., M/2 - 1\}$

denotes the Doppler index. The tapered spectral estimate $H^{(G_w)}$ is calculated as

$$H^{(G_w)}[r_t, n, p] = \sum_{q'=-N/2}^{N/2-1} \sum_{m'=-M/2}^{M/2-1} G_w[m', q'] \\ \times H[m' + \Delta_t r_t + M/2, \ q' + N/2] \ e^{-j2\pi(pm'-nq')}$$
(2.3)

where the relative time and frequency indexes within each region are m' and q', respectively, and the window functions G_w are localized within the $[-M/2, M/2 - 1] \times [-N/2, N/2 - 1]$ region. The tapers are chosen as the discrete prolate spheroidal sequences (DPSS) [9] for their optimal side-lobe suppression and pairwise orthogonality.

2.1.3 Stationarity region estimation

For calculating the stationarity region, we first need to estimate the LSF assuming a minimum region of stationarity. The size of this region should be small enough not to include non-stationarity, while having enough resolution in time and frequency to capture the correlation in the CCF. Previous studies suggest a stationarity frequency range larger than the measured bandwidth (above 150 MHz according to [6]). Hence, we focus in our analysis on the stationarity time. and include the whole bandwidth of N = Y = 512 samples. We choose the dimension in time domain M = 128 samples corresponding to 124.8 ms. This needs to be validated after we calculate the stationarity time; that it is indeed larger than the assumed value. The sliding time shift is selected to be half of the region dimension, i.e. $\Delta_t = 64$ samples, and the number of used tapers is K = 3 and L = 3 in both time and frequency domains to balance the noise variance and the square bias [6]. With these parameters, we obtain a LSF estimate every 62.4 ms of delay resolution $\tau_s = 1/B = 20$ ns, and Doppler resolution $v_s = 1/(Mt_s) = 8$ Hz.

The stationarity region represents the region in time and frequency within which the LSF is highly correlated. The stationarity time can be calculated from the spread of the CCF about the origin in the Doppler lag direction, as shown in (1.7). We use a discrete time implementation of the CCF in (1.4), omitting the explicit dependence of CCF on $\Delta \tau$ and only considering the Δv dependence. Hence, the discrete CCF is the 3-D Fourier transform of the LSF estimate

$$\hat{A}[\Delta m, \Delta q, r_{\Delta v}] = \mathbf{F}^3\{\hat{C}[r_t, n, p]\}$$
(2.4)

where Δm , Δq and $r_{\Delta v}$ are the time lag, frequency lag and Doppler lag indexes, respectively. Similarly, we can write the CCF Doppler moment in discrete form as

$$\hat{s}^{(r_{\Delta v})} = \frac{1}{\|\hat{A}\|_1} \sum_{r_{\Delta v}} \sum_{\Delta q} \sum_{\Delta m} |r_{\Delta v}| |\hat{A}[\Delta m, \Delta q, r_{\Delta v}]|$$
(2.5)



Figure 2.4: CCF spread in the Doppler lag direction over the entire route

from which the stationarity time can be evaluated as

$$T_{\rm s} = \frac{1}{\hat{s}^{(r_{\Delta v})}}.\tag{2.6}$$

The bound on LSF variation and the accuracy of approximating LSF to be constant within the stationarity region are provided in [10].

Based on (2.4), the LSF correlation can be determined by the CCF spread. Figure 2.4 shows the marginal CCF as a function of the Doppler lag, by summing over the other variables. As expected for a correlation function, the CCF is symmetric and has its maximum at the origin. According to the calculations done to our measurement data of 48 s, we estimate a stationarity time $T_s = 567$ ms. This is indeed larger than the assumed minimum value of 124.8 ms used for LSF estimation.

In order to get an intuitive understanding regarding the influence of the scenario, a simpler alternative definition of the stationarity time can be used as $\overline{T}_s = 1/\Delta v_{max}$, where the maximum Doppler correlation lag Δv_{max} (i.e. the largest Δv for which CCF is effectively nonzero) is used instead of the weighted summation in (2.5). Consequently, this definition gives a lower bound of T_s [10]. The violation of WSSUS assumptions can be associated with correlated scatterers corresponding to the same physical object (e.g. building surface). Assuming a maximum angular spread and Doppler shift of the scatterers in our scenario to be $\delta = 4^{\circ}$ and $v_{max} = 50$ Hz, respectively, implies $\Delta v_{max} \approx 2v_{max}\sin(\delta/2) = 3.49$ Hz [10]. From Figure 2.5, the marginal CCF drops to 10% of its peak value at $\Delta v = 3.9$ Hz,



Figure 2.5: Mean LRS versus the corresponding threshold applied to the collinearity of LSF

matching well with our assumptions. This yields $\overline{T}_s = 287 \text{ ms} < T_s$. Hence, as the relative speed increases or the scenario changes, e.g. to an urban area with denser scatterers of larger angular spread, the stationarity time is expected to decrease accordingly, which is evident in the results found in [6].

2.1.4 LSF collinearity comparison

Another method of measuring stationarity that is used in the literature is via the collinearity of LSF. The collinearity is a bounded metric $\in [0, 1]$ that compares different power spectra. First, the collinearity between each two time instances of the LSF is computed for the entire route as shown in (1.6). Secondly, the local region of stationarity (LRS) is estimated as the time span during which the collinearity exceeds a certain threshold. Being an empirical measure, collinearity results are highly dependent on the selection of the threshold value. Figure 2.5 shows the mean LRS calculated from our measurement data versus the applied threshold value. For the mean LRS to have the same value of $T_s = 567$ ms, the threshold is found to be 0.95.

While T_s is estimated for the entire route, LRS on the other hand is estimated per time instance. In order to compare both measures, we calculate a local CCF per time instance over regions of 1.25 s. The local marginal CCF spread in the Doppler lag direction is depicted in Figure 2.6 for the entire route. Notice the increase



Figure 2.6: Local CCF spread in the Doppler lag direction per regions of 1.25 s



Figure 2.7: Stationarity time and LRS for the entire route

in the CCF spread around the time Rx crosses Tx position (35 s), indicating a smaller stationarity time. Figure 2.7 compares T_s and LRS with the 0.95 threshold value over the entire route. The minimum values of T_s and LRS are 337 ms and 62.42 ms, respectively. Although some correlation can be observed between the two metrics (Pearson correlation coefficient of 0.37), the variance of T_s around the mean value is smaller compared to LRS (0.009 and 0.024, respectively). Indeed, the

stationarity time represents a characteristic of the entire propagation environment. While large-scale parameters like coherence time is expected to change over time, T_s should not change much on a time instance basis. Another difference between the two metrics is that LRS values are discrete, confined only to multiples of the minimum time difference between instances of the LSF, while T_s can take any value. Hence, we conclude that the stationarity time T_s based on the CCF gives a more accurate characterization of the channel.

2.1.5 RMS delay and Doppler spreads modelling

The second-order central moments of the PDeP and PDoP are of great importance and relevance to fading channels characterization and systems design. They have been usually assumed constant for a certain environment. However, the nonstationarity of vehicular channels allows such parameters to be defined only within a local region of stationarity. Therefore, it is reasonable to characterize the delay and Doppler spreads as time-varying channel parameters.

The PDeP \hat{P} and PDoP \hat{Q} are the projections of the LSF estimate on the delay and Doppler domains, respectively. They can be regarded as the sampled estimate of P_{TF} and Q_{TF} from (1.9) as

$$\hat{P}[r_t, n] = \sum_{p=-M/2}^{M/2-1} \hat{C}[r_t, n, p],$$
$$\hat{Q}[r_t, p] = \sum_{n=0}^{N-1} \hat{C}[r_t, n, p].$$
(2.7)

Based on the estimated profiles, the time-varying RMS delay and Doppler spreads can be calculated, respectively as

$$\hat{\sigma}_{\tau}[r_t] = \sqrt{\frac{\sum_{n=0}^{N-1} (n\tau_s)^2 \hat{P}[r_t, n]}{\sum_{n=0}^{N-1} \hat{P}[r_t, n]} - \left(\frac{\sum_{n=0}^{N-1} n\tau_s \hat{P}[r_t, n]}{\sum_{n=0}^{N-1} \hat{P}[r_t, n]}\right)^2}$$
(2.8)

and

$$\hat{\sigma}_{\upsilon}[r_t] = \sqrt{\frac{\sum_{p=-M/2}^{M/2-1} (p\upsilon_s)^2 \hat{Q}[r_t, p]}{\sum_{p=-M/2}^{M/2-1} \hat{Q}[r_t, p]} - \left(\frac{\sum_{p=-M/2}^{M/2-1} p\upsilon_s \hat{Q}[r_t, p]}{\sum_{p=-M/2}^{M/2-1} \hat{Q}[r_t, p]}\right)^2$$
(2.9)

For the non-stationary channel, the fading parameters can be accurately evaluated within each stationarity region, so that the channel modelling becomes physically meaningful. Based on our estimation of the stationarity time, the corresponding number of samples in time domain M = 580 samples. Hence, the LSF estimate is recomputed using a sliding time shift of half the stationarity region dimension.

In Figure 2.8, the PDeP and PDoP from the measurements are depicted. From 0 to 35 s, Rx is approaching Tx with an average speed of 40 km/h, which can be seen from the decreasing delay of the LOS in the PDeP and the positive Doppler shift of 50 Hz in the PDoP. At 35 s, Rx crosses Tx position, resulting in the minimum LOS delay and the Doppler shift from positive to negative 50 Hz. After that, Rx starts to move away from Tx, hence the LOS delay starts to increase again while the Doppler shift remains around negative 50 Hz. Several MPCs can be observed in the profiles. Components from fixed scatterers are showing in the PDoP with less power and Doppler shifts between +/- 50 Hz, while short lasting components resulting from moving scatterers in both directions can reach higher positive and negative Doppler shifts.

Based on the estimated profiles, the time-varying RMS delay and Doppler spreads can be calculated using (2.8, 2.9). Before calculating the spreads, preprocessing is carried out separately for each stationarity region. No significant components are found with delay values larger than 3 μ s, so we limit the LSF to this value. In order to avoid spurious and noise components, we decide on a power threshold below which we set all the components of the estimated LSF to zero. The threshold is chosen to be 6 dB above the noise level [11].

The RMS delay and Doppler spreads are shown in Figure 2.9. The two parameters show quite similar behaviors, indicating a high correlation between both spreads. The Pearson correlation coefficient is calculated as 0.45 over the entire route. The mean of the spread values (48.91 ns and 11.82 Hz) are much smaller than typical values in cellular scenarios (0.1-10 μ s) due to the dominant LOS condition [12]. Few studies of vehicular channels in the 2 GHz band are available in the literature. The work in [13] reports a delay spread of 102 ns in an urban T-intersection for obstructed LOS, and 53 ns in an expressway LOS scenario at 2.4 GHz. However, the mean values or statistics are not mentioned. The V2V channel is characterized in an urban environment in [14] at 2.3 and 5.25 GHz. It shows that the mean delay spread slightly decreases at the higher frequency (33.3 ns to 28.3 ns), which can be considered insignificant. In the 5 GHz band, several studies in similar scenarios report mean delay spread values that are in the same range of our results (e.g. 40-50 ns in [2], 45 ns in [3], 47 ns in [5] and 35.8 ns in [15]). As reported in [2], other vehicles driving beside Tx and Rx may not represent relevant scatterers. This is because the placement of the antennas in our setup is slightly above the other vehicles. Large scattering objects such as trucks, buildings or metallic structures constitute more relevant MPCs.



Figure 2.8: Time-varying PDeP (a) and PDoP (b) for the scenario of crossing Tx position at 35 s with constant speed of 40 km/h



Figure 2.9: Time-varying RMS delay and Doppler spreads of the crossing scenario with constant speed of 40 km/h

In order to statistically characterize the spreads over the entire route, we use the Kolmogorov-Smirnov (KS) test [16] to select the distribution by comparing the p-value of different models: lognormal, normal, Nakagami, Rayleigh, Weibull, and Rician. It is found that the lognormal distribution gives the best fit to the measured parameters among the candidate models. Table 2.1 summarizes the details of the lognormal distribution for both parameters. We also include the maxima of the spreads, as they represent critical values for communication systems.

A measure of the channel selectivity that is directly related to the delay and Doppler spreads is the coherence region. T_c and F_c are calculated from the maximum RMS Doppler spread and delay spread, respectively, according to (1.10). Based on our measurements, we obtain $T_c = 4.97$ ms and $F_c = 1.62$ MHz. This results in a coherence region $T_cF_c \approx 8 \times 10^3 \gg 1$ indicating that the channel is dispersion-underspread (i.e the channel's dispersion spread in both delay and Doppler is small). Mainly all real-world radio channels are dispersion-underspread, because the delay and Doppler of any propagation path are both inversely proportional to the speed of light. In order to verify the other part of the inequality in (1.11), we need to calculate the stationary region. We use the estimated stationarity time $T_s = 567$ ms. For the stationarity bandwidth, we adopt the minimum value of $F_s = 150$ MHz reported for similar scenarios in [6]. Hence, the stationarity region is considered to be $T_sF_s \approx 8.5 \times 10^7$, verifying that the channel is indeed

Spread	Mean	Max.	KS-test p-value	$\mu(\log)$	$\sigma(\log)$
$\hat{\sigma}_{ au}$	48.91 ns	98.49 ns	0.092	3.86	0.24
$\hat{\sigma}_{\upsilon}$	11.82 Hz	32.03 Hz	0.722	2.36	0.46

Table 2.1: Statistics of the rms delay and doppler spreads ($\hat{\sigma}_{\tau}, \hat{\sigma}_{\upsilon}$) log-normal distributions

doubly-underspread (DU).

2.1.6 Stationarity application relevance

The assumptions of WSSUS fading channel have lead to the simplification of transceivers design, simulation, and evaluation of many communication systems. Long-term channel properties are evaluated and assumed stationary, while dispersions are regarded as results of uncorrelated scatterers. Unfortunately, practical channels, specially in vehicular communications, do not satisfy these assumptions; this influences the performance of such systems. For example, the gain of transmission methods utilizing adaptive modulation, channel coding, diversity in time, frequency, delay or Doppler is limited by the amount of correlation in each domain of the channel [17, 18]. In this section, we briefly discuss the relevance of the non-stationarity characterization to some practical aspects as suggested in [10].

2.1.6.1 Ergodic capacity

It is well known that in order to achieve ergodic capacity, a very long Gaussian codebook is required, where the length is dependent on the dynamics of the fading process. In particular, it must be long enough for the fading to reflect its ergodic nature, i.e. the coding should cover numerous independent identically distributed (i.i.d.) fading realizations [1]. This can be formulated as

$$C_{erg} = \mathbb{E}[B \log_2(1+\gamma)] = \int B \log_2(1+\gamma)P(\gamma) \,\mathrm{d}\gamma \tag{2.10}$$

where γ is the instantaneous signal-to-noise ratio (SNR) with the channel state perfectly known to Rx. Whether sufficient averaging can be achieved for this equality to hold depends on the number of i.i.d. fading coefficients offered by the channel.

For double-selective channels, independent fading coefficients are obtained every T_c in time and F_c in frequency, and the fading statistics remain constant over a region of T_sF_s . Hence, the value $N_i = T_sF_s/(T_cF_c)$ approximately characterizes the number of i.i.d. fading coefficients offered by the channel. For the WSSUS channels, $T_sF_s \to \infty$ so that N_i is large enough and C_{erg} can be achieved. However, as the stationarity region decreases, C_{erg} can only be defined for sufficiently large N_i . Based on our measurement, Figure 2.10 shows the value of N_i across



Figure 2.10: Number of i.i.d. channel realizations per stationarity region across the entire route

different regions of stationarity in time. It is important to note that the value of N_i changes across different stationarity regions due to the variation of the size of the coherence region.

In order to illustrate the (in-)validity of the ergodic assumption for this channel, we simply calculate the capacity of a Rayleigh fading channel using different values of N_i . This is not the ergodic capacity which is defined only as $N_i \rightarrow \infty$, but rather the capacity supported by the stationarity region's i.i.d realizations. Calculating the ergodic capacity in this case would span different stationarity regions and thus would not equal the ensemble average over the Rayleigh distribution.

Figure 2.11 shows the capacity versus mean SNR by averaging over the maximum, mean and minimum values of N_i based on our measurements. We compare these to the ergodic capacity (WSSUS channel) calculated from the ensemble average of the Rayleigh distribution. Table 2.2 lists the relative error of the capacity between each case and the WSSUS channel. These results indicate that the channel may not support coding schemes with enough averaging for the validity of the ergodic capacity. Such scenarios can then be characterized using the outage capacity [1]. Unlike the ergodic scenario, schemes designed to achieve outage capacity allow for channel errors. The capacity-versus-outage performance is determined by the probability that the channel cannot support a given rate, i.e. an outage probability is associated to any given rate.



Figure 2.11: Channel capacity averaged over different N_i values for several SNRs using *i.i.d.* Rayleigh coefficients

	WSSUS	Min.	Mean	Max.
N_i	∞	622	2020	7660
RE (%)	0	2.15	1.23	0.63

Table 2.2: Relative error (RE) between the capacity for several N_i values and the WSSUS channel

2.1.6.2 Fading mitigation

The stationarity and correlation parameters influence the limitations of transmission schemes that use the long-term properties and selectivity of the channel to combat fading. For example, diversity techniques essentially aim at providing Rx with multiple independently faded replicas of the signal. It is evident that diversity gain improves monotonically with increasing the number of i.i.d. channel realizations. In fact, as the number $\rightarrow \infty$, the performance of coherent diversity reception converges to the performance over a non-fading additive white gaussian noise (AWGN) channel [18]. The dispersive wireless channel has inherent diversity that can be exploited with appropriate schemes. Common techniques include time diversity, frequency diversity, delay diversity and Doppler diversity, as well as joint diversity between several domains [17].

Interleaving over several coherence times, often used with error correction cod-



Figure 2.12: Effective diversity order of several techniques per stationarity region across the entire route

ing, is a form of time diversity. With the vehicular channel being non-stationary, the effective gain achieved will change depending on the varying coherence parameters of the channel. For the multipath-Doppler RAKE receivers [18], the amount of diversity order achievable will be limited by the amount of delay and Doppler correlation in the channel. In addition, the variation of delay and Doppler spreads will result in a varying effective diversity for the non-stationary channel. Hence, the joint knowledge of stationarity and coherence/spread parameters and their statistical behavior can be employed to improve the performance of such methods.

In order to quantify the influence of the non-stationarity assumption on the effective diversity, we consider the maximum achievable diversity order of time, frequency, Doppler and delay diversities, with the diversity orders given respectively as

$$d_t = \frac{T_s}{T_c}, \qquad d_f = \frac{F_s}{F_c}, d_v = \frac{\sigma_v}{s_{\text{TF}}^{(\Delta v)}}, \quad d_\tau = \frac{\sigma_\tau}{s_{\text{TF}}^{(\Delta \tau)}}.$$
(2.11)

Figure 2.12 shows the effective diversity orders across different regions of stationarity based on our measurement, where the delay correlation $s_{TF}^{(\Delta \tau)}$ is calculated from the stationarity bandwidth value of 150 MHz. Since the diversity orders are proportional to the RMS delay and Doppler spreads with only a scaling factor as in (2.11), their statistical distribution should follow a lognormal model as well. Note that the use of the maximum excess spread instead of the RMS spread for the



Figure 2.13: MIMOSA channel sounder transmitter as a RSU with dual-polarized patch antenna array

calculation of the delay and Doppler diversity orders would result in higher values than the ones depicted in Figure 2.12.

2.2 Directional dual-polarized propagation modelling

2.2.1 Measurements setup and scenario

We use the MIMOSA channel sounder with 80 MHz of transmission bandwidth, and dual-polarized (H/V) patch antenna arrays as shown in Figure 2.13. For this measurement campaign, horizontal uniform linear arrays with 15 cm inter-element spacing (0.7λ) are used at both Tx and Rx. Measurements have been carried out at the same campus shown in Figure 2.2 using the same route and Tx and Rx locations. For the Rx, we use two patch antenna, one in each lane direction, while the Tx transmits using four patch antennas, two facing each direction. We only analyse the co-polarized channels (VV, HH) and discard the cross-polarized ones (VH ,HV) due to their lower power level.

With more parallel channels, the sampling rate is decreased and the snapshot repetition time $t_s = 3.92$ ms. We achieve a maximum Doppler shift of $1/2t_s = 128$ Hz and a minimum resolvable delay resolution of 12.5 ns. For the LSF estimation, the number of used tapers is K = 2 and L = 2 in both time and frequency domains. We choose the window dimension in time domain M = 64 samples and we include the whole bandwidth of N = Y = 819 samples in frequency domain. The sliding time shift is selected to be half of the frame size, i.e. $\Delta_t = 32$ samples. With these parameters, we obtain a LSF estimate of delay resolution $\tau_s = 1/B = 12.5$ ns, and Doppler resolution $v_s = 1/(Mt_s) = 4$ Hz.

2.2.2 Delay and Doppler spreads

The LSF is estimated for each Tx-Rx antenna pair, hence, a total of $4 \times 2 = 8$ links are evaluated per polarization. We consider the combined LSF to resemble a bidirectional antenna radiation pattern by averaging the LSF estimates of all 8 links. The PDeP \hat{P} and PDoP \hat{Q} are the projections of the combined LSF on the delay and Doppler domains, respectively. Before calculating the spreads, pre-processing is carried out for each LSF separately. No significant multipath components are found with delay larger than 2 μ s, so we limit the LSF to this value in the delay domain, and align all LSFs to the same absolute mean delay. In order to avoid spurious and noise components, we set all the components of the estimated LSF that are below the noise level plus 6 dB to zero [11].

The RMS delay and Doppler spreads are depicted in Figure 2.14 for the V-polar channel. The two parameters are showing quite similar behaviors, specially after Rx crosses Tx position around 17 s, indicating a high correlation between both spreads. The Pearson product-moment correlation coefficient is calculated as 0.49 over all frames. Spread values are smaller than the previous ones from the v-polar omni-directional measurement shown in section 2.1.5. This is somehow expected, since directional antennas give more weight to the LOS in the broadside, while discarding reflections from wider angles.

In order to statistically characterize the spreads, we use the KS test to select the distribution by comparing the p-value of different models. It is found that the lognormal distribution gives the best fit to the measured parameters. Figure 2.15 shows the histograms of the RMS delay and Doppler spreads of the V-polar channel and their corresponding best fit models. Similar characteristics are found for the H-polar channel. Table 2.3 lists the details of the lognormal distributions for both channels, where it shows that the H-polar channel has slightly larger mean delay and Doppler spreads compared to the V-polar channel.



Figure 2.14: RMS delay and Doppler spreads of the V-polar channel

Spread		Mean	KS-test p-value	$\mu(\log)$	$\sigma(\log)$
$\hat{\sigma}_{ au}$	V	33.39 ns	0.52	3.42	0.42
	Η	42.50 ns	0.36	3.66	0.42
$\hat{\sigma}_{\upsilon}$	V	7.31 Hz	0.80	1.92	0.37
	Н	10.26 Hz	0.82	2.25	0.38

Table 2.3: Statistics of the rms delay and Doppler spreads log-normal distribution

2.2.3 Small-scale fading amplitude modelling

The investigation of the small-scale amplitude is conducted in the delay domain across consecutive time frames. For that purpose, we apply an inverse discrete Fourier transform to the CTF in (2.1) using a Hann window to obtain the time-varying channel impulse response (CIR). Then, we align the CIRs so that the maximum LOS components have the same absolute delay. Finally, we can estimate the small-scale fading by removing the path loss and large-scale fading using a moving average filter of the same size as the LSF estimation window.

Traditionally, the Rayleigh fading is the common assumption in mobile communications for worst-case performance analysis, while the Rician fading is used when there exists a dominant path component (e.g. LOS). However, more severe fading distributions have been reported, specially for vehicular communications where WSSUS assumptions are no longer valid [19, 20]. In this section, we aim to characterize the distribution of the small-scale fading amplitude per delay tap. Ac-



Figure 2.15: Histograms of the (a) RMS delay spread and (b) RMS Doppler spread of the V-polar channel and the corresponding lognormal models

cording to Table 2.3, the mean delay spread of both polarizations are well covered by the first 4 delay taps (50 ns). We again use the KS-test with a 95% confidence interval per frame to compare the most common distributions: Rician, Rayleigh, Nakagami-m, and Weibull.

Table 2.4 lists the mean p-values of the H-polar channel frames that passed the KS-test and the success rate of each candidate distribution for the H-polar channel. Although all the p-values are satisfactory, deciding based on the p-values alone can be misleading. For example, while the Rayleigh model has the highest p-value for the first tap, it has the lowest success rate among the candidate models. Similar fading behavior is observed for the V-polar channel.

To better understand the behavior of each delay tap, we use a flexible parametric model to express the severity of fading. We estimate the Nakagami *m*-factor for the first 4 taps using the maximum-likelihood estimator [21]. The *m* is also called the shape factor, since a larger *m* means a smaller fading depth. The *m* estimate per frame for the 4 taps of the H-polar channel is depicted in Figure 2.16. Indeed, the first tap has large values of m > 1 indicating a better-than-Rayleigh fading, while the other taps suffer from more severe fading with m = 1 (Rayleigh) and m < 1 (worse-than-Rayleigh).

Based on the previous analysis, we choose to model the first tap with a Rician fading as it has the highest success rate. However, for the later taps, we select the Nakagami-m fading. While both the Weibull and Nakagami models have higher



Figure 2.16: m-factor estimate of the small-scale fading for the H-polar channel

Tap	Rician		Rayleigh		Nakagami		Weibull	
	(p)	(%)	(p)	(%)	(p)	(%)	(p)	(%)
0	0.44	77.88	0.58	2.88	0.44	75.00	0.40	71.15
1	0.44	65.38	0.31	19.23	0.36	63.46	0.43	65.38
2	0.65	72.12	0.40	34.62	0.58	75.00	0.62	76.92
3	0.58	81.73	0.34	48.08	0.49	88.46	0.54	93.27

 Table 2.4: Mean significance value (p) and success rate (%) of the KS-test for small-scale fading amplitude of H-polar channel

success rates, the Nakagami distribution is widely studied in the literature and can be treated more easily in theoretical investigations, compared to the purely empirical Weibull distribution [3]. The K-factor of the first tap is estimated using the method of moments [22]. Figure 2.17 shows the best fit lognormal model to the statistical distribution of the estimated parameters for the H-polar channel, and Table 2.5 lists the statistics of the lognormal models for H and V channels. We notice that the mean K-factor of the first tap (tap 0) is slightly larger for the V-polar channel than for the H-polar channel. This is consistent with the results in Table 2.3 that show larger mean delay and Doppler spreads for the H-polar channel. A reason for that can be stronger scattering components in H-polar from ground and other reflectors with larger horizontal geometry (e.g., vehicles).



Figure 2.17: Cumulative distribution function (CDF) of the small-scale fading parameters (K-factor for tap 0 and m-factor for later taps) and the corresponding lognormal models for the H-polar channel

Тар		Mean (dB)	KS-test p-value	$\mu(\log)$	$\sigma(\log)$
0	V	19.68	0.22	4.11	1.02
(K-factor)	Н	18.30	0.77	3.72	1.05
1	V	4.13	0.13	0.66	0.66
(m-factor)	H	4.61	0.11	0.80	0.65
2	V	1.85	0.37	0.20	0.61
(m-factor)	Н	2.60	0.23	0.40	0.59
3	V	2.80	0.15	0.41	0.64
(m-factor)	H	1.07	0.48	0.14	0.45

Table 2.5: Statistics of the small-scale fading parameters log-normal distribution

2.3 Conclusions

Due to rapid changes in the environment, vehicular communication channels no longer satisfy the assumption of wide-sense stationary uncorrelated scattering. The non-stationary fading process can be characterized by assuming local stationarity regions with finite extent in time and frequency. In this chapter, the non-stationary fading process of vehicular channels is analyzed based on V2I channel measurements at 1.35 GHz in a suburban environment.

We apply the framework of the local scattering function (LSF) and channel correlation function to characterize the stationarity time and find it to be more accurate than the empirical collinearity estimate. A stationarity time of 567 ms is calculated for the crossing scenario at 40 km/h speed. Based on the LSF, time-varying delay and Doppler power profiles are obtained and used to calculate the corresponding second-order central moments. The empirical distribution of the RMS delay spread and Doppler spread is best fitted by a lognormal model. Both vertical and horizontal polarization show a similar behavior, with the mean spreads of H-polar channel being slightly larger than V-polar channel.

In addition, the small-scale fading is investigated per delay tap. The smallscale fading of the strongest path is found to be Rician distributed, while the later delay taps show occasional worse-than-Rayleigh behavior. The parameters of the Rician fading for the first tap and Nakagami fading for the later taps are estimated and statistically modeled. The best fit is found to be the lognormal model. Finally, practical relevance of the non-stationarity of the channel is briefly discussed. Results show that as the assumption of WSSUS is violated, the assumption of ergodic capacity and its application becomes unreliable. Moreover, the gain of the effective diversity varies with the stationarity and coherence parameters of the channel. Hence, the optimal performance of communication systems can be obtained by considering the varying nature of such parameters via adaptive schemes. In Chapter 3, we further analyse the wireless channel for vehicular communications in other challenging environments like tunnels. We use the non-parametric LSF and stationarity time estimators discussed in this chapter to characterize the nonstationarity and statistically model the channel parameters of the tunnel scenario.

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3

Mobile channel modelling in tunnels

In this chapter, we extend the channel modelling for vehicular communications from urban scenarios of Chapter 2 to the tunnel environment. We characterize the non-stationary V2I channel measured in a rectangular tunnel in Antwerp, Belgium under real traffic conditions. We explore the impact of antenna polarization on the propagation characteristics by modelling the H/V dual-polarized (DP) propagation channel. The power gain (G), co-polarization ratio (CPR), and cross-polarization discrimination (XPD) are modelled. In addition to polarization, the impact of antenna radiation pattern is also explored by comparing the results of omni-directional and bi-directional antennas. It has been shown that directional antennas can potentially increase the mean duration of a connection by a factor of 4 when connecting from a vehicle to existing access points in suburban environment [1]. On the vehicular network level, the distribution of received frames over different angles of arrival in city-wide simulations shows a dominance of angles around 0° and 180° [2]. This indicates that most packets were received from vehicles in the front or in the back, that is, vehicles on the same street or even lane. Hence, bi-directional antennas provide a valid candidate for vehicular communications.

Moreover, we investigate the stationarity time based on the channel correlation function (CCF) introduced in Chapter 2 for the tunnel scenario here in Chapter 3, and statistically model the RMS delay and Doppler spreads in the channel across stationarity regions. Few studies have measured the stationarity time of DP channels [3, 4]; they use the empirical collinearity method in outdoor environments other than tunnels. We model the small-scale fading of the channel, and point to the impact of traffic conditions on the different channel parameters. Moreover, we investigate



Figure 3.1: Entrance of the Beveren Tunnel in Antwerp.

the multiple-input multiple-output (MIMO) capacity for DP channels, and give qualitative indications on the impact of different parameters like normalization, CPR, XPD, and correlation coefficients.

Finally, we study the propagation of the MIMO channel in an arched road tunnel in France. The measurements are carried out in two lanes: the open lane along the center of the tunnel, and the closed lane near the tunnel wall. We first determine the path loss, CPR, XPD, and delay spread. Then, we investigate the MIMO channel for different scenarios of antennas spacing and polarization, and determine the correlation level of the channel and its capacity performance along the tunnel.

The chapter is structured as follows. Section 3.1 includes the propagation modelling in the rectangular tunnel, where we investigate the impact of traffic as well as the antenna characteristics. The propagation in the arched tunnel is modelled in Section 3.2, and conclusions are drawn in Section 3.3.

3.1 Rectangular tunnel environment

3.1.1 Measurements setup and scenario

Channel measurements are performed with the MIMOSA radio channel sounder, shown in Section 1.4. It uses 80 MHz of transmission bandwidth, centered around 1.35 GHz. Identical sets of antennas are used at the Tx and Rx. For the omnidirectional measurement (OM), the wideband antenna is used from Cobham Antenna Systems, model XPO2V-0.8-6.0/1441. It features vertical polarisation, 0.8 -6 GHz bandwidth, and 2 dBi gain. For the bi-directional measurement (BM), two custom-made DP patch antennas of H/V polarizations are used back-to-back, with one facing forward and the other facing backward. The peak gain is 7.4 dBi and the half-power beam width is 120°.


Figure 3.2: Tx as a roadside unit with the antenna fixed inside the tunnel through an emergency exit (left) and the van loaded with Rx and the antenna mounted on the rooftop (right).

Measurements have been carried out in the Beveren tunnel in Antwerp, Belgium. The one-kilometer tunnel has two rectangular tubes of approximately $15 \text{ m} \times 5 \text{ m}$ cross-section, with two lanes per direction, in addition to a roadside lane. Along the tunnel, there are lights, pipes and concrete blocks on the sides, as shown in Figure 3.1. In order to follow the V2I scenario, the Tx antenna is placed inside around the middle of the tunnel through an emergency exit door at 2 m height, as shown in Figure 3.2. The Rx antenna is mounted on the rooftop of a van carrying the Rx inside. The van is driven through the tunnel at 90 km/h speed, crossing the Tx position during a measured trip of 33 seconds.

Two types of trips are made for the OM: medium-traffic (MT) trip where 10 to 15 vehicles are present inside the tunnel during measurements, and low-traffic (LT) trip where the number of vehicles is less than five. We obtain a snapshot repetition time $t_s = 975.3 \ \mu$ s. With this parameters setting, we capture a total number of snapshots S = 44032 snapshots, each with Q = 819 samples in frequency domain, and we achieve a maximum Doppler shift of $1/2t_s = 512$ Hz and a minimum resolvable delay resolution of 12.5 ns. For the BM, the radio channel is captured with a snapshot repetition time of 3.92 ms. With this setting, we capture a total number of 8256 snapshots per DP subchannel (VV, HV, VH, and HH). Each snapshot has 819 samples in the frequency domain. We achieve a maximum Doppler shift of 128 Hz and a minimum resolvable delay resolution of 12.5 ns.

3.1.2 Impact of traffic density

In this section, we study the impact of traffic density on different channel parameters. For that, we model the OM channel from the LT and MT trips.

3.1.2.1 LSF and stationarity time

The local scattering function (LSF) is a TF-dependent representation of the power spectrum of the observed fading process in the delay and Doppler domains (τ, υ) . We use the discrete version of the LSF multitaper-based estimator presented in Section 2.1.2. We estimate the LSF for consecutive regions in time, within which the channel is assumed to be WSSUS. A sliding window is used with an extent of $M \times N$ samples in time and frequency domains, respectively. We choose M = 128 samples and include the whole bandwidth of N = Q = 819 samples in frequency domain. The sliding time shift is selected to be half of the frame size, i.e. 64 samples. With these parameters, we obtain a LSF estimate of 12.5 ns delay resolution and 4 Hz Doppler resolution.

Figure 3.3 shows two LSF estimates at different instants during the trip: (a) when Rx is approaching Tx, which can be seen from the positive Doppler shift of the LOS component around 100 Hz, and (b) after Rx crosses Tx position, resulting in the LOS Doppler shift from positive to negative 100 Hz. Several multipath components can be observed; components from fixed scatterers are showing with less power and Doppler shifts between +/- 100 Hz, while short-lasting components resulting from moving scatterers can have different positive and negative Doppler shifts.

As aforementioned, the stationarity time represents the region in time within which the LSF is highly correlated. The LSF correlation can be determined by the CCF spread about the origin in the Doppler lag direction [5]. According to (2.5), the CCF Doppler moment measures the Doppler correlation, which is related to the stationarity time T_s as shown in (2.6). Based on our measurement data of the complete trip in the tunnel, we estimate a stationarity time $T_s = 330$ ms. This is indeed larger than the assumed minimum value of 124.8 ms for the LSF estimation. Both LT and MT trips have almost the same stationarity time, indicating that the difference in traffic density is not enough to have an impact on the stationarity.

3.1.2.2 Delay and Doppler spreads

For the non-stationary channel, the fading parameters can be accurately evaluated within each stationarity region, so that the channel modelling becomes physically meaningful. Based on our estimation of the stationarity time, the corresponding number of samples in time domain is M = 340 samples. Hence, the LSF estimate is recomputed using a sliding time shift of half the stationarity region dimension. By projecting the LSF in the delay and Doppler domains, we get the PDeP and



Figure 3.3: LSF estimates at two instants before (a) and after (b) crossing the Tx position.

PDoP, respectively. Figure 3.4 depicts the PDeP and PDoP for the central parts of the LT (upper) and MT (lower) trips inside the tunnel. The figure shows a strong reflection (i) in the first half of the tunnel in the PDeP of both trips. This can be related to the metal structure at the entrance of the tunnel, visible in Figure 3.1, that would have a MPC with increasing delay as Rx goes into the tunnel. The tunnel passes under the canal, hence, it goes downwards in the first half then upwards as shown in Figure 3.5. This explains why the reflection from the entrance is only visible during the first half of the trip. In addition, the difference in traffic densities can be observed in the rich MPCs (ii) in the MT PDeP compared to the LT one.



Figure 3.4: Time-varying (a) PDeP and (b) PDoP for different trips: LT (upper) and MT (lower)



Figure 3.5: Blue print of the tunnel structure showing the change in elevation



Figure 3.6: RMS delay and Doppler spreads for different trips: (a) LT and (b) MT

Based on the estimated profiles, the time-varying RMS delay and Doppler spreads can be calculated from (2.8) and (2.9). Pre-processing is carried out for each stationarity region separately before calculating the spreads. In order to avoid spurious and noise components, we only consider components within 40 dB from the peak level of the estimated LSF. All components below that power threshold are set to zero [6]. The corresponding RMS delay and Doppler spreads are shown in Figure 3.6. It can be seen that the spreads in the first half of the tunnel are larger compared to the second half in both trips. This can be related to the reflection (i) in Figure 3.4 (a) coming from the entrance of the tunnel. In addition, Figure 3.6 shows

Spread	Trip	Mean	KS-test p-value	$\mu(\log)$	$\sigma(\log)$
Delay (ns)	LT	130.02 ns	0.17	4.33	1.08
	MT	184.29 ns	0.12	4.86	0.85
Doppler (Hz)	LT	25.08 Hz	0.77	2.96	0.73
	MT	27.57 Hz	0.78	3.18	0.53

Table 3.1: Statistics of the rms delay and Doppler spreads log-normal distribution

Trip	First half	Second half
LT	0.92	0.39
MT	0.69	0.38

 Table 3.2: Pearson correlation coefficient between log(delay) and log(Doppler) for each half
 of the tunnel

that the spreads in the MT trip (b) are relatively larger than in the LT trip (a). In order to statistically characterize the spreads, we use the KS test to select the distribution by comparing the p-value of different models: lognormal, normal, Nakagami, Rayleigh, Weibull, and Rician. It is found that the lognormal distribution gives the best fit to the measured parameters. Table 3.1 lists the details of the lognormal distributions for both trips, where it shows that the MT trip has slightly larger mean delay and Doppler spreads compared to the LT one.

In both trips, the delay and Doppler spreads are showing quite similar behaviors, indicating a high correlation between the two parameters. The correlation seems different in the first half of the tunnel compared to the second half. Hence, the Pearson correlation coefficient is calculated separately for each half of the tunnel. Figure 3.7 shows the scatter plots of the delay and Doppler spreads in log domain for both trips. It clearly shows the difference between the two halves of the tunnel in terms of parameters value as well as correlation. This is reflected in the correlation values presented in Table 3.2, where the correlation is found to be larger in the first half compared to the second half. Again, this can be related to the MPC reflected from the tunnel entrance (i) in Figure 3.4, which is only showing during the first half of the tunnel. In addition, the correlation is relatively larger in the LT trip compared to the MT one, which is expected due to the less random scatterers (ii) in Figure 3.4.

3.1.2.3 Small-scale fading amplitude

The investigation of the small-scale amplitude is conducted in the time domain across consecutive stationarity regions. We remove the path loss and large-scale fading using a moving-average filter of the same size as the LSF estimation window.



Figure 3.7: Scatter plot of delay and Doppler spreads in log domain for different trips: (a) LT and (b) MT

Trip	Rician		Rayleigh		Nakagami		Weibull	
	(p)	(%)	(p)	(%)	(p)	(%)	(p)	(%)
LT	0.57	85.62	0.129	0.35	0.50	74.63	0.39	79.61
MT	0.56	89.95	0.064	0.23	0.49	76.45	0.41	87.29

 Table 3.3: Mean significance value (p) and success rate (%) of the KS-test for small-scale fading amplitude

This is then averaged over the whole frequency bandwidth. The fading distribution is acquired by calculating the CDF of the channel amplitude and comparing it to the classical fading distributions like Nakagami, Rayleigh, Weibull, and Rician [7]. In order to decide on the best fitting distribution, we use the KS test.

Table 3.3 lists the mean p-values of the stationarity regions that passed the KS-test and the success rate of each candidate distribution for the complete trip. The Rician distribution appears to best fit the experimental results for both trips, similar to the results reported in [8, 9]. This is mainly due to the LOS conditions. The K-factor per region is depicted in Figure 3.8 for the two trips, where the LT trip is shown to have a larger mean value (17.54 dB) compared to the LT one (15.1 dB). Using the KS test again with a 5% significance level against the most common distributions, the K-factor is found to follow a lognormal distribution for the MT trip with p-value = 0.19. However, the LT trip did not pass the test of several candidate distributions, with the best p-value = 0.016 for the lognormal model. Figure 3.9 shows the CDF of the K-factor and the lognormal model parameters for the two trips.



Figure 3.8: K-factor of the Rician fading amplitude for both trips



Figure 3.9: CDF of the K-factor and lognormal model fit for both trips

3.1.3 Impact of antenna characteristics

Next, we investigate the impact of the antenna characteristics on the channel parameters. We model the DM and OM channels from the same MT trip.

3.1.3.1 Path gain and polarization power ratios

The channel gain is calculated from the CTF h(d, f) by averaging the power gain over the 819 frequency subcarriers for each polarization as a function of distance

$$G_{ij} = \mathbf{E}\{|h_{ij}|^2\},\tag{3.1}$$



Figure 3.10: Path gain versus distance for different polarization combinations.

	OM	VV	HV	VH	HH
G_0	-42.6	-37.00	-49.22	-48.84	-39.54
n	1.19	1.24	1.23	1.20	1.27
σ	3.47	4.66	4.12	4.30	3.38

Table 3.4: Path Gain Model Parameters

where $i, j \in \{V, H\}$ is the polarization at Tx and Rx, respectively. According to [10], a one-slope model can be used to fit the path loss in tunnels with road traffic conditions. Hence, we use the following log-distance path loss model

$$G(d) = G_0 - n \ 10 \log_{10}(d) + X_{\sigma}, \tag{3.2}$$

where G(d) is the path gain in dB at distance d from Tx, G_0 is the reference value at 1 m, n is the path loss exponent, and X_{σ} is a random variable with normal distribution of zero mean and σ standard deviation. These parameters are determined by a least-squares fit to the measurement data. Figure 3.10 shows the measured channel gain versus distance during the second half of the tunnel, i.e. after Rx crosses Tx, and the corresponding model for different polarizations of the BM. Table 3.4 summarizes the model parameters, where the results of the OM model is also included for comparison.

A general observation is that the path loss exponent is smaller than in freespace and typical outdoor environments. This is due to the guiding effect of the tunnel, making it closer to indoor scenarios like industrial environments [11]. We also notice a periodic pattern in the fading over distance. In empty tunnels, the field fluctuations are mainly related to the richness in terms of propagating modes. According to the modal theory [12], the superposition of several hybrid modes supported by the structure of the tunnel is what gives rise to large pseudo-periods with distance on the large scale. However, the traffic condition and structure irregularities disturb the propagating modes, making the pseudo-periods in Figure 3.10 less clear than in empty tunnels [13].

Regarding the polarization dependence, we see that the cross-polarized subchannels have lower reference gain than the co-polarized subchannels, as expected. While the two cross-polarized models are almost identical, the co-polarized models show some differences: the HH subchannel has a slightly lower path gain than the VV channel. According to [14], a deterministic ray approach for empty smooth walled tunnels composed of uniform material predicts the opposite; the H path gain is higher than the V path gain. Since the geometry of the tunnel is such that the width is larger than the height, the H waves reflected from the ground and ceiling are stronger than the V waves reflected from the walls of the tunnel, due to the Brewster's angle phenomenon [15, 16]. However, this effect can not be observed in the measurements. The reason is likely the non-uniformity of materials and shapes present in the propagation path (e.g. traffic condition, side pipes, trays and emergency exits), resulting in more scattering for the HH subchannel and a lower path gain.

We also investigate the effect of the antenna pattern by comparing the directional VV and OM models of same polarization. Due to the gain difference between the two antennas, the reference gain for the OM is 5.6 dB lower compared to the BM. In fact, the average gain within the HPBW of the BM is calculated as 5 dBi, and with a gain of 2 dBi for the OM, the gain difference $= 2 \times (5 - 2) = 6$ dB. This is quite similar to the difference in the reference gain of the two models. This implies that, while the OM has a wider angle into the propagation environment, most of the multipath components with significant power arrive within the HPBW. Indeed, only rays impinging the tunnel walls with a grazing angle of incidence play a leading part in the propagation at large distance [13].

We further investigate the polarization dependence over distance in terms of CPR and XPR. The CPR is the power ratio between the two co-polarized subchannels gain, given by the following formula in dB

$$CPR = 10 \log_{10} \left(\frac{G_{\rm VV}}{G_{\rm HH}} \right). \tag{3.3}$$

The XPD is the power ratio between a co-polarized subchannel gain and the corresponding cross-polarized subchannel gain. It shows the amount of depolarization or power leakage that each of the H and V subchannel goes through. The following



Figure 3.11: CPR and XPD versus distance for different polarization combinations.

	mean (dB)	σ (dB)	R_0 (dB)	R_n (dB/100m)
CPR	3.53	3.57	0.35	1.0
XPD_V	12.03	2.93	10.9	0.1
XPD _H	11.29	3.49	10.6	-0.6

Table 3.5: Statistical Model and Distance-dependent Model Parameters of CPR and XPD

formula represents XPD in dB

$$XPD_{V} = 10 \log_{10} \left(\frac{G_{VV}}{G_{VH}} \right), \qquad (3.4)$$

$$XPD_{\rm H} = 10 \log_{10} \left(\frac{G_{\rm HH}}{G_{\rm HV}} \right). \tag{3.5}$$

Figure 3.11 shows the CPR and XPD over the second half of the tunnel. It shows a slow increase in the CPR with distance, which can be related to the small difference in the path loss exponent of VV and HH in Table 3.4. On the other hand, the XPD does not drop at far distances and the waves remain highly polarized, confirming previous results [13, 17]. The ray theory of propagation in tunnels predicts that depolarization only happens at small range, where the waves impinging the tunnel walls are not polarized along the direction parallel or perpendicular to the plane of incidence [18].

Table 3.5 includes the mean values and the distance-dependence parameters of

T _s (ms)	OM	VV	HV	VH	HH
overall	330	400	367	375	380
mean	428	435	432	427	436
std.	53	48	48	47	47
min.	268	325	315	299	303

 Table 3.6: Stationarity Time statistics in ms for Different Radiation Patterns and Polarizations

the power ratios (PR), where a linear dependence in dB is assumed as

$$\mathbf{PR} = R_0 + R_n \, d. \tag{3.6}$$

In addition, the CPR and XPD are statistically modeled. Based on previous measurements and ray-tracing simulations, there is quite an agreement in the standardized models that both parameters follow a lognormal distribution [19, 20], hence the estimated standard deviation is included in Table 3.5. The results match with the values found in the literature for similar scenarios [19]. We notice that, while the instantaneous XPD_V and XPD_H are not identical, their models are similar, on average.

3.1.3.2 Stationarity region

As aforementioned, the stationarity time represents the region in time within which the LSF is highly correlated. The LSF correlation can be determined by the CCF spread [5]. The CCF Doppler moment in (2.5) measures the CCF spread in the Doppler lag dimension, which is related to the stationarity time T_s in (2.6). For calculating the stationarity time, we first need to estimate the LSF assuming a minimum stationarity region. This initial region should be small enough not to include non-stationary variations, and large enough to include sufficient resolution in the delay and Doppler domains. We choose the region's dimension in time domain M = 32 samples, corresponding to 125 ms or 15 λ , approximately. The sliding time shift is selected to be half of the window size, i.e. 62 ms in this case. With these parameters, we obtain a LSF estimate of 12.5 ns delay resolution and 8 Hz Doppler resolution. It is worth noting that the CCF estimate from (2.4) may vary depending on the time interval of estimation. We choose to calculate it over the complete duration of the trip, thus, characterizing the degree of non-stationarity of the entire scenario. This is more practical from an operational perspective since it gives an estimate for the stationarity region that represents the environment in an average sense, i.e., a single value per type of environment.

Based on our measurement data of the overall trip in the tunnel, Table 3.6 lists the estimated stationarity time in ms for each case. In addition, we add the mean,

minimum and standard deviation statistics of the stationarity time calculated per a 2 s period (240 λ). It is clear that the stationarity time is indeed larger than the assumed minimum value of 125 ms for the LSF estimation. The results show that the co-polarized subchannels have longer stationarity times compared to the crosspolarized subchannels. This is expected as reported in [3], since the depolarized waves would undergo more variations due to reflection and scattering. We also notice that the HH subchannel has a shorter stationarity time than the VV subchannel. This can again be related to the conclusion that the HH subchannel experiences more scattering, and thus more time variation. The same conclusion can be drawn when comparing the OM with the VV subchannel; since the OM antenna has a wider angle of uniform gain, it captures more significant multipath components, contributing to a faster fading [21]. This results in the shortest stationarity time for the OM, compared to all subchannels of the BM.

3.1.3.3 Delay and Doppler spreads

Based on our estimation of the stationarity time, the corresponding number of samples in the time domain is about M = 100 samples. Hence, the LSF estimate is recomputed using a sliding window of the stationarity region dimensions. By integrating the LSF over the Doppler and delay domains, we get the PDeP and PDoP, respectively. Figure 3.12 depicts the PDeP and PDoP for the VV subchannel. The LOS component can be easily recognized; the delay decreases as Rx approaches Tx with positive Doppler shift, then after crossing the Tx position around 11 s, the delay starts increasing again and the Doppler shift becomes negative. Several multipath components can be observed; components from fixed scatterers are showing similar pattern to the LOS, i.e. Doppler shifts between +/-100 Hz as Rx passes by, but with less power. Components resulting from moving scatterers in the same movement direction have different Doppler shifts that are more consistent, depending on their relative speed and position.

The corresponding RMS delay and Doppler spreads are shown in Figure 3.13 for the VV and HH subchannels. The delay spread in the first half of the tunnel is larger compared to the second half. As aforementioned, this can be related to the reflection coming from the metallic structure at the entrance of the tunnel, visible in Figure 3.1. In addition, Figure 3.13 shows that the spreads in the HH subchannel are relatively larger than in the VV subchannel. This confirms the previous conclusion, that the channel is more dispersive in the H polarisation, resulting in smaller path gain and stationarity time.

Previous studies find that a lognormal distribution is the best fit for the delay spread in tunnels [6]. We verify this using the Lilliefors test [22]. It is a two-sided goodness-of-fit test when the parameters of the tested normal distribution are unknown and must be estimated, thus is suitable for our case. With 5% significance level, the test shows that both the delay and Doppler spreads from the measurements



Figure 3.12: Time-varying PDoP (a) and PDeP (b) for the VV subchannel in dB.

follow the lognormal distribution. An example of the delay spread histogram for the VV and HH subchannels is shown in Figure 3.14. Table 3.7 lists the estimated parameters of the lognormal distributions for different polarization combinations of the BM, in addition to the OM.

Looking at the BM results, the co-polarized subchannels have a larger delay spread but slightly smaller Doppler spread relative to the cross-polarized subchannels. Additionally, the HH subchannel has larger delay and Doppler spreads than the VV subchannel, as already mentioned. To show the impact of the antenna pattern, we compare the values of the OM and VV subchannel. The OM has larger delay and Doppler spreads, indicating that an antenna with wider angle captures more multipath components that increase dispersion. Hence, the impact of the



Figure 3.13: RMS delay (a) and Doppler (b) spreads for VV and HH subchannels with Tx location in red.

		Delay (ns)				
	mean	μ (dB)	σ (dB)	mean	μ (dB)	σ (dB)
OM	184.29	4.86	0.85	27.57	3.18	0.53
VV	87.96	4.2	0.74	18.88	2.73	0.63
HV	71.74	4.1	0.59	26.34	3.15	0.5
VH	72.1	4.1	0.63	23.28	3.02	0.5
HH	109.74	4.46	0.69	23.1	2.99	0.54

Table 3.7: Statistics of The RMS Delay and Doppler Spreads Lognormal Distribution



Figure 3.14: Histograms of the RMS delay spread for the VV (a) and HH (b) subchannels and the corresponding lognormal models.

antenna pattern on the spreads is larger than its impact on the power gain mentioned in Section 3.2.3.1. The reason is that the RMS spread includes the effect of both the power and the delay/Doppler of the multipath components, while only the average power is accounted for when calculating the gain.

3.1.3.4 Dual-polarized MIMO channel capacity and normalization

MIMO technology offers multiplexing and diversity gains without increasing the total system power and bandwidth, thus offering substantial improvements in channel capacity and spectral efficiency. DP MIMO has the benefit of reducing the antennas' form factor by having co-located DP antennas while maintaining low correlation, a condition usually required by MIMO systems [23]. However, in order to compare DP systems to other MIMO or even SISO systems, normalization is needed. The main idea is to isolate the small-scale characteristics of the channel from the effects of path loss and other large-scale fading, so that the intrinsic characteristics of the MIMO matrix are compared at certain SNR. We will discuss three types of normalization below. The goal is to investigate the effect of normalization on the accuracy of the DP channel capacity calculation, and propose a more accurate normalization approach.

For a narrowband system of n_T Tx antennas and n_R Rx antennas, the maximum capacity expressed in bits/s/Hz, with uniform power allocation and the presence of

additional white Gaussian noise is given by the generalized formula

$$C = \log_2 \det \left(\mathbf{I}_{n_R} + \frac{\mathrm{SNR}}{n_T} \mathbf{H} \mathbf{H}^{\dagger} \right), \tag{3.7}$$

where \mathbf{I}_{n_R} is the identity matrix of size n_R , SNR is the average signal-to-noise ratio per Rx antenna, **H** is the $n_T \times n_R$ CTF matrix, and $(.)^{\dagger}$ is the Hermitian transpose. The wideband capacity is calculated by averaging C over the frequency bandwidth.

In our scenario, the CTF matrix is expressed as

$$\mathbf{H} = \begin{bmatrix} h_{\rm VV} & h_{\rm VH} \\ h_{\rm HV} & h_{\rm HH} \end{bmatrix}.$$
 (3.8)

Since the actual SNR varies as a function of Rx location, channel normalization is required to facilitate comparison of the results at a constant SNR. One common normalization is to scale the channel matrices such that the average power transfer between a single Tx and single Rx antenna is unity. The unity power gain constraint is equivalent to setting the squared Frobenius norm of the normalized matrix as $E\{||\mathbf{H}||_F^2\} = n_R n_T$ [24–26].

The Frobenius normalization, as already mentioned, would result in an average SISO SNR of unity on all the subchannels for a spatial array configuration. On the other hand, DP configurations suffer from power imbalances, which need to be accounted for in their capacity calculations. If the same normalization is used, the performance of these systems is overestimated [25, 26]. While some studies did use the Frobenius normalization for DP systems [4, 17, 24], others suggested normalizing the power of co-polarized subchannels [3, 25], or only one of the co-polarized subchannels (e.g. VV [27]) to unity.

To investigate the effect of normalization on the DP capacity, we calculate the capacity at 10 dB SNR using the different normalization approaches. Figure 3.15 shows the DP capacity CDF when normalizing the CTF matrix to the power of the co-polarized subchannels and the VV subchannel. The plots also include the SISO capacity of each subchannel, in addition to the DP capacity using the Frobenius normalization. We add the capacity of a 2×2 i.i.d. complex Gaussian MIMO channel as well for comparison. The theoretical average capacity at 10 dB SNR = $\log_2(1+10) = 3.46$ b/s/Hz for SISO, and 6.92 b/s/Hz for any 2×2 MIMO system. It is clear from the figures that the Frobenius normalization of the DP channel gives unrealistic results, as its capacity is larger than that of the i.i.d. Gaussian channel. The effect of the power imbalance among the subchannels can be seen in the SISO capacity; the cross-polarized subchannels capacity is much lower than that of the co-polarized subchannels. That is because their SNR is lower than 10 dB due to the XPD. The effect of the CPR can be seen in the co-polarized subchannels capacity; in Figure 3.15 (a) where the SNR is normalized to the co-polarized power, both VV and HH average capacities are around the theoretical value. Figure 3.15 (b)



Figure 3.15: CDF of the channel capacity when normalizing the power of the co-polarized subchannels (a) and the VV subchannel (b) to 10 dB SNR.

shows the average VV capacity exactly at the theoretical value as expected, since its power is normalized. On the other hand, the HH capacity curve is more gradual, as its SNR deviates from the 10 dB of the VV subchannel due to the CPR.

Comparing the DP capacity of the two normalization approaches, we see that they do not overestimate the performance like the Frobenius normalization, as shown in Figure 3.15. However, the power imbalance of the DP channel is still impacting the effective SNR, hence, the intrinsic MIMO matrix characteristics are not truly isolated. To show this, we need a parameter that describes the MIMO performance but does not depend on the channel normalization. The condition number is defined as the ratio of the maximum to minimum singular value of the channel matrix. The lower the condition number, the more potential the channel has



Figure 3.16: The condition number during the second half of the tunnel, with the average in red.



Figure 3.17: Scatterplot of the condition number versus the DP capacity when normalizing the power of the co-polarized subchannels (a) and the VV subchannel (b) to 10 dB SNR, with the average condition number in red.

for large multiplexing gains [26]. Figure 3.16 shows the condition number of the CTF matrices during the second half of the tunnel. The average condition number is 5.5 dB, which is good for having multiplexing gain in practice [28, 29]. We notice that the condition number remains relatively low as the SNR drops with distance. Figure 3.17 shows the scatterplot of the condition number versus the capacity of the



Figure 3.18: CDF of the channel capacity (a) and its scatterplot versus the condition number (b) using the proposed normalization to 10 dB SNR.

DP channel using the two normalization approaches. It is clear that the capacity is not correlated with only the condition number, indicating the impact of the power imbalance on the effective SNR.

3.1.3.5 Power conservation approach for normalization

The problem with these normalization approaches is that they do not assume a conservation of power or energy, where the channel cannot output more power than what is transmitted [23]. When normalizing to one or both of the co-polarized subchannels, the power imbalance due to CPR, and leakage from one polarization to the other due to XPD are not compensated for in the effective SNR. This makes the channel introduce more energy which is good for the performance, but unfortunately is unrealistic. Hence, we propose to normalize the channel matrix such that

$$\mathbf{E}\{\|\tilde{\mathbf{H}}\|_{\rm F}^2\} = \frac{n_R n_T}{2}.$$
(3.9)

In this normalization, the power is conserved by subtracting from the co-polarized subchannels SNR the corresponding amount of power that has leaked into the cross-polarized subchannels, i.e. we use $E\{|h_{VV}|^2\} + E\{|h_{VH}|^2\} = 1$ and $E\{|h_{HH}|^2\} + E\{|h_{HV}|^2\} = 1$ as constraints. Figure 3.18 shows the capacity CDF and the scatterplot with the condition number using the proposed normalization. We notice that the capacity is fully correlated with the condition number, and has an average value of 4.82 b/s/Hz. This implies that the proposed approach gives more accurate results, as it reflects the intrinsic MIMO gain, while insuring that the effective SNR is not overestimated.

3.1.3.6 Dual-polarized subchannels correlation

Finally, we investigate the correlation among DP subchannels. In spatial MIMO, low correlation between antenna elements is often desired to enhance system capacity [30]. It was shown that DP waves in many NLOS scenarios fade almost independently, and they remain orthogonal throughout the channel in LOS scenarios [23]. We calculate the full correlation matrix using the following expression for its elements

$$\rho_{i,j} = \frac{\mathrm{E}\{h_i h_j^*\} - \mathrm{E}\{h_i\} \mathrm{E}\{h_j^*\}}{\sqrt{\mathrm{E}\{|h_i|^2 - |\mathrm{E}\{h_i\}|^2\} \mathrm{E}\{|h_j|^2 - |\mathrm{E}\{h_j\}|^2\}}},$$
(3.10)

where $i, j \in \{VV, VH, HV, HH\}$ are the subchannels under consideration. The correlation matrix **R** is calculated as

$$\mathbf{R} = \begin{bmatrix} 1.00 & 0.86 & 0.87 & 0.90 \\ 0.86 & 1.00 & 0.85 & 0.86 \\ 0.87 & 0.86 & 1.00 & 0.87 \\ 0.90 & 0.86 & 0.87 & 1.00 \end{bmatrix}.$$
 (3.11)

The results indicate high correlation values for the tunnel scenario. Similar results were observed for LOS scenarios in [4].

An alternative way to describe the channel correlation is to utilize the Kronecker model. In that model, the MIMO system is decomposed into two interconnected subsystems, with one having the correlation matrix at Tx side and the other at Rx side. The model approximates the correlation matrix as the Kronecker product of correlation matrices at Tx and Rx separately. It works well at large Tx-Rx distances where the propagation at Tx and Rx can be considered independent [30, 31]. Since the Kronecker model is merely an approximation, the difference between the model and the measured results can be quantified using the second order error statistics given by [32]

$$\epsilon = \frac{\|\mathbf{R}_K - \mathbf{R}\|_{\mathrm{F}}}{\|\mathbf{R}\|_{\mathrm{F}}},\tag{3.12}$$

where \mathbf{R}_K and \mathbf{R} are the correlation matrices from the Kronecker model and measurements, respectively.

The Kronecker model is used to re-calculate the correlation matrix as

$$\mathbf{R}_{K} = \begin{bmatrix} 1.00 & 0.86 & 0.86 & 0.75 \\ 0.86 & 1.00 & 0.75 & 0.86 \\ 0.86 & 0.75 & 1.00 & 0.87 \\ 0.75 & 0.86 & 0.87 & 1.00 \end{bmatrix} .$$
(3.13)

The model provides lower correlation values compared to the measurement results. The introduced error is evaluated using the second order statistics $\epsilon = 7.58\%$, which implies that the Kronecker model may not be suitable for this scenario. Same conclusions are found in [26, 30, 31].



Figure 3.19: Subchannels correlation coefficients during the second half of the tunnel.

These results appear to be in contradiction with those presented in Figure 3.16, where the condition number remains relatively low throughout the tunnel. We further calculate the correlation coefficients per stationarity region and plot them versus distance in Figure 3.19. Indeed, the correlation coefficients remain high throughout the tunnel and no correlation is found between them and the condition number. This suggests that the main source of the multiplexing gain (i.e. having singular values of similar power representing parallel orthogonal subchannels) is not the decorrelation of the DP subchannels, but rather the DP orthogonality or diagonalization of the channel matrix that is maintained by high XPD and CPR close to unity. Figure 3.20 depicts the scatterplots of the condition number versus CPR and XPD_H. The plots are split into three parts according to the CPR level: CPR>3 dB (red), CPR < -3 dB (blue), and in between (green). Figure 3.20 (a) shows that there is a correlation between the CPR and the condition number, especially in the high CPR regions (red and blue) where the condition number decreases as CPR approaches 0 dB. It also shows that the condition number is lower-bounded by the magnitude of the CPR. Figure 3.20 (b) shows that the condition number decreases as XPD_{H} increases in the green and red regions. In other words, even when the power of VV is higher than HH (red), having less leakage from the HH (higher XPD_{H}) improves the channel multiplexing gain. For the red and green regions combined, the Pearson coefficient of correlation is calculated between the condition number and the magnitude of the CPR and XPD, and is found to be 0.8 and -0.6, respectively.



Figure 3.20: Scatterplots of the condition number versus CPR(a) and $XPD_H(b)$.

3.2 Arched tunnel environment

Few studies investigate arched tunnels; they model the channel in terms of path loss for SISO propagation [8, 33, 34]. In [35], authors study the narrowband propagation in arched tunnels using switching antennas, by measuring the capacity and correlation over distance for different polarizations. Authors in [17] use virtual arrays to study the wideband propagation in arched tunnels, again by investigating the path loss and capacity over distance for different polarizations. The same authors study the field distribution in the transverse plane and the correlation in both transverse and longitudinal directions in [36]. However, these studies investigate propagation under no traffic condition and do not include dispersion parameters like delay spread as in [37]. In addition, the Tx is usually placed at or near the center of the tunnel's cross-section.

In this section, we study the propagation of DP MIMO channels in an arched road tunnel under real traffic conditions. The measurements are carried out in two lanes. Hence, we investigate the influence of the Rx transversal location on propagation while the Tx is fixed near the tunnel wall, representing a realistic V2I scenario.

3.2.1 Measurements setup and scenario

Channel measurements are performed with the MIMOSA radio channel sounder by the TELICE group from the University of Lille, France. The transmission bandwidth is 80 MHz, centered around a carrier frequency of 1.35 GHz. For this measurement campaign, uniform linear arrays of four DP (H/V) patch antennas



Figure 3.21: Cross-section of the tunnel with Tx in the closed lane (left) and Rx in the van in the open lane (right) (Source: TELICE, University of Lille)

with 34 cm inter-element spacing (1.5 λ) are used at both Tx and Rx, giving rise to 8 parallel Tx and Rx channels. The acquisition time of the 8×8 channel snapshot each of 819 sub-carriers takes up 163.84 μ s.

Measurements have been carried out in an arch-shaped road tunnel located in Le Havre, France. The tunnel has two separate tubes in opposite directions. Since the two tubes are identical, only one direction was investigated. This straight tunnel is 590 m long and has approximate transverse dimensions of 9.7 m width and 4.63 m height. Along the tunnel, there are lights, pipes and reflective poles as shown in Figure 3.21. Two emergency exits on the closed lane side with metal fence and small parking space exist at one-quarter and half the distance along the tunnel. The tunnel has two lanes: the lane along the center is open for traffic, while the lane on the left side is closed.

For capturing the propagation channel along the tunnel, the Rx was mounted on the roof-top of a measurement van at a height of 2 m as shown in Figure 3.21. The van moved along the open lane with a 50 km/h speed limit and then made another



Figure 3.22: Average channel gain and the deduced model for the closed lane

round along the closed lane with almost half the speed. In both rounds, there was traffic along the open lane, and the Tx was mounted at the same height in the closed lane next to the tunnel wall, maintaining LOS with Rx. Hence, we captured for the closed lane double the data size of the open lane (600 and 292 frames for the closed and open lane, respectively). During the measurements, one of the Rx antenna cables was found defected and as a result, the corresponding data captured is not included in the analysis. Hence, for each measurement point along the tunnel, we capture a CTF matrix of size 4 Tx antennas \times 3 Rx antennas \times 4 polarizations \times 819 subcarriers. The four polarizations are VV, VH, HV and HH, where the first polarization refers to Tx and the second to Rx. In addition, the sounding snapshot mode used for this measurement campaign resets the phase every symbol. As a result of not tracking the phase, no Doppler analysis is possible.

3.2.2 Path gain and polarization power ratios

The path loss is deduced from the CTF matrix by averaging the power gain over all antennas and frequencies. As mentioned in Section 3.1.1, a one-slope model is used to characterize the path loss for both lanes of the tunnel. Figure 3.22 and 3.23 plot the measured channel gain of different polarizations versus distance for the closed and open lane, respectively. The corresponding curves for the deduced models are also plotted along with the free space model. Table 3.8 summarizes the model parameters in (3.2) for different polarizations, where the standard deviation σ of the measured gain from the predicted model values has been added to indicate the level of field fluctuation in dB.

The power ratios between polarizations are shown in Figure 3.24 and 3.25 for



Figure 3.23: Average channel gain and the deduced model for the open lane

		VV	VH	HV	HH
Closed lane	G ₀	-34.97	-43.81	-42.15	-39.10
	n	0.89	1.03	1.17	0.70
	σ	3.76	1.70	1.36	4.42
Open lane	G ₀	-28.42	-38.71	-43.68	-33.70
	n	1.25	1.33	1.11	1.01
	σ	2.80	2.04	1.84	2.19

Table 3.8: Path Loss Parameters

the closed and open lanes, respectively. Both CPR (VV/HH) and XPD (VV/VH and HH/HV) are plotted versus distance. The mean CPR averaged over distance is 0.19 dB in the open lane and 0.27 dB in the closed one. The average XPD of H-polar channel is larger than that of V-polar channel in the closed lane (16.7 dB compared to 13.7 dB), while it is almost the same in the open lane (13.16 dB).

These results show that the guiding effect of the tunnel results in a smaller path loss exponent than typical outdoor and indoor environments [38]. From Table 3.8, we notice that the attenuation rate of H-polar channel is less than V-polar channel (0.7 and 1.01 compared to 0.89 and 1.25). This comes from the fact that the wave polarized normal to the plane of incidence is reflected more than the one polarized parallel to the plane of incidence, in a phenomenon known as the Brewster's angle. Since the geometry of the tunnel is such that the width is larger than the height, the H-polar wave reflected from the ground and ceiling are more than the V-polar one reflected from the walls of the tunnel, which is also observed in previous



Figure 3.24: XPD and CPR versus distance for the closed lane



Figure 3.25: XPD and CPR versus distance for the open lane

studies [17, 39]. This explains the decrease in CPR that can be seen at far distances in the curves of both the closed and open lanes.

On the other hand, XPD does not drop at far distances and the waves stay highly polarized, confirming previous results [13, 31]. This can be related to Table 3.8, where the co-polar channels have smaller reference attenuation and path loss exponent than the cross-polar channels. The ray theory of propagation in tunnels predicts that depolarization only happen at small range, where the waves impinging the tunnel walls are not polarized along the direction parallel or perpendicular to the plane of incidence [40]. At large distances, only the rays reflecting with a grazing angle, polarized along these directions, play a leading part in the propagation and thus no depolarization occurs [13]. Also, if the difference between H and V reflection coefficients is large, the depolarization increases and the XPD drops. This difference is largest for medium angles of incidence, which explains the drop in the XPD at the equivalent medium distances of the tunnel.

Comparing between the two lanes of the tunnel, we see from Table 3.8 that cross-polar channels have similar behavior in both lanes. On the other hand, co-



Figure 3.26: Time-varying PDeP of HH channel in the open lane

polar channels have larger reference attenuation and smaller path loss exponent in the closed lane compared to the open lane. Also the standard deviation is larger in the closed lane compared to the open lane. According to the modal theory and depending on the geometry and excitation conditions of the tunnel, the farther you move away from the center towards the sides of the tunnel, the larger the average and standard deviation of the attenuation [41, 42].

3.2.3 Delay spread

We measure the time dispersion along the tunnel by calculating the RMS delay spread as in (2.8). We first deduce the PDeP by taking the inverse Fourier transform of the CTF and calculating the power of each delay component. The CTF at each distance point is averaged over all the antennas, normalized by a moving-average filter to remove large-scale fading, and then windowed using a Hanning window before applying the transform. In order to avoid spurious and noise components, we decide on a power threshold below which we set all the components to zero. The threshold is chosen to be 6 dB above the noise level. Figure 3.26 shows the timevarying PDeP along the tunnel for HH channel in the open lane. We notice that the PDePs are aligned in the delay domain due to the aforementioned snapshot mode of the measurements. We also notice the different components comprising the PDeP: the LOS being the strongest component, components with constant delay which probably come from the other vehicles moving at similar speed, and components with increasing or decreasing delay indicating reflecting objects moving away from or towards Rx, respectively. Since Rx antennas are facing the opposite direction of movement, the components moving away from Rx appear stronger.

We then calculate the RMS delay spread for different polarizations after applying the threshold. Figure 3.27 and 3.28 plot the RMS delay spread versus the distance for the co-polar channels in the closed and open lanes, respectively. It is



Figure 3.27: RMS delay spread along the closed lane



Figure 3.28: RMS delay spread along the open lane

observed that the delay spread slightly increases as the distance increases. After a certain distance, the higher order modes are attenuated in the far region and fewer modes are left. As a result, the delay spread decreases again according to [39, 42]. However, we notice the local increase in RMS spread at almost one quarter and half the tunnel range, which are more severe in the closed lane compared to the open lane. This can be related to the two emergency exit areas located at the same distances along the tunnel.

To decide on the distribution of the RMS delay spread, we again use the Kolmogrov-Smirnov test to compare it with theoritical distributions, as shown



Figure 3.29: RMS delay spread of HH channel in the open lane (a) CDF compared to theoretical distributions (b) histogram with log-normal best fit distribution

mean spread (ns)	VV	VH	HV	HH
Closed lane	12.94	22.17	23.57	15.35
Open lane	12.35	21.10	19.42	14.07

Table 3.9: Mean RMS Delay Spread

in Figure 3.29 (a) for the HH channel. We find the best fit to be a lognormal distribution [6] shown in Figure 3.29 (b). The parameters for the fitted log-normal distribution are ($\mu = -18.10$, $\sigma = 0.18$) for the open lane, and ($\mu = -18.05$, $\sigma = 0.33$) for the closed lane. Table 3.9 lists the mean RMS spread values over the tunnel in nanoseconds. They are relatively larger than the values found in [37], since our scenario represents larger frequency, tunnel geometry, obstacles and traffic conditions. It can be observed that the cross-polar channels have larger average spread than the co-polar channels, while the HH channel spread is larger than VV channel for both lanes. This can be again related to the Brewster angle phenomenon, where the width of both the tunnel and vehicles being larger than the height allows for stronger reflections of the H-polar rays compared to V-polar rays [42]. On the other hand, we see that the closed lane being closer to the tunnel walls has no significant impact on the average spread, compared to the open lane along the center of the tunnel.



Figure 3.30: Correlation coefficient amplitude r_{ij} between Rx antennas i and j for the VV channel in (a) the closed lane and (b) the open lane

3.2.4 Channel correlation and singular values

Subchannel correlation along the tunnel strongly influences the performance of MIMO systems. It depends on the antenna spacing and is related to the channel capacity which varies along the tunnel [43]. It is thus of interest to investigate the variation in subchannel correlation along the tunnel range. From the symmetry of the tunnel structure, it is enough to study the correlation at either Tx or Rx [35]. Figure 3.30 plots the correlation coefficient amplitude of the VV channel calculated between Rx antennas along both lanes of the tunnel using (3.10). It can be observed that correlation fluctuates rapidly around a mean value at close distances and then moves towards 1 at far distances of the tunnel. This can be explained according to the modal theory, where the uncorrelation in tunnel is attributed to the different hybrid modes propagating in the tunnel, giving rise to amplitude and phase variation of the fields in the transverse plane [12]. At large distances, high-order modes are subject to strong attenuation and hence only few number of modes result in the high correlation at far distances.

To capture the effect of antenna spacing on correlation, Figure 3.31 shows the average correlation coefficient amplitude along the tunnel as a function of Rx antennas inter-element spacing for different polarizations in both lanes of the tunnel.



Figure 3.31: Average correlation coefficient amplitudes along the tunnel in (a) the closed lane and (b) the open lane

It is highlighted that the correlation at Rx decreases as antenna spacing increases. We also notice that the average correlation of the co-polar channels is larger than that of the cross-polar channels, with the H-polar correlation being higher than V-polar correlation. This can be attributed again to the geometry of the tunnel.

A low spatial correlation of the MIMO subchannels does not guarantee a high capacity performance. This is because the capacity also depends on the number of equivalent independent parallel subchannels and the weights of these subchannels. This is accurately represented by the singular value decomposition of the CTF matrix. The matrix **H** can be expressed as a function of its singular values as follows

$$\mathbf{H} = \sum_{k} \mathbf{u}_{k} s_{k} \mathbf{v}_{k}^{*} \tag{3.14}$$

where s_k , \mathbf{u}_k and \mathbf{v}_k are the kth singular values, right and left singular vectors of \mathbf{H} , respectively. Hence, the rank of \mathbf{H} , representing the number of non-zero singular values, and the condition number of \mathbf{H} , representing the ratio between these singular values, both affect the MIMO channel performance gain.

It is possible to have a rank deficient matrix with high condition numbers, even if correlation among antennas is low. Therefore, it is important to investigate the condition numbers of the CTF matrix along the tunnel range. For the 4x3 configuration, the CTF matrix has 3 singular values. Figure 3.32 plots the ratios of the first singular value to the second and third values versus the distance in both lanes of the tunnel for the VV channel. We observe that at small distances the



Figure 3.32: Variation of the singular values ratios for the VV channel in (a) the closed lane and (b) the open lane

ratios are low indicating a high capacity gain. However, as the distance increases, the ratios begin to increase as well, resulting in a lower capacity gain. This shows that the attenuation of the higher order modes at far distances is large enough to degrade the MIMO channel performance. Similar behavior was observed for other polarizations.

3.2.5 MIMO channel capacity

We investigate the channel capacity for MIMO systems in the tunnel by calculating the CDF of the capacity for a mean SNR of 10 dB. We consider 2x2 and 4x3 MIMO configurations. The measurement setup allows us to capture the influence of the inter-element spacing of Tx and Rx antennas on the capacity of the 2x2 MIMO system. The capacity CDF for spacing of 1.5λ , 3λ and 4.5λ are plotted for the closed and open lanes in Figure 3.33 and 3.34, respectively. We also add the performance using a single antenna (SISO) for comparison.

It is evident that, as the inter-element spacing increases, the MIMO capacity increase. However, there is no much difference after a spacing of 3λ . This can be related to the subchannel correlation as observed in Figure 3.31, where the Rx correlation decreases with the Rx antennas spacing and starts to saturate at 3λ .



Figure 3.33: Capacity CDF for 2x2 MIMO system with different antenna spacing in the closed lane



Figure 3.34: Capacity CDF for 2x2 MIMO system with different antenna spacing in the open lane

Comparing the two lanes, we observe that for an outage probability of 0.5, the capacity reaches 5.8 bits/s/Hz in the open lane and 5.2 bits/s/Hz in the closed lane, compared to the SISO capacity of 3.3 bits/s/Hz. The effect of polarization on the capacity performance is insignificant as observed in the figures.

To investigate the maximum achievable capacity with our system, we consider the 4x3 MIMO configuration. Figure 3.35 compares the 4x3 configuration with the theoretical 4x3 Rayleigh channel in both lanes. We notice again the open lane



Figure 3.35: Capacity CDF for 4x3 MIMO system in the closed and open lanes

capacity being larger than the closed lane (7 bits/s/Hz compared to 6.5 bits/s/Hz for an outage probability of 0.5 in the VV channel). This can be attributed to the singular values ratios reaching higher levels in the closed lane compared to the open lane as observed in Figure 3.32. The results in Figure 3.35 also indicate that the V-polar channel capacity slightly exceeds the H-polar channel capacity [17, 35]. This is expected from Figure 3.31, which shows the VV channel having less average Rx correlation than the HH channel.

3.3 Conclusions

Accurate characterization of radio propagation in tunnels is needed, specially in real traffic conditions and arbitrary tunnel shapes. In this chapter, we present a measurement-based analysis of the non-stationary V2I DP wireless channel in different road tunnel environments. The first measurement is performed at 90 km/h in a rectangular tunnel under low and medium traffic conditions. We investigate the impact of antenna polarization and radiation pattern, as well as the traffic condition, on the non-stationary V2I channel. Basic channel evaluation metrics are examined including path gain, CPR, and XPD. In addition, the stationarity region is estimated using the channel correlation function approach, and used to calculate the time-varying delay and Doppler power profiles. The path gain is modeled using the one-slope model. Statistical models are presented for CPR, XPD, RMS delay and Doppler spreads, where the lognormal distribution is found to provide the best fit.

The traffic density is found to have no effect on the stationarity time. On the other hand, it increases the delay and Doppler spreads, while reducing the correlation between them, as well as the average K-factor of the fading amplitude. Investigating the impact of antenna polarization shows that the V polarization is more advantageous, as it provides higher path gain and longer stationarity time by 5%, in addition to smaller delay and Doppler spreads (by 19% and 18% on average, respectively) compared to the H polarization. As for the impact of antenna radiation pattern, a more directional antenna is found to provide a longer stationarity time by 21%, as well as smaller delay and Doppler spreads (by 52% and 32% on average, respectively), thus proving to be more beneficial than a wide-angle type of antenna pattern. Moreover, the impact of normalization on the DP capacity is investigated, and a new approach is proposed that maintains the conservation of energy.

The second measurement is conducted in an arched tunnel at 50 km/h. The MIMO channel was measured for different polarizations in the open lane along the center of the tunnel and in the closed lane on the side next to the tunnel wall. We investigated channel parameters related to path loss, time dispersion and MIMO capacity. Our analysis shows that a single-slope model describes well the attenuation in a tunnel under road traffic conditions. The guiding effect of the tunnel results in a path loss exponent smaller than typical indoor and outdoor environments. Waves are highly polarized even at far distances, with a measured XPD of about 13 dB. The RMS delay spread remains around the mean values in the range of 12 ns to 24 ns, with the mean RMS spread of the H-polar channel being larger than that of the V-polar channel. The distribution of the spread variation along the tunnel can be fitted to a log-normal distribution, with larger standard deviation in the closed lane than in the open lane.

Finally, the main conclusions for the MIMO system performance are as follows. Subchannel correlation increases at farther distances in the tunnel, with H-polar channel correlation being higher than V-polar channel correlation. The condition number of the MIMO channel matrix increases slightly with distance. The increase of the singular values ratio and the decrease of the Rx correlation amplitude, both indicate a decrease of MIMO capacity with distance in the tunnel for a constant SNR. The capacity CDF of 2x2 MIMO system is investigated for different antenna elements spacing at a constant SNR of 10 dB. It is found that the capacity increases for larger inter-element spacing, with insignificant difference after 3λ . For an outage probability of 0.5, capacity reaches 5.7 bits/s/Hz compared to 3.3 bits/s/Hz for SISO. The open lane along the center of the tunnel provides higher capacity than the closed lane near the tunnel wall. In Chapter 4, the simulation of the non-stationary fading process is investigated using an autoregressive modelling approach for the vehicular channels. Measurements in the rectangular tunnel from this chapter will be used in Chapter 4 to model the non-stationary V2I channel in tunnels.
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Auto-regressive modelling for non-stationary channel simulation

The mobile radio channel poses significant challenges to the design of communication systems due to time and frequency dispersions. In previous chapters 2 and 3, the non-stationarity of vehicular channels was measured and used to statistically model the large-scale fading parameters in different environments. Nevertheless, an accurate and concise channel model to regenerate or predict the measured channel behavior is useful for channel simulation, performance evaluation, and further design of communication systems [1]. In this chapter, a framework is proposed for long-term vehicular channel simulation based on the vector time-frequency autoregressive model for a sparse parametric description of nonstationary multivariate random processes. Based on the V2I tunnel measurements presented in Chapter 3, we estimate the vector time-frequency auto-regressive (VTFAR) model parameters and validate the model by comparing the parametric and non-parametric spectra of the measured channel in terms of the delay spread and stationarity time. In addition, the VTFAR model stability is investigated and an approximation for the correlated scattering channel is proposed. Hence, the novelty of this chapter includes the framework and parameterization of the VTFAR model for a high-speed tunnel environment with stable correlation approximation.

The chapter is organized as follows. Section 4.1 briefly explains the VTFAR model and the parameters estimation. Section 4.2 presents the measurement campaign and the simulation framework for the measured channel response. Section 4.3 discusses the correlated scattering channel and VTFAR model stability. Section 4.4



Figure 4.1: Block diagram of the VTFAR model where T is a time shift operator, D is a Doppler shift operator, and the diamond shape is a matrix multiplication

includes the model validation. Finally, conclusions are drawn in Section 4.5.

4.1 Methodology of modelling

4.1.1 VTFAR model

The non- wide-sense stationary (WSS) uncorrelated scattering (US) channel can be described by an innovation system, shown in Figure 4.1, where the 2-D channel impulse response (CIR) is obtained by passing white innovations noise $\mathbf{e}[n]$ into a nonrandom linear time-variant (LTV) system $\mathbf{V}[n,m]$ as follows

$$\mathbf{h}[n] = \sum_{m} \mathbf{V}[n,m]\mathbf{e}[n-m]. \tag{4.1}$$

Here, the CIR is expressed in a vector form as $\mathbf{h}[n] = [h[n, 0]...h[n, \tau_m - 1]]^T$, where τ_m is the number of delay taps and n = 0, 1, ..., N - 1 is the innovations index, which can then be up-sampled to a desired sampling rate, i.e. n = Kt. This can be done as the channel variation is limited to slower Doppler rates. According to the VTFAR model [2], the innovations IIR filter $\mathbf{V}[n, m]$ is represented by Doppler shifts (*l*) in addition to the time shifts (*m*). Rewriting (4.1) in the VTFAR form gives

$$\mathbf{h}[n] = -\sum_{m=1}^{M} \sum_{l=-L}^{L} \mathbf{A}_{m,l} e^{j\frac{2\pi}{N}nl} \mathbf{h}[n-m] + \mathbf{e}[n], \qquad (4.2)$$

where M and L denote the (temporal and spectral) model order, the $\tau_m \times \tau_m$ matrices $\mathbf{A}_{m,l}$ contain the AR model parameters, and $\mathbf{e}[n]$ is the complex Gaussian, temporally uncorrelated, circularly symmetric innovations noise vector with correlation matrix $\mathbf{E}\{\mathbf{e}[n]\mathbf{e}^*[n']\} = \mathbf{C}[n]\delta(n-n')$. The model is depicted in Figure 4.1. According to (4.2), elements of the $\mathbf{V}[n,m]$ matrices are constrained to lie in the subspace spanned by the complex exponentials with Doppler frequencies l = -L, ..., L. A similar restriction is imposed on the innovations correlation matrix

$$\mathbf{C}[n] = \sum_{l=-2L}^{2L} \mathbf{C}_l \ e^{j\frac{2\pi}{N}nl},\tag{4.3}$$

such that a matrix square root $C^{1/2}[n]$ with Doppler order L can be found [2].

Another restriction in the VTFAR(M,L,B) is band-limiting the matrices $\mathbf{A}_{m,l}$ and \mathbf{C}_l , i.e., elements of these matrices with indices (τ, τ') are zero for $|\tau - \tau'| > B$, where B denotes the (one-sided) matrix bandwidth ($B \in \{0, 1, ..., \tau_m - 1\}$). This is motivated by the fact that correlation decays with delay taps in doubly-underspread (DU) channels (for US channels B = 0). Consequently, the number of parameters characterizing the banded VTFAR model is shown to be $\mathbb{N} = (M + 1)(2L + 1)(\tau_m(2B+1) - B(B+1))$ [2]. Thus, the parsimony of the VTFAR model is better for smaller M, L, τ_m , and B, making it particularly suited for the DU channels where $ML \ll N$. This plays an important role in developing computationally efficient parameter estimators for $\mathbf{A}_{m,l}$ and \mathbf{C}_l [2].

4.1.2 VTFAR parameters estimation

We consider the estimation of VTFAR model parameters from a single channel realization $\mathbf{h}[n]$ obtained from a measurement campaign. Estimation of the $\mathbf{A}_{m,l}$ involves solving a system of multichannel time-frequency Yule–Walker (TFYW) linear equations, similar to the classical YW equations. An approximation for the DU channels derived from (4.2) reads as follows [2]

$$\sum_{m=1}^{M} \sum_{l=-L}^{L} \mathbf{A}_{m,l} \mathbf{F}_{h}[m'-m,l'-l] = -\mathbf{F}_{h}[m',l'], \qquad (4.4)$$

where $\mathbf{F}_{h}[m, l]$ is the average expected ambiguity function (EAF). In practice, the EAF is usually unknown and has to be estimated from a given observation of $\mathbf{h}[n]$. When multiple observations are available, the EAF can be estimated as [2]

$$\mathbf{F}_{\mathbf{h}}[m,l] = \mathbf{E} \Big\{ \sum_{n=0}^{N-1} \mathbf{h}[n] \mathbf{h}^*[n-m] \ e^{-j\frac{2\pi}{N}nl} \Big\}.$$
(4.5)

In order to efficiently solve (4.4) for $\mathbf{A}_{m,l}$, the matrix equations are rewritten element-wise and re-stacked with a suitable order to reach a single matrix equation

involving a two-level block-Toeplitz (2LBT) matrix as [2]

$$\mathbb{Z} \mathbf{a} = -\mathbf{z}.\tag{4.6}$$

Here, the matrices \mathbb{Z} and \mathbf{z} contain the $\mathbf{F}_{h}[m, l]$ elements , and \mathbf{a} contains the $\mathbf{A}_{m,l}$ elements. The 2LBT structure of \mathbb{Z} is the basis for a fast solution algorithm developed in [2], called the multichannel Wax-Kailath algorithm, from which the VTFAR parameters can be extracted. Once $\mathbf{A}_{m,l}$ are estimated, the evaluation of the innovations matrices \mathbf{C}_l can be derived as [2]

$$\mathbf{C}_{l} = \frac{1}{N} \sum_{m=0}^{M} \sum_{l'=-L}^{L} \mathbf{A}_{m,l'} \mathbf{F}_{h}^{*}[m,l'-l].$$
(4.7)

The correlation matrices C[n] can then be obtained from (4.3) via an iterative scheme that alternately enforces positive definiteness and Doppler and matrix band-limitations [2].

4.2 Simulation Framework for Vehicular channels

In this section, we propose a framework for simulating vehicular radio channels using the VTFAR model. The parameters estimator requires at least one realization of the channel in order to calculate the EAF. The framework is thus applied to the CIR from a V2I measurement campaign. As a long-term simulation, we use a 8 s duration of the measured channel, corresponding to approximately eight thousand snapshots over 900λ .

4.2.1 Measurement campaign

Measurements of the V2I channel in the Beveren tunnel presented in Section 3.2.1 are used. The sounder uses 80 MHz of transmission bandwidth centered around a carrier frequency of 1.35 GHz. The Tx antenna is placed around the middle of the tunnel through an emergency exit door at a 2 m height. The Rx antenna is mounted on the rooftop of a van carrying the Rx inside. The van moves through the tunnel at a 90 km/h speed, crossing the Tx position halfway. During the trip, the radio channel is sampled with a snapshot repetition time of 975.3 μ s, each with 819 frequency samples. Further details can be found in Section 3.2.1, where the setup is shown in Figure 3.2.

4.2.2 Proposed framework

4.2.2.1 Pre-processing

The channel sounder captures the channel transfer function (CTF) in the time and frequency domains. It includes both large-scale (path loss, shadowing,..) and

small-scale fading effects. We first apply an inverse Fourier transform to the CTF using a Hann window to obtain the time-varying CIR. Then, we align the CIRs so that the maximum LOS components have the same absolute delay. Finally, we remove the large-scale fading using a moving-average filter with a window size of 10λ . This results in normalised CIRs that preserve the small-scale fading like what is commonly used for link-level simulations.

4.2.2.2 Bandwidth

The ITS spectrum for V2X communications supports direct low-latency connections over short distances, without the involvement of the cellular network. Standards like C-V2X and 802.11p can co-exist in the ITS spectrum by employing different channels within the band, where just 10 MHz of spectrum is required to support essential safety services [3, 4]. This makes V2X channels particularly suitable for the VTFAR model, since a small bandwidth means fewer delay taps and thus fewer model parameters. Consequently, we divide the measured CTF into 8 channels of 10 MHz bandwidth. The CIR is then calculated as mentioned above for each channel, from which the average EAF is estimated as in (4.5) by averaging over the 8 channels.

4.2.2.3 Sampling rate

The sampling rate used for link simulation and performance evaluation is typically orders of magnitude larger than physical Doppler frequencies, i.e. the delay tap processes are very narrowband. In that sense, a subsampled VTFAR model at an intermediate sampling rate that is close to the maximum Doppler frequency is followed by an optimum multistage interpolator in order to match the actual system sampling rate. In our scenario, the multi-path components (MPCs) Doppler frequencies span up to 128 Hz. Thus, we sample the CIR at 256 Hz, which gives $\mathbf{h}[n]$.

4.2.2.4 Number of taps

The number of delay taps τ_m directly impacts the parsimony of the VTFAR model. It is desirable to include the minimum number of taps that is sufficient to model the channel. To that aim, we propose to set τ_m based on the second-order statistics of the channel, namely, the RMS delay and Doppler spreads. These parameters play a vital role in system performance and design, making them a relevant criterion. Figure 4.2 shows the CDF of the RMS delay spread for different number of delay taps. Only MPCs within 30 dB from the peak value are considered for calculating the delay spread. The 100-tap CDF represents the full channel since no MPCs exist beyond that. In order to decide on the number of taps, we use the two-sample Kolmogorov-Smirnov test and compare the p-values at 5% significance level. The



Figure 4.2: CDF of the RMS delay spread for different number of taps

Taps	2	3	4	5	6	7	8
Delay	0	0	0	0	0.225	0.271	0.59
Doppler	0	0.005	0.06	0.225	0.225	0.81	0.98

 Table 4.1: KS-test p-values of the delay and Doppler spreads CDFs for different number of taps

test checks whether the spread of a certain τ_m comes from the same distribution as that of the full channel. The same procedure is done for the RMS Doppler spread, and the minimum number of taps whose spreads' distributions pass the tests is chosen to represent the channel. Table 4.1 shows the p-values for the delay and Doppler spreads at different number of taps, where it is clear that the distributions with 6 taps pass both tests.

4.3 Correlated Scattering and VTFAR Stability

In the previous section, we explained how to extract the CIR, calculate from it the average EAF $\mathbf{F}_{h}[m, l]$, and use it to estimate the matrices $\mathbf{A}_{m,l}$ and \mathbf{C}_{l} . We can then generate the channel coefficients $\mathbf{h}[n]$ by passing the innovations vector $\mathbf{e}[n]$ with the correlation matrix $\mathbf{C}[n]$ into the VTFAR model depicted in Figure 4.1. However, the AR model is an IIR filter that is not guaranteed to be stable.

4.3.1 Stability analysis

A stable process is one that will not diverge to infinity (blow up). This means that the characteristic polynomial in the denominator of the transfer function vanishes only within the unit circle in the complex frequency plane (z-plane). From (4.2), the stability condition can be formulated as [5]

$$det(\mathbf{I}_{\tau_m} + \mathbf{A}_{1,n} z^{-1} + \dots + \mathbf{A}_{M,n} z^{-M}) \neq 0 \quad for \ |z| \ge 1,$$
(4.8)

where $\mathbf{A}_{m,n} = \sum_{l=-L}^{L} \mathbf{A}_{m,l} e^{j2\frac{2\pi}{N}nl}$ are the time-varying filter matrices at time n and \mathbf{I}_{τ_m} is a unitary matrix, all of size τ_m .

For the case of US channels (B = 0), all system matrices become diagonal. This means that the vector process $\mathbf{V}[n, m]$ can be modeled as τ_m scalar processes in parallel. This simplifies the stability condition, as the characteristic polynomial per process is now a scalar function rather than a matrix function. It is shown in [6] that such a system can be stabilized using an iterative algorithm based on the concept of root reflection/shrinkage known from the time-invariant case by applying it to the time-varying instantaneous roots of (4.8).

4.3.2 Correlation analysis

According to [7], the observed fading process in vehicular channels shows a much stronger violation of the WSS assumption than the US one. Channels show correlated scattering due to several MPCs that are close in the delay-Doppler domain reflecting off the same physical object, or leakage due to bandwidth/time limitations at Tx or Rx. This happens when the signal's bandwidth is larger than the stationarity bandwidth. It is observed in [7] that the stationarity bandwidths from a large set of measurements in different vehicular scenarios are above 150 MHz on average. This is very much larger than the required 10 MHz communication bandwidth for V2X systems. It is thus expected that the taps correlation will not be significant in our scenario.

We investigate the correlation as a function of the delay taps separation. Figure 4.3 shows the CDF of the correlation coefficient between delay taps up to 5 taps apart. It is clear that a correlation of 0.7 on average can be found only with the adjacent tap, while taps separated by two taps or more have insignificant correlation (below 0.3 on average). Moreover, it shows that there is no much variation around the mean value, only a standard deviation of 0.07 for the adjacent tap.

4.3.3 Correlation approximation for stable modelling

In order to simulate the correlated scattering channel with a stable AR model, we propose to set B = 0, resulting in a diagonal (uncorrelated) matrices $\mathbf{A}_{m,n}$ and $\mathbf{C}[n]$. The model can now be stabilized as aforementioned in the US case. Then,



Figure 4.3: CDF of the correlation coefficient for different taps separation

we approximate the taps correlation to the mean value, since its time-variation is limited as depicted in Figure 4.3. The correlation is introduced to the innovations matrix as follows

$$\widehat{\mathbf{C}}[n] = \mathbf{C}^{1/2}[n] \mathbf{R} \mathbf{C}^{1/2}[n], \qquad (4.9)$$

where **R** is the $\tau_m \times \tau_m$ correlation matrix calculated from the measurements by averaging over the total duration. In other words, instead of passing uncorrelated multivariate innovations, $\mathbf{e}[n]$ are now correlated based on **R**, thus $\widehat{\mathbf{C}}[n]$ is no longer diagonal.

We simulate the 6-tap channel with the proposed approximation, where the model orders (M,L) per tap are estimated using the minimum description length information criterion presented in [6]. The simulated channel is upsampled to have the same sampling rate as the measurement, i.e. K = 4. Figure 4.4 compares segments of the CIR power from both measurements and simulation. It shows that the model generates a stable process that resembles the measured channel. To check the validity of the correlation approximation, we compare the measured and simulated 1-tap separation correlation coefficient, which is the most significant one. Figure 4.5 shows that the correlation of the generated channel approximates that of the measurement quite well over a long duration with RMSE of 0.08.

4.4 Model Validation

Non-stationary channels can be characterized by the local scattering function (LSF), which is the time-varying second order statistics of the channel. We validate the



Figure 4.4: CIR power in dB from measurements (a) and simulation (b)



Figure 4.5: 1-tap separation correlation coefficient from measurements and simulation



Figure 4.6: Non-parametric power profiles in delay (a) and Doppler (c) versus the parametric profiles in delay (b) and Doppler (d) in dB

VTFAR model by comparing the parametric LSF of the model to a non-parametric LSF calculated from the measurement as shown in Chapter2.

4.4.1 Parametric vs. non-parametric spectra

Since we are more interested in the non-WSS nature of the channel, we discard the LSF's dependency on frequency and only consider the time dependency. This makes the LSF a 3-D function in time, delay and Doppler. The time evolution can be investigated by projecting the LSF on the delay and Doppler domains, resulting in the delay and Doppler power profiles or spectra. The model validation is based on comparing the spectra estimated from the non-parametric multi-tapers approach presented in Chapter2, to the parametric spectra of the VTFAR model. According to [2], the parametric LSF is expressed as

$$\widehat{C}_{\mathrm{H}}[n;\nu,\tau] = \frac{\widehat{\mathbf{C}}[n]}{|\mathbb{F}_{l\to n}^{-1} \mathbb{F}_{m\to\nu}\{\mathbf{A}_{m,l}\}|^2}.$$
(4.10)

Figure 4.6 shows the parametric spectra versus the non-parametric spectra for an 8 s duration of the 6-tap channel. The parametric spectra are evaluated by summing the LSF from (4.10) in the delay and Doppler dimensions. The details of estimating



Figure 4.7: Model validation in terms of the RMS delay spread (a) and stationarity time (b)

the non-parametric spectra from the measurement can be found in Section 2.1.1. The finite-dimensional spaces of the parametric model can be clearly noticed in the smooth nature of its spectra, compared to the sample-based non-parametric spectra. Nonetheless, we notice the similarity between the two spectra in both delay and Doppler domains. The power-delay profiles are aligned to have the LOS component at zero delay as discussed in the pre-processing step, while the Doppler spectra show the LOS component's shift from positive to negative Doppler frequencies as the Rx crosses the Tx position in the tunnel.

4.4.2 Comparing spectra for model validation

We validate the model by investigating how well it matches the time-varying behaviour of the non-stationary channel. Hence, we compare the parametric and non-parametric spectra at two levels: (i) the channel's coherence level, represented by the delay spread, and (ii) the channel's stationarity level, represented by the stationarity time. While the delay spread measures the time dispersion of the channel, which may cause inter-symbol interference, the stationarity time measures how often this dispersion varies in time. The stationarity time is estimated as in (2.6).

For validation, we compare the time evolution of both parameters to measure

how well the model matches the time-varying behaviour of the channel. Figure 4.7 shows the RMS delay spread and stationarity time for the parametric vs. non-parametric spectra. We discard the first second to provide enough initialization time for the IIR filter's transient response to settle [8]. We see that both parameters show good similarity between the two spectra. We quantify the RMSE to be 0.01 for the delay spread and 0.4 for the stationarity time.

4.5 Conclusion

In the previous chapters, the non-stationary V2I channel was characterised in terms of stationarity region and large-scale parameters, where the relevance to communication systems design was explained. Channel simulation is also needed for the performance evaluation of such systems. In this chapter, parametric modelling of non-stationary processes is applied to simulate the measured V2I channel in a tunnel in Belgium. We propose a framework for long-term simulation based on the vector time-frequency autoregressive (VTFAR) model. We analyse the stability of the model and propose an approximation for the correlated scattering channel that guarantees stability. A 6-tap channel is simulated based on the measurement, where the VTFAR model parameters are estimated using the proposed approach. Moreover, the parametric spectra of the model are compared to non-parametric spectra of the measured channel from Chapter 3. We validate the model in terms of the delay spread and stationarity time. The model is found to simulate the measured channel very well with RMSE of 0.01 for the delay spread and 0.4 for the stationarity time. This measurement-based and computationally inexpensive approach provides an efficient alternative for non-stationary channel simulations. This chapter concludes Part I of our work. In the coming chapters, we focus on the indoor channel in industrial scenarios and characterise the reverberation at the mmwave bands for such reflective environments. Applications for human sensing in such environments are also proposed, including occupancy and fall detection in ships.

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Part II

Indoor Channel Modelling in Metallic Environments

Human sensing in a reverberant ship environment

In the first part of this work, we studied the outdoor propagation channel and modelled the fading parameters related to vehicular communications in different environments. Here, we shift the focus to the indoor channel and particularly to enclosed metallic environments that can be found in industrial scenarios and applications. This chapter investigates the reverberating nature of confined metallic environments such as those found in ships. The design of an algorithm for device-free occupancy detection is presented in reverberant environments based on room electromagnetics and the reverberation time (RT). The algorithm uses the channel impulse responses (CIR) and thus can be integrated in wideband communication systems. In addition, the experimental validation of the algorithm in a realistic ship environment is provided using a radio channel sounder as well as commercial off-the-shelf (COTS) devices for UWB communications. The possibility of fall detection in reverberant environments based on the CIRs is explored and a Doppler-based method is experimentally evaluated as a complementary technique for safety monitoring and alert applications.

The outline of this chapter is as follows. Section 5.1 is dedicated to the RTbased occupacy detection. The measurement setup and scenario are described in Section 5.2.1. Section 5.2.2 describes the methodology to extract the RT, while in Section 5.2.3 processing of the measurement data is presented. Section 5.2.4 shows the estimation results for the number of people, while the fall detection is discussed in Section 5.3. Finally, conclusions are drawn in Section 5.4.



Figure 5.1: The rectangular antenna array of the channel sounder (left) and the equivalent UWB nodes array (right)

5.1 RT-based occupancy estimation

5.1.1 Measurement setup and scenarios

Channel measurements are first performed with the MIMOSA radio channel sounder. The multidimensional polarimetric CIR is measured in the spatial and polarization dimensions to investigate the reverberant behavior of the room. It is then used to test the occupancy detection algorithm when the people are standing still. The next step is to verify the algorithm performance with COTS products that provide the CIR. Hence, UWB devices are used for the occupancy detection when the people move in the same room, which is a more realistic scenario. This section includes the details of the measurement configurations and scenario.

5.1.1.1 Standing-people scenario with channel sounder

The sounder operates with a carrier frequency of 1.35 GHz and the transmission bandwidth is 80 MHz as mentioned in Section 1.4. It uses dual-polarized patch antenna arrays with horizontal (H) and vertical (V) polarization. For this measurement campaign, 8-element rectangular arrays are used at both Tx and Rx as shown in Fig. 5.1 (left), thus measuring the total 16×16 channels. The measurement campaign is carried out in the steering gears room of a bulk carrier vessel, shown in Fig. 5.2. The Tx and Rx of the channel sounder are placed inside the room and the



Figure 5.2: Below-deck ship compartment with rectangular antenna arrays of the channel sounder

door is kept closed during the measurement. The room has a height of 4 m and a floor area of 150 m², approximately. The Rx antenna array is fixed at 2 m height, pointed towards the corner of the room [1]. The reverberating nature of the room is first investigated by comparing the RT at different locations inside the room. This is done by placing the Tx antenna array at 6 random locations to measure the CIRs. Then, the Tx is fixed and the CIRs are recorded for different numbers of people inside the room, ranging from 0 to 6 persons standing still at different random locations. The channel in each case is measured 200 times in static conditions and averaged to reduce measurement noise. Hence, a total of $7 \times 64 \times 4$ averaged power-delay profiles (PDeP) are calculated, where the value 64 results from the 8×8 antenna elements, and 4 from the TxRx polarization combinations (VV, HV, VH, HH).

5.1.1.2 Moving-people scenario with COTS devices

UWB is one of the most promising technologies for real-time location systems indoors due to its accurate positioning capabilities, immunity against multipath fading, and excellent resilience against narrowband interference [2]. In our experiment, we use a newly developed open source hardware platform based on Decawave's DW1000 UWB transceiver chips with support of both long-range sub-GHz and 2.4 GHz back-end communication between nodes [3]. An external omni-directional antenna with vertical polarization is connected to each node as shown in Figure 5.1. To calculate the distance between 2 nodes based on the time-of-flight, asymmetric two-way ranging protocol [4] is used at a rate of 25 Hz. One of the optional outcomes of this protocol is the CIR estimate of size equal to 1016 samples. Hence, the CIRs are recorded with 900 MHz bandwidth around 4 GHz center frequency using channel 4 of the DW1000 chip [4]. The same scenario with the channel sounder is repeated using the UWB nodes with the difference that the people are allowed to move inside the room. A setup of 8x8 UWB nodes is used to measure the 64 spatially uncorrelated CIRs 200 times for each number of people. The Rx antennas setup is shown in Fig. 5.1 (right).

5.1.2 Methodology of occupancy detection

In order to predict the number of people inside the room, we first need to extract the RT. In indoor propagation, multiple reflections and scattering lead to an exponential decay of power with a decay constant τ representing the RT. The diffuse scattering model in Fig. 1.11 of Chapter 1 can be expressed as

$$P(t) = P(0) \exp(-t/\tau)$$
 (5.1)

where t is the time of arrival on the delay axis and P(t) is the corresponding received power. According to room electromagnetics, the RT can be expressed as [5]

$$\tau = \frac{4V}{cA_n} \tag{5.2}$$

where V is the room volume, A_n is the total absorption area and c is the velocity of light. In a fixed environment, where the contents of the room do not change except for the number of people inside, the total absorption area can be written as

$$A_n = A_0 + n \times ACS \tag{5.3}$$

where A_0 is the absorption area of the room without people, n is the number of people in the room and ACS is the whole-body absorption cross-section area of the human body [6]. Each additional person in the room increases the total absorption area by the amount of the ACS of the human body. The PDeP is calculated as

$$PDeP = \frac{1}{N} \sum_{N} |CIR|^2$$
(5.4)

where N is the number of CIRs aligned to the same LOS delay as in [7]. Once the RT is extracted from the PDeP, it is possible to assess the absorption area A_n from (5.2). Assuming the ACS is known, the number of people n can then be calculated from (5.3).



Figure 5.3: PDeP and linear regression for different polarizations in case of an empty room

For the extraction of the RT, the slope of the PDeP exponential decay needs to be calculated. However, the tail of the PDeP is not perfectly linear due to noise, LOS and specular components. A least squares regression line is thus used to fit the PDeP over a delay range, and the choice of this range is done automatically. First, to avoid LOS, the starting point is taken as the mean arrival time T_m given by

$$T_m = \frac{\sum t P(t)}{\sum P(t)} \tag{5.5}$$

Second, the noise level is calculated by averaging the power values at large delays from the PDeP where no multipath components above the noise are expected. Finally, in order to avoid the noise floor, the ending point of the delay range is taken when the power level reaches 6 dB above the calculated noise level.

5.1.3 Pre-processing experimental data

5.1.3.1 RT extraction

In order to investigate the reverberating nature of the environment, the RT is calculated at six different locations in case of an empty room. The PDeP per location is measured using the channel sounder and spatially averaged over all the antenna elements before extracting the RT, to remove small-scale fading. Figure 5.3 shows the PDeP at one location for different polarizations. The figure shows the identical diffuse power level of the co-polar and cross-polar channels, suggesting that the polarization states in the room are uniformly distributed (XPD of one),



Figure 5.4: RT at 6 locations for different TxRx polarization combinations in case of an empty room

as is expected in a reverberating environment. To further validate the assumption of reverberating fields, the RT is compared at six random locations in the room. Figure 5.4 shows the RT at each location for different polarizations. It is clear that the RT value is independent of the location as well as the polarization of the antennas, with a relative standard deviation of 0.99%. This verifies the reverberating nature of the room, in accordance with [8].

With the Tx fixed, the RT is calculated when the room is occupied by people, starting from 1 up to 6 persons. Figure 5.5 shows the RT versus the number of people for different polarizations. The figure clearly indicates that the RT is inversely proportional to the number of people. This validates the relation between the RT, absorption area, and the number of people in the room for different polarizations. Figure 5.5 also shows that the RT for VV is slightly lower than the average of all polarizations, suggesting that the human body is more prone to absorbing vertically polarized waves. Nevertheless, the RT values for different polarizations are aggregated to form a larger sample size to be used for the occupancy detection in the next section, as they are similar enough with relative standard deviation of 0.61%.

5.1.3.2 Absorption area and calibration

Since the average ACS of the people inside the room is assumed to be known, it would be of interest to first calculate the ACS based on our measurements and compare it to prior studies. From (5.3), the ACS is the slope of the linear



Figure 5.5: RT versus the number of people inside the room for different polarizations

	Full data	Calibration set (20%)
ACS/V	22.17	21
A_0/V	607.33	609.5

Table 5.1: Parameters Calibration in $(10^{-4}/m)$

regression of different absorption areas A_n related to different numbers of people (n = 0, 1, ..., 6). The calculation of A_n is given in (5.2) by averaging the PDePs of all polarizations before extracting the RT. This gives an ACS of 1.3 m² based on our experiment. The whole-body ACS was measured in a reverberation chamber in [6] and found to be 1.11 m² for a 1.73 m and 63 kg person. A reason for this small deviation is the complex structure of the room in our scenario, making the calculation of the exact volume a difficult task. Moreover, the value from our experiment is the average ACS of all six persons. It is thus expected to be different from the one reported in [6] of only one human subject.

In order not to require the exact volume of the room, the parameters ACS and A_0 used for estimation based on (5.2) and (5.3) can be replaced by the scaled versions ACS/V and A_0/V , respectively. This requires a measurement-based calibration of these ratios to be able to estimate the number of people from the RT with optimal performance. To that end, the measurement data are randomly split into two sets: a calibration set of 20% of the data for calculating the ACS/V and A_0/V , and a testing set of 80% to actually estimate the number of people based on the calibrated values. Table 5.1 summarizes the calculated calibration values from



Figure 5.6: Occupancy detection algorithm with 2-point calibration

both the full data set and the calibration set of the channel sounding. The small difference between the values of the two sets indicates how well the estimation performance is expected to be. Since this is a regression model with two unknown parameters, a basic occupancy detection algorithm can be used in practice that only requires two measurement points, that is, RT for two different number of people in the room. Figure 5.6 depicts the algorithm where calibration is based on measuring the RT when no person and N_{cal} persons are in the room.

5.1.4 Occupancy estimation analysis

In this section, the number of people inside the room is estimated. The performance is measured in terms of the estimation error e defined as the absolute difference between the estimate and the actual number of people

$$e = |n - \hat{n}| \tag{5.6}$$



Figure 5.7: Estimation error (e = 0.6 persons) histogram of the number of people in the room for different spatial averaging sizes via channel sounding

5.1.4.1 Results of channel sounding

Table 5.1 lists the calibrated ratios to be used for estimation, while A_n/V is calculated based on the measured RT from (5.2) for each case. From (5.3), the estimate number of people is obtained as

$$\widehat{n} = \left[\frac{A_n/V - A_0/V}{ACS/V}\right] \tag{5.7}$$

where a simple round operator [.] is used to get the integer estimate. The estimation performance depends on the RT calculation as aforementioned. For a more accurate RT calculation, averaging of PDePs from several spatial links is used beforehand. Since the antenna elements capture uncorrelated CIRs of the same environment, averaging PDePs of the same number of people will smooth the decaying tail. This results in a more accurate regression line for the RT calculation.

Figure 5.7 presents the estimation error histogram for m number of averaged PDePs from the testing set. For only a single spatial link (m=1), the estimation error can reach up to 6 persons with an estimation success rate of only 21.4%. As m increases, the estimation performance improves in terms of higher success rate and smaller number of persons as estimation error. With m=16, the success rate is 88% with only a 1-person error of 12%. Figure 5.8 shows the confusion matrix for m=16. It gives the details of the estimation percentage for each case of the observed number of people. This clearly shows the good performance of the estimation algorithm, where all the cases have a success rate above 81%, and all the estimation



Figure 5.8: Confusion matrix for the estimation percentage of the number of people in the room with spatial averaging m=16 via channel sounding

error larger than 1-person is 0%. It is worth noting that while the persons inside the room may not be identically exposed to the propagating waves, nor having the same physical surface area, this method assumes they are. This is clear from (5.3), which directly influences the estimation performance. By increasing the number of antennas and the spatial averaging size, the accuracy of the RT calculation, and hence, the overall estimation performance can be further improved.

5.1.4.2 Results of COTS UWB

The MIMOSA channel sounder is a dedicated device for measuring the CIR with high accuracy and precision. In order to test the feasibility of our method, we use COTS products of a radio access technology that is available in communication networks. UWB nodes, usually deployed for RTLS and communication networks, are used to measure the CIRs in the same scenario. Figure 5.1 (right) shows the UWB nodes array used to have the same 8×8 MIMO setup. The Rx and Tx arrays are placed at the same locations as those of the channel sounder. The 6 people are again introduced into the room one by one, with the difference that they are allowed to move freely while capturing the CIRs. Hence, the 200 CIRs measured per number or people can be considered uncorrelated, and consequently, PDePs averaging over time can enhance the accuracy of RT extraction, as an addition to spatial averaging.

Another difference that impacts the RT extraction is the characteristics of the CIRs. MIMOSA captures around 10 us of delay range with 12.5 ns resolution, of



Figure 5.9: Estimation error (e = 0-6 persons) histogram of the number of people in the room for different spatial averaging sizes m via UWB



Figure 5.10: PDeP and linear regression from UWB nodes

which only the first 5 us are plotted in Figure 5.3. The used UWB chip records around 1 us of delay range starting from the LOS, with 1 ns resolution as shown in Figure 5.10. Figure 5.3 shows that the PDeP in our scenario spans almost 2.5 us from the LOS. Thus, only the first 40% of the PDeP following the LOS is used for calculating the regression line in the case of UWB. This is expected to degrade the accuracy of the RT calculation. Figure 5.9 shows the estimation error histogram for



Figure 5.11: Confusion matrix for the estimation percentage of the number of people in the room with spatial averaging m=64 via UWB

different sizes of only spatial averaging. Although a larger averaging size results in a higher success rate, the performance is lower compared to the channel sounder. With m=16, the success rate is about 53% with up to 3-person errors in the case of UWB. In order to reach the channel sounding performance of 88% success rate and only 1-person error, the spatial averaging size should increase to 64, as shown in Figure 5.9. The confusion matrix for the estimation percentage with m=64 is shown in Figure 5.11. It again shows the good performance of the algorithm using UWB, where all the errors above 1-person are 0%.

In addition to spatial averaging, time averaging of PDePs can be used to enhance the estimation performance as aforementioned. Figure 5.12 shows the estimation error histogram for spatial averaging size m=32 and different time averaging sizes w. With only w=8, the same performance of the 64 spatial averaging can be achieved with less number of antennas (m=32). Increasing the time averaging size results in higher success rate, reaching 95% with w=40 as shown in Figure 5.12. While it is easier to reach higher time averaging size compared to having more antennas for spatial averaging, the performance enhancement of time averaging highly depends on the scenario. In a stationary environment, where movement is limited, having uncorrelated CIRs over time is difficult. Thus, spatial averaging is considered more robust compared to time averaging, even though it requires more antennas.



Figure 5.12: Estimation error (e = 0.1 person) histogram of the number of people in the room for spatial averaging m=32 and different time averaging sizes w via UWB

5.2 Doppler-based fall detection

Knowledge of the location of people on ships has a wide range of applications in commercial solutions and during the duty of state officials. In the previous section, we showed that the number of people inside reverberant environments like ship compartments can be accurately estimated using CIRs available in many communication systems. A highly critical situation is when a crew member working alone in isolated areas falls on the ground. In this section, we investigate the possibility of detecting a fall from a standing position in a reverberant environment using CIRs of communication systems, which are measured at a much lower rate compared to radar sensors.

5.2.1 Measurement setup

The MIMOSA channel sounder is used in the same below-deck chamber as shown in Figure 5.13. The Tx is fixed to face the Rx in a LOS condition, and a mattress is located in the middle so that the plane of the fall is perpendicular to the LOS. This represents a worst-case scenario since the fall movement is in the plane orthogonal to the LOS direction, reducing the effective Doppler shift. The impact of the fall orientation has been studied in many papers. Doppler signature is sensitive to the direction of motion defined by the aspect angle, which is the angle between target motion trajectory and the radial LOS path between the radar and the target. The most distinctive signatures appear when target is moving towards or away from



Figure 5.13: Measurement setup for fall detection via MIMOSA channel sounder

the radar, leading to the maximum Doppler shift. As the aspect angle increases, the Doppler effect also decreases. When the aspect angle approaches 90° , Doppler signal becomes strongly attenuated. It is reported that the fall detection performance can drop approximately to below 50% for target directions with angles close to 90° [9]. This is in case of non-reverberating environments, where diffuse scattering is not dominant and the Doppler paths can be distinguished.

5.2.2 Methodology of fall detection

The experiment consists of a person walking, sitting (squatting down) and falling on the mattress. Each activity is repeated 3 times of 5 s measurement duration. Eight dual-polarized antenna elements at the Tx and one at the Rx are used to measure the CIRs while the person is doing the activity, thus making use of the parallel transmission to have a larger sample size. Motion in the environment can be detected using the power-Doppler profile (PDoP); faster movements result in larger Doppler spreads. A person can fall to the ground at 4 m/s, with the head impact velocity exceeding 6 m/s from standing [10]. This corresponds to around 18 Hz of Doppler shift. Thus, CIRs are captured at a 64 Hz rate, providing Doppler


Figure 5.14: Time evolution of power-Doppler profiles in dB for a fall event. The blue region indicates the Doppler components resulting from the fall

frequencies up to 32 Hz, according to the Nyquist theorem. Each PDoP is calculated by applying the Fourier transform to 64 consecutive CIRs averaged over the whole bandwidth per polarization per antenna. Figure 5.14 shows the time evolution of PDoPs in dB, over the 5 s duration of one fall activity. It shows the constant LOS component with zero Doppler, since both Tx and Rx are fixed. The components representing the fall are in the area marked by the blue lines, which are below 20 Hz as expected. Two constant components at +/-21 Hz can be seen, probably due to the vibration caused by the ship's engine.

Figure 5.15 shows the RMS Doppler spread calculated from the PDoP over the 5 s duration. PDoPs per event are first averaged over all antennas and polarizations to have three records per activity. To calculate the RMS Doppler spread, the PDoPs are clipped to remove components above 20 Hz unrelated to the fall event. A fall can be detected when a peak in the Doppler spread is captured, which marks the increasing and then decreasing velocity of the fall. This differentiates the fall from other activities like walking and sitting. Figure 5.15 clearly shows that the Doppler spread for the fall has higher peak values compared to the other normal activities.

5.2.3 Features extraction and classification results

After verifying that a fall can be differentiated by the Doppler spread pattern, a classifier is needed to detect a fall event based on certain features. We choose a Naive Bayes classifier with only one feature for simplicity [11]. The feature is



Figure 5.15: RMS Doppler spread for fall, walk and sit activities, each performed 3 times

extracted from each Doppler spread pattern of 5 s duration. These patterns are calculated from the PDoP per antenna, per polarization, and per event resulting in a total of 48 patterns per class of activity, shown in Figure 5.16. Several features are investigated, e.g., the mean, peak, peak-to-mean ratio, maximum gradient, and variance of the Doppler spread patterns. It is found that the variance of the Doppler spread patterns are separation among the 3 classes, namely fall, walk and sit shown in Figure 5.17.

The sample data are split into a training set for the classifier model development and a testing set for the model validation. Since the data size is limited to 48 samples per class, the k-fold cross-validation method is used with k=3. The data are split into 3 folds where each fold is used as the testing set while the others as the training set, as shown in Figure 5.18. Finally, the classification results are averaged over the 3 splits. Even though we have 3 classes, our main aim is to detect only the fall event. Thus, performance metrics for binary classification (positive/negative) are used. These include detection accuracy (ratio of true to total predictions), precision (ratio of true positive to total positive predictions) and sensitivity (ratio of true positive predictions to total positive observations). Figure 5.19 shows the confusion matrix for the class predictions as percentage of the observations, averaged for k=3 folds. It shows that 100% of the fall events are detected, and only 4.17% of the sit events are mispredicted as falling. It also shows that this classifier can not differentiate between sit and walk events, since 62.5% of the sit events are mispredicted as walking.

Table 5.2 lists the performance metrics for the fall detection. With k=3 folds,



Figure 5.16: Aggregation of Doppler spread patterns over antennas, polarizations and events of (a) falling, (b) walking, and (c) sitting



Figure 5.17: Doppler spread variance over the 5 s duration for each class of activity, used as a classification feature with good separation



Figure 5.18: K-fold method for classifier model development and validation for k=3

one third of the data are used for validation, while 66% (32 samples per class) are for training. This gives a very good performance as the metrics consisting of accuracy, precision and sensitivity (recall) are all above 96%. The table also includes performance metrics when only 17% of the data (8 samples per class) are used for training. While the sensitivity is still 100%, a small degradation in accuracy and precision can be noticed. Nevertheless, all metrics are above 94%, which is a good performance for a single feature classifier with only 8 training samples per class.



Figure 5.19: Confusion matrix for the classification of the testing set with k = 3 folds, with prediction types indicated

Training set per class	32 samples (66%)	8 samples (17%)
Accuracy	98.61%	97.92%
Precision	96%	94.12%
Sensitivity	100%	100%

Table 5.2: Fall Detection Performance Metrics

5.3 Conclusions

Industrial environments are characterized by high temporal and angular dispersion due to scattering from complex metallic structures. Such environments experience reverberation behaviour similar to cavities. Based on the theory of room electromagnetics, this chapter explores the feasibility of estimating the number of people inside a reverberant ship compartment by means of only measuring the reverberation time. We observe that the reverberation time is the same, independent of the antenna or the location used for measurement inside the room. Our findings verify that there is an inverse relation between the number of people inside the room and the reverberation time. More people absorb more energy, decreasing the reverberation time. A calibration of the absorption parameters of the empty room and the average human body is needed before performing the estimation, which is done via measurements. While the estimation performance is very low in case of a single antenna, it can be enhanced via spatial averaging from multiple antennas. In addition, time-averaging can be used to further enhance the estimation performance when the measured channel is non-stationary due to the movement of people. The estimation algorithm depends on the CIR, a metric that can be found in wideband communication systems. With COTS UWB nodes that are originally used for localization and communication, we estimated the number of people ranging from 0 to 6 persons with a success rate of 95% and only a 1-person error.

Moreover, the CIRs can be used to detect when a person alone has fallen to the ground via Doppler analysis. Doppler frequencies up to 20 Hz are used, so the radio channel can be sampled at only 40 Hz rate. While most studies on fall detection use micro-Doppler signatures extracted with sampling rates above 1 kHz, they only focus on residential environments where such signatures can be easily detected. In a reverberant scenario, we found that the RMS Doppler spread has a peak that differentiates a fall from sitting or walking. A simple Bayes classifier is used for fall detection, with the variance of the Doppler spread as its feature. Using 3-fold cross-validation, the fall is detected with 98.6% accuracy, 96% precision, and 100% sensitivity. In Chapter 6, we discuss the different approximations used to model the reverberation according to room electromagnetics. The frequency-dependency of the RT is experimentally evaluated and modelled up to 40 GHz.

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Frequency-dependency of reverberation time up to 40 GHz

6.1 Introduction

Room electromagnetics theory was investigated in a ship environment in Chapter 5, where the reverberation model of Sabine was utilized to estimate the number of people in a metallic compartment. Such highly reflective environments are characterised by a reverberation behaviour similar to a lossy cavity. In this chapter, a novel model for the reverberation time (RT) is proposed, based on the room electromagnetics theory summarized in Section 1.3.1. An indoor lab environment is hence considered, where radio channel measurements up to 40 GHz are carried out. A general description of the reverberation time is based on Sabine's reverberation theory [1]. It assumes homogeneous repartition of energy within the room, and consequently uniformly distributed absorption, and that the field is completely diffuse. In general, the field will be sufficiently diffuse if the basic dimensions of the room are almost the same, walls are not parallel, and most absorbing surfaces are divided into parts and uniformly distributed. In practice, most of these requirements are not fulfilled simultaneously [2]. In the case of a room in which absorption is not uniformly distributed, the RT characteristics cannot be predicted accurately using classical reverberation theories.

Different approaches have been adopted to obtain more accurate approximations of the reverberation time. Among others, Eyring described the reverberation in highly absorbent enclosures based on the mean free path between reflections [3]. While his model considers absorption based on a constant rate of wall interactions within a given time, the model proposed in this chapter takes the variance of interactions into account. Moreover, the frequency-dependency of electromagnetic reverberation characteristics in indoor environments is experimentally investigated from 1 to 40 GHz. The reverberation time is found to be a decreasing function of frequency. A model is then developed to predict the room's quality factor (Q) and average absorption coefficient. Good agreement is obtained with the limited results reported in the literature for similar scenarios. This approach aims to be an accurate alternative to the reverberation time measurements and computations in indoor environments by linking it to the theory of electromagnetic fields in cavities.

The chapter is structured as follows. Section 6.2 introduces the proposed reverberation model. Measurement setup and scenario are presented in Section 6.3. The frequency-dependency of the RT is modelled in Section 6.4 along with the quality factor. Section 6.5 discusses the average absorption coefficient, and conclusions are drawn in Section 6.6.

6.2 Proposed reverberation model

The original work of Sabine for room acoustics relies on the assumption of a diffuse field that is homogeneously distributed inside the room [2]. However, Sabine's model is not appropriate for rooms with high absorption rate, as pointed out by Eyring [3]. For low-Q or "dead" rooms, Eyring proposed another model that is based on the mirror source theory. For cavities, the received energy is the incoherent summation of rays from infinitely many mirror sources representing multiple wall reflections [2]. Energy received from each mirror source is reduced by the absorption coefficient α when crossing a boundary of an image room. Therefore, the average energy density W(t) received at time t is approximately equal to [4]

$$W(t) = \frac{E_0}{V} (1 - \alpha)^{nt} = \frac{E_0}{V} \exp(-t/\tau)$$
(6.1)

where V is the volume of the room, E_0 is the initial energy generated by mirror sources, and n is the average rate of wall interactions or boundary crossings as aforementioned. The assumption of a diffuse field reveals that $n = \frac{cA}{4V}$ [2]. Hence, the decay rate of the energy density, which defines the RT, can be expressed as

$$\tau = \frac{-4V}{c\,A\ln(1-\alpha)}\tag{6.2}$$

where A is the surface area of the room and c is the speed of light. This represents Eyring's formula for the RT in dead rooms.

One of the simplifications (6.1) is based on is the replacement of the actual number of wall interactions N in a given time by its average E[N] = nt [2]. This

approximation can be improved by introducing the probability $P_t(N)$ of exactly N wall interactions occurring in a time t and calculating the energy density as the expectation with respect to this probability distribution. This can be formulated as

$$W(t) = \frac{E_0}{V} \sum_{N=0}^{\infty} P_t(N) \exp(-Na)$$
(6.3)

where the absorption exponent $a = -\ln(1 - \alpha)$ is introduced. Using a series expansion of the exponential term and truncating it after the second order, we obtain [2]

$$W(t) = \frac{E_0}{V} \exp(-nta)(1 + \frac{1}{2}\sigma_N^2 a^2)$$
(6.4)

where $\sigma_N^2 = \sum_N (N-nt)^2 P_t(N)$ is the variance of N. The number of interactions N in a given time can be related to the actual free path length l traveled between the interactions, whose distribution around the mean \bar{l} and its variance depend on the shape of the room. According to [2], it can be assumed that

$$\sigma_N^2 = nt\gamma^2 \tag{6.5}$$

where $\gamma^2 = \frac{\overline{l^2} - (\overline{l})^2}{(\overline{l})^2}$ is the relative variance of the path length l. As long as $\frac{1}{2}\sigma_N^2 a^2 < 1$, substituting (6.5) in (6.4) approximately yields

$$W(t) = \frac{E_0}{V} \exp\left[-nta(1-\frac{1}{2}\gamma^2 a)\right]$$
(6.6)

Accordingly, the modified RT can be expressed as

$$\tau_m = \frac{-4V}{c A \ln(1-\alpha) \left[1 + \frac{\gamma^2}{2} \ln(1-\alpha)\right]}$$
(6.7)

On the other hand, the decay-time method relates Q to the RT by the expression in (1.15). Since the RT is a function of V/A, It would be useful to work with a Q density that is independent of the room's dimensions. Hence, the Q per unit (volume per area) can be defined as [5]

$$Q_d = 2\pi f \tau \frac{A}{V} \tag{6.8}$$

which describes the frequency-dependency of the RT as a function of the Q density

$$\tau(f) = \frac{Q_d}{2\pi f} \times \frac{V}{A}.$$
(6.9)



Figure 6.1: The lab environment for measurements

6.3 Measurements setup and scenario

6.3.1 Scenario

The scenario for the channel sounding measurements is a laboratory in Universidad Politécnica de Cartagena, Spain shown in Figure 6.1. The measurement scenario is depicted in Figure 6.2 (a), in which Rx is fixed in one position, while Tx positions are uniformly distributed across the room (marked 1 to 14). For all positions, a 0.8 m (1.2 m) distance was selected between each Tx row (column). All distances were measured with a laser to obtain the most accurate precision possible. The laboratory size is approximately $9.1 \times 4.8 \times 4.1$ m³. It is furnished with several cupboards, chairs, and shelves. The walls are typical interior plasterboard, while the floor and ceiling are made of concrete.

6.3.2 Measurements

In order to perform the channel sounding, a vector network analyzer of type Rohde & Schwarz (R&S ZVA67 10 MHz - 67 GHz) and a radio-over-fiber link (EMCORE Optiva OTS-2, 50 MHz - 40 GHz) are used to measure the complex gain of the indoor UWB channel ranging from 1 GHz up to 40 GHz. UWB antennas (STEATITE Q-par Antennas, 0.8-40 GHz) at the Tx and Rx sides are used, with vertical polarization and omnidirectional radiation pattern in the horizontal plane. All elements are calibrated, and the antenna patterns are measured in an anechoic chamber from 1 to 40 GHz [6]. Figure 6.3 shows the antenna patterns at four different frequencies in that range. The antenna gains range from -2.2 dBi to 6.9 dBi and the 3-dB beam width from 20 to 140 degrees. A scheme of the full measurement setup is shown in Figure 6.2 (b).

At both ends of the measurement system, a virtual antenna array was created by an automated positioning system on which the antennas were mounted. This virtual MIMO measurement system consists of a 10-element uniform linear array at the Tx and a 6×6 uniform rectangular array at the Rx. The separation of the array elements





Figure 6.2: (a) Top view of the laboratory used as measurement scenario (b) Measurement setup scheme [6]



Figure 6.3: Measured radiation patterns in dB for different frequencies: (a) 10 GHz, (b) 20 GHz, (c) 30 GHz, (d) 40 GHz [6]

was 3 mm (less than half the wavelength at 40 GHz, i.e. 3.7 mm). Hence, a total of 360 complex transfer functions have been recorded within a duration of around 20 hours for each measured snapshot. During that time, the doors remained closed to prevent entry, thus guaranteeing static conditions. At each position, the VNA measured the complex gain by sampling the 39 GHz span over 8192 uniformly spaced frequency points with intermediate frequency of 100 Hz.

6.3.3 Processing

According to the theory of room electromagnetics [7], the decay rate of the power density is independent of the position of measurement. The power-delay profile

(PDeP) per Tx position is calculated by averaging the square of the channel impulse response over all the elements of the Tx and Rx antennas. Since we only care for the slope of the PDeP, a more accurate RT can be estimated by spatially averaging the PDePs over all the Tx positions [4]. Hence, The averaged PDeP (APDP) used for the RT estimation is calculated as

$$APDP = \sum_{p=1}^{14} \sum_{tx=1}^{10} \sum_{rx=1}^{36} \left| \text{IDFT}\{H[f]\} \right|^2$$
(6.10)

where IDFT{.} is the inverse discrete Fourier transform, H[f] is the measured channel transfer function, and rx, tx and p are the indexes for the Rx antenna element, Tx antenna element and Tx position, respectively.

The slope of the APDP is determined automatically by fitting a least-square regression line to the values of the APDP within a certain delay interval. The fitting interval was chosen between the mean excess delay and the delay corresponding to 6 dB above the noise level, in order to minimize the influence of the LOS and noise components on the slope estimate [8]. The RT can then be experimentally determined as [4]

$$\tau = \frac{-10\log(e)}{slope} \tag{6.11}$$

6.4 RT frequency-dependent models

The frequency range of 1-40 GHz is divided into sub-bands of 900 MHz bandwidth each, where the RT is estimated at each center frequency using (6.11). The estimated values are then used in (6.8) to obtain the quality factor density Q_d , where V =160 m³ and A = 195 m² in our scenario. Figure 6.4 presents the experimental Q_d and the proposed fitting model as a function of frequency. The model for frequencies below 10 GHz in [5] was chosen as a cubic polynomial fit, motivated by the fact that Q is a cubic function of frequency. However, our measurements suggest that a simpler quadratic model can be a good fit for frequencies up to 40 GHz, since Q_4 becomes of minor contribution at high frequencies as discussed in Section 1.3.1.2.

The dependence of the RT, and thus Q_d , on the bandwidth was discussed in [5]. It showed insignificant relative variation over bandwidths from 100 MHz till 900 MHz and concluded that τ can be considered constant over bands up to 900 MHz or more. Similar behavior is observed in our scenario, and hence, a bandwidth of 900 MHz is considered for the rest of the study, which provides enough samples for the APDP slope regression as well as the Q_d model fitting. Therefore, the model of Q_d is formulated as

$$Q_d(f) = -0.86 f^2 + 109.25 f + 29.49$$
(6.12)



Figure 6.4: Experimental estimate of Q density and the proposed model as a function of the center frequencies with 900 MHz bandwidth

Ref.	V (m ³)	$A(m^2)$	Freq. (GHz)	RT (ns)	RE (%)
[9]	335.6	299.6	1.5	21.8	4.2
[5]	94.5	132	7.5 - 8.5 - 9.5	14.3 - 13 - 12.2	9.5
[5]	169	195	8 - 9 - 10	14.2 - 12.1 - 13	9.3

Table 6.1: RT Model Validation From The Literature

where f is the frequency in GHz and the goodness of fit in terms of the coefficient of determination (\mathbb{R}^2) equals 0.99. By substituting in (6.9), the frequency-dependent RT model is obtained

$$\tau(f) = \frac{(-0.86 f^2 + 109.25 f + 29.49) V}{2\pi f A} \ [ns] \tag{6.13}$$

The RT model is depicted in Figure 6.5 (a) where it clearly shows that the RT is inversely proportional to the frequency. To validate our model, we compare the RT values to results reported in the literature. Since the RT also depends on the absorption rate of the environment, we consider the studies where the environment is similar to our scenario. However, a limited number of studies provide the dimensions of the indoor scenario, and most of them are at lower frequencies. Table 6.1 summarizes the collected data and the relative error (RE) to the proposed model, where small deviations have been obtained.



Figure 6.5: Frequency-dependent models for (a) reverberation time and (b) average absorption coefficient and the experimental estimates with 900 MHz bandwidth

6.5 Average absorption coefficient

Most of the results for the average absorption coefficient reported in the literature are based on the models of Sabine and Eyring [4] where the assumption of a constant wall interaction rate is adopted. The modified RT in (6.7) takes the variance of the number of interactions into account by relating it to γ^2 . The latter can only be calculated analytically for a limited number of room shapes [2], while other shapes can be determined by computer simulation. Hence, for our scenario, γ^2 is computed via ray-tracing simulation and is found to be 0.325. This matches well with the results in [2], indicating that, for most rectangular rooms, γ^2 is close to 0.4.

The frequency-dependent model of the average absorption coefficient $\alpha(f)$ can easily be determined from (6.7) and (6.9) and is shown in Figure 6.5 (b) along



Figure 6.6: Overview of reverberation models performance for our scenario

with the experimental values. To show the improvement gained using the modified model, Figure 6.6 shows the RT calculated based on (6.7) versus α and compares it to the models of Sabine and Eyring for our scenario. It shows that the modified RT is generally smaller than that obtained from Sabine's model, but larger than Eyring's.

The difference between the models can be attributed to the underlying assumptions. Sabine assumes a steady-state uniform isotropic diffuse field [10] (i.e. one energy value everywhere), which is not valid for high absorption. During energy decay, the room is not in steady-state, and the higher the absorption, the less it is in steady-state [2]. This results in a smaller effective energy loss and, thus, larger RT. On the other hand, Eyring assumes a constant rate of wall interactions and a step-wise energy decay [3] (i.e. all rays lose energy at the same time) as shown in (6.1). This is valid for a 1-dimensional enclosure, where all paths have exactly the same length [2]. For a more accurate RT, we modified the model to take the variance of wall interactions into account. As the variance increases, the energy decay transitions from the step-wise assumption of Eyring to the continuous assumption of Sabine, and hence, the RT increases.

6.6 Conclusions

In Chapter 5, the room electromagnetics theory was investigated in a ship environment and the classical Sabine's model for reverberation time was used for estimating the number of people in below-deck compartments. This chapter extends the reverberation modelling, where the frequency-dependency of the electromagnetic Q-factor and reverberation time is experimentally investigated in an indoor lab scenario from 1 to 40 GHz. The results demonstrate that the reverberation time decreases smoothly as the frequency increases, indicating that the higher the frequency, the faster the fading of diffuse fields. Models that predict the Q-factor and reverberation time are presented based on the theory of electromagnetic fields in cavities. These models extend the results found in the literature to new higher frequencies up to 40 GHz. Moreover, a model that predicts the average absorption coefficient from the reverberation time is proposed. The model that is based on the mirror source theory takes the variance of the rate of interactions into account, thus is considered theoretically more accurate than the commonly used models.

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Conclusions

This final chapter presents the overall conclusions based on the accomplished work in this dissertation, and proposes some opportunities for future research.

7.1 Conclusions

In this dissertation, we focus on the modelling of wireless radio channels for different scenarios and applications, that will help develop more efficient and robust communication and sensing solutions. The first part is dedicated to studying the behavior of wireless channels for vehicular communications with a focus on stochastic modelling of propagation parameters for the non-stationary fading process. The goal of the second part is to investigate the indoor propagation channel in highly reflective industrial scenarios. The reverberant characteristics of such environments are modelled based on the theory of room electromagnetics, and exploited for human sensing applications.

7.1.1 Outdoor vehicular channel modelling

Due to rapid changes in the environment, vehicular communication channels no longer satisfy the assumptions of wide-sense stationary uncorrelated scattering process. Classical cellular wireless networks have been designed based on these assumptions, which say that the statistics of the underlying radio propagation channels do not change neither over time nor frequency. Most of the algorithms that are currently used, especially regarding the feedback of information from Rx to Tx side, are designed under this assumption of stationarity. Hence, by modelling the non-stationarity of rapidly time-varying channels as in vehicular communications, already existing algorithms could be improved by taking into account the varying description of radio propagation channel statistics. The non-stationary fading process can be characterized by assuming local stationarity regions with finite extent in time and frequency. Once the stationarity region has been characterized, the non-stationary fading parameters can be accurately evaluated and the channel modelling becomes physically meaningful.

To that end, several measurement campaigns are conducted in this work to investigate the vehicle-to-infrastructure (V2I) radio channel at 1.35 GHz in different environments, including sub-urban, rectangular and arched tunnels under road traffic conditions. The MIMOSA channel sounder allows us to capture the channel transfer function of the mobile radio channel that is used to model each scenario. We first measure the stationarity time by applying the framework of the local scattering function (LSF) and channel correlation function (CCF). We find it to be more accurate than the empirical collinearity metric to characterize the stationarity region. Then, the time-varying channel parameters are evaluated and stochastically modelled across the different stationarity regions. Based on the LSF, fading parameters like the RMS delay and Doppler spreads, and K-factor are modelled for different polarizations. More specifically, the impact of traffic density and antenna characteristics on these parameters are investigated in the tunnel environment. In addition, the modelling of MIMO channel parameters such as capacity, normalization and correlation is discussed. A summary of the main conclusions is as follows.

Stationarity

The overall stationarity time of 567 ms is calculated in the sub-urban scenario, with a minimum value of 337 ms. For the rectangular tunnel, the overall stationarity time is 330 ms and the minimum is 268 ms. The same V-polar omni-directional antennas are used for both measurements. The difference in the stationarity time can be partially attributed to the difference in speed. While the sub-urban scenario is a low-speed campus environment (40 km/h), the tunnel scenario represents a high-speed highway environment (90 km/h). Another factor is that in the tunnel, being a closed environment, reflected components do not need to travel far, and thus have higher power compared to the open campus scenario. The variation of the LSFs is thus stronger and has more contribution to the correlation calculated by the CCF. In addition, the traffic density is found to have no effect on the stationarity time in the tunnel scenario. So larger traffic densities may be required to impact the stationarity time. On the other hand, investigating the impact of the antenna polarization shows that the V polarization provides longer stationarity time by 5% compared to the H polarization. As for the impact of the antenna radiation pattern, a more directional

antenna is found to provide a longer stationarity time by 21%, thus proving to be more beneficial than a wide-angle type of antenna pattern. Moreover, the practical relevance of the non-stationarity of the channel is briefly discussed. Results show that as the assumption of WSSUS is violated, the assumption of ergodic capacity and its application becomes unreliable. Moreover, the gain of the effective diversity varies with the stationarity and coherence parameters of the channel. Hence, the optimal performance of communication systems can be obtained by considering the varying nature of such parameters via adaptive schemes.

Delay and Doppler spreads

Based on the LSF, time-varying delay and Doppler power profiles are obtained and used to calculate the corresponding second-order central moments. The empirical distribution of the RMS delay and Doppler spreads is best fitted by a lognormal model in all the investigated scenarios. For the sub-urban scenario, both vertical and horizontal polarization show a similar deviation behavior in the spread values, with the mean spreads of the H-polar channel (42.5 ns, 10.3 Hz) being slightly larger than that of the V-polar channel (33.4 ns, 7.3 Hz). While these values are measured with a directional patch antenna, an omni-directional antenna captures slightly larger values (48.8 ns, 11.82 Hz). This is expected since more MPCs of wider angles are included, which may have larger delay and Doppler. For the tunnel scenario, larger mean values are observed for delay and Doppler spreads (130 ns, 25 Hz). This can be attributed again to stronger MPCs due to the tunnel's reflective materials and enclosure, compared to the sub-urban scenario. It is also found that higher traffic density in the tunnel increases the delay and Doppler spreads, while reducing the correlation between them. Investigating the impact of antenna polarization shows that the V polarization is more advantageous, as it provides smaller delay and Doppler spreads (by 19% and 18% on average, respectively) compared to the H polarization. As for the impact of antenna radiation pattern, a more directional antenna is found to provide smaller delay and Doppler spreads (by 52% and 32% on average, respectively), thus proving to be more beneficial than a wide-angle type of antenna pattern.

Fading

For the sub-urban scenario, the small-scale fading is investigated per delay tap. The small-scale fading of the strongest path is found to be Rician distributed, while the later delay taps show occasional worse-than-Rayleigh behavior. The parameters of the Rician fading for the first tap and Nakagami fading for the later taps are estimated and statistically modeled. Both V and H polarizations have similar mean values and the best fit is found to be the lognormal model. The traffic density in the tunnel scenario is found to reduce the average K-factor of the fading

amplitude, due to more scattering resulting from the traffic. In addition, channel power evaluation metrics are examined including path gain, CPR, and XPD in the tunnel environments. Our analysis shows that a single-slope model describes well the attenuation in a tunnel under road traffic conditions. The guiding effect of the tunnel results in a path loss exponent smaller than typical indoor and outdoor environments (<2). The impact of antenna polarization depends on the geometry of the tunnel as well as the traffic condition. while the H-polar has a higher reference path-loss, the path-loss exponent is smaller compared to the V-polar, based on the arched tunnel measurements. The rectangular tunnel measurements show that the difference in the path-loss exponent can become insignificant. Deterministic ray approach for empty smooth walled tunnels composed of uniform material predicts that the H-polar loss is lower than the V-polar loss. Since the geometry of the tunnel is such that the width is larger than the height, the H wave reflected from the ground and ceiling are stronger than the V one reflected from the walls of the tunnel, due to the Brewster's angle phenomenon. However, this effect can be reduced due to the non-uniformity of materials and shapes present in the propagation path (e.g. traffic condition, side pipes, trays and emergency exits), resulting in more scattering for the H-polar channel and a higher path-loss exponent. Nevertheless, waves are highly polarized even at far distances, with a measured XPD of about 13 dB in the arched tunnel and 12 dB in the rectangular tunnel. Statistical models are presented for CPR and XPD using the lognormal distribution.

Tunnel lanes

For the arched tunnel, the channel is measured in the open lane along the center of the tunnel and in the closed lane on the side next to the tunnel wall. Co-polar channels have larger reference path-loss and smaller path-loss exponent, and the standard deviation of the fading is larger in the closed lane compared to the open lane. Also, the XPD is larger in the closed lane than in the open lane. Conclusions regarding the time dispersion include the following. The RMS delay spread remains around the mean values in the range of 12 ns to 24 ns, with the co-polar channels spread being smaller than cross-polar channels spread. The mean RMS spread of the H-polar channel is larger than the V-polar channel, which is similar to the rectangular tunnel case. However, mean values is much lower that the rectangular tunnel. This can be attributed again to the differences in geometry (e.g. the arched tunnel is smaller) and materials (e.g. metallic structure at the entrance of the rectangular tunnel) of the tunnel structure. The closed lane has several rises in the delay spread at the middle of the tunnel compared to the open lane, since it is more sensitive to the variation in the tunnel walls structure. The distribution of the spread variation along the tunnel can be fitted to a log-normal distribution, with larger standard deviation in the closed lane than in the open lane configuration.

MIMO performance

The MIMO channel was measured for the arched tunnel in the open lane along the center of the tunnel and in the closed lane on the side next to the tunnel wall. The main conclusions of the spatial MIMO system performance for different polarizations are as follows. Subchannel correlation increases at farther distances in the tunnel, which is attributed to the attenuation of the higher-order propagating modes according to the waveguide modal theory. The average Rx correlation amplitude decreases as the inter-element spacing of Rx antenna increases. The co-polar channels are more correlated than the cross-polar channels, with the Hpolar channel correlation being higher than the V-polar channel correlation. The condition number of the MIMO channel matrix increases slightly with distance. The increase of the singular values ratio and the decrease of the Rx correlation amplitude, both indicate a decrease in MIMO capacity with distance in the tunnel for a constant SNR. The capacity of 2×2 MIMO increases for larger inter-element spacing, with insignificant difference after 3λ . For an outage probability of 0.5 and 10 dB SNR, capacity reaches 5.7 bits/s/Hz compared to 3.3 bits/s/Hz for SISO. The open lane along the center of the tunnel provides higher capacity than the closed lane near the tunnel wall. The V-polar channel provides slightly higher capacity than the H-polar channel. This is shown in the 4×3 MIMO capacity of the open lane, reaching 7 and 6.6 bits/s/Hz for V-polar and H-polar channels respectively, compared to the Rayleigh channel capacity of 8.8 bits/s/Hz for an outage probability of 0.5. On the other hand, the dual-polarized (DP) MIMO channel is investigated based on the rectangular tunnel measurements. The impact of normalization on the DP capacity is investigated, and a new approach is proposed that maintains the conservation of energy. The DP channel is found to have a low condition number on average (5.5 dB), which is good for multiplexing gain. The correlation properties are measured using the full correlation matrix, while the Kronecker model is found to provide less accurate results by 7.58%. Large correlation (>0.7) among DP subchannels is observed, and no correlation is found with the condition number. The condition number is found to depend on the orthogonality rather than the decorrelation of the DP subchannels, giving DP MIMO an advantage over spatial MIMO in LOS scenarios.

Autoregressive modelling

Accurate channel simulation is needed for the performance evaluation of wireless systems, especially when dealing with non-stationary channels. The parametric modelling of non-stationary processes is applied to simulate the measured V2I channel from the rectangular tunnel. We propose a framework for long-term simulation based on the vector time-frequency autoregressive (VTFAR) model. We analyse the stability of the model and propose an approximation for the correlated

scattering channel that guarantees stability. A 6-tap channel is simulated based on the measurement, where the VTFAR model parameters are estimated using the proposed approach. Moreover, the parametric spectra of the model are compared to non-parametric spectra estimated from the measured channel using the multi-taper approach. We validate the model in terms of the delay spread and stationarity time. The model is found to simulate the measured channel very well with RMSE of 0.01 for the delay spread and 0.4 for the stationarity time. This measurement-based and computationally inexpensive approach provides an efficient alternative for non-stationary channel simulations.

7.1.2 Indoor reverberant channel modelling

Industrial environments are characterized by high time and angular dispersion due to scattering from complex metallic structures. Such harsh environments experience reverberation behaviour similar to cavities, which can be explained by the room electromagnetics theory. The reverberation time (RT), being a principal parameter in characterizing the reverberation behaviour, is studied and exploited for human sensing applications in ships. Additionally, its frequency-dependency is modelled up to 40 GHz bands in an indoor lab environment.

Human sensing in ships

Based on the theory of room electromagnetics, we explored the feasibility of estimating the number of people inside a reverberant ship compartment by means of only measuring the reverberation time. An inverse relation between the number of people inside the room and the reverberation time is verified. More people absorb more energy, decreasing the reverberation time. The reverberant nature of the room is also verified by showing that the reverberation time is independent of the antenna or the location used for measurement inside the room. Measurements are used first to calibrate of the absorption parameters of the empty room and the average human body before performing the occupancy estimation. While the estimation performance is very low in case of a single antenna, it can be enhanced via spatial averaging from multiple antennas. Such rich scattering environments produce large angular dispersion, hence antennas with enough separation in space are uncorrelated. In addition, time-averaging can be used to further enhance the estimation performance when the measured channel is non-stationary, e.g., due to the movement of people.

The estimation algorithm depends on the channel impulse response (CIR), a metric that can be found in wideband communication systems. With commercial off-the-shelf UWB nodes originally used for localization and communication, we estimated the number of people ranging from 0 to 6 persons with a success rate of 95% and only 1-person error. Moreover, the CIRs can be used to detect when a

person alone has fallen to the ground via Doppler analysis. Doppler frequencies up to 20 Hz are used, so the radio channel can be sampled at a rate of only 40 Hz. Even in the reverberant scenario, we found that the RMS Doppler spread has a peak that differentiates a fall from sitting or walking. A simple Bayes classifier is then used for fall detection, with the variance of the Doppler spread as its feature. The variance showed a good separation between the different classes compared to other features of the Doppler behaviour. Using 3-fold cross-validation, the fall is detected with 98.6% accuracy, 96% precision, and 100% sensitivity. Hence, the reverberation time proves to be a very practical parameter in industrial reverberant environments.

Reverberation at mmWave frequencies

The frequency-dependency of the electromagnetic Q-factor and reverberation time is experimentally investigated in an indoor lab scenario from 1 to 40 GHz. The results demonstrate that the reverberation time decreases smoothly as the frequency increases, indicating that the higher the frequency, the faster the fading of diffuse fields. Models that predict the Q-factor and reverberation time are presented based on the theory of electromagnetic fields in cavities. These models extend the results found in the literature to higher frequencies up to 40 GHz. They are used to estimate the average absorption rate of the environment based on the room electromagnetics theory. Moreover, a model that predicts the average absorption coefficient from the reverberation time is proposed. The model that is based on the mirror source theory takes the variance of the rate of interactions into account, thus is considered theoretically more accurate than the commonly used models. With the rise of industrial IoT and industry 4.0, modelling the radio channel at high frequency bands is considered essential for the design of the communication and sensing solutions.

7.2 Future work

Directions for the future work are as follows. For the stationarity assessment of vehicular channels, multiple antennas can be used to fully capture the doubledirectional polarimetric channel characteristics. This will allow us to more accurately estimate the stationarity region by including the space domain, especially with the new version of the MIMOSA channel sounder (MaMIMOSA) for massive number of antennas. The channel transfer function becomes a function of time, frequency and space which leads to a LSF that is also 3-dimensional in delay, Doppler and angle. With the new LSF, the stationarity time and bandwidth can be accurately estimated using the channel correlation function taking also the spatial/angular correlation into account. Moreover, with the introduction of massive MIMO, the statistical channel properties becomes important in the space dimension, giving rise to space or array non-stationarity. Array non-stationarity refers to the fact that clusters may appear or disappear from the viewpoint of one antenna element to the next one, which means different antenna elements could see different cluster sets. It also means that parameters, such as power and delay drift, are to be considered over different antenna elements. Hence, measuring the 3-dimensional stationarity region will prove to be very useful for future wireless systems.

Another aspect to consider is intelligence-enabling radio communications and channel modelling. Propagation models may be able to predict radio environments and hence provide accurate-enough channel state information (CSI) at link ends to aid radio communication systems and applications. As an example, a few studies have addressed the real-time use of deterministic propagation models to help estimating CSI. Their real-time use in localisation, beamforming and resource allocation algorithms is still in its infancy. Artificial intelligence and machine learning (ML) are expected to play a pivotal role towards the provision of such intelligent operation. Prediction of channel parameters like path-loss, NLOS identification, delay and angle spreads and clusters, etc. can be done based on ML algorithms, which can deduce the mapping relationship between physical environment information and the channel characteristics. That is because the channel parameters are highly correlated with the network layout, including Tx and Rx locations, carrier frequency, and scatterers distribution.

Extending the work on human sensing further, we propose to conduct several measurement campaigns for different scenario in order to characterize the performance of the RT-based occupancy estimation algorithm. Factors like, frequency, number of antennas, number of people, room material, size, etc., will be studied to measure their impact on the estimation performance. In addition, the fall detection algorithm needs to be further validated in different environments and across different human activities. Different ML techniques will be investigated with more features extracted from the radio channel characteristics. An interesting direction is to explore the wideband delay-Doppler channel response to further detect the activity in delay/distance and well as speed/Doppler dimensions.



the dynamic nature of a wave.