Channel modeling for V2V communication: Enhancing road safety and intelligent transportation

Zhengyu Jin

School of Communication and Information Engineering, Shanghai University, Shanghai, 200444, China

jinzhengyuxx@shu.edu.cn

Abstract. The advancement of the Internet of Things (IoT) and Vehicle-to-Vehicle (V2V) communication networks has led to increased research efforts toward developing efficient and innovative V2V communication systems. These systems are designed to achieve the goal of improving road safety and enabling intelligent transportation. A critical aspect of this effort is channel modeling. In this context, this paper summarizes the characteristics of V2V communication channels. It categorizes them into three main types: Deterministic models, Non-geometry stochastic models (NGSMs), and Geometry-based stochastic models (GBSMs). It then reviews recent literature on these three types of channel modeling methods and discusses future development directions and challenges for V2V channel modeling. The study highlights the importance of accurate channel modeling for successful V2V communication systems and emphasizes the need to consider the unique features of V2V channels. It also identifies the limitations of existing channel models and suggests areas of research that can lead to more reliable and efficient V2V communication systems.

Keywords: V2V, wireless communication, channel modeling, geometry-based, non-geometry, stochastic

1. Introduction

V2V wireless communication realizes the establishment of a wireless network between vehicles for information exchange and has many applications and assumptions regarding traffic safety and avoiding traffic accidents. Under the general trend of Internet of Things (IoT), researchers attribute V2V wireless communication to a part of the Internet of Vehicles, and the basis of any excellent communication system network and any complete communication protocol is an accurate and reliable channel model. As early as the beginning of the 21st century, the US frequency regulator FCC allocated 75MHz in the 5.9GHz frequency band to Dedicated Short-range Communications (DSRC), a solution dedicated to vehicle communication systems. And IEEE officially announced IEEE standard 802.11p in 2010[1], also known as WAVE (Wireless Access in the Vehicular Environment), this is a standard non-geometry stochastic model specifically for wireless communication used in vehicle electronics, to some extent in order to comply with Intelligent Transportation Systems (ITS) related applications. In addition, 3GPP's TR38.901 protocol was released in December 2017, which provides a widely used geometry-based random channel modeling method called 3GPP 3D channel model. This model provides a detailed channel modeling capable of simulating how wireless signals propagate in real environments. The 3GPP

3D channel model is divided into indoor and outdoor parts, corresponding to different scenarios. It is a widely used random channel modeling method based on geometry. So in the face of dual-end high-speed movement, synchronization of receiving machines, multi-antenna measurement, etc, in recent studies, if channel simulation is needed and there is no high demand for scene subdivision, many researchers would adopt the channel model in the 3GPP TR 38.901 protocol, which can provide accurate channel simulation for evaluating the performance of wireless communication systems. However, many researchers will autonomously propose innovative channel modeling methods to suit the channel model for specific scenes better.

Over the past half-decade, there has been a significant increase in research efforts dedicated to specific applications and channel models for future 6G networks, with a particular emphasis on millimeter-wave and machine learning. Several notable advancements have been made. These include conducting analysis and modeling of V2V channel characteristics in underground garages [2], studying the impact of vehicular component speeds on scatter mobility power spectral density in V2V [3], synthesizing directional path loss based on a large amount of RL modeling [4], discussing challenges in millimeter-wave V2V channel measurement and modeling [5], and conducting multi-frequency multi-scenario millimeter-wave MIMO channel measurement using a 4×4 antenna at 28, 32, and 39 GHz [6]. Furthermore, a novel framework has been proposed for ML-based VVLC channel modeling to improve the accuracy of path loss models by considering multiple input variables related to vehicle mobility and environmental impact [7]. Non-stationary vehicular channel characteristics in complex scenarios, such as overpasses, tunnels, and cuttings, have also been studied to fill the gap [8]. Lastly, researchers have investigated a geometry-based stochastic model for truck communication channels in highway scenarios and proposed a hybrid geometric stochastic model for the T2X channel in highway environments [9]. The vehicular communication system’s overall performance is often impacted by communication interruption hotspots in complex scenarios such as overpasses, tunnels, and cuttings due to the unique and adverse channel characteristics in these areas.

In this paper, the author explains some important principles in V2V communication channel modeling within his area of expertise, including the non-stationary nature of V2V communication channels and some visualizing methods of V2V communication channels. The author categorizes existing V2V communication channel models into deterministic models, non-geometry stochastic models (NGSMs), and geometry-based stochastic models (GBSMs). The author then reviews and summarizes literatures on each modeling approach and concludes by discussing future challenges and expectations for V2V channel modeling.

2. Principal/theoretical analysis of V2V communication channel modeling

2.1. Non-stationarity

In non-stationary V2V communication scenarios, the channel can be analyzed in space, time, and frequency [10]. The time-domain non-stationarity is reflected in the rapid creation and destruction of scattering objects, which correspond to the Tx, RX, and scatters. With the advent of massive MIMO antenna arrays in B5G, the spatial non-stationarity of the channel has become more prominent due to the change in antenna dimensions. Additionally, the frequency-domain non-stationarity is caused by the frequency-selective fading of the signal’s different frequency components, as well as the effect of the signal’s coherent bandwidth, which is becoming wider as a result of advances in communication systems and higher carrier frequencies. This phenomenon is especially significant in recent years with the increasing use of millimeter-wave/terahertz communication. Thus, the non-stationarity of the V2V channel occurs simultaneously in the time, space, and frequency domains, and it is particularly severe.

The multipath signal within a channel can be characterized by three double domains: time domain and Doppler frequency domain, frequency domain and delay domain, and space domain and angle domain. Each paired domain exhibits equivalent non-stationarity, in which non-stationarity across time, space, and frequency domains correspond to correlated scattering across the Doppler frequency, angle, and delay domains, respectively. The Fourier can illustrate the transform and inverse Fourier transform relationships between the double domains. Correlated scattering objects within the Doppler frequency, angle, and delay domains, such as scatters and clusters, can elucidate non-stationarity. This includes the correlation of scattering objects in the delay domain.

2.2. power spectral density (PSD)/average power delay profile (APDPnhan/delay-doppler profile

In terms of visualizing the model performance, besides the traditional graphs that describe the signal power fading as a function of propagation distance, most papers achieve this by showcasing or comparing the following three spectra: power spectral density (PSD), average power delay profile (APDP), and delay-doppler profile. For PSD, a Doppler power spectral density graph is plotted with Doppler shift as the x-axis, which reflects the signal power at different Doppler shift values and can be used to describe Doppler frequency shift. APDP is a graph with propagation delay as the x-axis, showing the signal power distribution at different delay values, which can be used to describe signal time delay spread. The y-axis can also be replaced with time to describe the time-varying delay power spectrum, where color shading is used to represent signal power. Lastly, the delay-doppler profile is a graph with propagation delay as the x-axis, doppler shift as the y-axis, and color shading representing signal power, which can be used to study signal Doppler characteristics and observe the Doppler-resolved impulse response.

3. Three different V2V channel modeling methods

3.1. Deterministic models

In deterministic models, such as[11], [12], researchers mostly solve Maxwell’s equations or their approximations using boundary conditions in specific scenarios and model them using ray tracing-based methods. This approach requires a lot of physical attributes such as location and shape, and detailed environmental conditions need to be obtained for a specific location, down to each scattering object, which requires intensive computations. Although this approach can well reflect reality, the model is specific to a particular location and cannot be generalized to other locations. V2V communication is characterized by significant uncertainties in both the communication endpoints and the environment, making deterministic models unsuitable for V2V scenarios.

3.2. Non-geometry stochastic models (NGSMs)

Non-Geometric Stochastic Models (NGSMs) represent the channel solely in terms of stochastic processes and variables, based on a large amount of measurement data, without any physical scattering geometry derivation.

Both [13] and [14] use traditional non-stationary Gaussian scattering models (NGSMs) with a tapped delay line (TDL) structure. In [13], the modeling method, which is standardized in IEEE 802.11p, identifies the LoS component using Rician fading based on the assumption of wide-sense stationary uncorrelated scattering (WSSUS). However, it is unable to simulate severe fading in V2V communication. [14]considers non-stationarity and severe fading. It employs a first-order bimodal Markov chain to generate related random variables in both the time and frequency domains, describes non-stationarity, and adopts a Weibull distribution to describe the severe fading of taps. However, it cannot identify the existence of LoS components, a significant feature of V2V. Therefore, [15]proposes a new NGSM for V2V modeling, which is divided into three parts: non-WSS modeling, non-US modeling, and severe fading modeling, and allows the simultaneous description of severe fading and identification of LoS components. The comparison with[14]and[15]’s power spectral density is shown in Figure 1. And the non-uniform phase distribution of taps and the Weibull distribution of tap amplitude are used instead of the uniform phase distribution in[14], which cannot include LoS components.

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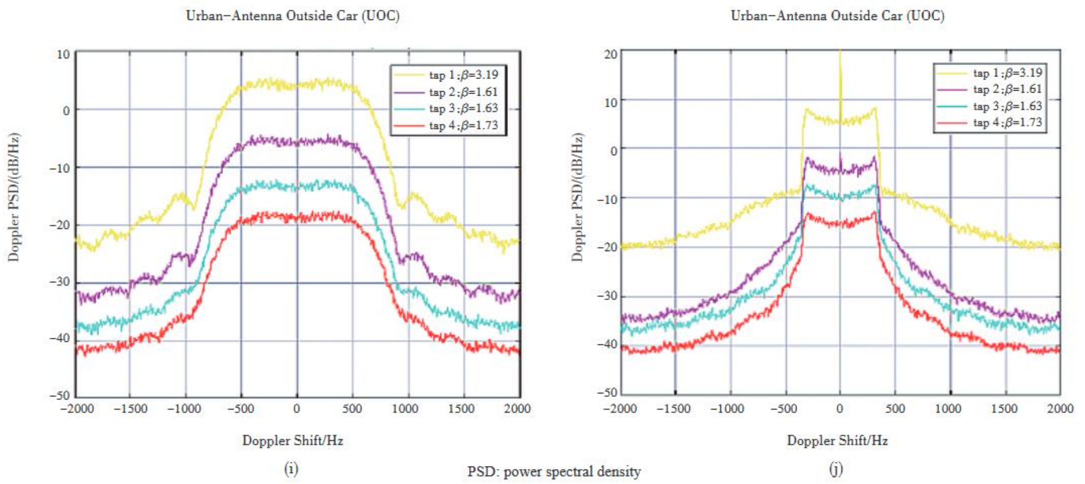

Figure 1. The power spectral density comparison.

In[16]NGSM, the authors simplified the phase of the Doppler frequency by expanding it into a Taylor series. They also derived closed-form solutions for the time auto-correlation function (TACF) and the spatial cross-correlation function (SCCF). They concluded that the arrival angle (AOA) and departure angle (AoD) follow the Von Mises distribution. The model presented in[16]is suitable for V2V communication scenarios with arbitrary velocity changes and motion trajectories.

3.3. Geometry-based stochastic models（GBSMs）

In geometry-based stochastic models (GBSMs), statistical regularities are obtained from a large amount of measurement data. One fundamental approach of GBSMs is making an assumption about the random distribution of scatters based on geometry first, followed by applying simplified wave propagation principles to derive the model. Some researchers choose to distinguish the shape of the scatters more finely, although this distinction is not made in the subsequent text. Moreover, because the geometric distribution of scatters and the scattering area are varied, researchers can control the complexity of the model by changing different geometric regions. Therefore, to some extent, GBSM is flexible and suitable for the flexible scenario of V2V channel modeling. GBSM’s general modeling steps are shown in Figure 2:

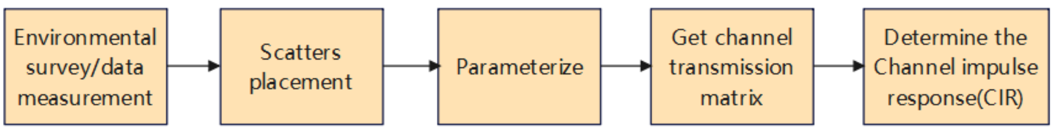

Figure 2. The process of GBSM.

In [17], the authors introduce a V2V channel model specifically for intersection scenarios. They point out that the traditional GBSM proposed in [18] is effective for highway and rural scenarios but is not suitable for intersections due to its lack of consideration for obstacles, diffraction, and higher-order interactions. To address this, [17] incorporates a simplified ray tracing method and a stochastic description of scatter positions and characteristics. The authors also introduce an angular gain function for scatters and estimate the width of the scattered band and the surface density of scatter points for each order of scattering points. To obtain a scatter distribution model, they apply the RANSAC algorithm to remove outlier noise and use the rejection sampler algorithm to ensure uniform distribution of scatters in the scattering area. The path gain model is based on a classical long-distance power law to account

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for distance dependence. The authors use measurement data from an intersection in Berlin, Germany, and discovered that the gamma process is the most suitable model for capturing the power decay of a single multipath component that exhibits exponential auto-correlation behavior. The paper includes a comparison of simulation and measurement results for different types of intersections, presented in Figure 3.

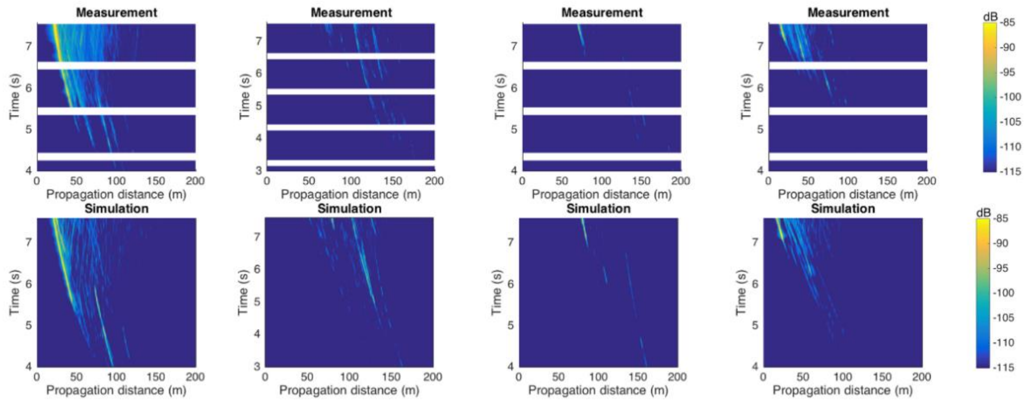

Figure 3. Comparison of power-delay profiles.

According to [19], current V2V models only account for horizontal MultiPath Components (MPCs), disregarding vertical MPCs and poorly modeling dynamic clusters of MPCs. A 3D channel model was introduced in [19] to address these limitations. This model employs a spatial alternating generalized expectation maximization algorithm to extract and identify MPCs and uses clustering and tracking algorithms to differentiate between different MPC clusters based on the SV model. Finally, all identified MPC clusters are classified into global and scattered clusters, represented by parameters within and between clusters. In recognition of multipath clusters, first, the multipath parameters of each snapshot were estimated, and then the snapshots were clustered using a clustering algorithm. Next, a tracking algorithm was used to determine whether there was an inheritance, new creation, or death relationship between the clusters within each snapshot and those in the preceding and subsequent snapshots. This allowed for the identification of persistent and dynamic multipath clusters in vehicular networks, which were subsequently classified into two categories based on the actual situation: globally persistent clusters with long durations caused by line-of-sight propagation or persistent divergent objects on the ground, and scatter clusters caused by short-lived objects that appear briefly in the surroundings. In the subsequent modeling of multipath clusters, the logarithmic distance model was used to describe the large-scale characteristics of global clusters. The study employed an arrival angle offset that followed a Laplace distribution to model the angle deviation from the cluster center. Furthermore, the power factor of the global cluster was utilized to capture the relationship between the global cluster's energy and its total energy. In addition, in the modeling of scatter clusters, the strong correlation between cluster energy and the delay was taken into account, and the decay factor of the cluster was used to quantitatively characterize the process of energy decay with increasing delay. The scatter cluster's lifetime (observable time) was then modeled using an approximately normal distribution, and the arrival interval and arrival angle represented the birth and death processes of the cluster in the time and space dimensions. Finally, the multipath within the scattered cluster was modeled, and it was found that the number of multipath within the cluster followed a normal distribution, allowing for the modeling of various parameters of the multipaths. However, the data only came from two types of areas: urban and suburban, and the interesting points proposed by the authors were limited to a comparison between urban and suburban areas.

4. Conclusion

This paper provides a comprehensive review and summary of the recent progress in vehicle-to-vehicle communication channel modeling. Specifically, the V2V channel modeling methods are divided into deterministic models, non-geometry stochastic models (NGSMs), and geometry-based stochastic models (GBSMs). Literature that utilizes one of these three modeling methods is reviewed in detail. The non-stationary nature of V2V channels is analyzed, and it is concluded that GBSM is the most suitable flexible modeling method for V2V channel modeling. Then, while the process of GBSM is presented, it is important to acknowledge existing limitations that system simulation and channel application are not mentioned in this paper.

As the IoT landscape progresses toward the deployment of B5G and 6G technologies, smart transportation will be a vital part of the IoT application scenario, so the development of V2V communication in connected vehicles is a growing trend. In the future, the direction of V2V channel modeling should focus on highly segmented scenarios and AI intelligence development.

With the rise of smart transportation, the V2V communication network must continuously adapt to its environment and maintain a high level of reliability. One of the primary challenges is the unpredictable behavior of the environment with complex obstructions on the road, leading to sudden changes in channel conditions. Additionally, as the number of connected vehicles becomes numerous, severe network congestion may occur, which can negatively impact the reliability of V2V communication.

In order to overcome these challenges and meet the demands of smart transportation, V2V communication networks need to adopt new technologies and methods. One promising approach is to use advanced machine learning techniques to optimize the V2V communication system. By using machine learning algorithms to analyze traffic patterns and predict channel conditions, the V2V communication network can be made more efficient and reliable. Besides, the potential direction of development is to figure out the combining characteristics of joint spacetime–frequency channel non-stationarity.

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