Deep-learning-based radio channel prediction for vehicle-to-vehicle communications

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16. Abstract Reliable and efficient V2V communications are essential for driver-assistance systems to reduce accidents and improve energy efficiency through efficient convoying. A key challenge is that resource allocation for communication must rely on the current propagation channel state, but vehicles only have past measurements. Therefore, effective channel prediction methods are crucial. Traditional methods using simplified models and classical tracking/extrapolation perform poorly in real-world environments. This motivates the use of Machine Learning (ML), which handles complex data well but faces challenges like limited channel measurement data and mismatched neural network structures for V2V channels. Our project addresses these issues by leveraging extensive past measurements available in our lab and developing new neural network structures tailored for multi-dimensional channel prediction in various vehicular scenarios, such as campus and city roads. Finally, we validate the effectiveness of these predictions in actual resource allocation.		

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Abstract

Reliable and efficient vehicle-to-vehicle (V2V) communications are crucial for driver-assistance systems to reduce accidents and improve energy efficiency through better convoying. A major challenge is that resource allocation for communication must rely on the current propagation channel state, but vehicles only have past measurements. Therefore, effective channel prediction methods are essential. Traditional methods using simplified models and classical tracking/extrapolation perform poorly in real-world environments, motivating the use of Machine Learning (ML). ML excels with complex data but faces challenges such as limited channel measurement data and mismatched neural network structures for V2V channels.

Our project addresses these issues by leveraging extensive past measurements from our lab and developing new neural network structures tailored for multi-dimensional channel prediction in various vehicular scenarios, such as campus and city roads. Case studies show that our methods achieved superior prediction results, with over 3 dB and 5 dB mean squared error (MSE) gain in same-geo and cross-geo tests, respectively. Finally, we validate the effectiveness of these predictions in actual resource allocation.

Deep-learning-based radio channel prediction for vehicle-to-vehicle communications

Executive Summary

We want to describe the progress with the following stages and accompanying timeline:

Stage I: 1) July 1st~31st, 2023: We preprocessed data collected from the University of Southern California (USC) campus and a nearby street. This included synchronizing V2V Multiple-Input – Multiple-Output (MIMO) Channel State Information (CSI) with video data, removing outliers from CSI data using spectrum analysis, and exploiting data sparsity. We analyzed power delay angular profiles, Doppler angular profiles, and power delay profiles to understand CSI characteristics for downstream preprocessing. **August 1st to 31st, 2023:** We reviewed existing deep learning methods for data analysis, focusing on models like DeepConvLSTM (Deep Convolutional Long Short Term Memory) and PredRNN (Predictive Recurrent Neural Network) for channel prediction. We also proposed new predictive methods that integrate CSI physics into deep learning design. **September 1st to 30th, 2023:** We formulated the problem for deep-learning-based radio channel prediction, proposing a five-dimensional (5D) approach covering space, time, frequency, Doppler, and antenna domains. Implementing models like Deep ConvLSTM and PredRNN, we achieved MSEs of 0.0056, 0.0031, and 0.0045, respectively, depending on V2V system parameters and data collection scenarios. These results validate the use of existing deep learning models for V2V channel prediction, though improvements are needed for generalization across different geometries. We proposed a new method utilizing unlabeled CSI data from various contexts, combining recurrent networks and a novel attention module, achieving an average MSE of 0.0027, outperforming existing methods.

Stage II: October 1st to 31st, 2023: During this period, we focused on data preprocessing for the data collected along highways and in city canyons, specifically in downtown LA. Our data preprocessing efforts included synchronizing the V2V MIMO CSI data with the corresponding video data, identifying and removing outliers from the CSI data through spectrum analysis, and leveraging data sparsity. We examined power delay angular profiles, Doppler angular profiles, and power delay profiles to understand the characteristics of CSI data from various domains, laying the groundwork for downstream data preprocessing. **November 1st to 30th, 2023:** In this phase, we evaluated deep learning algorithms using the data collected from the aforementioned routes. We implemented five state-of-the-art deep learning models found in the literature. Our case studies revealed the challenges faced by existing deep learning models in effectively extracting features, particularly when dealing with data collected from diverse geometries and containing varying dynamics. Furthermore, these existing network models exhibited poor generalization across different geometries, primarily due to cumulative errors. **December 1st to 30th, 2023:** During this period, we conducted extensive case studies to assess

our proposed method using CSI data from three different routes. Our findings demonstrated that the proposed network model excels at feature extraction and representation learning for CSI data across diverse geometries. This success is attributed to the advanced design of long and short-term memories within the proposed network. Additionally, the adaptive teacher component helped reduce cumulative errors, a common issue in Recurrent Neural Network (RNN)-based network models, thereby enhancing the generalization capabilities of our proposed method across various geometries.

Stage III: January 1st to 31st, 2024: We tackled CSI prediction using data from three environments: USC campus, downtown Los Angeles, and the I10 highway. We introduced SE-LSTM, a model designed for CSI sequence modeling. It combines a Squeeze-and-Excitation (SE) module and an attention mechanism within an Long Short Term Memory (LSTM) architecture, managing dependencies within and between sequences. SE-LSTM outperformed existing methods in various performance metrics (MSE, MAE, etc.). **February 1st to 29th, 2024:** We conducted cross-environment testing of our method, revealing that all RNN-based methods accumulate errors. To mitigate this, we developed adaptive meta-learning, which reduces performance degradation in cross-geometry tests, keeping performance loss within 3 dB. **March 1st to 31st, 2024:** We applied our training strategy to existing methods like ConvLSTM and PredRNN, confirming its effectiveness in maintaining acceptable performance loss. We also evaluated computational complexity, including parameters, Floating Point Operations (FLOPs), memory usage, and training/testing time. Our findings show that the proposed methods and certain existing ones, like ConvLSTM, are efficient enough for practical applications.

Stage IV: April 1st to June 15th, 2024: We applied the predicted CSI to a well-established scheduler to evaluate the performance of our predictions in the context of resource allocation. Case studies confirmed the effectiveness of the predicted CSI. Additionally, we launched a website to make our new ML network and the related dataset publicly available. Lastly, we dedicated time to completing the final report.

Introduction

V2V communications are vital for the future of driving, particularly for assisted or autonomous driving scenarios. These communications enable vehicles to warn those behind them of imminent emergency braking or to coordinate smooth lane changes. However, widespread adoption of V2V has been slow, influenced by both economic factors and the limited and unpredictable performance of these systems. This performance variability is due to challenging operating environments, including signal propagation issues between transmitters (TX) and receivers (RX) and the high density of devices, which leads to strong interference and potential packet loss.

Therefore, further research to improve the reliability and latency of V2V communications is urgently needed. Reliable and efficient data communications between vehicles are essential for driver-assistance systems, which reduce the likelihood of accidents and improve energy efficiency by enabling more efficient convoy formations. One of the main challenges for these systems is resource allocation (spectrum, power) based on the current state of the propagation channel, while vehicles only have access to past measurements. Thus, it is critical to develop suitable channel prediction methods that allow vehicles to infer the current state from past observations.

The importance of channel estimation and prediction for V2V scenarios is well recognized in the literature, with numerous papers published on this topic. Most of these studies rely on classical methods, such as Extended Kalman Filters (e.g., [1, 2]), or sparsity-based methods (e.g., [3]). While these algorithms perform well with theoretical channel models, they face challenges when applied to real-world data due to mismatches between the underlying models and physical reality, and they struggle to predict channels over longer timescales. Machine Learning (ML) provides a framework for making decisions and predictions from available data without relying on specific analytical models [5]. This has revolutionized approaches to previously insurmountable computational challenges. Therefore, ML-based channel estimation is hypothesized to perform better, as it can predict channels over larger distances and uncover hidden relationships over time [6, 7]. Consequently, ML has been applied in various contexts, such as channel prediction in massive MIMO [8], high-mobility massive MIMO-OFDM (Orthogonal Frequency Division Multiplexing) [9, 10], vehicle-to-infrastructure [11], cross-band channel prediction [4], vehicular edge networks [12], and Unmanned Arial Vehicle (UAV) channels [13].

Despite the interesting applications, none directly apply to V2V channels, whose dominant propagation effects differ fundamentally from infrastructure-based communications [14]. While ML-based V2V channel prediction studies exist (e.g., [15-17]), those using actual data are extremely rare. The only directly applicable investigations, to the best of our knowledge, are [18], which uses only path loss, and [19], which extracted CSI from 802.11p on-board units to predict received power. However, these units were not calibrated, and only single-antenna measurements were performed, whereas future 5G New Radio (NR) V2V systems will utilize multiple antenna elements. We believe this gap is due to a lack of measurement data in groups working with ML. Our group not only has considerable experience with ML but also a large dataset (several TeraByte (TB)) of measurement data for wideband, multi-antenna V2V channels.

Models		Architecture	Predictions	Other Notes
From Wireless Communication and Vehicle Technology research	Deep Multimodal Learning (2020) [21]	MLP, No recurrent unit	Real-valued CSI	Taking several kinds of measurements as input
	Complex-valued Neural Network (2021) [9]	CNN, No recurrent unit	Complex-valued CSI variant	Focusing on spatial dynamics
	Adversarially-Trained RNN (2022) [22]	RNN	CSI and Transmitter Authentication	Enhancing temporal importance
	Our Model [21]	Spatial-temporal Convolutional LSTM	Enhanced Complex-valued CSI	Boost with attention and gradient highway
From Computer Science research	ConvLSTM (2015) [23]	Convolutional LSTM	Real-valued Image	Spatiotemporal feature
	TrajGRU (2017) [24]	Trajectory GRU	Real-valued Radar Echo	Spatial variation
	Conv-TT-LSTM (2020) [25]	Convolutional Tensor-train LSTM	Real-valued Activity data	higher-order memory relationship
	PredRNN (2022) [26]	Spatiotemporal LSTM	Real-valued motion	Gradient Highway

Table I Representative prediction methods comparison. MLP: Multi-layer Perceptron; CNN: Convolutional Neural Network; GRU: Gated Recurrent Unit.

The spatial, temporal, or spatio-temporal prediction problem is critically important, particularly for wireless communication, and has been explored from various perspectives in multiple research communities (see Table I for key references). A review of papers from the wireless communication and vehicle technology communities reveals that these studies focus on handling the complex structure of CSI data using expert knowledge but often neglect the design and optimization of the neural network structure. Conversely, papers from the computer science field elaborate on the design of exemplary RNN structures with real-valued imagery data, which differ from the V2V communication problem due to, for example, the lack of consideration for non-stationary time series. For the CSI prediction problem in V2V networks, it is crucial to consider three vital factors:1) Environmental dependence and variations in both spatial and temporal domains.2) High dynamics on large-scale and small-scale timescales (e.g., sudden and deep shadowing caused by a truck merging between two communicating cars. 3) Complicated data structure. Motivated by representative network structures and based on fieldwork and comprehensive data preprocessing studies, we propose a network that integrates a recurrent neural network (RNN)-based structure with modifications inspired by physical propagation processes to tackle the challenging V2V channel prediction problem.

The remainder of this report is structured as follows: Section II presents the measurement campaign and fundamental data analysis. Following this, we discuss our ML-based solutions and comprehensive case studies. Our applications and conclusions are provided in Section IV.

Chapter I: An introduction to the V2V Measurement Campaign

The V2V Measurement Campaign is an innovative initiative designed to advance the understanding of V2V communication channels through comprehensive empirical data collection and analysis. At the heart of this campaign is the deployment of a state-of-the-art channel sounder, a sophisticated device engineered to capture high-resolution channel characteristics with precision and accuracy. This channel sounder facilitates the detailed examination of signal propagation behaviors in various real-world vehicular environments, enabling the identification of critical factors that influence V2V communication performance. By systematically conducting measurements across diverse scenarios and conditions, the V2V Measurement Campaign aims to develop robust models and enhance the reliability and efficiency of V2V communication systems, ultimately contributing to safer and more efficient transportation networks.

I.1 Channel Sounder

The measurement of wireless channel properties, known as channel sounding, is a fundamental task in wireless communication. Channel sounding provides a detailed visualization of how the channel functions. During this process, the transmitter (Tx) sends out a signal that stimulates the channel, while the receiver (Rx) observes the channel's output. The transmitted signal comprises modulated, periodically repeated pulses. Each measurement run, or burst, consists of N pulses (snapshots) transmitted at fixed intervals.

The channel sounder used in this instance is based on the NI-USRP (National Instruments Universal Software Radio Peripheral) RIO software-defined radio platform and performs switched-array Multiple Input Multiple Output (MIMO) measurements. It transmits an Orthogonal Frequency Division Multiplexing (OFDM)-like sounding signal at approximately 5.9 GHz with a bandwidth of 15 MHz. The output power is around 26 dBm. Because the NI-USRP RIO platform employs a direct upconversion (DUC) architecture, intermediate frequency (IF) sampling is implemented for both the Tx and Rx. This approach minimizes the negative effects of the Direct Current (DC) offset problem, which typically affects wireless transceivers with DUC architectures. The Local Oscillator (LO) operates at a frequency of 5.888 GHz, which is 12 MHz lower than the center frequency of the sounding signal. More details have been given in Table II.

Parameter	Value
Carrier frequency	5.9 GHz
Bandwidth	15 MHz
Transmit power	26 dBm
Sampling rate	20 MS/s
MIMO signal duration	640 µs
Number of MIMO per burst	30
Rate of bursts	20 Hz
Number of bits in ADC	16

Table 2: Parameters of the real-time MIMO channel sounder.

I.2 Data in MIMO Snapshots

A MIMO snapshot is a sequence of training sequences, each transmitted and received by a different antenna pair. From a single snapshot, we can extract key parameters such as the direction of arrival, direction of departure, and the power of the snapshot. MIMO bursts are composed of multiple snapshots grouped together. This grouping is typically done to track the evolution of the channel across all snapshots within a single burst, enabling the extraction of Doppler effects. In the given measurement data, each burst consists of 30 snapshots, with bursts occurring at a rate of 20 Hz (20 bursts per second). The choice of 30 snapshots per burst is determined by the hardware constraints of the Rx, as this is the maximum number that can be buffered at one time. The duration of a single burst is 18.6 milliseconds, with each snapshot having a duration of 640 microseconds. The Snapshots were obtained in a campaign (as shown in **Figure 1**): Duration: Tx-8 mins 59 sec, Rx-8 mins 30 sec, Route length: 1 km.

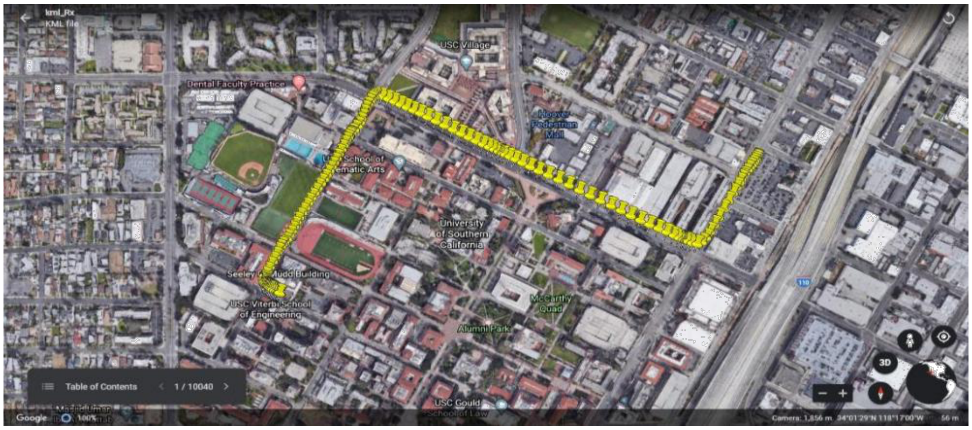


Figure 1a: Trajectory of TX.

Figure 1b: Trajectory of RX.

I.3 Data Preprocessing and Analysis

In this subsection, we present a fundamental analysis of the collected data, focusing on key metrics such as the power delay profile (PDP) and Doppler spectra across various scenarios. The power delay profile provides insight into the time dispersion characteristics of the channel, illustrating how the signal power is distributed over different time delays. This is crucial for understanding the multipath propagation effects in the measured environments. On the other hand, the Doppler spectra analysis reveals the frequency dispersion characteristics, indicating the relative motion between the transmitter and receiver and its impact on the signal's frequency components. By examining these metrics under different conditions, we aim to capture a comprehensive picture of the channel behavior, enabling more accurate modeling and enhancement of V2V communication systems.

$$Doppler(m,n,\tau) = \frac{1}{61}\sum_{f=1}^{61}\left|\mathrm{fft}\left(H(m,n,f,b)\right)\right|^2, \tag{1}$$

where fft is the fast Fourier transform, H is the transfer function matrix, depending on Tx and Rx antenna elements *m,n*, subcarrier *f*, and location pair *b,* and

$$PDP(b) = \frac{1}{MN}\sum_{m,n=1}^{8}\left|\mathrm{ifft}\left(H(m,n,f,b)\right)\right|^{2}. \quad (2)$$

We presented basic analysis for the measurements in the following: See Figure 2-4 for static case and Figure 5-7 for dynamic case, respectively.

(1) Measurements collected in the static case (TX and RX are static)

Figure 2. Snapshot from a recorded video by a 360 camera for the location where the static-case measurements below were taken.

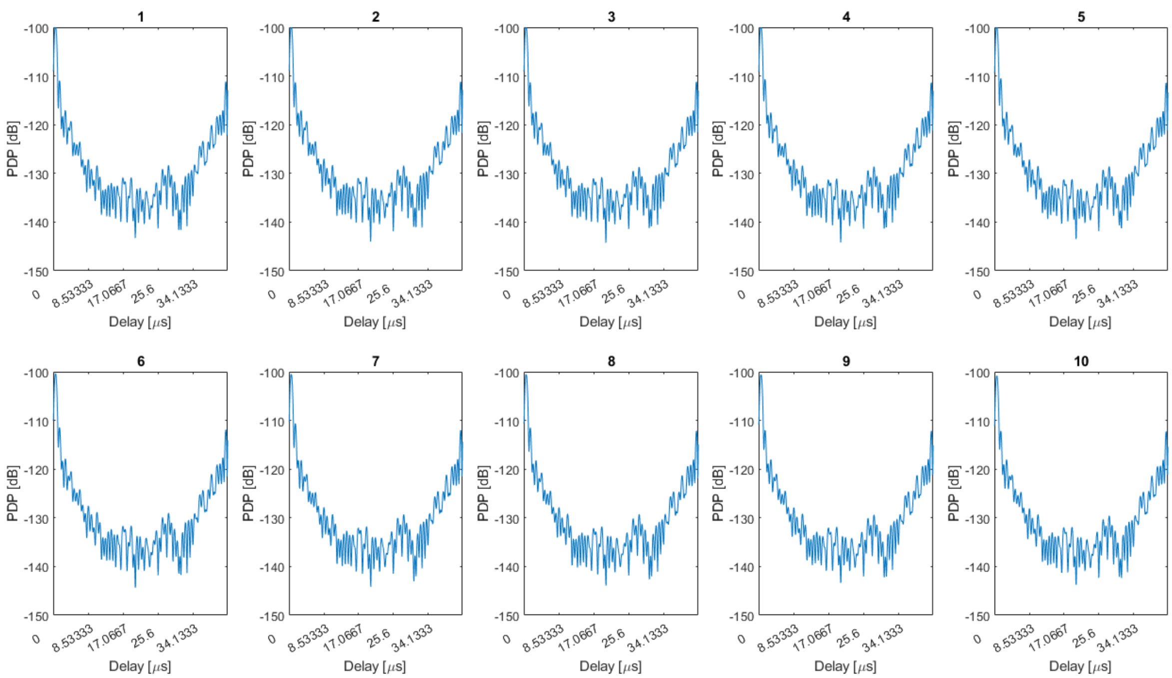


Figure 3. PDP plot of the ten consecutive (odd) bursts of CSI data in static scenario.

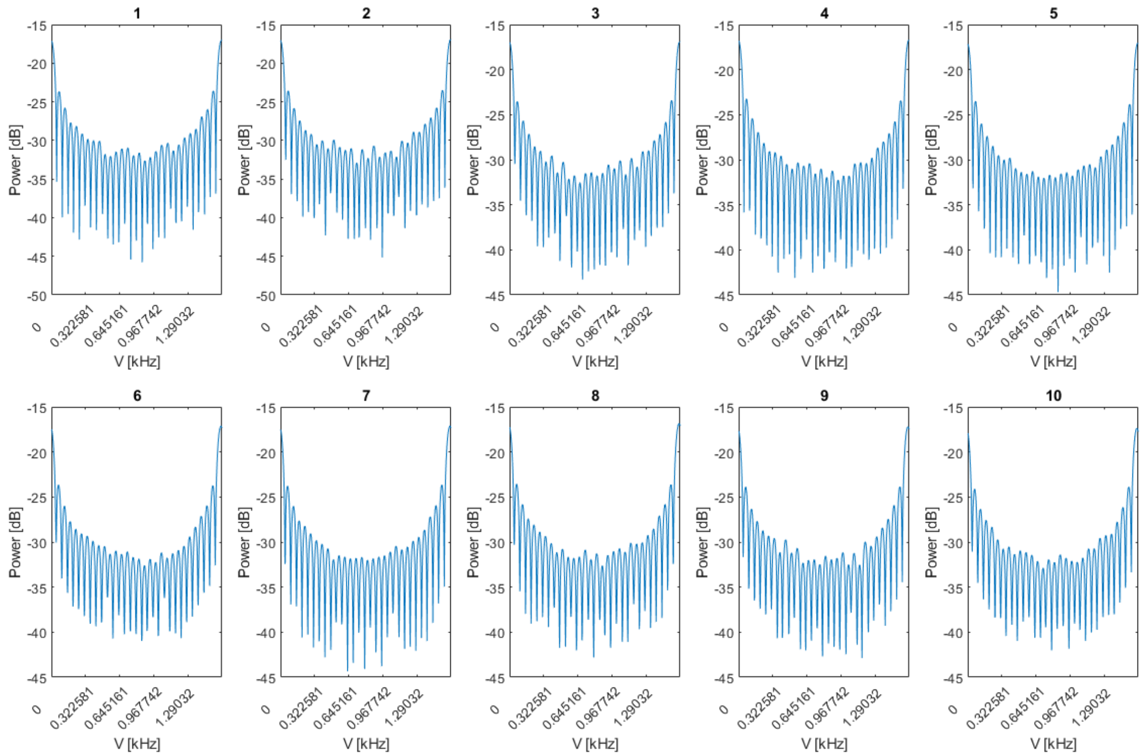


Figure 4. Doppler spectra plot of the ten consecutive odd bursts of CSI data in static scenario. In this figure, we averaged CSI data in the spatial domain (TX and RX).

(2) Measurements collected in the dynamic case (TX and RX are moving)

Figure 5. Snapshot from the recorded video from a 360 camera in dynamic case.

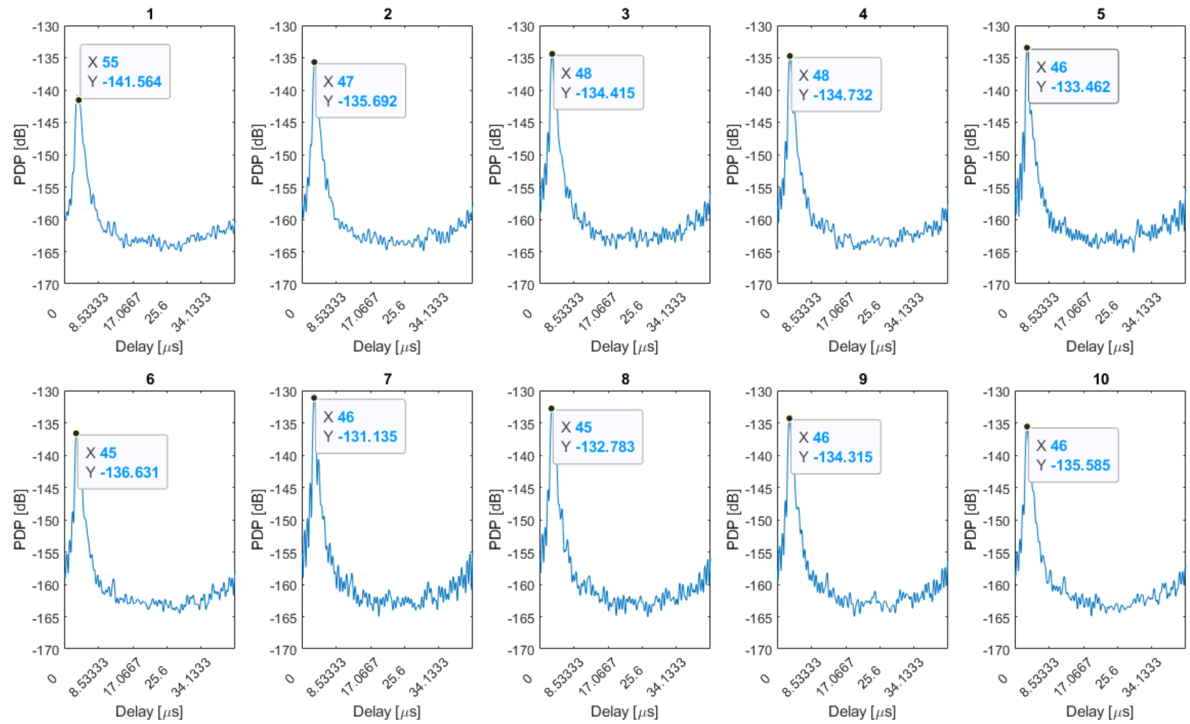


Figure 6. **PDP plot of the ten consecutive bursts of CSI data in the dynamic scenario.**

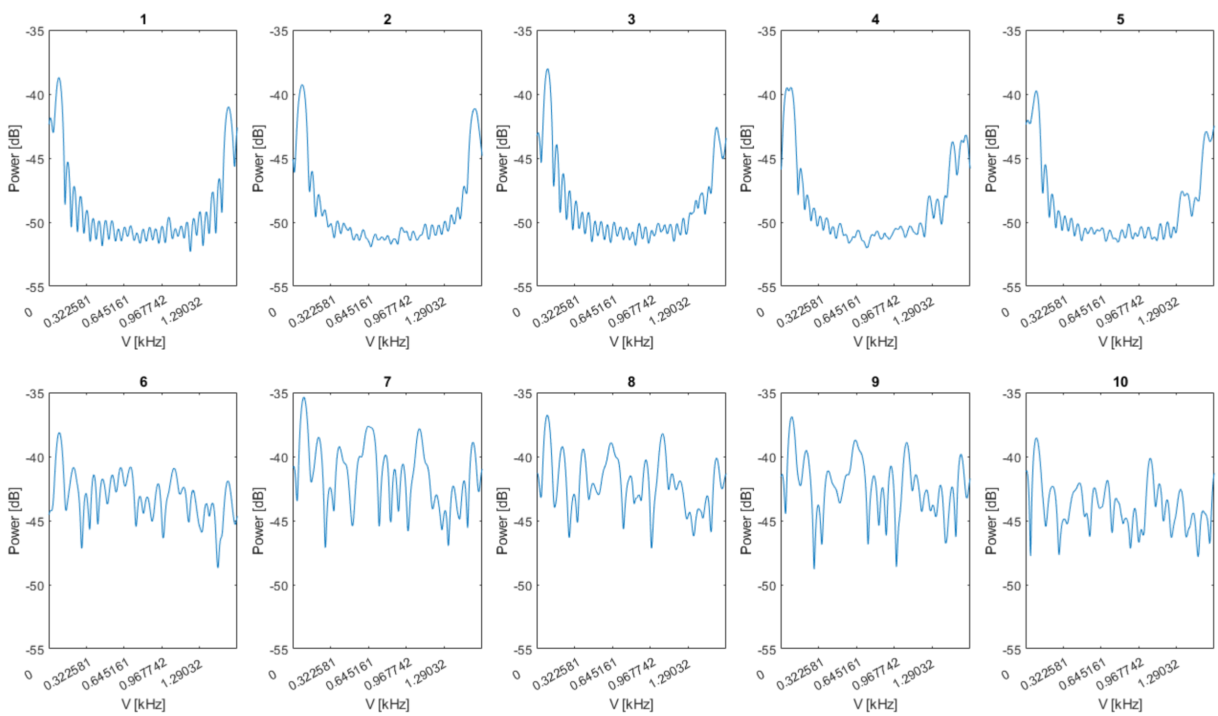


Figure 7. **Doppler spectra plot of the ten consecutive odd bursts of CSI data in dynamic scenario.**

The plots of the PDP and Doppler Spectra provide a detailed visualization of the V2V communication channel characteristics under various scenarios. The PDP plots illustrate how signal power is distributed over different time delays, highlighting the multipath effects and the time dispersion of the signal. These plots typically show peaks corresponding to the direct path and reflected paths, providing insights into the propagation environment; note that the increase of the power for large delays is a wraparound from the Fast Fourier Transform applied in the processing. By analyzing these peaks, we can infer the presence of various obstacles and the distances at which reflections occur, which are crucial for understanding the communication reliability and signal quality in different settings.

The Doppler spectra plots, on the other hand, depict the frequency shift and spread due to relative motion between the vehicles, indicating the dynamic nature of the communication channel. These spectra reveal how the relative speeds and directions of the vehicles influence the signal, causing Doppler shifts that must be accounted for in the design of robust V2V communication systems. In scenarios with high relative speeds, such as highways, the Doppler shift is more pronounced, whereas in slower-moving environments like urban areas, the shift is less significant but can be more complex due to the presence of numerous reflecting surfaces.

The accompanying video further enhances this analysis by showcasing how these measurements vary across different scenarios, such as urban, suburban, and highway environments. The video provides a dynamic visualization of how the PDP and Doppler Spectra evolve in real-time, illustrating the impact of changing environmental conditions and vehicle dynamics. For instance, in urban settings, the PDP may show numerous closely spaced peaks due to the dense scattering environment, while the Doppler Spectra may exhibit a wide range of shifts due to the varied speeds and directions of vehicles. In contrast, highway scenarios might present fewer but more distinct PDP peaks and a narrower Doppler spectrum concentrated around the vehicles' relative speeds.

By comparing these different scenarios, the video highlights the unique features and challenges each environment presents for V2V communication. This multi-faceted approach, combining static plots with dynamic video analysis, enables a comprehensive understanding of the channel characteristics. It underscores the importance of context-specific strategies for optimizing V2V communication performance, ensuring reliable and efficient data transmission regardless of the driving conditions. Through this detailed examination, we can better design and implement V2V communication systems that are resilient to the diverse and dynamic nature of real-world driving environments.

We finally comment on the generalizability of the channel sounder data. The sounder is designed with two perspectives in mind: (i) the setup allows the extraction of the double-directional channel representation, i.e., the directions, delays, and strengths of the multipath components, from which transfer function matrices can be synthesized for any antenna arrays. (ii) when using directly the measured transfer function matrices, then the setup emulates the behavior of an antenna array built into (more precisely, on top of the roof of) a car. Correlation properties of the signals at the different antenna elements will thus differ from those observed with, e.g., antennas on a handset. For a description of a handset, the extraction of MPCs, and synthesizing of the response with the array characteristics of the handset antennas (according to application (i) would be required.

Chapter II: Spatial-temporal predictive learning for reliable V2V channel prediction

Trustworthy V2V communications are crucial for the effectiveness of driver-assistance systems, significantly impacting accident reduction and vehicle energy efficiency. A major challenge in these systems is the need for planning transmission parameters, including modulation and coding scheme, resource allocation, and scheduling, which rely heavily on the state of the propagation channel at the future time of transmission. The primary issue is that vehicles typically only have access to past and possibly present data and pilot signals, creating a significant gap between the available information and the required future CSI. This gap underscores the need for effective channel prediction methods that can accurately infer the future state from past observations. Therefore, developing and refining channel prediction techniques is vital for enhancing the safety and efficiency of vehicular networks.

Traditional methods like sparsity-based approaches and Extended Kalman Filters have shown effectiveness in theoretical models but often struggle with real-world data, highlighting a gap between theory and practice. In response, machine learning-based methods have gained prominence as promising alternatives. These ML-based approaches, being model-free, are more adaptable to the complexities and variability of real-world data. They have proven superior in various scenarios, such as massive MIMO-OFDM systems and high-mobility environments.

In the realm of data prediction, machine learning-based methodologies are generally divided into two categories: those based on RNNs and recurrent-free methods. RNN-based approaches are noted for their favorable memory designs like spatiotemporal memory and attention-guided mechanisms, which enable them to learn dependencies within data sequences effectively. On the other hand, recurrent-free methods utilize transformer-based architectures with an encoder-decoder structure and multiple attention mechanisms to create robust inter-data representations. Recent comprehensive surveys show that RNN-based algorithms generally outperform others in various datasets, though they may demand higher computational resources. This study, therefore, opts for the RNN approach, aiming to address the complex requirements of holistic V2V channel prediction.

This research tackles the specific challenges of V2V channel prediction, recognizing that methods effective in infrastructure-based communications often falter due to the distinct propagation characteristics of V2V environments. Additionally, ML research, rich in methodologies, typically overlooks V2V scenarios, focusing more on image and video data processing, which significantly differs from V2V channel data characteristics. To address this, our study is focused on the holistic prediction of V2V channels through deep predictive learning. We introduce a novel SE-LSTM network, tailored to simultaneously model CSI sequences across Time, Doppler, Delay, Angular, and Geometry domains. Enhancing the model's flexibility for various geometrical setups, we integrate the meta Pseudo-Label learning method, substantially boosting the generalization ability of our approach across diverse scenarios.

II.1 Problem Formulations

The objective of CSI prediction is to utilize previously or currently observed CSI data to forecast future CSI values. This is particularly relevant in most V2V systems, including the advanced 5G NR frameworks, where data transmissions are structured into units called frames, which are further broken down into subframes and slots. The time frame required for these predictions can extend up to 200 ms. Given that the periodicity of our sounding signal bursts, termed as 'frame-length,' is 20 ms, this necessitates the prediction of up to 10 frames ahead.

This work focuses on deploying ML based techniques to tackle the intricate problem of predicting CSI. We employ a specific neural network, represented as φ_{θ}, and utilize a sequence of observed CSI frames, denoted by $\chi_1, \chi_2, \ldots, \chi_J$. The aim is to predict a future sequence of length K using the neural network φ_{θ}, based on J previous observations:

$$\{\chi_1,\cdots,\chi_J\}\overset{\varphi_\theta}{\Rightarrow}\{\chi_{J+1},\cdots,\chi_{J+K}\}$$

We maintain that the length of historical observations J is equivalent to the length of the future sequence K, where J = K =10. The dynamic and non-stationary nature of CSI frames in variable environments poses a significant challenge, yet it underscores the necessity of robust CSI prediction. Furthermore, our ambition is to develop a neural network that can proficiently model the CSI across four essential domains, as outlined earlier. The subsequent section will elaborate on our approach to achieving this ambitious goal.

II.2 Spatial-temporal Predictive Learning Methods

(1) Basic Designs

In the realm of time series data analysis, LSTM-based RNNs have established themselves as a foundational approach, as highlighted in foundational studies such as Gers et al. (2002). Subsequently, Shi et al. (2015) introduced the ConvLSTM architecture, a significant enhancement tailored to manage spatial-temporal data more adeptly. This model has proven particularly effective in modeling the dependencies inherent in wireless channels, as detailed by Liu et al. (2022).

Our research is dedicated to devising a neural network model, specifically engineered to model the unique sequential dependencies found in CSI. A key challenge encountered with the application of ConvLSTM and its derivatives on our data pertains to their typical neglect of channel interdependencies, especially in the Doppler domain where data exhibits higher dimensionality than the usual three-channel configuration seen in image or video data. This complexity necessitates a robust model capable of addressing intricate interdependencies across all dimensions of the CSI data.

Moreover, the substantial dimensionality of our input data often renders the spatial convolution operations in standard ConvLSTM architectures excessive, thereby requiring adjustments for efficient processing of our CSI sequences. Addressing these pivotal issues is crucial for the development of an effective neural network model tailored to our specific data requirements.

Our model represents a significant advancement over the traditional ConvLSTM framework by integrating transformed inputs and the Gradient Information Embedding (GIE) vector, offering enhanced capabilities in handling complex spatiotemporal data. This innovation leverages a novel spatiotemporal memory mechanism that aggregates and averages all historical (transformed) inputs at each time step. This process effectively mitigates temporal variations within the intra-CSI sequence, addressing issues of temporal instability noted in recent studies like that of Wang et al. (2022). Additionally, our approach incorporates the GIE of CSI data into the cell outputs and output gates. This integration ensures that the integrity of feature representation is preserved, particularly in the Doppler domain, which is critical for our data's dynamic and multi-dimensional nature. By embedding the GIE vector, our model not only maintains but enhances the feature representation, ensuring that each temporal phase contributes meaningfully to the overall model accuracy. These enhancements are designed to meet the specific needs of nuanced sequence modeling required by our CSI data. By refining the spatiotemporal interactions and embedding crucial gradient information, our model aims to offer a more robust framework for predicting complex dependencies and interactions within CSI data sequences.

(2) Advanced Training

Inspired by pioneering studies in meta-learning, our research introduces the concept of meta pseudo labels to significantly reduce prediction errors in channel state information analysis. This approach is rooted in a framework that involves the interaction between two types of neural networks: a teacher network and a student network. These networks are differentiated by their unique sets of parameters. In our model, the teacher network uses its parameters to predict outcomes based on unlabeled data. Similarly, the student network makes predictions on both labeled and unlabeled data. The learning process is centered around the teacher network guiding the student by aiming to minimize the differences in their predictions on the same unlabeled data. This guidance helps improve the accuracy of the student's predictions.

To further refine this process, as shown in Figure 8, the optimized parameters from the student network are then used to enhance the teacher network. This cyclical optimization not only improves the individual performance of each network but also deepens the overall learning process. The networks continuously evolve and adjust through iterative learning based on the feedback and corrections they receive from each other. This advanced learning setup does more than just utilize pseudo labels; it integrates them into the core of the network optimization process. This integration significantly boosts the performance of both the teacher and student networks. Although the optimization process is complex and not the main focus of this paper, it is crucial for achieving a deep level of learning. For those interested in the technical specifics of these processes, we recommend consulting key publications in the field. By adopting meta pseudo labels, our method not only tackles the challenges associated with modeling unlabeled data but also markedly improves the learning capabilities of the networks involved. This approach sets a new standard in the use of meta-learning techniques for training neural networks.

This section addresses the complex challenge of predicting CSI in urban canyon settings, where the interference and reflections from buildings significantly complicate data analysis. To tackle this, we introduce a groundbreaking prediction model, the SE-LSTM, which is specifically tailored for modeling CSI sequences. This innovative model is adept at managing both the intra-sequence and inter-sequence dependencies that are crucial for accurate forecasting in such dynamic environments.

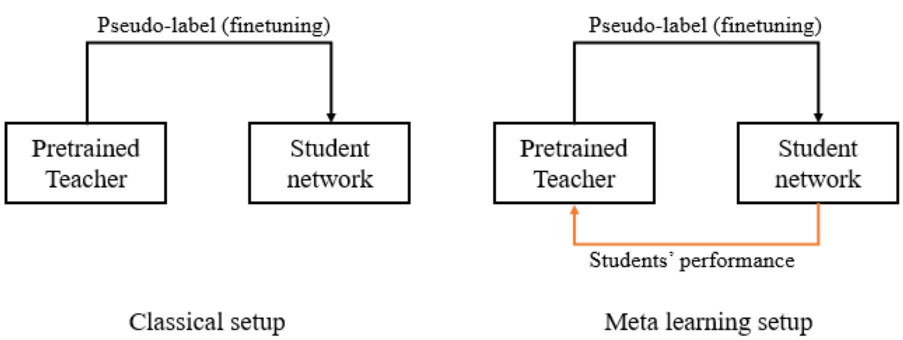


Figure 8 The idea of meta learning for network training.

The SE-LSTM combines a SE module with an attention mechanism, seamlessly integrating these features within the traditional LSTM framework. The SE module enhances the model's ability to focus on important features within the data, while the attention mechanism provides a nuanced understanding of the temporal relationships across different sequences. This dual approach allows the SE-LSTM to effectively handle the varying dynamics and dependencies of CSI data, making it particularly suitable for the complex scenarios presented by urban canyons.

Our empirical analysis, which utilized V2V measurement data from urban canyon environments, confirms the exceptional capabilities of the SE-LSTM. The model demonstrated remarkable effectiveness in its predictions, outperforming standard methods. This success highlights the potential of integrating advanced neural network features like SE modules and attention mechanisms into traditional models to enhance their predictive accuracy in highly specific and challenging environments

II.3 Case Studies

Measurements were carefully conducted around USC campus, located in a suburban area of Los Angeles, California, USA. The measurement route consisted primarily of two streets. The first street, within the USC campus, features an environment enriched with nearby buildings and parked trucks, which contribute to a complex signal landscape. The second street, outside the USC campus, is characterized by large sidewalks and sporadically placed road signs. The dynamic urban backdrop during the measurement campaign included moving pedestrians and various types of vehicles, introducing significant variations in the collected Channel State Information (CSI) frames.

For these measurements, both the transmitter and receiver vehicles were arranged to travel one behind the other along a street canyon near the USC campus, as illustrated in Figure 1. The distance between these vehicles ranged from 5 meters to 250 meters, allowing other vehicles to intermittently pass between them and affect the signal transmission. A total of 4800 and 2900 bursts of CSI frames were collected on the first and second streets, respectively. We processed this data using a non-overlapping sliding window approach, where each window captured 10 CSI frames. Two specific scenarios were set up for neural network training and testing: **Case I:** Data from the first street was used for both training and testing the neural network, with an allocation ratio of 80 % for training and 20 % for testing. This setup assessed the network's performance in a consistent environmental condition, termed 'same-geometry' evaluation. **Case II:** Here, the training data was sourced from the first street, while the testing was conducted using data from the second street. This arrangement, referred to as 'cross-geometry evaluation,' tests the network's ability to adapt and perform accurately across different urban geometries.

For evaluating the neural network's performance, we used MSE and Mean Absolute Error (MAE) as performance metrics. These metrics compare the measured CSI frames with their corresponding predicted frames, providing a comprehensive assessment of the neural network's accuracy in predicting CSI under varying urban conditions.

KPI	Algorithms	11	12	13	14	15	16	17	18	19	20	Avg.
MSE	ConvLSTM	0.112±0.056	0.107±0.054	0.115±0.058	0.127±0.064	0.129±0.066	0.133±0.066	0.156±0.079	0.145±0.073	0.144±0.073	0.141±0.071	0.131±0.015
	ST-ConvLSTM	0.106±0.053	0.096±0.048	0.099±0.051	0.105±0.053	0.103±0.052	0.104±0.052	0.122±0.062	0.112±0.056	0.113±0.057	0.111±0.055	0.107±0.007
	Proposed	0.079±0.040	0.069±0.035	0.072±0.037	0.077±0.039	0.076±0.039	0.077±0.039	0.094±0.047	0.085±0.043	0.087±0.044	0.085±0.043	0.081±0.005
MAE	ConvLSTM	0.056±0.049	0.051±0.047	0.054±0.052	0.058±0.057	0.059±0.059	0.061±0.059	0.079±0.068	0.068±0.065	0.069±0.064	0.067±0.063	0.063±0.008
	ST-ConvLSTM	0.055±0.045	0.048±0.042	0.049±0.044	0.051±0.046	0.050±0.046	0.051±0.045	0.066±0.052	0.057±0.049	0.058±0.049	0.056±0.048	0.054±0.005
	Proposed	0.042±0.037	0.035±0.038	0.036±0.037	0.037±0.040	0.038±0.034	0.038±0.034	0.051±0.034	0.042±0.032	0.044±0.030	0.043±0.034	0.041±0.005

Table 3 MSEs and MAEs of predictions results. We use 10 historical bursts of CSI as inputs and aim to predict the next 10 bursts (indexed 11-20).

The results shown in Table 3 and Figure 9 meticulously compare the performances of three algorithms—ConvLSTM, ST-ConvLSTM, and a Proposed algorithm—over a series of time points using two key performance indicators: MSE and MAE. The analysis provides a snapshot of each algorithm's ability to predict with precision and consistency. The ConvLSTM algorithm demonstrates a gradual increase in MSE from the start to the midpoint, stabilizing towards the end. The overall average indicates a moderate level of variability in its predictive accuracy. Similarly, the MAE for ConvLSTM shows a steady rise to a peak in the mid-series, followed by a slight decrease, reflecting its overall predictability over time.

In contrast, the ST-ConvLSTM algorithm maintains a steadier MSE throughout the series, with only a slight elevation towards the middle before tapering off, suggesting a relatively stable performance. Its MAE mimics this pattern, beginning with minimal fluctuation and peaking modestly midway through the series before decreasing again, showcasing a consistent level of error across the observed time points. Meanwhile, the Proposed algorithm outshines both, with significantly lower MSE and MAE values across the board. It starts off strong and maintains a narrow range of error, peaking slightly before returning to low values. This consistent performance across all metrics highlights its superior efficiency and accuracy, making it an exceptional candidate for applications that demand high precision and reliability in predictions.

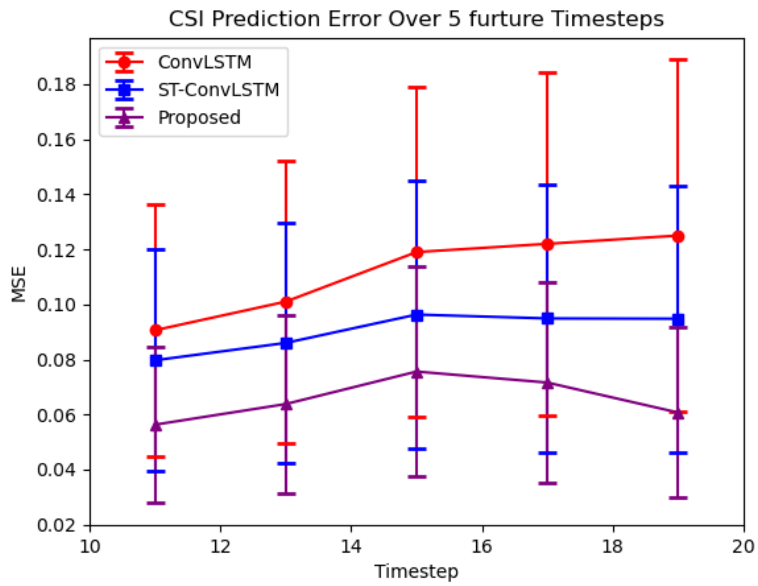


Figure 9. MSEs of the CSI prediction.

The bar chart (Figure 10) presents an analysis of relative performance changes (RPC) measured in decibels (dB) for three distinct learning scenarios: without meta-learning (w.o. Meta), with meta-learning (w. Meta), and with adaptive meta-learning (w. adaptive Meta). This comparative evaluation spans two different experimental cases, namely Case I and Case II, highlighting the variable impacts of meta-learning approaches under differing conditions. In Case I, the data show a stark contrast in performance enhancements. The approach without meta-learning delivers the highest boost, significantly outstripping the others by peaking just above 12 dB. This suggests a robust advantage when meta-learning techniques are not applied in this specific setting. In contrast, the scenario implementing standard meta-learning cuts this gain by about half, achieving just over 6 dB, while adaptive meta-learning offers a slight improvement over the standard approach, reaching around 8 dB. This indicates that introducing adaptivity to meta-learning provides a moderate increase in performance, hinting at the potential benefits of more dynamic learning strategies.

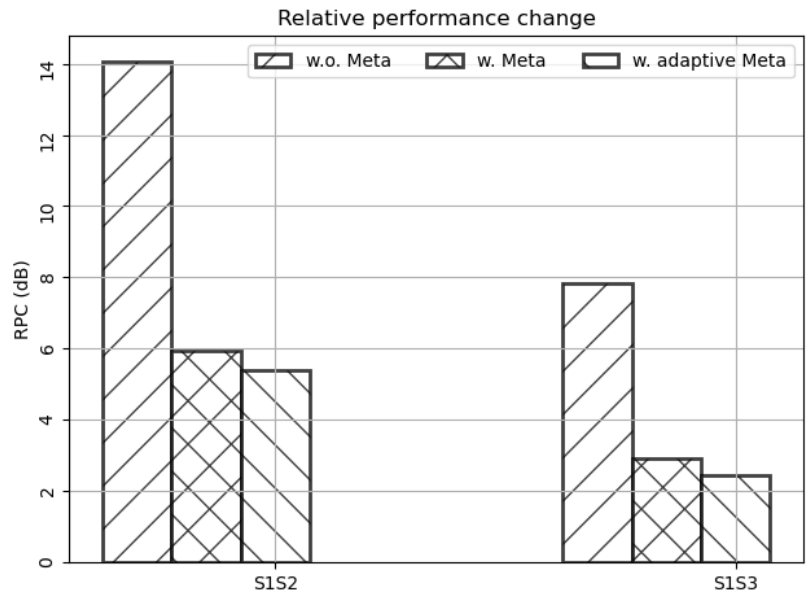
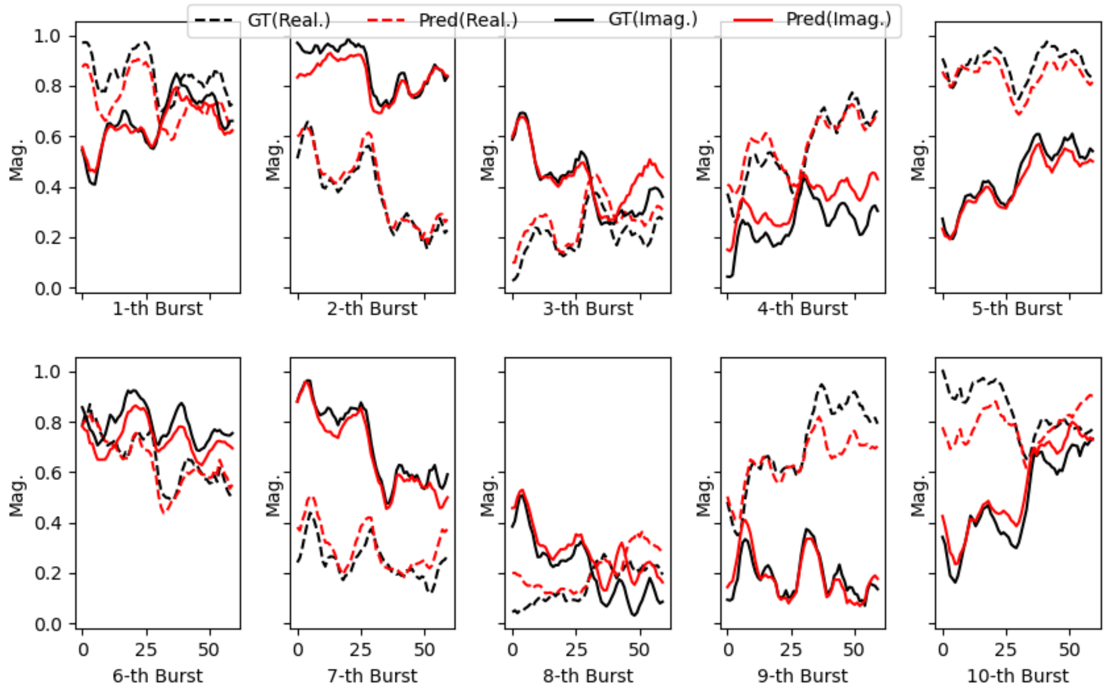


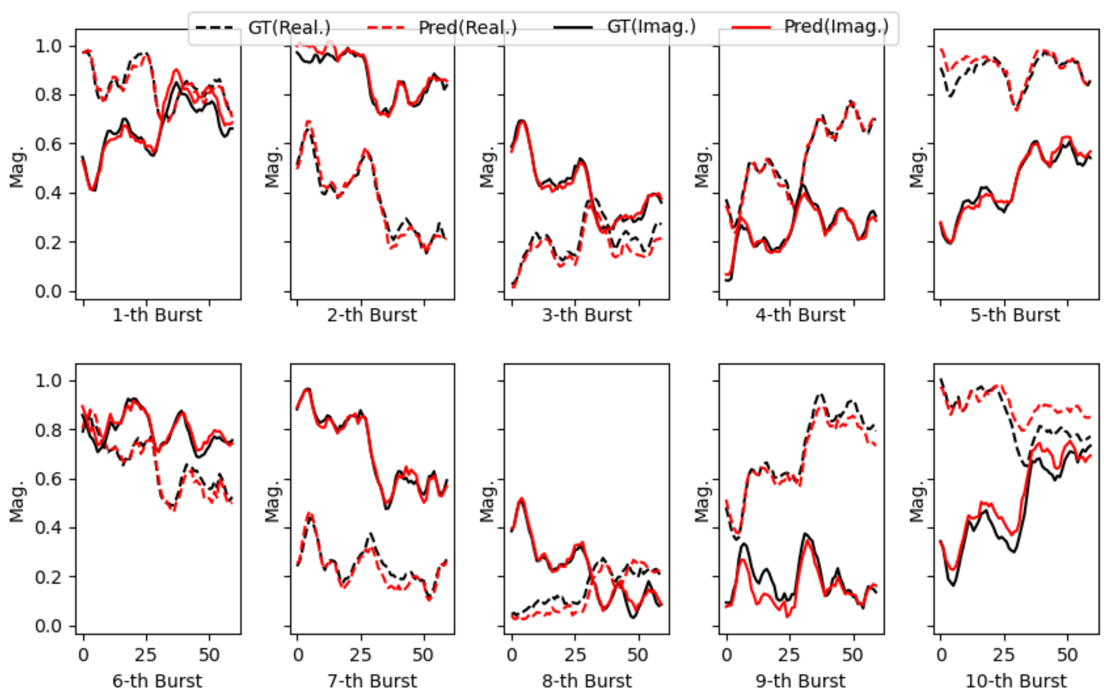
Figure 10. Performance gain of meta learning training.

Case II, however, tells a different story where the results diverge from those observed in Case I. Here, the highest increase in performance is attributed to the scenario with adaptive meta-learning, which achieves slightly above 4 dB, suggesting that adaptive methods may be more suited to the conditions of this case. Interestingly, the performance enhancements for the scenarios without meta-learning and with standard meta-learning are almost identical, each hovering just below 2 dB. This minimal improvement indicates that the meta-learning techniques, whether adaptive or not, have a less pronounced impact in Case II compared to Case I. The contrast between the two cases underscores the significance of the context and specific conditions under which these learning methodologies are applied. It emphasizes that while meta-learning can offer substantial benefits, its effectiveness is highly dependent on the scenario, necessitating careful consideration and customization of the learning approach to suit the specific challenges and requirements of each case.

For a more detailed illustration, the results are presented in Figure 11.



(1) Without AER



(2) with AER

Figure 11. Plots of prediction in different burst with and without AER.

Chapter III: Applications and Conclusions

III.1 Channel Prediction Applications

Predicted CSI in V2V resource application is critical for enhancing communication and safety in intelligent transportation systems. CSI represents the condition of the communication channel, including factors such as signal strength, interference, and noise levels. Predicting CSI involves using advanced analytical techniques and machine learning models to forecast these channel conditions, thus enabling more efficient and reliable V2V communication. To accurately predict CSI in V2V contexts, extensive data collection is essential. This involves real-time monitoring of signal quality, vehicle mobility patterns, and historical data on channel variations under different traffic and environmental conditions. Machine learning models process this data to identify trends and predict future channel states. By leveraging these predictions, V2V systems can make informed decisions about resource allocation, such as adjusting transmission power, selecting optimal communication paths, and timing data transmissions to reduce interference and enhance signal reliability.

Utilizing predicted CSI in V2V applications significantly improves the quality of service (QoS) for vehicular communication networks. It ensures robust, low-latency, and high-speed connectivity between vehicles, which is crucial for safety-critical applications like collision avoidance, real-time traffic updates, and autonomous driving coordination. Furthermore, it allows for dynamic adaptation to changing road conditions and vehicular movements, optimizing resource use and reducing communication delays. Ultimately, accurate CSI prediction in V2V communication fosters safer and more efficient roadways, contributing to the advancement of intelligent transportation systems and the realization of fully connected vehicular networks.

In the development of our resource allocation scheduler, we adopted an opportunistic scheduling (OS) approach as thoroughly explained in Chapter 20.3.2 on pages 509-510 of [19]. It is important to emphasize that our primary objective in this context is to demonstrate the application of predicted CSI within an existing scheduling framework. It's worth noting that while selecting alternative scheduling strategies might result in varying performance outcomes, such variations would not fundamentally alter the utilization of CSI predictions. This approach ensures that our focus remains on the efficacy of CSI forecasting in enhancing the scheduler's performance, irrespective of the specific scheduling algorithm employed. We employ the sum rate as a performance indicator:

$$C\left(\mathbf{H}\right) = BW \cdot \log_2(\det(\mathbf{I} + \frac{\rho}{n_T}\mathbf{H}\mathbf{H}^H))$$

We compared the results with two methods: OS scheduler and no scheduler with ground truth CSI and predicted ones.

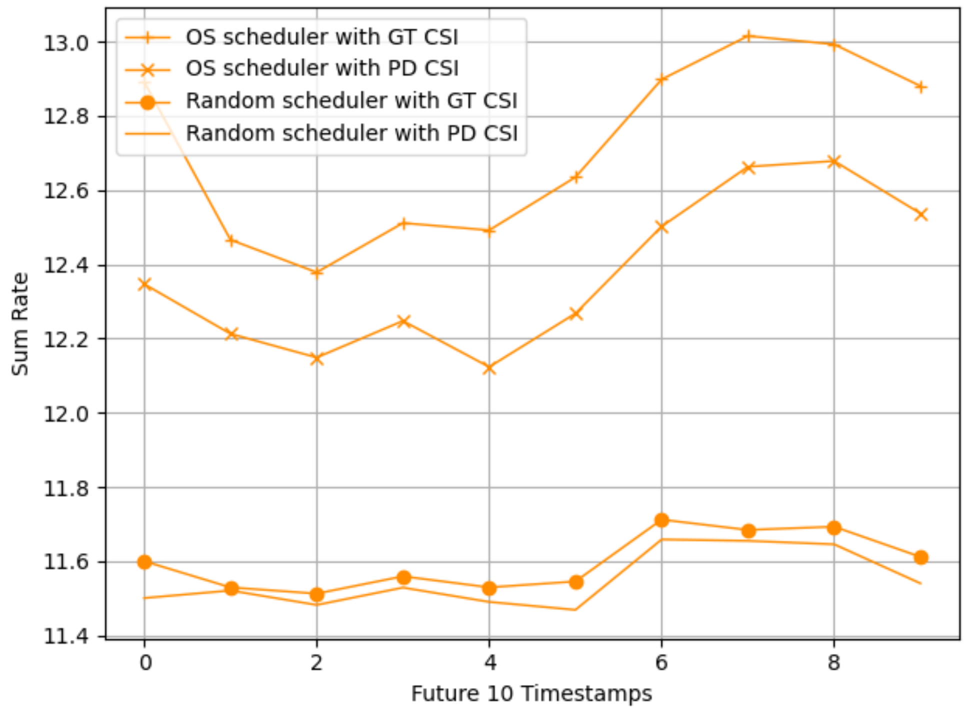


Figure 12. Application of Predicted CSI in two schedulers, showing achieved sum rate over time.

The case studies shown Figure12 provide a comparative analysis of various scheduling strategies, specifically focusing on how these strategies perform over time when using either ground truth (GT) or predicted CSI. The graph plots the performance of opportunistic and random scheduling strategies under the conditions of having either accurate, real-time CSI or predicted (PD) CSI. It is clear from the graph that the opportunistic scheduling strategy leveraging ground truth CSI significantly outperforms the other combinations across the time series. This underscores the effectiveness of opportunistic scheduling when it has access to precise, real-time channel data, achieving higher sum rates consistently.

Furthermore, the graph demonstrates that the accuracy of the CSI plays a crucial role in the efficiency of the scheduling strategies. While the opportunistic scheduling strategy with predicted CSI shows reduced performance compared to its ground truth counterpart, it still outperforms the random scheduling under similar conditions, highlighting the sensitivity of opportunistic scheduling to the quality of CSI. In contrast, the performance of the random scheduling strategy exhibits minimal variation, whether it uses ground truth or predicted CSI, suggesting that it is less dependent on precise channel information. This resilience to variations in CSI accuracy makes random scheduling a potentially reliable option in scenarios where precise channel information is not available, although it does not achieve as high a sum rate as the more sensitive opportunistic strategy. Overall, the graph not only illustrates the relative performances of these scheduling strategies over time but also reflects on the critical impact of channel state information accuracy on the system's overall throughput.

III.2 Project Conclusions

This project introduces significant innovation by basing machine learning (ML)-based vehicular channel extrapolation on actual measurements rather than simplified channel models used previously. These measurements involve multi-antenna (8x8 MIMO) channels, enabling the use of directional information and beamforming to improve SNR and reduce interference. To our knowledge, developing such V2V MIMO channel predictions with ML has not been addressed in the literature. To bridge these gaps, we develop new ML algorithms for channel extrapolation, transmission parameter adaptation, and scheduling. We focus on neural network design, training strategies, data augmentation, and evaluating whether separate or joint approaches for channel prediction and scheduling are superior. These novel ML designs and carefully planned time schedules are assessed using actual V2V measurements collected in various scenarios, such as car-to-car on campus and city streets.

The key outcome of this project is a methodology for optimizing resource assignment in V2V communications. The channel prediction component is independent of the system type, making it relevant regardless of whether the IEEE 802.11p/WAVE system or 5G NR is used. The resource allocation algorithms developed in the second part show differences in absolute performance depending on the system but still provide significant improvements over the state of the art, where suboptimal resource allocation causes inefficiencies and outages in V2V communications. These outcomes lead to the following advancements: 1) Improved traffic safety by reducing packet drops and insufficient coverage, ensuring vehicles receive safety-critical information or warnings in time to react. On-board sensors alone are insufficient to avoid all accidents, highlighting the importance of V2V communications. 2) Energy savings, as more reliable communications allow cars to drive closely in convoy formations, reducing energy consumption due to decreased wind drag and traffic jams by improving road throughput.

Acronyms

ADC	Analog to Digital Converter
AER	Accumulative Error Reduction
CNN	Convolutional Neural Network
CSI	Channel State Information
DC	Direct Current
DUC	Direct Upconversion
FLOPs	Floating Point Operations
GIE	Gradient Information Embedding
GRU	Gated Recurrent Unit
GT	Ground Truth
IF	intermediate frequency
LO	Local Oscillator
LSTM	Long Short Term Memory
MAE	Mean Absolute Error
MIMO	Multiple-Input – Multiple-Output
ML	Machine Learning
MLP	Multi-layer Perceptron
MSE	Mean Squared Error
NI	National Instruments
NR	New Radio
OFDM	Orthogonal Frequency Division Multiplexing
OS	opportunistic scheduling
PDP	power delay profile
RNN	Recurrent Neural Network
RPC	relative performance changes
Rx	Receiver
SE	Squeeze-and-Excitation
Tx	Transmitter
TB	TeraByte
UAV	Unmanned Arial Vehicle
USC	University of Southern California
USRP	Universal Software Radio Peripheral
V2V	vehicle-to-vehicle

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Data Management Plan

Products of Research

Describe the data that were collected and used for the study.

In our study, we utilized data that were collected (not part of the project) with the V2V channel sounder described in detail in reference [20]. The data collection process was conducted through a measurement campaign that included both an on-campus road at the University of Southern California (USC) and a road located off-campus; these locations are illustrated in Figure 1. To facilitate data analysis, we have developed and provided a comprehensive Matlab function. This function is designed not only to read the raw data collected but also to perform basic data preprocessing tasks. Among these tasks are normalization processes, which are essential for the subsequent case studies we conducted. This preprocessing step ensures that the data is standardized, making it suitable for comparative and analytical purposes in our later investigations.

Data Format and Content

Channel Matrix/ Hmatrix

i. The files existing in the server location is in an encoded format. After extraction, it is basically a 4-dimensional matrix as 61x8x8x30, in which, 61 represents frequency points, 8 represents the number of Rx antenna, next 8 represents the number of Tx antennas and 30 represents the number of snapshots in time.
ii. 30 is the total number of time snapshots we have, and a snapshot is basically, a sequence of training sequences, each of which is sent/received by a different antenna pair.
iii. Here, we refer 1 Burst = 30 snapshots for this project.
iv. 7700 is the total number of bursts recorded for the entire route. Therefore, we have Hmatrix_N.mat where N is the burst number.

Data Access and Sharing

Our V2V dataset will be publicly available on our research website. Interested parties can access the dataset through the following URL: https://wides.usc.edu/#matlabCode . In addition to providing the dataset, we will also offer detailed example functions that will guide users on how to load, utilize, and analyze the data effectively. Furthermore, we will include a benchmark channel prediction algorithm. This algorithm serves as a foundational tool for users to develop and test their own models and hypotheses using our dataset. This comprehensive provision aims to facilitate a deeper understanding and enhanced utilization of the data we have collected, supporting further research and development in the field of V2V communications.

Reuse and Redistribution

State the restrictions on how the data can be reused and redistributed by the general public.

Data can be downloaded and used by other researchers, on condition that they cite the source of the data as

"Propagation channel data copyright by Wireless Devices and Systems (WiDeS) group (A. F. Molisch, head) at the University of Southern California, and made available at wides.usc.edu/#matlabCode. Data were measured with the channel sounder described in \cite{wang2017real}.

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@inproceedings{wang2017real,
  title={A real-time MIMO channel sounder for vehicle-to-vehicle propagation
channel at 5.9 GHz},
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Seun and Virk, Usman T and Molisch, Andreas F},
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