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

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Project Objective

Driver-assistance systems are essential to reduce accidents and improve energy efficiency through efficient convoying. To improve their effectiveness, it is important that vehicles are able to communicate with each other, informing each other of their intentions, and warning each other of obstacles or cross traffic that only some of the vehicles might see. However, since such communication must be done wirelessly, reliability and latency of the communication might become an issue. The objective of this project is to improve these aspects of the communication, by means of improved radio channel prediction.

Problem Statement

A key challenge for wireless vehicle-to-vehicle (V2V) communication is that resource allocation for communication must rely on the current propagation channel state, but vehicles only have past measurements. Therefore, it is important to find effective methods for *predicting* how the channel will look like in the future (typically, up to 1 second from the current time). 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 goal is to find new ML-based prediction methods that alleviate these problems.

Research Methodology

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.

Results

The investigations of this project are all based on real-world measurements. This is important because while much of the work in this field is based on simplified simulations of the signal propagation from transmitter to receiver, the training of machine learning, as well as the assessment of the performance, is not realistic in this case. We used data obtained with a special equipment for channel measurements (channel sounder) that we created in our group. The measurements had been performed mostly in urban environments.

Our 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 network, SE-LSTM (which combines a Squeeze-and-Excitation (SE) module and an attention mechanism within a long-short-term memory architecture, managing dependencies within and between sequences). It is tailored to simultaneously model CSI (channel state information)) 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. The difference between conventional and meta learning is shown in Fig. 1 below.

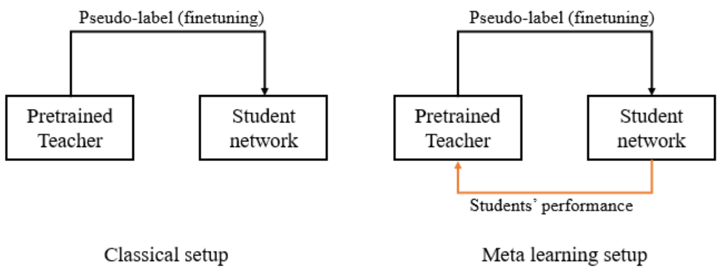

Figure 1 Principle of meta learning for network training

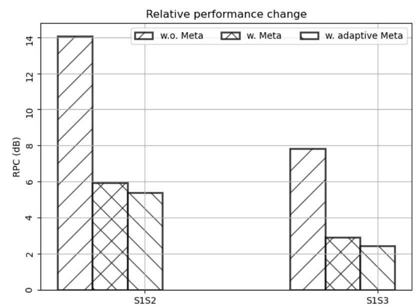

Figure 2 Prediction error over ten future timesteps for different prediction methods.

The new approach is capable of predicting the channels in future timesteps considerably more accurately than existing methods, as shown in Figure 2. The importance of this lies in the ability to make a communication system more robust and efficient by means of this prediction. In particular, resource allocation must always be done for *future* timesteps, i.e., we need to decide now what users get resources for data transmission several timesteps (typically tens of milliseconds) from now. Only by knowing what the channel will be at that time can we have efficient and reliable communication.

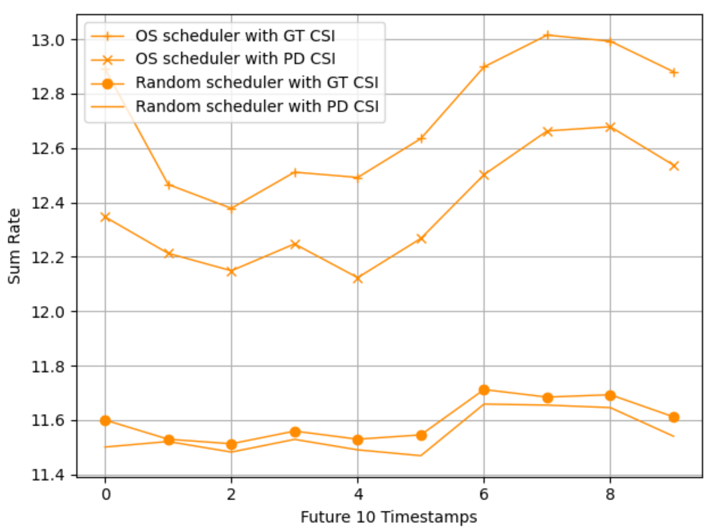

Figure 3 Data rate achieved with different prediction methods and schedulers (resource allocation methods).

The importance of this prediction can be seen in Figure 3. We are comparing here the achievable data rates with different schedulers (resource allocations) when either using the opportunistic (OS) scheduler, or a random scheduler. We are furthermore comparing the scheduling based on “ground truth” (GT), i.e., the true channel state information that we would get from a genie predicting the future accurately, versus the performance with our predictor. We see that the performance is very similar in all cases. This shows again the effectiveness and usefulness of the algorithms and methods for channel prediction we have developed in this project.