Channel Prediction in Vehicular Networks: A Gaussian Process Regression-Based Approach

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Abstract

Achieving reliable estimates of wireless channels is a key enabler for ultra-reliable low latency communications in 5G and beyond. Due to the highly dynamic nature of vehicular networks, getting prior knowledge about the wireless channels is challenging. In this paper, we propose a channel prediction model to obtain a real-time knowledge about the wireless channels in vehicular networks. Specifically, a Gaussian Process Regression (GPR) based framework is developed that can estimate the statistical channel gain of each V2V link in a distributed manner. Simulation results validate the performance of the proposed approach. In particular, the results show that the proposed GPR model is able to provide robust predictions under uncertainty and hence a reliable channel estimation can be achieved which enhances the transmission performance over the V2V links.

Keywords - Channel prediction, GPR, V2V communications, URLLC, 5G.

1. Introduction

Adapting wireless transmissions according to the received channel state information (CSI) is a key enabler to meet the Quality of Service (QoS) requirements in wireless networks. One way to estimate the CSI is by modeling the propagation in the wireless environment. This approach is efficient in particular environments with static wireless networks. However, the modeling approach is limited in the highly dynamic networks, where the wireless environment varies rapidly. Another direction to obtain the CSI is feedback measurements. The later may work efficiently in the conventional wireless networks where a moderated transmission latency is required. However, the acquisition of CSI at the transmitter side entails time overhead which may fail in the case of wireless networks with a critical low latency requirement [1–5].

The vehicle-to-vehicle (V2V) wireless environment is highly dynamic. Moreover, Ultra-reliable and Low Latency Communications (URLLC) is essential over V2V links [6–8]. Therefore, both the modeling and the feedback CSI measurements may fail to provide a reliable channel estimation in vehicular networks. To this end, this work aims at providing a real-time prediction-based channel estimation for V2V communication links.

Recently, some studies have tried to explore the V2V channels. The work in [9] leveraged the spectral-temporal average to handle the Doppler Effect at the V2V channel. The authors in [10] proposed a deep learning-based algorithm for CSI estimation in vehicular networks. The study conducted in [11] used the presented a deep learning algorithm for CSI estimation in orthogonal frequency-division multiplexing systems. The work in [12] studied the channel characteristics of vehicle-to-infrastructure in the urban environment at the 28 GHz wide-band. In [13], the authors proposed a channel prediction model based on the Long Short-Term Memory (LSTM) to provide long-term channel predictions in wireless body area networks.

Unlike the aforementioned works, we propose a Gaussian Process Regression (GPR) based framework to learn V2V channel statistics and predict the channel gain of each V2V links in a distributed manner. In particular, the GPR model can provide predictions under uncertainty and hence a reliable channel estimation can be achieved which enhances the transmission performance over the V2V links.

The rest of this paper is organized as follows: Section 2 introduces an overview of the GPR model. In Section 3, we present the proposed channel prediction algorithm for V2V communications. Section 4 discusses the performance of the proposed algorithm. Finally, we conclude the paper in Section 5.

2. Gaussian Process Regression

The Gaussian process is a class of Bayesian nonparametric machine learning models. Unlike other machine learning models, the Gaussian process optimizes the hyperparameters based on the Bayes theorems and thus it can greatly enhance the prediction accuracy. Moreover, the Gaussian process can also provide a measure of uncertainty over the predicted results leading to robust estimates of the wireless channel. In fact, the Gaussian process, which is a class of the kernel-based machine learning, is a collection of random variables that have Gaussian distributions [14–16]. Here, we focus on the Gaussian process that is completely defined by a kernel function and a mean function. We consider the following regression model:

$$y = f(x) + \varepsilon, \tag{1}$$

where $y \in \mathbb{R}$ is the prediction output which is a scalar value, ε is a Gaussian distribution random variable with σ_ε^2 variance and zero mean represents the independent noise, and

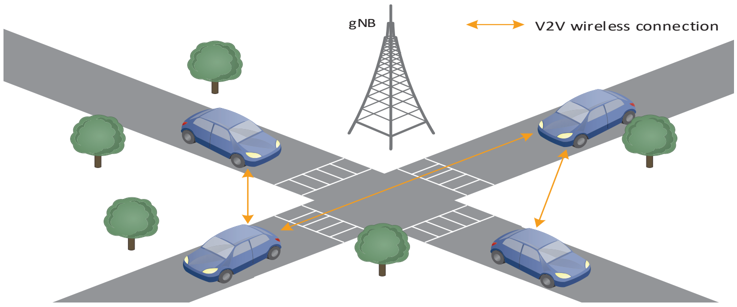

Figure 1: System model.

$f(x)$ is the regression function which can be modeled based on Gaussian process as

$$f(x) \sim \mathcal{GP}(\mu(x), g(x_i, x_j; \boldsymbol{\theta})), \quad (2)$$

where $\mu(x)$ is the mean function which is set to zero when there is no prior knowledge, and $g(x_i, x_j; \boldsymbol{\theta})$ is the kernel function where $\boldsymbol{\theta}$ represents the hyper-parameters that determine the kernel function.

For a given training dataset $\mathcal{D} \triangleq \{\boldsymbol{x}, \boldsymbol{y}\}$, where $\boldsymbol{x}$ and $\boldsymbol{y}$ are the training input and output data, respectively, our objective is predict $\boldsymbol{y}^*$ for a given test input $\boldsymbol{x}^*$ according to the predictor distribution $\mathrm{P}(\boldsymbol{y}^*|\mathcal{D}, \boldsymbol{x}^*; \boldsymbol{\theta})$. The kernel function is given by [17]

$$g(x_i, x_j; \boldsymbol{\theta}) = \exp(\frac{-1}{\theta_1} \sin^2(\frac{\pi}{\theta_2}(x_i - x_j))), \quad (3)$$

where θ_1 and θ_2 are are the length and period hyper-parameters, respectively.

3. GPR-based Channel Prediction Model for V2V Communications

We consider a wireless network, where a number of vehicles communicate with each other under the coverage of a Next Generation Node B (gNB) as shown in Fg. 1. Let $\mathcal{K}$ be the set of V2V communication links and let $h_k(t)$ be the channel gain of the k^{th} link at time slot t. Our aim is to perform an online prediction for the channel gain of the next time slot $\hat{h}_k(t+1)$ at each time slot t. To achieve that, we update the learning parameters over a moving window. Let N be the window size, i.e., the window composed of the last N time slots. The model parameters at each V2V link are trained on the data, i.e., channel gain, inside the window. Then, trained parameters are used to predict the channel gain of the next time slot.

In this view, for a finite data set $(t_n, h(t_n))$, $\forall n \in \mathcal{N}$, the prediction model can be written as

$$\hat{h}_k(t+1) = f(h_k(t)) + \varepsilon, \ \forall k \in \mathcal{K}, \quad (4)$$

and the kernel function $g(\cdot)$ is given by

$$g\big(h(t-m), h(t-n), \boldsymbol{\theta}\big) = \exp\left(\frac{-1}{\theta_1} \sin^2\left(\frac{\pi}{\theta_2}\big(h(t-m) - h(t-n)\big)\right)\right), \quad (5)$$

where $m, n \in \{0, 1, 2, \ldots, N\}$. Accordingly, the channel prediction at time slot $t+1$ is given as

$$\hat{h}_k(t+1) = g^{\dagger}(t)\boldsymbol{G}^{-1}[h_k(t-N), h_k(t-N+1, \ldots h_k(t))], \quad (6)$$

where $\boldsymbol{G} = [g(t-m, t-n)]$, and $g(t) = [g(t, t-n)]$, $\forall m, n \in \mathcal{N}$. Moreover, the variance (uncertainty) on the predicted value is given by

$$\mathsf{Var}\big(\hat{h}_k(t+1)\big) = g(t,t) - g^{\dagger}(t)\boldsymbol{G}^{-1}g(t). \quad (7)$$

The channel prediction is obtained from (6) and exploring highly uncertain channels provides more insight.

4. Performance Evaluation

In this section, we study the performance of the proposed model. Du to the unavailability of the real dataset, we test the proposed model on a synthetic dataset. We train the proposed GPR model on data consisted of $N = 1000$ samples, i.e., the window size is set to 1000. Moreover, we test the model over a 1000 time slot.

We evaluate the accuracy of the proposed prediction model in Fig. 2. In doing so, we first use 1000 data points (window size) as the training set and predict the next data points of the next window. The training data set is iteratively updated by adding one data point and removing the oldest one, and keep going. Then, we plot the real data and test predictions with the prediction confidence interval over time slots. We can visually notice that the proposed GPR model generates robust and accurate predictions. Moreover, the result shows that the real values fall into the predicted confidence interval.

5. Conclusion

In this work, we studied the wireless channels of the V2V communication links in vehicular networks. Due to the highly dynamic nature of V2V wireless channels, both the modeling and the feedback CSI measurements may fail to provide a reliable channel estimation. In this work, we proposed a real-time prediction-based channel estimation for V2V communication links. Specifically, we developed a GPR-based framework to learn V2V channel statistics and

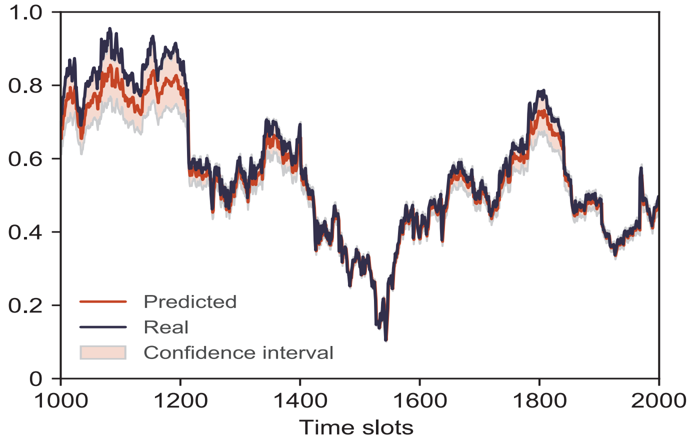

Figure 2: Predictions for the channel gain with confidence intervals.

predict the channel gain of each V2V links. Simulation results showed that the proposed GPR model can provide predictions under uncertainty and hence a reliable channel estimation can be achieved which enhances the transmission performance over the V2V links. As future work, we will design a resource management system for V2V communications that can leverage the proposed prediction model to allocate resources efficiently and satisfy the QoS requirements of each V2V link.

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