On CQI Estimation for Mobility and Correlation Properties of Gaussian Process Regression

Samira Homayouni, Stefan Schwarz†, Markus Rupp

Institute of Telecommunications, Technische Universität (TU) Wien
Gusshausstrasse 25/389, A-1040 Vienna, Austria
† Christian Doppler Laboratory for Dependable Wireless Connectivity for the Society in Motion
Email: {samira.homayouni,sschwarz,mrupp}@nt.tuwien.ac.at

***Abstract*—Channel quality prediction is an essential function for anticipatory and proactive radio resource allocation. In this paper, we propose a channel quality prediction method based on the concept of Gaussian Process Regression (GPR) in which the spatio-temporal correlation of the wireless channel is used for wireless channel prediction. The objective of the paper is to find the optimal channel quality prediction for non-static users. Furthermore, we propose our analytical optimization in the choice of users which enhances the spatio-temporal correlation of the wireless channel and results in performance improvements in terms of BLER and rate loss. Simulation results show the potential of our proposed method.**

***Index Terms*—5G, channel state information, mobility, optimization, Gaussian process regression.**

I. Introduction

Future wireless cellular networks are envisioned to support extremely high data rates for an increased number of users [1]. More connected devices require proportionally more signalling overhead. To overcome these challenges, overhead reduction methods have to be implemented both in time and space [2], [3], [4], [5]. The primary goal of our research work is to reduce uplink Channel Quality Indicator (CQI) feedback overhead, while guaranteeing the BLock Error Ratio (BLER) requirements of 10%. This is a typical operation value for mobile communication systems [6].

In [7], we proposed a CQI prediction scheme to estimate users' channel quality variation at the Base Station (BS) side. The proposed CQI estimation approach is based on the concept of Gaussian Process Regression (GPR) which has been shown to be efficient in the present of noisy observation [8], [9]. To reduce the signalling overhead we exploited the spatial correlation of the wireless propagation channel. We considered only static users. The proposed method selects a subset of users to provide feedback and predicts the CQI for the remaining users. However, if the user moves we can also exploit the temporal correlation of the channel in addition to the spatial correlation to improve the prediction quality, and we are able to reduce the feedback granularity in time. To reduce the granularity of the feedback in time, i.e., reporting feedback information less frequently, it is important to know in what range of distance from the initial user location, the properties of a spatial correlation can still provide an acceptable prediction quality. The larger the range is, the less frequent the CQI reporting becomes, thus the signalling overhead reduces even more. The spatio-temporal correlation between the channels of multiple users depends on the density, location and the velocity of the users and has a large influence on the performance. The selection of users that provide feedback to predict the performance based on our proposed Gaussian regression model, has to be such that it provides the highest spatio-temporal correlation.

The rest of the paper is organized as follows. In Section II, we position our work to the existing literature. Section III, introduces the considered system model. We present our analytical optimization in the choice of users which provide the highest spatio-temporal correlation and results in a significant performance improvement in terms of BLER and minimum sum rate-loss in Section IV. Results and comparative analysis are discussed in Section V. Finally, in Section VI, we conclude our work and identify directions for progressing further.

II. Related Works

In this section, we discuss some considerable related works that have been devoted by research community to either channel quality prediction or feedback overhead reduction. In [10], the authors present a channel feedback model with robust Signal-to-Interference-and-Noise Ratio (SINR) prediction and conclude that high gains can be expected at low user speed. In [11], the authors study several CQI predictors used to compensate the effect of CQI delay. The predictor takes into account the Doppler shift of each user to determine the time duration of the channel quality estimation; this procedure, although well established, might lead to erroneous predictions, a negative correlation is generally present between Doppler shift and prediction quality. Furthermore, a high speed user might witness a better, less variable channel than a low speed user.

In [12], the authors propose a Dynamic CQI Resource Allocation (DCRA) algorithm which selects a subset of users to send CQI among all the users to be scheduled in next frame. DCRA derives the optimal average feedback window values based on the user velocity and service class for a target packet error rate. In [13], the same authors extended their works by

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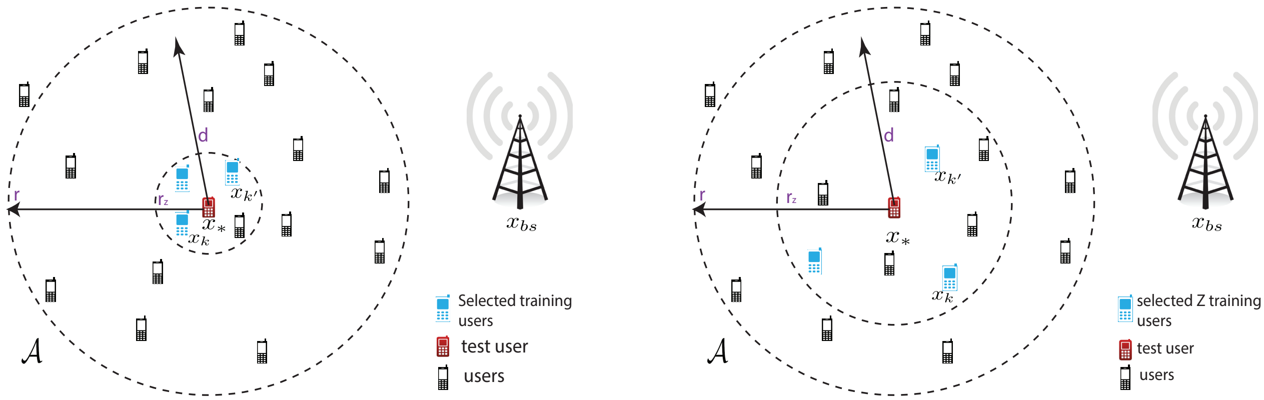

(a) small r_z (b) large r_z

Fig. 1: System model scenarios.

including CQI prediction at the BS and using a linear predictor and compensating errors by changing the prediction window based on the users' packet loss. They show that the proposed method improves the system performance especially for high mobility scenarios.

In [14], the authors present a non-predictive signalling reduction strategy where only users with the lowest average Signal-to-Noise Ratio (SNR) are allowed to feed back expensive instantaneous CQI information. The proposed strategy is more beneficial at low values of the user velocity. A time domain channel quality estimation based on the GPR method is presented in [15]. The authors present a GPR method to predict the CQI for various user mobility profiles, limiting the loss incurred by increasing the time sampling period. Their results show that the proposed channel prediction method is able to provide consistent gain, in terms of packet loss rate, for users with low and average mobility, while its efficacy is reduced for high-velocity users.

III. System Model

Consider a BS located at x_{bs} that transmits a signal with power P_{TX} to the receivers located at $x_k \in \mathcal{A} \subseteq \mathbb{R}^2$, where $\mathcal{A}$ denotes the region of interest (ROI). Figure 1 illustrates this scenario. The received power at receiver k can be expressed in dB scale as

$$P(x_k) = P_{TX} - 10\alpha\log_{10}(\|x_{bs} - x_k\|) + X_{x_k}, \qquad (1)$$

where α is the path-loss exponent and X_{x_k} is the location dependent shadow fading such that $X_{x_k} \sim \mathcal{N}(0, \sigma^2_{\mathcal{X}})$, where $\sigma_{\mathcal{X}}$ is the standard deviation in dB of the shadowing loss. Since the fading gain changes quickly within small distances, we assume that it does not impact the power at the receiver by averaging over the small-scale fading [16]. The noise corrupted observation of the received power at user k^{th} is $y(x_k) = P(x_k) + n_k$, where $n_k \sim \mathcal{N}(0, \sigma_n^2)$ is a zero mean additive white Gaussian noise with variance σ_n^2.

We assume that the users are locally distributed based on a Poisson point process with user density λ, such that $\Phi = \{x_k \in \mathcal{A}; k = 1, ..., K \in \mathbb{N}\}$ represents the location of the users. Hence, the probability of having K users in a circle of radius r is $\mathbb{P}(K, \mathcal{A}) = [\lambda L(\mathcal{A})]^k e^{-\lambda L(\mathcal{A})}/K!$, where $L(\mathcal{A}) = \pi r^2$ (cf. [17]).

Here, we design a sequential spatio-temporal GPR algorithm. Given the collection of corrupted observations from users up to time $t \in \mathbb{Z} \geq 0$, we want to predict the received power at an unobserved test location x_* and current (or future) time t_*. To do this, supposing that we have a collection of Z training observations $\mathcal{D} = \{x_k, y(x_k) \mid k = 1, ..., Z \subseteq K\}$ from K mobile users up to time t. Based on the spatio-temporal Gaussian process, the distribution of the observation given the set of hyperparameters $\theta = [P_{TX}, d_c, \alpha, \sigma^2_{\mathcal{X}}, \sigma_n^2]$ is Gaussian with mean $\mu(x_k) = P_{TX} - 10\alpha\log_{10}(\|x_{bs} - x_k\|)$, and a correlation function

$$C(x_k, x_{k'}) = \sigma^2_{\mathcal{X}} \exp\left(\frac{-\|x_k - x_{k'}\|}{d_c}\right), \qquad (2)$$

where d_c denotes the decorrelation distance of the shadowing [18]. The predicted mean received power at x_* at time t_* is then expressed as [19]

$$\check{P}(x_{*t_*}) = \mu(x_{*t_*}) + \mathbf{C}^T_{*,\mathbf{x}}(\mathbf{C}_{\mathbf{xx}} + \sigma_n^2\mathbf{I})^{-1}(\mathbf{y}_{1:t} - \mu(\mathbf{x}_{1:t})), \; (3)$$

where $[\mathbf{C}_{*,\mathbf{x}}]_k = C(x_*, x_k)$ is the $Z \times 1$ vector representation of the cross-correlation, and $[\mathbf{C}_{\mathbf{xx}}]_{kk'}$ is the $Z \times Z$ covariance matrix representation of $C(.,.)$ evaluated pairwise across the elements of x_k and $x_{k'}$. Accordingly, the predicted SNR at x_{*t_*} is determined by $\hat{\gamma}(x_{*t_*}) = \check{P}^{lin}(x_{*t_*})/W^{lin}$, where $\check{P}^{lin}(x_{*t_*})$ is the received power and W^{lin} is the receiver thermal noise both measured in a linear scale. The predicted SNR value is subsequently mapped to a quantized CQI value

$\{Q_j\}_{j=0}^{J}$. In our work, we assume $J = 15$ quantization level, however, it is generally applicable for any J. The MCS is assigned to each quantization level Q_j and a corresponding data rate of $R(Q_j)$, [20]. Equation (3) allows us to predict the CQI at future locations and time. It uses the data from the past time $1 : t$, to make a prediction at current (or future) time t_*.

IV. User Selection Method and Analytical Calculation of Minimum Sum Rate-Loss

As each user is usually requested to send CQIs to the serving BS, it causes a huge feedback overhead. With the constrained uplink signalling resource, we proposed a feedback reduction method which selects an appropriate number of users that provide feedback and predicts the CQIs for the remaining users, [7]. We described a baseline scenario in which the BS makes use of GPR to estimate the CQI at an arbitrary test user. The test user is surrounded by many other users, and hence, selecting the best among them is a crucial issue for an improved channel quality estimation, where the quality of the estimation stems from the correlation of shadow fading. We showed that for an acceptable channel estimation, it is sufficient to consider 15 users who are in the closest vicinity of the tested one. Additional users only provide redundant information in terms of estimating the CQI at the interested location, resulting in computational cost. Unfortunately, the desired performance does not seem to be easily obtained for mobile users. Mobility changes the mutual distances of the test user with the surrounded users and, consequently, it varies dynamically their correlation. In this section, we show conditions under which we can make an optimal prediction. An optimal prediction is possible when the spatio-temporal correlation between the selected training users and the predicted test locations is large. This conditions translate to find the most proper subset of training users.

The algorithm begins by selecting a subset $Z \subseteq K$ of users which lies inside a circle with a user-defined search radius $r_z \leq r$, representing the euclidean distance from the center, i.e., initial test location (see Figure 1). Since there are no directional influences, the test user moves uniformly in random directions within the circle starting from the center point, $[0, 0]$, to the distance d. The distance travelled by the user depends on the velocity. The Z users are static and randomly chosen inside the r_z. We fix r_z, and by using the information obtained from Z training users, we predict the CQI at the initial test location at time t_* based on Equation (3). Then, we predict the CQI for the next test location at time $t_* + 1$ using the information of fixed Z training users in addition to the previous estimated CQI. In other words, starting from the obtained estimation at the initial test location plus information of Z training users, we sequentially predict the CQIs for future locations and time.

In case that the radius r_z is small, Figure 1a, the selected training users are closer to the initial test user. This results in a better prediction at the initial location, because the training data are rather dense in the covariate space and the posterior mean is smooth. However, with the movement, as the locations of the test user get farther away from its initial location, correlation starts to fade, therefore, the farther predicted CQIs will have a lower accuracy of estimation compared to the CQIs close to the initial location. This is due to the fact that measurements are taken from nearby locations have strong correlation and the correlation decays as the distance increases.

In case that the radius r_z is large, Figure 1b, the selected training users are more sparse and are in farther distances from the initial test user. Compared with small r_z, it results in poor estimation at the initial test location and better at remote distances. As the space dimensions increase, this large low-density region causes smoother estimation in all different locations of the path to be estimated. Because there are also some users available in farther distances from the initial

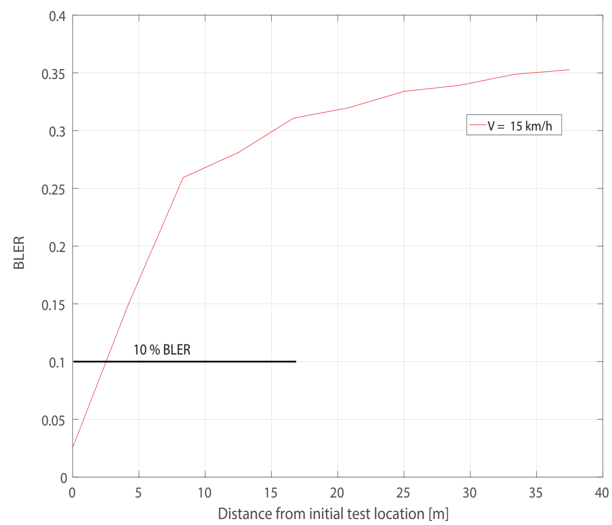

Fig. 2: BLER performance versus distance.

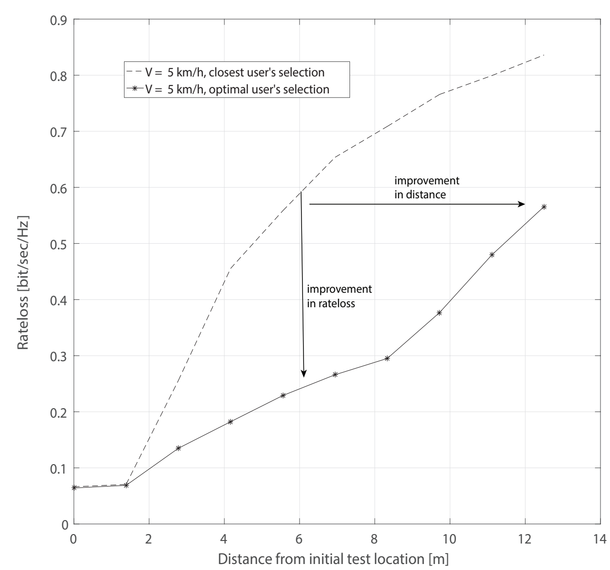

Fig. 3: Rate loss versus distance.

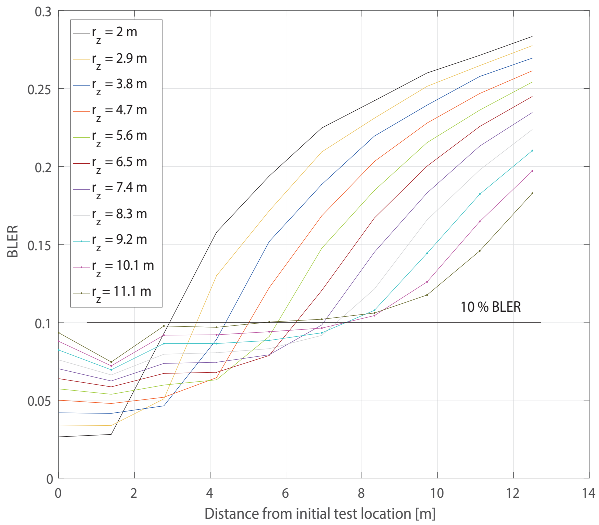

Fig. 4: BLER versus distance d from the initial test location.

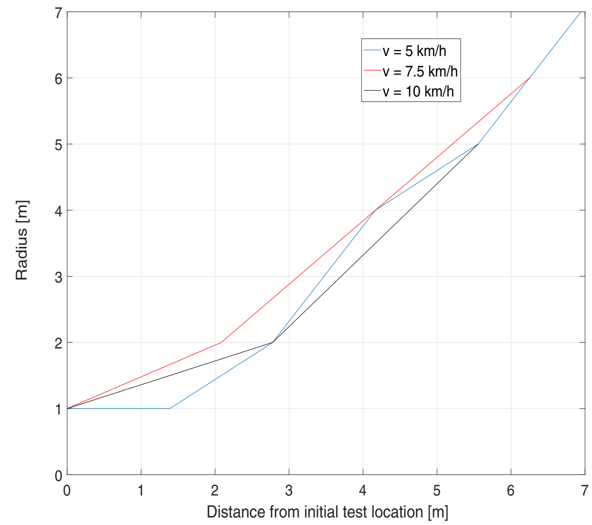

Fig. 5: Radius r_z versus distance d from the initial test location.

TABLE I: Simulation Parameters

Parameter	Value	Parameter	Value
α	2	x_{bs}	$[200 \;\; 0]$ m
d_c	40 m	σ_n^2	0.01
$\sigma_{\mathcal{X}}^2$	10 dB	r	100 m
λ	1	T	1 sec
W	-57 dB	P_{TX}	0 dB

test location results in increasing estimation accuracy of the locations lying in far distances from the initial location.

Therefore, an appropriate r_z remains as a key challenge in this study. It changes the density of the training users, and consequently, the spatio-temporal correlation of the whole estimated path. Therefore, we search for a radius that minimizes the sum rate-loss for a test user moving a distance d from its initial location. Where, the rate loss is defined by the difference between the actual and predicted rate. We presented the caluclation of the rate loss in [20]. To do so, considering 10% BLER, the minimum sum rate-loss is expressed as:

$$\begin{aligned} \underset{r_z}{\text{minimize}} \quad & \overline{\Delta R}_{tot}(r_z) \\ \text{subject to} \quad & BLER(r_z, x) < 0.1, \forall x \in (0, d). \end{aligned}$$

$$\overline{\Delta R}_{tot}(r_z) = \int_0^d \overline{\Delta R}(r_z, d)dx \tag{4}$$

V. Simulation Results

Our simulation and analytical calculation are carried out by parameters listed in Table I. We averaged the results over 10^6 random realizations of user positions. In order to make the proposed framework applicable, it is assumed that the small scale fading has been averaged out.

The effect of our proposed GPR method for CQI prediction is presented in Figure 2. The figure shows the BLER versus distance d from the initial test location. The users are distributed with $\lambda = 1$. For an arbitrary test user that is located at the origin of $\mathcal{A}$, at time t_0, the BS uses the information of only 25 closest users to predict the CQI value for the test user. We assume that the test user moves straight in a random direction with a constant velocity $v = 15$ km/h. We choose that for the next test user location, the CQI is predicted every $T = 1$ sec. For a constant T, the speed is directly proportional to the distance. It is clear that when the user operates in high velocity, the prediction degrades over time, since the user moves further within the given interval. For a high mobility user, the BS has to choose a smaller prediction window size T. From the figure, we observe that after 3m distance the BLER exceeds the target value of 10%.

In Section IV, we described how to select a set of users not to be the closest users to the tested one, so that it enables us to predict the CQI for further distances from the initial location which results in a further overhead reduction in time. Figure 4, shows the BLER versus distance d for $Z = 15$ users. In order to observe the effect of r_z, we performed simulations by varying r_z from 2m to 11m. From the figure, at small distances d close to zero the predictor performs better for the smaller r_z because the training selected users are closer to the initial test locations. However, by moving further away from the initial location the performance gets rapidly worse. This is due to the availability of no training users in far distances. Furthermore, in the further distances of $d = 7$ m the predictor behaves better for larger r_z. The reason is that the users are spread more dispersive and in estimation in far distances the availability of the training users are more probable. Therefore, in far distances the estimator performs better with the cost of poor accuracy in low distances.

Figure 3 shows the rate loss as a function of distance d. The results show the performance improvement for an example scenario of $v = 5$ km/h with optimal user's selection compared to the closest user's selection. The relation between radius r_z and spatial distance d is plotted in Figure 5. It is approximately linear. The figure depicts only for the values that satisfies the BLER target 10%. It shows up to 7m distance, meaning that increasing the radius does not improve the performance thereafter. Because as it is also shown in Figure 4, for instances, for a radius of $r_z = 11$m, the density of the users are not sufficient resulting in bias CQI estimation.

VI. Conclusion

The main contributions of our paper lies in two folds. On one hand, we extended our work on the analysis of the channel prediction and overhead reduction to non-static users. Due to the Gaussian nature of the SNR distribution and the inherent flexibility of Gaussian Processes for regression models, these have been selected in our work. Therefore, we proposed a channel quality estimation method based on the concept of Gaussian process regression to predict users channel states for mobile users. We selected a subset of users to send CQI among all the users, while keeping the system throughput maximum. To achieve this goal, on the other hand, we proposed an analytical optimization method that minimises a user's rate loss. The proposed method selects a subset of training users that provides the highest spatio-temporal correlation of the wireless channel, depending on the distance of the test user from its initial location. By optimization, we show that anticipatory and proactive allocation is practicable which offers to compare our novel method with the classical instantaneous pilot-based channel estimation.

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