Thesis for the Degree of Licentiate of Engineering

# Wireless Channel Prediction with Location Uncertainty

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To *my family*.

"All truths are easy to understand once they are discovered; the point is to discover them."

-Galileo Galilei

# Abstract

Spatial wireless channel prediction is important for future wireless networks, and in particular for anticipatory networks to perform proactive resource allocation at different layers of the protocol stack. In this thesis, we study location-aware channel prediction with uncertainty in location information and understand its utilization to enhance the communication capabilities in wireless networks.

Paper A discusses challenges of 5G networks, which include an increase in traffic and number of devices, robustness for mission-critical services, and a reduction in total energy consumption and latency. We then argue how location information can be leveraged in addressing several of the key challenges in 5G with location-aware channel prediction by maintaining a channel database. We use Gaussian processes (GP) from machine learning in developing a framework for location-aware channel prediction. We then give a broad overview of using location-aware channel prediction in addressing the aforementioned challenges across different layers of the protocol stack.

In Paper B, we investigate two frameworks, classical Gaussian processes (cGP) and uncertain Gaussian processes (uGP), and analyze the impact of location uncertainty during both training and testing. We have demonstrated that, when heterogeneous location uncertainties are present, the cGP framework is unable to (i) learn the underlying channel parameters properly; (ii) predict the expected channel quality metric. By introducing a GP that operates directly on the location distribution, we find uGP, which is able to both learn and predict in the presence of location uncertainties.

Paper C studies the tradeoffs in utilizing location information in the robust link scheduling problem (RLSP) at the medium access control layer. We compare two approaches to RLSP, one using channel gain estimates and the other using location information. Our comparison reveals that both approaches yield similar performances, but with different overhead.

**Keywords:** Gaussian processes, location-aware channel prediction, location uncertainty.

# Publications

The thesis is based on the following appended papers:

[A] R. Di Taranto, L. S. Muppirisetty, R. Raulefs, D. Slock, T. Svensson, and H. Wymeersch, "Location-aware communications for 5G networks", in *IEEE Signal Processing Magazine*, vol. 31, no. 6, pp. 102-112, Nov. 2014.

[B] L. S. Muppirisetty, H. Wymeersch, and T. Svensson, "Location-aware channel prediction", in preparation.

[C] L. S. Muppirisetty, R. Di Taranto, and H. Wymeersch, "Robust link scheduling with channel estimation and location information", in *Proceedings of Forty Seventh Asilomar Conference on Signals, Systems and Computers*, pp. 1695-1699, Nov. 2013.

Other contributions by the author (not included in this thesis):

[D] G. E. Garcia, L. S. Muppirisetty, E. M. Schiller, and H. Wymeersch, "On the trade-off between accuracy and delay in cooperative UWB localization: performance bounds and scaling laws", in *IEEE Transactions on Wireless Communications*, vol. 13, no. 8, pp. 4574-4585, Aug. 2014.

[E] G. E. Garcia, L. S. Muppirisetty, and H. Wymeersch, "On trade-off between accuracy and delay in cooperative UWB navigation", in *Proceedings of IEEE Wireless Communications and Networking Conference*, pp. 1603-1608, Apr. 2013.

[F] C. Lindberg, L. S. Muppirisetty, K. Dahlen, V. Savic, and H. Wymeersch, "MAC delay in belief consensus for distributed tracking", in *Proceedings of 10th Workshop on Positioning, Navigation and Communication*, pp. 1-6, Mar. 2013.

[G] G. E. Garcia, L. S. Muppirisetty, and H. Wymeersch, "On the trade-off between accuracy and delay in UWB navigation", in *IEEE Communications Letters*, vol. 17, no. 1, pp. 39-42, Jan. 2013.

# Contents

# II Included papers 25

# Acknowledgments

“No matter what accomplishments you make, somebody helped you.”

-Althea Gibson

First and foremost, I would like to express my deepest gratitude to my main supervisor, Associate Prof. Henk Wymeersch for giving me this opportunity of pursuing PhD studies in the Communication Systems (ComSys) group. Thank you very much for your guidance, encouragement, and for giving me the freedom to explore and work on new and interesting problems. I am always impressed with your turn around times: for reviewing and giving feeding back; response to emails no matter where you are (airport, conference, even in a different time zone). I owe a big thank you, for providing an extra support during the difficult times, which gave me a lot of strength and also made me to believe that I am not alone. I am really very proud to be a part of the group.

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Many thanks to Gabriel for the collaboration, which helped me a lot to understand about positioning. It was pleasure working with you. Thanks to Christopher for being the best office mate possible. I would also like to thank COOPNET team members: Gabriel, Christopher, Erik, Markus, Robert, and Jie for many interesting discussions and for the constructive feedback on the articles.

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*L. Srikar Muppirisetty*
*Gothenburg, November, 2014.*

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# Part I

# Overview

# Chapter 1

# Introduction

## 1.1 Motivation

Location awareness has received intense interest from the research community, in particular with respect to cognitive radio [1], where radio environment map (REM) enabled databases are being used to exploit TV white spaces [2]. REM provides various network and user related context information such as geo-location data, propagation models, interference maps, spectral usage regulations, user and service policies [3]. REM has been applied to various problems such as interference management in two-tier cellular networks [3], coverage hole detection and prediction [4], and compensating time-varying Doppler spread for railways [5]. However, recent studies have revealed that location information (part of context information) can be harnessed not only cognitive networks, but also cellular and ad-hoc networks [6]. In particular, location-aware resource allocation techniques can reduce overheads and delays due to their ability to predict channel quality beyond traditional time scales. In [7] it was demonstrated that a communication system can benefit from location information if it can exploit not only short term channel coherence, but also mid-term/long-term coherence of the users' location and movement: this is achieved by the mobile devices reporting back their current location and their navigation routes and destinations to base stations. The concept of location-aware communication is shown in Fig. 1.1, where a user provides its up-to-date location information to the base station, which, based on a spatial channel model, can allocate resources among users.

Future networks are expected to deal with an exponentially increasing number of devices. This puts great stress on resource allocation methods, both in terms of scalability and signaling overhead. Location-information can be the key to address this challenge, and complement existing methods at time and space scales that are currently not considered. We envision that context information in general, and location information in particular can be utilized by these networks across all layers of the communication protocol stack, since location and communication are tightly coupled (see Fig. 1.2). This vision is based on two assumptions: (i) the availability

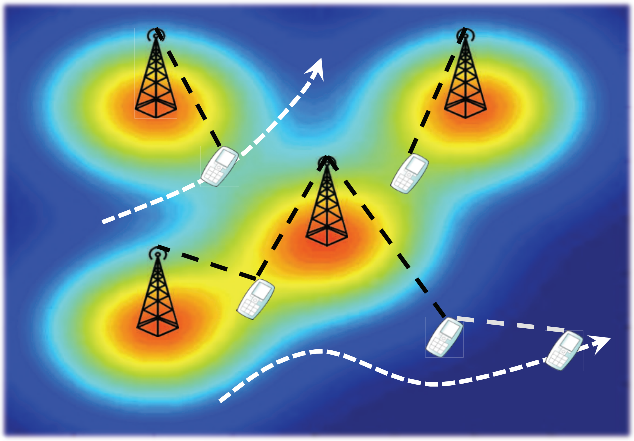

**Figure 1.1:** Location-aware communication: the main idea. The user has an expected navigation path. The background shows the long term channel quality, including base-station-specific path-loss, and a common spatial field for shadowing. The base stations can adjust their transmission strategy (at different levels of the protocol stack) if accurate and up-to-date location information is available.

of accurate location information; (ii) the possibility for the network operator to collect and store geo-tagged channel quality information. The first assumption is met by the introduction of sophisticated network localization methods (see [8] and references therein) and new localization technologies (such as Galileo [9]), which enable sufficient resolution to capture path-loss and shadowing. The second assumption is based on minimization of drive test (MDT) feature in 3GPPP Release 10 [10]. In MDT, users collect radio measurements and associated location information in order to assess network performance. The geo-tagged channel quality metrics (CQM) (received signal strength, RMS delay spread, interference levels etc.) from users enable the construction of a dynamic database, and this allows the prediction of CQM at arbitrary locations and future times. In order to predict the CQM in locations where no previous CQM was available, a flexible location-aware predictive engine is needed. The location-aware CQM predictions can be utilized in several aspects such as in handling proactive caching strategies [11] and in anticipatory networks for predictive resource allocation [12].

## 1.2 Scope and Aim of the Thesis

The thesis aims in bridging the gap between the interaction of the research topics (positioning and communication), and understand how and to what extent location information with uncertainty may aid communication capabilities across the different layers of the protocol stack in cooperative networks. In particular, we analyze statistical channel models, which tie locations to channels and how

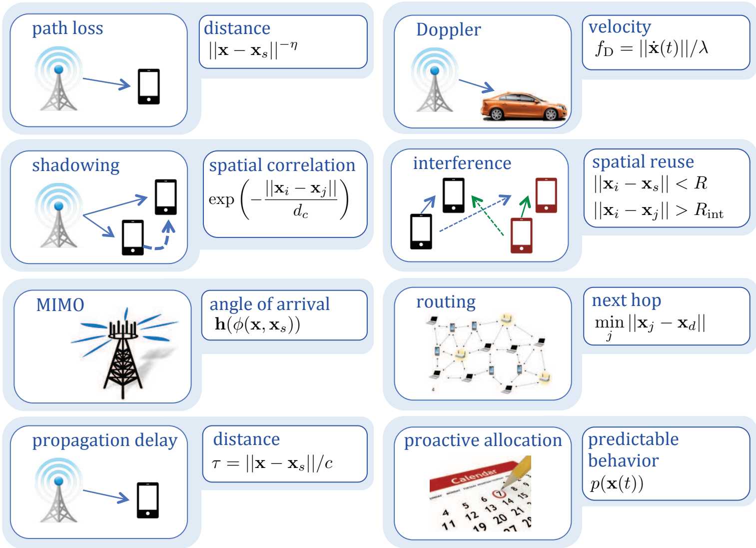


**Figure 1.2:** Communication systems are tied to location information in many ways, including through distances, delays, velocities, angles, and predictable user behavior. The notations are as follows (starting from the top left downward): $\mathbf{x}$ is the user location, $\mathbf{x}_s$ is the base station or sender location, $\eta$ is the path loss exponent; $\mathbf{x}_i$ and $\mathbf{x}_j$ are two user locations, $d_c$ is a correlation distance; $\phi(.)$ is an angle of arrival between a user and a base station, $\mathbf{h}$ is a MIMO channel, which includes path-loss, shadowing, and small-scale fading; $c$ is the speed of light, $\tau$ is the propagation delay; $f_{\mathrm{D}}$ is a Doppler shift, $\dot{\mathbf{x}}(t)$ is the user velocity, $\lambda$ is the carrier wavelength; $R$ is a communication range, $R_{\mathrm{int}}$ is an interference range; $\mathbf{x}_d$ is a destination; $p(\mathbf{x}(t))$ is a distribution of a user location at a future time $t$.

to deal with uncertainties in location and channel measurements. Furthermore, we develop a framework for spatial prediction of wireless channels with uncertain location information.

## 1.3 Organization of the Thesis

In Sweden, the Licentiate degree is a pre-doctoral degree which is considered to be equivalent to half way towards a doctoral degree. There are two choices to write the thesis: one is monograph and the other is collection of papers. This thesis is written as collection of papers and is divided in to two parts. Part I gives an introduction and motivation to the topic and necessary background material to understand the appended papers in part II of the thesis. Part I is structured as follows: we start Chapter 2 with basics on wireless channel model and show its dependency on location. Later, in Chapter 3, we introduce a spatial regression tool, referred to as Gaussian processes from machine learning, and show its use in predicting channel based on location information. In Chapter 4, we show the exploitation of location information across the different layers of the protocol stack in particular using such spatial regression. Finally, the contributions of this thesis are summarized in Chapter 5.

# Chapter 2

# Basics of Wireless Channels

## 2.1 Introduction

In this chapter, we review the basics of wireless propagation channels. The characteristics of wireless radio channels have been studied quite extensively in the literature [13]. The wireless propagation channel is traditionally modeled as a stochastic process with three major dynamics which occur at different length scales namely path-loss, shadowing, and small scale fading. On a larger length scale, path-loss captures power attenuation of the radio signal with distance, which decays linearly with the logarithm of the distance from the transmitter. Shadowing captures the medium length scale power variations of the signal around the path-loss, which occur due to obstacles in the propagation environment such as hills, buildings, trees, etc. Path-loss and shadowing vary over longer distances and are hence called large scale fading. Finally, small scale fading captures power fluctuations on a shorter length scale due to multi-path propagation effects of the signal in the environment.

## 2.2 Statistical Model

Consider a geographical region $\mathcal{A} \subset \mathbb{R}^2$, where a transmitter is located at $\mathbf{x} \in \mathbb{R}^2$ and transmits a signal with power $P_{\mathrm{TX}}$ to a receiver located at $\mathbf{x}_i \in \mathbb{R}^2$ through a wireless propagation channel. The received power $P_{\mathrm{RX}}(\mathbf{x}_i, t)$ at receiver $i$ can be expressed as

$$P_{\mathrm{RX}}(\mathbf{x}_i, t) = P_{\mathrm{TX}}\, g_0\, ||\mathbf{x} - \mathbf{x}_i||^{-\eta}\, \psi(\mathbf{x}_i, t)\, |h(\mathbf{x}_i, t)|^2, \tag{2.1}$$

where $g_0$ is a constant that captures antenna and other propagation gains, $\eta$ is the path-loss exponent, $\psi(\mathbf{x}_i, t)$ is the location-dependent shadowing and $h(\mathbf{x}_i, t)$ is the component from small scale fading.

In this thesis, we assume measurements are averaged over small-scale fading, either in time (measurements taken over a time window) or frequency (measurements represent average power over a large frequency band). Therefore, the resulting received signal power from the transmitter to receiver $i$ can be expressed

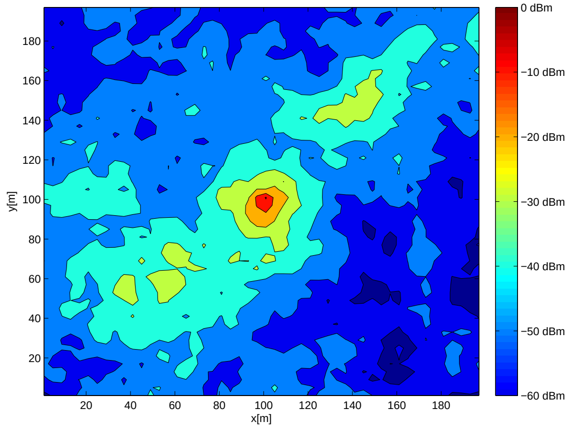


**Figure 2.1:** A typical 2D channel realization with base station (BS) placed at the center.

in dB scale as

$$P_{\mathrm{RX}}(\mathbf{x}_i)[\mathrm{dBm}] = L_0 - 10\,\eta\,\log_{10}(||\mathbf{x} - \mathbf{x}_i||) + \Psi(\mathbf{x}_i), \tag{2.2}$$

where $L_0 = P_{\mathrm{TX}}[\mathrm{dBm}] + G_0$ with $G_0 = 10\,\log_{10}(g_0)$ and $\Psi(\mathbf{x}_i) = 10\,\log_{10}(\psi(\mathbf{x}_i))$. The log-normal distribution is a common choice for modeling shadowing in wireless systems in which it is assumed that the received power in dB is distributed as Gaussian. Thus shadowing in log domain follows a zero mean Gaussian distribution with variance $\sigma_\Psi^2$ i.e., $\Psi(\mathbf{x}_i) \sim \mathcal{N}(0, \sigma_\Psi^2)$ .

Spatial correlations of shadowing are studied extensively and well-established models exist in the literature [14]. The Gudmundson model [15] is a widely used shadowing correlation model. According to the model, the spatial auto covariance function of the shadowing between receivers at locations $\mathbf{x}_i$ and $\mathbf{x}_j$ follows an exponential decay function as

$$C(\mathbf{x}_i, \mathbf{x}_j) = \mathbb{E}[\Psi(\mathbf{x}_i), \Psi(\mathbf{x}_j)|\mathbf{x}_i, \mathbf{x}_j] = \sigma_\Psi^2 \exp\left(-\frac{||\mathbf{x}_i - \mathbf{x}_j||}{d_c}\right), \tag{2.3}$$

where $d_c$ is the correlation distance.

A typical 2D radio environment map is depicted in Fig. 2.1. It can be observed that received powers are spatially correlated. Thus, it is possible to predict the slow component (path-loss and shadowing) of the wireless channel with location. In Chapter 3, we show how this can be achieved using a spatial regression framework provided perfect location information is available.

## 2.3 Challenges

Localization is subject to errors as the algorithms need to cope with harsh propagation conditions, delays, receiver dynamics and is also highly dependent on the environment. The accuracies of various common localization technologies are as follows: the global positioning system (GPS) is the most widely used localization technology in outdoor scenarios, whose accuracy is around few meters [16]; ultra-wide bandwidth (UWB) systems provide sub-meter accuracy and are mainly used in indoor scenarios [17]; WiFi-based positioning gives accuracy on the order of few meters [17]. Undoubtedly, there is a need for a framework to mathematically characterize and understand the spatial predictability of wireless channels with location uncertainty.

# Chapter 3

# Gaussian Processes

In this chapter, we introduce Gaussian processes (GP), a tool for spatial regression from the machine learning field. Spatial regression tools generally comprise a training/learning phase (in which the underlying parameters are estimated based on the available training database) and a testing/prediction phase (in which predictions are made at the test inputs using learned parameters and training database). Among these tools, GP is a powerful and commonly used regression framework, since it is generally considered to be flexible and provides prediction uncertainty information [18]. First, we give a brief treatment on how to make predictions using GP, later we connect it to the location-aware channel prediction for the slowly varying (combined path-loss and shadowing) component of the wireless channel.

## 3.1 Gaussian Processes Basics

**Definition 1** *A Gaussian process is a collection of random variables, any finite number of which have a joint Gaussian distribution [18].*

Let $f(\mathbf{x})$ be a stochastic process, for $\mathbf{x} \in \mathbb{R}^D$ with mean function $\mu(\mathbf{x}) = \mathbb{E}[f(\mathbf{x})]$ and covariance function $C(\mathbf{x}_i, \mathbf{x}_j) = \mathbb{E}[(f(\mathbf{x}_i) - \mu(\mathbf{x}_i))\,(f(\mathbf{x}_j) - \mu(\mathbf{x}_j))]$. We write a GP $f(\mathbf{x})$ as

$$f(\mathbf{x}) \sim \mathcal{GP}(\mu(\mathbf{x}), C(\mathbf{x}_i, \mathbf{x}_j)). \tag{3.1}$$

There are many choices for covariance function of which squared exponential is the most widely used in machine learning, and is written as [18]

$$C(\mathbf{x}_i, \mathbf{x}_j) = \sigma_f^2 \exp\left(-\frac{\|\mathbf{x}_i - \mathbf{x}_j\|^2}{2\,l^2}\right), \tag{3.2}$$

where $l$ is the correlation length and $\sigma_f^2$ is the variance of the process.

Let $y_i$ be the noisy observation of $f(\mathbf{x}_i)$, which is written as $y_i = f(\mathbf{x}_i) + n_i$, where $n_i$ is a zero mean additive white Gaussian noise with variance $\sigma_n^2$. We introduce $\mathbf{X} = [\mathbf{x}_1^{\mathrm{T}}, \mathbf{x}_2^{\mathrm{T}}, \ldots, \mathbf{x}_N^{\mathrm{T}}]^{\mathrm{T}}$ as the collection of $N$ measurement inputs and

$\mathbf{y} = [y_1, y_2, \ldots, y_N]^{\mathrm{T}}$ be the vector of noisy observations at those inputs. The resulting training database is thus $\{\mathbf{X}, \mathbf{y}\}$. Due to the GP model, the joint distribution of the $N$ training observations exhibits a Gaussian distribution [18]

$$p(\mathbf{y}|\mathbf{X}, \Theta) = \mathcal{N}(\boldsymbol{\mu}(\mathbf{X}), \mathbf{K}), \tag{3.3}$$

where $\boldsymbol{\mu}(\mathbf{X}) = [\mu(\mathbf{x}_1), \mu(\mathbf{x}_2), \ldots, \mu(\mathbf{x}_N)]^T$ is the mean vector and $\mathbf{K}$ is the covariance matrix given as

$$\mathbf{K} = \begin{bmatrix} C(\mathbf{x}_1, \mathbf{x}_1) + \sigma_n^2 & C(\mathbf{x}_1, \mathbf{x}_2) & \cdots & C(\mathbf{x}_1, \mathbf{x}_N) \\ C(\mathbf{x}_2, \mathbf{x}_1) & C(\mathbf{x}_2, \mathbf{x}_2) + \sigma_n^2 & \cdots & C(\mathbf{x}_2, \mathbf{x}_N) \\ \vdots & \vdots & \ddots & \vdots \\ C(\mathbf{x}_N, \mathbf{x}_1) & C(\mathbf{x}_N, \mathbf{x}_2) & \cdots & C(\mathbf{x}_N, \mathbf{x}_N) + \sigma_n^2 \end{bmatrix} \tag{3.4}$$

with entries $[\mathbf{K}]_{ij} = C(\mathbf{x}_i, \mathbf{x}_j) + \sigma_n^2\, \delta_{ij}$, where $\delta_{ij} = 1$ for $i = j$ and zero otherwise, and $\Theta = [\sigma_n, \sigma_f, l]$ denote the model parameters.

### 3.1.1 Learning

The objective during learning is to infer the model parameters $\Theta$ from observations at known inputs. The model parameters can be learned through maximum likelihood estimation, given the training database, by minimizing the negative log-likelihood function with respect to $\Theta$:

$$\begin{aligned} \hat{\Theta} &= \arg\min_{\Theta} \{-\log(p(\mathbf{y}|\mathbf{X}, \Theta)\} \qquad (3.5) \\ &= \arg\min_{\Theta} \Big\{ \frac{N}{2} \log(2\pi) + \frac{1}{2} \log|\mathbf{K}| + \frac{1}{2} (\mathbf{y} - \boldsymbol{\mu}(\mathbf{X}))^T \,\mathbf{K}^{-1}\, (\mathbf{y} - \boldsymbol{\mu}(\mathbf{X})) \Big\} \end{aligned}$$

The negative log-likelihood function is usually not convex and can contain multiple local minima that might not explain the measurements properly. Once $\Theta$ is estimated from $\{\mathbf{X}, \mathbf{y}\}$, the training process is complete.

### 3.1.2 Prediction

Once $\hat{\Theta}$ is obtained, we can determine the predictive distribution of $f(\mathbf{x}_*)$ at new and arbitrary test input $\mathbf{x}_*$, given the training database $\{\mathbf{X}, \mathbf{y}\}$. We first form the joint distribution as [18]

$$\begin{bmatrix} \mathbf{y} \\ f(\mathbf{x}_*) \end{bmatrix} \sim \mathcal{N}\left( \begin{bmatrix} \boldsymbol{\mu}(\mathbf{X}) \\ \mu(\mathbf{x}_*) \end{bmatrix}, \begin{bmatrix} \mathbf{K} & \mathbf{k}_* \\ \mathbf{k}_*^{\mathrm{T}} & k_{**} \end{bmatrix} \right), \tag{3.6}$$

where $\mathbf{k}_*$ is the $N \times 1$ vector of cross-covariance $C(\mathbf{x}_*, \mathbf{x}_i)$ between $\mathbf{x}_*$ and the training inputs $\mathbf{x}_i$, and $k_{**}$ is the prior variance, given by $k_{**} = C(\mathbf{x}_*, \mathbf{x}_*) = \sigma_f^2$.

Conditioning on the observations $\mathbf{y}$, we obtain the Gaussian posterior predictive distribution $p(f(\mathbf{x}_*)|\mathbf{X}, \mathbf{y}, \hat{\Theta}, \mathbf{x}_*)$ for the test input $\mathbf{x}_*$. The mean $(\bar{f}(\mathbf{x}_*))$ and variance ($\tilde{f}(\mathbf{x}_*)$) of this distribution turn out to be [18]

$$\begin{aligned}\bar{f}(\mathbf{x}_*) =& \mu(\mathbf{x}_*) + \mathbf{k}_*^{\mathrm{T}}\,\mathbf{K}^{-1}\,(\mathbf{y} - \boldsymbol{\mu}(\mathbf{X})) \qquad (3.7)\\ =& \mu(\mathbf{x}_*) + \sum_{i,j=1}^{N} [\mathbf{K}^{-1}]_{ij}\,(y_j - \mu(\mathbf{x}_j))\,C(\mathbf{x}_*, \mathbf{x}_i)\\ =& \mu(\mathbf{x}_*) + \sum_{i=1}^{N} \beta_i\, C(\mathbf{x}_*, \mathbf{x}_i).\\ \tilde{f}(\mathbf{x}_*) =& k_{**} - \mathbf{k}_*^{\mathrm{T}}\,\mathbf{K}^{-1}\,\mathbf{k}_* \qquad (3.8)\\ =& k_{**} - \sum_{i,j=1}^{N} [\mathbf{K}^{-1}]_{ij}\, C(\mathbf{x}_*, \mathbf{x}_i)\, C(\mathbf{x}_*, \mathbf{x}_j),\end{aligned}$$

where $\beta_i = \sum_{j=1}^{N} [\mathbf{K}^{-1}]_{ij}\,(y_j - \mu(\mathbf{x}_j))$.

Fig. 3.1 demonstrates an example of regression using a GP. Observe the decrease in predictive variance for test inputs which are closer to the training inputs.

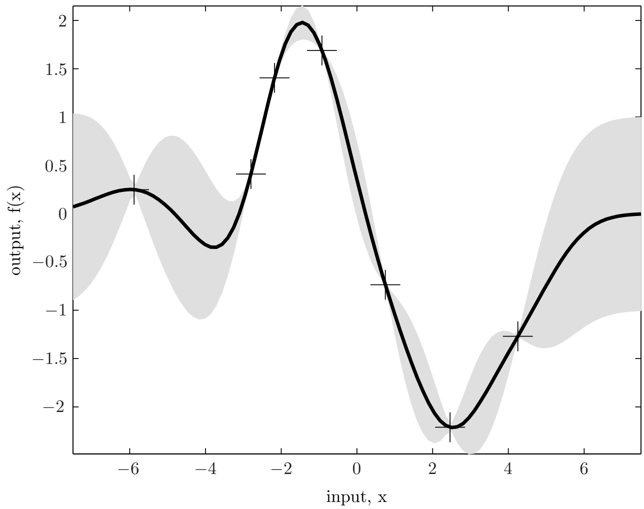


**Figure 3.1:** Example of a GP regression: marked in (+) are 7 training inputs, solid line depicts the predictive mean and shaded area represents the point wise predictive mean plus and minus the predictive standard deviation for each input value.

## 3.2 Location-aware Channel Prediction Using GP

As slowly varying component of the wireless channel is spatially correlated over tens of meters, spatial regression tools such as GP can be utilized for its prediction. The following steps show the use of GP as a tool for location-aware channel prediction. Let $\bar{P}_{\mathrm{RX}}(\mathbf{x}_*)$ denotes the mean and $\tilde{P}_{\mathrm{RX}}(\mathbf{x}_*)$ denotes the variance of the channel prediction at a location $\mathbf{x}_*$.

1. Model $P_{\mathrm{RX}}(\mathbf{x}_i)$ as $P_{\mathrm{RX}}(\mathbf{x}_i) \sim \mathcal{GP}(\mu(\mathbf{x}_i), C(\mathbf{x}_i, \mathbf{x}_j))$ GP with input $\mathbf{x}_i$:
   (a) $\mu(\mathbf{x}_i) = L_0 - 10\,\eta\,\log_{10}(||\mathbf{x} - \mathbf{x}_i||)$
   (b) $C(\mathbf{x}_i, \mathbf{x}_j) = \mathbb{E}[\Psi(\mathbf{x}_i), \Psi(\mathbf{x}_j)|\mathbf{x}_i, \mathbf{x}_j] = \sigma_\Psi^2 \exp\left(-\frac{||\mathbf{x}_i - \mathbf{x}_j||}{d_c}\right)$
2. Data collection:
   (a) $y_i = P_{\mathrm{RX}}(\mathbf{x}_i) + n_i,\ n_i \sim \mathcal{N}(0, \sigma_n^2)$
   (b) $\mathbf{y} = [y_1, y_2, \ldots, y_N]^{\mathrm{T}}$ and $\mathbf{X} = [\mathbf{x}_1^{\mathrm{T}}, \mathbf{x}_2^{\mathrm{T}}, \ldots, \mathbf{x}_N^{\mathrm{T}}]^{\mathrm{T}}$
3. Training:
   (a) Learn the channel parameters $\Theta = [\sigma_n, d_c, L_0, \eta, \sigma_\Psi]$ for $\{\mathbf{X}, \mathbf{y}\}$
4. Prediction at new location $\mathbf{x}_*$:
   (a) $\bar{P}_{\mathrm{RX}}(\mathbf{x}_*) = \mu(\mathbf{x}_*) + \mathbf{k}_*^{\mathrm{T}}\,\mathbf{K}^{-1}\,(\mathbf{y} - \boldsymbol{\mu}(\mathbf{X}))$
   (b) $\tilde{P}_{\mathrm{RX}}(\mathbf{x}_*) = k_{**} - \mathbf{k}_*^{\mathrm{T}}\,\mathbf{K}^{-1}\,\mathbf{k}_*$

Fig. 3.2 demonstrates an example of radio channel prediction using a GP. A base station is placed in the center and a 2D radio propagation field is simulated with sampling points on a square grid of 200 m × 200 m and a resolution of 4 m. Based on measurements at marked locations, the mean and standard deviation of the prediction are obtained for any location. Observe the increased uncertainty in Fig. 3.2 (c) in regions where few measurements are available.

It is clear that while GP are flexible, they are faced with challenges. The two main limitations of GP are its computational complexity [19–22] and dealing with uncertain inputs [23, 24].

- Complexity: The prediction step of GP requires inversion of the $N \times N$ covariance matrix $\mathbf{K}$, whose complexity scale as $\mathcal{O}(N^3)$. To alleviate the computational complexity, various sparse GP techniques have been proposed in [19–21] while in [22] the connection between GP and Kalman filtering is studied.
- Uncertainty in inputs: The impact of input uncertainty was studied in [23, 24], which showed that GP was adversely affected, both in training and testing. The input uncertainty to GP in our case translates to location uncertainty.

This thesis demonstrates that not considering location uncertainty in GP leads to poor learning of the channel parameters and poor prediction of channel gain values at other locations. We then discuss how to integrate this location uncertainty in to the GP channel prediction framework.

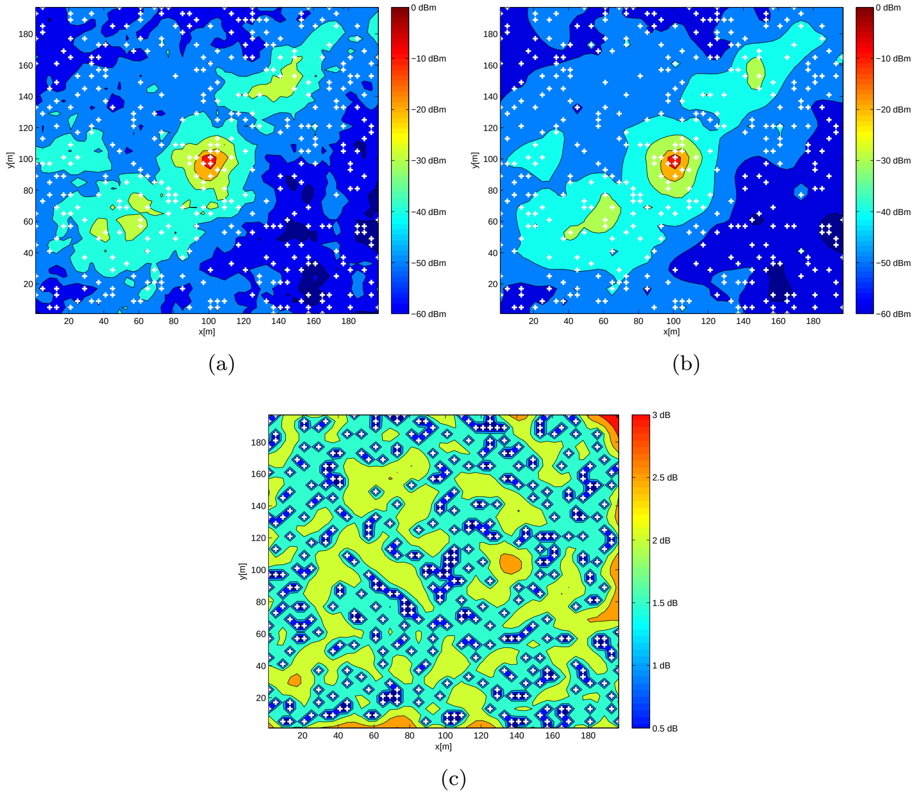


**Figure 3.2:** Radio channel prediction in dB scale, with hyperparameters $\Theta = [\sigma_n = 0.1, d_c = 70\text{ m}, L_0 = 10\text{ dB}, \eta = 3, \sigma_\Psi = 9\text{ dB}]$, $N = 400$ measurements (+ signs). The channel prediction is performed at a resolution of 4 m. Inset (a) shows the true channel field, (b) the mean of the predicted channel field $\bar{P}_{\mathrm{RX}}(\mathbf{x}_*)$, and (c) the standard deviation (obtained from the square root of $(\tilde{P}_{\mathrm{RX}}(\mathbf{x}_*))$ of the predicted channel field.

# Chapter 4

# Location-aware Communication

In this chapter, we give a brief overview of possible usages of location information in modern wireless networks, and provide insights on how this may aid communication capabilities at various layers of the protocol stack.

## 4.1 Introduction

Resource allocation in wireless networks happens at extreme time scales (see Fig. 4.1). On the one hand, there is the fast time scale of power and rate adaptation, occurring at the millisecond level. This type of resource allocation requires a great deal of signaling overhead, and tends not to scale well in dense ad-hoc settings. On the other hand, there is network deployment and network planning at the month or year level, relying on time-consuming computer simulations or drive tests by network operators. In between these extreme time scales, there is room for resource allocation based on predictions of user behavior, channel statistics, and interference levels, at a time scale varying from seconds to hours and even days. One way to achieve this is through location-awareness as we discussed in Chapter 1. In the following, we present specific examples of location information that are useful at each layer of the protocol stack.

## 4.2 Physical Layer

In the lowest layer of the protocol stack, location information can be harnessed to reduce interference and signaling overhead, to avoid penalties due to feedback delays. The best known application is spatial spectrum sensing for cognitive radio [25], where a GP allows the estimation of power emitted from primary users at any location through collaboration among secondary users. The GP database also

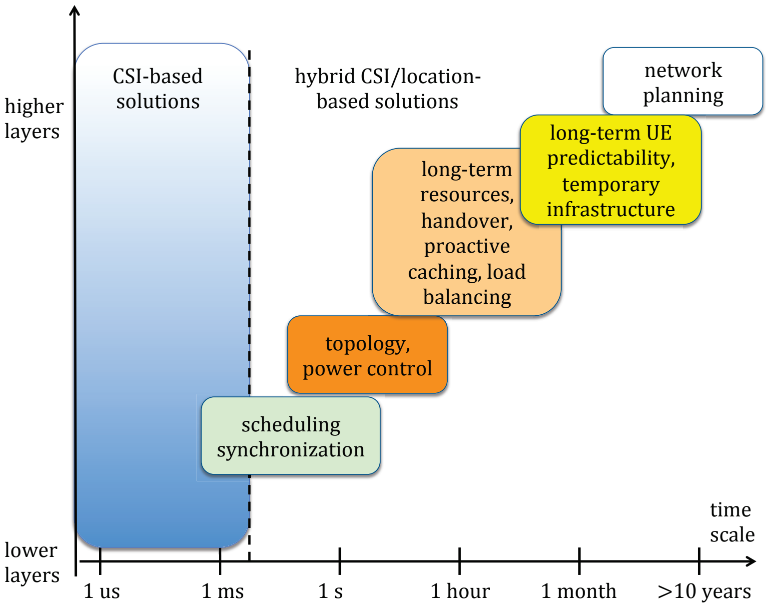


**Figure 4.1:** At very short time scales, resource allocation (especially in the lower layers) must rely on instantaneous channel state information (CSI). At longer time scales, location information can be harnessed to complement CSI. UE stands for user equipment.

provides useful information in any application that relies on a priori channel information, such as slow adaptive modulation and coding or channel estimation [7]. It is demonstrated that location-aware adaptive systems achieve large capacity gains compared to state-of-the-art adaptive modulation schemes for medium to large feedback delays. Locations can also be utilized in a different manner, by converting them not to channel gains, but to other physical quantities, such as Doppler shifts (proportional to the user's relative velocity), arrival angles (used in [26] for location-based spatial division multiple access), or timing delays (which are related to the distance between transmitter and receiver). As the above works indicate, location information provides valuable side-information about the physical layer.

## 4.3 Medium Access Control Layer

In the medium access control (MAC) layer, location information can be used to define interference regions around devices. As an example, knowing that transmission from certain devices will not interfere due to their physical separation (e.g., distance among them) provides an input to scheduling of resources (time slots and frequencies). In [27], location-based multicasting is considered, assuming a disk model, and is shown to both reduce the number of contention phases and increase the reliability of packet delivery, especially in dense networks. In [28], a decentralized location-based channel access protocol for inter-vehicle communication is studied. Using a pre-stored cell-to-channel mapping, vehicles know when to transmit on which channel, alleviating the need for a centralized coordinator for channel allocation. Location information is also beneficial in reducing the overhead associated with node selection mechanisms (e.g., users, relays), by allowing base stations to make decisions based solely on the users' positions [6]. Finally, location information is a crucial ingredient in predicting interference levels in small/macro cell coexistence, in multi-cell scenarios, and in all cognitive radio primary/secondary systems [6, 29].

## 4.4 Network and Transport Layer

At the network and transport layers, location information has been shown to improve scalability and to reduce overhead and latency. A full-fledged location-based network architecture is proposed in [1] for cognitive wireless networks, dealing with dynamic spectrum management, network planning and expansion, and in handover. In particular a location-aided handover mechanism significantly reduces the number of handovers compared with signal strength-based methods [30]. Most other works at the network layer have focused on the routing problem. A well-known technique in this area is geographic routing (geo-routing) [31], which takes advantage of geographic information of nodes to move data packets to gradually approach and eventually reach their intended destination. Recently, it has gained considerable attention, as it promises a scalable and efficient solution for information delivery in emerging wireless ad-hoc networks.

## 4.5 Higher Layers

At the higher layers, location information will naturally be critical to provide navigation and location-based services. First of all, we have classical context awareness, which finds natural applications in location-aware information delivery [32] (e.g., location-aware advertising) and multimedia streaming [33]. For the latter application, [33] tackles the problem of guaranteeing continuous streaming of multimedia services while minimizing the overhead involved, by capturing correlated mobility patterns, predicting future network planning events. A second class of applications is in the context of intelligent transportation systems [34]. Finally, location information also has implications in the context of security and privacy [35].

In this thesis, we present how location information can improve scalability, latency, and robustness across different layers of protocol stack for 5G networks. Location awareness bears great promise to the 5G revolution, provided we can understand the right tradeoffs for each of the possible use cases.

# Chapter 5

# Contributions

## Paper A

5G networks will be the first generation to benefit from location information that is sufficiently precise to be leveraged in wireless network design and optimization. We argue that location information can aid in addressing several of the key challenges in 5G, complementary to existing and planned technological developments. These challenges include an increase in traffic and number of devices, robustness for mission-critical services, and a reduction in total energy consumption and latency. This paper gives a broad overview of the growing research area of location-aware communications across different layers of the protocol stack. We highlight several promising trends, tradeoffs, and pitfalls.

## Paper B

Spatial wireless channel prediction is important for future wireless networks, and in particular for proactive resource allocation at different layers of the protocol stack. Various sources of uncertainty must be accounted for during modeling and to provide robust predictions. We investigate two frameworks, classical Gaussian processes (cGP) and uncertain Gaussian processes (uGP), and analyze the impact of location uncertainty during both training and testing. We observe that cGP generally fails to learn the channel parameters and to predict the channel in new locations with location uncertainties. In contrast, uGP considers the location uncertainty and is able to learn and predict the wireless channel.

## Paper C

In this paper, we analyze the tradeoffs in utilizing location information at the MAC layer. We study the robust link scheduling problem (RLSP) based on a physical interference model with errors in channel state information. The objective of

RLSP is to find a robust minimum length schedule using spatial time division multiple access. We compare two approaches to RLSP, one using channel gain estimates and the other using location information. Our comparison reveals that both approaches yield similar performances, but with different overhead.

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# Part II

# Included papers