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FOUNDATIONS IN SIGNAL PROCESSING, COMMUNICATIONS AND NETWORKING

VOLUME 2

Robust Signal Processing for Wireless Communications

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Springer

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With 88 Figures and 5 Tables

Springer

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ISBN 978-3-540-74246-3 e-ISBN 978-3-540-74249-4

DOI 10.1007/978-3-540-74249-4

Springer Series in
Foundations in Signal Processing, Communications and Networking ISSN 1863-8538

Library of Congress Control Number: 2007937523

Cover design: eStudioCalamar S.L., F. Steinen-Broo, Girona, Spain

Printed on acid-free paper

9 8 7 6 5 4 3 2 1

springer.com

Foundations in Signal Processing, Communications and Networking

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ISBN 978-3-540-68478-7

Vol. 2. Dietrich, F. A.
Robust Signal Processing for Wireless Communications, 2008
ISBN 978-3-540-74246-3

To my family

Preface

Optimization of adaptive signal processing algorithms is based on a mathematical description of the signals and the underlying system. In practice, the structure and parameters of this model are not known perfectly. For example, this is due to a simplified model of reduced complexity (at the price of its accuracy) or significant estimation errors in the model parameters. The design of *robust signal processing algorithms* takes into account the parameter errors and model uncertainties. Therefore, its robust optimization has to be based on an explicit description of the uncertainties and the errors in the system's model and parameters.

It is shown in this book how *robust optimization* techniques and estimation theory can be applied to optimize robust signal processing algorithms for representative applications in wireless communications. It includes a review of the relevant *mathematical foundations* and literature. The presentation is based on the principles of estimation, optimization, and information theory: Bayesian estimation, Maximum Likelihood estimation, minimax optimization, and Shannon's information rate/capacity. Thus, where relevant, it includes the modern view of signal processing for communications, which relates algorithm design to performance criteria from information theory.

Applications in three key areas of signal processing for wireless communications at the *physical layer* are presented: Channel estimation and prediction, identification of correlations in a wireless fading channel, and linear and nonlinear precoding with incomplete channel state information for the broadcast channel with multiple antennas (multi-user downlink).

This book is written for research and development engineers in industry as well as PhD students and researchers in academia who are involved in the design of signal processing for wireless communications. Chapters 2 and 3, which are concerned with estimation and prediction of system parameters, are of general interest beyond communication. The reader is assumed to have knowledge in linear algebra, basic probability theory, and a familiarity with the fundamentals of wireless communications. The relevant notation is defined in Section 1.3. All chapters except for Chapter 5 can be read independently from each other since they include the necessary signal models. Chapter 5 additionally requires the signal model from Sections 4.1 and 4.2 and some of the ideas presented in Section 4.3.

Finally, the author would like to emphasize that the successful realization of this book project was enabled by many people and a very creative and excellent environment.

First of all, I deeply thank Prof. Dr.-Ing. Wolfgang Utschick for being my academic teacher and a good friend: His steady support, numerous intensive discussions, his encouragement, as well as his dedication to foster fundamental research on signal processing methodology have enabled and guided the research leading to this book.

I am indebted to Prof. Dr. Björn Ottersten from Royal Institute of Technology, Stockholm, for reviewing the manuscript and for his feedback. Moreover, I thank Prof. Dr. Ralf Kötter, Technische Universität München, for his support.

I would like to express my gratitude to Prof. Dr. techn. Josef A. Nossek for his guidance in the first phase of this work and for his continuous support. I thank my colleague Dr.-Ing. Michael Joham who has always been open to share his ideas and insights and has spent time listening; his fundamental contributions in the area of precoding have had a significant impact on the second part of this book.

The results presented in this book were also stimulated by the excellent working environment and good atmosphere at the Associate Institute for Signal Processing and the Institute for Signal Processing and Network Theory, Technische Universität München: I thank all colleagues for the open exchange of ideas, their support, and friendship. Thanks also to my students for their inspiring questions and their commitment.

Munich, August 2007 *Frank A. Dietrich*

Contents

Chapter 1
Introduction

Wireless communication systems are designed to provide high data rates reliably for a wide range of velocities of the mobile terminals. One important design approach to increase the spectral efficiency[1] envisions multiple transmit or receive antennas, i.e., Multiple-Input Multiple-Output (MIMO) systems, to increase the spectral efficiency.

This results in a larger number of channel parameters which have to be estimated accurately to achieve the envisioned performance. For increasing velocities, i.e., time-variance of the parameters, the estimation error increases and enhanced adaptive digital signal processing is required to realize the system. Improved concepts for *estimation* and *prediction* of the channel parameters together with *robust* design methods for *signal processing* at the physical layer can contribute to achieve these goals efficiently. They can already be crucial for small velocities.

Before giving an overview of the systematic approaches to this problem in three areas of physical layer signal processing which are presented in this book, we define the underlying notion of robustness.

1.1 Robust Signal Processing under Model Uncertainties

The design of adaptive signal processing relies on a model of the underlying physical or technical system. The choice of a suitable model follows the traditional principle: It should be as accurate as necessary and as simple as possible. But, typically, the complexity of signal processing algorithms increases with the model complexity. And on the other hand the performance degrades in case of model-inaccuracies.

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[1] It is defined as the data rate normalized by the utilized frequency band.

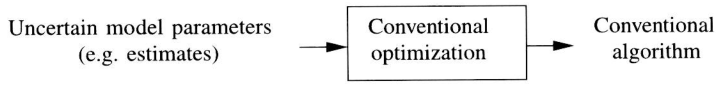


Fig. 1.1 Conventional approach to deal with model uncertainties: Treat the estimated parameters and the model as if they were true and perfectly known. The parameters for the signal processing algorithm are optimized under these idealized conditions.

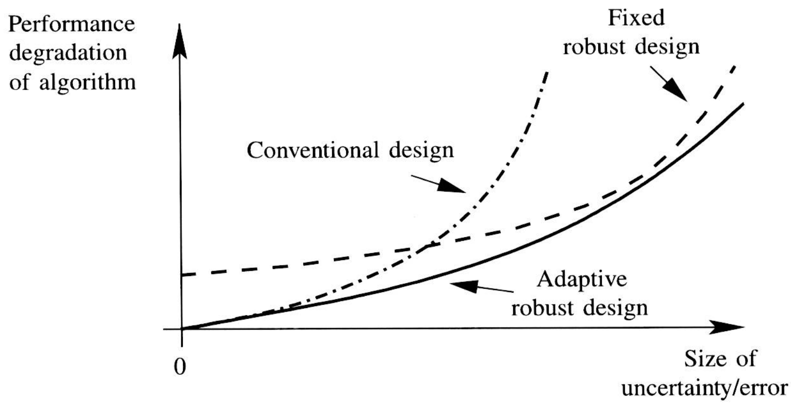


Fig. 1.2 Sensitivity of different design paradigms to the size of the model uncertainty or the parameter error.

For example, the following practical constraints lead to an imperfect characterization of the real system:

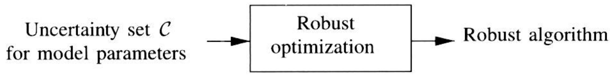
- To obtain an acceptable complexity of the model, some properties are not modeled explicitly.
- The model parameters, which may be time-variant, have to be estimated. Thus, they are not known perfectly.

Often a pragmatic design approach is pursued (Figure 1.1) which is characterized by two design steps:

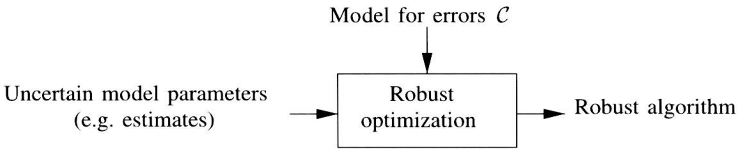
- An algorithm is designed assuming the model is correct and its parameters are known perfectly.
- The model uncertainties are ignored and the estimated parameters are applied as if they were error-free.

It yields satisfactory results as long as the model errors are "small".

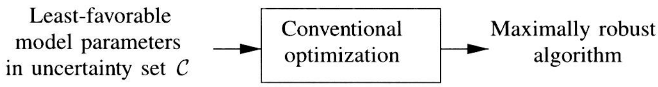
A *robust algorithm design* aims at minimizing the performance degradation due to model errors or uncertainties. Certainly, the first step towards a robust performance is an accurate parameter estimation which exploits all available information about the system. But in a second step, we would like to find algorithms which are robust, i.e., less sensitive, to the remaining model uncertainties.



(a) General approach to robust optimization based on a set $\mathcal{C}$ describing the model/parameter uncertainties.



(b) Robust optimization based on estimated model parameters and a stochastic or deterministic description $\mathcal{C}$ of their errors.



(c) Optimization for the least-favorable choice of parameters from an uncertainty set $\mathcal{C}$ for the considered optimality criterion of the algorithm: This parameterization of the standard algorithm (as in Figure 1.1) yields the maximally robust algorithm for important applications.

Fig. 1.3 General approach to robust optimization of signal processing algorithms under model uncertainties and two important special cases.

Sometimes suboptimum algorithms turn out to be less sensitive although they do not model the uncertainties explicitly: They give a *fixed robust design* which cannot adapt to the size of uncertainties (Figure 1.2).

An *adaptive robust design* of signal processing yields the optimum performance for a perfect model match (no model uncertainties) and an improved or in some sense optimum performance for increasing errors (Figure 1.2). Conceptually, this can be achieved by

- defining a mathematical model of the considered uncertainties and
- constructing an optimization problem which includes these uncertainties.

Practically, this corresponds to an enhanced interface between system identification and signal processing (Figure 1.3(a)). Now, both tasks are not optimized independently from each other but *jointly*.

In this book, we focus on three important types of uncertainties in the context of wireless communications:

1. Parameter errors with a stochastic error model,
2. parameter errors with a deterministic error model, and
3. unmodeled stochastic correlations of the model parameters.

The two underlying design paradigms are depicted in Figures 1.3(b) and 1.3(c), which are a special case of the general approach in Figure 1.3(a):

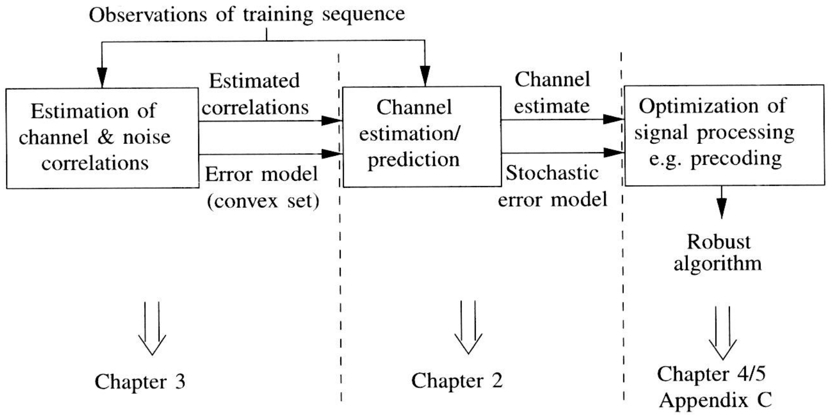


Fig. 1.4 Robust optimization of signal processing in the physical layer of a wireless communication system: Interfaces between signal processing tasks are extended by a suitable model for the parameter errors or uncertainties.

The first clearly shows the enhanced interface compared to Figure 1.1 and is suitable for treating parameter errors (Figure 1.3(b)). The second version guarantees a worst-case performance for the uncertainty set $\mathcal{C}$ employing a maxmin or minimax criterion: In a first step, it chooses the least-favorable model or parameters in $\mathcal{C}$ w.r.t. the conventional optimization criterion of the considered signal processing task. Thus, optimization of the algorithm is identical to Figure 1.1, but based on the worst-case model. In important practical cases, this is identical to the problem of designing a maximally robust algorithm (see Section 2.4).

Finally, we would like to emphasize that the systematic approach to robust design has a long history and many applications: Since the early 1960s, robust optimization has been treated systematically in mathematics, engineering, and other sciences. Important references are [97, 226, 122, 61, 16, 17, 171] which give a broader overview of the subject than this brief introduction. Other relevant classes of uncertainties and their applications are treated there.

1.2 Overview of Chapters and Selected Wireless Applications

The design of adaptive signal processing at the physical layer of a wireless communication system relies on *channel state information*. Employing the traditional stochastic model for the wireless fading channel, the channel state consists of the parameters of the channel parameters' probability distribution and their current or future realization. We treat three related fundamental signal processing tasks in the physical layer as shown in Figure 1.4:

- Estimation and prediction of the channel parameters (Chapter 2),
- estimation of the channel parameters' and noise correlations (Chapter 3), and
- linear and nonlinear precoding with partial channel state information for the broadcast channel (Chapters 4 and 5).[2]

We propose methods for a robust design of every task. Moreover, every chapter or main section starts with a survey of the underlying theory and literature with the intention to provide the necessary background.

- *Chapter 2: Channel Estimation and Prediction*
  The traditional approaches to *estimation* of the frequency-selective wireless channel using training sequences are introduced and compared regarding the achieved bias-variance trade-off (Section 2.2). This includes more recent techniques such as the reduced-rank Maximum Likelihood estimator and the matched filter.
  Prediction of the wireless channel gains in importance with the application of precoding techniques at the transmitter relying on channel state information. In Section 2.3, we focus on minimum mean square error (MMSE) prediction and discuss its performance for *band-limited* random sequences, which model the limited temporal dynamics of the wireless channel due to a maximum velocity in a communication system.
  Channel estimation as well as prediction relies on the knowledge of the channel parameters' probability distribution. It is either unknown, is only specified partially (e.g., by the mean channel attenuation or the maximum Doppler frequency), or estimates of its first and second order moments are available (Chapter 3). In Section 2.4, a general introduction to *minimax mean square error* (MSE) optimization is given: Its solution guarantees a worst-case performance for a given uncertainty set, proves that the Gaussian probability distribution is least-favorable, and provides the maximally robust estimator.
  We apply the minimax-results to robust MMSE channel estimation and robust MMSE prediction for band-limited random sequences. For example, for prediction of channels with a maximum Doppler frequency we provide the uncertainty set which yields the following predictor: MMSE prediction based on the rectangular and band-limited power spectral density; it is maximally robust for this uncertainty set.
- *Chapter 3: Estimation of Channel and Noise Covariance Matrices*
  Estimation of the covariance matrix for the channel parameters in space, delay, and time dimension together with the spatial noise correlations can be cast as the problem of estimating a structured covariance matrix. An

[2] This serves as an example for adaptive processing of the signal containing the information bearing data.

overview of the general Maximum Likelihood problem for structured covariance matrices is given in Section 3.1. The focus is on Toeplitz structure which yields an ill-posed Maximum Likelihood problem.
First, we present an iterative Maximum Likelihood solution based on a generalization of the expectation-maximization (EM) algorithm (Section 3.3). It includes the combined estimation of channel correlations in space, delay, and time as well as special cases.
If only the decimated *band-limited autocovariance sequence* can be estimated and the application requires the *interpolated* sequence, the decimated sequence has to be completed. As a constraint, it has to be ensured that the interpolated/completed sequence is still positive semidefinite. We propose a minimum-norm completion, which can be interpreted in the context of minimax MSE prediction (Section 3.4).
For estimation of correlations in space and delay dimensions, the Maximum Likelihood approach is rather complex. Least-squares approaches are computationally less complex and can be shown to be asymptotically equivalent to Maximum Likelihood. Including a positive semidefinite constraint we derive different suboptimum estimators based on this paradigm, which achieve a performance close to Maximum Likelihood (Section 3.5).

Chapters 2 and 3 deal with estimation of the channel state information (CSI). As signal processing application which deals with the transmission of data, we consider precoding of the data symbols for the wireless *broadcast channel*.[3] For simplicity, we treat the case of a single antenna at the receiver and multiple transmit antennas for a frequency flat channel[4]. Because precoding takes place at the transmitter, the availability of channel state information is a crucial question.

The last two chapters present *robust precoding* approaches based on MSE which can deal with partial channel state information at the transmitter. Its foundation is the availability of the channel state information from estimators of the channel realization and correlations which we present in Chapters 2 and 3.

- *Chapter 4: Linear Precoding with Partial Channel State Information*
  For linear precoding, we introduce different optimum and suboptimum performance measures, the corresponding approximate system models, and emphasize their relation to the information rate (Section 4.3). We elaborate on the relation between SINR-type measures to MSE-like expressions. It includes optimization criteria for systems with a common training channel instead of user-dedicated training sequences in the forward link.
  The central aspect of this new framework is the choice of an appropriate receiver model which controls the trade-off between performance and complexity.

[3] If restricted to be linear, precoding is also called preequalization or beamforming.

[4] This is a finite impulse response (FIR) channel model of order zero.