Optimal Combining and Detection

Statistical Signal Processing for Communications

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Optimal Combining and Detection

Statistical Signal Processing for Communications

With signal combining and detection methods now representing a key application of signal processing in communication systems, this book provides a range of key techniques for receiver design when multiple received signals are available. Various optimal and suboptimal signal combining and detection techniques are explained in the context of multiple-input multiple-output (MIMO) systems, including successive interference cancellation (SIC) based detection and lattice reduction (LR) aided detection. The techniques are then analyzed using performance analysis tools. The fundamentals of statistical signal processing are also covered, with two chapters dedicated to important background material. With a carefully balanced blend of theoretical elements and applications, this book is ideal for both graduate students and practicing engineers in wireless communications.

JINHO CHOI is currently a Professor in the School of Engineering, and Chair of the Wireless Group, at Swansea University, UK. He is the author of *Adaptive and Iterative Signal Processing in Communications* (Cambridge University Press, 2006) and the recipient of the 1999 Best Paper Award for Signal Processing from EURASIP. A Senior Member of the IEEE, his current research interests include wireless communications and array/statistical signal processing.

Preface

Statistical signal processing is a set of statistical techniques that have been developed to deal with random signals in a number of applications. Since it is rooted in detection and estimation theory, which are well established in statistics, the fundamentals are not changed although new applications have emerged. Thus, I did not have any strong motivation to write another book on statistical signal processing until I was convinced that there was a sufficient amount of new results to be put together with fundamentals of detection and estimation theory in a single book.

These new results have emerged in applying statistical signal processing techniques to wireless communications since 1990. We can consider a few examples here. The first example is smart antenna. Smart antenna is an application of array signal processing to cellular systems to exploit spatial selectivity for improving spectral efficiency. Using antenna arrays, the spatial selectivity can be used to mitigate incoming interfering signals at a receiver or control the transmission direction of signals from a transmitter to avoid any interference with the receivers which do not want to receive the signal. The second example is based on the development of code division multiple access (CDMA) systems for cellular systems. In CDMA systems, multiple users are allowed to transmit their signals simultaneously with different signature waveforms. The matched filter can be employed to detect a desired signal with its signature waveform. This detector is referred to as the single-user detector as it only detects one user's signal. Although this single-user detector is able to provide a reasonable performance, it is also possible to improve the performance to detect multiple signals simultaneously. This detector is called the multiuser detector. The third example is multiple-input multiple-output (MIMO) systems. In MIMO systems, multiple signals are transmitted and multiple signals are received. Thus, it is required to detect multiple signals simultaneously. These new applications promote advances of statistical signal processing. In particular, new and advanced techniques for signal combining and detection have emerged.

This book is intended to provide fundamentals of signal detection and estimation together with new results that have been developed for the new applications mentioned above.

I would like to thank many people for supporting this work, in particular: I. M. Kim (Queens University), C. Ling (Imperial College), and F. Adachi (Tohoku University). They helped me by providing constructive comments and proofreading. Needless to say the responsibility for the remaining errors, typos, unclear passages, and weaknesses is mine. I would also like to thank those people who inspire and encourage me all the time:

F. Adachi (Tohoku University) for encouragement as my mentor, J. Ritcey (University of Washington) for long-term friendship, and many others including my students for useful discussions.

Special thanks go to J. Ha, Y. Han, and H. J. Lee (Korea Advanced Institute of Science and Technology) who hosted me and offered an opportunity to teach a summer course with most of the materials in this book in 2008 at Information Communications University which became part of Korea Advanced Institute of Science and Technology in 2009. It was my great pleasure to teach young and talented students at Information Communications University. Their comments were very helpful in shaping this book.

Finally, I would like to offer very special thanks to my wife, Kila, and children, Seji and Wooji, for their generous support, understanding, and love.

Symbols

General

```
j = \sqrt{-1}
  \mathbb{F}_2: binary field
  \mathbb{Z}: set of integer numbers
  \mathbb{R}^n: real-valued n-dimensional vector space
  \mathbb{C}^n: complex-valued n-dimensional vector space
   x: Cartesian product (if it does not mean the product)
  |\mathcal{A}|: cardinality of set \mathcal{A} or the number of the elements in \mathcal{A}
  Ø: empty set
  U: set union
  ∩: set intersection
   \: set difference or set-minus
  \mathcal{A}^c: the complementary set of set \mathcal{A}
  u(x): step function
  \delta(x): Dirac delta function
Statistics related symbols
   f_X(x): pdf of random variable X
   F_X(x): cdf of random variable X
   Pr(A): probability of random event A
  \mathcal{E}[X]: statistical expectation of X
   Var(X): variance of X
   Q(x): Q-function, Q(x) = \int_{x}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{z^2}{2}} dz
  \mathcal{N}(\mathbf{x}, \mathbf{R}): Gaussian probability density function with mean \mathbf{x} and covariance \mathbf{R}
  \mathcal{CN}(\mathbf{x}, \mathbf{R}): circularly symmetric complex Gaussian probability density function with
   mean x and covariance R
Vector/Matrix related symbols
   ||\cdot||_p: p-norm
   ||\cdot||_F: Frobenius norm
   (\cdot)^{T}: transpose
   (\cdot)^{H}: Hermitian transpose
   det(\cdot): determinant of a square matrix
   tr(\cdot): trace of a square matrix
   Diag(a_1, a_2, \ldots, a_N): N \times N diagonal matrix whose elements are a_1, a_2, \ldots, a_N
```

 $[\mathbf{a}]_n$: *n*th element of a vector \mathbf{a}

 $[\mathbf{A}]_{m,n}$: (m, n)th element of a matrix \mathbf{A}

 $[\mathbf{A}]_{m_1:m_2,n_1:n_2}$: a submatrix of \mathbf{A} obtained by taking the elements in the m_1 th to m_2 th columns and the n_1 th to n_2 th rows

 $[A]_{:,n}$: *n*th column vector of **A**

 $[\mathbf{A}]_{n,:}$: *n*th row vector of \mathbf{A}

Abbreviations

AR autoregressive

ARV array response vector ASK amplitude shift keying

AWGN additive white Gaussian noise

BER bit error rate

BSC binary symmetric channel cdf cumulative distribution function CDMA code division multiple access

CLT central limit theorem CRB Cramer–Rao Bound

CSCG circularly symmetric complex Gaussian

CVP closed vector problem
DFE decision feedback equalizer
DMC discrete memoryless channel
DMI direct matrix inversion

DPSK differential phase shift keying

EGC equal gain combining

FA false alarm

GLR generalized likelihood ratio GLRT generalized likelihood ratio test

GSDC generalized selection diversity combining iid independent and identically distributed

ISI intersymbol interference

LCMV linearly constrained minimum variance

LLR log-likelihood ratio LMS least mean square

LR lattice reduction or likelihood ratio

LS least square

MAC multiple access channel

MAP maximum a posteriori probability
MIMO multiple-input multiple-output
MISO multiple-input single-output

ML maximum likelihood

MLE maximum likelihood estimate

MMSE minimum mean square error
MRC maximal ratio combining

MSE mean square error

MSNR maximum signal to noise ratio MUSIC multiple signal classification

MVDR minimum variance distortionless response

MVUE minimum variance unbiased PAM pulse amplitude modulation pdf probability density function PEP pairwise error probability

QAM quadrature amplitude modulation QPSK quadrature phase shift keying

RLS recursive least square

ROC receiver operating characteristics

SD selection diversity
SDR software defined radio
SLLN strong law of large numbers
SMI sample matrix inversion

SIC successive interference cancellation

SIMO single-input multiple-output SISO single-input single-output

SINR signal to interference-plus-noise ratio

SNR signal to noise ratio
SVP shortest vector problem
ULA uniform linear array

WLLN weak law of large numbers WLS weighted least square WSS wide-sense stationary

ZF zero-forcing

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1 Introduction

Statistical signal processing is a set of tools for dealing with random signals. As a set of tools, statistical signal processing has a broad range of applications from radars and sonars to speech and image processing. There are a number of books on this topic (e.g. (Scharf 1991) and (Orfanidis 1988)). In this book, instead of providing a comprehensive description of statistical signal processing with a broad range of applications, we focus on key approaches for communications. In particular, we attempt to present mainly signal detection and combining techniques in the context of wireless communications.

1.1 Applications in digital communications

The main aim of digital communications is to transmit a sequence of bits over a given channel to a receiver with minimum errors. In implementing digital communication systems, however, there are various constraints to be taken into account. For example, the transmission power is usually limited and the complexity of receiver is also limited. With practical implementation constraints including computational complexity, statistical signal processing plays a crucial role in designing a receiver for digital communications. Although there are a number of different roles that statistical signal processing can play, we confine ourselves to two main topics in this book: one is signal detection and the other is signal combining.

Signal detection has been well established as the main topic in communications. However, advances in multiuser detection have opened up a whole new approach for joint detection (Verdu 1998). In this book, we focus on optimal and suboptimal approaches for joint detection in the context of multiple-input multiple-output (MIMO) communications.

Signal combining is to combine multiple observations and plays a crucial role in both array signal processing and wireless communications. In particular, in wireless communications, signal combining is essential to mitigate fading at the receiver equipped with multiple receive antennas. Furthermore, signal combining can be generalized to mitigate interfering signals as it can provide spatial selectivity in smart antennas. In this book, we discuss signal combining based on this generalized view.

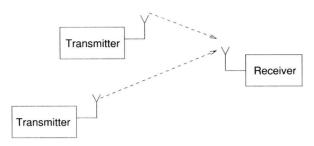


Figure 1.1 Multiuser communication.

1.2 Detection problems

Signal detection (Whalen 1971) (Kay 1998) is an application of statistical hypothesis testing in statistics. In statistical hypothesis testing, there are a finite number of hypotheses. With a set of observations, statistical hypothesis testing attempts to choose a hypothesis that explains observations best under a certain performance criterion. In signal detection, the set of hypotheses is decided by the signal alphabet for transmitted signals. Let $\mathcal S$ denote the signal alphabet. Then, the received signal over a memoryless channel at a receiver is given by

$$r = hs + n, (1.1)$$

where $s \in \mathcal{S}$ is the transmitted signal, h is the channel gain, and n is the background noise. The receiver is to detect s from r provided that h is known and the statistical properties of n are also known. In general, the size of \mathcal{S} is finite in digital communications. According to statistical hypothesis testing, signal detection is to choose a signal from \mathcal{S} , which can most likely generate r according to a certain criterion. Thus, it is important to define a detection criterion. Various decision criteria, which can be possibly employed for signal detection, have been proposed in statistical hypothesis testing. Some examples are the maximum likelihood (ML), Bayesian, maximum a posteriori probability (MAP) decision criteria. Since the theory of statistical hypothesis testing is well established in statistics, its application to signal detection is straightforward. In Chapter 2, we present an overview of detection theory based on the theory of statistical hypothesis testing.

While detection theory heavily relies on the theory of statistical hypothesis testing, the issues related to implementation with practical constraints are not quite covered by the theory. Most implementation issues are subject to a computational complexity constraint. To illustrate this issue, we can consider the signal detection problem in a multiuser communication system. If there are two users who transmit signals simultaneously as shown in Fig. 1.1, the received signal is given by

$$r = h_1 s_1 + h_2 s_2 + n, (1.2)$$

where h_k and s_k are the channel gain and transmitted symbol from the kth user, respectively. For the signal detection in this case, which is called multiuser detection (Verdu 1998), we need to extend the signal alphabet as $S \times S$, where \times denotes the