Xizhi Shi
史习智

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盲信号处理——理论与实践

Blind Signal Processing

Theory and Practice

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Preface

In this information age, digital signal processing technology is playing an increasingly important role in various fields of science and technology. Blind signal processing (BSP) has been an active research area in signal processing because the "blind" property doesn't require on *a priori* knowledge about either the signal or training data. As a powerful statistical signal processing method, BSP has been successfully used in many fields, including acoustics, sonar, speech separation, image processing, biomedical signal processing, remote sensing, communications, geophysics, and economics.

Since the late 1990, students at Shanghai Jiao Tong University have actively probed this research area with much success "using for reference-innovation-practice" guiding principle. This book contains the results of this research, with the goal of furthering our academic work and providing a bridge for further domestic and international academic exchanges.

The book consists of three parts.

The first part, Chapters 1 to 5, gives the mathematical foundation of BSP, and introduces basic concepts, definitions, and representative algorithms.

The second part, Chapters 6 to 8, applies BSP using deconvolution, probability density estimation and joint diagolinization. In Chapter 6, the convolution mixtures and the techniques of deconvolution are explained. Compared with the linear instantaneous mixtures problem, the convolution mixtures problem matches well with the real environment. Because the convolution in the time-domain corresponds to the multiplication operation in the frequency-domain, the mixing process can be considered as the product of the finite impulse response (FIR) filter corresponding to the transmission channel and the z-domain expression of the mixed signal vector. Therefore, the blind separation of the convolution mixtures in the time-domain is changed to the blind separation of the instantaneous mixtures in the frequency-domain. The dual problems faced by the solution in the frequency-domain are the requirement for higher computation efficiency and the alignment connection of the separated frequency segment due to the permutation indeterminacy. The alignment method of the adjacent frequency segment developed in this book takes the correlation parameters as the criteria to correctly connect the signal of each frequency segment together. In Chapter 7, the estimation of the probability density function of the source function forms the central topic. In the case where the distribution function of the signal is unknown with enough sample data, the non-parametric estimation method of the probability density function can guarantee that the estimate converges to any complex unknown density. This property is consistent with the condition that the source signals are unknown in blind separation. The probability density function-based separating algorithm we developed is more effective than the popular EASI algorithm. For any signals with a complex distribution, increasing the accuracy of the separation algorithms should cause the estimated probability density function to approach the true probability density function of the signal as much as possible. For this reason, we developed the Gaussian mixtures model-based probability density estimator, and verified the performance of the algorithm with speech signals and ship-radiated noise signals. Meanwhile, the estimation method of the probability density function is extended to the blind deconvolution problem where Gram-Charlier expansion is introduced to approximate the probability density function. This approach is suitable to the hybrid mixed signal containing the super-Gaussian signal as well as the sub-Gaussian signal along with improved computation and real-time performance. In Chapter 8, we extend the joint approximate diagonalization method to the non-stationary signal through the time-frequency distribution function matrix instead of through the power spectrum function matrix. After the convolution mixing model is transformed to a higher dimensional instantaneous mixing model, the joint approximate block diagonalization is adopted to implement the blind deconvolution of the time-frequency feature of the source signals. Combining the developed non-parametric estimation method with the time-frequency distribution fully utilizes the limited samples to obtain more information in the time and frequency domains; therefore improving the performance of the algorithm.

The third part, Chapters 9 and 10, introduces extensions to BSP theory and provide applications in varied fields. In Chapter 9, we discuss in detail some key problems, including how to speed up the convergence, the underdetermined model, the complex valued method, and constrained independent component analysis. The developed second-order statistics based algorithm is more suitable to the convolution mixtures of the multi-input and multi-output system. On the basis of the prior distribution expressed by the Gaussian mixtures model, the

MoG-uICA algorithm with a parameter learning capability has been developed; that algorithm can recover the source signals with different distributions from the mixed signals without undue limitation. Recent study shows that on the basis of the state-space model of the signal, the particle filtering method combining with MoG-uICA algorithm is very effective to deal with the blind separation of non-Gaussian noise and non-linear mixtures. And the study of a complex-valued domain extends the application areas while it increases the computation speed of existing algorithms. In Chapter 10, we present a wide range of prospective problems for future research. Our illustrative areas have included speech, underwater acoustics, medical imaging, data compression, image feature extraction, and bioinformatics.

In surveying this book, readers can realize that key problems faced by blind processing include nonlinear mixtures, the effect of noise on the performance of separation, non-stationary signal models and the underdetermined model. Though some progress, as reported in this book, has been achieved regarding the above topics, there is still plenty of space for development in theory and applications.

Since the word "blind" excludes prior assumption on system characteristic, reliance is made of the cognitive model, constructed by statistical reasoning and machine learning, to perform blind separation of real signals. The cognitive model indicates how to transfer the indeterminacy of the mixed signal in the mixing process. The classical statistical reasoning method is the Bayesian theorem; however, it is only optimal in the case of a known prior probability distribution. In order to overcome the obstacle of the prior probability distribution, we need to develop the data-driven based statistical reasoning learning method under the Bayesian framework to find an effective approach method. The time series-based Bayesian reasoning can deal with the transfer of indeterminacy very well. If the blind separation problem is described as a distribution model, in which all hidden variables are deduced from observation variables, then the blind separation problem is reduced to the Bayesian structure learning process. In a general sense, Bayesian learning is an information-based knowledge reasoning system. The key to successful separation is how to select a suitable probability distribution to approach the initial distribution of the mixed signals. The non-parametric Bayesian method uses the random process to depict the infinite dimensional space, namely the Dirichlet process. The joint application of Dirichlet process mixtures-based general purpose density estimator and nonlinear decoupling technology of the indeterminacy transfer for system state and distribution estimation, can widen the successful application of blind signal processing.

I have written this book to show the partial research results by twelve Ph.D. students in recent years achieved in a collaborative, harmonious atmosphere. I would like to express my thanks to Hong Pan, Ze Wang, Xizhong Shen, Fengyu Cong, Wei Kong, Shanbao Tong, Yingyu Zhang, Yanxue Liang and Haixiang Xu for their respective contributions to Section 9.2; Section 1.4, Section 9.9, Section 10.5 and Section 10.6; Section 7.7 and Section 9.3; Section 2.6, Section 4.1, Section 9.6/9.10, and Section 10.1; Section 5.6, Section 7.5, Section 9.5/9.6, and Section 10.10; Section 10.2; Section 9.4 and Section 10.3; Section 10.7; Section 8.7.

I want to express my appreciation to the following experts for their concerns and support in the proposal and writing process; they are: Prof. Z. Y. He (Southeast University, China), Prof. C. H. Chen (Massachusetts University, Dartmouth, US), Prof. B. Z. Yuan (Northern Jiao Tong University, China), Prof. G. Meng, Prof. T. G. Zhuang, Prof. Z. Z. Han, Prof. Z. Z. Wang, Prof. J. Yang, Prof. Y. S. Zhu, Prof. L. Q. Zhang, and Prof. J. Chen of our laboratory.

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In early 2006, I had to stop my writing due to a sudden eye disease. Special thanks go to Prof. X. H. Sun for his treatment so that I could continue my writing.

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Xizhi Shi
Shanghai Jiao Tong University
05/10/2010

Symbols

$\mathrm{A}=[a_{ij}]$	mixing matrix
a_{ij}	ijth element of matrix $\boldsymbol{A}$
$\boldsymbol{C}$	mixing-separating composite matrix
$\boldsymbol{C}_x$	covariance matrix of $\boldsymbol{x}$
$\boldsymbol{C}_{xy}$	cross-covariance matrix of $\boldsymbol{x}$ and $\boldsymbol{y}$
$\boldsymbol{C}(\omega)$	matrix in frequency-domain
$\boldsymbol{D}$	diagonal matrix with full rank
$\boldsymbol{D}(t,f)$	distribution function matrix in time-domain
$\det(\boldsymbol{A})$	determinant of matrix $\boldsymbol{A}$
$\mathrm{diag}\ (d_1, d_2, \cdots, d_n)$	diagonal matrix with main diagonal elements $(d_1, d_2, \cdots, d_n)$
$E\{\cdot\}$	expectation operator
$\boldsymbol{G}$	generalized partition matrix
$\boldsymbol{H}^{-1}$	inverse of nonsingular matrix $\boldsymbol{H}$
$H(z)$	transfer function of discrete time filter
$\boldsymbol{H}(z)$	matrix transfer function of discrete time filter
$\boldsymbol{H}(\omega)$	mixing matrix in frequency-domain
$H(x)$	entropy of random variable x
$\boldsymbol{I}$	identity matrix
$\boldsymbol{I}_{n\times n}$	identity matrix of dimension $n\times n$
$I(x,y)$	mutual information of random variable $\boldsymbol{x}$ and $\boldsymbol{y}$
$\mathrm{Im}(\cdot)$	imaginary part of
$J(\boldsymbol{w})$	evaluation function
$K(x)$	kernel function
$KL(\cdot)$	Kullback-Leibler divergence (distance)
k	discrete-time or number of iterations
n	number of inputs and outputs, sequence number of discrete-time
N	data length
m	number of sensors
$p(x)$	probability density function of x
$\boldsymbol{P}$	permutation matrix
$\boldsymbol{P}(f)$	power spectrum matrix
$R_{xy}(m)$	cross-correlation function of discrete- time sequence $x(n)$ and $y(n)$ with time delay m

$R_{xy}(\tau)$	cross-correlation function of continuous-time function $x(t)$ and $y(t)$ with time delay τ
R^n	real space of dimension x
$\boldsymbol{R}_x$	autocorrelation matrix of $\boldsymbol{x}$
$\boldsymbol{R}_{xy}$	cross-correlation matrix of $\boldsymbol{x}$ and $\boldsymbol{y}$
$\boldsymbol{R}_x(\omega)$	correlation matrix of mixed signals in frequency-domain
$\boldsymbol{R}_y(\omega)$	correlation matrix of output signals in frequency-domain
$\mathrm{Re}(\cdot)$	real part of
$\boldsymbol{s}$	source signal vector
$s(t)$	continuous-time signal
$\boldsymbol{s}(k)=[s_1(k),\cdots,s_n(k)]^{\mathrm{T}}$	source signal vector of kth sample
$\boldsymbol{s}(z)$	z-transform of source signal vector $\boldsymbol{s}(k)$
$\mathrm{sgn}(x)$	sign function
$\mathrm{tr}(\boldsymbol{A})$	trace of matrix $\boldsymbol{A}$
$\boldsymbol{U}$	orthogonal matrix
$\boldsymbol{w}$	system parameters of state-space model
$\boldsymbol{W}=[w_{ij}]$	separating matrix, demixing matrix
$\boldsymbol{W}^{\mathrm{H}}=(\boldsymbol{W}^*)^{\mathrm{T}}$	complex conjugate transpose of $\boldsymbol{W}$
$\boldsymbol{W}(z)$	matrix transfer function of deconvolution filter
$\boldsymbol{W}(\omega)$	separating matrix in frequency domain
x,y	random variable
$\boldsymbol{x}(k)$	observed signals vector, mixed signals vector
$\lVert \boldsymbol{x} \rVert$	norm of vector $\boldsymbol{x}$
$\boldsymbol{y}$	separated (output) signals vector
$Y(w)$	frequency spectrum of output signal
Z^{-1}	inverse z-transform
δ_{ij}	Kronecker symbol
η	learning rate of discrete-time algorithm
$\Gamma(\cdot)$	Gamma function
λ	eigenvalue of correlation matrix
$\boldsymbol{\Lambda}$	diagonal matrix
$\phi(\cdot)$	contrast function, nonlinear activating function of neuron
ω	normalized angle frequency
∇	gradient operator
$\hat{\boldsymbol{\theta}}$	estimate of parameters $\boldsymbol{\theta}$

Contents

Chapter 1 Introduction

1.1 Introduction

Since the digital information age, signal processing has performed an increasingly important function in the areas of science and technology, among which blind signal processing (BSP), as one of the focal points, has great potential. The word "Blind" in BSP means that there are no training data and no prior knowledge of system parameters, so BSP can be utilized very generally.

BSP contains the following three areas: separation and extraction, deconvolution, and equalization of blind signal. And Independent component analysis (ICA) as a parallel method can be used in the three areas, and will be explained in the next chapters. BSP mainly concerns statistical and adaptive signal processing, so the theoretical basis is rigorous. However, the validity of model and algorithms is closely dependent on their specific applications, which afford additional information to BSP. The author's work expands along these application-dependent lines.

The book is composed of three parts. Part 1(Chapter 1~5) contains introductions, basic concepts and definitions, and some general algorithms; Part 2 (Chapter 6~8) concerns the progress of several important and typically related themes and recent progress; Part 3 (Chapter 9~10) introduces the expansion and development of basic models, as well as some application examples resulting from the author's researches.

This book can be used as a reference for researchers or textbook for graduate students.

1.2 Blind Source Separation

Let us consider the situation where multiple sensors receive different signals sent by several physical sources. The typical example is that several persons talk simult-aneously in a room, in which a set of sensors have been placed in different locations, so signals received by sensors are mixed ones composed with differently weighted original speech signals. The problem is to separate and identify the original speech signal out of the mixed one, which is called the cocktail party problem. The problem can be taken as impulse responses of a linear system. For speech, signals are transmitted in medium of air. And considering the reverberation effect, the cocktail party problem actually is a blind deconvolution problem of multi-channels. There is a similar multi-channels abnormality problem with underwater signals. Another example in this area is separation of EEG signal. The electrode on the head records the mixed signals from different sources. It is an instantaneous mixing problem without delay considerations to which BSP can be successfully applied.

To explain the model and characteristics of blind source separation method, we first discuss linear instantaneous mixing problem.

1.2.1 Linear Instantaneous Mixing Problem

As mentioned above, blind source separation is to recover the unobserved original signal from multiple signal mixtures. Generally, the observed signals come from the output of a set of sensors, each sensor receiving different original mixed signals, as shown in Fig. 1.1.

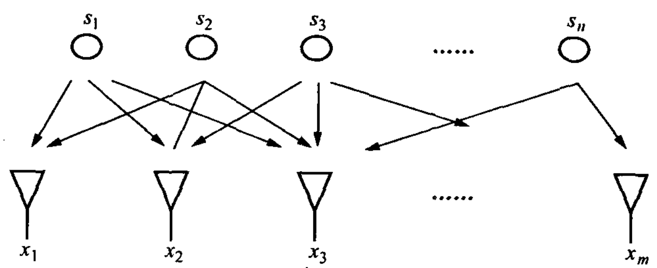

Fig. 1.1 Signal mixing process

In Fig. 1.1, signal source s_1, s_2, $\cdots$, s_n sends signals to sensors with the outputs x_1, x_2, $\cdots$, x_m. The transmission is assumed to be instantaneous, that is different signals arrive at each sensor simultaneously, and sensors receive linear mixtures from each signal sources. The output of i th sensor is

$$x_i(t) = \sum_{j=1}^{n} a_{ij} s_j(t) + n_i(t) \qquad i = 1,2,\cdots,m \tag{1.2.1}$$

where a_{ij} is mixing coefficient, $n_i(t)$ is observed noise of i th sensor. Another form with vector and matrix is

$$\boldsymbol{x}(t) = \boldsymbol{A}\boldsymbol{s}(t) + \boldsymbol{n}(t) \tag{1.2.2}$$

where $s(t)=[s_1(t), s_2(t), \cdots, s_n(t)]^T$ is an $n\times 1$ vector of source signal. Namely, $x(t)$ is an $m\times 1$ vector of mixed signals, $n(t)$ is an $m\times 1$ vector of noise, and matrix A is an $m\times n$ mixing matrix whose elements a_{ij} are mixing coefficients.

Without consideration of observation noise, in other words, assuming that noise can be ignored, Equation (1.2.2) can be rewritten as

$$x(t) = As(t) \tag{1.2.3}$$

Blind Signal source separation is to estimate source signal vector $s(t)$ or mixing matrix A without knowledge of both source signals and mixing coefficient a_{ij} by using only the mixed signal $x(t)$ received by the sensors. Signal source separation problem can also be represented as follows: in the case that the source signals vector $s(t)$ and mixing matrix A are unknown, find an $n\times m$ matrix W statisfying

$$y(t) = Wx(t) \tag{1.2.4}$$

that yields a reliable estimate for the source vector $s(t)$ or one of its components. generally, matrix W is called the separating matrix.

By combining Eqs. (1.2.3) and (1.2.4), we obtain

$$\begin{aligned} y(t) &= Wx(t) \\ &= WAs(t) \\ &= Cs(t) \end{aligned} \tag{1.2.5}$$

where $C = WA$ is an $n\times n$ matrix, this is called mixing-separating composite matrix.

Actually, the blind separation problem is a multiple solution problem, because for an observed signal $x(t)$, there may be an infinite group of mixing matrices A and the source signals $s(t)$ satisfying Eqs. (1.2.2) or (1.2.3). So to make the problem meaningful, some basic assumption must be made.

With regard to the different signal sources, $s_1, s_2, \cdots, s_n$ it is reasonable to assume that they are statistically independent. Let $p(s)$ represent the joint probability density function of source signal vector $s(t)$ and $p_1(s_1), p_2(s_2), \cdots, p_n(s_n)$ represent the marginal probability density function of then source signals respectively. Then the assumption of statistical independence among all components of the source signal vector can be written as

$$p(s) = p_1(s_1)p_2(s_2)\cdots p_n(s_n) = \prod_{i=1}^{n} p_i(s_i) \tag{1.2.6}$$

i.e. the joint probability density function of the source signal vector $s(t)$ equals to the product of the marginal probability density function of each component. This statistically independent assumption of source signals is the basis of most blind signal source separation algorithms.

Beside the statistically independent assumption regarding every component