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Audio Source Separation and Speech Enl	nancement	

# **Audio Source Separation and Speech Enhancement**

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# **Preface**

Source separation and speech enhancement are some of the most studied technologies in audio signal processing. Their goal is to extract one or more source signals of interest from an audio recording involving several sound sources. This problem arises in many everyday situations. For instance, spoken communication is often obscured by concurrent speakers or by background noise, outdoor recordings feature a variety of environmental sounds, and most music recordings involve a group of instruments. When facing such scenes, humans are able to perceive and listen to individual sources so as to communicate with other speakers, navigate in a crowded street or memorize the melody of a song. Source separation and speech enhancement technologies aim to empower machines with similar abilities.

These technologies are already present in our lives today. Beyond "clean" single-source signals recorded with close microphones, they allow the industry to extend the applicability of speech and audio processing systems to multi-source, reverberant, noisy signals recorded with distant microphones. Some of the most striking examples include hearing aids, speech enhancement for smartphones, and distant-microphone voice command systems. Current technologies are expected to keep improving and spread to many other scenarios in the next few years.

Traditionally, *speech enhancement* has referred to the problem of segregating speech and background noise, while *source separation* has referred to the segregation of multiple speech or audio sources. Most textbooks focus on one of these problems and on one of three historical approaches, namely sensor array processing, computational auditory scene analysis, or independent component analysis. These communities now routinely borrow ideas from each other and other approaches have emerged, most notably based on deep learning.

This textbook is the first to provide a comprehensive overview of these problems and approaches by presenting their shared foundations and their differences using common language and notations. Starting with prerequisites (Part I), it proceeds with single-channel separation and enhancement (Part II), multichannel separation and enhancement (Part III), and applications and perspectives (Part IV). Each chapter provides both introductory and advanced material.

We designed this textbook for people in academia and industry with basic knowledge of signal processing and machine learning. Thanks to its comprehensiveness, we hope it will help students select a promising research track, researchers leverage the acquired cross-domain knowledge to design improved techniques, and engineers and developers

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choose the right technology for their application scenario. We also hope that it will be useful for practitioners from other fields (e.g., acoustics, multimedia, phonetics, musicology) willing to exploit audio source separation or speech enhancement as a pre-processing tool for their own needs.

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Emmanuel Vincent, Tuomas Virtanen, and Sharon Gannot

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# **Notations**

# Linear algebra

$\boldsymbol{x}$	scalar
X	vector
г э	4

 $\begin{array}{ll} [x_i]_i & \text{vector with entries } x_i \\ (\mathbf{x})_i & i\text{th entry of vector } \mathbf{x} \\ \mathbf{0}_I & I \times 1 \text{ vector of zeros} \\ \mathbf{1}_I & I \times 1 \text{ vector of ones} \end{array}$ 

X matrix

 $[x_{ij}]_{ij}$  matrix with entries  $x_{ij}$   $(\mathbf{X})_{ij}$  (i,j)th entry of matrix  $\mathbf{X}$  I

 ${\cal X}$  tensor/array (with three or more dimensions) or set

 $\{x_{ijk}\}_{ijk}$  tensor with entries  $x_{ijk}$ 

 $Diag(\mathbf{x})$  diagonal matrix whose entries are those of vector  $\mathbf{x}$ 

 $X \circ Y$  entrywise product of matrices X and Y

tr(X) trace of matrix X

 $\det(\mathbf{X}) \qquad \qquad \det \text{eterminant of matrix } \mathbf{X} \\
 \mathbf{x}^T \qquad \qquad \text{transpose of vector } \mathbf{x}$ 

 $\mathbf{x}^H$  conjugate-transpose of vector  $\mathbf{x}$ 

 $x^*$  conjugate of scalar x  $\Re(x)$  real part of scalar xj imaginary unit

#### **Statistics**

p(x)	probability distribution of continuous random variable $x$
$p(x \mid y)$	conditional probability distribution of $x$ given $y$
P(x)	probability value of discrete random variable $x$
$P(x \mid y)$	conditional probability value of $x$ given $y$
$\mathbb{E}\{x\}$	expectation of random variable $x$
$\mathbb{E}\{x \mid y\}$	conditional expectation of $x$
$\mathbb{H}\{x\}$	entropy of random variable $x$
$\mathcal{N}(\mathbf{x} \mid \boldsymbol{\mu}, \boldsymbol{\Sigma})$	real Gaussian distribution with mean $\mu$ and covariance $\Sigma$
$\mathcal{N}_{c}(\mathbf{x} \mid \boldsymbol{\mu}, \boldsymbol{\Sigma})$	complex Gaussian distribution with mean $\mu$ and covariance $\Sigma$
$\hat{x}$	estimated value of random variable $x$ (e.g., first-order statistics)

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```

$rac{\sigma_x^2}{\widehat{\sigma}_x^2}$	variance of random variable $x$
$\widehat{\sigma}_x^2$	estimated second-order statistics of random variable $x$
	autocovariance of random vector <b>x</b>
$\frac{\Sigma_{\mathbf{x}}}{\widehat{\Sigma}_{\mathbf{x}}}$	estimated second-order statistics of random vector $\mathbf{x}$
$\Sigma_{xy}$	covariance of random vectors <b>x</b> and <b>y</b>
$egin{array}{l} oldsymbol{\Sigma}_{ ext{xy}} \ oldsymbol{\hat{\Sigma}}_{ ext{xy}} \ \mathcal{C}^{ ext{cost}}(oldsymbol{ heta}) \end{array}$	estimated second-order statistics of random vectors $\mathbf{x}$ and $\mathbf{y}$
$C^{\rm cost}(oldsymbol{ heta})$	cost function to be minimized w.r.t. the vector of parameters $ heta$
$\mathcal{M}^{ ext{objective}}(oldsymbol{ heta})$	objective function to be maximized w.r.t. the vector of parameters $\theta$
$\mathcal{Q}(oldsymbol{ heta},\cdot)$	auxiliary function to be minimized or maximized, depending on the
	context

# **Common indexes**

I	number of microphones or channels
i	microphone or channel index in $\{1, \dots, I\}$
J	number of sources
j	source index in $\{1, \dots, J\}$
T	number of time-domain samples
t	sample index in $\{0, \dots, T-1\}$
L	time-domain filter length
au	tap index in $\{0, \dots, L-1\}$
N	number of time frames
n	time frame index in $\{0, \dots, N-1\}$
F	number of frequency bins
f	frequency bin index in $\{0, \dots, F-1\}$
$\nu_f$	frequency in Hz corresponding to frequency bin $f$
x(t)	time-domain signal $x$
x(n,f)	complex-valued STFT coefficient of signal $x$

# Signals

$x_i$	input signal recorded at microphone <i>i</i>
x	$I \times 1$ multichannel input signal, e.g. $\mathbf{x}(t) = [x_1(t), \dots, x_I(t)]^T$
X	matrix of input signals, e.g. $\mathbf{X} = [x_i(t)]_{it}$ or $\mathbf{X} = [x(n, f)]_{fn}$
$ \mathbf{X} $	input magnitude spectrogram, i.e. $ \mathbf{X}  = [ x(n,f) ]_{fn}$
$\mathcal{X}$	tensor/array/set of input signals, e.g. $\mathcal{X} = [x_i(n,f)]_{ifn}$
$S_{j}$	point source signal
s	$J \times 1$ vector of source signals, e.g. $\mathbf{s}(t) = [s_1(t), \dots, s_I(t)]^T$
S	matrix of source signals, e.g. $\mathbf{S} = [s_i(t)]_{it}$
$c_{ij}$	spatial image of source $j$ as recorded on microphone $i$
$\mathbf{c}_{j}^{'}$	$I \times 1$ spatial image of source j on all microphones
Ć	tensor/array/set of spatial source image signals, e.g. $C = [c_{ij}(n,f)]_{ijfn}$
$a_{ij}$	acoustic impulse response (or transfer function) from source <i>j</i> to
,	microphone i
$\mathbf{a}_{i}$	$I \times 1$ vector of acoustic impulse responses (or transfer functions)
,	from source <i>j</i> , mixing vector
$\mathbf{a}_{j}$	

 $I \times I$  matrix of acoustic impulse responses (or transfer functions), A

mixing matrix

 $I \times 1$  noise signal 11

#### **Filters**

\* convolution operator

single-output single-channel filter (mask), e.g.  $\hat{s} = w^*x$ w single-output multichannel filter (beamformer), e.g.  $\hat{s} = \mathbf{w}^H \mathbf{x}$ w

W multiple-output multichannel filter, e.g.  $\hat{\mathbf{s}} = \mathbf{W}^H \mathbf{x}$ 

# Nonnegative matrix factorization

 $\mathbf{b}_k$ kth nonnegative basis spectrum В matrix of nonnegative basis spectra kth activation coefficient in time frame n $h_k(n)$ vector of activation coefficients in time frame n $\mathbf{h}(n)$ 

Н matrix of activation coefficients

#### Deep learning

Н number of layers layer index in  $\{1, \dots, H\}$ h number of neurons in layer h $K_h$ neuron index in  $\{1, \dots, K_h\}$ k

 $\mathbf{Z}_h$ matrix of weights and biases in layer h

activation function in layer h  $g_h$ 

multivariate nonlinear function encoded by the full DNN  $g_{z}$ 

## Geometry

$\mathbf{m}_i$ 3D location of microphone $i$ with respect to the array origin

 $\ell_{ii'}$ distance between microphones i and i'

3D location of source *j* with respect to the array origin  $\mathbf{p}_i$ 

distance between source i and microphone i $r_{ii}$ 

azimuth of source *j* elevation of source *j* speed of sound in air

time difference of arrival of source j between microphones i and i' $\Delta_{ii'i}$