

Contents

Preface	xv
List of Abbreviations	xx
Chapter 1 Introduction	1
1.1 Motivation	1
1.1.1 Categories of EEG data	1
1.1.2 Signal processing of EEG data	2
1.2 Example of Conventional ERP Data Processing	3
1.3 Linear Transform Model of ERP Data	5
1.4 Existing Problems in Conventional ERP Data Processing and Their Solutions	7
1.4.1 Assumptions for the averaging step	7
1.4.2 Problems in the assumptions of the averaging step	7
1.4.3 Solutions	9
1.5 ERP Data for the Demonstration in This Book	10
References	10
Chapter 2 Wavelet Filter Design Based on Frequency Responses for Filtering ERP Data With Duration of One Epoch	15
2.1 Correlation	15
2.2 Impulse Response and Frequency Response	16
2.3 Moving-Average Model-Based FIR Digital Filter	18
2.3.1 Interpreting the digital filter in terms of correlation	18

2.3.2	Problems of the digital filter in removing artifacts and their solutions	18
2.4	DFT-Based Digital Filter	20
2.4.1	Definition of DFT	20
2.4.2	Interpreting DFT using correlation	20
2.4.3	DFT-based digital filter	21
2.4.4	Problems of the DFT filter and their corresponding solutions	23
2.5	Wavelet Transform	24
2.5.1	Definition of wavelet transform	24
2.5.2	Interpreting the wavelet transform using correlation	25
2.5.3	Differences between the Fourier and wavelet transforms	25
2.5.4	Implementation of DWT	26
2.6	Wavelet Filter Design Based on Frequency Response	27
2.6.1	Introduction to wavelet filter	27
2.6.2	Key issues in the wavelet filter design	28
2.6.3	Determination of the number of levels	28
	2.6.3.1 Existing problem and current solution	28
	2.6.3.2 New solution	28
2.6.4	Frequency division at different DWT levels: Overlapped frequency contents at different levels	29
2.6.5	Frequency division in the first level of DWT: The cutoff frequency of the LP and HP filters is $F_s/2$ instead of $F_s/4$	31
2.6.6	Selection of the detail coefficients at some levels for signal reconstruction	31
	2.6.6.1 Existing problem and current solution	31
	2.6.6.2 New solution	33
2.6.7	Choosing the wavelet for the wavelet filter in ERP studies	33
	2.6.7.1 Existing problem and current solution	33
	2.6.7.2 New solution	33

2.6.8	Effect of sampling frequency on the wavelet filter	36
2.7	Linear Superposition Rule of the Wavelet Filter and Benefit of the Wavelet Filter in Contrast to the Digital Filter	37
2.8	Comparison Between the Wavelet and Digital Filters: Case Study on the Waveform and Magnitude Spectrum	39
2.9	Recommendation for the Wavelet Filter Design	41
2.10	Summary: ERP Data Processing Approach Using DFT or Wavelet Filter	41
2.11	Existing Key Problem and Potential Solution	42
2.12	MATLAB Codes	42
2.12.1	DFT filter function	42
2.12.2	Wavelet filter function	43
2.12.3	Frequency responses of DFT filter and wavelet filter	44
	References	48

**Chapter 3 Individual-Level ICA to Extract the ERP
Components from the Averaged EEG Data** 51

3.1	Classic ICA Theory	51
3.1.1	Brief history	51
3.1.2	ICA model, assumptions, and solution in obtaining independent components	52
3.1.2.1	Model	52
3.1.2.2	Classification of the ICA models	54
3.1.2.3	Assumptions	54
3.1.2.4	Solution	54
3.1.3	ICA algorithm and indeterminacies of independent components	55
3.1.3.1	Classification of ICA algorithms based on the ICA models	55
3.1.3.2	ICA algorithm for the determined model	55
3.1.3.3	Implementation of the ICA algorithm	56

3.1.3.4	Definitions of the global and local optimization of ICA	56
3.1.3.5	Indeterminacies of the independent components	57
3.2	ICA Theory in ERP Data Processing: Back Projection . . .	58
3.2.1	Reconsideration of the linear transform model of EEG	60
3.2.2	Back-projection of an ICA component to correct the indeterminacies in the variance and polarity	65
3.2.2.1	Introduction to back-projection	65
3.2.2.2	Back-projection under global optimization	66
3.2.2.3	Back-projection under local optimization	71
3.3	Indeterminacies and Determinacies of ICA on EEG	73
3.3.1	Indeterminacies of ICA on EEG	78
3.3.2	Determinacies in ICA on EEG	78
3.3.3	Obtaining the determinacies of ICA on EEG in practice	78
3.4	Practical Consideration of the ICA Model of EEG	79
3.4.1	Noisy or noise-free ICA models	79
3.4.2	Can correcting artifacts and extracting the ERP components be realized simultaneously?	80
3.4.3	Group- or individual-level ICA	81
3.4.4	Converting the over-determined model to the determined model	82
3.4.5	Converting the under-determined model to the determined model	83
3.5	MOS to Determine the Number of Sources	83
3.5.1	Introduction to MOS	83
3.5.2	Theoretical eigenvalues and MOS	84
3.5.3	MOS in practice	85
3.5.3.1	Information-theory-based methods	85
3.5.3.2	SORTE	86
3.5.3.3	RAE	87
3.5.3.4	Simulation for MOS	87

3.6	Key Practical Issues for ICA to Extract the ERP Components	91
3.6.1	Are the concatenated single-trial or averaged EEG data better for ICA to extract the ERP components under the assumption of independence?	91
3.6.2	Number of samples and number of sources	92
3.6.3	Reducing the number of sources in averaged EEG data and increasing the SNR	92
	3.6.3.1 Filtering the averaged EEG data	92
	3.6.3.2 Appropriately designed wavelet filter	93
3.6.4	Validation of the stability of ICA decomposition	95
3.7	Systematic ICA Approach on the Extraction of ERP Components from Averaged EEG Data (Responses of Stimuli) Collected by a High-Density Array	97
3.7.1	Ordinary ERP data: Ordinarily averaged EEG data over single trials of one stimulus and one subject	97
3.7.2	Wavelet filtering of averaged EEG data	99
3.7.3	Converting the over-determined model to the determined model: Dimension reduction	99
3.7.4	ICA decomposition and stability analysis	101
3.7.5	Selection of the components of interest	107
3.7.6	Back-projection of selected components	107
3.8	Systematic ICA Approach to Extract the ERP Components from the Averaged EEG Data (DW) Collected by Low-Density Array	107
3.8.1	Motivation	107
3.8.2	Introduction to DW	108
3.8.3	Six steps of the systematic ICA approach to extract the MMN component from the DW	108
3.9	Reliability of the Independent Components Extracted by the Systematic ICA Approach from Averaged EEG Data	114
3.9.1	Simulation study: Sufficiency of several hundreds of samples in extracting a few dozens of sources	114

3.9.2	Are bump-like independent components reasonable when the systematic ICA approach is applied on the averaged EEG data?	116
3.10	Benefits of the Wavelet Filter in the Systematic ICA Approach to Extract the ERP Components from Averaged EEG Data	117
3.11	Relationship among the Global Optimization of the ICA Decomposition, Stability of the ICA Decomposition, ICA Algorithm, and Number of Extracted Components	118
3.12	Summary	119
3.13	Existing Key Problems and Potential Solutions	120
3.14	MATLAB Codes	121
3.14.1	Systematic ICA approach on averaged EEG data collected by high-density array	121
3.14.2	Model order selection	123
3.14.3	Systematic ICA approach on averaged EEG data collected by low-density array	124
	References	124

Chapter 4 Multi-Domain Feature of the ERP Extracted by NTF: New Approach for Group-Level Analysis of ERPs 131

4.1	TFR of ERPs and High-Order Tensor	131
4.1.1	TFR of ERPs: Evoked and induced brain activity	131
4.1.1.1	Difference in the TFR of an ERP between the evoked and induced brain activities	132
4.1.1.2	TFR of an ERP used in this study: TFR of the averaged EEG	132
4.1.1.3	ROI of the TFR of the ERP	133
4.1.2	High-order ERP tensor	134
4.1.2.1	ERP waveform tensors	134
4.1.2.2	ERP tensors of TFRs of averaged EEG data	134
4.2	Introduction of the Tensor Decomposition	135
4.2.1	Brief history	135

4.2.2	Basis for tensor decomposition	136
4.2.2.1	Inner and outer products	136
4.2.2.2	Outer product of multiple vectors	137
4.2.2.3	Mode- n tensor matrix product	137
4.2.3	CPD model	137
4.2.3.1	Simple illustration of the CPD	137
4.2.3.2	General definition of CPD	138
4.2.3.3	Uniqueness analysis of CPD	138
4.2.3.4	Difference between matrix decomposition and CPD	139
4.2.4	Tucker decomposition model	139
4.2.5	Difference between the CPD and Tucker decomposition models	140
4.2.6	Fit of a tensor decomposition model	141
4.2.7	Classic algorithms of the CPD and Tucker decomposition	142
4.2.8	NTF	143
4.2.9	Why is a nonnegative ERP tensor of the TFR used instead of an ERP tensor of a waveform?	143
4.3	Multi-Domain Feature of ERP	144
4.3.1	Conventional features of an ERP (averaged EEG) versus features of spontaneous and single-trial EEGs	144
4.3.1.1	Conventional features of an ERP (averaged EEG)	144
4.3.1.2	Features of spontaneous and single-trial EEGs for pattern recognition	145
4.3.1.3	Difference between the conventional features of an ERP for cognitive neuroscience and the features of spontaneous and single-trial EEGs for pattern recognition	145
4.3.2	Brief review of the EEG data analysis by tensor decomposition	146
4.3.3	Multi-domain feature of ERPs extracted by NCPD from the fourth-order ERP tensor of TFRs	147

4.3.3.1	Feature extraction	147
4.3.3.2	Feature selection	149
4.3.3.3	Group-level analysis of the multi-domain feature of an ERP	150
4.3.3.4	Drawback in using the fourth-order ERP tensor of TFRs	152
4.3.4	Multi-domain feature of ERPs extracted by NCPD from a third-order ERP tensor of the TFRs	153
4.3.5	Multi-domain feature of an ERP extracted by NTD	154
4.3.6	Third-order ERP tensor of the TFRs for NTF	159
4.3.6.1	ERP tensor of the TFRs for individual topographies	159
4.3.6.2	ERP tensor of the TFRs for individual temporal components	159
4.3.6.3	ERP tensor of the TFRs for individual spectra	159
4.3.7	Uniqueness analysis	159
4.4	Adaptive and Objective Extraction of ROI from the TFRs of the ERPs	160
4.5	Key Issues in Using the NTF to Extract the Multi- Domain Feature of an ERP from the ERP Tensor of the TFRs	160
4.5.1	LRA-based fast NTF algorithm	160
4.5.2	Determining the number of extracted components	161
4.5.2.1	MOS	162
4.5.2.2	ARD	162
4.5.2.3	Data-driven methods	163
4.5.3	Stability of the multi-domain feature of the ERP extracted by the NTF	164
4.5.4	How many components can be appropriately extracted by the NTF with knowledge of ERPs taken into account?	166
4.5.5	Which tensor decomposition model should be chosen for the NTF?	167

4.6	Summary	168
4.7	Existing Key Problem and Potential Solution	171
4.8	MATLAB Codes	171
	References	172
Chapter 5 Analysis of Ongoing EEG by NTF During Real-World Music Experiences		179
5.1	Motivation	179
5.2	Third-Order Ongoing EEG Tensor of a Spectrogram	180
5.3	Musical Features of the Naturalistic Music	181
5.4	NTF on the Spectrogram of Ongoing EEG	183
5.5	Summary	187
5.6	Existing Problem and Solution	187
	References	187
Appendix Introduction to Basic Knowledge of Mismatch Negativity		191
A.1	Brief History of MMN	191
A.2	Paradigm to Elicit MMN	192
A.3	Basic Psychological Knowledge of MMN	195
A.4	Properties of MMN	195
	A.4.1 Temporal property	196
	A.4.2 Spectral property	196
	A.4.3 Time-frequency property	197
	A.4.4 Topography	199
	References	200