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Advanced State Space Methods for Neural and Clinical Data

This authoritative work provides an in-depth treatment of state space methods, with a range of applications in neural and clinical data.

Advanced and state-of-the-art research topics are detailed, including topics in state space analyses, maximum likelihood methods, variational Bayes, sequential Monte Carlo, Markov chain Monte Carlo, nonparametric Bayesian and deep learning methods. Details are provided on practical applications in neural and clinical data, whether this is characterizing time series data from neural spike trains recorded from the rat hippocampus, the primate motor cortex, or the human EEG, MEG or fMRI, or physiological measurements of heartbeats or blood pressures.

With real-world case studies of neuroscience experiments and clinical data sets, and written by expert authors from across the field, this is an ideal resource for anyone working in neuroscience and physiological data analysis.

Zhe Chen is Assistant Professor at the New York University School of Medicine, having previously worked at the RIKEN Brain Science Institute, Harvard Medical School, and Massachusetts Institute of Technology. He is a Senior Member of the IEEE and an editorial board member of *Neural Networks* (Elsevier). Professor Chen has received a number of awards including the Early Career Award from the Mathematical Biosciences Institute, and has had his work funded by the US National Science Foundation.

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CAMBRIDGE
UNIVERSITY PRESS

University Printing House, Cambridge CB2 8BS, United Kingdom

Cambridge University Press is part of the University of Cambridge.

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www.cambridge.org

Information on this title: www.cambridge.org/9781107079199

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First published 2015

Printed in the United Kingdom by TJ International Ltd, Padstow Cornwall

A catalogue record for this publication is available from the British Library

Library of Congress Cataloguing in Publication data

Advanced state space methods for neural and clinical data / edited by Zhe Chen.

p. ; cm.

Includes bibliographical references.

ISBN 978-1-107-07919-9 (Hardback)

I. Chen, Zhe, 1976–, editor.

[DNLN: 1. Models, Statistical. 2. Neurology. 3. Stochastic Processes. WL 100]
RC346

616.8001'1–dc23 2015003085

ISBN 978-1-107-07919-9 Hardback

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Contents

	<i>List of contributors</i>	page xv
	<i>Preface</i>	xix
1	Introduction	1
	Z. Chen	
	1.1 A brief overview of state space analysis	1
	1.1.1 Mathematical background	1
	1.1.2 Unobserved variables and stochastic dynamical systems	1
	1.1.2.1 State equation	2
	1.1.2.2 Observation equation	2
	1.1.3 Observability, controllability and stability	3
	1.1.4 Bayes' rule	3
	1.1.5 Recursive Bayesian estimation	4
	1.1.6 Two illustrated examples	5
	1.2 Inference and learning	7
	1.3 Applications in neuroscience and medicine	9
	References	10
2	Inference and learning in latent Markov models	14
	D. Barber and S. Chiappa	
	2.1 Probabilistic time series models	14
	2.1.1 A graphical depiction	14
	2.2 Fully observed Markov models	15
	2.2.1 Scalar higher-order and equivalent vector model	16
	2.3 Latent Markov models	17
	2.3.1 Inference in latent Markov models	18
	2.3.1.1 Filtering	18
	2.3.1.2 Parallel smoothing	19
	2.3.1.3 Correction smoothing	19
	2.3.1.4 Prediction	20
	2.3.2 Discrete state latent Markov models	20
	2.3.2.1 Explicit-duration models	21
	2.3.3 Continuous state latent Markov models	22

2.3.4	Inference in linear dynamical systems	23
2.4	The switching LDS	23
2.4.1	Exact inference is computationally intractable	24
2.4.2	Gaussian sum filtering	24
2.4.3	Gaussian sum smoothing	25
2.4.4	Clinical example	25
2.5	Reset models	29
2.6	Deterministic latent Markov models	30
2.6.1	Time-varying variance AR models	31
2.6.2	Parameter estimation	32
2.6.3	Neural models	33
2.6.3.1	Hopfield membrane potential	34
2.6.3.2	An augmented Hopfield network	35
2.6.3.3	Dynamic synapses	35
2.6.3.4	Leaky integrate-and-fire models	37
2.7	Approximate inference	38
2.7.1	Monte Carlo methods	38
2.7.2	Variational inference	39
2.7.3	Assumed density filtering and smoothing	39
2.7.4	Importance sampling	40
2.7.5	Sequential importance sampling	41
2.7.6	Particle filtering as assumed density filtering	42
2.8	Parameter estimation	43
2.8.1	Estimation in discrete state Markov models	44
2.8.2	Autoregressive (AR) models	45
2.8.3	Variational Bayes	46
2.9	Summary	47
	Acknowledgements	48
	References	48
Part I State space methods for neural data		51
3	State space methods for MEG source reconstruction	53
	M. Fukushima, O. Yamashita and M. Sato	
3.1	Introduction and problem formulation	53
3.2	Overview of source reconstruction methods	54
3.2.1	Norm regularization methods	55
3.2.2	Bayesian methods	56
3.2.3	State space methods	57
3.2.4	Challenges	57
3.2.5	Solutions	58
3.2.5.1	Reducing computation time	58
3.2.5.2	Reducing the number of parameters	58

3.3	Details of new methods	59
3.3.1	Diagonal state space method (dSSM)	59
3.3.1.1	Probabilistic model	59
3.3.1.2	Estimation algorithm	61
3.3.2	Full state space method (fSSM)	64
3.3.2.1	Probabilistic model	64
3.3.2.2	Estimation algorithm	65
3.3.2.3	Computation of structural connectivity	66
3.4	Results: method evaluation	66
3.4.1	Diagonal state space method (dSSM)	66
3.4.1.1	Simulation analysis	66
3.4.1.2	Real data analysis	68
3.4.2	Full state space method (fSSM)	69
3.4.2.1	Simulation analysis	69
3.4.2.2	Real data analysis	71
3.5	Discussion	71
3.6	Future directions	74
3.7	Conclusion	75
	Acknowledgments	75
	References	76
4	Autoregressive modeling of fMRI time series: state space approaches and the general linear model	79
	A. Galka, M. Siniatchkin, U. Stephani, K. Groening, S. Wolff, J. Bosch-Bayard and T. Ozaki	
4.1	Introduction	79
4.2	Structure of fMRI time series	81
4.3	Innovation approach and maximum-likelihood estimation	82
4.4	Maximum-likelihood estimation in practice	84
4.5	GenLM as a deterministic state space model	85
4.5.1	fMRI modeling by GenLM	85
4.5.2	Colored observation noise	86
4.5.3	A state space model for the HRF	87
4.5.4	From continuous time to discretized time	88
4.5.5	Introducing colored observation noise	89
4.5.6	The state space GenLM model	90
4.6	General linear state space models for fMRI	92
4.6.1	Multivariate AR/ARX models	92
4.6.2	Nearest-neighbor AR modeling	93
4.6.3	Spatial whitening	94
4.6.4	The NNARX model with spatial whitening	96
4.6.5	State space generalization of the NNARX model	96
4.6.6	The case of non-Gaussian data	97
4.6.7	The state space NNARX model with spatial whitening	98

4.7	Estimation of model parameters	99
4.7.1	NNARX model	99
4.7.2	GenLM-SS model	100
4.7.3	NNARX-SS model	101
4.8	Clinical fMRI time series example	102
4.8.1	Experimental setup and preprocessing	102
4.8.2	Numerical results of model fitting	104
4.8.3	Model comparison by AIC and BIC	104
4.8.4	Further results	106
4.9	Discussion	107
	Acknowledgments	110
	References	110
5	State space models and their spectral decomposition in dynamic causal modeling	114
	R. Moran	
5.1	Introduction	114
5.2	Overview of the literature	116
5.3	Methodology	119
5.3.1	A neural mass model in the time domain	119
5.3.2	State space formulation	122
5.3.2.1	Inhibitory cells in supragranular layers	122
5.3.2.2	Excitatory spiny cells in granular layers	122
5.3.2.3	Excitatory pyramidal cells in infragranular layers	123
5.3.3	A linear approximation to the neural mass model	123
5.3.4	The modulation transfer function using the linear approximation	124
5.3.4.1	Poles, zeros and Lyapunov exponents	125
5.3.5	Spectral generation in nonlinear models	126
5.4	Applications	127
5.5	Discussion	130
	References	133
6	Estimating state and parameters in state space models of spike trains	137
	J. H. Macke, L. Buesing and M. Sahani	
6.1	Introduction	137
6.1.1	State space models for neural population spike trains	137
6.1.2	PLDS models in context	138
6.2	State space models with linear dynamics and count-process observations	139
6.3	Reconstructing the state from neural spike trains	141
6.3.1	Inferring the state using the Laplace approximation	142
6.3.2	Inferring the state distribution using Gaussian variational inference	144
6.4	Estimating model parameters	147

6.4.1	Expectation maximization (EM): estimating parameters via iteratively optimizing a cost function	147
6.4.2	Learning parameters of the model through spectral learning	149
6.4.2.1	Subspace-ID for GLDS models	150
6.4.2.2	Subspace-ID for the PLDS model by moment conversion	151
6.5	Results	152
6.6	Discussion	155
6.7	Summary	155
	Acknowledgements	156
	References	156
7	Bayesian inference for latent stepping and ramping models of spike train data	160
	K. W. Latimer, A. C. Huk and J. W. Pillow	
7.1	Background: dynamics of neural decision making	160
7.2	Overview	161
7.3	Point-process models of decision making	163
7.3.1	Markov chain Monte Carlo (MCMC) inference	164
7.3.2	Diffusion-to-bound model	166
7.3.2.1	Inference for diffusion-to-bound model	168
7.3.2.2	Step 1: Sampling the latent trajectories	168
7.3.2.3	Step 2: Sampling the parameters	171
7.3.3	Switching model	173
7.3.3.1	Step 1: Sampling the latent states	175
7.3.3.2	Step 2: Sampling the parameters	176
7.3.4	Model comparison	177
7.4	Results	178
7.4.1	Comparison to moment-based methods	180
7.5	Discussion	182
7.6	Conclusion	183
	Acknowledgments	183
	References	184
8	Probabilistic approaches to uncover rat hippocampal population codes	186
	Z. Chen, F. Kloosterman and M. A. Wilson	
8.1	Background	186
8.2	Decode unsorted neuronal spikes from the rat hippocampus	186
8.2.1	Overview	186
8.2.2	Bayesian decoding	187
8.2.3	Likelihood for a spatiotemporal Poisson process	188
8.2.4	Kernel density estimation (KDE)	190
8.2.5	Recursive Bayesian estimation via state space analysis	192

8.2.6	Experimental result	193
8.3	Uncover neural representation of hippocampal population codes	195
8.3.1	Overview	195
8.3.2	Probabilistic generative model: spatial navigation as a Markov chain	196
8.3.3	Variational Bayes (VB) inference	196
8.3.4	Visualization as a topology graph	198
8.3.5	Experimental result	198
8.4	Discussion and future work	201
8.4.1	Spike sorting-free decoding	201
8.4.2	Model selection for HMM	201
8.4.3	Overdispersed Poisson model	202
8.4.4	Analysis of sleep-associated ensemble spike data	202
8.5	Conclusion	202
	Acknowledgments	203
	References	203
9	Neural decoding in motor cortex using state space models with hidden states	207
	W. Wu and S. Liu	
9.1	Introduction	207
9.1.1	Previous methods and their limitations	208
9.1.2	Hidden state framework	209
9.2	Classical state space models	209
9.2.1	Kalman filter model	210
9.2.2	Generalized linear model (GLM)	211
9.3	State space framework with hidden states	212
9.3.1	Kalman filter model with hidden states	212
9.3.1.1	Model identification of KFHS	212
9.3.1.2	Decoding using KFHS	214
9.3.2	Generalized linear model with hidden states	215
9.3.2.1	Model identification of GLMHS	216
9.3.2.2	Decoding using GLMHS	217
9.4	Application in experimental data	218
9.4.1	Data collection	218
9.4.2	Identification in the KFHS model	219
9.4.3	Identification in the GLMHS model	220
9.4.3.1	IPP case	220
9.4.3.2	NPP case	222
9.4.4	Decoding using KFHS and GLMHS	222
9.5	Discussion	224
9.6	Conclusion	226
	Acknowledgements	227
	References	227

10	State space modeling for analysis of behavior in learning experiments	231
	A. C. Smith	
10.1	Introduction	231
10.2	Literature overview	232
10.2.1	Methods for analysis of learning	232
10.2.2	State space analysis of learning	232
10.3	Methods	233
10.4	Results	237
10.4.1	Learning in an example data set	237
10.4.2	Response bias	239
10.4.2.1	Response bias in an example T-maze task	240
10.4.2.2	Response bias in an object–place association task	242
10.4.3	Deep brain stimulation: comparison with logistic regression	244
10.5	Discussion	247
10.6	Limitations and future directions	248
10.7	Conclusions	249
	Acknowledgements	249
	References	249
Part II	State space methods for clinical data	255
11	Bayesian nonparametric learning of switching dynamics in cohort physiological time series: application in critical care patient monitoring	257
	L. H. Lehman, M. J. Johnson, S. Nemati, R. P. Adams and R. G. Mark	
11.1	Introduction	257
11.2	Bayesian nonparametric switching Markov modeling of cohort time series	258
11.2.1	Overview of Bayesian nonparametric learning of switching Markov processes	258
11.2.1.1	The AR-HMM	259
11.2.1.2	The MNIW prior for the VAR dynamic parameters	259
11.2.1.3	The HDP prior for the HMM	259
11.2.1.4	The sticky HDP-AR-HMM and HDP-AR-HSMM	260
11.2.1.5	The BP-AR-HMM	261
11.2.2	Inference algorithms and implementations	262
11.2.2.1	A Gibbs sampler for the sticky HDP-AR-HMM	263
11.2.2.2	Sampling $z_{1:T} \pi, \theta, y_{1:T}$	264
11.2.2.3	Sampling $\theta z_{1:T}, y_{1:T}$	264
11.2.2.4	Sampling $\beta, \pi z_{1:T}$	265
11.2.2.5	MCMC for the HDP-AR-HSMM and BP-AR-HMM	266
11.2.2.6	Computational complexity and scalability	267
11.3	Materials and methods	267
11.3.1	Data sets	268

	11.3.1.1 Tilt-table experiment	268
	11.3.1.2 MIMIC II data set	268
	11.3.2 Bayesian nonparametric model settings	268
	11.3.2.1 MNIW prior settings	268
	11.3.2.2 Sticky HDP-AR-HMM settings	269
	11.3.2.3 HDP-AR-HSMM settings	269
	11.3.2.4 BP-AR-HMM settings	269
	11.3.3 Evaluation methods and statistical analysis	270
	11.3.3.1 Time series classification and patient risk stratification	270
	11.3.3.2 MIMIC association analysis	270
11.4	Results	271
	11.4.1 Tilt-table experiment	271
	11.4.2 MIMIC II: performance in estimating mortality risks of patients	271
	11.4.3 MIMIC II association analysis	272
	11.4.4 Example blood pressure dynamics of survivors vs. non-survivors	274
	11.4.4.1 Evolution of cardiovascular dynamics of survivor vs. non-survivor	274
11.5	Discussion and conclusion	274
	Acknowledgments	279
	References	279
12	Identifying outcome-discriminative dynamics in multivariate physiological cohort time series	283
	S. Nemati and R. P. Adams	
	12.1 Background	283
	12.2 Time series classification and switching vector autoregressive modeling	285
	12.2.1 Marginals-based learning via error back-propagation	287
	12.2.1.1 Global label from hidden state proportions	287
	12.2.1.2 Sequential labels from local marginals	288
	12.3 Experiments	289
	12.3.1 Simulated time series with switching dynamics	289
	12.3.2 Tilt-table experiment	290
	12.3.3 Decoding cortical local field potentials	293
	12.4 Discussion and conclusion	295
	Acknowledgments	296
	Appendix	297
	References	300
13	A dynamic point process framework for assessing heartbeat dynamics and cardiovascular functions	302
	Z. Chen and R. Barbieri	
	13.1 Introduction	302
	13.2 Model-based approaches	303

13.3	Overview of the point process framework	304
13.3.1	Probability models for the heartbeat interval	304
13.3.2	Instantaneous indices of HR and HRV	306
13.3.3	Autonomic cardiovascular control and modeling heartbeat dynamics	307
13.3.3.1	Wiener–Volterra expansions	307
13.4	State space analysis applied to point process models	310
13.4.1	Adaptive point process filtering	310
13.4.2	Time-varying frequency analysis	311
13.4.2.1	Estimating the feedback-loop frequency response	311
13.4.2.2	Estimating the feedforward-loop frequency response	312
13.4.2.3	Estimating the dynamic R-R spectrum	312
13.4.2.4	Estimating the dynamic coherence	313
13.4.3	Time-varying bispectrum and nonlinearity assessment	313
13.4.4	Modeling trend nonstationarity of heartbeat time series	314
13.4.5	Model order selection and goodness-of-fit assessment	315
13.5	Experimental data and results	316
13.5.1	Tilt-table protocol data	316
13.5.2	General anesthesia data	317
13.5.2.1	Tracking examples and estimated indices	317
13.5.2.2	Example of applying the ARIMA model	319
13.5.3	Correlation assessment between brain and autonomic activity	321
13.6	Discussion and future work	323
13.6.1	Modeling robustness	323
13.6.2	Strengths and limitations	323
13.6.3	Application in real-time clinical monitoring	324
13.7	Conclusion	325
	Acknowledgments	325
	References	326
14	Real-time segmentation and tracking of brain metabolic state in ICU EEG recordings of burst suppression	330
	M. B. Westover, S. Ching, M. M. Shafi, S. S. Cash and E. N. Brown	
14.1	Introduction	330
14.2	Background	331
14.2.1	Neurophysiology of burst suppression	331
14.2.2	Existing models of burst suppression	332
14.3	Methods	333
14.4	Probabilistic modeling and estimation of burst suppression	333
14.4.1	Simplified burst suppression model	333
14.4.2	Estimation of burst suppression level via BSP	337
14.4.3	Automatic EEG segmentation	337
14.4.4	State space modeling of burst suppression	338

14.4.5	Inference of metabolic state	339
14.5	Conclusion	342
14.5.1	Summary	342
14.5.2	Future directions	343
	Acknowledgments	343
	References	343
15	Signal quality indices for state space electrophysiological signal processing and vice versa	345
	J. Oster and G. D. Clifford	
15.1	Background	345
15.2	State space fusion approach for improved heart rate estimation	346
15.2.1	State-of-the-art	347
15.2.2	Method	348
15.2.2.1	SQIs for ECG	348
15.2.2.2	State space modeling for heart rate estimation	349
15.2.3	Results	351
15.2.4	Discussion	352
15.3	State space filtering for signal quality evaluation	353
15.3.1	State-of-the-art	353
15.3.2	Theory	355
15.3.2.1	ECG model-based Bayesian filtering	355
15.3.2.2	Switching Kalman filters	356
15.3.2.3	The X-factor	356
15.3.3	Method	357
15.3.4	Results	358
15.3.5	Discussion	359
15.4	Limitations and future directions	361
15.5	Conclusion	362
	Acknowledgments	362
	References	363
	<i>Index</i>	367

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Cambridge University Press

978-1-107-07919-9 - Advanced State Space Methods for Neural and Clinical Data

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Preface

In the modern age of the digital world, gigantic amounts of data have been recorded or collected. It remains a great challenge to process and analyze the “big data”. Many neurophysiological, physiological, clinical and behavioral data are dynamic by the nature of the experiments or the way they are collected. These signals could be complex, noisy, and often multivariate and multimodal. How to develop efficient statistical methods to characterize these data and extract information that reveals underlying biological or physiological mechanisms remains an active and important research topic. In recent years, numerous advanced computational statistics, signal processing, and machine-learning methods have been developed and there is rapidly growing interest in applying these methods to data analysis in neuroscience, physiology and medicine.

The state space model (SSM) is referred to a class of probabilistic graphical models (Koller & Friedman 2009), which describe the probabilistic dependence between the latent state variable and the observed measurement. The state or the measurement can be either continuous or discrete. The term “state space” originated in 1960s in the area of control engineering (Kalman 1960). SSM provides a general framework for analyzing deterministic and stochastic dynamical systems that are measured or observed through a stochastic process. The SSM framework has been successfully applied in engineering, statistics, computer science and economics to solve a broad range of dynamical systems problems. The most celebrated examples of SSM include the linear dynamical system and the associated inference algorithm: Kalman filter (Kalman 1960), and the hidden Markov model (HMM) (Rabiner 1989). Despite plenty of successful examples applying state space analyses to neural and clinical data, there remain many challenges in data analysis, for either developing new mathematical theories and statistical models, or developing efficient algorithms tuned for large-scale data sets, or catering for highly complex (multimodal or multiscale) and nonstationary data. In order to pave the way for further advancement in these research areas, it is important to recognize these challenges and exchange new ideas among researchers and practitioners.

It is important to point out that the modeling and analysis principles discussed in this book are general and equally valuable for time series analyses in many other disciplines, such as climatology, politics, finance, chemical engineering, consumer marketing and computer networking.

Road map and readership

This edited volume aims to recognize these challenges and provide a forum to discuss new ideas and new applications along the line of SSMs and state space analysis. Active and expert researchers with diverse backgrounds have contributed their recent innovative work and shared their critical thinking with the reader who have special interests in signal processing or statistical analysis as applied to the aforementioned research fields. The topics of this edited volume include switching SSMs, Bayesian inference, variational and Monte Carlo methods, EEG (electroencephalography) or MEG (magnetoencephalography) inverse problems, neural decoding and prosthetics, cardiovascular signal processing, data mining and onsite clinical monitoring.

The book is divided into two main parts. The first part focuses on state space modeling and analysis for neural data, and the second part focuses on state space methods for clinical data. Each chapter covers a specific topic of the SSM or its application area. Individual chapters are content independent and can be read or used separately for educational purpose. For starters, it is recommended to follow the arranged chapter order to study the materials.

The first two chapters are for pedagogic purpose. Following the introductory Chapter 1, Chapter 2 by Barber and Chiappa presents a tutorial overview of latent Markov models and related inference or learning methods. Part I consists of eight chapters (Chapters 3 through 10). Chapter 3 by Fukushima, Yamashita and Sato presents a detailed overview of state space methods for MEG source reconstruction problem. Chapter 4 by Galka and colleagues discusses autoregressive (AR) modeling of fMRI (functional magnetic resonance imaging) time series using state space analysis. Chapter 5 by Moran discusses SSMs and their spectral decomposition in dynamic causal modeling. Chapter 6 by Macke, Büsing and Sahani discusses the estimation of state and model parameters in SSMs of spike train observations. Chapter 7 by Latimer, Huk and Pillow discusses Bayesian inference for a class of latent stepping and ramping models derived from neuronal spike train data. Chapter 8 by Chen, Kloosterman and Wilson presents probabilistic approaches to analyze rat hippocampal ensemble spike data. Chapter 9 by Wu and Liu is dedicated to neural coding in motor cortex using SSMs with hidden states. Chapter 10 by Smith focuses on state space analysis of behavioral data in learning experiments. Part II consists of five chapters (Chapters 11 through 15). Chapter 11 by Lehman and colleagues presents a method for discovering shared dynamics in physiological time series and illustrates its application to patient monitoring in intensive care unit. Chapter 12 by Nemati and Adams presents a new approach to identify outcome-discriminative dynamics in multivariate physiological cohort time series. Chapter 13 by Chen and Barbieri presents a dynamic point process framework for assessing heartbeat dynamics and cardiovascular functions. Chapter 14 by Westover and colleagues presents a modeling and control platform for burst suppression in the case of managing medical coma. Finally, Chapter 15 by Oster and Clifford discusses the signal quality indices for state space electrophysiological signal processing.

Despite many diverse research themes, several important topics have been repeatedly visited in many chapters:

- Adaptive Bayesian filtering methods, which include the Kalman filter (Chapters 4, 9 and 15), particle filter (Chapter 7) and point process filter (Chapters 8 and 13).
- Switching probabilistic models, which include the switching AR model (Chapters 2, 11 and 12), switching Kalman filter (Chapters 2 and 15) and switching HMM (Chapters 2 and 11).
- The expectation maximization (EM) algorithm and its variants (Chapters 4, 6, 8, 9 and 12).
- Variational Bayes (VB) methods (Chapters 3 and 8).
- Markov chain Monte Carlo (MCMC) methods (Chapters 6, 7, 10 and 11).

This book will expect a wide range of readers (electrical/biomedical/medical engineers, statisticians, and computer scientists). As a practical guide, the book will appeal to researchers interested in applying statistics, signal processing and machine-learning techniques to neural and clinical data. State-of-the-art techniques and a comprehensive bibliography are provided. As an educational source, the book can also be used as complementary teaching material for graduate students in engineering or medical schools. No specific knowledge is required to read this book, although a basic background in probability theory would be helpful.

It is noteworthy that the topic of SSM is rather broad, and it is nearly impossible to cover every aspect or all technical details in this volume. As complementary reading materials, several excellent books may be used for study:

- Barber, D., Cemgil, A. T. & Chiappa, S., editors (2011). *Bayesian Time Series Models*, Cambridge University Press.
- Ozaki, T. (2012). *Time Series Modeling of Neuroscience Data*, Chapman & Hall/CRC Press.
- Oweiss, K. G., editor (2010). *Statistical Signal Processing for Neuroscience and Neurotechnology*, Academic Press.
- Durbin, J. & Koopman S. J. (2001). *Time Series Analysis by State Space Methods*, Oxford University Press.
- Cohen, M. X. (2014). *Analyzing Neural Time Series Data: Theory and Practice*, MIT Press.

Acknowledgments

I am very grateful to the editors and staff members of Cambridge University Press. In particular, Michelle Carey has been a constant source of encouragement and support since the beginning of this book project. From the start of the project, Heather Brolly has helped me keep everything in order. I would like to thank the generous support of the US National Science Foundation (NSF) and National Institutes of Health (NIH);

I also thank the support of the New York University School of Medicine, including my department chairs – Professor Charles Marmar (Department of Psychiatry) and Professor Richard Tsien (Department of Neuroscience and Physiology). I would like to thank the valuable input, review comments and proofreading from a few colleagues.

The brain mosaic image used in the book cover illustration was originally generated by Dr. Akira O'Connor (University of St Andrews, Scotland). With his kind permission, I further modified and edited it to the current form.

References

- Kalman, R. E. (1960). A new approach to linear filtering and prediction problems. *Transactions of the ASME–Journal of Basic Engineering* **82**, 35–45.
- Koller, D. & Friedman, N. (2009). *Probabilistic Graphical Models: Principles and Techniques*, Cambridge, MA: MIT Press.
- Rabiner, L. R. (1989). A tutorial on hidden Markov models and selected applications in speech recognition. *Proceedings of the IEEE* **77**(2), 257–286.