

---

# Contents

---

<b>INTRODUCTION</b> . . . . .	xi
Jean-François GIOVANNELLI and Jérôme IDIER	
<b>CHAPTER 1. 3D RECONSTRUCTION IN X-RAY TOMOGRAPHY: APPROACH EXAMPLE FOR CLINICAL DATA PROCESSING</b> . . . . .	1
Yves GOUSSARD	
1.1. Introduction . . . . .	1
1.2. Problem statement . . . . .	2
1.2.1. Data formation models . . . . .	2
1.2.2. Estimators . . . . .	5
1.2.3. Algorithms . . . . .	5
1.3. Method . . . . .	7
1.3.1. Data formation models . . . . .	7
1.3.2. Estimator . . . . .	10
1.3.3. Minimization method . . . . .	11
1.3.4. Implementation of the reconstruction procedure . . . . .	14
1.4. Results . . . . .	15
1.4.1. Comparison of minimization algorithms . . . . .	15
1.4.2. Using a region of interest in reconstruction . . . . .	18
1.4.3. Consideration of the polyenergetic character of the source . . . . .	21
1.5. Conclusion . . . . .	26
1.6. Acknowledgments . . . . .	27
1.7. Bibliography . . . . .	28
<b>CHAPTER 2. ANALYSIS OF FORCE-VOLUME IMAGES IN ATOMIC FORCE MICROSCOPY USING SPARSE APPROXIMATION</b> . . . . .	31
Charles SOUSSEN, David BRIE, Grégory FRANCIUS, Jérôme IDIER	
2.1. Introduction . . . . .	31

2.2. Atomic force microscopy . . . . .	32
2.2.1. Biological cell characterization . . . . .	32
2.2.2. AFM modalities . . . . .	33
2.2.3. Physical piecewise models . . . . .	37
2.3. Data processing in AFM spectroscopy . . . . .	40
2.3.1. Objectives and methodology in signal processing . . . . .	40
2.3.2. Segmentation of a force curve by sparse approximation . . . . .	41
2.4. Sparse approximation algorithms . . . . .	43
2.4.1. Minimization of a mixed $\ell_2$ - $\ell_0$ criterion . . . . .	44
2.4.2. Dedicated algorithms . . . . .	44
2.4.3. Joint detection of discontinuities . . . . .	46
2.5. Real data processing . . . . .	49
2.5.1. Segmentation of a retraction curve: comparison of strategies . . . . .	49
2.5.2. Retraction curve processing . . . . .	50
2.5.3. Force-volume image processing in the approach phase . . . . .	52
2.6. Conclusion . . . . .	52
2.7. Bibliography . . . . .	53
<b>CHAPTER 3. POLARIMETRIC IMAGE RESTORATION BY NON-LOCAL MEANS . . . . .</b>	<b>57</b>
Sylvain FAISAN, François ROUSSEAU, Christian HEINRICH, Jihad ZALLAT	
3.1. Introduction . . . . .	57
3.2. Light polarization and the Stokes–Mueller formalism . . . . .	58
3.3. Estimation of the Stokes vectors . . . . .	61
3.3.1. Estimation of the Stokes vector in a pixel . . . . .	61
3.3.2. Non-local means filtering . . . . .	64
3.3.3. Adaptive non-local means filtering . . . . .	66
3.3.4. Application to the estimation of Stokes vectors . . . . .	69
3.4. Results . . . . .	72
3.4.1. Results with synthetic data . . . . .	72
3.4.2. Results with real data . . . . .	75
3.5. Conclusion . . . . .	77
3.6. Bibliography . . . . .	78
<b>CHAPTER 4. VIDEO PROCESSING AND REGULARIZED INVERSION METHODS . . . . .</b>	<b>81</b>
Guy LE BESNERAIS, Frédéric CHAMPAGNAT	
4.1. Introduction . . . . .	81
4.2. Three applications . . . . .	82
4.2.1. PIV and estimation of optical flow . . . . .	82
4.2.2. Multiview stereovision . . . . .	84
4.2.3. Superresolution and non-translational motion . . . . .	86

4.3. Dense image registration . . . . .	88
4.3.1. Direct formulation . . . . .	90
4.3.2. Variational formulation . . . . .	91
4.3.3. Extension of direct formulation for multiview processing . . . . .	92
4.4. A few achievements based on direct formulation . . . . .	92
4.4.1. Dense optical flow by correlation of local window . . . . .	92
4.4.2. Occlusion management in multiview stereovision . . . . .	97
4.4.3. Direct models for SR . . . . .	99
4.5. Conclusion . . . . .	104
4.6. Bibliography . . . . .	106

**CHAPTER 5. BAYESIAN APPROACH IN PERFORMANCE MODELING:  
APPLICATION TO SUPERRESOLUTION . . . . . 109**

Frédéric CHAMPAGNAT, Guy LE BESNERAIS, Caroline KULCSÁR

5.1. Introduction . . . . .	109
5.1.1. The hiatus between performance modeling and Bayesian inversion . . . . .	109
5.1.2. Chapter organization . . . . .	110
5.2. Performance modeling and Bayesian paradigm . . . . .	111
5.2.1. An empirical performance evaluation tool . . . . .	111
5.2.2. Usefulness and limits of a performance evaluation tool . . . . .	111
5.2.3. Bayesian formalism . . . . .	113
5.3. Superresolution techniques behavior . . . . .	113
5.3.1. Superresolution . . . . .	114
5.3.2. SR methods performance: known facts . . . . .	115
5.3.3. An SR experiment . . . . .	117
5.3.4. Performance model and properties . . . . .	122
5.4. Application examples . . . . .	126
5.4.1. Behavior of the optimal filter with regard to the number of images . . . . .	127
5.4.2. Characterization of an approximation: shifts rounding . . . . .	129
5.5. Real data processing . . . . .	130
5.5.1. A concrete measure to improve the resolution: the RER . . . . .	132
5.5.2. Empirical validation and application field . . . . .	134
5.6. Conclusion . . . . .	136
5.7. Bibliography . . . . .	137

**CHAPTER 6. LINE SPECTRA ESTIMATION FOR IRREGULARLY  
SAMPLED SIGNALS IN ASTROPHYSICS . . . . . 141**

Sébastien BOURGUIGNON, Hervé CARFANTAN

6.1. Introduction . . . . .	141
6.2. Periodogram, irregular sampling, maximum likelihood . . . . .	144
6.3. Line spectra models: spectral sparsity . . . . .	146
6.3.1. An inverse problem with sparsity prior information . . . . .	147
6.3.2. Difficulties in terms of sparse approximation . . . . .	149

6.4. Prewhitening, CLEAN and greedy approaches . . . . .	151
6.4.1. Standard greedy algorithms . . . . .	151
6.4.2. A more complete iterative method: single best replacement . . . . .	153
6.4.3. CLEAN-based methods . . . . .	154
6.5. Global approach and convex penalization . . . . .	155
6.5.1. Significance of $\ell_1$ penalization in $\mathbb{C}$ . . . . .	156
6.5.2. Existence and uniqueness . . . . .	156
6.5.3. Minimizer and regularization parameter characterization . . . . .	157
6.5.4. Amplitude bias and <i>a posteriori</i> corrections . . . . .	157
6.5.5. Hermitian symmetry and specificity of the zero frequency . . . . .	158
6.5.6. Optimization algorithms . . . . .	158
6.5.7. Results . . . . .	159
6.6. Probabilistic approach for sparsity . . . . .	159
6.6.1. Bernoulli–Gaussian model for spectral analysis . . . . .	160
6.6.2. A structure adapted to the use of MCMC methods . . . . .	161
6.6.3. An extended BG model for improved accuracy . . . . .	162
6.6.4. Stochastic simulation and estimation . . . . .	162
6.6.5. Results . . . . .	163
6.7. Conclusion . . . . .	164
6.8. Bibliography . . . . .	165
<b>CHAPTER 7. JOINT DETECTION-ESTIMATION IN FUNCTIONAL MRI . . . . .</b>	<b>169</b>
Philippe CIUCIU, Florence FORBES, Thomas VINCENT, Lotfi CHAARI	
7.1. Introduction to functional neuroimaging . . . . .	169
7.2. Joint detection-estimation of brain activity . . . . .	171
7.2.1. Detection and estimation: two interdependent issues . . . . .	171
7.2.2. Hemodynamics physiological hypotheses . . . . .	173
7.2.3. Spatially variable convolutive model . . . . .	175
7.2.4. Regional generative model . . . . .	176
7.3. Bayesian approach . . . . .	178
7.3.1. Likelihood . . . . .	178
7.3.2. <i>A priori</i> distributions . . . . .	178
7.3.3. <i>A posteriori</i> distribution . . . . .	182
7.4. Scheme for stochastic MCMC inference . . . . .	183
7.4.1. HRF and NRLs simulation . . . . .	183
7.4.2. Unsupervised spatial and spatially adaptive regularization . . . . .	184
7.5. Alternative variational inference scheme . . . . .	184
7.5.1. Motivations and foundations . . . . .	184
7.5.2. Variational EM algorithm . . . . .	186
7.6. Comparison of both types of solutions . . . . .	190
7.6.1. Experiments on simulated data . . . . .	190
7.6.2. Experiments on real data . . . . .	193

7.7. Conclusion . . . . .	194
7.8. Bibliography . . . . .	195

**CHAPTER 8. MCMC AND VARIATIONAL APPROACHES FOR BAYESIAN INVERSION IN DIFFRACTION IMAGING . . . . . 201**

Hacheme AYASSO, Bernard DUCHÊNE, Ali MOHAMMAD-DJAFARI

8.1. Introduction . . . . .	201
8.2. Measurement configuration . . . . .	204
8.2.1. The microwave device . . . . .	204
8.2.2. The optical device . . . . .	205
8.3. The forward model . . . . .	206
8.3.1. The microwave case . . . . .	207
8.3.2. The optical case . . . . .	207
8.3.3. The discrete model . . . . .	208
8.3.4. Validation of the forward model . . . . .	210
8.4. Bayesian inversion approach . . . . .	211
8.4.1. The MCMC sampling method . . . . .	213
8.4.2. The VBA method . . . . .	214
8.4.3. Initialization, progress and convergence of the algorithms . . . . .	217
8.5. Results . . . . .	220
8.6. Conclusions . . . . .	220
8.7. Bibliography . . . . .	222

**CHAPTER 9. VARIATIONAL BAYESIAN APPROACH AND BI-MODEL FOR THE RECONSTRUCTION-SEPARATION OF ASTROPHYSICS COMPONENTS . . . . . 225**

Thomas RODET, Aurélia FRAYSSE, Hacheme AYASSO

9.1. Introduction . . . . .	225
9.2. Variational Bayesian methodology . . . . .	228
9.3. Exponentiated gradient for variational Bayesian . . . . .	229
9.4. Application: reconstruction-separation of astrophysical components . . . . .	232
9.4.1. Direct model . . . . .	232
9.4.2. <i>A priori</i> distributions . . . . .	234
9.4.3. <i>A posteriori</i> distribution . . . . .	235
9.5. Implementation of the variational Bayesian approach . . . . .	236
9.5.1. Separability study . . . . .	236
9.5.2. Update of the approximation distributions . . . . .	236
9.6. Results . . . . .	240
9.6.1. Simulated data . . . . .	241
9.6.2. Real data . . . . .	244
9.7. Conclusion . . . . .	246
9.8. Bibliography . . . . .	246

<b>CHAPTER 10. KERNEL VARIATIONAL APPROACH FOR TARGET TRACKING IN A WIRELESS SENSOR NETWORK</b>	251
Hichem SNOUSSI, Paul HONEINE, Cédric RICHARD	
10.1. Introduction	251
10.2. State of the art: limitations of existing methods	252
10.3. Model-less target tracking	254
10.3.1. Construction of the likelihood by matrix regression	255
10.3.2. Variational filtering for the tracking of mobile objects	258
10.4. Simulation results	261
10.5. Conclusion	264
10.6. Bibliography	264
<b>CHAPTER 11. ENTROPIES AND ENTROPIC CRITERIA</b>	267
Jean-François BERCHER	
11.1. Introduction	267
11.2. Some entropies in information theory	268
11.2.1. Main properties and definitions	268
11.2.2. Entropies and divergences in the continuous case	270
11.2.3. Maximum entropy	272
11.2.4. Escort distributions	272
11.3. Source coding with escort distributions and Rényi bounds	273
11.3.1. Source coding	274
11.3.2. Source coding with Campbell measure	274
11.3.3. Source coding with escort mean	275
11.4. A simple transition model	277
11.4.1. The model	277
11.4.2. The Rényi divergence as a consequence	279
11.4.3. Fisher information for the parameter $q$	279
11.4.4. Distribution inference with generalized moment constraint	281
11.5. Minimization of the Rényi divergence and associated entropies	281
11.5.1. Minimization under generalized moment constraint	282
11.5.2. A few properties of the partition functions	283
11.5.3. Entropic functionals derived from the Rényi divergence	285
11.5.4. Entropic criteria	287
11.6. Bibliography	289
<b>LIST OF AUTHORS</b>	293
<b>INDEX</b>	297