

Chein-I Chang

Real-Time Progressive Hyperspectral Image Processing

Endmember Finding and Anomaly Detection

Contents

1	Overview and Introduction	1
1.1	Introduction	2
1.2	Why Real-Time Processing?	4
1.3	Various Processes	7
1.3.1	Sample-Wise Progressive Sample Processes	8
1.3.2	Band-Wise Progressive Band Processes	10
1.3.3	Recursive Processes	11
1.3.4	Real-Time Processes	12
1.3.5	Causal Processes	12
1.3.6	Parallel Processes	13
1.3.7	Other Processes	14
1.4	Scope of Book	15
1.4.1	PART I: Preliminaries	15
1.4.2	PART II: Sequential Endmember-Finding Algorithms	16
1.4.3	PART III: Progressive Endmember-Finding Algorithms	17
1.4.4	PART IV: Hyperspectral Anomaly Detection	17
1.5	Simulated Data to Be Used in This Book	18
1.5.1	Laboratory Data	18
1.5.2	Cuprite Data	18
1.6	Real Hyperspectral Images to Be Used in This Book	19
1.6.1	AVIRIS Data	19
1.6.2	HYDICE Data	22
1.7	Synthetic Images to Be Used in This Book	26
1.8	How to Use This Book	30
1.9	Notations and Terminologies to Be Used in This Book	30
	References	32

Part I Preliminaries

2	Linear Spectral Mixture Analysis	37
2.1	Introduction.	37
2.2	Solving LSMA Problems	39
2.2.1	Least Squares Error (LSE).	39
2.2.2	Signal to Noise Ratio (SNR)	39
2.3	Abundance-Constrained LSMA	40
2.3.1	Abundance Sum-to-One Constrained LSMA	41
2.3.2	Abundance Non-negativity Constrained LSMA	42
2.3.3	Abundance Fully Constrained LSMA	44
2.3.4	Modified FCLS	44
2.4	Weighted LSMA	48
2.4.1	Weighting Matrix Derived from Parameter Estimation Perspective	50
2.4.2	Weighting Matrix Derived from Fisher's Linear Discriminant Analysis Perspective	51
2.4.3	Weighting Matrix Derived from Orthogonal Subspace Projection Perspective.	52
2.5	Kernel-Based WAC-LSMA	54
2.5.1	$A =$ Inverse of Covariance Matrix, K^{-1}	57
2.5.2	$A =$ Inverse of Covariance Matrix, R^{-1}	58
2.5.3	$A =$ Inverse of Within-Class Matrix, S_W^{-1}	58
2.5.4	$A =$ Unwanted Signature Projection Matrix, $P_{U_\phi}^\perp$	60
2.5.5	$A =$ Signature Projection Matrix, P_{M_ϕ}	61
2.5.6	Note on Kernelization.	61
2.6	Unsupervised LSMA	62
2.6.1	Least Squares-Based Approaches for Finding Signatures	63
2.6.2	Component Analysis-Based Approaches for Finding Signatures.	69
2.7	Conclusions.	72
	References	72
3	Finding Endmembers in Hyperspectral Imagery	75
3.1	Introduction.	75
3.2	Issues of Characterizing Endmembers	76
3.2.1	Endmember Variability	77
3.2.2	Endmember Discriminability	77
3.3	Issues of Finding Endmembers.	77
3.4	Issues of Implementating EFAS	78
3.5	Criteria for Finding Endmembers	79
3.5.1	Orthogonal Projection	79
3.5.2	Convex Cone Volume Analysis	85
3.5.3	Simplex Volume Analysis	86

- 3.5.4 Least Squares Error 95
- 3.5.5 Sample Spectral Statistics 98
- 3.5.6 Non-negative Matrix Factorization 101
- 3.6 Conclusions. 101
- References 102
- 4 Linear Spectral Unmixing With Three Criteria, Least Squares Error, Simplex Volume and Orthogonal Projection 105**
 - 4.1 Introduction. 105
 - 4.2 Linear Spectral Unmixing and Simplex Volume. 108
 - 4.3 Linear Spectral Unmixing and Least Squares Abundance Fraction Estimates 113
 - 4.4 Linear Spectral Unmixing and Orthogonal Subspace Projection 114
 - 4.5 Synthetic Image Experiments. 116
 - 4.6 Real Image Experiments 124
 - 4.7 Conclusions. 128
 - References 128
- 5 Hyperspectral Target Detection 131**
 - 5.1 Introduction. 131
 - 5.2 Active Target Detection 132
 - 5.2.1 Target Detection Using Complete Target Knowledge: Supervised Target Detection 132
 - 5.2.2 Target Detection Using Partial Target Knowledge: Semi-supervised Target Detection. 135
 - 5.2.3 Target Detection Using no Prior Target Knowledge . . . 145
 - 5.3 Passive Target Detection 148
 - 5.3.1 Anomaly Detection. 148
 - 5.3.2 Endmember Finding 164
 - 5.4 Conclusions. 167
 - References 170

Part II Sample-Wise Sequential Processes for Finding Endmembers

- 6 Fully Geometric-Constrained Sequential Endmember Finding: Simplex Volume Analysis-Based N-FINDR 175**
 - 6.1 Introduction. 176
 - 6.2 Sequential Versions of N-FINDR 178
 - 6.2.1 SeQUential N-FINDR (SQ N-FINDR). 179
 - 6.2.2 SuCcessive N-FINDR (SC N-FINDR). 180
 - 6.3 Random Issues of Implementing N-FINDR 181
 - 6.3.1 EIA-Driven N-FINDR. 181
 - 6.3.2 Iterative N-FINDR 182
 - 6.3.3 Random N-FINDR 186

6.4	Finding Feasible Regions for N-FINDR	188
6.4.1	Data Sphering	188
6.4.2	PPI.	189
6.4.3	Random PPI	189
6.4.4	History of Development of N-FINDR	189
6.5	Causal and Real-Time N-FINDR	191
6.5.1	Real-Time SQ N-FINDR	191
6.5.2	Real-Time Circular N-FINDR	193
6.6	Multiple-Pass Sequential N-FINDR	196
6.6.1	Real-Time Multiple-Pass Successive N-FINDR	196
6.6.2	Multiple-Pass Sequential IN-FINDR	197
6.6.3	Multiple-Pass Sequential Random N-FINDR	199
6.6.4	Computational Complexity of N-FINDR	200
6.7	Synthetic Image Experiments	201
6.7.1	Target Implantation (TI)	202
6.7.2	Target Embeddedness (TE)	210
6.8	Real Image Experiments	217
6.8.1	HYDICE Data	218
6.8.2	Cuprite Data	227
6.9	Real-Time Demonstration	234
6.10	Analysis of Comparative Performance.	237
6.11	Conclusions.	239
	References	241
7	Partially Geometric-Constrained Sequential Endmember	
	Finding: Convex Cone Volume Analysis	243
7.1	Introduction.	243
7.2	Convex Cone Analysis Approach to Finding Endmembers	245
7.3	Convex Cone Volume-Based Approaches Finding Endmembers	246
7.4	Sequential Convex Cone Volume Analysis	250
7.4.1	Algorithms for Simultaneous CCVA.	250
7.4.2	Algorithms for Sequential CCVA	251
7.4.3	Algorithms for Successive CCVA	252
7.5	Random Issues in Convex Cone Volume Analysis	253
7.5.1	EIA-Driven CCVA.	253
7.5.2	Iterative CCVA	253
7.5.3	Random CCVA	254
7.6	Discussions on CCVA	255
7.6.1	VD and DR.	256
7.6.2	Fast Computation.	256
7.6.3	Comparison Between CCVA and N-FINDR	257
7.7	Synthetic Image Experiments.	258

7.8	Real Image Experiments	262
7.8.1	HYDICE Data	263
7.8.2	AVIRIS Cuprite Data	263
7.9	Conclusions	268
	References	270
8	Geometric-Unconstrained Sequential Endmember Finding:	
	Orthogonal Projection Analysis	273
8.1	Introduction	274
8.2	Causal Iterative PPI (C-IPPI)	275
8.3	Random C-IPPI (RC-IPPI)	277
8.4	Synthetic Image Experiments	278
8.5	Real Image Experiments	282
8.5.1	HYDICE Data	282
8.5.2	AVIRIS Data	285
8.6	Conclusions	287
	References	288
9	Fully Abundance-Constrained Sequential Endmember Finding:	
	Linear Spectral Mixture Analysis	291
9.1	Introduction	292
9.2	Fully Constrained LSMA-Based Endmember Finding	293
9.2.1	Sequential FCLS-EFA	294
9.2.2	Successive FCLS-EFA	295
9.3	Random Issues Solve by LSMA-Based EFAS	295
9.3.1	Initialization-Driven FCLS-EFA	295
9.3.2	Iterative FCLS	296
9.3.3	Random FCLS-EFA	297
9.4	Synthetic Image Experiments	298
9.4.1	TI Experiments	299
9.4.2	TE Experiments	305
9.5	Real Image Experiments	310
9.6	Discussions on RFCLS-EFA	317
9.7	Conclusions	320
	References	321
Part III	Sample-Wise Progressive Processes for Finding	
	Endmembers	
10	Fully Geometric-Constrained Progressive Endmember Finding:	
	Growing Simplex Volume Analysis	325
10.1	Introduction	325
10.2	Progressive N-FINDR	327
10.2.1	p -Stage Progressive SC N-FINDR	327
10.2.2	Multiple-Stage Progressive IN-FINDR	328
10.2.3	Multiple-Stage Progressive RN-FINDR	328

10.3	Real Time SGA	329
10.4	RT SGA Using Various Criteria	336
10.4.1	Real-Time SGA Using Orthogonal Projection as a Criterion	336
10.4.2	Real-Time SGA Using LSE as a Criterion	337
10.4.3	Real-Time SGA Using Maximin as a Criterion	338
10.4.4	Real-Time SGA Using Minimax as a Criterion	339
10.5	Synthetic Image Experiments	340
10.6	Real Image Experiments	344
10.6.1	HYDICE Image Experiments	344
10.6.2	AVIRIS Image Experiments	352
10.7	Conclusions	358
	References	359
11	Partially Geometric-Constrained Progressive Endmember Finding: Growing Convex Cone Volume Analysis	361
11.1	Introduction	361
11.2	Progressive Partially Geometric-Constrained Convexity-Based Approaches	363
11.2.1	Unsupervised Non-negativity Constrained Least Squares	363
11.2.2	Vertex Component Analysis	365
11.2.3	Growing Convex Cone Volume Analysis	366
11.3	Synthetic Image Experiments	367
11.4	Real Image Experiments	371
11.4.1	HYDICE Data	371
11.4.2	Cuprite Data	373
11.4.3	Quantitative Analysis for Cuprite Experiments	377
11.4.4	Discussions on VCA, UNCLS, and GCCVA	382
11.5	Conclusions	385
	References	386
12	Geometric-Unconstrained Progressive Endmember Finding: Orthogonal Projection Analysis	389
12.1	Introduction	389
12.2	Progressive IPPI (P-IPPI)	392
12.2.1	P-IPPI	392
12.3	Generalizations to P-IPPI	394
12.3.1	Joint Implementation of P-IPPI and C-IPPI	394
12.3.2	Random P-IPPI	394
12.3.3	Varying Skewer Set C-IPPI (VC-IPPI)	394
12.3.4	Growing Skewer Set Progressive Iterative PPI (GP-IPPI)	396
12.4	Comparative Analysis Between IPPI and IN-FINDR	398
12.5	Synthetic Image Experiments	400

12.6	Real Image Experiments	405
12.7	Conclusions	410
	References	411
13	Endmember-Finding Algorithms: Comparative Studies and Analyses	413
13.1	Introduction	414
13.2	Discussions on Endmember-Finding Algorithms	416
13.3	Comparative Study Between N-Findr and CCVA Via Simplex Volume	419
13.3.1	Synthetic Image Experiments	420
13.3.2	Real Image Experiments	426
13.4	Comparative Study Among ATGP, VCA and SGA Via Orthogonal Projection	433
13.4.1	Algorithm Analysis	433
13.4.2	Specifics of Test Algorithms	438
13.4.3	Experiments	443
13.4.4	Discussions	464
13.5	Conclusions	465
	References	466
 Part IV Hyperspectral Anomaly Detection		
14	Anomaly Detection Characterization	471
14.1	Introduction	471
14.2	Causal Anomal Detection	474
14.3	Adaptive Causal Anomaly Detection (ACAD)	475
14.4	Issues Arising in Anomaly Detection	477
14.4.1	How Large a Size for a Target to Be Considered as an Anomaly?	477
14.4.2	How Strong for an Anomaly Responding to Its Surroundings?	482
14.4.3	How Sensitive Is an Anomaly to Noise?	483
14.4.4	How Can Anomalies Be Detected as Different Anomalies?	485
14.5	Real Hyperspectral Image Experiments	488
14.6	Real-Time Causal Implementation of ACAD	490
14.7	Conclusions	491
	References	492
15	Anomaly Discrimination and Categorization	495
15.1	Introduction	495
15.2	Anomaly Discrimination	497
15.2.1	K-AD	498
15.2.2	R-AD	498

15.3	Anomaly Categorization	500
15.4	Synthetic Image Experiments	501
15.4.1	TI Experiments	502
15.4.2	TE Experiments	505
15.5	Real Image Experiments	509
15.6	Discussions	516
15.7	Conclusions	518
	References	518
16	Anomaly Detection and Background Suppression	521
16.1	Introduction	521
16.2	Anomaly Intensity and Contrast	524
16.3	Background Suppression Issues	526
16.4	Background Suppression by Causal Anomaly Detection	527
16.5	3D ROC Analysis	529
16.6	Real Image Experiments	531
16.6.1	AVIRIS Data	531
16.6.2	HYDICE Panel + Vehicles + Objects Data	534
16.7	Experiments of Real Time Causal Processing	536
16.7.1	Background Suppression by Real Time Causal Processing	536
16.7.2	Detection Performance and 3D ROC Analysis	536
16.7.3	Background Suppression	541
16.8	Conclusions	544
	References	545
17	Multiple Window Anomaly Detection	547
17.1	Introduction	547
17.2	Anomaly Detectors	552
17.2.1	Dual Window-Based Anomaly Detectors	552
17.2.2	Nested Spatial Window-Based Anomaly Detector	553
17.3	Multiple Window Anomaly Detection	557
17.3.1	Multiple-Window K-AD (MW-K-AD)	558
17.3.2	Multiple Window Nested Window Anomaly Detector (MW-NSWTD)	559
17.3.3	Multiple Window DWEST (MW-DWEST)	560
17.3.4	Discussions on MWAD	561
17.4	Experiments	563
17.4.1	First Set of Experiments	565
17.4.2	Second Set of Experiments	566
17.5	Nearly Real-Time Implementation	573
17.6	Conclusions	574
	References	575

18 Anomaly Detection Using Causal Sliding Windows	577
18.1 Introduction	577
18.2 Design of Causal Sliding Windows	579
18.2.1 Causal Sliding Square Matrix Windows	579
18.2.2 Causal Sliding Array Windows	581
18.2.3 Causal Sliding Rectangular Matrix Window	582
18.3 Causal Anomaly Detection	583
18.4 Recursive Anomaly Detection	584
18.4.1 Derivations	584
18.4.2 Computational Complexity	585
18.5 Real Image Experiments	586
18.6 Conclusions	594
References	595
19 Conclusions	597
19.1 Introduction	597
19.2 Endmember Finding	599
19.3 Hyperspectral Anomaly Detection	601
19.4 Hyperspectral Progressive Band Processing	601
19.5 Future Topics of Interest	602
19.5.1 Endmember Variability Clustering Approach	602
19.5.2 Fisher Ratio-Based Endmember Variability Approach	604
References	604
Bibliography	607
Index	621