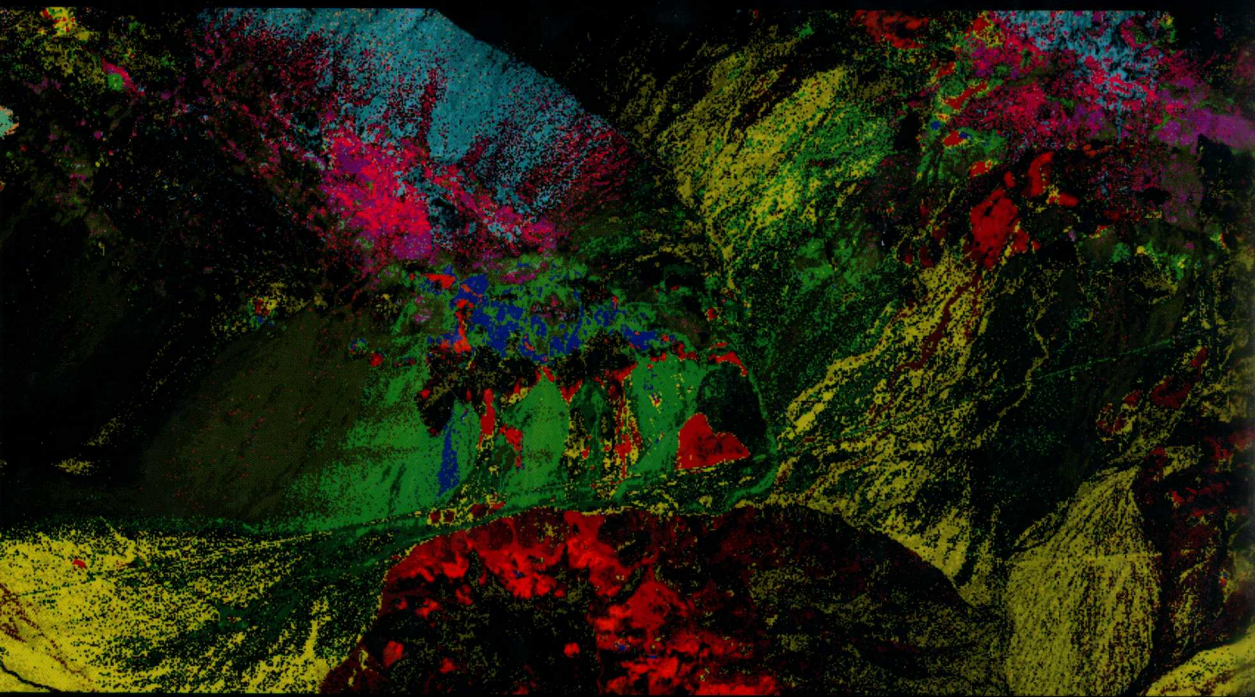


# HYPERSPECTRAL DATA PROCESSING

**Algorithm Design and Analysis**

CHEIN-I CHANG



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**Chein-I Chang**

*University of Maryland, Baltimore County (UMBC), Maryland, USA*



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# **HYPERSENSPECTRAL DATA PROCESSING**

*This book is dedicated to members of my family, specifically my mother who provided me with her timeless support and encouragement during the course of preparing this book. It is also dedicated to all of my students who have contributed to this book.*

# Preface

Hyperspectral imaging has witnessed tremendous growth over the past few years. Still its applications to new areas are yet to be explored. Many hyperspectral imaging techniques have been developed and reported in various venues. My first book, *Hyperspectral Imaging: Techniques for Spectral Detection and Classification*, referenced as Chang (2003a), was written in an attempt to summarize the research conducted at that time in my laboratory (remote sensing signal and image processing laboratory, RSSIPL) and to provide readers with a peek of this fascinating and exciting area. With rapid advancement in this area many signal processing techniques have been developed for hyperspectral signal and image processing. This book has been written with four goals in mind. One is to continuously explore new statistical signal processing algorithms in this area for various applications. Many results in this book are new, particularly some in Chapters 2, 4, 5–6, 11, 16, 18–19, 23, 24, 29, 30–31, and 33. A second goal is to supplement Chang (2003a), where many potential research efforts were only briefly mentioned (in Chapter 18 of the book). A third goal is to distinguish this book from Chang (2003a) in many ways. Unlike Chang (2003a) where the main theme was hyperspectral target detection and classification from a viewpoint of subpixel and mixed pixel analysis, this book is focused on more in-depth treatment of hyperspectral signal and image processing from a statistical signal processing point of view. A fourth and last goal is to focus on several unsettled but very important issues that have been avoided and never addressed in the past.

One issue is “how many spectral signatures are required to unmix data?” arising in linear hyperspectral unmixing. This has been a long-standing and unresolved issue in remote sensing image processing, specifically hyperspectral imaging, since the number of signatures to be used for data unmixing has a significant impact on image analysis while its accurate number is never known in real applications. Another is “how many pure spectral signatures, referred to as endmembers, are supposed to be present in the data to be processed?” It is common practice to assume that the number of signatures used for spectral unmixing is the same number of endmembers. Unfortunately, such a claim, which has been widely accepted by the community, is not always true in practical applications (see Chapter 17). The issue of endmembers has not received much interest in multispectral image analysis because of its low spectral and spatial resolutions that generally result in mixed data sample vectors. However, due to recent advances in hyperspectral imaging sensors with hundreds of contiguous spectral bands endmember extraction has become increasingly important since endmembers provide crucial “nonliteral” information in spectral interpretation, characterization, and analysis. Interestingly, this issue has never been seriously addressed until recently when it has been investigated by a series of papers (Chang, 2006ab; Chang and

Plaza, 2006; Chang *et al.*, 2006; Plaza and Chang 2006) by introducing a new concept of virtual dimensionality (VD). Besides, some controversial issues result from misinterpreting VD. Therefore, one of the major chapters in this book is Chapter 5, which revisits VD to explore its utility in various applications. Unlike the intrinsic dimensionality (ID), also known as effective dimensionality (ED), which is somewhat abstract and defined as the minimum number of parameters to represent general high-dimensional multivariate data, VD is more practical and realistic. It is defined as the number of “*spectrally*” distinct signatures particularly developed for hyperspectral data in which the non-literal (spectral) information is more crucial and vital than information provided by other dimensions such as spatial information. In particular, an issue arises in how to define the spectral distinction among signatures in VD estimation. Furthermore, unlike ID that is a one-size-fits-all definition for all data sets, VD should adapt to data sets used for different applications as well as vary with the techniques used to estimate VD. In order to address this issue, Chapter 5 explores two types of VD criteria, data characterization-driven criteria and data representation-driven criteria, to define spectrally distinct signatures, and further decouples the concept of VD from the techniques used to estimate VD. Consequently, when VD is poorly estimated by one technique for a particular data set, it is not the definition of VD to be blamed, but rather the technique used for VD estimation that is not applicable to this particular data set. In addition, an issue related to VD is “characterization of pixel information.” For example, an anomaly is not necessarily an endmember and vice versa. So, the issues “what is the distinction between these two?” and “how do we characterize these two?” become interesting issues in hyperspectral data exploitation to be discussed in Chapter 18.

Another interesting topic presented in this book is a new concept of “hyperspectral information compression” introduced in Chapters 19–23. It is different from the commonly used so-called hyperspectral data compression in the sense that hyperspectral information compression is generally performed based on the information required to be retained rather than the size of hyperspectral data to be compressed. Therefore, a more appropriate term to be used is “exploitation-based lossy hyperspectral data compression.” Nevertheless, it should be noted that the definitions and terminologies used in these chapters are by no means standard.

Finally, an issue of “multispectral imagery versus hyperspectral imagery” is also investigated. It seems that there is no cut-and-dried definition to distinguish these two terminologies. A general understanding of distinguishing these two is that a hyperspectral image is acquired by hundreds of *contiguous* spectral channels/bands with very high spectral resolution, while a multispectral image is collected by tens of *discrete* spectral channels/bands with low spectral resolution. If this interpretation is used, we run into a dilemma, “how many spectral channels/bands are enough for a remotely sensed image to be called a hyperspectral image?” or “how fine the spectral resolution should be for a remote sensing image to be considered as a hyperspectral image?” For example, if we take a small set of hyperspectral band images with spectral resolution 10 nm, say five spectral band images, to form a five-dimensional image cube, do we still consider this new-formed five-dimensional image cube as a hyperspectral image or simply a multispectral image? If we adopt the former definition based on the number of bands, this five-dimensional image cube should be viewed as a multispectral image. On the other hand, if we adopt the latter definition based on spectral resolution, the five-dimensional image cube should be considered as a hyperspectral image. Thus far, it seems that there is no general consensus on this issue. In Chapter 31, an attempt is made to address this issue from a viewpoint of how two versions of independent component analysis (ICA), over-complete ICA, and under-complete ICA can be used to resolve this long-debated issue in the context of linear spectral mixture analysis (LSMA). After all, some of these issues may never be settled or standardized for years to come. Many researchers can always argue differently at their



discretion and provide their own versions of interpretation. I have no intention of disputing any of them, but rather respect their opinions.

Since processing hyperspectral signatures as one-dimensional signals and processing hyperspectral images as three-dimensional image cubes are rather different, this book makes a distinction by treating hyperspectral image processing and hyperspectral signal processing in two separate categories to avoid confusion. To this end, three categories are specifically outlined in this book: Category A: hyperspectral image processing; Category B: hyperspectral signal processing; and Category C: applications.

For better understanding, a set of six chapters is included in PART I as preliminaries that cover fundamentals and provide a basic background required for readers to follow algorithm design and development discussed in this book. Category A is made up of 15 chapters (Chapters 7–23) treated separately in four different parts, Part II to Part V. Category B consists of six chapters (Chapters 24–29) in two separate parts, Part VI and Part VII. Finally, applications make up Category C.

It is worth noting that many materials presented in this book have been only available after Chang (2003a). Theses include endmember extraction (Chapters 7–11), algorithm design using different levels of information (supervised linear hyperspectral mixture analysis in Chapters 12–15), pixel characterization and analysis (unsupervised hyperspectral analysis in Chapters 16–18), exploitation-based hyperspectral information compression (Chapters 19–23), hyperspectral signature coding and characterization (Chapters 24–29), and applications (Chapters 30–32) in Category C.

There are three unique features in this book that cannot be found in Chang (2003a): (1) Part I: preliminaries (Chapters 2–6); (2) extensive studies of synthetic image-based experiments for performance evaluation; and (3) an appendix on algorithm compendium that compiles recently developed signal processing algorithms developed in the RSSIPL, all of which are believed to be useful and beneficial to those who design and develop algorithms for hyperspectral signal/image processing. Because this book also addresses many issues that were not explored in Chang (2003a), it can be used in conjunction with Chang (2003a) without much overlap, where the latter provides necessary basic background in design and development of statistical signal processing algorithms for hyperspectral image analysis, especially for subpixel detection and mixed pixel classification. Therefore, on one end, those who have been involved in hyperspectral imaging and are familiar with hyperspectral imaging techniques will find this book useful as reference material. On the other end, those who are new will find this book a good and valuable guide on the topics that may interest them.

I would like to thank the Spectral Information Technology Applications Center (SITAC) that provides its HYDICE data to be used for experiments in this book. I would also like to acknowledge the use of Purdue's Indiana Indian Pine test site and the AVIRIS Cuprite image data website.

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many experiments described in Chapters 21–23, Dr. Su Wang who did all the work mentioned in Chapter 29, Dr. Englin Wong who performed all the experiments described in Chapter 32, and Professor Antonio J. Plaza who contributed to some part of Chapter 18 when he was on sabbatical leave from the Computer Science Department, University of Extremadura, Spain, in 2004 to visit my laboratory. This book could not have been completed without their contributions.

I would also like to thank the Ministry of Education in Taiwan for supporting me as a Distinguished Lecture Chair within the Department of Electrical Engineering from 2005 to 2006, a Chair Professorship of Reduction Technology within the Environmental Restoration and Disaster Reduction Research Center and Department of Electrical Engineering from 2006 to 2009, and a Chair Professorship of Remote Sensing Technology within the Department of Electrical Engineering from 2009 to 2012, at National Chung Hsing University where Professor Yen-Chieh Ouyang of Electrical Engineering has been a very supportive host during my visit. In particular, during the period 2009–2010, I was on sabbatical leave from UMBC to visit National Chung Hsing University where my appointment as a distinguished visiting fellow/fellow professor was supported and funded by the National Science Council in Taiwan under projects of NSC 98-2811-E-005-024 and NSC 98-2221-E-005-096. All their support is highly appreciated.

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As a final note, I would like to share that this book was supposed to be delivered by 2008. The most important factor that caused the delay is the urge to include the latest reports on hyperspectral data analysis. It is very difficult and challenging to keep a track of such new developments. Nevertheless, this book has grown three times larger than what I had originally proposed. Those who are interested in my forthcoming 2013 book can have a quick peek of these topics briefly discussed in Chapter 33, which includes a new development of target-characterized virtual dimensionality (VD), real-time and progressive processing of endmember extraction, unsupervised target detection, anomaly detection, as well as their field programmable gate array (FPGA) implementation.

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# Contents

<b>PREFACE</b>	<b>xxiii</b>
<b>1 OVERVIEW AND INTRODUCTION</b>	<b>1</b>
1.1 Overview	2
1.2 Issues of Multispectral and Hyperspectral Imageries	3
1.3 Divergence of Hyperspectral Imagery from Multispectral Imagery	4
1.3.1 Misconception: Hyperspectral Imaging is a Natural Extension of Multispectral Imaging	4
1.3.2 Pigeon-Hole Principle: Natural Interpretation of Hyperspectral Imaging	5
1.4 Scope of This Book	7
1.5 Book's Organization	10
1.5.1 Part I: Preliminaries	10
1.5.2 Part II: Endmember Extraction	12
1.5.3 Part III: Supervised Linear Hyperspectral Mixture Analysis	13
1.5.4 Part IV: Unsupervised Hyperspectral Analysis	13
1.5.5 Part V: Hyperspectral Information Compression	15
1.5.6 Part VI: Hyperspectral Signal Coding	16
1.5.7 Part VII: Hyperspectral Signal Feature Characterization	17
1.5.8 Applications	17
1.5.8.1 Chapter 30: Applications of Target Detection	17
1.5.8.2 Chapter 31: Nonlinear Dimensionality Expansion to Multispectral Imagery	18
1.5.8.3 Chapter 32: Multispectral Magnetic Resonance Imaging	19
1.6 Laboratory Data to be Used in This Book	19
1.6.1 Laboratory Data	19
1.6.2 Cuprite Data	19
1.6.3 NIST/EPA Gas-Phase Infrared Database	19
1.7 Real Hyperspectral Images to be Used in this Book	20
1.7.1 AVIRIS Data	20
1.7.1.1 Cuprite Data	21
1.7.1.2 Purdue's Indiana Indian Pine Test Site	25
1.7.2 HYDICE Data	26
1.8 Notations and Terminologies to be Used in this Book	29
	<b>vii</b>

<b>I: PRELIMINARIES</b>	<b>31</b>
<b>2 FUNDAMENTALS OF SUBSAMPLE AND MIXED SAMPLE ANALYSES</b>	<b>33</b>
2.1 Introduction	33
2.2 Subsample Analysis	35
2.2.1 Pure-Sample Target Detection	35
2.2.2 Subsample Target Detection	38
2.2.2.1 Adaptive Matched Detector (AMD)	39
2.2.2.2 Adaptive Subspace Detector (ASD)	41
2.2.3 Subsample Target Detection: Constrained Energy Minimization (CEM)	43
2.3 Mixed Sample Analysis	45
2.3.1 Classification with Hard Decisions	45
2.3.1.1 Fisher's Linear Discriminant Analysis (FLDA)	46
2.3.1.2 Support Vector Machines (SVM)	48
2.3.2 Classification with Soft Decisions	54
2.3.2.1 Orthogonal Subspace Projection (OSP)	54
2.3.2.2 Target-Constrained Interference-Minimized Filter (TCIMF)	56
2.4 Kernel-Based Classification	57
2.4.1 Kernel Trick Used in Kernel-Based Methods	57
2.4.2 Kernel-Based Fisher's Linear Discriminant Analysis (KFLDA)	58
2.4.3 Kernel Support Vector Machine (K-SVM)	59
2.5 Conclusions	60
<b>3 THREE-DIMENSIONAL RECEIVER OPERATING CHARACTERISTICS (3D ROC) ANALYSIS</b>	<b>63</b>
3.1 Introduction	63
3.2 Neyman–Pearson Detection Problem Formulation	65
3.3 ROC Analysis	67
3.4 3D ROC Analysis	69
3.5 Real Data-Based ROC Analysis	72
3.5.1 How to Generate ROC Curves from Real Data	72
3.5.2 How to Generate Gaussian-Fitted ROC Curves	73
3.5.3 How to Generate 3D ROC Curves	75
3.5.4 How to Generate 3D ROC Curves for Multiple Signal Detection and Classification	77
3.6 Examples	78
3.6.1 Hyperspectral Imaging	79
3.6.1.1 Hyperspectral Target Detection	79
3.6.1.2 Linear Hyperspectral Mixture Analysis	80
3.6.2 Magnetic Resonance (MR) Breast Imaging	83
3.6.2.1 Breast Tumor Detection	84
3.6.2.2 Brain Tissue Classification	87
3.6.3 Chemical/Biological Agent Detection	91
3.6.4 Biometric Recognition	95
3.7 Conclusions	99

4	DESIGN OF SYNTHETIC IMAGE EXPERIMENTS	101
4.1	Introduction	102
4.2	Simulation of Targets of Interest	103
4.2.1	Simulation of Synthetic Subsample Targets	103
4.2.2	Simulation of Synthetic Mixed-Sample Targets	104
4.3	Six Scenarios of Synthetic Images	104
4.3.1	Panel Simulations	104
4.3.2	Three Scenarios for Target Implantation (TI)	106
4.3.2.1	Scenario TI1 (Clean Panels Implanted into Clean Background)	106
4.3.2.2	Scenario TI2 (Clean Panels Implanted into Noisy Background)	107
4.3.2.3	Scenario TI3 (Gaussian Noise Added to Clean Panels Implanted into Clean Background)	108
4.3.3	Three Scenarios for Target Embeddedness (TE)	108
4.3.3.1	Scenario TE1 (Clean Panels Embedded in Clean Background)	109
4.3.3.2	Scenario TE2 (Clean Panels Embedded in Noisy Background)	109
4.3.3.3	Scenario TE3 (Gaussian Noise Added to Clean Panels Embedded in Background)	110
4.4	Applications	112
4.4.1	Endmember Extraction	112
4.4.2	Linear Spectral Mixture Analysis (LSMA)	113
4.4.2.1	Mixed Pixel Classification	114
4.4.2.2	Mixed Pixel Quantification	114
4.4.3	Target Detection	114
4.4.3.1	Subpixel Target Detection	114
4.4.3.2	Anomaly Detection	122
4.5	Conclusions	123
5	VIRTUAL DIMENSIONALITY OF HYPERSPECTRAL DATA	124
5.1	Introduction	124
5.2	Reinterpretation of VD	126
5.3	VD Determined by Data Characterization-Driven Criteria	126
5.3.1	Eigenvalue Distribution-Based Criteria	127
5.3.1.1	Thresholding Energy Percentage	127
5.3.1.2	Thresholding Difference between Normalized Correlation Eigenvalues and Normalized Covariance Eigenvalues	128
5.3.1.3	Finding First Sudden Drop in the Normalized Eigenvalue Distribution	128
5.3.2	Eigen-Based Component Analysis Criteria	128
5.3.2.1	Singular Value Decomposition (SVD)	128
5.3.2.2	Principal Components Analysis (PCA)	129
5.3.3	Factor Analysis: Malinowski's Error Theory	129
5.3.4	Information Theoretic Criteria (ITC)	130
5.3.4.1	AIC	131
5.3.4.2	MDL	131
5.3.5	Gershgorin Radius-Based Methods	131
5.3.5.1	Thresholding Gershgorin Radii	134
5.3.5.2	Thresholding Difference Gershgorin Radii between $R_{L \times L}$ and $K_{L \times L}$	134

5.3.6	HFC Method	135
5.3.7	Discussions on Data Characterization-Driven Criteria	138
5.4	VD Determined by Data Representation-Driven Criteria	140
5.4.1	Orthogonal Subspace Projection (OSP)	140
5.4.2	Signal Subspace Estimation (SSE)	142
5.4.3	Discussions on OSP and SSE/HySime	143
5.5	Synthetic Image Experiments	144
5.5.1	Data Characterization-Driven Criteria	144
5.5.1.1	Target Implantation (TI) Scenarios	145
5.5.1.2	Target Embeddedness (TE) Scenarios	146
5.5.2	Data Representation-Driven Criteria	149
5.6	VD Estimated for Real Hyperspectral Images	155
5.7	Conclusions	163
6	DATA DIMENSIONALITY REDUCTION	168
6.1	Introduction	168
6.2	Dimensionality Reduction by Second-Order Statistics-Based Component Analysis Transforms	170
6.2.1	Eigen Component Analysis Transforms	170
6.2.1.1	Principal Components Analysis	170
6.2.1.2	Standardized Principal Components Analysis	172
6.2.1.3	Singular Value Decomposition	174
6.2.2	Signal-to-Noise Ratio-Based Components Analysis Transforms	176
6.2.2.1	Maximum Noise Fraction Transform	176
6.2.2.2	Noise-Adjusted Principal Component Transform	177
6.3	Dimensionality Reduction by High-Order Statistics-Based Components Analysis Transforms	179
6.3.1	Sphering	179
6.3.2	Third-Order Statistics-Based Skewness	181
6.3.3	Fourth-Order Statistics-Based Kurtosis	182
6.3.4	High-Order Statistics	182
6.3.5	Algorithm for Finding Projection Vectors	183
6.4	Dimensionality Reduction by Infinite-Order Statistics-Based Components Analysis Transforms	184
6.4.1	Statistics-Prioritized ICA-DR (SPICA-DR)	187
6.4.2	Random ICA-DR	188
6.4.3	Initialization Driven ICA-DR	189
6.5	Dimensionality Reduction by Projection Pursuit-Based Components Analysis Transforms	190
6.5.1	Projection Index-Based Projection Pursuit	191
6.5.2	Random Projection Index-Based Projection Pursuit	192
6.5.3	Projection Index-Based Prioritized Projection Pursuit	193
6.5.4	Initialization Driven Projection Pursuit	194
6.6	Dimensionality Reduction by Feature Extraction-Based Transforms	195
6.6.1	Fisher's Linear Discriminant Analysis	195
6.6.2	Orthogonal Subspace Projection	196
6.7	Dimensionality Reduction by Band Selection	196

6.8	Constrained Band Selection	197
6.9	Conclusions	198

## II: ENDMEMBER EXTRACTION 201

7	SIMULTANEOUS ENDMEMBER EXTRACTION ALGORITHMS (SM-EEAs)	207
7.1	Introduction	208
7.2	Convex Geometry-Based Endmember Extraction	209
7.2.1	Convex Geometry-Based Criterion: Orthogonal Projection	209
7.2.2	Convex Geometry-Based Criterion: Minimal Simplex Volume	214
7.2.2.1	Minimal-Volume Transform (MVT)	214
7.2.2.2	Convex Cone Analysis (CCA)	214
7.2.3	Convex Geometry-Based Criterion: Maximal Simplex Volume	215
7.2.3.1	Simultaneous N-FINDR (SM N-FINDR)	216
7.2.3.2	Iterative N-FINDR (IN-FINDR)	216
7.2.3.3	Various Versions of Implementing IN-FINDR	218
7.2.3.4	Discussions on Various Implementation Versions of IN-FINDR	222
7.2.3.5	Comparative Study Among Various Versions of IN-FINDR	222
7.2.3.6	Alternative SM N-FINDR	223
7.2.4	Convex Geometry-Based Criterion: Linear Spectral Mixture Analysis	225
7.3	Second-Order Statistics-Based Endmember Extraction	228
7.4	Automated Morphological Endmember Extraction (AMEE)	230
7.5	Experiments	231
7.5.1	Synthetic Image Experiments	231
7.5.1.1	Scenario TI1 (Endmembers Implanted in a Clean Background)	232
7.5.1.2	Scenario TI2 (Endmembers Implanted in a Noisy Background)	233
7.5.1.3	Scenario TI3 (Noisy Endmembers Implanted in a Noisy Background)	234
7.5.1.4	Scenario TE1 (Endmembers Embedded into a Clean Background)	235
7.5.1.5	Scenario TE2 (Endmembers Embedded into a Noisy Background)	235
7.5.1.6	Scenario TE3 (Noisy Endmembers Embedded into a Noisy Background)	236
7.5.2	Cuprite Data	237
7.5.3	HYDICE Data	237
7.6	Conclusions	239
8	SEQUENTIAL ENDMEMBER EXTRACTION ALGORITHMS (SQ-EEAs)	241
8.1	Introduction	241
8.2	Successive N-FINDR (SC N-FINDR)	244
8.3	Simplex Growing Algorithm (SGA)	244
8.4	Vertex Component Analysis (VCA)	247
8.5	Linear Spectral Mixture Analysis-Based SQ-EEAs	248
8.5.1	Automatic Target Generation Process-EEA (ATGP-EEA)	248
8.5.2	Unsupervised Nonnegativity Constrained Least-Squares-EEA (UNCLS-EEA)	249



8.5.3	Unsupervised Fully Constrained Least-Squares-EEA (UFCLS-EEA)	250
8.5.4	Iterative Error Analysis-EEA (IEA-EEA)	251
8.6	High-Order Statistics-Based SQ-EEAS	252
8.6.1	Third-Order Statistics-Based SQ-EEA	252
8.6.2	Fourth-Order Statistics-Based SQ-EEA	252
8.6.3	Criterion for $k$ th Moment-Based SQ-EEA	253
8.6.4	Algorithm for Finding Projection Vectors	253
8.6.5	ICA-Based SQ-EEA	254
8.7	Experiments	254
8.7.1	Synthetic Image Experiments	255
8.7.2	Real Hyperspectral Image Experiments	258
8.7.2.1	Cuprite Data	258
8.7.2.2	HYDICE Data	260
8.8	Conclusions	262
9	INITIALIZATION-DRIVEN ENDMEMBER EXTRACTION ALGORITHMS (ID-EEAs)	265
9.1	Introduction	265
9.2	Initialization Issues	266
9.2.1	Initial Conditions to Terminate an EEA	267
9.2.2	Selection of an Initial Set of Endmembers for an EEA	267
9.2.3	Issues of Random Initial Conditions Demonstrated by Experiments	268
9.2.3.1	HYDICE Experiments	268
9.2.3.2	AVIRIS Experiments	270
9.3	Initialization-Driven EEAs	271
9.3.1	Initial Endmember-Driven EEAs	272
9.3.1.1	Finding Maximum Length of Data Sample Vectors	272
9.3.1.2	Finding Sample Mean of Data Sample Vectors	273
9.3.2	Endmember Initialization Algorithm for SM-EEAs	274
9.3.2.1	SQ-EEAs	274
9.3.2.2	Maxmin-Distance Algorithm	275
9.3.2.3	ISODATA	275
9.3.3	EIA-Driven EEAs	275
9.4	Experiments	278
9.4.1	Synthetic Image Experiments	278
9.4.2	Real Image Experiments	281
9.5	Conclusions	283
10	RANDOM ENDMEMBER EXTRACTION ALGORITHMS (REEAs)	287
10.1	Introduction	287
10.2	Random PPI (RPPI)	288
10.3	Random VCA (RVCA)	290
10.4	Random N-FINDR (RN-FINDR)	290
10.5	Random SGA (RSGA)	292
10.6	Random ICA-Based EEA (RICA-EEA)	292
10.7	Synthetic Image Experiments	293
10.7.1	RPPI	293

10.7.2	Various Random Versions of IN-FINDR	296
10.7.2.1	Scenario TI2	297
10.7.2.2	Scenario TI3	299
10.7.2.3	TE2	301
10.7.2.4	TE3 Scenario	303
10.8	Real Image Experiments	305
10.8.1	HYDICE Image Experiments	305
10.8.1.1	RPPI	306
10.8.1.2	RN-FINDR	306
10.8.2	AVIRIS Image Experiments	309
10.8.2.1	RPPI	309
10.8.2.2	RN-FINDR	310
10.9	Conclusions	313
11	EXPLORATION ON RELATIONSHIPS AMONG ENDMEMBER EXTRACTION ALGORITHMS	316
11.1	Introduction	316
11.2	Orthogonal Projection-Based EEAs	318
11.2.1	Relationship among PPI, VCA, and ATGP	319
11.2.1.1	Relationship Between PPI and ATGP	319
11.2.1.2	Relationship Between PPI and VCA	320
11.2.1.3	Relationship Between ATGP and VCA	321
11.2.1.4	Discussions	322
11.2.2	Experiments-Based Comparative Study and Analysis	323
11.2.2.1	Synthetic Image Experiment: TI2	323
11.2.2.2	Real Image Experiments	325
11.3	Comparative Study and Analysis Between SGA and VCA	330
11.4	Does an Endmember Set Really Yield Maximum Simplex Volume?	339
11.5	Impact of Dimensionality Reduction on EEAs	344
11.6	Conclusions	348
III:	SUPERVISED LINEAR HYPERSPECTRAL MIXTURE ANALYSIS	351
12	ORTHOGONAL SUBSPACE PROJECTION REVISITED	355
12.1	Introduction	355
12.2	Three Perspectives to Derive OSP	358
12.2.1	Signal Detection Perspective Derived from (d,U)-Model and OSP-Model	359
12.2.2	Fisher's Linear Discriminant Analysis Perspective from OSP-Model	360
12.2.3	Parameter Estimation Perspective from OSP-Model	362
12.2.4	Relationship Between $\delta_{\alpha_p}^{LS}(\mathbf{r})$ and Least-Squares Linear Spectral Mixture Analysis	362
12.3	Gaussian Noise in OSP	364
12.3.1	Signal Detector in Gaussian Noise Using OSP-Model	365
12.3.2	Gaussian Maximum Likelihood Classifier Using OSP-Model	366
12.3.3	Gaussian Maximum Likelihood Estimator	367
12.3.4	Examples	367