CHAPTER 1

OVERVIEW

CHEIN-I CHANG
Remote Sensing Signal and Image Processing Laboratory, Department of Computer Science and Electrical Engineering, University of Maryland—Baltimore County, Baltimore, MD 21250

1.1. INTRODUCTION

Hyperspectral imaging has become a fast growing technique in remote sensing image processing due to recent advances of hyperspectral imaging technology. It makes use of as many as hundreds of contiguous spectral bands to expand the capability of multispectral sensors that use tens of discrete spectral bands. As a result, with such high spectral resolution many subtle objects and materials can now be uncovered and extracted by hyperspectral imaging sensors with very narrow diagnostic spectral bands for detection, discrimination, classification, identification, recognition, and quantification. Many of its applications are yet to be explored. It has been common sense to think of hyperspectral imaging as a natural extension of multispectral imaging with band expansion. Accordingly, all techniques developed for multispectral imagery are considered to be readily applicable to hyperspectral imagery. Unfortunately, this intuitive interpretation may be somewhat misleading. To understand the fundamental difference between multispectral and hyperspectral images from a data processing perspective, we use a good example in mathematics for illustration, which is the difference between real analysis and complex analysis where the variables considered are real variables in real analysis as opposed to complex variables in complex analysis. Since real variables can be considered as real parts of complex variables, this may lead many to a belief that real analysis is a special case of complex analysis, which is certainly not true. One piece of clear evidence is derivatives. When a derivative is considered in real analysis, it has only two directions along the real line: left limit and right limit. However, in complex analysis, the direction of a derivative can be any curve in the complex plane. As a result, only partial derivatives in complex analysis can be considered as a natural extension of derivatives in real analysis. When a complex variable is

Hyperspectral Data Exploitation: Theory and Applications, Edited by Chein-I Chang

differentiable in the complex plane, it is usually called total differentiable or analytic because it must satisfy the so-called Cauchy–Riemann equation. This simple example provides a similar interpretation to explain the key difference between multispectral and hyperspectral images. In the early days, multispectral imagery was used in remote sensing mainly for land cover/use classification in agriculture applications, disaster assessment and management, ecology, environmental monitoring, geology, geographical information system (GIS), and so on. In these cases, low spectral resolution multispectral imagery may provide sufficient information for data analysis, and the techniques developed for multispectral image processing are primarily derived from the traditional two-dimensional spatial domain-based image processing that takes advantage of spatial correlation to perform various tasks. Compared to multispectral imagery, hyperspectral imagery utilizes hundreds of spectral bands for data acquisition and collection with two prominent improvements, very fine spectral resolution, and hundreds of spectral bands. It is these differences that distinguish hyperspectral imagery from multispectral imagery in their utility in many applications as demonstrated by the chapters presented in this book.

1.2. ISSUES OF MIXED PIXELS AND SUBPIXELS

Due to its low spectral resolution, a multispectral image pixel may not have information that is as rich as that of a hyperspectral image pixel. In this case, it must rely on its surrounding image pixels to provide spatial correlation and information to help to make up insufficient spectral information provided by multiple discrete spectral bands. Because of that, this may be one of main reasons that early development of multsipectral image processing has been focused on spatial domain-based techniques. The issues of subpixels and mixed pixels usually arise from very high spectral resolution produced by hyperspectral imagery and have become crucial but may not be critical to multispectral imagery. First of all, targets or objects of interest are different. In multispectral imagery, land covers or patterns are often of major interest. Therefore, the techniques developed for multispectral image analysis generally perform pattern classification and recognition. As a complete opposite, the objects of interest in hyperspectral imagery usually appear either in a form mixed by a number of material substances or at subpixel level with targets embedded in a single pixel due to their sizes smaller than the ground sampling distance (GSD). In both cases, these objects may not be identified *a priori* or by visual inspection. Therefore, they are generally considered as insignificant targets but are indeed of major interest from an intelligence or information point of view. More specifically, in hyperspectral data exploitation the objects of particular interest are those targets which have their small spatial presence and low probability existence in either form of a mixed pixel or a subpixel. Such targets may include special spices in agriculture and ecology, toxic wastes in environmental monitoring, rare minerals in geology, drug/smuggler trafficking in law enforcement, military vehicles and landmines in battlefields, chemical/biological agents in bioterrorism, and weapon concealment and mass graves in intelligence gathering. Under such circumstances, they can only be detected at mixed or subpixel level, and the traditional spatial domain (i.e., literal)-based image processing techniques may not be suitable and may also not be effective even if they can be applied. So, a great challenge in extraction of such targets is that these targets provide very limited spatial information and are generally difficult to be visualized in data. Therefore, the techniques developed for hyperspectral image analysis generally perform *target*-based detection, discrimination, classification, identification, recognition, and quantification as opposed to *pattern*-based multispectral imaging techniques. Consequently, a direct extension of multispectral imaging techniques to hyperspectral imagery may not be applicable in hyperspectral data exploitation. In order to address this issue, an approach directly from a hyperspectral imagery point of view is highly desirable and may offer insights into design and development of hyperspectral imaging algorithms because a single hyperspectral image pixel alone may already provide a wealth of spectral information for data processing without appealing to its spatial correlation with other sample pixels due to its limited spatial information.

1.3. PIGEON-HOLE PRINCIPLE

The advent of hyperspectral imagery has changed the way we think of multispectral imagery because we now have hundreds of spectral bands available for our use. Thus, one major issue is how to effectively use and take advantage of spectral information provided by these hundreds spectral bands to perform target detection, discrimination, classification and identification. This interesting issue can be addressed by the following well-known pigeon-hole principle in discrete mathematics [1].

Suppose that there are 13 pigeons flying into a dozen pigeon holes (nests). According to the pigeon-hole principle, there exists at least one pigeon hole that must accommodate at least two pigeons. Now, assume that L is the total number of spectral bands and p is the number of target classes to be classified. A hyperspectral image pixel is actually an L-dimensional column vector. By virtue of the pigeon-hole principle, we interpret a pigeon hole as a spectral band while a pigeon is considered as a target (or an object) so that we can actually use a spectral band to detect, discriminate, and classify a distinct target. With this interpretation, L spectral bands can be used to classify L different targets. Since there are hundreds of spectral bands available from hyperspectral imagery, technically speaking, hundreds of spectrally distinct targets can be also classified and discriminated by these spectral bands. In order to make this idea work, three issues need to be addressed. One is that the number of spectral bands must be greater than or equal to the number of targets to be classified; that is, $L \geq p$, which always seems true for hyperspectral imagery, but not valid for multispectral imagery, in which $L < p$, such as three-band SPOT data that may have more than three target substances present in the data. Furthermore, the first issue also gives rise to a second issue that is a well-known curse of dimensionality [2]—that is, to determine the value of p if $L \geq p$. This has been a most difficult and challenging issue for any hyperspectral image analyst to resolve, since it is nearly impossible to know the exact value of p in real-world problems and it may not be reliable even if the value of p is provided by prior knowledge. In multivariate data analysis, the value of p can be estimated by so-called intrinsic dimensionality (ID) [3], which is defined as the minimum number of parameters used to specify the data. However, this concept is only of theoretic interest, and no method has been proposed for this purpose in the literature regarding how to find it. A common strategy is on a trial-and-error basis. A similar problem is also encountered in passive array processing where the number of signal sources arriving at an array of sensors is of major interest and a key issue. In order to estimate this number, two criteria—an information criterion (AIC) suggested by Akaike and minimum description length developed by Schwarz and Rissanen [4]—have been shown successfully in such estimation. Unfortunately, a key assumption made on these criteria is that the noise must be independent identically distributed, which is usually not a valid assumption in hyperspectral images as shown in Chang [5] and in Chang and Du [6]. In order to cope with this dilemma, a new concept coined and suggested by Chang [5], called virtual dimensionality (VD), was recently proposed to estimate the number of spectrally distinct signatures in hyperspectral imagery. Its applications to hyperspectral data exploitation such as linear spectral unmixing (Chapters 4–6 in this book), dimensionality reduction (Chapter 8 in this book), band selection (Chapters 9 and 10 in this book), and so on, are also reported in Chang [7, 8]. Finally, the third and last issue is that once a spectral band is being used to accommodate one target, it cannot be used again to accommodate another distinct target. How do we make sure that this will not happen? One way to do so is to perform orthogonal subspace projection (OSP) developed in Harsanyi and Chang [9] on the hyperspectral imagery so that no two or more distinct targets will be accommodated by a single spectral band. This implies that no two pigeons will be allowed to fly into a single pigeon hole (nest) in terms of the pigeon-hole principle. Once these three issues—that is, (1) $L \geq p$, (2) determination of p, and (3) no two distinct target signatures to be accommodated by a single spectral band—are addressed, the idea of using the pigeon-hole principle for hyperspectral data exploitation can be realized and becomes feasible. Most importantly, it provides an alternative approach that uses spectral bands as a means to perform detection, and discrimination, classification, and identification without counting on spatial information or correlation. This is particularly important for targets that are small or insignificant due to their limited spatial presence and cannot be captured by spatial correlation or information. As a result, hyperspectral imaging techniques developed from this aspect are generally carried out on a pixel-by-pixel basis rather than on a spatial domain basis.

1.4. ORGANIZATION OF CHAPTERS IN THE BOOK

This book has 13 chapters contributed by researchers from various disciplinary areas whose expertise is in hyperspectral data exploitation. Each of these chapters addresses different problems caused by the above-mentioned issues. In particular, these 13 chapters are organized into three categories, Part I: Tutorials, Part II: Theory, and Part III: Applications.

1.4.1. Part I: Tutorials

The tutorials part consists of two tutorial chapters that review some basics of hyperspectral data exploitation, hyperspectral imaging systems, and algorithm design rationale for target detection and classification. Chapter 2 by Kerekes and Schott offers an excellent introduction of hyperspectral imaging systems including two popular airborne hyperspectral imagers, known as Airborne Visible/InfraRed Imaging Spectrometer (AVIRIS) and Hyperspectral Digital Image Collection Experiment (HYDICE), and a satellite-operated HYPERION. It is then followed by Chapter 3 by Chang, which is a review of matched filter-based target detection and classification algorithms.

1.4.2. Part II: Theory

The theory part is comprised of eight chapters that essentially address key issues in data modeling and representation by various approaches: linear mixing model (LMM) with deterministic endmembers (Chapter 4) and random endmembers (Chapters 5 and 6), endmember extraction (Chapter 7), dimensionality reduction (Chapter 8), band selection (Chapter 9), band partition (Chapter 10), and semisupervised support vector machines (Chapter 11).

Chapter 4 by Bowles and Gillis describes an optical real-time adaptive spectral identification system developed by the Naval Research Laboratory, known as ORASIS, which is a collection of algorithms to perform a series of tasks in sequence, an exemplar set selection, basis selection, endmember selection, and spectral unmixing. While the endmembers considered in Chapter 4 for spectral unmixing are deterministic, Chapter 5 by Eismann and Stein develops a stochastic mixing model (SMM) to describe statistical representation of hyperspectral data where the endmembers used in the model are considered as random vectors with probability density functions described by finite Gaussian mixtures. As an alternative to the stochastic mixing model discussed in Chapter 5, Chapter 6 by Nascimento and Dias presents Independent Component Analysis (ICA) and Independent Factor Analysis (IFA) for spectral unmixing where the abundance fractions of endmembers used in the linear mixing model for the ICA/IFA are described by a mixture of Dirichlet densities as opposed to a mixture of Gaussian densities assumed in the SMM in Chapter 5. Two common and key issues shared by Chapters 4–6 are (1) finding an appropriate set of endmembers to be used to form a linear mixing model and (2) performing data dimensionality reduction to reduce computational complexity. To address the first issue, Chapter 7 by Winter revisits his well-known endmember extraction algorithm, N-finder algorithm (N-FINDR), and further develops a new improved version of the N-FINDR, called maximum volume transform (MVT). Chapter 8 by Jia and Richards addresses the second issue by investigating data representation of hyperspectral data to cope with the so-called curse of dimensionality where feature extraction becomes a powerful and effective means to resolve this issue, such as variance used by the PCA, Fisher's ratio, or Rayleigh quotient used by Fisher's linear discriminant analysis (FLDA). Another approach to address the issue of data dimensionality reduction is band selection. Chapter 9 by Shen develops an entropy-based genetic algorithm to select optimal band sets for spectral imaging systems including five existing multispectral imaging systems and further substantiates the utility of optimal band selection in target detection and material identification. As an alternative to band selection, Chapter 10 by Serpico et al. proposes an approach to band partition which is based on feature extraction/selection for a specific classification application. Finally, Chapter 11 by Bruzzone et al. improves a well-known supervised classifier, support vector machines (SVMs), by introducing semisupervised SVMs for classification of hyperspectral remote sensing images.

1.4.3. Part III: Applications

The applications part consists of three chapters that address various data exploitation issues by different approaches using classification as an application. Chapter 12 by Benediktsson and co-workers proposes a generic framework to fuse decisions of multiple classifiers for hyperspectral classification including morphology-based classifier, neural network classifier, and SVMs. Chapter 13 by Plaza develops a morphology-based classification approach and its potential in parallel computing. Finally, this book concludes with one of the most important applications in hyperspectral data exploitation, namely, hyperspectral data compression. Chapter 14 by Fowler and Rucker which overviews 3-D wavelet-based hyperspectral data compression with classification as an application.

1.5. BRIEF DESCRIPTIONS OF CHAPTERS IN THE BOOK

In order to provide a quick glimpse of all the chapters presented in the book, this section intends to help the reader walk through each of these chapters by briefly summarizing their works and suggesting coherent connections among different chapters as follows.

Part I: Tutorials

Chapter 2. Hyperspectral Imaging Systems

John P. Kerekes and John R. Schott
Chester F. Carlson Center for Imaging Science
Rochester Institute of Technology, Rochester, NY, USA

This chapter offers an excellent overview of some currently used hyperspectral imaging systems: JPL/NASA developed the 224-band Airborne Visible InfraRed Imaging Spectrometer in 1987, Hughes/NRL developed the 210-band HYperspectral Digital Image Collection Experiment (HYDICE) in 1994, and TRW/NASA developed the 220-band HYPERION in 2000. In addition, two sensor models are also introduced for simulation in development and application of sensor technology: (1) Digital Imaging and Remote Sensing Image Generation (DIRSIG) developed by the Rochester Institute of Technology (RIT) and (2) Forecasting and Analysis of Spectroradiometric System Performance (FASSP) developed by Massachusetts Institute of Technology (MIT) Lincoln Laboratory. This chapter provides a good tutorial introduction of hyperspectral sensor design and technology to researchers working in the hyperspectral imaging area.

Chapter 3. Information-Processed Matched Filters for Hyperspectral Target Detection and Classification

Chein-I Chang

Remote Sensing Signal and Image Processing Laboratory

Department of Computer Science and Electrical Engineering

University of Maryland—Baltimore County, Baltimore, MD, USA

This chapter reviews hyperspectral target detection and classification algorithms from a matched filter perspective. Since most such algorithms share the same design principles of using a matched filter as a framework, this chapter presents an information-processed matched-filter approach to unifying these algorithms. It interprets a hyperspectral target detection and classification algorithm using two sequential filter operations. The first filter operation is an information-processed filter that processes *a priori* or *a posteriori* target information to suppress unwanted interference and noise effects. The follow-up second filter operation is a matched filter that extracts targets of interest for detection and classification. Three well-known specific techniques—Orthogonal Subspace Projection (OSP), Constrained Energy Mimimization (CEM), and Reed–Yu's RX-anomaly detection—are selected for this interpretation, each of which represents a particular category of algorithms that process a different level of information to enhance performance of the follow-up matched filter. While the OSP requires a complete prior knowledge, the RX-anomaly detection relies only on the *a posteriori* information provided by data samples. The CEM is somewhere in between, which requires *a priori* information of the desired targets used in the matched filter with *a posteriori* information obtained from data samples to suppress interfering effects while performing target extraction. The relationship among these three types of techniques shows how *a priori* target knowledge is approximated by *a posteriori* information as well as how a matched filter is affected by the information used in its matched signal.

Part II: Theory

Chapter 4. An Optical Real-Time Adaptive Spectral Identification System (ORASIS)

Jeffery H. Bowles and David B. Gillis

Remote Sensing Division

Naval Research Laboratory, Washington, DC, USA

This chapter presents a popular system, called the Optical Real-Time Adaptive Spectral Identification System (ORASIS), developed by the authors with their colleagues in the Naval Research Laboratory. It is a collection of a number of algorithms that are designed to perform various tasks in sequence. In its first-stage process, it develops a prescreener that finds an exemplar set and uses the found exemplar set as a code book to encode all image spectral signatures. This is followed by a second-stage process, which is basis selection that projects the exemplar set into a low-dimensional space spanned by an appropriate set of bases. This process is similar to dimensionality reduction that is commonly accomplished by the Principal Components Analysis (PCA). With this reduced data space the third-stage process performs a simplex-based endmember extraction to select a desired set of endmembers that are used to form a linear mixing model for least-squares error-based spectral unmixing that is carried out in the fourth and final state process to exploit three applications: automatic target recognition, terrain categorization, and compression.

Chapter 5. Stochastic Mixture Modeling

Michael T. Eismann[1] and David W. J. Stein[2]

[1]AFRL's Sensors Directorate, Electro Optical Technology Division
Electro Optical Targeting Branch, Wright-Patterson AFB, OH, USA

[2]MIT Lincoln Laboratory, Lexington, MA, USA

This chapter develops a stochastic mixing model (SMM) to address limitations of the commonly used linear mixture model (LMM) by capturing data variation that cannot be well described by linear mixing. Unlike the LMM which considers image endmembers as deterministic signatures, the SMM treats image endmembers used in a linear mixture model as random signatures. More specifically, a data sample is described by a linear mixture of a finite set of random endmembers that can be modeled by mixtures of Gaussian distributions. Two approaches are developed to estimate mixture density functions: (1) discrete SMM, which imposes physical abundance constraints, and (2) normal composition model (NCM), which is a continuous version of the SMM with no constraints imposed on abundance fractions. As a result, the NCM does not make assumption of existence of pure pixels as does in the discrete SMM. In order to estimate mixture density functions used to describe both models, the well-known Expectation-Maximization (EM) algorithm is used for this purpose. Interestingly, a similar approach using linear mixtures of random endmembers can be also found in Chapter 6 where two models, mixtures of Gaussian distrivutions and mixtures of Dirichlet distributions are introduced as counterparts of the discrete SMM and NCM dealing with the issue of presence of pure pixels in the data. The readers are strongly recommended to read this chapter along with Chapter 6 to have maximum benefits in gaining insights into linear mixtures of random endmembers.

Chapter 6. Unmixing Hyperspectral Data: Independent and Dependent Component Analysis

Jose M. P. Nascimento[1] and Jose M. B. Dias[2]
[1]Instituto Superior De Engenharia de Lisboa, Lisbon, Portugal
[2]Instituto de Telecomunicações, Lisbon, Portugal

This chapter presents approaches using independent component analysis (ICA) and independent factor analysis (IFA) to unmix hyperspectral data, and it further addresses issues of limitations on data independency and dependency due to constraints imposed on abundance fractions in the unmxing processing. The criterion used for finding an unmixing matrix for the ICA and IFA is the minimization of mutual information based on the calculation of a finite mixture of Gaussian distributions via the expectation–maximization (EM) algorithm to estimate mixture density functions where the resulting unmixng matrix is generally far from the true one if there are no pure pixels present in the data. In order to mitigate this problem, it introduces a new blind separation source unmixing technique where abundance fractions are modeled by mixtures of Dirichlet sources which enforce two physical constraints, namely, non-negativity and sum-to-one abundance fraction constraints. Once again, the EM algorithm is also used to estimate mixture density functions. Interestingly, the work in this chapter follows a very similar approach to the work in Chapter 5, where a data sample is also described by a finite mixture of Gaussian random endmembers whose mixture density functions are estimated by the EM algorithm. It will be very beneficial to the readers if both Chapter 5 and Chapter 6 are read together to gain their ideas developed for the models.

Chapter 7. Maximum Volume Transform for Endmember Spectra Determination

Michael E. Winter
Hawaii Institute of Geophysics and Planetology
University of Hawaii, Honolulu, HI, USA

This chapter revisits the well-known endmember extraction algorithm, called the N-finder algorithm (N-FINDR), which was developed by the author and further presents a new development of the N-FINDR, called the N-FINDR-based maximum volume transform (MVT). Endmember extraction has been a fundamental issue arising in hyperspectral data exploitations (as indicated in Chapters 4–6), where endmembers form a base of a linear mixing model. The N-FINDR is probably one of most widely used endmember extraction algorithms available in the literature. The work presented in this chapter offers a good review of the N-FINDR which should interest researchers working in automatic exploitation of hyperspectral imagery.

Chapter 8. Hyperspectral Data Representation

Xiuping. Jia[1] and John A. Richards[2]
[1]Australian Defense Force Academy, Australia
[2]The Australia National University, Australia

This chapter investigates hyperspectral data representation to explore the issue of the curse of dimensionality. In doing so, several selected supervised classification methods including standard maximum likelihood classification (MLC) with its variants—block-wise MLC, regularized MLC, and nonparametric weighted feature extraction (NWFE)—are used to reduce data dimensionality. In order to conduct a comparative analysis among these four algorithms, two sets of hyperspectral image data, Hyperion data, and Purdue's Indiana Indian Pine AVIRIS data are used for performance evaluation.

Chapter 9. Optimal Band Selection and Utility Evaluation for Spectral Systems

Sylvia S. Shen
The Aerospace Corporation, Chantilly, VA, USA

This chapter considers optimal band selection and utility evaluation for spectral imaging systems. For a given number of bands, it develops an information theoretic criterion-based genetic algorithm to find an optimal band set that yields the highest possible material separability. One of interesting findings in this chapter is to use 612 adjusted spectra obtained from a combined data base to conduct a comparative study of various optimal band sets with their respective five different existing spectral imaging systems: Landsat-7 ETM+, Multispectral Thermal Imager (MTI), Advanced Land Imager (ALI), Daedalus AADS 1268, and M7. Additionally, in order to assess utility of optimal band sets, two applications of anomaly detection by spectral unmixing and material identification by spectral matching are investigated for performance evaluation where two HYDICE data cubes are used for experiments to perform qualitative and quantitative study. The results demonstrate that a judicious selection of a band subset from original bands (e.g., as few as nine bands) can perform very effectively in separating man-made objects from natural background. This useful information provide insights into the development and optimization of multiband spectral sensors and algorithms using an exploitation-based optimal band selection to reduce data transmission and storage while retaining features used for target detection and material identification.

Chapter 10. Feature Reduction for Classification Purpose

Sebastiano B. Serpico, Gabriele Moser, and Andrea F. Cattoni
Department of Biophysical and Electronic Engineering
University of Genoa, Genoa, Italy

This chapter investigates approaches to feature extraction-based band partition where four band partition algorithms, called sequential forward band partitioning (SFBP), steepest ascent band partitioning (SABP), fast constrained band partitioning (FCBP), and convergent constrained band partitioning (CCBP), are developed with the Jeffries–Matusita distance used as the criterion for band partition from a classification point of view. It is interesting to compare the work in this chapter to that in Chapter 9, where the former performs a classification-based band partition, whereas the latter proposes a genetic algorithm-based band selection with its utility substantiated by anomaly detection and material identification.

Chapter 11. Semisupervised Support Vector Machines for Classification of Hyperspectral Remote Sensing Images

Lorenzo Bruzzone, Mingmin Chi, and Mattia Marconcini
Department of Information, and Communication Technology
University of Trento, Trento, Italy

This chapter presents an approach based on semisupervised support vector machines (SVMs) which combine advantages of semisupervised classification approaches with the advantages of distribution-free kernel-based methods based on SVMs so as to achieve better classification. Two such semisupervised SVM techniques are developed. One is a transductive SVM based on an iterative self-labeling procedure implemented in the dual formulation of the optimization problem related to the learning of the classifier. The other is a transductive SVM based on the cluster assumption implemented in the primal formulation of the optimization problem associated with the learning of the classification algorithm. A comparative analysis between these two techniques along with a standard inductive SVM is conducted by using a real hypersepctral data set for experiments. Experimental results demonstrate that the proposed semisupervised support vector machines perform effectively and increase the classification accuracy compared to standard inductive SVMs.

Part III: Applications

Chapter 12. Decision Fusion for Hyperspectral Classification

Mathieu Fauvel[1,2], Jocelyn Chanussot[1], and Jon Atli Benediktsson[2]
[1] Laboratoire des Images et des Signaux, Saint Martin d'Heres, France
[2] Department of Electrical and Computer Engineering
University of Iceland, Reykjavik, Iceland

This chapter presents a generic framework where the redundant or complementary results provided by multiple classifiers can actually be aggregated. Taking advantage of the specificities of each classifier, the decision fusion thus increases the overall classification performances. The proposed fusion approach is in two steps. In a first step, data are processed by each classifier separately and the algorithms provide for each pixel membership degrees for the considered classes. Then in a second step, a fuzzy decision rule is used to aggregate the results provided by the algorithms according to the classifiers' capabilities. The general framework proposed for combining information from several individual classifiers in multiclass classification is based on the definition of two measures of accuracy. The first one is a pointwise measure that estimates for each pixel the reliability of the information provided by each classifier. By modeling the output of a classifier as a fuzzy set, this pointwise reliability is defined as the degree of uncertainty of the fuzzy set. The second measure estimates the global accuracy of each classifier. It is defined *a priori* by the user. Finally, the results are aggregated with an adaptive fuzzy fusion ruled by these two accuracy measures. The method is illustrated by considering the classification of hyperspectral remote sensing images from urban areas. It is tested and validated with two classifiers on a ROSIS image from Pavia, Italy. The proposed method improves the classification results when compared with the separate use of the different classifiers.

Chapter 13. Morphological Hyperspectral Image Classification: A Parallel Processing Perspective

Antonio J. Plaza
Computer Science Department
University of Extremadura, Caceres, Spain

This chapter provides a detailed overview of recently developed approaches to morphological analysis of remotely sensed data. It first explores vector ordering strategies for the generalization of concepts from mathematical morphology to multichannel image data and further develops new, physically meaningful distance-based organization schemes to define morphological vector operations by extension. The problem of ties resulting from partial vector ordering is also addressed. Then, two new morphological algorithms for hyperspectral image classification are developed, which are (1) a supervised mixed pixel classification algorithm which integrates spatial and spectral information in simultaneous fashion and (2) an unsupervised morphological watershed-based image segmentation algorithm that first analyzes the data using spectral information and then refines the result using spatial context. While such integrated spatial/spectral approaches hold great promise in several applications, they also introduce new processing challenges. Several applications exist, however, where having the desired information calculated in (near) real time is highly desirable. For that purpose, this chapter also develops efficient parallel implementations of the morphological techniques addressed above. Three parallel computing platform used in experiments is a massively parallel Beowulf cluster called Thunderhead, made up of 256 processors and located at NASA's Goddard Space Flight Center in Maryland.

Chapter 14. Three-Dimensional Wavelet-Based Compression of Hyperspectral Imagery

James E. Fowler and Justin T. Rucker

Department of Electrical and Computer Engineering

GeoResources Institute

Mississippi State University, Mississippi State, MS USA

This chapter overviews 3D embedded wavelet-based algorithms with their applications to hyperspectral data compression. Six JPEG2000-based compression algorithms, (1) JPEG2000-band-independent fixed-rate (BIFR), (2) 2D JPEG2000-band-independent fixed-rate (BIFR), (3) JPEG2000-band-independent rate allocation (BIRA), (4) 2D JPEG2000-band-independent rate allocation (BIRA), (5) JPEG2000 multicomponent (JPEG2000-MC), (6) 2D JPEG2000 multicomponent (JPEG2000-MC), are studied for compression of hyperspectral image data. It is well known that the commonly used compression criteria mean-squared error (MSE) and signal-to-noise ratio (SNR) are not appropriate measures to evaluate hyperspectral data compression. In order to address this issue, this chapter introduces an application specific measure, called preservation of classification (POC), as a compression criterion where an unsupervised classifier, ISODATA, is used for evaluation of classification performance. Three hyperspectral AVIRIS data—Moffett, Jasper Ridge, and Cuprite—are then used to conduct a comparative analysis among the six considered compression algorithms using three different compression criteria, MSE, SNR, and POC. The experimental results have demonstarted that JPEG2000 can always benefit from a 1D spectral wavelet transform.

Finally, in order to provide a guide for what topics and techniques are discussed in each of the chapters, Table 1.1 summarizes the major tasks accomplished in each of chapters with acronyms defined as follows for reference. However, it should be noted that since Chapter 2 is completely devoted to design and development of hyperspectral imaging systems, it is not included in Table 1.1.

ACRONYMS

DR	Dimensionality reduction
EM	Expectation–maximization algorithm
FE	Feature extraction
GA	Genetic algorithm
ICA	Independent component analysis
IFA	Independent factor analysis
LMM	Linear–mixing model
LSE	Least–squares error
MNF	Maximum noise fraction
MLE	Maximum likelihood estimation

TABLE 1.1. Techniques Used to Perform Various Functionalities in Chapters

Chapters	Data Model and Representation	Endmember Extraction	Spectral Unmixing	Applications
Chapter 3	OSP-DR, LMM		OSP	Detection, classification
Chapter 4	Basis-DR, LMM	Simplex	LSE	Detection, classification, compression
Chapter 5	PCA-DR, SMM/NCM	N-FINDR	MLE	
Chapter 6	PCA-DR, LMM	Mutual information	ICA/IFA	
Chapter 7	MNF-DR	N-FINDR		
Chapter 8	FE-DR		MLE	Classification
Chapter 9	GA-based Band selection		Unspecified	Spectral matching, detection, identification
Chapter 10	Band partition			SVM/classification
Chapter 11				SVM/classification
Chapter 12				Morphology-NN SVM/classification
Chapter 13	PCA/MNF-DR			Morphology classification
Chapter 14	3D wavelet compression			ISODATA/ classification

NCM	Normal composition model
NN	Neural network
NWFE	Nonparametric weighted feature extraction
OSP	Orthogonal subspace projection
PCA	Principal components analysis
SMM	Stochastic mixing model
SVM	Support vector machine

Additionally, Table 1.2 also provides information about the types of image data that are used in Chapters 2–14, where a check symbol "$\surd$" indicates that an image scene is not specified in a particular chapter.

1.6. CONCLUSIONS

Hyperspectral imaging offers an effective means of detecting, discriminating, classifying, quantifying, and identifying targets via their spectral characteristics captured by high spectral-resolution sensors without accounting for their spatial information. The processing techniques that only make use of spectral properties

TABLE 1.2. Data Used in Various Chapters

Chapters	AVIRIS	HYDICE	HYPERION	Other Images
Chapter 2	√	√	√	DIRSIG
Chapter 3	Lab data			
Chapter 4	Cuprite	Forest		PHILLS
Chapter 5	Cuprite	Forest	√	
Chapter 6	Indian Pine			
Chapter 7	Cuprite			HyMap (Cuprite)
Chapter 8	Indian Pine		√	
Chapter 9		√		Landsat, ALI, MTI, Daedalus, M7
Chapter 10	Indian Pine			
Chapter 11			√	
Chapter 12				ROSIS
Chapter 13	Salinas Valley			
Chapter 14	Moffett, Cuprite, Jasper Ridge			

without taking into account spatial information are generally referred to as nonliteral (spectral) processing techniques as opposed to literal techniques referred to as traditional spatial domain-based image processing techniques. Over the past years, significant research efforts have been devoted to design and development of such nonliteral processing techniques with applications in hypespectral data exploitation. Many results have been published in various journals and presented in different conference meetings. Despite the fact that several books have recently been published [5,10–13], the subjects covered in these books are somewhat selective. The chapters presented in this book provide the most recent advances of many techniques which are not available in these books. In particular, it addresses many important key issues that should serve as a nice guide for researchers who are interested in exploitation of hyperspectral data.

REFERENCES

1. S. S. Epp, *Discrete Mathematics with Applications*, 2nd edition, Brooks/Cole, Pacific Grove, CA, 1995.
2. R. O. Duda and P. E. Hart, *Pattern Classification and Scene Analysis*, John Wiley & Sons, New York, 1973.
3. K. Fukunaga, *Statistical Pattern Recognition*, 2nd edition, Academic Press, New York, 1990.
4. M. Wax and T. Kailath, Detection of signals by information criteria, *IEEE Transactions on Acoustic, Speech, and Signal Processes*, vol. ASSP-33, no. 2, pp. 387–392, 1985
5. C.-I Chang, *Hyperspectral Imaging: Techniques for Spectral Detection and Classification*, Kluwer Academic/Plenum Publishers, New York, 2003.

6. C.-I Chang and Q. Du, Estimation of number of spectrally distinct signal sources in hyperspectral imagery, *IEEE Transactions on Geoscience and Remote Sensing*, vol. 42, no. 3, pp. 608–619, 2004.
7. C.-I Chang, Exploration of virtual dimensionality in hyperspectral image analysis, *Algorithms and Technologies for Multispectral, Hyperspectral, and Ultraspectral Imagery XII*, SPIE Defense and Security Symposium, Orlando, Florida, April 17–21, 2006.
8. C.-I Chang, Utility of Virtual Dimensionality in Hyperspectral Signal/Image Processing, Chapter 1, *Recent Advances in Hyperspectral Signal and Image Processing*, edited by C.-I Chang, Research Signpost, Trivandrum, Kerala, India, 2006.
9. J. C. Harsanyi and C.-I Chang, Hyperspectral image classification and dimensionality reduction: An orthogonal subspace projection approach, *IEEE Transactions on Geoscience and Remote Sensing*, vol. 32, no. 4, pp. 779–785, 1994.
10. P. K. Varshney and M. K. Arora (Ed.), *Advanced Image Processing Techniques for Remotely Sensed Hyperspectral Data*, Springer-Verlag, Berlin, 2004.
11. C.-I Chang (Ed.), *Recent Advances in Hyperspectral Signal and Image Processing*, Research Signpost, Transworld Research Network, Trivandrum, Kerala, India, 2006.
12. A. J. Plaza and C.-I Chang (Ed.), *High Performance Computing in Remote Sensing*, CRC Press, Boca Raton, FL, 2007.
13. C.-I Chang, *Hyperspectral Imaging: Signal Processing Algorithm Design and Analysis*, John Wiley & Sons, Hoboken, NJ, 2007.