Chapter 1
Introduction

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Hyperspectral imaging entails acquiring a large number of images over hundreds (to thousands) of narrowband contiguous channels, spanning the visible and infrared regimes of the electromagnetic spectrum. The underlying premise of such imaging is that it captures the underlying processes (e.g., chemical characteristics, biophysical properties, etc.) at the pixel level. Recent advances in optical sensing technology (miniaturization and low-cost architectures for spectral imaging) and sensing platforms from which such imagers can be deployed (e.g., handheld devices, unmanned aerial vehicles) have the potential to enable ubiquitous multispectral and hyperspectral imaging on demand to support a variety of applications, such as biomedicine and sensing of our environment. In many applications, it is possible to leverage data acquired by other modalities (e.g., Synthetic Aperture Radar, SAR, and Light Detection and Ranging (LiDAR)) in conjunction with hyperspectral imagery to paint a complete picture—for example, hyperspectral imagery and LiDAR data when used together provide information about the underlying chemistry (e.g., as provided by hyperspectral data) and the underlying topography (as provided by LiDAR data) and can facilitate robust land-cover classification. Although this increase in the quality and quantity of diverse multi-channel optical data can potentially facilitate improved understanding of fundamental scientific questions, there is a strong need for robust image analysis methods that can address the challenges posed by these imaging paradigms. While machine learning approaches for image analysis have evolved

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to exploit the rich information provided by hyperspectral imagery and other high-dimensional imagery data, key challenges remain for effective utilization in an operational environment, including the following:

- Representation and effective feature extraction from such high-dimensional datasets,
- Design of effective learning strategies that are robust to a limited quantity of training samples (*in situ data*), missing or noisy labels, and spatial–temporal non-stationary environments,
- Design and optimization of analysis algorithms that can effectively handle nonlinear, complex decision boundaries separating classes (objects of interest on ground) in the feature space,
- The need to address variability in light source → sensor → object geometry and variation in orientation and scale of objects in ubiquitous sensing environments from a multitude of sensors and sensing platforms, and
- Effective utilization of the rich and vast quantity of unlabeled data available in geospatial imagery in conjunction with limited ground truth for robust analysis.

This book focuses on advances in machine learning and signal processing for hyperspectral image analysis and presents recent algorithmic developments toward robust image analysis that address challenges posed by the unique nature of such imagery. We note that although a majority of the chapters in this book focus on hyperspectral imagery, these ideas extend to data obtained from other modalities, such as microwave remote sensing, multiplexed immunofluorescence imaging, etc. Chapters in this book are grouped in the challenges they address based on the following broad thematic areas.

Challenges in Supervised, Semi-Supervised, and Unsupervised Learning: The high-dimensional nature of hyperspectral imagery implies that many learning algorithms that seek to leverage the underlying spatial–spectral information are associated with a large number of degrees of freedom, necessitating a rich (in both quality and quantity) representative ground reference data. Leveraging the limited quantity and varying quality of labeled data associated with remote sensing and biomedicine applications is a critical requirement of successful learning algorithms, and a vast number of recent developments address this aspect of learning, under the umbrella of supervised, semi-supervised, and unsupervised learning. Further, the end goal of learning may not always be discrete classification. Numerous applications with hyperspectral imagery entail mapping spectral observations to prediction (e.g., posed as a regression problem) of continuous-valued quantities (such as biophysical parameters)—although there exist commonalities between learning algorithms that are carrying out discrete classification and regression, care must be taken to understand the needs and constraints of each application.

In Chap. 2, Moreno-Martinez et al. survey recent developments in machine learning for estimating spatial and temporal parameters from multi-channel earth-observation images (both microwave imaging and passive optical imaging). Chapters 3 and 4 are a two-part series introducing the foundations of deep learning as applied to hyperspectral image analysis. In Chap. 3 (Part I), Berisha et al. review the foundations of convolutional and recurrent neural networks as they can be applied for spatial–spectral analysis of hyperspectral imagery. In Chap. 4 (Part II), Shahraki et al. present practical architectures and design strategies to successfully deploy such networks for hyperspectral image analysis tasks. Results with hyperspectral imagery in the areas of remote sensing and biomedicine are presented, along with a detailed discussion of the "successful" network configurations relative to the data characteristics. In Chap. 5, Zhou and Prasad review recent developments in deep learning that address the label scarcity problem—including semi-supervised, transfer, and active learning. In Chap. 6, Jiao et al. present multiple instance learning as a mechanism to address imprecise ground reference data that is commonly encountered in hyperspectral remote sensing. In Chap. 7, Rise et al. survey supervised, semi-supervised, and unsupervised learning for hyperspectral regression tasks. In Chap. 8, Wu et al. survey sparse-representation-based methods for hyperspectral image classification. In Chap. 9, Gu et al. review multiple kernel learning for hyperspectral image classification.

Subspace Learning and Feature Selection: Given the high dimensionality of spectral features and the inherent inter-channel correlations due to the dense, contiguous spectral sampling, algorithms that learn effective subspaces (e.g., subspaces where much of the discriminative information is retained) and that learn the most relevant spectral channels are often a crucial pre-processing to image analysis. In Chap. 10, Zhu et al. present a low-dimensional manifold model for hyperspectral image reconstruction. In Chap. 11, Taherkhani et al. present a deep sparse band selection for hyperspectral face recognition.

Change and Anomaly Detection: In many applications, the ability to reliably detect changes between sets of hyperspectral imagery is highly desirable. In Chap. 12, Ziemann and Matteoli present recent developments toward robust detection of large-scale and anomalous changes.

Spectral Unmixing: The spatial resolution of hyperspectral imagery acquired from airborne or spaceborne sensors often is not fine enough relative to the size of objects of interest in the scene, resulting in mixed pixels. Over recent years, numerous advances have been made in the area of spectral unmixing—the process of estimating the relative abundance of the endmembers (e.g., objects in these mixed pixels) in each mixed pixel. In Chap. 13, Zhang et al. review recent advances in spectral unmixing using sparse techniques and deep learning.

Image Superresolution: In many remote sensing applications, a common imaging scenario entails simultaneous acquisition of very high spatial resolution color/multispectral/monochromatic(pan) images and lower spatial resolution hyperspectral images. One can leverage this by extracting spatial information available in the higher resolution imagery, which can then be fused in the lower resolution hyperspectral imagery. In Chap. 14, Yang et al. present a deep-learning-based approach to fuse high spatial resolution multispectral imagery with hyperspectral imagery.

Target Detection: An important application of hyperspectral imagery has been identification of targets of interest in a scene. In Chap. 15, Bitar et al. present an automatic target detection approach for sparse hyperspectral images.