# Processing of Imaging Spectroscopy Data – Advanced Technologies

A. Plaza*, J. A. Benediktsson, J. Boardman, J. Brazile, L. Bruzzone, G. Camps-Valls,
J. Chanussot, M. Fauvel, P. Gamba, A. Gualtieri, J. C. Tilton

*Department of Computer Science, University of Extremadura
Avda. de la Universidad s/n, E-10071 Cáceres, SPAIN
Phone: +34 927 257195 – Fax: +34 927 257203
E-mail: aplaza@unex.es

## Abstract

Imaging spectroscopy, also known as hyperspectral remote sensing, is concerned with the measurement, analysis, and interpretation of spectra acquired from a given scene (or specific object) at a short, medium or long distance by an (airborne or satellite) sensor. The final goal of this imaging technique is to identify materials and objects in the air, land and water on the basis of the unique reflectance patterns that result from the interaction of solar energy with the molecular structure of the material. The concept of imaging spectroscopy originated in the 1980's, when Dr. Alexander F. H. Goetz and his colleagues at Jet Propulsion Laboratory began a revolution in remote sensing by developing new instruments including first AIS (Airborne Imaging Spectrometer) and then called AVIRIS (for Airborne Visible Infra-Red Imaging Spectrometer), which is now able to cover the wavelength region from 0.4 to 2.5 μm using more than two hundred spectral channels at nominal spectral resolution of 10 nm. The AVIRIS system has been upgraded and improved in a continuous effort to meet the requirements of investigators using hyperspectral data for science research and applications. Following the path initiated by AVIRIS, several new airborne instruments have been successfully employed in Earth-based and planetary exploration missions, including the Hyperspectral Digital Imagery Collection Experiment (HYDICE), the Compact Airborne Spectrographic Imager (CASI), the Digital Airborne Imaging Spectrometer (DAIS 7915), or the HyMap system. Unlike airborne sensors, space-based sensors are able to image any portion of the globe and can allow for periodic repeat coverages. Examples include NASA's Hyperion sensor on the EO-1 satellite, the Compact High Resolution Imaging Spectrometer (CHRIS) carried on board the PROBA (Project for On Board Autonomy) space platform of the European Space Agency (ESA), or the Moon Mineralogy Mapper (M3) mission.

The special characteristics of hyperspectral images pose different processing problems, which must be necessarily tackled under specific mathematical formalisms, such as classification, regression, modeling, image coding, spectral unmixing, etc., and that also require specific dedicated processing software and hardware platforms. A diverse array of techniques has been applied to extract information from hyperspectral data during the last decade. They are inherently either *full pixel* techniques or *mixed pixel* techniques, where each pixel vector in a hyperspectral scene provides a "spectral signature" that uniquely characterizes the underlying materials at each site in a scene. The underlying assumption governing full pixel techniques is that each pixel vector measures the response of one single material. In contrast, the underlying assumption governing mixed pixel techniques (also called "spectral unmixing" approaches) is that each pixel vector measures the response of multiple underlying materials at each site. A hyperspectral scene (sometimes referred to as "data cube") is often a combination of the two situations, where a few sites in a scene are pure materials, but many other are mixtures of materials. The inherent overdeterminacy of hyperspectral data, where we have more spectral channels than unique spectral endmembers, stands in contrast to the underdeterminacy of more traditional multispectral data. It is this overdeterminacy that permits a direct and unique solution of the spectral unmixing problem.

Most available techniques for hyperspectral data processing focus on analyzing the data without incorporating information on the spatially adjacent data, i.e., the hyperspectral data is treated not as an image but as an unordered listing of spectral measurements. It is worth noting that such spectral-based techniques would yield the same result for a data cube, and for the same data cube where the spatial positions have been randomly permuted. However, one of the distinguishing properties of hyperspectral data is the multivariate information coupled with a two-dimensional (pictorial) representation amenable to image interpretation. Subsequently, there is a need to incorporate the spatial component of the data in the development of techniques for hyperspectral data exploitation.

The main goal of this paper is to provide a seminal view on recent, consolidated advances in technologies for efficient processing of hyperspectral imagery. Our main focus is on the development of joint spatial/spectral developments, able to exploit: i) *a priori* knowledge about the shape of the objects in the scene; ii) to take advantage of the spatial distribution; iii) to properly exploit the information present in all labeled and unlabelled samples for a proper learning of the processing algorithms. The discussed techniques are able to improve analysis results even when ground spatial resolution results in mixed pixels on the borders of scene objects. Techniques include Markov random fields, mathematical morphology, artificial neural networks, and kernel machines. Another important spatial/spectral data processing methodology addressed in this work is the hierarchical segmentation (HSEG) algorithm, developed at NASA. HSEG is a hybrid of hierarchical step-wise optimization and constrained spectral clustering that produces a segmentation hierarchy, i.e., a set of several image segmentations of the same image at different levels of detail. A single segmentation level can be selected out of the segmentation hierarchy by analyzing the spatial and spectral characteristics of the individual regions, and also by tracking the behavior of the image segmentations (in automated or semi-automated fashion) throughout the different levels of detail. This constitutes a completely novel approach to extracting information from hyperspectral image data sets.

The paper further investigates classification of remote sensing data with inductive support vector machines (ISVMs), which are one of the most promising algorithms for analyzing high-dimensional input spaces where traditional statistical techniques generally under-perform. This problem is related to the well-known "curse of dimensionality" or *Hughes* effect. Using a kernel method, ISVMs circumvent this problem by mapping the data into a higher dimensional space to increase their separability, and then try to fit a hyperplane to separate the data. The generalization capabilities of ISVMs, as well as their ability to deal with high-dimensional feature spaces, are illustrated in this work by using several types of kernels and analysis scenarios with limited training sets available. The good classification performance demonstrated by ISVMs using the spectral signature as input features can be further increased by developing classification algorithms which includes: i) contextual (or even textural) information in the classifier by means of the *composite kernels* framework, in which one exploits the properties of Mercer's kernels; ii) semi-supervised or transductive SVMs (TSVMs) learning procedures, which exploits both labeled and unlabeled pixels in the training of the classifier. These novel formulations open a wide range of future efficient developments in which: i) spatial and spectral information can be easily integrated and analyzed by using proper kernel functions; ii) the capability of semi-supervised SVMs to capture the intrinsic information present in the unlabeled data can further mitigate the Hughes phenomenon and the problems related to the non-stationary behavior of the spectral signatures of classes in the spatial domain (which are very critical issues in the processing of hyperspectral data).

While integrated spatial/spectral developments hold great promise for hyperspectral image analysis, they also introduce new processing challenges. In particular, the price paid for the wealth of spatial and spectral information available from hyperspectral sensors is the enormous amounts of data that they generate. Several applications exist, however, where having the desired information calculated in near real-time is highly desirable. Such is the case of automatic target recognition for military and defense/security deployment. Other relevant examples include environmental monitoring and assessment, urban planning and management studies, risk/hazard prevention and response including wild-land fire tracking, biological threat detection, monitoring of oil spills and other types of chemical contamination. With the recent explosion in the amount and complexity of hyperspectral imagery, parallel processing has soon become a tool of choice in many remote sensing missions, especially with the advent of low-cost systems such as commodity clusters. Further, the new processing power offered by Grid computing environments can be employed to tackle extremely large remotely sensed data sets and to get reasonable response times in complex image analysis scenarios. Our contribution also explores the development of parallel processing support for several of the algorithms addressed above, with particular interest on at-sensor product generation and the development of a generic data processing framework. Performance data for the tested parallel algorithms are given in a variety of high-performance computing architectures, including massively parallel Beowulf clusters, low-scale heterogeneous networks of workstations, field programmable gate arrays (FPGAs) and Grid environments.