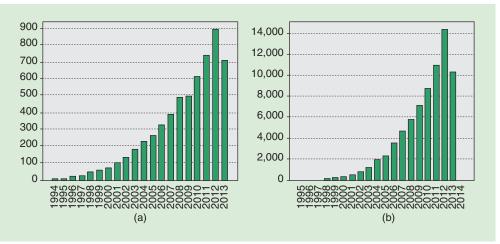
Signal and Image Processing in Hyperspectral Remote Sensing

n recent years, it has become clear that hyperspectral imaging has formed a core area within the geoscience and remote sensing community. Armed with advanced optical sensing technology, hyperspectral imaging offers high spectral resolution—a hyperspectral image can contain more than 200 spectral channels (rather than a few channels as in multispectral images), covering visible and near-infrared wavelengths at a resolution of about 10 nm. The

result, on one hand, is significant expansion in data sizes. A captured scene can easily take 100 MB, or more. On the other hand, the vastly increased spectral information content available in hyperspectral images (or large spectral degrees of freedom in signal processing languages) creates a unique opportunity that may have previously been seen as impossible in multispectral remote sensing. We can detect difficult targets, for example, those appearing at a subpixel level. We can perform image classification with greatly improved accuracy. We can also identify underlying materials in a captured scene without prior information of the materials to be encountered, by carrying out blind unmixing.

There are many other exciting advances contributed by researchers in hyperspectral remote sensing, and their great effort has resulted in an enormous number of applications, such as



[FIG1] The number of published papers having the keyword "hyperspectral" and the corresponding citations. Data is obtained from the SCI-Expanded database, ISI Web of Science. (a) Published items in each year. (b) Citations in each year.

surveillance, reconnaissance, environment monitoring, land-cover mapping, and mineral identification, just to name a few. Hyperspectral imaging is also a key technique for planetary exploration, astrophysics, and nonremote sensing problems such as food inspection and forensics.

There has been much growth in research activities related to hyperspectral imaging lately. Figure 1 shows a report on the number of publications and citations in the "hyperspectral" topic. The results were obtained by searching the Science Citation Index (SCI)-Expanded database of the ISI Web of Science with the topic "hyperspectral" from 1994 to September 2013. A sharp rise with both the publications and citations counts can be observed from 2010 to 2013. While major research activities on hyperspectral remote sensing are in the geoscience and remote sensing community, hyperspectral remote sensing is also an area that contains many interesting and important signal processing problems. In fact, this area has attracted

growing attention and contributions from different communities, such as signal processing, image processing, machine learning, and optimization—and this is what motivates us to organize this special issue.

IEEE Signal Processing Magazine published a special issue on signal processing for hyperspectral image exploitation in 2002, which was particularly relevant at the time. After more than ten years, we believe that now would be an appropriate time to consider another special issue on this topic, chronicling recent advances, challenges, and opportunities. Also, this issue has a unique theme—to provide a balanced collection of tutorial-style articles that introduce prominent and frontier signal processing topics in hyperspectral remote sensing and demonstrate the insight and uniqueness of signal processing techniques established in those topics. We also intend to take this opportunity to bridge the gap between remote sensing and signal processing by showing readers a

Digital Object Identifier 10.1109/MSP.2013.2282417 Date of publication: 5 December 2013 sample of relevant problems in hyperspectral remote sensing.

We would like to thank those who showed interest in this special issue. We received approximately 40 white papers. The topics proposed are very diverse from one another, and many of them are indeed interesting in their own rights: we have seen numerous excellent white papers, and in some cases, we are comparing apples and oranges. However, there are page limitations, and consequently only nine articles can be accommodated. Again, we appreciate the enthusiasm received.

The special issue can roughly be divided into four theme topics: detection, classification, unmixing, and compressive sensing (CS). It begins with the detection topic. Manolakis et al. give an overview on the hyperspectral target detection problem. The authors then show that some state-of-the-art detectors can in fact provide consistently good performance for practically relevant applications by resorting to classical detection theory and physics-based signal models. Performance analysis is presented to support the authors' claims.

Next, Nasrabadi explores the detection topic further by looking into recent advances in hyperspectral target detection techniques. In particular, Nasrabadi's contribution highlights novel detection techniques based on concepts in statistical signal processing and machine-learning theory, such as subspace-based detectors, the support vector machine, kernel-based nonlinear detectors, fusion of detectors, and sparsity-based detectors.

The third article considers the classification topic. Classification in hyperspectral images is far from being a generic image classification problem; it is challenging owing to the high dimensionality of data, few training samples, nonlinearity, and a number of other factors. Camps-Valls et al. overview the topic by presenting a statistical learning theory (SLT) framework for hyperspectral image classification. Under the SLT framework, the article covers techniques such as standard regularization; active, semisupervised, and sparse learning

approaches; spatial-spectral regularization; and adaptation of classifiers and feature representations.

Nonlinear manifold learning is another promising framework for hyperspectral image classification, and it has also received much attention. In this framework, the topology of high-dimensional nonlinear data sets is represented in lower, but still meaningful, dimensions for classification or other purposes. Lunga et al. provide an overview on this representative research direction. The article reviews traditional approaches under a graph embedding framework and describes new techniques for modeling hyperspectral data on manifolds, such as multidimensional artificial field embedding and spherical stochastic neighbor embedding.

The next three articles are related to the unmixing topic. Ma et al. overview blind (or unsupervised) hyperspectral unmixing techniques under the linear mixing model (LMM) setting. It is worthwhile to mention that this blind problem from remote sensing has a strong connection to blind source separation and sensor array processing in signal processing. The authors select four significant blind unmixing approaches—pure pixel search, convex geometry, sparse regression, and nonnegative matrix factorization—and use a signal processing researcher's view to describe each approach and appreciate the methodological beauty within.

The LMM is not always valid in the real world. Recently there has been much interest in unmixing based on nonlinear models. Dobigeon et al. present an overview of recent advances dealing with the nonlinear unmixing problem. Representative nonlinear models, such as intimate mixtures, bilinear models, and postnonlinear mixing models, are presented and their validity discussed. Then, the main classes of unmixing strategies, in supervised and unsupervised frameworks, are described. The article also addresses an emerging subtopic—detecting nonlinear mixtures in hyperspectral images.

In the unmixing topic, most models assume that the endmember signatures are invariant across the whole image. This assumption can be violated in reality, owing to various reasons related to measurement and environment. In Zare and Ho's article, the authors review a representative set of methods designed to cope with endmember variablity. The methods are organized in two classes: 1) endmember sets and 2) endmember as statistical distributions. The former class is nonparametric and deterministic, while the latter class stochastic. The article reviews important methods in both classes and highlights their advantages, limitations, and challenges.

The last two articles describes a relatively new front—CS for hyperspectral images. This is a well-motivated topic since hyperspectral data, in their raw form, are often tremendous in size. Arce et al.'s article is an overview of the fundamental optical phenomena behind compressive spectral imaging sensors. It describes the mathematical concepts and optimization framework for designing optimal coded apertures (i.e., measurements) in hyperspectral image reconstruction, spectral selectivity, and superresolution. All of these ideas and concepts are concretized in a specific type of spectral imagers known as coded aperture snapshot spectral imagers (CASSI). Many practical aspects are described and illustrated with real data and imagery.

The last article, by Willett et al., provides a fundamental overview on how CS can make a difference in the hyperspectral context. It describes how novel sparse models enable the design of new hyperspectral imaging hardware and acquisition methods. Performance limits and tradeoffs arising from practical issues, such as noise, quantization, and dynamic range, are discussed. The authors also consider hyperspectral target detection using CS measurements without having to reconstruct the raw hyperspectral data.

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