Foreword to the Special Issue on Spectral Unmixing of Remotely Sensed Data

MORE than two decades after the first efforts toward the application of spectral mixture analysis techniques to remotely sensed data [1], [2], effective spectral unmixing still remains an elusive exploitation goal. Regardless of the available spatial resolution, the spectral signals collected in natural environments are invariably a mixture of the signatures of the various materials found within the spatial extent of the ground instantaneous field view of the remote sensing imaging instrument [3]. The availability of hyperspectral imaging instruments [4] (also called imaging spectrometers [5]) with a number of spectral bands that exceeds the number of spectral mixture components has fostered many research efforts. Spectral unmixing has been a very active research area in recent years since it faces important challenges [6], [7].

In order to present the state-of-the-art and most recent developments in this area, it is our great pleasure to introduce this special issue on *Spectral Unmixing of Remotely Sensed Data* of the IEEE TRANSACTIONS ON GEOSCIENCE AND REMOTE SENSING. The special issue is the first one of its kind in the literature since this topic has not been addressed in the form of a dedicated monograph in any other journal in the past. The special issue brings together distinguished experts to provide a remarkable sample of latest-generation techniques in the field. A large number of submissions (45) were received for this special issue, of which 20 papers were selected after rigorous review. In the remainder of this foreword, we review key issues and topics of current interest related to spectral unmixing that are covered by this special issue.

A. Linear and Nonlinear Spectral Unmixing

Linear spectral unmixing [8] is a standard technique for spectral mixture analysis that infers a set of pure spectral signatures, called *endmembers* [9], [10], and the fractions of these endmembers, called *abundances* [11], in each pixel of the scene. This model assumes that the spectra collected by the imaging spectrometer can be expressed in the form of a linear combination of endmembers, weighted by their corresponding abundances. Because each observed spectral signal is the result of an actual mixing process, it is expected that the driving abundances satisfy two constraints, i.e., they should be nonnegative [12] and the sum of abundances for a given pixel should be unity [13]. Although the linear model has practical advantages, such as ease of implementation and flexibility in different applications, nonlinear unmixing describes mixed spectra (in physical [14], [15], or statistical [16] sense) by assuming that part of the source radiation is multiply scattered before being collected at the sensor. The distinction between the linear and the nonlinear unmixing has been widely studied in recent years [17].

In this special issue, several contributions are directly related to these topics. In [18], improvements over fully constrained least squares techniques for linear spectral unmixing [11] are discussed. In [19], a new component analysis-based strategy for linear spectral unmixing is presented. These techniques assume that all endmember signatures are available in advance. In the case that this requirement is not satisfied, partial unmixing has emerged as a suitable alternative to solve the abundance estimation problem. One widely used partial unmixing technique is mixture-tuned matched filtering (MTMF), which is described in detail in another contribution of this special issue [20]. Additional results of MTMF are also illustrated for the Cuprite Mining District, Nevada, USA, on this special issue cover.

Finally, two new techniques for nonlinear spectral unmixing are also introduced in this special issue. In [21], a generalized bilinear model and a hierarchical Bayesian algorithm for nonlinear unmixing of hyperspectral images are proposed, following previous efforts on the application of Bayesian techniques to spectral unmixing [22], [23]. In [24], a novel approach based on neural networks for the extraction of pixel abundances from hyperspectral data is developed. This work expands over previous efforts in the literature focused on using neural networks for nonlinear unmixing purposes [25]–[28].

B. Endmember Determination and Pure Class Modeling

Early approaches to endmember determination were principally manual [29], [30]. More recent development of automatic or semiautomatic endmember extraction algorithms has resulted in significant steps forward. While many available approaches associate a single spectral signature to each endmember, multiple endmembers have also been used to account for within (pure) class spectral variation [31]–[34]. When multiple spectra are used to represent a pure class, the term endmember refers to all spectra in the modeled pure class.

Notwithstanding the importance of multiple endmember-based approaches, a majority of algorithms have been designed under the pure pixel assumption, i.e., they assume that the remotely sensed data contain one pure observation for each distinct material present in the scene. This allows validation of extracted endmembers with regard to reference signatures

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using different distance metrics [35]. Perhaps, due to their ease of computation and clear conceptual meaning, these are the most widely used class of algorithms for endmember determination, with a plethora of algorithms designed under this assumption (see [36]–[61], among several others). It should be noted, however, that some of the aforementioned algorithms require a dimensionality estimation step [62]. Under the linear mixture assumption, this amounts to estimating the number of endmembers [63], [64].

This special issue includes two new contributions on endmember determination under the pure pixel assumption. In [65], a new algorithm is developed for this purpose based on discrete particle swarm optimization concepts. In [66], the well-known N-FINDR endmember extraction algorithm originally developed in [41] is revisited, and two new algorithms are derived from alternative optimization strategies, namely, alternating optimization and successive optimization.

C. Endmember Determination Without Pure Pixel Assumption

Although the maximum volume procedure adopted by N-FINDR and related algorithms is successful when pure signatures are present in the data, given the available spatial resolution of state-of-the-art imaging spectrometers and the presence of the mixture phenomenon at different scales (even at microscopic levels), in some cases, the pure pixel assumption may not be valid. To address this issue, several endmember determination techniques have been developed without assuming the presence of pure signatures in the input data. These methods aim at generating *virtual* endmembers [67] (not necessarily present in the set comprised by input data samples) by finding the simplex with minimum volume that encompasses all observations [68]–[73].

In this special issue, a new minimum-volume enclosing algorithm is developed [74]. It accounts for the noise effects in the observations by employing chance constraints and improves over a previously developed algorithm [72].

D. Incorporation of Spatial Information Into Endmember Determination and Spectral Unmixing

Most of the techniques discussed so far for endmember determination and spectral unmixing rely on the exploitation of spectral information alone. However, one of the distinguishing properties of remotely sensed data is the multivariate information coupled with a 2-D (pictorial) representation amenable to image interpretation. Subsequently, unmixing techniques can benefit from an integrated framework in which both the spectral information and the spatial arrangement of pixel vectors are taken into account. This aspect has been widely studied in the unmixing literature [75]–[81].

In this special issue, four contributions are directly related with this issue, including the development of new techniques for spatial–spectral endmember determination [82], [83] and the incorporation of spatial information into hyperspectral image unmixing [84], [85].

E. Sparse Regression-Based Unmixing

A recently developed approach to tackle the problems related to the unavailability of pure spectral signatures is to model mixed pixel observations as linear combinations of spectra from a library collected on the ground by a field spectroradiometer. Unmixing then amounts to finding the optimal subset of signatures in a (potentially very large) spectral library that can best model each mixed pixel in the scene [86]. In practice, this is a combinatorial problem that calls for efficient sparse regression techniques based on sparsity-inducing regularizers since the number of endmembers participating in a mixed pixel is usually very small compared with the (ever-growing) dimensionality and availability of spectral libraries.

In this special issue, two contributions are provided on the topic of sparse regression applied to spectral unmixing. In [87], a new method for subpixel modeling, mapping, and classification of hyperspectral images is presented. It uses learned block-structured discriminative dictionaries [88], where each block is adapted and optimized to represent a specific material in a compact and sparse manner. A spatial–spectral coherence regularizer is also applied. In [89], a sparsity constraint is included in nonnegative matrix factorization, a widely used technique to unmix hyperspectral images and recover the material endmembers [90], [91].

F. Unmixing of Remotely Sensed Data With Moderate Spectral Resolution

Although most of the techniques discussed so far have been designed to unmix remotely sensed hyperspectral scenes with a large number of spectral bands, such as those provided by the National Aeronautics and Space Administration (NASA) Airborne Visible/Infrared Imaging Spectrometer [92] or the Hyperion instrument onboard the Earth Observing 1 satellite [93], the unmixing of scenes with moderate spectral resolution is also of high interest, as high spectral resolution data are not always available.

In this special issue, two contributions deal with this relevant issue. In [94], a new method to unmix remotely sensed data collected by NASA's moderate resolution imaging spectrometer is presented. In [95], a time series of images collected by the European Space Agency's Medium Resolution Imaging Spectrometer is unmixed, both for each image and also by layer stacking all the images in the time series, thus addressing multitemporal spectral unmixing problems.

G. Connections Between Spectral Unmixing and Classification

Spectral unmixing and *hard* classification methods [96], [97] can be seen as complementary techniques since the latter are more suitable for the classification of pixels dominated by a single land cover class, while the former are devoted to the analysis of mixed pixels and can be seen as a form of *soft* classification. Because remotely sensed images contain areas with both pure and mixed pixels, the combination of these two techniques provides an interesting analysis approach.

This topic has been explored in previous contributions [33], [98]–[100].

In this special issue, the contribution [101] addresses this synergistic data processing trend by developing a new unmixing-to-classification conversion model that treats the abundance quantification task as a classification problem.

H. Applications of Spectral Unmixing

Numerous applications related to the monitoring of the environment and the retrieval of biogeophysical parameters have been addressed using spectral unmixing techniques, covering (to name a few) vegetative [102]–[104], soil [105]–[107], urban [108]–[110], and planetary [111]–[113] surfaces. Three application-oriented contributions are included in this special issue. In [114], the retrieval of canopy closure and leaf area index from Moso bamboo (an important forest type in subtropical areas of China) is investigated through linear spectral unmixing. In [115], the capability of spectral unmixing for analyzing hyperspectral images from Mars is explored. In [116], the unmixing of atmospheric trace gases from hyperspectral satellite data is addressed.

Combined, the different topics included in this special issue provide an excellent snapshot of the state of the art in the area of spectral unmixing, offering a thoughtful perspective on the potential and emerging challenges of applying unmixing techniques to different types of remotely sensed data. The Guest Editors would like to take this opportunity to gratefully thank the Editor-in-Chief, Prof. Christopher S. Ruf, for his constant support and encouragement to this special issue. The Guest Editors also gratefully thank all the contributors and reviewers who participated in the evaluation of manuscripts for the special issue. Without their outstanding contributions, the special issue could not have been completed.

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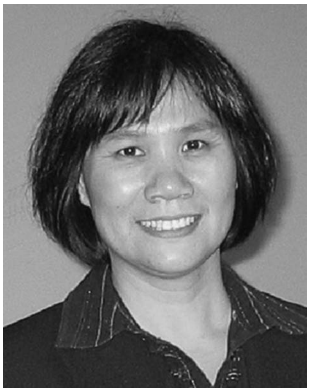

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