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Regional clustering-based spatial preprocessing for hyperspectral unmixing

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A R T I C L E I N F O

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A B S T R A C T

Hyperspectral unmixing is an important technique for remote sensing image exploitation. It aims to decompose a mixed pixel into a collection of spectrally pure components (called *endmembers*), and their corresponding proportions (called *fractional abundances*). In recent years, many studies have revealed that unmixing using spectral information alone does not sufficiently incorporate the spatial information in the remotely sensed hyperspectral image, as the pixels are treated as isolated entities without taking into account the existing local correlation among them. To address this issue, several spatial preprocessing methods have been developed to include spatial information in the spectral unmixing process. In this paper, we present a new spatial preprocessing method which presents several advantages over existing methods. The proposed method is derived from the Simple Linear Iterative Clustering (SLIC) method, which adapts the global search scope of the clustering into local regions. As a result, the spatial correlation and the spectral similarity are intrinsically incorporated at the clustering step, which results in $O(N)$ computational complexity of the clustering procedure with N being the number of pixels in the image. First, a regional clustering is iteratively performed by using spatial and spectral information simultaneously. The obtained result is a set of clustered partitions that exhibit both spectral similarity and spatial correlation. Then, for each partition we select a subset of candidate pixels with high spectral purity. Finally, the obtained candidate pixels are gathered together and fed to a spectral-based endmember extraction method to extract the final endmembers and their corresponding fractional abundances. Our newly developed method naturally integrates the spatial and the spectral information to retain the most relevant endmember candidates. Our experimental results, conducted using both synthetic and real hyperspectral scenes, indicate that the proposed method can obtain accurate unmixing results with less than 0.5% of the number of pixels used by other state-of-the-art methods. This confirms the advantages of integrating spatial and spectral information for hyperspectral unmixing purposes.

1. Introduction

Pixels in a hyperspectral image are often a mixture of different substances (Schaepman et al., 2009). Spectral unmixing (Bioucas-Dias et al., 2012) allows us to model each mixed pixel as a combination of pure materials (*endmembers*), weighted by their corresponding proportions (*fractional abundances*). Endmember extraction is a very important step in the hyperspectral unmixing chain (Plaza et al., 2009). The endmember spectral signatures can be obtained from existing spectral libraries which are acquired from field or laboratory measurements (Somers et al., 2011; Roberts et al., 1993; Herold et al., 2004; Roberts et al., 2004; Okin et al., 2013). Many known spectral libraries are now publicly available, such as the U.S. Geological Survey (USGS) digital spectral library (available online: http://speclab.cr.usgs.gov/spectral-lib.html), which contains over 1300 mineral spectral signatures. Also, the endmember spectral signatures can be acquired from the image itself (Somers et al., 2011; Dennison and Roberts, 2003). Compared with the former approach, the latter exhibits consistent acquisition and temporal conditions with the image pixels, and thus it can bring more accurate explanatory ability for subsequent unmixing purposes.

Due to the aforementioned reasons, many automatic or semi-automatic techniques have been developed for image endmember extraction, where the endmembers are directly extracted from the image data. Available techniques can be grouped into two main categories: 1) methods that assume the availability of pure signatures in the image, such as the Pixel Purity Index (PPI) (Boardman et al., 1995), Vertex

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Component Analysis (VCA) (Nascimento and Bioucas-Dias, 2005), Orthogonal Subspace Projection (OSP) (Harsanyi and Chang, 1994), N-FINDR (Winter, 1999) or Iterative Error Analysis (IEA) (Neville et al., 1999), among many others (Bioucas-Dias et al., 2012); and 2) methods that do not assume the presence of pure signatures in the image, such as the Minimum Volume Spectral Analysis (MVSA) (Li et al., 2015), the Simplex Identification via Split Augmented Lagrangian (SISAL), among many others (Bioucas-Dias et al., 2012). In the recent literature, several techniques have been developed to exploit a potentially very large spectral library; the unmixing then amounts to choosing an optimal subset of library endmembers to model each pixel (Iordache et al., 2011). Methods, such as Orthogonal Matching Pursuit (OMP) (Pati et al., 1995), Basis Pursuit (BP) (Chen et al., 2001), Basis Pursuit Denoising (BPDN) (Chen et al., 2001), and Iterative Spectral Mixture Analysis (ISMA) (Rogge et al., 2007b), belong to this category.

The above mentioned techniques used a fixed number of endmember spectra, i.e. one single endmember spectrum per endmember class, which is simple and easy to implement. However, due to environmental, atmospheric and temporal factors, endmember variability commonly exists in hyperspectral image data. Relevant reviews on this topic have been provided in Somers et al. (2011) and Zare and Ho (2014). Compared with the use of a fixed number of endmember spectra, the use of multiple endmembers per class can provide more accurate spectral signature representation and fractional abundance estimation. Numerous techniques and applications have been proposed to consider endmember variability in spectral unmixing, such as Iterative Endmember Selection (IES) (Roth et al., 2012; Schaaf et al., 2011). Of particular importance is the Multiple Endmember Spectral Mixture Analysis (MESMA) techniques (Roberts et al., 1998; Somers and Asner, 2013; Liu and Yang, 2013; Quintano et al., 2013; Fernández-Manso et al., 2012; Delalieux et al., 2012; Thorp et al., 2013; Franke et al., 2009; Powell et al., 2007), which use variable endmember sets to unmix each pixel of the scene.

In recent years, several studies have revealed that hyperspectral unmixing by using spectral information alone does not sufficiently exploit the spatial information in the scene (Shi and Wang, 2015), as the pixels are treated as isolated entities without taking into account the existing local correlation between them. In real hyperspectral images, pure pixels are more likely to be present in spatially homogeneous regions, and the existing spatial correlation among neighboring pixels can be exploited. To address this important issue, several endmember extraction algorithms have been designed with the goal of integrating the spatial and the spectral information. According to the cooperative use of spectral and spatial information, these methods can be divided into two categories: 1) integrated spatial-spectral methods, such as the Automatic Morphological Endmember Extraction (AMEE) (Plaza et al., 2002), Spatial-Spectral Endmember Extraction (SSEE) (Rogge et al., 2007a), Successive Projection Algorithm (SPA) (Zhang et al., 2008), Spatial Purity based Endmember Extraction (SPEE) (Mei et al., 2010), the Hybrid Automatic Endmember Extraction Algorithm (HEEA) (Li and Zhang, 2011), Spatial Adaptive Linear Unmixing Algorithm (SALUA) (Goenaga et al., 2013), the Unsupervised Unmixing based on Multiscale Representation (UUMR) (Torres-Madronero and Velez-Reyes, 2014), or the Image-based Endmember Bundle Extraction Algorithm (Xu et al., 2015), among many others (Bioucas-Dias et al., 2012); and 2) spatial preprocessing methods, which provide an (optional) preprocessing step before the application of a spectral-based endmember extraction algorithm. In this case, the output of the preprocessing is not the final endmember set, but a set of candidate pixels that need to be fed to an existing spectral-based endmember extraction algorithm to obtain the final endmember set. Available methods in this category include the Spatial Preprocessing (SPP) (Zortea and Plaza, 2009), Region-based Spatial Preprocessing (RBSPP) (Martín and Plaza, 2011), Spatial-Spectral Preprocessing (SSPP) (Martín and Plaza, 2012), Superpixel Endmember Detection Algorithm (SEDA) (Thompson et al., 2010), Spatial Edges and Spectral Extremes based Preprocessing (SE^2PP) (Lopez et al., 2013), a Fast Spatial-Spectral Preprocessing Module (SSPM) (Kowkabi et al., 2016b), Clustering and Over-segmentation-based Preprocessing (COPP) (Kowkabi et al., 2016a), etc.

Compared with integrated spatial-spectral methods, spatial preprocessing methods can be flexibly included with existing spectral-based endmember extraction methods without modifying such methods. Also, since the number of candidate pixels is much smaller than the number of original image pixels, the computational burden is significantly reduced. However, a general issue with available spatial preprocessing methods is that they generally prioritize one of the two sources of information (spatial or spectral) when conducting the preprocessing, which can have an important influence on the final results as some important candidates may be lost in the preprocessing (Martín and Plaza, 2012).

In this paper, we develop a new method for spatial preprocessing for hyperspectral unmixing. The proposed method naturally balances the spatial and the spectral information by means of a regional clustering procedure that is similar to the one performed by the Simple Linear Iterative Clustering (SLIC) (Achanta et al., 2012) method. Compared with conventional global clustering procedures, the proposed method presents two key differences. First, as conventional clustering algorithms need to search the whole image domain to find the clusters, we restricted the search scope to a local neighborhood around each clustering center. Second, we adopted a clustering criterion that integrates spatial and spectral information simultaneously. After the clustering procedure, we obtain a set of clustering partitions that exhibit both spatial correlation and spectral similarity, which are highly desirable properties for spatial preprocessing purposes. Then we select a subset of candidate pixels from each partition by accounting for their spectral purity. Finally, the obtained candidate pixels are gathered together and fed to a spectral-based endmember extraction method to obtain the final endmember set. Our experimental results with synthetic and real hyperspectral scenes indicate that, compared with other available strategies for spatial preprocessing, the newly proposed method is fast and able to consistently provide candidate pixels with higher quality regarding their spatial and spectral information, which represents a significant improvement over other existing methods.

The remainder of this paper is organized as follows. Section 2 provides a review of the endmember extraction methods considered in our experiments. Section 3 describes the newly proposed method in step-by-step fashion. Section 4 performs an extensive validation and quantitative assessment of the proposed method by using both synthetic and real hyperspectral data sets. Finally, Section 5 concludes the paper with some remarks and hints at plausible future research.

2. Related work

The goal of our proposed spatial-spectral preprocessing strategy is to extract spectrally pure candidates from the original image data set, thus reducing the number of candidate endmembers and improving unmixing accuracy simultaneously. Considering that spectrally pure signatures are more likely to appear in spatially homogeneous areas, and that most pure candidates generally exhibit the most singular signature in such homogeneous area, many existing methods adopted certain *homogeneous criteria* to characterize spectral purity. In the AMEE method (Plaza et al., 2002), a Morphological Eccentricity Index (MEI) is assigned to the purest pixel (obtained by the dilation operation) in a spatial kernel, where the MEI is calculated by using the Spectral Angle Distance (SAD) between itself and the most highly mixed pixel (obtained by the erosion operation) in the spatial kernel. In the HEEA method (Li and Zhang, 2011), a joint Spectral Information Divergence and Spectral Angle Mapper (SID-SAM) metric (Du et al., 2004),