ANALYSIS OF DIFFERENT STRATEGIES FOR INCORPORATING SPATIAL INFORMATION IN THE DESIGN OF ENDMEMBER EXTRACTION ALGORITHMS FROM HYPERSPECTRAL DATA

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1. ABSTRACT

Endmember extraction is the process of selecting a collection of pure signature spectra of the materials present in a remotely sensed hyperspectral scene [1]. These pure signatures are then used to decompose the scene into abundance fractions by means of a spectral unmixing algorithm. Over the last decade, several algorithms have been developed for automatic or semi-automatic extraction of spectral endmembers from the hyperspectral image data. Classic techniques include the pixel purity index (PPI) [2], the N-FINDR algorithm [3], the vertex component algorithm (VCA) [4], an iterative error analysis (IEA) algorithm [5], the optical real-time adaptive spectral identification system (ORASIS) [6], the convex cone analysis (CCA) algorithm [7], and an orthogonal subspace projection (OSP) technique [8]. Other advanced techniques for endmember extraction have been recently proposed, including ICE [9], a statistical approach, a minimum volume constrained nonnegative matrix factorization approach [10], a simplex growing algorithm (SGA) [11], a technique based on independent component analysis (ICA) [12], a support vector algorithm for detecting endmembers [13], or a technique based on the concept of sparsity [14], among others [1]. Most of these techniques have been focused on analyzing the hyperspectral data without incorporating information on the spatially adjacent data. As a result, the search is conducted by treating the data as a collection of spectral measurements with no spatial arrangement. 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, most endmember extraction algorithms listed above could benefit from an integrated framework in which both the spectral information and the spatial arrangement of pixel vectors are taken into account.

Only a few attempts exist in the literature aimed at including the spatial information in the process of extracting spectral endmembers. Three of the most representative efforts are listed below:

1. The automatic morphological endmember extraction (AMEE) [15] algorithm runs on the full data cube with no dimensional reduction, and begins by searching spatial neighborhoods around each pixel in the image for the most spectrally pure and mostly highly mixed pixel. This task is performed by using extended mathematical morphology operators of dilation and erosion, respectively. Each spectrally pure pixel is assigned an "eccentricity" value, which is calculated as the spectral angle distance between the most spectrally pure and mostly highly mixed pixel for the given spatial neighborhood. This process is repeated iteratively for larger spatial neighborhoods up to a maximum size that is pre-determined. At each iteration the "eccentricity" values of the selected pixels are updated. The final endmember set is obtained by applying a threshold to the resulting greyscale "eccentricity" image. The final endmembers are extracted after a region growing process.

2. The spatial spectral endmember extraction (SSEE) [16] algorithm comprises four steps. First, it divides the scene in sub regions and applies singular value decomposition for obtaining a set of eigenvectors that explain most of the spectral variability of each particular spatial subset. Then, it projects the entire image data onto the compiled eigenvector set to determine a set of candidate endmember pixels representative of all image. In a third step, the algorithm analyzes the spatial and spectral characteristics of the candidate endmember set to average spectrally similar endmember candidates that are spatially related. Finally, the endmember set derived in the previous step is reordered based on spectral angle, thus listing endmember candidates in order of spectral similarity (from highest to lowest similarity).

3. Recently, a spatial pre-processing (SPP) approach for endmember extraction has also been developed [17]. This method can be easily used in combination with available imaging spectral-based endmember extraction algorithms such as those methods in [2,3,4,8,11]. This approach estimates, for each pixel vector, a scalar, spatial-derived factor which relates to the spectral similarity of pixels lying within a certain spatial neighborhood. This scalar value is then used to weight the importance of the spectral information associated to each pixel in terms of its spatial context. Two key aspects of the preprocessing approach are: 1) no modification of existing imaging endmember methods is necessary in order to apply the proposed approach, and 2) the method enhances the search for spectral endmembers in spatially homogeneous areas.

In this paper, we present a thorough analytical comparison of methods including spatial information (AMEE, SSEE, SPP) and a few selected algorithms which are exclusively based on spectral information[1]. Our experimental assessment of endmember extraction accuracy has been conducted using both synthetic and real hyperspectral data. The synthetic scenes were artificially generated using fractals to simulate naturally-inspired spatial patterns, combined with spectral signatures obtained from different spectral libraries. The real hyperspectral scenes comprise two well-known data sets collected by the NASA Jet Propulsion Laboratory's Airborne Visible Infra-Red Imaging Spectrometer (AVIRIS) over the Cuprite mining district in Nevada and the Indian Pines region in Indiana, respectively. Our quantitative and comparative assessment of algorithm accuracy and computational performance provides interesting findings about the potential benefits that can be obtained after incorporating spatial information into the design of endmember extraction algorithms.

2. REFERENCES

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[1] All the methods compared in this work have been implemented using the Orfeo toolbox distributed by the Centre National d'Etudes Spatiales (CNES), see http://www.orfeo-toolbox.org for additional details