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An Efficient Technique for Hyperspectral Endmember Extraction based on SE^2PP

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Abstract-
Hyperspectral Endmember extraction of a set of accurateendmembers is critical for the proper unmixing of Hyperspectral image. Several preprocessing algorithms such as spatial preprocessing (SPP), region based spatial preprocessing (RBSPP), and spatial spectral preprocessing (SSPP) have been developed for the extraction of endmembers. These algorithms require complex operations and huge computational effort. Thus, this paper proposes an efficient preprocessing technique for hyperspectralendmember extraction called SE^2PP which is based on the integration of spatial and spectral information. The proposed approach can be combined with the existing algorithms for endmember extraction reducing the computational complexity of those algorithms while providing similar figures of accuracy.
Index Terms- spatial preprocessing (SPP), region based spatial preprocessing (RBSPP), and spatial spectral preprocessing (SSPP),Spatial Edges and Spectral Extremes PP(SE^2PP)

I. INTRODUCTION

Remote sensing can be broadly defined as the collection and interpretation of information about an object, area, or event without being in physical contact with the object. Aircraft and satellites are the common platforms for remote sensing of the earth and its natural resources. Aerial photography in the visible portion of the electromagnetic wavelength was the original form of remote sensing but technological developments has enabled the acquisition of information at other wavelengths including near infrared, thermal infrared and microwave. Collection of information over a large numbers of instinct wavelength bands is referred to as multispectral or hyperspectral data. The development and deployment of manned and unmanned satellites has enhanced the collection of remotely sensed data and offers an inexpensive way to obtain information over large areas. The capacity of remote sensing to identify and monitor land surfaces and environmental conditions has expanded greatly over the last few years and remotely sensed data will be an essential tool in natural resource management.It is the science and art of obtaining information about an object, area, or phenomenon through the analysis of data acquired by a device that is not in contact with it. Requires platform and sensor.

The data collected by each satellite sensor can be described in terms of spatial, spectral and temporal resolution.

Multispectral and hyperspectral images consists of several bands of data. For visual display, each band of the image may be displayed one band at a time as a grey scale image, or in combination of three bands at a time as a color composite image. Interpretation of a multispectral color composite image will require the knowledge of the spectral reflectance signature of the targets in the scene.

Major use of Remote sensing are,

- Large Area Data Collection
- Comprehensive Sampling
- Objectivity in Data Collection
- Repeatability / Intercomparability of Data
- High Temporal Resolution

The existing methods are SPP (Spatial Preprocessing), RBSPP (Region based Spatial Preprocessing) and SSPP (Spatial Spectral Preprocessing) which are considered to be the preprocessing approaches.

These algorithms suffer, at least, from the following three drawbacks.

First is, They are based on guiding the endmember extraction process to spatially large homogeneous areas expected to contain the purest signatures available in the scene.

Second is, when combined with computationally competitive endmember extraction approaches such as the algorithm,it takes more time than directly applying the VCA algorithm to the original non preprocessed image.Thus it provides computationally complex operation.

Third is, these Algorithms show execution patterns that leave little room for introducing parallelism at the programming level,which is crucial for applications under real-time constraints.

These algorithms require complex operations and huge computational effort. Thus, this paper proposes an efficient preprocessing technique for hyperspectralendmember extraction called SE^2PP which is based on the integration of spatial and spectral information. The proposed approach can be combined with the existing algorithms for endmember extraction reducing the computational complexity of those algorithms while providing similar figures of accuracy.The key idea behind SE^2PP is to identify and select a reduced set of pixels in the hyperspectral image. So that there is no need to process a large amount of data to get accurate spectral unmixing results.

II. REVIEW OF EXISTING METHOD

The SPP introduces the spatial information in the endmember extraction process, so that the pre-processing can be combined with classic methods for endmember extraction. In this way, the endmembers can be obtained based on spatial and spectral features. The main idea behind the SPP framework is to estimate, for each input pixel vector, a scalar factor ρ which is intimately related to the spatial similarity between the pixel and its spatial neighbors, and then use this scalar factor to spatially weight the spectral information associated to the pixel.

The RBSPP assumes that pure signatures are less likely to be found in transition areas, and more likely to be present in well-defined, spatially homogeneous regions. If we assume that homogeneous areas are more likely to provide good candidate pixel vectors for endmember extraction algorithms, then it is also possible to use spatial information to intelligently direct the spectral-based endmember search process to these regions. However, such regions should also be spectrally pure when compared to others, since there is a possibility that a spatially homogeneous region is also made up of mixed pixels.

The SSPP performs a spectral-based unsupervised clustering coupled with spectral purity indexing to identify a subset of spatially homogeneous and spectrally pure pixels from the scene. These pixels constitutethe new set of endmember candidates.

III. PROPOSED SE^2PP ALGORITHM

The Proposed method is SE^2PP, which is based on selecting the pixels that are in the spatial edges (SEs) and in the spectral extremes (SEs) of the hyperspectral image under analysis. The proposed approach, called SE^2PP, solvesthe identified drawbacks while maintaining the same degree of accuracy than RBSPP and SSPP when coupled with traditional endmember extraction algorithms.

The SE^2PP algorithm proposed in thisletter, whose ultimate goal is to select a subset of pixels from a given hyperspectral image that will be the input to a subsequent endmember extraction algorithm. The current section has been divided into three subsections: The first and second subsections are devoted to explain how these pixels are chosen from a spatial and a spectral points of view, respectively, while the third subsection details how both approaches are combined in the proposed SE^2PP algorithm.

A. Spatial domain Analysis

The previous approaches are based on promoting the spatially homogeneous areas as the ones in which it is most likely to find pure pixels where, for the scope of this work, a spatially homogeneous area can be coarsely defined as a region of the image in which the dissimilarities between all its pixels are below a certain and typically small threshold.

One of the assumptions on which the SE^2PP algorithm is based is that, theoretically, and if no more information is provided, all the pixels enclosed in a region identified as a spatially homogeneous area have the same probability of becoming an endmember of the image. Moreover, in the surroundings of the frontier between two of these regions coexist pixels from both of them. Hence, if, rather than selecting a small amount of spatially large homogenous areas, a large amount of spatially small heterogeneous areas are selected at the PP level, the same extraction accuracy levels can be obtained while a fewer number of pixels are retained from the original image, as it will be demonstrated in the next section of this letter. In order to identify these small heterogeneous areas located in the frontier between two spatially homogenous areas without incurring in an excessive computational cost, the following measurement of the Spatial Activity(SA) of a region of pixels is introduced.

$$SA = \sum_{i=m1}^{m2} \sum_{j=n1}^{n2} |\mathrm{Ravg}(i,j) - ?| \qquad (1)$$

where Ravg represents an image that has the same pixels as R and only one spectral value per pixel obtained as the average of all the spectral bands of R i.e., if R has P pixels of N spectral bands each as indicated in (1), then Ravg will have P pixels of one spectral value per pixel, which is obtained for each pixel as $r$avg= $((r1 + r2 + \cdots + rN)/N)$); $(m1, n1)$ and $(m2, n2)$ denote the absolute spatial coordinates of the region of the image being processed; and finally, μ represents the average value of all the pixels enclosed in the targeted region of the *R*avg image. It can be easily concluded that spatially homogenous areas will have low SA values

B. Spectral Domain Analysis

Traditional endmember extraction algorithms, such as the NFINDR algorithm, operate in such a way that pixels with extreme values in any of the spectral bands of the sensed hyperspectral image are prone to be in the set of the final endmembers or, at least, prone to show a good match with one of them. Hence, the proposed SE^2PP algorithm takes advantage of this property by selecting, for each spectral band of *R*, only the 1% of the pixels that correspond with the highest values and the 1% of the pixels that correspond with the lowest values within each band of the image, following a similar strategy to the one recently disclosed in.

C. SE^2PP Algorithm

As it has been mentioned before, the proposed SE^2PP algorithm is based on selecting a reduced set of pixels from the original image in order to process only those pixels in a posterior endmember extraction stage. In order to do so, it first computes the *R*avg image from the *R* image and then divides *R*avg into nonoverlapped square blocks of pixels with the same spatial dimensions, which means that $(m2 - m1) = (n2 - n1) = M$. The SA of each of these blocks is further obtained, selecting only the pixels corresponding to blocks with a very high SA value, i.e., with a SA value above a predefined threshold (SAth), which has been defined in this work as follows:

$$SA_{th} = M^2 . \mu . f \qquad (2)$$

Where *f* represents a scaling factor that modulates the amount of spatial heterogeneity associated to a block of pixels in order to be selected by the SE^2PP algorithm. In particular, we have set *f* to 0.05 because this was the value that empirically resulted in the best compromise between endmember extraction accuracy and speed for all the synthetic and real hyperspectral images that were tested in our experiments. In addition, the SE^2PP algorithm also selects those pixels in *R* that are identified as spectral extremes according to the procedure described in the previous subsection. Once this process is completed, the output (reduced) hyperspectral image provided by the SE^2PP algorithm is obtained by simply

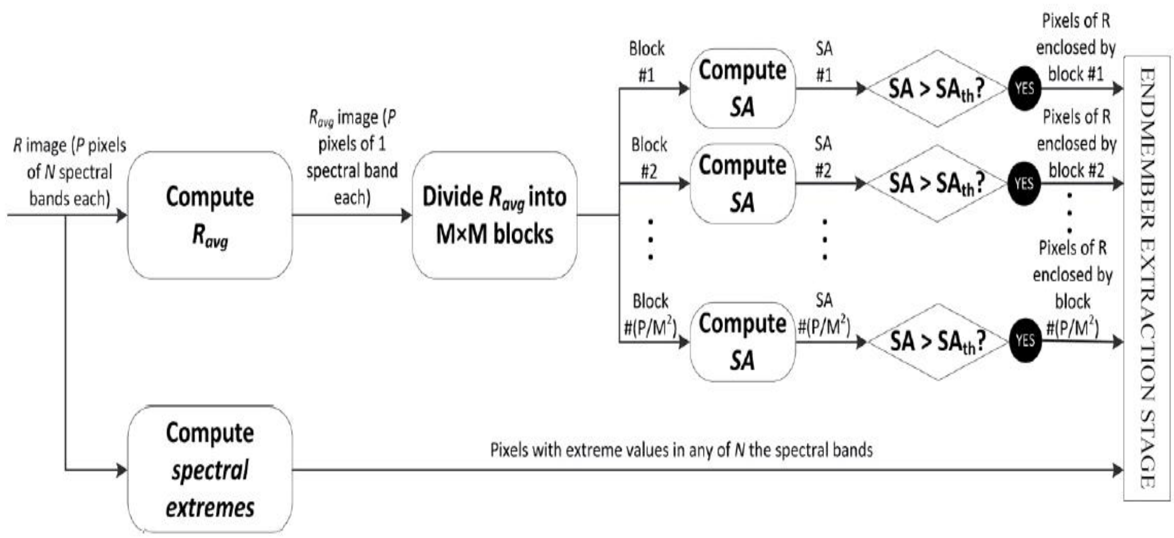

Fig.1. Block diagram of the proposed SE^2PP algorith

combining the pixels retained by both procedures, and those pixels are then transferred to the subsequent endmember extraction stage. For the sake of clarity, Fig.1 provides a block diagram that summarizes the whole process carried out by the proposed SE^2PP stage.

Algorithm

- Compute $R_{avg.}$ (R_{avg}– Image that has same pixels of R)
- Compute SA (Spatial activity) for each block.

$$SA = \sum_{i=m1}^{m2} \sum_{j=n1}^{n2} |Ravg(i,j) - \mu| \quad (3)$$

where μ represents the average value of all pixels enclosed in the targeted region of the Ravg image.

- Divide Ravg into M x M blocks which means that $(m_2 - m_1) = (n_2 - n_1) = M$.
- The SA of each blocks is obtained by selecting only the pixels corresponding to blocks with very high SA value (SA_{th}).

$SA_{th} = M^2 . \mu . f$ (f – scaling factor) (4)

- Compute spectral extremes.
- Endmember extraction stage.

Finally, it is important to highlight two main differences of the proposed SE^2PP algorithm with respect to the previous PP strategies. First, all the operations involved in the SE^2PP algorithm are computationally simple and enables SE^2PP to be much faster. Moreover, all these operations can be easily implemented using a reduced amount of hardware resources, which is of crucial importance for real-time onboard systems. Second, the computations in the spatial domain are independent of the ones to be carried out in the spectral domain. Furthermore, in the spatial domain, the SA of each block of pixels can be computed independently from each other, while in the spectral domain, all the bands can be also independently processed. All these feature

clearly distinguish the proposed SE^2PP algorithm as a low cost, computationally simple, and highly parallelizable algorithm. In order to test the proposed SE^2PP algorithm in a more realistic scenario, the AVIRIS Cuprite image has also been used in this work. This scene is well understood mineralogically and has been widely used to validate the accuracy of endmember extraction algorithms. It consists of 350 × 350 pixels and 224 spectral bands between 0.4 and 2.5 μm. Prior to the analysis,different bands have been removed due to water absorption and low SNR resulting in a total of 188 spectral bands. In order to determine the number of endmembers of the image, the virtual dimensionality has been estimated by means of the noise-whitened Harsanyi–Farrand–Chang eigenthresholding method using the Neyman–Pearson test with the falsealarm probability set to 10^{-5}, resulting in a total number of 19 different pure materials. This value is in agreement with the estimates provided by the well-known hyperspectral subspace identification method.

The pixels of Cuprite selected by the SE^2PP algorithm with $M = 2$ and with $M = 4$ together with the original image as well as the histograms of the SA values obtained for this image with $M = 2$ and with $M = 4$. The amount of blocks with large SA values is very small, and hence, the proposed SE^2PP algorithm retains a reduced amount of pixels from the original image.

IV. CONCLUSION

The Proposed SE^2PP which isbased on the integration of spatial and spectral information has been presented.. The current section has been divided into three subsections: The first and second subsections are devoted to explain how these pixels are chosen from a spatial and a spectral points of view, respectively, while the third subsection details how both approaches are combined in the proposed SE^2PP algorithm.All these operations can be easily implemented using a reduced amount of hardware resources, which is of crucial importance for real-time onboard systems. The computations in the spatial domain are independent of the ones to be carried out in the spectral domain. All these features clearly distinguish the proposed SE^2PP algorithm as a low cost, computationally simple and highly parallelizable algorithm.

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