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Effect of Denoising on Dimensionally Reduced Sparse Hyperspectral Unmixing

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Abstract

In hyperspectral images, spectral mixing occurs when objects lying beside each cannot be distinguished as different entities due to its low spatial resolution. Other hurdles in hyperspectral imaging are its huge dimension and noisy bands. In this paper, a new approach for spectral unmixing is presented where, the data is reduced dimensionally and, the bands eliminated during this are denoised using the existing denoising methods. Then, dataset with these bands is dimensionally reduced and their presence after reduction is validated using spectral unmixing methods. The effectiveness of this method is evaluated using parametric measures such as RMSE and classification accuracy.

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Keywords: Spectral unmixing; Denoising; Least square; dimensionality reduction; Hyperspectral images. Type your keywords here, separated by semicolons ;

1. Introduction

The term ‘Hyperspectral’ refers to too much information from the spectrum. The hyperspectral images (HSI) are called so since, they are captured over 200 or more spectral bands making them a huge pool of resourceful data. These images have the finest detail of an object captured over several spectral bands [1]. Hence, making them very important in the field of research. Having a rich spectral resolution comes with a backdrop of low spatial resolution i.e decrease in the geometric information about an object. When the number of bands increase, the light required to capture the information has to be split among the various bands thus, reduction in spatial resolution [3]. Hyperspectral images are actively used in applications such as tracking of wildfire, environmental monitoring, target detection, spectral unmixing, sub pixel mapping and many more [1]. Currently, several preprocessing tools such as: dimensionality reduction, data clustering, classification, compression and reconstruction have been established for hyperspectral data analysis. Techniques such as classification and clustering are carried out assuming that, every pixel vector corresponding to the

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data is pure i.e the reflectance values it comprises of is that of a single material (endmember). But, for a data with degraded spatial resolution this will not be the case wherein, the reflectance values of two or more endmembers can occupy a single pixel vector known as spectral mixing.

In [3] [8] [9] several unmixing techniques such as Independent Component Analysis (ICA), Vertex Component Analysis (VCA), Orthogonal Matching Pursuit (OMP), Alternating Direction Multiplier Method (ADMM) have been explained where, the objective of this process is to estimate the abundance (proportion) of each endmember in a pixel, given a global spectral library comprising of the reflectance values of almost all the elements present on earth. During spectral unmixing, challenges like high dimension of the data and noisy bands are encountered. Among the 100's of bands present in an HSI, almost only 50% of the bands are the most informative and the remaining bands are corrupted by noise or atmospheric interference or may have almost similar information as that contained by the adjacent bands [2].

Dimensionality reduction techniques such as Inter-Band block correlation (IBBC) as described in [2], target and eliminate the bands with similar information and noisy bands. The reduced dataset from IBBC is then processed via SVD-QR decomposition [7], where only the most informative bands are selected and this reduced is used other processing techniques.

Among the noisy bands eliminated via IBBC, there might be bands containing more information than the bands actually selected. But, the information in these bands is shadowed by the noise corrupting them.

In our proposed method, in-order to retrieve this information, only the the eliminated bands are subjected to denoising via different methods such as LS [14], LF [11], TV [10] and wavelet [12], and the denoised bands are incorporated into the original dataset, which is reduced via IBBC followed by SVD-QR decomposition and from the most informative bands selected, the presence of the denoised bands are checked for and the effect of these bands on OMP and ADMM based hyperspectral unmixing [8] is analyzed. Where, the unmixed results obtained after dimensionality reduction, with and without the presence of the denoised bands are compared based on the standard metrics such as: RMSE, classification accuracies and visual perception. Also, the results obtained with LS denoised bands are compared with that obtained with the other denoising techniques for both the unmixing methods, using the standard unmixing datasets such as, 'Samson' and 'Jasper Ridge'.

2. Proposed Work Flow

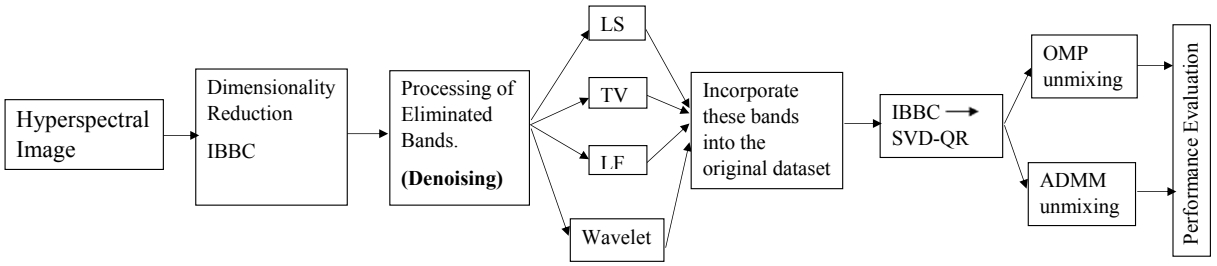

Fig. 1. Work flow of proposed method

The flow of work carried out in this paper is as depicted in Fig.1. Here, the hyperspectral datasets namely: 'Samson' and 'Jasper Ridge' are dimensionally reduced using Inter-Band Block Correlation (IBBC) method where, all the noisy and water absorption bands are eliminated [2]. The next step involves the processing of these eliminated noisy bands and to recover the information present in them. This is done using the different denoising techniques such as the LS, LF, TV and wavelet denoising methods.

These denoised bands then replace their corresponding noisy bands in the original dataset which, is again dimensionally reduced using IBBC followed by SVD-QR decomposition. SVD-QR decomposition only selects the most informative bands by arranging them in the order of high to least informative bands, from which the top most informative bands can be selected for processing. From the bands selected, the presence of denoised bands which were once eliminated was noticed, after SVD-QR decomposition. To analyze the importance of the information carried out