SPECTRAL IMAGE PROCESSING USING SPARSE LINEAR TRANSFORMS

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ABSTRACT

Spectral image processing is a powerful technique for many real world applications such as agriculture, mining, emergency management, defense and environmental monitoring. However, spectral imagery, and in particular hyper and ultra spectral data (with hundreds to thousands of image bands) tend to be more difficult to process due to high dimensionality [1]. To address this problem, feature extraction techniques such as Principal Component Analysis (PCA), Independent Component Analysis (ICA), or Nonnegative Matrix Factorization (NMF) have been applied. In each of these methods, the resulting components are linear combinations of all the original hyperspectral bands [2], making the results difficult to interpret and the transformed data expensive to further process.

In this paper, we propose for consideration the employment of sparse linear feature extraction. Sparse transforms are methods for finding a representation of data in which each of the components of the representation is only rarely significantly active [3]. Unlike segmented transforms, sparse feature extraction imposes restrictions (such as cardinality or norm relationships) that result on the generation of the sparse mappings not necessarily contiguous. In most of the cases, the sparseness is produced using a gradient descent optimization algorithm. The resulting sparse components are the sets of sparse (non-zero loadings of variables) vectors spanning a low-dimensional space that explain most of the information present in the data. Sparse data representations are generally desirable because sparse representations helps in human understanding, reduce computational costs, and provide better generalization in learning models. Sparseness in the hyperspectral data will help in feature selection, automatic relevance determination and classification.

Sparse representations for most of the linear feature extraction algorithms are actively being researched. In Zou et al.'s approach called sparse PCA (SPCA) [4], it finds modified components with zero loading in very large problems, by writing PCA as a regression-type optimization problem. Direct sparse PCA (DSPCA) [5], improves the sparseness of the principal components by directly incorporating a sparse criterion in the PCA problem formulation, then forming a convex relaxation of the problem that turns out to be a semi definite program. In contrast, Segmented PCA divides hyperspectral image cubes into several non-overlapping blocks in accordance with band-to-band cross-correlations, followed by PCA performed in each block [6]. In a sequence of studies, Zibulevsky ([7,8]) and Chichoki ([9]) and their collaborators devise sparse representations for ICA and show that sparseness can significantly improve the accuracy and the computational efficiency of existing ICA algorithms. In [10], the authors introduce a sparse NMF algorithm that can control the degree of sparseness in the coefficient transform matrix via alternating non-negativity-constrained least squares, and apply it successfully to microarray data.

In this paper we provide a model for describing sparseness in spectral data and propose to extend the use of sparse linear transforms for representing hyperspectral imagery. Sparse transforms reduce the data volume/dimensionality without loss of critical information, so that it can be processed efficiently and assimilated by a human. They make possible separation of the results into isolated and easily identifiable effects. We compare sparse PCA, ICA and NMF with their 'regular' counterparts and analyze the effect on hyperspectral data classification using maximum likelihood. The experiments are performed on both artificial and real-life AVIRIS data. The results suggest that sparse transforms are highly flexible approaches to feature extraction, able to provide accurate representation of the data in a low dimensional space.

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