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High-level hyperspectral image classification based on spectro-spatial dimensionality reduction

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A B S T R A C T

Spectro-spatial dimensionality reduction in HyperSpectral Images (HSI) classification is a challenging task due to the problem of curse dimensionality, i.e. the high number of spectral bands and the heterogeneity of data. In this context, many dimensionality reduction methods have been developed to overcome the high correlation between bands and the redundancy of information in order to improve the classification accuracy. Most of these methods represent the original HSI as a set of vectors. Therefore, they only exploit spectral properties, neglecting the spatial information, i.e. the spatial rearrangement is lost. To jointly take advantage of spatial and spectral information, HSI has been recently represented as a tensor. In order to preserve the spatial and spectral information, we develop a hybrid method using both the Tensor Locality Preserving Projections method (TLPP) projecting the original data into a lower subspace and the Constrained Band Selection method (CBS) to select the relevant bands. These two methods will be jointly used to get high-level quality classification. Moreover, since the two obtained classifications are uncertain and imprecise, we propose to fuse them using the Dempster–Shafer's Theory (DST) to obtain an accurate classification preserving the spectro-spatial information. The proposed approach has

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been applied on real HSI showing its efficiency compared with conventional dimensionality reduction methods.

1. Introduction

The development of image sensor technology allows capturing image data in hundreds of bands covering a broad spectrum of wavelength range (0.4–2.5 μm). A pixel in HyperSpectral Images (HSI) is typically a high-dimensional vector of intensities as a function of wavelength with a large spectral range and a high spectral resolution, which facilitates the superior discrimination of land cover types. However, HSI classification still faces some challenges, among which are the following: (1) the high number of spectral bands; (2) the spatial variability of spectral signature; and (3) the high cost of true sample labeling. In particular, the high number of spectral bands and the low number of training samples pose the problem of the curse of dimensionality. Therefore, the most important and urgent issue is how to reduce the computation complexity and the high correlation between original bands without degrading the classification accuracy. Dimensionality reduction algorithms, as the name suggests, are typically designed to reduce the dimensionality of the feature space without losing desirable information, it seeks to decrease computational complexity and ameliorate statistical ill-conditioning by discarding redundant features that can potentially deteriorate classification performance. So, the goal of dimensionality reduction is to reduce complexity of input data while some desired intrinsic information of the data is preserved. In HSI context, dimensionality reduction can be achieved by a band selection method (primitives selection) or a projection method (features extraction). Band selection methods find a subset of the original spectral bands that hopefully contain the most important characteristics of the image. Depending on the availability of labeled samples, band selection methods can be categorized as supervised and unsupervised. If no labeled samples is available, unsupervised band selection is used for dimensionality reduction. The main idea of unsupervised band selection methods is to find the most distinctive and informative bands. Projection methods transform the data into a low-dimensional space by using linear or nonlinear combinations of original bands. In this paper, we propose to use both methods simultaneously for dimensionality reduction in order to obtain an accurate HSI classification. The remainder of this paper is organized as follows. Section 2 introduces the related works about dimensionality reduction of HSI. In Section 3, we present the proposed approach. We first introduce the multi-linear algebra method based on Tensor Locality Preserving Projections (TLPP) as well as Constrained Band Selection (CBS). Then, we go into details about the decision fusion phase. In Section 4, we show experimental results of HSI classification using our approach with a comparative study with respect to well established approaches of the field. We conclude and suggest future work in the last section.

2. Related works

Dimensionality reduction is commonly applied as a preprocessing step for HSI analysis in order to reduce the dimensionality of the data and ensure a well-conditioned representation of the class-conditional statistics. In the literature, there are many band selection and projection methods that have been used for this matter. The most used band selection methods are Mutual Information (MI) (Sahrouni et al., 2012; Kamandar, 2011), Progressive Band Selection (PBS) (Chang, 2014), Affinity Propagation (AP) (Qian et al., 2009), Bands Clustering (BandClust) (Chang, 2014), and CBS (Chang, 2006). Generally, band selection methods attempt to select a subset of bands based on specific criterion such as entropy, variance, skewness, and kurtosis or any other criterion that preserve as much as possible the physical properties i.e., spectral information of HSI. Projection methods transform the original data space into a new features space using linear or nonlinear combinations of original bands. Main projection methods are Principal Component Analysis (PCA) (Xia et al., 2014;