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Low-rank group inspired dictionary learning for hyperspectral image classification

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ABSTRACT

Dictionary learning has yielded impressive results in sparse representation based hyperspectral image (HSI) classification. However, challenges remain for exploiting spectral-spatial characteristics. In this paper, we make the first attempt to classify the HSI via low-rank group inspired dictionary learning (LGIDL). Core ideas of the LGIDL are threefold: (1) super-pixel segmentation is implemented to obtain homogeneous regions, which can be viewed as spatial groups for LGIDL; (2) non-negative low-rank coefficient and dictionary are updated alternatively in the optimization problem of LGIDL. The low-rank group prior helps to seek lowest-rank representation of a collection of data samples jointly. Pixels in the same group share common low-rank pattern, which facilitates the integration of spectral-spatial information; (3) the low-rank coefficients of test samples are adopted to determine the corresponding class labels in linear support vector machine (SVM). Experimental results demonstrate that the LGIDL achieves better performance to the state-of-the-art HSI classification methods on several challenging datasets even with small labeled samples.

1. Introduction

Hyperspectral imaging sensors capture the radiance of materials from hundreds of contiguous narrow spectral bands, providing rich information for various land covers [1–3]. Due to the significant advances in remote sensing, hyperspectral image (HSI) has attracted extensive attention over the past decade. One of the fundamental tasks for HSI is classification [4–6], which can potentially benefit from the discriminative information contained in high spectral resolution pixels.

In HSI classification, sufficient training samples are usually crucial to obtain reliable results due to the curse of dimensionality, i.e. Hughes phenomenon [7]. Unfortunately, the difficulty in determining the class labels of samples poses a great challenge to the classification task. Despite the high spectral resolution of HSI, identical land covers may have quite different spectral signatures, whereas distinct materials may share similar spectral signatures. The above-mentioned problems, together with other disadvantages such as noise from the sensors, will seriously influence the classification accuracy.

To deal with the obstacles described above, several feature extraction/selection [4,8,9] and classification techniques [10,11] have sprung up over the past few years. However, the discriminative information will get lose in case too few dimensions are reserved in feature extraction/selection methods. On

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the other hand, a plenty of kernel methods have also been applied to the classification of HSI, among which support vector machine (SVM) [12,13] is a state-of-the-art approach that performs well in high-dimensional data. Many variations of SVM-based methods have been developed to improve the classification performance, including SVM with composite kernel (SVMCK) [14], which combines both spectral and spatial information in kernels, and multiple kernel learning (MKL) [15,16], which enhances the flexibility of kernels in machine learning. However, SVM-based methods are sensitive to parameters selection.

More recently, the sparse representation classifier (SRC) [17–19], which is derived from the compressed sensing, has opened up new avenues for the classification of HSI. Motived by the sparsity prior of HSI, an unknown test sample can be approximately represented by the combination of a few training samples from the entire dictionary whereas the corresponding sparse representation vector encodes the class information implicitly. Significant efforts have been carried out in the literature to exploit the inherent structure of neighboring pixels. Typical methods include the joint sparsity model (JSM) [20], group sparse coding (GSC) [21], Laplacian regularized Lasso [22] and collaborative group Lasso [23]. However, the dictionary of SRC is conventionally constructed by all of the training samples, which is inefficient for capturing the crucial class-discriminative information. In this regard, one needs to learn a dictionary from specific training samples.

Much work has been carried out to gain suitable dictionary, and two major categories can be highlighted:

- Determining a dictionary by mathematical mode-based method. Several traditional dictionaries [24], such as Fourier, curvelet, contourlet, bandelet and discrete cosine transform (DCT) based dictionaries, belong to this category. Those methods characterize the dictionary by analytic formulations and fast implementations. However, the dictionaries are fixed and cannot represent the high-dimensional HSI adaptively.
- Learning a dictionary to perform best on the training samples. Many dictionary learning methods have been proposed to learn a compact and discriminative dictionary, which include the method of optimal directions (MOD) [25], K-Singular Value Decomposition (K-SVD) [26] and online dictionary learning [27]. To incorporate the contextual information, the learning vector quantization (LVQ) [28] based dictionary are customized for patch-based SRC, whereas the spatial-aware dictionary learning (SADL) [29] method is designed by dividing the pixels of HSI into a number of contextual groups. Those methods are flexible to adapt to specific data and gaining popularity in recent years. However, the sparsity criterion fails to capture global structure of the data, and the HSI is forcibly partitioned into many squared patches, which ignores the dissimilarity of different neighboring pixels.

Moreover, the low-rank representation (LRR), which is initially presented by Liu et al. [30,31], has achieved great success in various applications, including subspace clustering [31], objective detection [32], image classification [33], etc. Specifically, LRR has also drawn great attention in the HSI community. The spatial structure of the abundance vectors is exploited by LRR model in [34]. Low-rank prior [23] is enforced on the coefficient matrix to obtain more flexible and significant performance than joint sparsity prior. A maximum a posteriori (MAP) framework is constructed upon LRR for hyperspectral segmentation in [35]. Low-rank constraint [36] is employed to exploit the global redundancy and correlation (RAC) in spectral domain for HSI denoising. Low-rank reconstruction is incorporated in [37] to obtain a robust domain adaptation method for semi-supervised classification of remote sensing image.

In this paper, a low-rank group inspired dictionary learning (LGIDL) method is proposed for HSI classification. We integrate a low-rank group term to sparse representation for dictionary learning: (1) principle component analysis (PCA) is employed to obtain the first principle component (PC1) and a fast super-pixel segmentation method [38] is implemented on the PC1 to obtain homogeneous regions, which can be taken as spatial groups for LGIDL; (2) an optimization problem is constructed to alternatively update the non-negative low-rank coefficient by inexact augmented Lagrange multiplier (IALM) [31,39] and the dictionary by block coordinate descent (BCD) strategy [40]; (3) notably that the low-rank coefficients are discriminative enough, a linear SVM is trained to classify each test sample. As will be shown later, the pixels in the same group are able to incorporate both spectral and spatial characteristics, and the low-rank group prior in the optimization problem facilitates to capture the global structure of HSI, providing an effective strategy for dictionary learning in HSI classification.

The main contributions of this paper are as follows:

- We apply a fast super-pixel segmentation method to gain spatial groups in more natural forms.[1]
- We propose a LGIDL method to learn structured dictionary for capturing global structure of the HSI.

The layout of this paper is as follows. Section 2 describes the proposed LGIDL together with its optimization strategies. Experimental results are discussed in Section 3, and conclusions are drawn in Section 4. Moreover, the acronyms used in this paper are summarized in Table 1 for convenience.

2. The proposed LGIDL method

2.1. Construction of spatial groups

Notably that pixels within a small contextual patch usually consist of similar land covers, a fast super-pixel segmentation approach [38] is employed to over-segment the PC1 into homogenous regions, which can be viewed as the spatial groups for LGIDL. The super-pixel segmentation can not only provide spatial groups for the subsequent dictionary learning step but also detect much more flexible

[1] As opposed to artificial shapes.

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