Applied Mathematics and Computation 228 (2014) 531–545

Contents lists available at ScienceDirect

Applied Mathematics and Computation

journal homepage: www.elsevier.com/locate/amc

A kernel-based block matrix decomposition approach for the classification of remotely sensed images

Jianqiang Gao *, Lizhong Xu, Aiye Shi, Fengchen Huang

College of Computer and Information Engineering, Hohai University, Nanjing 210098, PR China

ARTICLE INFO

Keywords:
QRcp
SVD
SVMs
Image classification
Kernel
Spectral
Texture

ABSTRACT

The classification problem of remotely sensed images with hyperspectral and hyperspatial resolution images is being paid more and more attention. The success of remotely sensed images classification depends on many facts, such as the availability of high-quality images and ancillary data, proper classification procedure, and the analytical ability of scientific researcher. Therefore, lots of methods of combing spatial, spectral and texture information were proposed. However, these methods may ignore these facts as below. On the one hand, many details of the original remotely sensed images may be covered up by the too much overlapping information. On the other hand, the classification process is time-consuming. Therefore, a new and efficient classification of remotely sensed images method is introduced to overcome these shortcomings. The proposed method deals with the original information provided by the remotely sensed images is considered. The block matrix is made of training samples of the same class. The details of original remotely sensed images is obtained from the QR decomposition with column pivoting (QRcp) or singular value decomposition (SVD). And then, using fisher linear discriminant analysis (FLDA) methods, the projection data information of original remotely sensed images is jointly used for the classification through a support vector machines (SVMs) formulation. Experiments on hyperspatial and hyperspectral images are performed to test and evaluate the effectiveness of the proposed method.

1. Introduction

Remotely sensed images classification has long attracted the attention of many scientists and practitioners because classification results are the basis for many environmental and socioeconomic applications. In order to improve classification, lots of researchers have made great efforts [1–11]. However, there are many factors may affect the success of a classification, such as the availability of high-quality remotely sensed images and ancillary data, selected remotely sensed data, and proper classification methods. In lots of remote reports, supervised, semi-supervised and unsupervised are the three popular leaning methods for images classification in hyperspectral and hyperspatial remotely sensed images, for instance, maximum-likelihood classifiers, neural networks and neurofuzzy models [12–14]. However, in hyperspectral images, there is an important Hughes phenomenon [15], which is the high number of spectral bands and relatively low number of labeled training. Therefore, it takes a long time to deal with the high-dimensional data.

Quan et al. [16] proposed a multiscale method for the segmentation of the synthetic aperture radar (SAR) images, which is combining the probabilistic neural network (PNN) with the multiscale autoregressive model. Zhang et al. [17] proposed a

* Corresponding author.
E-mail addresses: jianqianggaoHH@126.com (J. Gao), lzhxu@hhu.edu.cn (L. Xu).

0096-3003/$ - see front matter © 2013 Elsevier Inc. All rights reserved.
http://dx.doi.org/10.1016/j.amc.2013.12.001

hybird classifier for polarimetric SAR images. Using PNN method, the span image, H/A/α decomposition and the GLCM-based texture features of feature set are jointly used for the classification. At present, most researchers believe that kernel methods (e.g., SVMs, kernel fisher discriminant analysis (KFDA)) is one of the best tools for solving high-dimension hyperspectral images classification [18–21] or face recognition [22,23]. A practical application of SVMs classifier combined with multispectral Landsat TM image Mediterranean landscape in Greece [24]. A wavelet feature based supervised scheme for fuzzy classification of land covers method by Uma Shankar et al. [25] proposed to handle multispectral remotely sensed images. Fauvel et al. [18–20] considered the definition of the spatial neighborhood and spatial information. And then, using kernel methods, the spatial and spectral information were jointly used for the classification through a support vector machine formulation. In fact, the kernel trick [26] is applied to project the original data into a feature space in which the data become linearly (or approximate linearly) separable.

It is worth noting that in doing remotely sensed images classification, many researchers only focus on analyzing the spectral features and spatial information, and may ignore the texture or structure information of images itself. That means we should treat remotely data as images, not only a mere collection of independent and identically distributed pixels [27]. Therefore, we should treat the training data as image block (or block matrix in computer).

In this paper, we propose a kernel-based block matrix decomposition approach for remotely sensed images classification. The proposed method is a three-step process, firstly, the original block matrix and its approximations which are evaluated from the original block matrix and from its transpose applying QRcp (or SVD) are all used to get the training samples. And secondly, we obtain the transformation matrix of remotely sensed images by employing eigenvalue decomposition of the optimal problem. At last, the SVMs classifier is applied to testing samples similar to some published reports.

The remainder of this paper is organized as follows. Section 2 briefly reviews the formulations of FLDA and SVMs classifier. In Section 3, the derivation process of the proposed method is described in detail. The effectiveness of the proposed method is demonstrated in Section 4 by experiments on several real remotely sensed images. Finally, Section 5 concludes this paper.

2. Review of FLDA and SVMs classifiers

2.1. Fisher linear discriminant analysis (FLDA)

The main goal of FLDA is to perform dimension reduction while preserving as much information as possible. Linear discriminant analysis aims to find the optimal transformation matrix such that the class structure of the original high-dimension space is preserved in the low-dimensional space. But in hyperspectral remotely sensed images classification issues generally dimension of the feature vectors are very high with respect to the number of feature vectors. Therefore, the FLDA cannot be directly employed because within-class scatter matrix has zero eigenvalues. In order to solve this problem, lots of researcher proposed several algorithms, such as LDA/QR [28], null subspace discriminant method [29], median-LDA method [30], median MSD-based method [31], and median null (S_w)-based method [32]. However, we focus on that Kong et al. [33] proposed two-dimension fisher discriminant analysis (2D-FLDA) algorithm. This method can be summarized as follows:

In this subsection, we first introduce some important notations used in this paper. Let c be the number of classes, N_i be the number of selected samples from ith class, N be the number of total selected samples from each class, A_j^i be the jth image from ith class and m_i be the mean image of ith class.

$$N = \sum_{i=1}^{c} N_i, \tag{1}$$

$$m_i = \frac{1}{N}\sum_{j=1}^{N_i} A_j^i, \quad (i = 1, \cdots, c). \tag{2}$$

The optimal projection matrix $G = [g_1, g_2, \cdots, g_l]$ can be found in 2D-FLDA. Where l is at most min $(c-1, N)$. We can obtain the optimal projection matrix via maximizing the following criterion:

$$J(G) = \frac{G^T S_b G}{G^T S_w G}, \tag{3}$$

where, S_b and S_w are the between-class and within-class scatter matrices, respectively. m_0 is the global mean image of all classes.

$$S_b = \sum_{i=1}^{c} (m_i - m_0)^T (m_i - m_0), \tag{4}$$

$$S_w = \sum_{i=1}^{c}\sum_{j=1}^{N_i} (A_j^i - m_i)^T (A_j^i - m_i), \tag{5}$$

$$m_0 = \frac{1}{c}\sum_{i=1}^{c} m_i. \tag{6}$$