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Multi focus image fusion based on spatial frequency

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Abstract:*Spatial–spectral feature fusion is well acknowledged as an effective method for hyper spectral (HS) image classification. Many previous studies have been devoted to this subject. However, these methods often regard the spatial–spectral high-dimensional data as 1-D vector and then extract informative features for classification. In this paper, we propose a new HS image classification method. Specifically, matrix-based spatial–spectral feature representation is designed for each pixel to capture the local spatial contextual and the spectral information of all the bands, which can well preserve the spatial–spectral correlation. Then, matrix-based discriminant analysis is adopted to learn the discriminative feature subspace for classification. To further improve the performance of discriminative subspace, a random sampling technique is used to produce a subspace ensemble for final HS image classification. Experiments are conducted on three HS remote sensing data sets acquired by different sensors, and experimental results demonstrate the efficiency of the proposed method.*

Index Terms—hyperspectral (HS) image classification, matrix-based discriminant analysis (MDA), support vector machine (SVM).

I. INTRODUCTION

The rapid development of imaging spectroscopy technologies, current sensors are able to acquire hyperspectral (HS) data with high spatial and spectral resolutions simultaneously. For instance, the Reflective Optics System Imaging Spectrometer (ROSIS) sensor covers a range of 115 spectral channels with the spatial resolution of 1.3 m. HS data can be presented as a 3-D cube consisting of two spatial dimensions and one spectral dimension, which provides an avenue for accurate classification of land cover scenes. HS image classification often suffers from two issues. The first one is that the widely used classification models based on pixelwise spectral information always lead to a salt and pepper thematic map because the intraclass spectral responses vary and interclass land covers may have very similar spectral natures in the study scene. The other one is that classifiers often need to process high-dimensional data with a small number. A typical HS image contains hundreds of spectral bands.

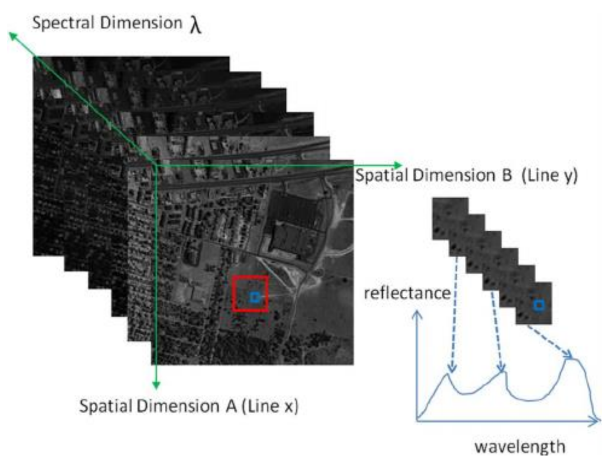

Figure.1 HS data cube structure.

2. Proposed System

MDA is first introduced to extract the spatial and spectral features of remote sensing images simultaneously. Subspace ensemble method based on random samplings used to derive diverse discriminant subspaces and, in some extent, alleviate the imbalanced data distribution problem in remote sensing image classification, thus promoting the classification performance.

2.1 Matrix-Based Spatial–Spectral Feature Representation

HS scene is denoted by a 3-D matrix $X \in R^{m\times n\times l}$ with $m \times n$ pixels and l spectral bands. Assume that $X(k)$ ij denotes the pixel at the spatial location (i, j) in band

k,where $i \in (1, 2, . . .,m)$, $j \in (1, 2, . . . , n)$, and $k \in (1, 2, . . . , l)$. Since the HS pixels within a small neighbourhood usually consist of similar materials we exploit the spatial neighborhood to combine the spectral and spatial–contextual information. Suppose the spatial window size is $\omega \times \omega$, which is an odd positive integer.

2.2 Matrix-Based Discriminative Feature Subspace Learning

Consider $Y \in R^{l \times \omega 2}$ is a new matrix representation for one pixel. To reduce the redundant information in this feature matrix and improve the discriminant ability of feature representation, we use MDA to map Y into a new subspace, in which the intraclass scatter is minimized and the interclass scatter is maximized.
Let us assume that $L =[\mu 1, \mu 2, . . . , \mu r]$
$R l^{\times r}$ and $R = [\nu 1, \nu 2, . . . , \nu c]$
$R^{\omega 2 \times c}$ are two transformation matrices.
Then, the projection of Y onto the $(r \times c)$-dimensional space can be expressed as

$$Z = L^T Y R$$

If there are N training pixels and C different classes to be classified. The jth training pixel is Y_j, where $j \{1, 2, . . .,N\}$.M andMi denote the mean of all training pixels and training pixels in class Πi, $i \in \{1, 2, . . ., C\}$, respectively.Ni is the number of training pixels in class Πi.

2.3 Learning Subspace Ensemble With Random Sampling

Ensemble Learning has been proved to be an efficient technique to improve the stability and accuracy of single weak classifier by training several different classifiers and combining their decisions.When forming ensemble, the accuracy is mainly affected by the diversity of classifiers,which can be achieved via different methods. One of the most widely used methods is bagging . Bagging has been used to construct an SVM ensemble for land cover classification, and the experiments suggest that an optimized ensemble method could lead to improved results.However, it costs so much time to train several SVM classifiers simultaneously.

2.4 Flowchart of the proposed method

Suppose that we have a training set Y, and Y_j represents the jth training pixel. First, n training subsets are randomly sampled from Y with replacement according to a certain proportion
and $Y_{(i)}$, i ⍰ $\{1, 2, . . . , n\}$ denotes the ith training
subset. Then, for every subset $Y(i)$, MDA is used to learn the optimal transformations Li and Ri as discussed in Section II-B.Thereafter, for every couple Li and Ri, the projection matrix$Z(i)j$ of Yj can be achieved according to (1). Therefore, we can obtain n projectionmatrices $\{Z_{(1)}$
$_j, Z_{(2)}$
$_j, . . . , Z_{(n)}$
Finally, all of these matrices are reshaped to vectors.

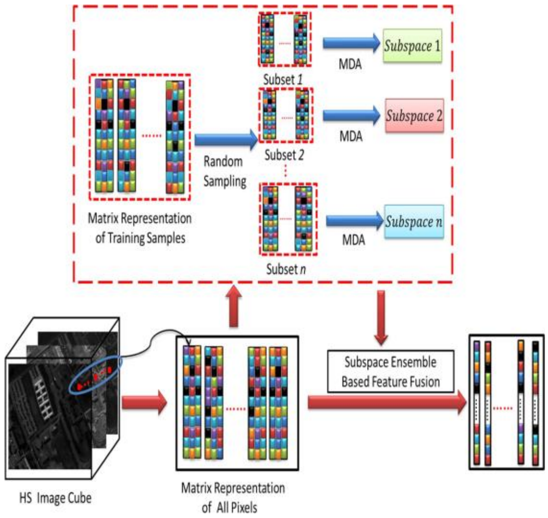

Figure.2

3. CONCLUSION

In this paper,we have proposed a novelmatrix-based discriminant subspace ensemble method for HS image spatial–spectral feature fusion. In the proposed method, matrix-based spatial– spectral feature representation is designed for each pixel to capture the local spatial contextual and the spectral information of all the bands, which can well preserve the spatial–spectral correlation. Then, MDA is adopted to learn the discriminative
feature subspace for classification. To further improve the performance of discriminative subspace, a random sampling technique is used to produce a subspace ensemble for final HS image classification. By conducting experiments on three data sets collected by different instruments (AVIRIS and ROSIS), we compared the proposed method with the classical pixelwise methods and the vectorized spectral–spatial fusion methods.

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