Contourlet based Hyperspectral Image Classification.

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Abstract
Classification of hyperspectral images in remote sensing has received attention during past decades. In this work, the feature extraction within images is based on Contourlet Transform (CT) and the classification is based on Support Vector Machine (SVM). In the existing system discrete wavelet transform is used to get detailed information with spectral and spatial characteristics of a pixel. But, it does not provide information about features in its directional components. The proposed system, to extract these features, Contourlet transform based laplacian pyramid followed by directional filter banks are used for feature extraction. Initially, the input hyper spectral image is decomposed into four sub bands by the application of stationary wavelet transform. Then the GLCM features are extracted from sub bands. The remaining sub bands are subjected to directional filter bank. The better classification is arrived by extracting and selecting the best features from the Contourlet Coefficients of the image and the outputs are used as an input to the Support Vector Machine classifier for classification with high accuracy.

Keywords: *Gray level co-occurrence matrix (GLCM), Feature Extraction, and Support Vector Machines(SVM)*

INTRODUCTION

Hyperspectral image classification is the evergreen field in remote Sensing Applications. Hyperspectral images contain contiguous spectral bands that captures the reflectance of the classes in the land cover data [1]. To identify the classes in the data, it is necessary to extract the spatial and spectral features [2]. There are so many multi resolution transforms available to extract the features in the hyperspectral data. One among them is Ridgelet Transform. The disappointing features of wavelets indicate that more powerful representations are needed in higher dimensions. Candues & Donoho (1999) introduced the ridgelet transform as a sparse expansion for functions on continuous spaces that smooth away from discontinuities along lines [3]. Do & Vetterli (2003) proposed the finite ridgelet transform for image representation. In this paper, an orthonormal version of the ridgelet transform for discrete and finite size images is proposed [4]. The construction uses the Finite Radon Transform (FRAT) as a building block. To overcome the periodization effect of a finite transform, a novel ordering of the FRAT coefficients is used. Taking the one-dimensional wavelet transform on the projections of the FRAT in a special way results in the Finite Ridgelet Transform (FRIT), which is invertible, non-redundant and computed via fast algorithms. Furthermore, this construction leads to a family of directional and orthonormal bases for images [5]. Ranganathan & Borries (2006) proposed sliced ridgelet transform for image denoising. This approach for image denoising is based on ridgelets computed in a localized manner. In this localized ridgelet transform, or sliced ridgelet [6]. Chen & Kegl (2007) proposed image denoising with complex ridgelets by incorporating the dual tree complex wavelets into the ordinary ridgelet transform. This method exploits the approximate shift invariant property of the dual tree complex wavelet and the high directional sensitivity of the ridgelet transform. These properties make this technique as a very good choice for image denoising. The line or curve singularities in the noisy images are well preserved by this method [7]. Curvelet transform is a block-based transform, having blocking effects. To avoid blocking effects overlapping is used. Overlapping windows increase redundancy (Do 2001) [8]. To overcome these limitations, Do & Vetterli (2004) pioneered a sparse representation for two- dimensional piecewise smooth signals that resemble images called contourlet transform; it can be designed to satisfy the anisotropy scaling relation for curves. It is a directional transform which is capable of capturing contour and fine details in an image [9]. The approach in this transformation starts with the discrete domain construction and then sparse expansion in the continuous domain. The main difference between contourlet and other transformations is that in the contourlet transform, Laplacian pyramid (Burt & Adelson 1983) along with the directional filter banks (Bamberger & Smith 1992) are used. As a result, contourlet transform not only detects the edge discontinuities, but also converts all these discontinuities into continuous domain. Since the contourlet transform is good at capturing the edges of the images, it can get better denoising results than wavelet transform if only an appropriate thresholding is chosen [10-11]. Contourlet transform is not a translation invariant transform. Due to the lack of translation invariance, image denoising by means of the contourlet transform introduces many visual artifacts due to the Gibb’s like phenomena. To overcome this limitation, Eslami & Radha (2003) proposed a new method for image denoising using the contourlet transform [12].

Eslami & Radha (2006) proposed a translation invariant contourlet transform and its application to image denoising. In this work, the authors studied and developed new methods to convert a general multichannel, multidimensional filter bank to a corresponding translation invariant framework [13]. Zhou & Shui (2007) proposed contourlet- based image denoising algorithm using directional windows which takes an advantage of the captured directional information of the images [14].

Above mentioned studies clearly indicate the better performance of Contourlet Transform over conventional Discrete Wavelet Transforms. So it is decided to use Contourlet transforms for the hyperspectral image classification purpose. Hence this is expected to be useful in extracting the features from the hyperspectral image in which classes are not uniformly distributed. Support Vector Machine is used for the classification process.

PROPOSED WORK

Classification is the process of assigning the pixels into the class based on the extracted features.

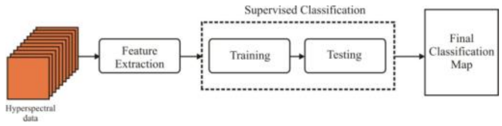

Fig.1. *Proposed Method*

Feature Extraction

A feature is nothing but the significant representative of an image which can be used for classification, since it has a property which distinguishes one class from other. The extracted features provide the characteristics of input pixel to the classifier. The spatial features can be extracted by statistical and co-occurrence methods.

Table 1. *Co-occurrence Features*

Feature	Formula
Entropy	$-\Sigma\Sigma$ P[i,j]×logP[i,j]
Energy	$\Sigma\Sigma$ P^2 [i, j]
Contrast	$\Sigma\Sigma$ $(i-j)^2$P [i, j]
Homogeneity	$\Sigma\Sigma$ (P [i, j] / (1 + |i – j|))
SumMean	(1/2) [$\Sigma\Sigma$ iP [i, j]+$\Sigma\Sigma$jP [i, j]]
Variance	(1/2)[$\Sigma\Sigma$ $(i-\mu)^2$P [i, j] + $\Sigma\Sigma$$(j-\mu)^2$ P [i, j]
Maximum Probability	Max {P[i,j]}
Cluster Tendency	Σ(i + j - 2μ) k P [i, j]

3. Support vector machines (SVM)
Support vector Machines performs the robust non-linear classification with kernel trick. It outperforms other classifiers even with small numbers of the available training samples.

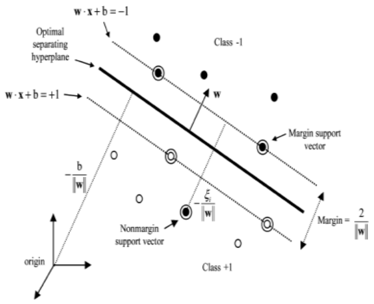

Fig. 3. *SVM Hyperplane*

SVM finds the separating hyper plane in some feature spaceinducted by the kernel function while all the computations aredone in the original space itself [29]. For the given training set,the decision function is found by solving the convex optimizationproblem.

When optimal solution is found, i.e. the λi, the classification of a sample X is achieved by looking to which side of the hyper plane it belongs:

$$f(x) = \left(sign(\sum_{i=1}^{k} \lambda_i y_i (x.x_i) + b \right)$$

EXPERIMENTAL RESULTS AND DISCUSSION

The proposed method is evaluated by making use of two sets of data. Indian Pines data which is taken over North-western Indiana captured by Airborne Visible Infrared Imaging spectrometer (AVIRIS) In this image there are145x145 pixels.

The input image is pre-processed by low pass filter. Then it will be subjected into DFB for decomposition. The directional features and textural features obtained from all the bands are applied to GLGM for feature selection. All the extracted features are concatenated together and are used for classification [15]. Fig 2 shows the output image.

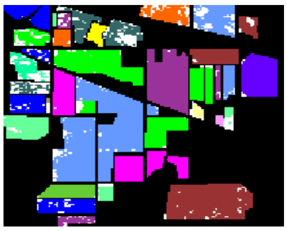

Fig. 2 *Classified Output*

The class Grass-Pasture Mowed produced the best results and all its pixels are correctly classified. Wheat is the class which is also produced better accuracy of 99.52%. Except Oats all other classes are showing better results. Oats is the very small class among the classes. The same is observed for the class Stone Steel Towers also. For the class corn also the accuracy is 56.41% only.

***Table 2** Classification Output using Contourlet Transform*

Class	No. of Pixels	Class Accuracy (%)
Alfalfa	54	62.96
Corn-Notill	1434	92.96
Corn-Min	834	91.13
Corn	234	56.41
Grass-Pasture	497	82.49
Grass-Trees	747	99.87
Grass-Pasture Mowed	26	100
Hay-Windrowed	489	98.16
Oats	20	30.00
Soybean-Notill	968	94.21
Soybean-Min	2468	92.22
Soybean-Clean	614	65.80
Wheat	212	99.52
Woods	1294	95.52
Building Grass Tree Drives	380	80.79
Stone Steel Tower	95	34.74
Overall Accuracy (in %)		89.84

CONCLUSION

This paper proposes a classification of multispectral images into various land use and land cover details. The proposed method explores the possible advantages of using Contourlet Transform (CT) and the classification is based on Support Vector Machine (SVM). Spectral and spatial features obtained from all the band is applied to feature reduction method. The experimental results show that the proposed work gives good result when compared to existing methods.

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