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Hyperspectral Image Classification Using SVM

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ABSTRACT

HyperSpectral image classification has been used for many purposes in remote sensing, and vegetation research, environmental monitoring and also for land cover classification. A hyperspectral image consists of many layers in which each layer represents a specific wavelength. This paper aims to classify the hyperspectral images to produce a thematic map accurately. Spatial information of hyperspectral images is collected by applying morphological profile and local binary pattern. Support vector machine (SVM) is an efficient classification algorithm for classifying the hyperspectral images. Genetic algorithm is used to obtain the best feature subjected for image classification. The classes and thematic map are generated by using future extraction. Experiment is carried out with AVIRIS Indian Pines and ROSIS Pavia University. This method produces the accuracy as 93% for Indian Pines and 92% for Pavia University.

KEYWORDS
Morphological Profile, Local Binary Pattern, Hyperspectral Image, Genetic Algorithm, Support Vector Machine

1.INTRODUCTION

Hyperspectral remote sensing techniques is obtaining the information about earth's surface or objects through the analysis of data collected by hyperspectral sensor. Hyperspectral imaging is a spectral imaging technique and also related to multispectral imaging. Hyperspectral images are narrow spectral bands over a continuous spectral range. Multispectral images are several images at discrete narrow bands. Different types of heterogeneous classes present in hyperspectral images is one of the research issue in remote sensing[1]. Feature extraction consists of classifying the pixels in the hyperspectral image and identifying the relevant class. It differentiates one class from other and the process of transforming the input data into the set of features. Spectral – spatial classification of hyperspectral image is proposed the method mathematical morphology , it is used for preprocessing of hyperspectral data. Opening and closing morphological transforms are used in order to isolate bright(opening) and dark (closing) structures in images[2]. The large dimensionality of the hyperspectral images make it harder for classification. A lot of redundancy in the data to be removed[3]. The consequent ground truth demand for supervised classification[4].According to Hughes phenomenon the required number of labeled training samples for supervised classification increases as a function of dimensionality. Unsupervised and supervised algorithms have been developed for classification of multispectral images .These algorithms failure to deliver high accuracy hyperspectral images.

SVM consists of feature selection and extraction[5] . SVM explains the linear domain classification, it gives the good results. hyperspectral domain is a non-linear.

Kernel methods provides a machine learning paradigm. It coverts nonlinear methods from linear ones[6],[7]. Many types of kernels like linear, polynomial, Radial Basis Function(RBF), sigmoid etc.., are available . Selection of proper kernels gives proper results. The usage of SVM classifier for hyperspectral image is shown[8].The support vector machine with kernel trick has been successfully used in hyperspectral image classification[9].

For adding classification methods features such as pixel wise, extended morphological profile and feature extraction using genetic algorithm is used. Spectral and spatial information of hyperspectral data is needed for accurate classification. Principal component analysis is applied to hyperspectral image as a feature extraction technique[10].

Local binary pattern is an operator for texture classification where the pixel is consider as a threshold for neighborhood pixels. Local binary pattern is experimentally evaluated for land cover classification. Texture characterization approach performs well when combined with grey-level variance[11].

2.PROPOSED METHODOLOGY

2.1 Morphological Processing

Morphological processing is a non-linear operation related to the shape or morphology of features in an image. The basic operators of morphology are dilation, erosion, opening and closing. The fundamental operators are applied to a hyperspectral image with a set of particular shape known as structuring element.

The work of hyperspectral data using erosion operator provides an output of the structuring element fits, the work of dilation gives an output of image where the structuring element hits the object in an image.

Opening smoothes the counter of an object and remove thin protrusions to isolate the bright structure of an image.

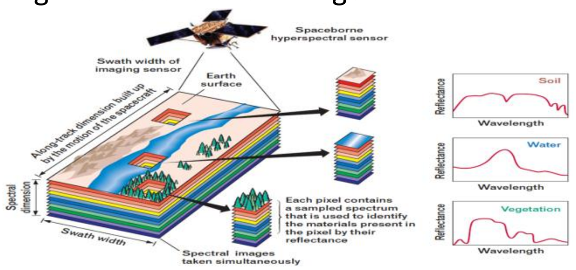


Figure 1: Spacebone Hyperspectral sensor

Closing the smooth sections of counters and removing small holes, filling gaps in the counters to obtain dark structures in images. The basic morphological operation is applied to obtain morphological profile.

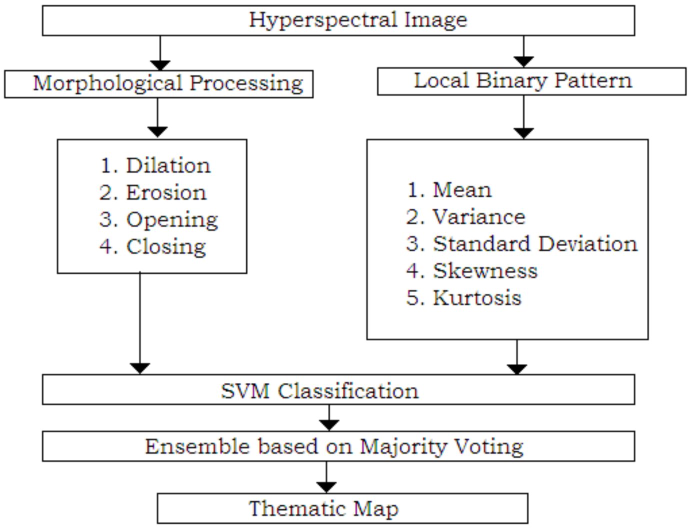


Figure 2:Proposed Methodology

2.2 Local Binary Patterns

Local Binary Patterns is effective texture operator. The pixels by thresholding the neighbourhood of each pixel and obtained result is a binary number.

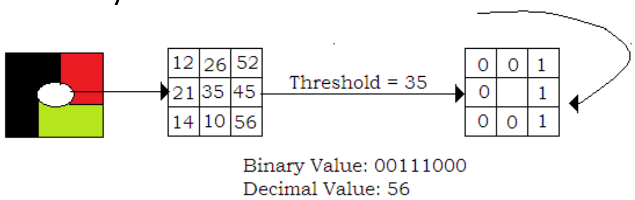


Figure 3: Concept of Local Binary Value

The concept of local binary pattern is follows. Consider a 3X3 matrix from hyperspectral image. Center pixel value is threshold for surrounding pixels. The surrounding pixel value is greater than threshold, the pixel value is 0 or 1.

The decimal value is obtained from the binary value, it calculates the clock-wise direction. The hyperspectral data is applied to statistical and co-occurrence features. The statistical features are mean, variance, standard deviation. The co-occurrence features are skewness, kurtosis is calculated.

Feature	Formula
Mean	$\mu_{ij} = \left(\sum_{1\le i\le M}\sum_{1\le j\le N} X_{ij}\right)/MN$
Variance	$\sigma_{ij} = \left(\sum_{1\le i\le M}\sum_{1\le j\le N}\left(X_{ij}-\mu_{ij}^{2}\right)\right)^{0.5}/MN$
Standard Deviation	$\sigma_{ij}^{2} = \left(\sum_{1\le i\le M}\sum_{1\le j\le N}\left(X_{ij}-\mu_{ij}^{2}\right)\right)^{1}/MN$
Skewness	$skew(x_{ij}) = \left(\sum_{1\le i\le M}\sum_{1\le j\le N}\left(X_{ij}-\mu_{ij}^{3}\right)\right)^{1}/\sigma_{ij}^{3}$
Kurtosis	$kurt(x_{ij}) = \left(\sum_{1\le i\le M}\sum_{1\le j\le N}\left(X_{ij}-\mu_{ij}^{4}\right)\right)^{1}/\sigma_{ij}^{4}$

Table -1 Formula for Statistical Features

2.3 Support Vector Machine

Support Vector Machine is based on class separation. Samples are mapped using kernel function to a higher feature space to linear seperability of data. The popular kernels are Polynomial, Linear and Radial Basis Function. Samples of two classes can be linearly separable by hyper plane in high feature space. SVM training consists of finding optimal hyper plane where distance between each can be maximized. For training samples, consider a set of n points as D=$\{(x_i, y_i)|x_i \in R^p, y_i \in \{-1,1\}\}_{i=1}^{n}$

Where y_i is 1 or -1 for x_i class and x_i is p-dimensional vector.

Select two hyper planes to separate hyperspectral data and distance between two plane is maximum. The hyper plane should satisfy the condition as w.x-b=0. The equation for hyper plane for separating the margins is w.x-b=1 or w.x-b=-1. Consider the constant for margin to prevent data falling from one to another. w.$x_i \ge 1$ for 1st class and w.$x_i - b \le -1$ for 2nd class. The distance between two hyper planes is $\frac{2}{\|w\|}$ and $\|w\|$ is minimum.

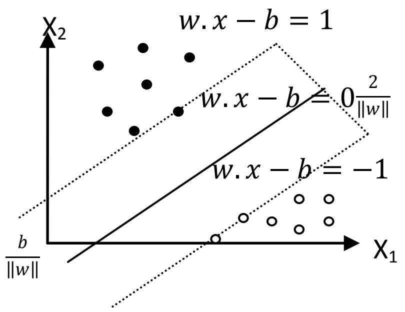


Figure4. Hyper plane separation

3. EXPERIMENTAL DESIGN

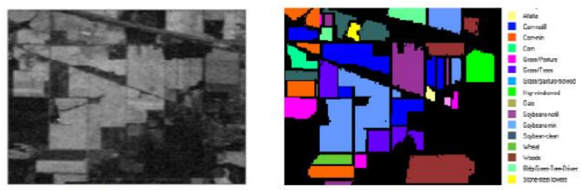
The Experiment carried out in two datasets such as , Indian Pines and Pavia University taken by AVIRIS(Airborne Visible/Infrared Imaging Spectrometer) and ROSIS(Reflective Optics System Imaging Spectrometer) sensor.

i . The Indian Pines Dataset is an agriculture area recorded over Northwestern Indiana, with 145X145 pixels and spatial resolution of 20m per pixel having 220 channels.

ii . The Pavia University dataset is an urban area recorded over the University of Pavia, Italy. The image is composed of 610X340 pixels with spatial resolution of 1.3m/pixel and a spectral range of 0.43μm having 103 bands.

At first dilation, erosion, opening and closing operations are performed. Statistical features and co-occurrence are calculated by using formulas. Genetic algorithm used inn majority voting for best feature is identified for classification. 30% training samples were used for final phase of testing.

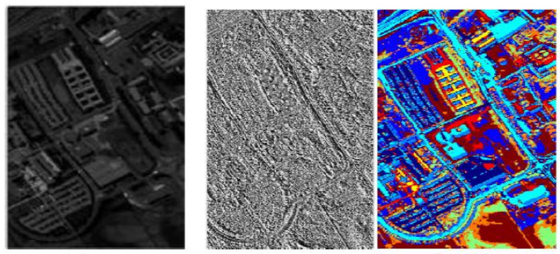
4.RESULTS



(a) ROSIS Indian Pines (b) Ground Truth

(c)Local Binary Pattern (d) Classification map

Figure 5 : Result for AVIRIS Indian Pines dataset



(a) (b) (c)

(b) Figure 6. (a) ROSIS Pavia University (b) Local Binary Pattern (c) Classification Map

Class Name	Dilation	Erosion	Opening	Closing	Mean	Variance	Standard Deviation	Kurtosis	Skewness
Alfalfa	70.98	71.56	69.23	69.71	71.78	60.92	62.54	75.96	64.65
Cornnot	92.76	93.97	84.12	91.94	92.43	80.98	86.96	84.12	97.85
Cornmin	80.72	82.68	75.556	79.53	83.74	70.56	73.65	75.16	72.98
Corn	91.86	93.54	90.47	79.52	93.66	82.99	92.19	86.91	83.65
Grasspasture	96.52	97.15	91.75	95.29	97.8	90.18	94.25	95.12	92.75
Grasstrees	98.9	98.63	97.23	90.74	97.64	98.43	98.96	96.15	97.74
Grasspasture	62.7	95.79	54.12	53.14	66.53	55.98	58.74	75.92	55.78
Hay	86.59	89.34	84.92	85.41	87.42	76.25	75.79	78.95	88.92
Oats	79.91	82.18	81.73	82.59	81.53	61.82	82.96	70.41	90.85
Soybean not	50.94	59.87	54.97	52.4	57.76	70.63	55.95	40.76	58.74
Soymint	71.99	82.97	75.64	76.35	83.92	81.58	87.95	78.68	87.52
Soyclean	69.42	74.48	70.09	75.12	76.54	59.6	65.74	69.87	66.74
Wheat	72.84	78.56	76.52	82.18	79.12	66.86	69.33	71.49	81.74
Woods	79.25	84.63	82.41	85.15	83.19	82.91	86.77	72.96	77.89
Trees	76.81	80.84	67.88	69.34	81.29	73.54	77.56	88.93	72.18
Steel	66.72	71.96	56.38	68.75	73.85	52.52	76.32	82.68	88.9
Overall Accuracy (%)	**78.06**	**83.63**	**75.81**	**77.32**	**81.76**	**72.86**	**77.85**	**77.75**	**79.93**

Table-2 : Accuracy table for Various classes in AVIRIS Indian Pines Dataset using SVM(%)

Class Name	Dilation	Erosion	Opening	Closing	Mean	Variance	Standard Deviation	Kurtosis	Skewness
Alfalfa	75.23	76.3	75.85	78.25	81.24	76.52	77.58	62.89	61.3
Meadow	89.56	90.25	89.96	87.23	89.56	83.45	85.27	88.98	85.96
Gravel	59.3	61.56	62.58	65.45	75.85	67.2	69.75	52.74	79.36
Trees	65.69	67.85	68.96	63.45	75.87	78.58	79.85	54.3	58.32
Sheets	82.954	83.69	82.89	87.85	93.54	88.96	89.74	80.25	82.63
Bare soil	91.58	85.9	87.41	82.47	86.43	87.23	89.57	91.2	91.78
Bitumen	97.96	89.54	90.74	86.56	89.21	87.41	84.12	85.64	84.1
Bricks	78.54	80.23	81.45	79.85	82.78	82.45	81.23	62.17	68.33
Shadow	50.96	55.89	60.74	60.85	76.2	65.52	74.92	45.95	66.54
Overall Accuracy (%)	**76.86**	**76.80**	**77.84**	**76.88**	**83.41**	**79.70**	**81.34**	**69.35**	**75.37**

Table 3 : Accuracy table for ROSIS Pavia university using SVM(%)

5.CONCLUSION

Hyperspectral sensors collects images in large number of spectral channels. Spectral signature for every spatial location gives more information about an image provides differentiate between materials and objects. Morphological profile and local binary pattern techniques given high classification accuracies for hyperspectral data. Genetic Algorithm is used for selecting best features among different features. Support Vector Machine is used for classifying the various types of classes present in the dataset. Proposed method produces accuracy as 93% for Indian Pines and 92% for Pavia University.

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