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Multilevel Classification Methods For Hyper Spectral Data Interpretation Using SVM

E.Catherin Reichal Jennifer [1], Dr.K.G.Revathi[2]
[1](PG Scholar,Department of Electronics and Communication Engineering,DMI College of Engineering,Chennai,India)
[2](Head of the Department,Department of Electronics and Communication Engineering, DMI College of Engineering, Chennai,India)

ABSTRACT: HyperSpectral and satellite geo science image classification has been used for many purposes in remote sensing, and plants research, ecological monitoring and also for land cover classification.The focus in many applications is to investigate an effective classifier in terms of accuracy. The conventional multiclass classifiers have the ability to map the class of interest but the significant efforts and large training sets are required to fully describe the classes spectrally. Support Vector Machine (SVM) is suggested in this paper to deal with the multiclass problem of hyper spectral imagery. Supportvectormachine(SVM)isaprofessionalclassificationalgorith mforclassifyingthehyperspectralimages.K means clusteringalgorithmisusedto obtain the best feature subjected for image classification. The classes and thematic map are generated by using feature extraction.

KEYWORDS: MorphologicalProfile,LocalBinaryPattern,Hyper spectralImage,k means clustering Algorithm,SupportVector Machine.

1.INTRODUCTION

Hyper spectral remote sensing technique is obtaining the information about earth's surfaceorobjectsthroughtheanalysisofdatacollected byhyper spectralsensor.Hyper spectralimagingis aspectralimagingtechniqueandalsorelatedto multispectral imaging. Hyper spectral images are narrow spectral bands over a continuous spectral range. Multispectral images are several imagesat discrete narrow bands. Different types of heterogeneous classes present in hyper spectralimages is one of the research issues in remote sensing [1]. Feature extraction consists of classifyingthepixelsinthehyper spectralimage and identifying the relevant class. It differentiatesone class from other and the process of transforming the input data into the set of features. Spectral – spatial classification of hyper spectral image is proposed the method mathematical morphology, it is used for preprocessing of hyper spectral data. Opening andclosing morphological transforms are used in order to isolatebright (opening) and dark (closing) structures in images [2]. The large dimensionalities of the hyper spectral images make it harderfor classification.Alotofredundancyinthedatato be removed [3]. The consequent ground truth demand for supervised classification [4].AccordingtoHughesphenomenontherequirednumberof labeled training samples for supervised classification increases as a function of dimensionality. Unsupervised and supervised algorithmshave been developed for classification of multispectral images .These algorithms failuretodeliverhighaccuracyhyper spectralimages. SVM consists of feature selection and extraction [5].SVMexplains the lineardomain classification, it gives the good results. Hyper spectraldomainisanon-linear.

A kernel method 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),sigmoidetc..,areavailable. Selectionofproper kernelsgivesproperresults.TheusageofSVM classifier for hyper spectral image is shown [8].The support vector machine with kernel trick has beensuccessfullyusedinhyper spectralimage classification [9].

For adding classification methods featuressuch as pixel wise, extended morphological profile and feature extraction using genetic algorithm is used. Spectral and spatial informationofhyper spectraldataisneededfor accurate classification. Principal component analysisisappliedtohyper spectralimageasa feature extractiontechnique [10].

Local binary pattern is an operator for textureclassificationwherethepixelisconsider as a threshold for neighborhood pixels. Local binary pattern is experimentally evaluated for landcover classification. Texture characterizationapproach performs well when combined with grey-levelvariance [11].

2. LITERATURE REVIEW

All The literature review of hyper spectral image classification fall under three categories supervised hyper spectral image classification, unsupervised hyper spectral image classification andsemi supervisedhyper spectral image classification to handle the various issues which are faced while classifying hyper spectral images such as large number of spectral channels, acquisition of labeled data etc. The task of acquisition of labeled data is time consuming and costly. And last part of this section introduces the some well-known applications of hyper graph.

Bands are selected using mutual information (MI). Mutual information term calculate the statistical dependence between two random variable form which it easy to understand relevance of that particular band to classification. Those most relevant bands are selected for further analysis of image which in turns handles the issue of high dimensionality [1].

Supervised Kernel nonparametric weighted feature extraction (KNWFE) method is proposed in [2] to extract the relevant features. This method combines kernel methods and

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nonparametric weighted feature extraction method to possess both linear and nonlinear transformation.

In [4] supervised method based on a stochastic minimum spanning forest (MSF) approach to classify hyper spectraldata is proposed. In this method a pixel wise classification is first performed on hyper spectral image .From this classification map, marker maps are created with random selection of pixels and labeling them as markers for the purpose building of MSFs. MSF is built from each of the marker maps and final classification map generated with a maximum vote decision rule.

As these methods fall under supervised category they make use of only labeled data to train the classifier and in case of hyper spectral images label data is a very few and obtaining labeled data is more time consuming and costly. So research goes towards such methods which will conduct hyper spectral image classification under a very few training samples or absence of samples

3. PROPOSEDMETHODOLOGY

3.1. MorphologicalProcessing

Morphological processing is a non-linear operationrelatedtotheshapeormorphologyof features in an image. The basic operators of morphology are dilation, erosion, opening and closing.Thefundamentaloperatorsareapplied toahyper spectralimagewithasetofparticular shapeknownasstructuringelement.

The work of hyper spectral data using erosion operator provides an output of the structuring elementfits,theworkofdilationgivesanoutput ofimagewherethestructuringelementhitsthe object in animage.

Opening smooth's the counter of an objectandremovethinprotrusionstoisolatethe brightstructureofanimage.

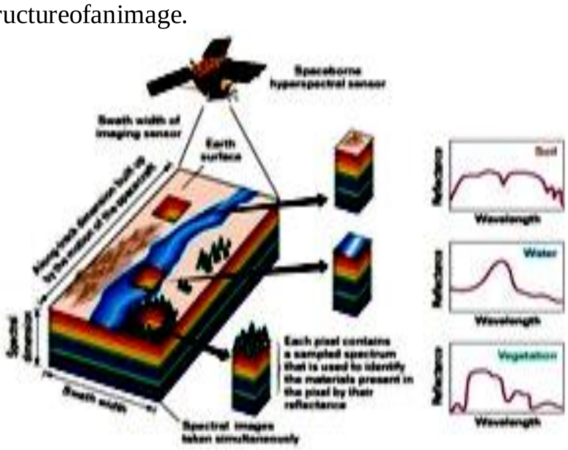

Figure 1: Space boneHyper spectral sensor

Closingthesmoothsectionsofcounters and removing small holes, filling gaps in the counterstoobtaindarkstructuresinimages.The basic morphological operation is applied to obtain morphologicalprofile.

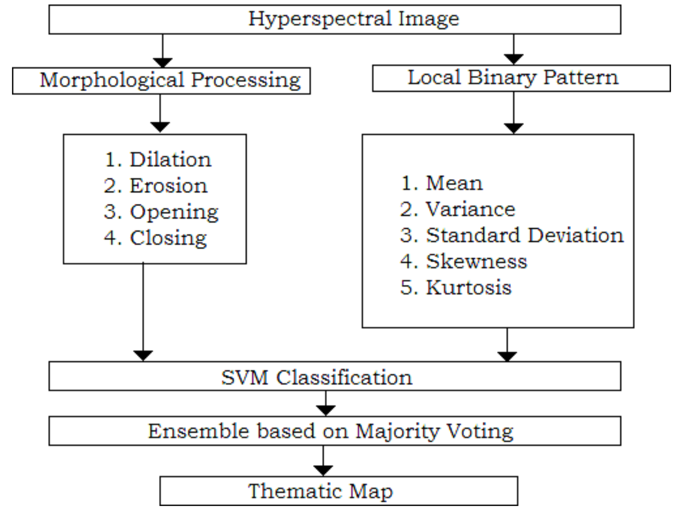

Figure 2: Proposed Methodology

3.2. Local BinaryPatterns

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

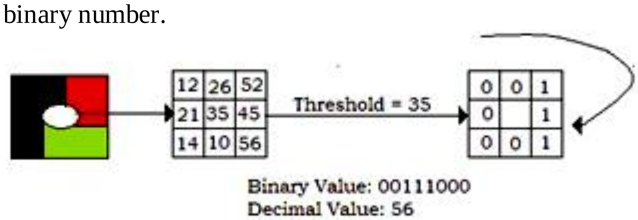

Figure 3: Concept of Local Binary Value

The concept of local binary pattern is follows. Considera3X3matrixfromhyper spectralimage. Center pixel value is threshold forsurrounding pixels.Thesurroundingpixelvalueisgreaterthan threshold,thepixelvalueis0or1.

The decimal value is obtained from the binary value, it calculates the clock-wise direction. The hyper spectral 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.

Table -1 Formula for Statistical Features

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	$kurt(x_{ij}) = \left(\sum_{1\le i\le M}\sum_{1\le j\le N}\left(X_{ij}-\mu_{ij}^{4}\right)\right)^{1}/\sigma_{ij}^{4}$

3.3. Support VectorMachine:

Support Vector Machineisbasedonclass separation. Samples are mapped usingkernel function to a higher feature space to linear seperability of data. The popular kernels are Polynomial, Linear and Radial BasisFunction. Samplesoftwoclassescanbelinearlyseparable by hyper plane in high feature space. SVM trainingconsistsoffindingoptimalhyperplane 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 hyper spectral data and distance between two planesaremaximum.Thehyperplaneshouldsatisfy theconditionasw.x-b=0.Theequationforhyper plane for separating the margins is w.x-b=1or w.x-b=-1. Consider the constant for margin to prevent data falling from one to another.w. for 1st class and w. for 2nd class. The distance between two hyper planes is $\frac{2}{\|w\|}$ and $\|w\|$ is minimum.

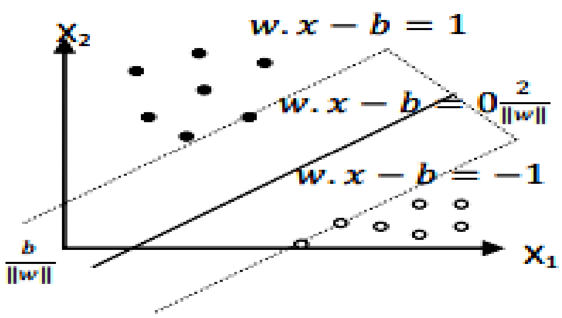

Figure4. Hyper plane separation

4. 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.

At first dilation, erosion, opening and closing operations are performed. Statistical features and co-occurrence are calculated by using formulas. Genetic algorithm usedinn majority voting for best feature is identified for classification.30%trainingsampleswereused forfinalphaseoftesting.

5. RESULTS:

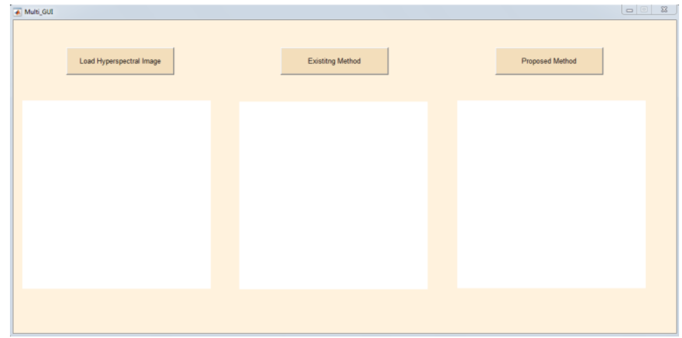

Fig 5:MATLAB GUI Model

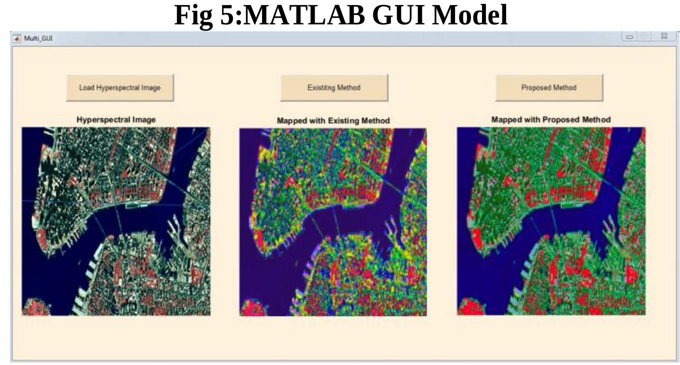

Figure 5: Result for satellite images

. The Indian Pines Dataset is an agriculture area recorded over Northwestern Indiana, with 145X145 pixels and spatial resolution of 20m perpixelhaving220channels.

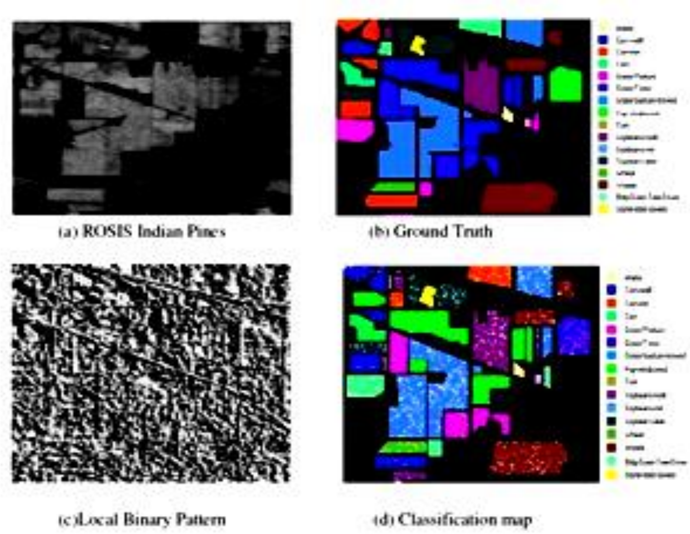

Figure6: Result for AVIRIS Indian Pines dataset

.ThePaviaUniversitydatasetisanurbanarea recordedovertheUniversityofPavia,Italy.The image is composed of 610X340 pixels with spatial resolutionof1.3m/pixelandaspectralrangeof 0.43 having 103bands.

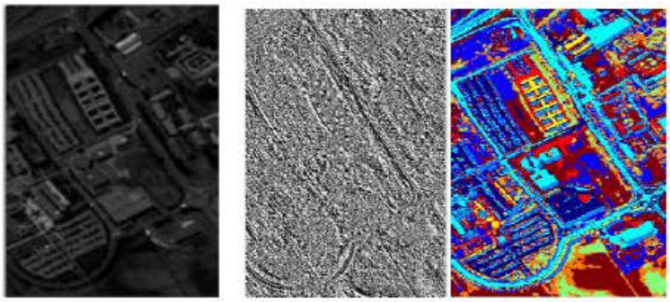

Figure7 : Result for Pavia University Dataset

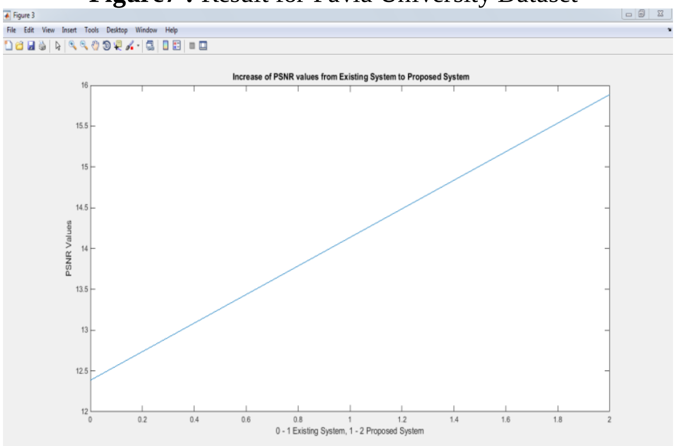

Figure8:comparison PSNR value with existing and proposed method

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:

A hyper spectral sensor collects images in largenumberofspectralchannels.Spectralsignaturefor everyspatiallocationgivesmoreinformationabout an image provides differentiate between materials and objects. Morphological profile and local binary pattern techniques given high classification accuracies for hyper spectral data. K means clustering algorithm isusedfor selecting best features among different features. Support Vector Machine is used for classifyingthe various types of classes present in the dataset. Proposed method produces accuracy as 93% for IndianPinesand92%forPaviaUniversity.

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