

## **Feature Extraction and Classification of Hyperspectral Image using SVM**

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**Abstract**—Hyperspectral image consists of consecutive number of bands. Partition the number of band in order to visualize the elements present in each band. First Denoising using canny edge detector to detect the edge from the image. Then super pixel segmentation segment the element based on color. In this paper proposed a method for decomposition as Contourlet Transform(CT) is to get contours.CT has Laplacian Pyramid and Directional Filter Bank(DFB) is used. Laplacian Pyramid(LP) decompose the bands into subbands and Directional Filter Bank(DFB) used to access each edges and the elements. Elements present in the image, classified by SVM classification. Thus proposed system make use of contourlet transform for detecting contours. Finally compare the proposed method with other decomposition mechanism for element identification. The experimental results show that the proposed method accesses the element along with contours.

**Keywords:** *Hyperspectral Image,Partition of bands,Contourlet Transform,SVM classification.*

### **I. INTRODUCTION**

Hyperspectral image a dynamic area in remote sensing. Airborne and space borne are the common platform of remote sensing for analyzing the earth and its natural resources.The rapidly growing number of earth observation satellites provides a better coverage's in space, time and the electromagnetic spectrum than in past decades. Remotely sensed satellite image analysis is a challenging task considering the volume of data with combination of channels in which image is acquired. Nowadays several imaging sensors mounted on satellites or airplanes can capture hyperspectral imagery with hundreds of contiguous band across electromagnetic spectrum. Hyperspectral image data is collected by various sensor such as NASA Airborne Visible Infra-Red Imaging Spectrometer(AVIRIS),Reflective Optics System Imaging Spectrometer,Mapping Reflected-Energy Spectrometer(MaRS) and Light Detecting and Ranging(LiDAR).Fusion of LiDAR and Hyperspectral image useful for analysing,particularly for geomorphology and hydrology.

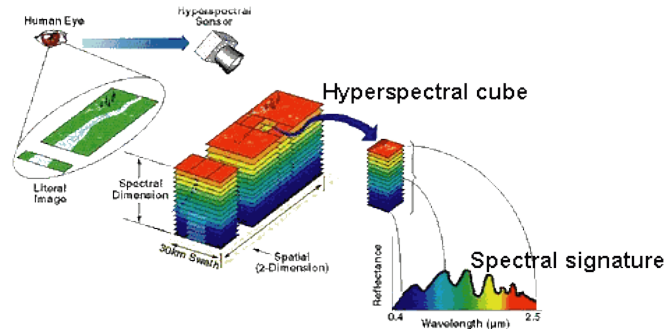
The goal of hyperspectral imaging to obtain the spectrum for each pixel in the image of a scene for finding objects and detecting minerals, vegetation.It is mainly concerned with analysis and spectra acquired from a scene at short, medium, and long distance by satellite or airborne sensor. Usually this type of image are of above 100 bands and measure reflectance spectra of range  $0.4\mu\text{m} - 2.5\mu\text{m}$ . All earth surface features including minerals, vegetation and snow have unique spectral reflectance signature. Hyperspectral images provide ample spectral information in order to identify and distinguish spectrally similar materials for more accurate and detailed information extraction. Images are composed of hundreds of consecutive narrow spectral bands from the visible to infrared region resulting in a continuous reflectance spectrum for each pixel.

Partition the total number of bands in the image in order to visualize the elements in each layer.Thus it is important to verify whether element has present or not and to identify using color.In existing works on hyperspectral image on band selection and partition only particular band get selected using various techniques such as Mutual Information(MI),Choquest Fuzzy Integral.In this MI,entropy is calculated based on the information present in each individual band and these are ranked in order.Bands are selected based on top-ranking entropy values.And also removing of band from the image by analysing and calculating the threshold values of individual band of an image.In

decomposition by Intrinsic Image Decomposition(IID) used,it take all the reflectance component and shadowing component in object based image.

The paper proposes a decomposition method as Contourlet Transform that has capable of capturing the contours. This proposed method has two categories as Laplacian Pyramid (LP) and Directional Filter Bank(DFB). First partitioned band get decomposed into single band and capturing the lines, edges from the image. Finally an element present in the image is classified by Support Vector Machine (SVM) algorithm that identifies and separate the elements in the image.

FIGURE.1 SENSOR CAPTURE-HYPERSPECTRAL IMAGE



The rest of this paper is structured as follows. Section 2 describes the related work of the proposed techniques. Identification of elements as minerals in hyperspectral image is explained in section 3. Section 4 describes the results and its discussion with suitable diagrams.In Section 5 provides the experiments and their result for identification of elements. finally the conclusion of this paper are presented in the section 6.

## II. RELATED WORK

The Spectral dimension of the hyperspectral image is reduced with averaging based image fusion.Dimensionally reduced image is partitioned into several subsets of adjacent bands.Reflectance components of object based hyperspectral image and becomes the main issue here. The paper (Xudong Kang and Shutao Li) solves the issue by applying the optimized Intrinsic Image Decomposition(IID) for feature extraction.i.e.,ability taking all the reflectance and shadowing components from the image.It takes all the reflectance and shadowing components but need of only target identification as mineral(elements) to be identified with edges. Therefore this implemented to solve all these issues mentioned in the paper.

Spectral Angle Mapping(SAM,CSES;Kruse) used to produce image map of the core showing spatial occurrences of specific minerals.SAM algorithm compares the angle in radians between reference spectrum and each image spectrum with bright and dark pixels.The paper(F.A.Kruse) identifies the four minerals in the core as Kaolinite,illite,monomorillonite and chlorite.Based on these observation and comparison of individual spectral and analyzing used to produce mineralogical maps of drill core. Since it producing only mineralogical maps with all spectral signature of the elements.

The Spatial information of hyperspectral images is collected by applying morphological profile and local binary pattern,All the methods are involved to produce a thematic map accurately. The paper(CH.BalaSubramanyam,G.Naga lakshmi) involves classification using SVM. In Morphological processing has of dilation,erosion,opening and closing then in local binary pattern calculating statistical and cooccurrence features.These approach that fail to deliver high accuracy of hyperspectral images.

The construction and processing of region-based hierarchical hyperspectral image representation relying on the binary partition tree.The paper(Philippe Salembier and Jocelyn Chanussot) proposed as representation for hyperspectral images.However BPT processing,merging,pruning strategies for extraction and classification But dimension is not applied globally.

In this paper,reduce the number of bands,in classification of hyperspectral images. The reference image of the region is called Ground Truth map (GT). The paper(Baofeng Guo and Steve R.Gunn)the problematic is how to find the good bands to classify the pixels of regions; because the bands can be

not only redundant, but a source of confusion, and decreasing in accuracy of classification. Some methods use Mutual Information (MI) and threshold, to select relevant bands. Recently there's an algorithm selection based on mutual information, using bandwidth rejection and a threshold to control and eliminate redundancy. The band top ranking the MI is selected, and if its neighbors have sensibly the same MI with the GT, they will be considered redundant and so discarded. Band selection scheme using Mutual information, and a rejection bandwidth algorithm to eliminate redundancy. Retaining the bands that have mutual information above the threshold and all other bands are discarded.

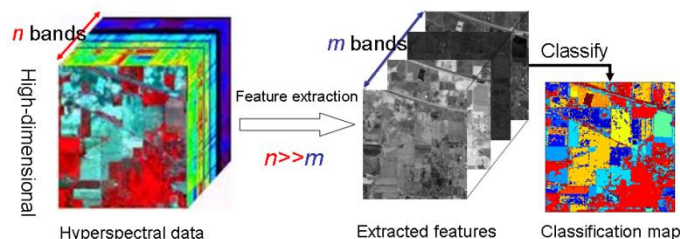
To detect multiple targets/endmembers accurately and efficiently. The paper (Muhammad Ahmad, Sungyoung Lee) Dimension is reduced and identifying the target by estimating correlation and for classification by K-means clustering method. Estimating SAM and classification accuracy is less but in our proposed method it identifies elements with contour and providing accurate classification by high accuracy.

### III. IDENTIFICATION OF ELEMENTS

#### A. Partition and superpixel segmentation

Hyperspectral image has consecutive number of bands in order to visualize the number of bands in the input image. Image partition is regarded as the process of partitioning a hyperspectral image into number of bands. In other words, image partitioning is to visualizing the each layer in the whole image in order to know the spectral signature of various elements present in it. The Image fusion process receives the image as the input from the partitioned image to fuse into a single image. Mean and Standard deviation is calculated to the partitioned image for fusion process. Mean and Standard deviation for whole partitioned bands of an image to visualize their spectral signature of each element present in it. Superpixel segmentation is segment the element for identification based on the color in the element.

FIGURE.2 SCHEMATIC REPRESENTATION OF PROPOSED METHOD



The paper proposed the cubical form of hyperspectral image has high dimension to be reduced by calculating its mean and standard deviation. Then partition those bands into single bands by decomposition for extracting the features along with edges (contours). Finally classify the elements from the image using SVM classification.

#### B. Multilevel fusion-Contourlet Transform

The Contourlet Transform (CT) which was developed and proposed by Do and Vetterli in 2002. It is a two-dimensional transform method for image representation. First, the partitioned image is to be reduced into single band along with another fusion technique involved as decomposition (CT). CT uses a double filter bank structure to get smooth contours of images. In this double filter bank, the Laplacian pyramid (LP) is used to capture the points, lines, edges discontinuities which are present in the image. Then in directional filter bank (DFB) is used to form those points discontinuities into a structure. Combination of both LP and DFB is also called as pyramid directional filter bank (PDFB). By this segmented image has single band then it can be accessed by CT in order to access those points, edges as contours to be detected and identify the elements present in it with color.

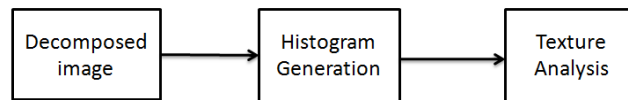
Normally it can be used in natural images or medical image to detect the lines, points but in our proposed system, detecting the contours in hyperspectral image.

#### C. Feature Extraction

Based on the spectral signature of each element with their texture and color. The feature computation process receives the decomposed image as the input and computes the feature for the decomposed

image. Decomposed single band image from multilevel fusion identify the elements from the image. Color (RGB) features to extracted by generating histogram for the image. In object based, vegetation based hyperspectral image identify the target using their color for as representation but in this paper identify those element as same as color in an histogram form for each RGB. Texture can be extracted using GLCM. Grey-Level Co-occurrence Matrix (GLCM), also known as the gray-level-spatial dependence matrix. Group of attributes that return statistical properties of a Grey-Level Co-occurrence Matrix (GLCM).

FIGURE.3 FEATURE EXTRACTION



GLCM texture attributes come from image processing and were developed to capture roughness / smoothness of an image. The attribute response is calculated in two steps: First the GLCM is computed for an area (volume) around the evaluation point. Secondly a statistical property from the GLCM is returned. The GLCM functions characterize the texture of an image by calculating how often pairs of pixel with specific values and in a specified spatial relationship occur in an image, creating a GLCM, and then extracting statistical measures from this matrix. GLCM attributes are of contrast, homogeneity, energy, correlation of it. The contrast use weights related to the distance from the GLCM diagonal along which neighboring values are equal. It can be easily calculated as

$$\text{Contrast} = \sum_{i,j=0}^N P_{i,j} (i - j)^2 \quad (1)$$

Where N denotes the size of the GLCM matrix; i refers to the column and j to the row. P is the GLCM Probability matrix. By calculating the contrast, intensity is measured throughout the image. The homogeneity measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal. If weights decrease away from the diagonal, the result will be larger for input areas (volumes) with little contrast. Homogeneity weights values by the inverse of the Contrast weight, with weights decreasing exponentially away from the diagonal.

$$\text{Homogeneity} = \sum_{i,j=0}^{N-1} \frac{P_{i,j}}{1 + (i - j)^2} \quad (2)$$

The Energy is sum of squared elements in the GLCM. Energy is also known as Angular Second Moment (ASM) or uniformity.

$$\text{ASM} = \sum_{i,j=0}^{N-1} P_{i,j}^2 \quad (3)$$

From 1,2,3 Contrast, homogeneity, energy calculated for texture feature present in the image. Entropy is statistical measurement of the image randomness. Entropy is the opposite of energy; it is a measure of chaos

$$\text{Entropy} = \sum_{i,j=0}^{N-1} P_{i,j} (-\ln P_{i,j}) \quad (4)$$

The Correlation texture measures the linear dependency of input amplitudes on those of neighbouring amplitudes. It can be calculated as

$$\text{GLCM Correlation} = \sum_{i,j=0}^{N-1} \left[ \frac{(i - \mu_i)(j - \mu_j)}{\sqrt{(\sigma_i^2)(\sigma_j^2)}} \right] \quad (5)$$

Mean, variance and standard deviation is calculated for correlation. It measures how correlated a pixel to its neighbour over the whole image. The features as texture with color along with contours to be identified by calculating these attributes and generating the histogram for each color to be classified using SVM in order to identify those element into an separate categories.

TABLE.1 TEXTURE VALUES-FOR EACH BAND

Contrast: 5.6657e+004  
 Correlation: 0.0010  
 Energy: 3.9342e-006  
 Homogeneity: 0.0183

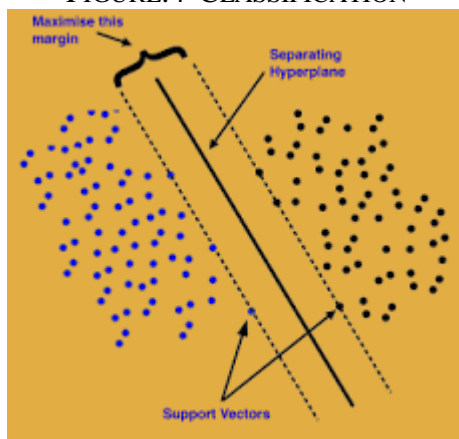
Bands	Entropy	Energy	Variance	Correlation
Band 1	1933	1925	1882	2002
Band 2	2225	1893	2028	1994
Band 3	2456	2455	2446	2446
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·				
·				
Band 124	3124	2924	3391	3417

Calculating these values for texture evaluation of elements present in the image.

*D. SVM Classification*

In support vector machines (SVM) are supervised learning models with associated learning algorithms that analyze data used for classification and regression analysis. In this given a set of training examples, each marked for belonging to one of two categories, an SVM training algorithm builds a model that assigns new examples into one category or the other, making it a non-probabilistic binary linear classifier. An SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible. The classification of element in the image from an single band along with the decomposition provide high accuracy, comparatively from other classification techniques.

FIGURE.4 CLASSIFICATION

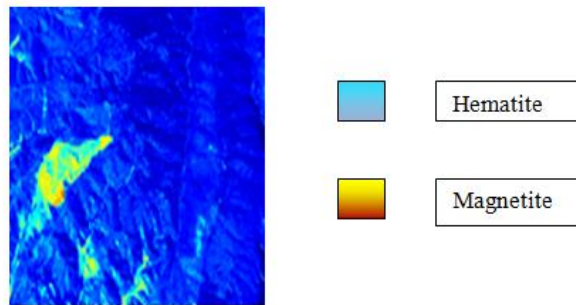


#### IV. EXPERIMENTS

Data Set: Remote sensing hyperspectral datasets i.e., Mineral based hyperspectral imagery, image is captured in location of Langban Värmland, Sweden are utilized in our experiments.

The image are captured by sensor as AVIRIS hyperspectral sensor was developed by Jet Population Laboratory (JPL) at California Institute of Technology and has been employed in a NASA ER-2 aircraft to acquire digital images with 224 spectral bands. Each bands having a spectral bandwidth of approximately  $0.01\mu\text{m}$  in wavelength of  $0.4$  to  $2.45\mu\text{m}$ . The image contain 224 band of  $512 \times 627$  and few noisy channels and to be discarded before decomposition and classification.

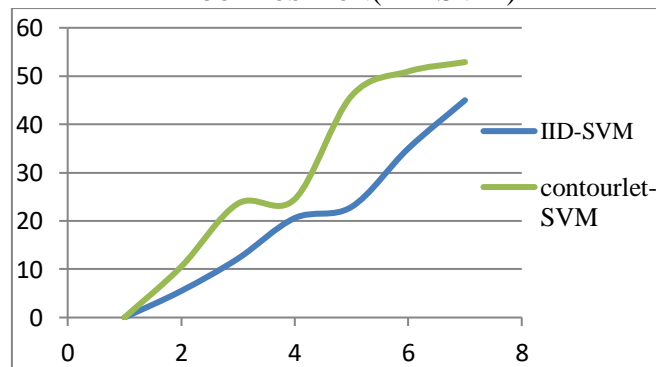
FIGURE.5 EXPERIMENTS RESULT-IDENTIFICATION OF ELEMENTS



#### V. RESULT ANALYSIS

The important techniques used in the proposed system are evaluated in this section. The Support Vector Machine (SVM) is used for classifying the elements present in the image as hematite and magnetite. The figure 2 shows that feature to be extracted for decomposed single band image for color and texture features along with contours. From the experimental result, it shows that identifying and separating the element present in the image and that shown in figure 5. Contourlet transform along with SVM provides high classification of elements than the existing method shown in figure 6. This figure also depicts that the Contourlet-SVM provide better performance.

FIGURE.6 COMPARISON OF CONTOURLET-SVM WITH EXISTING INTRINSIC IMAGE DECOMPOSITION(IID-SVM)



The Contourlet transform shows the accuracy and classification is better than the previous decomposition method.

#### VI. CONCLUSION

The paper proposed for extracting and capturing contours from the mineral based hyperspectral image using a decomposition method as contourlet transform. The proposed method combines LP and DFB of contourlet transform along with the classification method as SVM obtaining high accuracy in classification of elements along with the edges. Experimental results have shown that the proposed method improves the classification accuracies and provides classification maps with more homogeneous regions when compared to other classification. The developed scheme is particularly suitable for classification of images with large spatial and spectral structures of elements. Finally the proposed system is compared with the existing decomposition method on image and shows it is better than the existing method. The accuracy is high and capturing contours.



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