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A Study on The Hyperspectral Image Classification Methods for Mineral Prediction

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Abstract: Hyper spectral image classification methods have been employed to detect the mineral regions using the spectral information. In this research is concentrated on various mineral detection techniques to classify and predict the mineral compositions using the hyper spectral analysis on the hyper spectral satellite images. Major challenges in the hyper spectral image processing lies on following image characteristics, such as unmixing, increase in the computational complexity due to dimensionality and learning of trained labels. Identification of the endmembers and its spectral information is computed with reference to spectral and spatial information as it identifies the exact mineral associated in that particular region. Besides segmentation, the posterior probability distributions from the spatial and spectral information of the images are used to infer the class distribution of the testing hyper spectral data with high correlation. It characterize noise and highly mixed pixels with less training set with high training quality and utility with respect to spectral signatures and its spectral changes with less interaction for classification.

Keywords - Spectral Analysis, Mineral Identification, Hyper spectral Imaging (HSI) unmixing, Hyper spectral Image Classification, Unsupervised learning.

I. INTRODUCTION

Hyperspectral images consist of spatial location which is associated with spectrum, which represents the amount of radiation that is reflected from the surface at that location is proved by Camps-Valls et.al [1]. Segmentation of Hyperspectral images of high dimensional data sets is a difficult endeavour as it is based on the type of sensor data acquiring. Segmentation technique can be implemented for spectral band classification based on the known threshold and unknown threshold values of the spectral information in order to identify the material decomposition in that particular area .There were several techniques for the data classification of the hyper spectral images .Among them supervised Classification techniques arises the class imbalance problem due to dimensionality increases in the hyperspectral image dataset. Major cause to the problem is because the number of training samples used for the learning stage of the classifier is generally very limited compared with the number of available spectral bands.

Since each material is uniquely characterized by its spectrum. The Spectra in the image is used to identify the minerals or materials. N. Keshava [2] presented that Hyperspectral Image analysis is applied to predict the materials and their small segment as it is referred as mixing and unmixing. As mixing model is employed during absence of spectral distortion, S. Liangrocapart, [3] Dobigeon et al[4] represented that the mixing models are classified into linear mixing model and non linear mixing models based on the spectral information. The Material present in the particular region as pixel is associated with the weight of the particular spectra in spectrum. Unmixing model is employed during spectral distortions. Hence processing of hyperspectral data becomes complex in classifying the unmixing models, image distortions which becomes difficult to characterize due to lack of ground truth information and presences of noise.

The spectral graph is generated for unmixing model which is based on the eigenvectors of an affinity matrix; therefore it captures perceptually important non-local properties of an image. A typical spectral graph segmentation algorithm, normalized cuts incorporates both the dissimilarity between groups and similarity within groups by capturing global consistency and making the segmentation process more balanced and stable. For spectral graph partitioning, graph-image representation wherein each pixel is taken as a graph

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node and two pixels are connected by an edge based on certain similarity criteria.

In most cases, nearby pixels are likely to be in the same region, therefore each pixel is connected to its spatial neighbors in the normalized cut algorithm. However, this ignores the difference between distinct groups or the similarity within a group. Detailed survey will explain the importance of the hyperspectral image processing techniques in the mineral prediction. The rest of the papers are organized as follows section 2 explains the background knowledge regarding the related work. Section 3 explains and formulates the proposed System. The conclusion the study is at section 4.

II. METHODS AND ANALYSIS

2.1. Discriminative Low-Rank Gabor Filtering – Mixing model

Spectral-spatial classification of remotely sensed hyperspectral images uses Gabor filtering for feature extraction; its capacity to extract relevant information from both the spectral and the spatial domains of the image has not been fully explored. In this literature, discriminative low-rank Gabor filtering (DLRGF) method for spectral-spatial hyperspectral image classification is been analysed in detail. A main innovation of the approach by Lin He et.al [5] is that implementation is accomplished by decomposing the standard 3-D spectral-spatial Gabor filter into eight subfilters, which correspond to different combinations of low-pass and bandpass single-rank filters. Then, only one of the subfilters (i.e., the one that performs low-pass spatial filtering and bandpass spectral filtering) is actually appropriate to extract suitable features based on the characteristics of hyperspectral images. This allows performing spectral-spatial classification in a highly discriminative and computationally efficient way, by significantly decreasing the computational complexity (from cubic to linear order) compared with the 3-D spectral-spatial Gabor filter.

2.2. Graph-based algorithms - Non Mixing models

Graph Cut Algorithm is employed using normalized cut formulation for hyperspectral image segmentation. The graph Cut algorithm requires the number of segments in the image as an input since information on the number and shape of the material regions. N.Rohani et.al [6] explained that the geometric flows are used to generate segmentation with segments of similar size and shape. A hyperspectral image contains high spatial correlation among pixels, but each pixel is better described by its high dimensional spectral feature vector which provides more information when characterizing the similarities among every pair of pixels.

2.3. Agglomerative Graph based Segmentation –Un mixing model

The segmentation method which identifies segment boundaries based on relative divergence between pixels is represented as unmixing model. P. F. Felzenszwalb et.al [7] explains that Model merges the segments whenever the smallest edge weight between the segments is smaller than the largest edge weight in the minimum spanning tree (MST) of both segments. The merging is based on the threshold which ensures that pixels inside a segment are similar with very high probability. Thus, the threshold provides some guarantees on similarity inside the segments. The choice of such threshold still might merge spectra belonging to different classes, and the number of such errors depends on the prevalence of the spectra in the image. Y. Tarabalka et.al [8] proves that the overall quality of the segmentation depends on the image-specific properties.

III. OUTLINE OF PROPOSED MODEL

The unsupervised segmentation algorithm named as evolutionary component Analysis for remotely sensed hyper spectral image data for material identification in the spectral and spatial information is presented as research methodology. M. F. Duarte[9] explains Sparse multinomial logistic regression (SMLR) algorithm is first used to learn the posterior probability distributions from the spatial and spectral information of the images containing class imbalance information to infer the class distribution of the testing hyper spectral data will be employed and it is followed evolutionary multifactorial spectral analysis to better characterize noise and highly mixed pixels with less training set with high training quality and utility with respect to spectral signatures and its spectral changes with less interaction for classification. Also its derives most extreme spectra in the image endmembers

Some of the mineral classes considered have spectral shapes that differ only in small regions of the spectra. O. Rajadell et.al proves that mixed spectra resulting from combinations of such classes will exhibit even more significant similarities. The aggregation of nonneighboring segments is carried out using the thresholding model. Spatially separated pixels possess similar spectral characteristics (two outcrops with similar mineral composition).

3.1. Dataset Analysis

CRISM dataset contains information about MARS data. Mars data represented in form of hyper spectral images. Further Mar images are used to analyse the material composition in the space.

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IV. CONCLUSION

This survey is carried out in the Hyperspectral image classification method. Classification model have been analysed in order to determine the process to detect the mineral regions using the spectral information. The CRISM dataset have been applied on various mineral detection techniques to classify and predict the mineral compositions. Evolutionary multifactorial spectral analysis is outlined as research model to classify the hyperspectral images against the less training labels. Spectral quality of the endmembers is analysed using both the uniformity-based threshold segmentation maps.

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