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HYPERSPECTRAL IMAGE CLASSIFICATION THROUGH MULTILAYER GRAPH BASED LEARNING

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Abstract— ***Hyperspectral image classification with limited number of labeled pixels is a challenging task. hyperspectral image is sampled from hundreds or thousands of contiguous and narrow spectral bands by hyperspectral sensors.Many applications involving hyperspectral image analysis are in need of a semantic classification task i.e., partition and label the hyperspectral image into different semantic regions, such as trees and beaches, which remains to be a challenging problem. We propose a hyperspectral image classification framework by a multilayer graph based learning using labview.This multilayer graph is composed of a several bilayer layer of simple graph as well as a layer of hypergraph, which effectively exploits the underlying structure of the data. In the first-layer, a simple graph is constructed, where each vertex in the graph denotes one pixel and the similarity among vertices is determined by the feature based pairwise pixel distances.Learning is conducted on this layer to estimate the connectivity relationship among pixels.In the second-layer, a hypergraph structure is constructed, where each vertex denotes one pixel and the hyperedges are generated by using the neighborhood relationship produced from the first-layer.Here we use kernel nearest neighbour technique for distance calculation in second layer .Semi-supervised learning is conducted on the hypergraph structure to estimate the pixel labels to achieve hyperspectral image classification. Our experiments on three datasets validated the effectiveness of the proposed method, which compared favorably with state-of-the-art.***

Keywords— ***Hyperspectral imaging, image classification, graph based learning, hypergraph learning.***

I. INTRODUCTION

1.1 About Spectral Imaging

Spectral imaging is a branch of spectroscopy and photography in which a complete spectrum or some spectral information (such as the Doppler shift or Zeeman splitting of a spectral line) is collected at every location in an image plane. Various distinctions among techniques are applied, based on criteria including spectral range, spectral resolution, number of bands, width and contiguousness of bands, and application. The terms include multispectral imaging, hyperspectral imaging, full spectral imaging, imaging spectroscopy or chemical imaging. These terms are seldom applied to the use of only four or five bands that are all within the visible light range. Spectral images are often represented as an image cube, a type of data cube. . Applications include astronomy, solar physics, planetology, and Earth remote sensing [1][2][3].

1.2 Hyperspectral Imaging

Hyperspectral imaging collects and processes information from across the electromagnetic spectrum. The goal of hyperspectral imaging is to obtain the spectrum for each pixel in the image of a scene, with the purpose of finding objects, identifying materials, or detecting processes. Much as the human eye sees visible light in three bands (red, green, and blue), spectral imaging divides the spectrum into many more bands. This technique of dividing images into bands can be extended beyond the visible. In hyperspectral imaging, the recorded spectra have fine wavelength resolution and cover a wide range of wavelengths. Engineers build hyperspectral sensors and processing systems for applications in astronomy, agriculture, biomedical imaging, mineralogy, physics, and surveillance. Hyperspectral sensors look at objects using a vast portion of the electromagnetic spectrum. Certain objects leave unique 'fingerprints' in the electromagnetic spectrum. Known as spectral signatures, these 'fingerprints' enable identification of the materials that make up a scanned object. For example, a spectral signature for oil helps mineralogists find new oil fields.

1.3 Overview of Hyperspectral Imaging

Hyperspectral sensors collect information as a set of 'images'. Each image represents a narrow wavelength range of the electromagnetic spectrum, also known as a spectral band. These 'images' are combined to form a three-dimensional (x,y,λ) hyperspectral data cube for processing and analysis, where x and y represent two spatial dimensions of the scene, and λ represents the spectral dimension (comprising a range of wavelengths). Technically speaking, there are four ways for sensors to sample the hyperspectral cube: Spatial scanning, spectral scanning, snapshot imaging,[3][5] and spatio-spectral scanning. Hyperspectral cubes are generated from airborne sensors like the NASA's Airborne Visible/Infrared Imaging Spectrometer (AVIRIS), or from satellites like NASA's EO-1 with its hyperspectral instrument Hyperion. However, for many development and validation studies, handheld sensors are used. The precision of these sensors is typically measured in spectral resolution, which is the width of each band of the spectrum that is captured. If the scanner detects a large number of fairly narrow frequency bands, it is possible to identify objects even if they are only captured in a handful of pixels. However, spatial resolution is a factor in addition to spectral resolution. If the pixels are too large, then multiple objects are captured in the same pixel and become difficult to identify. If the pixels are too small, then the energy captured by each sensor cell is low, and the decreased signal-to-noise ratio reduces the reliability of measured features.The acquisition and processing of hyperspectral images is also referred to as imaging spectroscopy or, with reference to the hyperspectral cube, as 3D spectroscopy[4][5][6].

1.4 Application

Hyperspectral remote sensing is used in a wide array of applications. Although originally developed for mining and geology (the ability of hyperspectral imaging to identify various minerals makes it ideal for the mining and oil industries, where it can be used to look for ore and oil), it has now spread into fields as widespread as ecology and surveillance, as well as historical manuscript research, such as the imaging of the Archimedes Palimpsest. This technology is continually becoming more available to the public. Organizations such as NASA and the USGS have catalogues of various minerals and their spectral signatures, and have posted them online to make them readily available for researchers.

1.5 Image Classification

The intent of the classification process is to categorize all pixels in a digital image into one of several land cover classes, or "themes". This categorized data may then be used to produce thematic maps of the land cover present in an image. Normally, multispectral data are used to perform the classification and, indeed, the spectral pattern present within the data for each pixel is used as the numerical basis for categorization (Lillesand and Kiefer, 1994). The objective of image classification is to identify and portray, as a unique gray level (or color), the features occurring in an image in terms of the object or type of land cover these features actually represent on the ground.

II. RELATED WORK

2.1 Hyperspectral Image Classifications

Hyperspectral image classification with limited number of labeled pixels has attracted a lot of attention.One important issue is how to explore the relationship among pixels in both the spectral data and the spatial information. Targeting this, some spatial-related methods are introduced. Bernardetal. proposed a stochastic minimum span- ning forest for spectral-spatial classification of hyperspectral images. Eches et al. proposed to employ adaptive Markov Random Fields (MRF) to jointly unmix and segment hyper- spectral images. In Conditional Random Fields (CRF) was employed for hyperspectral image classification. A further extension with potentials was proposed in to capture the relations among pixels[7][8][9].

It is noted that the relevance in the whole hyperspectral image is important. Considering the recent progress on semi-supervised learning which has shown its superiority to address the issue of small training samples, it has been introduced in hyper spectral image classification. For example, Camps-Valls et al.modeled the hyperspectral image in a graph, and then conducted graph-based semi-supervised learning to estimate the relevance among pixels. Gu et al. Introduced a representative multiple-kernel learning approach which automatically com- bined multiple kernels in the learning procedure to train more discriminative classifier. In manifold learning was com- bined with a weighted KNN classifier to robustly classify the hyperspectral images. Sparse representation and SVM- based discriminative learning have also been inves- tigated in hyperspectral image classification to deal with the limited number of labeled pixels. Specifically, to explore the relations among pixels in a global stable state, a transductive graph Laplacian was further employed in combination with SVM. A semi-supervised neural network was used in for efficient hyperspectral image classification. And finally, Bali and Djafari formulated the classification task as a blind sources separation problem, and a hierarchical Markov model was employed to classify pixels[10][11][12].

It is noted that most of existing semi-supervised methods are limited on the exploration of the high-order information behind the hyperspectral data, which includes both the spectral data and the spatial information. Under

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these circumstances, a formulation which can jointly investigate the spectral and the spatial information is highly required.

2.2 Hypergraph Model

In hypergraph, more than two vertices can be connected by one hyperedge, which enables the hypergraph to capture the high-order relationships among different objects This property has led to a wide variety of applications, such as image retrieval and image classification. In image retrieval was conducted by a transductive learning procedure in a hypergraph. In this method, each image was denoted by a vertex and the heterogeneous image similarities in the feature space were employed to generate the hyperedges. Bu et al.applied the hyper graph learning method in music recommendation, in which multiple types of objects and relations in social networks associated with music were modeled by the hypergraph to measure the relationships among music tracks. A multiple hypergraph learning method has been proposed for 3D object retrieval in which each vertex in the hypergraph denoted one 3D object, and the hyperedges were generated by view clustering to formulate the relationships among the 3D objects in different granularities. Xia et al. proposed a class specific hypergraph to integrate local features and global geometric constraints for object recognition. As shown in these applications, the hypergraph structure can simultaneously explore the multiple relationships among the data, which makes it possible to be applied in the hyperspectral image classification task.

III. DESCRIPTION OF MULTILAYER GRAPH BASED LEARNING

Multilayer graph based learning framework for hyperspectral image classifica- tion. Figure 1 shows the schematic illustration of the proposed method. Due to the high dimensionality of hyperspectral images, we need to find effective relevance estimation method. In our proposed framework, we first conduct an unsupervised learning to estimate the relevance between each two pixels based on the original spectral data. This procedure can also be regarded as a feature transformation process, in which a sub- space of the full feature space between each two pixels is used to estimate the relevance among the pixels. In the subsequent semi-supervised learning procedure, all pixels are modeled in a hypergraph, upon which the learning is conducted to estimate the pixel labels.

3.1 Band Clustering

A hyperspectral image is spatially sampled from hundreds of contiguous and narrow spectral bands, and correspond- ingly each pixel location is associated with hundreds of measurements, leading to a high-dimensional representation. Inevitably, the pixel values among different bands are highly redundant, which is due to the similar sensor responses in two adjacent bands. The objective of band clustering in our method is to find the highly correlated bands aiming to make the feature more discriminative. There are many works on band selection for hyperspectral images, which have the similar behind these data. Here we first group different bands into band clusters using K-means clustering in which disjoint information is employed as the band distance measure. Then the raw feature can be divided into T parts, given T as the number of band clustering. For the ith cluster, all the bands are regarded as the ith feature for each pixel, and the relevance among pixels is analyzed in each band cluster to carry out a graph-based learning in the next procedure, i.e., first-layer graph based learning. In this procedure, we measure the spectral band distance by the disjoint information which measures the statistical dependency and information redundancy of random variables. The disjoint information of two random variables X and Y is defined as the difference between their joint entropy and mutual information.

The first dataset is the Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) image set which was taken over NW Indiana's Indian Pine test site in June 1992 mounted from an aircraft flown at 65,000 ft altitude. The image size of the Indian Pine dataset is 145 × 145 pixels and this dataset has 220 spectral bands ranging from 0.4 to 2.5 μm with a spatial resolution of 20 m. A few water absorption bands are removed and hence only 200 out of the 220 bands are used in our experiment (the removed bands are [104−108], [150−163] and 220). There are 16 classes in total which range in size from 20 to 2455 pixels.

The second dataset is the Salinas Valley dataset, which was collected by the AVIRIS sensor over Salinas Valley, California in 1998. The image size is 512 × 217 pixels and this image is characterized with high spatial resolution with 3.7 meter pixels. The number of spectral bands is 224. Again, the water absorption bands of [108−112], [154−167] and 224 are removed, and hence only 204 out of the 224 bands are used in our experiment. PaviaU is with the size of 610 × 340 pixels and is characterized with the high spatial resolution, i.e., 1.3 meter pixels. There are 9 classes in PaviaU and

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the original number of spectral bands is 115. 12 most noisy bands are moved and finally 103 out of the 115 bands are used in our experiment.

3.2 Distance Calculation

To evaluate the classification accuracy of the proposed multilayer graph based learning (denoted by BLGL) framework, the following state-of-the-art methods are compared.

3.2.1 Semi-Supervised Graph Based Method

In semi- supervised graph based method, the hyperspectral image classification is formulated as a graph based semi- supervised learning problem. It is able to exploit the wealth of unlabeled samples through the graph structure. For comparison, the “Cross+Stacked” kernel is chosen which shows the best result. This method is denoted by “SSG+CS”. In this method, the parameter α plays an important role in the semi-supervised learning procedure. We tune this parameter to the optimal value by a grid search in [0, 1] with a granularity of 0.05.

3.2.2 Conditional Random Fields (CRF)

In CRF, the hyperspectral image is modeled by a conditional random field, which is trained on local samples. The supervised inference on the CRF is conducted to infer pixel labels. There are two parameters λ_1 and λ_2 representing the fixed powers for the unary pairwise clique potentials. According to , λ_2 is fixed to be 1, and λ_1 is adjusted by using cross-validation.

Local Manifold Learning Based k-Nearest Neighbor (LML+KNN) LML+KNN combines the local manifold learning and the k-nearest neighbor classifier for hyperspectral image classification. In this method, local manifold learning is conducted to estimate the relationship among different pixels, and weighted KNN classifier is employed for classification. The Supervised Locally Linear Embedding (SLLE) method is employed as the weighting methods during the manifold construc- tion due to its steady performance. In this method, the parameter k for k-Nearest Neighbor is selected to be 20 through cross validation.For the proposed method, the band cluster size T is set to be 3, the number of selected neighbors for hypergraph construction K is set to be 20, and the two parameters ξ and λ in the graph based learning procedure are set to be
0.1 and 0.01 respectively.

3.3 Distance Transform

The distance transform is an operator normally only applied to binary images. The result of the transform is a graylevel image that looks similar to the input image, except that the graylevel intensities of points inside foreground regions are changed to show the distance to the closest boundary from each point.One way to think about the distance transform is to first imagine that foreground regions in the input binary image are made of some uniform slow burning inflammable material. Then consider simultaneously starting a fire at all points on the boundary of a foreground region and letting the fire burn its way into the interior. If we then label each point in the interior with the amount of time that the fire took to first reach that point, then we have effectively computed the distance transform of that region.

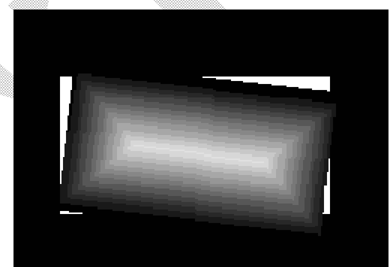

Fig 1: Distance transforms

Fig 1 shows a distance transform for a simple rectangular shape.There is a dual to the distance transform described above which produces the distance transform for the background region rather than the foreground region. It can be considered as a process of inverting the original image and then applying the standard transform as above.
There are several different sorts of distance transform, depending upon which distance metric is being used to determine the distance between pixels. The example shown in Figure 1 uses the `chessboard' distance metric but both the Euclidean and `city block' metrics can be used as well.Even once the metric has been chosen, there are many ways of computing the distance transform of a binary image.

3.4 Watershed Transform

The term watershed refers to a ridge that divides areas drained by different river systems. A catchment basin is the geographical area draining into a river or reservoir.The connection is through computer analysis of objects in digital images. The objects could be anything: blood cells, stars, toner spots on a printed page, DNA microarray elements, or even quantum semiconductor dots, as in this image Computer analysis of image objects starts with finding them-deciding which pixels belong to each object. This is called image segmentation, the process of

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separating objects from the background, as well as from each other. R. Gonzalez and R. Woods write in their widely used textbook (Digital Image Processing) that "segmentation of nontrivial images is one of the most difficult tasks in image processing.
Segmentation accuracy determines the success or failure of computerized analysis procedures."The latest release (Version 3) of the Image Processing Toolbox includes new functions for computing and applying the watershed transform, a powerful tool for solving image segmentation problems.Understanding the watershed transform requires that you think of an image as a surface. For example, consider the image below

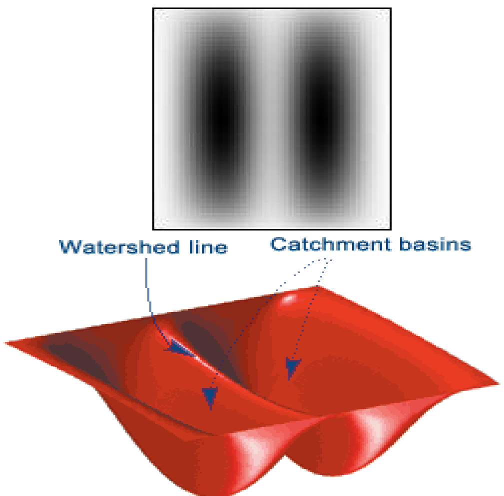

Fig 2: Watershed transform

The Image Processing Toolbox function watershed can find the catchment basins and watershed lines for any grayscale image. The key behind using the watershed transform for segmentation is Change your image into another image whose catchment basins are the objects required.

IV. RESULT AND DISCUSSION

Fig 3: Input image

The input is a hyperspectral image, which is downloaded from internet. To load the source image initially a file path should be mentioned then a temporary memory location for an image is been created. The file format can be a standard format (BMP, TIFF, JPEG, JPEG2000, PNG, and AIPD) or a nonstandard format known to the user. The read pixels are converted automatically into the image type passed by Image.

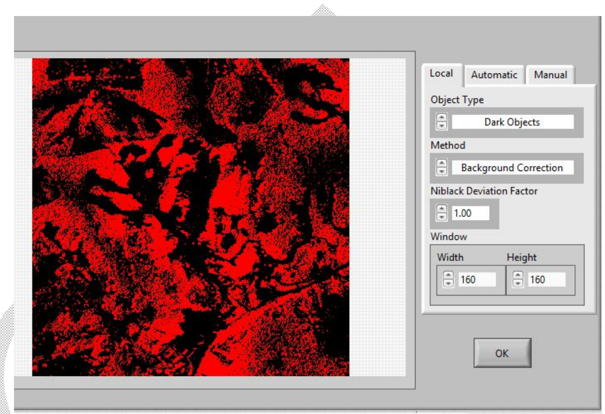

Fig 4: Threshold image.

The above image is obtained by choosing a threshold value .Each and every pixel in the input image is compared with the pre-defined threshold value .Based on the comparison the pixels are grouped as dark and bright pixels .The pixels having intensity value less than threshold value are shown as a bright pixels in the threshold image. while the pixels having intensity value greater than or equal to threshold value then those pixels differentiated as a dark pixels in the threshold image .This forms a simple layer .This image is also called binary image.

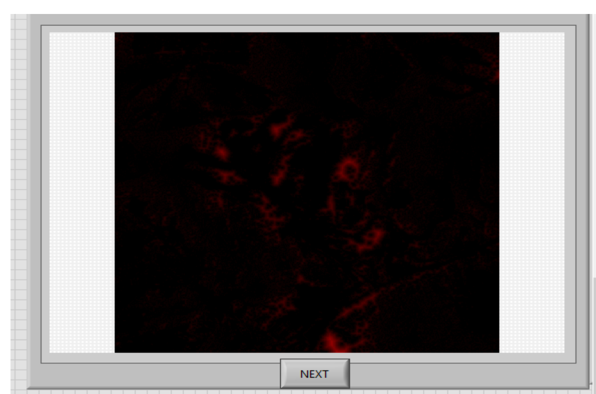

Fig 5: Distance transformed image.

Distance transform is applied to the threshold image .Distance transform is used to calculate the distance between the two unsimilar pixel .The transform is applied

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using the kernel nearest neighbor (Knn) algorithm .It is used to distinguish whether the point is inside or outside of the shape .It labels each pixel of the image with the distance to the nearest obstacle pixels i.e boundary pixel in a binary image.It gives the distance transform of image, in which the value of each pixel is replaced by its distance to the nearest background pixel so that the edges of the objects are identified .This forms the hypergraph layer.

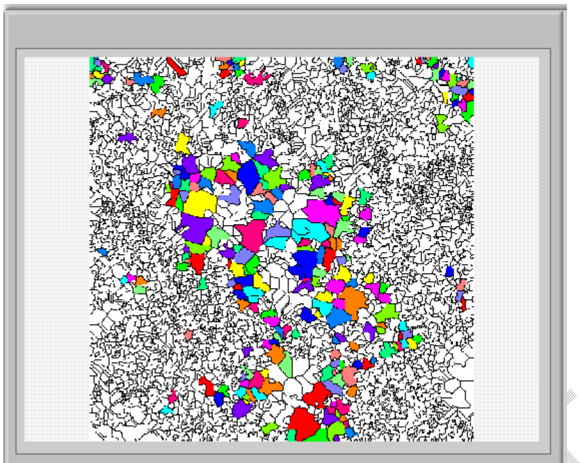

Fig 6: Image separation

The distance transform image is the input for the watershed transform. Watershed algorithm is used in image processing primarily for segmentation purposes. watersheds and catchment basins are found .The objects in the image is separated from one another and the background. It display the separated objects using different colors .Over-segmentation in watershed transform can be avoided in the next step. Region approach is used for the separation.

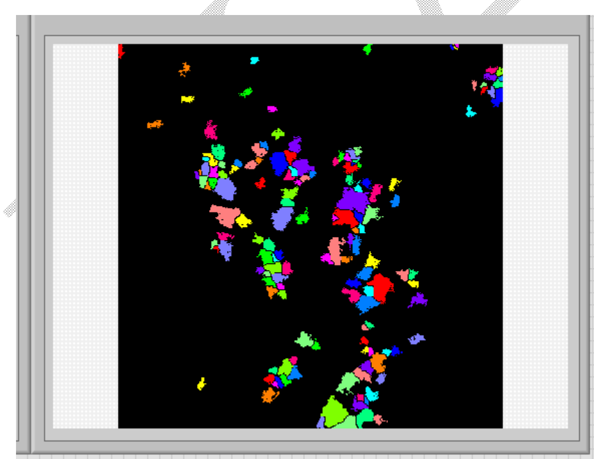

Fig 7: Segmented output

After applying watershed transform , a threshold value is applied to the image to produce a binary image .The binary images of the input hyperspectral image and the watershed transformed image are compared using AND operator .The pixels in the resultant image are labeled by applying a unique grayscale value to all pixels composing the same group of pixels (a particle). Finding which pixels belong to each object is called image segmentation, the process of separating objects from the background, as well as from each other. Regions are differentiated by different colors. These regions has some useful information which can extracted by further processing.

V. CONCLUSION

The hypergraph of kernel nearest neighbour to capture the high-order relationships among different objects. The hypergraph structure can simultaneously explore the multiple relationships among the data, which makes it possible to be applied in the hyperspectral image classification task. May fail to explore this relationship among different pixels in bilayer graph can be rectified using multilayer graph based classification.It creates challenges of both the complex relationship and the limited labeled samples in hyperspectral images.Distance calculation of hypergraph in multilayer using labview is one of the easiest ways in classification of hyperspectral images

VI. FUTURE WORK

The larger size of the testing dataset leads to higher computational cost. Therefore, how to deal with such high computational cost is one important issue.There are two possible solutions for this challenge. On onehand, the large dataset can be first split into small regions, and then hyperspectral image classification is conducted on each of these regions. In this direction, how to conduct the image splitting to minimize the degradation of classification performance is the key issue. On the other hand, a hierarchical graph learning scheme would be effective on reducing the computational cost.

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