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Hyperspectral Image Classification through Watershed Segmentation

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***Abstract*— In current times hyperspectral imaging is a prominent research topic in remote sensing. Hyperspectral image provides in detail information about earth surface object. For each and every earth surface object has distinctive reflectance signature with analysis of these signature it is highly possible to distinguish spectrally similar objects. But hyperspectral images are with hundreds of spectral bands which leads to lacking the availability labeled samples. To identify earth surface objects accurately both issues such as large number of spectral channels and limited availability of training samples should be addressed properly in classification task. In this paper, these two issues handled by building simple graph in first layer and building hypergraph in second layer on which semisupervised learning is conducted to get classification results. But with large size dataset computational burden increases, to address this issue first we divide the large dataset into segment with watershed segmentation algorithm. Then in each region simple graph is built and then in second layer one hypergraph is built from all simple graph on which bilayer graph based learning is employed to get a final classification result.**

Keywords—high number of spectral channels, hypergraph, watershed segmentation, semisupervised learning.

I. INTRODUCTION

Recent advances in hyperspectral remote sensor technology allows the simultaneous acquisition of hundreds of narrow contiguous spectral bands. Every earth object such as water, tree ,soil etc are defined with precise spectrum. Hyperspectral imagining provides rich multispectral, high spatial resolution and temporal resolution data. Extracting this rich information and knowlede is the main principle of remote sensing which can be used to identifying objects of interest from remotely sensed images[1]. Hyperspectral imaging have been used in numerous areas such geology, hydrology, urban planning, geography, cadastral mapping, cartography, and the military. Applications included above mentioned areas includes the remote sensing the earth resources from space, mapping the earth, helping manage water or agricultural resources, monitoring the environment, forestry, detecting and classifying hidden targets in operational theaters etc[2].

Though higher dimensionality of hyperspectral images improves capability to detect objects in the process of classification of those images, there are some issue which need to be addressed during classification process of those images. The most general issues associated with classification are the large number of the spectral signature and its spatial variability, the high cost of sample labeling, the quality of data. The high dimensionality of the data in the hyperspectral image leads to theoretical and practical problems [3].

In the remote sensing, many supervised and unsupervised classifiers have been proposed to tackle the hyperspectral data classification problem. The problem associated with supervised methods is that the pixel label learning procedure mainly depends on the quality and quantity of the training dataset. In case of hyperspectral images training data is rarely available or in a very small number which leads to high cost of labeling unlabeled samples. On the other hand, unsupervised learning methods are insensitive to the number of labeled samples, but in this case no guarantee about the relationship between clusters and classes. So in such situation semi-supervised learning are more attractive and improves the performance of system [4].

The main motive of this paper is that developing a new semisupervised classification technique which will able to solve issues related to hyperspectral image classification and also improves the classification performance with reduced complexity burden. In this paper, complex relationship among pixels is represented with hypergraph. Hypergraph construction conducted in two layers to handle the issues high dimensionality and lack of training samples. To reduce computational cost hyperspectral image segmented into regions with watershed algorithm and then the classification procedure based on bilayer graph based learning is conducted. In the first layer of bilayer graph based learning, simple graph to denote pixelwise relationship is generated in each region and then in second layer hypergraph is built with relevance obtained in first layer. On constructed hypergraph semisupervised learning is conducted to know the labels of unlabeled samples. In this way we get labels for all unlabeled samples. The rest of paper organized as: section II gives existing methodologies in the context of hyperspectral image classification. Section III focuses on proposed technique to get classification map of hyperspectral image. Section IV concludes the overall discussion regarding hyperspectral image classification.

II. RELATED WORK

A. Abbreviations and Acronyms

PCA- Principle Component Analysis
ICA- Independent Component Analysis

ICDA-Independent Component Discriminant Analysis
CRF-Conditional Random Field
NWFE-Nonparametric Weighted Feature Extraction
KNWFE- Kernel Nonparametric Weighted Feature Extraction
DBFE- Decision-Boundary Feature Extraction
IG- Information Gain
SVM-Support Vector Machine

Related work mainly focuses on existing methodologies in the context of hyperspectral image classification which handles one or more issues related to classification and conducts one of the label learning technique like supervised, unsupervised or semisupervised learning.

Hyperspectral sensors concurrently record hundreds of spectral bands from the electromagnetic spectrum. Due to which computation burden, storage space requirement and transmission bandwidth increases, so it is advantageous to remove those spectral bands which are redundant and which provides less discriminatory information. The removal of bands done with either the help of feature extraction or feature selection methods. Feature selection methods [5][6] retains the relevant original information. Feature extraction methods are categorized further as: Unsupervised feature extraction technique such as PCA [7], ICA [8], and ICDA [9]. Supervised technique includes KNWFE [10] which is an extension of NWFE and DBFE [11].

In [12], L. Zhang et al. proposed such a dimensionality reduction technique which looks for low dimensional representation of features after combining spectral, texture and shape features. In [13] dimensions are reduced by integrating of result of PCA and information gain.

Dimensionality reduction technique handles high dimensionality issue by reducing the dimension but unable to deal with reduced size training set as well as some of dimensionality reduction techniques needs normal distribution of samples. In PCA lower order PC components are ignored and that ignored component may contain valuable information.

To deal with reduced set of training samples semisupervised learning methods attracts the attention. Traditional semisupervised learning methods are generative in nature which estimate conditional density which have been applied in hyperspectral image classification. Recently discriminative approach such as TSVM[14], graph based methods[4], LapSVM[15].

In [16] F. Ratle et. al.presented a framework for semisupervised learning which is based on a neural network. Nadia Bali and Ali Mohammad-Djafari [17] proposed Bayesian estimation approach to provide joint solution to spectral classification, segmentation and data reduction. Manifold learning [18] and conditional random field [19] have been also used for hyperspectral image classification but these methods employ pairwise relationship in both spatial and feature space. But in case of hyperspectral image relationship is present among more than two pixels. To represent complex relationship hypergraph shows superiority than simple graph . Hypergraph has varieties of application in the field of image classification[20]-[22] and image retrieval [23]-[25].

R. Ji, Y. Gao et al. [21] observed that the relationship among pixels in both the feature space and the spatial space provides valuable information to classification process of hyperspectral image. In this framework hypergraph is constructed by constructing one hyperedge in spatial space by connecting spatial neighbors while another hyperedge by connecting k nearest neighbors in feature space. Semisupervised learning is used on hypergraph to classify hyperspectral image.

Yue Gao et. Al.[26] proposed bilayer graph based learning to classify hyperspectral images. But with this framework computational cost increases. One of leading solution to this issue is proposed in this paper.

III. HYPERSPECTRAL IMAGE CLASSIFICATION THROUGH WATERSHED SEGMENTATION ALGORITHM

In this section we have presented new framework for classifying hyperspectral images which is based on bilayer graph based method [26]. Fig. 1 shows the procedure our proposed framework. In this proposed framework at first hyperspectral image is divided into region using watershed segmentation algorithm which helps to reduce computation burden. After computing regions from hyperspectral image, bilayer graph based learning is applied on segmented image to get classification result .

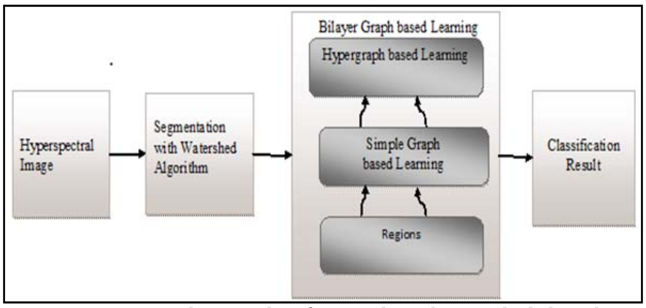

Fig. 1 Hyperspectral image classification through watershed algorithm

A. Segmetation with watershed algorithm

Applying bilayer graph based learning directly to large dataset we observed that computational cost increases. Therefore, in this paper our main aim is nothing but reducing computational cost along with obtaining high accuracy of classification result. To reduce computation cost we divide large dataset into region using watershed segmentation algorithm. The idea behind watershed algorithm comes from geology: it is that hyperspectral image considered as landscape which is flooded with water from minima and dam i.e watershed lines are build to avoid merging water from different catchment basins [27]. The resulted image is segmented image which provides regions for further processing.

B. Simple Graph based Learning

Simple graph is constructed in each region to estimate relevance among pixels. Let simple graph in i^{th} region be G (V_i, E_i, W_i) is built in which each pixel represented with vertex v_i^p and $E_i(v_i^p, v_i^q)$ be the edge between vertex

v_i^p and v_i^q in i[th] region. Edge E_i represents similarity with $W_i(v_i^p, v_i^q)$ given by,

$$W_i(v_i^p, v_i^q) = \exp\left(-\frac{d^2(v_i^p, v_i^q)}{\sigma^2}\right),$$

Where

$d(v_i^p, v_i^q)$ -Euclidean distance between v_i^p and v_i^q

$W_i(v_i^p, v_i^q)$ - Affinity matrix between v_i^p and v_i^q

Relevance matrix is built from obtained pairwise relevance from simple graph. Building simple graph and learning on that is done without use of any labeled data.

C. Hypergraph based Learning

One hyperedge is constructed in each region. Let there are T regions obtained from watershed algorithm. Hypergraph construction is based on procedure presented in [23] where each pixel in hyperspectral image considered as centroid and connecting their k-nearest neighbours from each region to generate one hyperedge. In this way hyperedges are generated in all regions. Therefore total number of hyperedges becomes n*T in which n corresponds to total number of pixels in hyperspectral image. All hyperedges are aggregated to construct hypergraph $G_h = (V_h, E_h, W_h)$ with n vertices corresponding total number of pixels in hyperspectral image.

Semisupervised learning is employed on hypergraph to obtain classified image.

IV. EXPERIMENTAL RESULTS

To evaluate performance of our system, system is tested on a satellite image of the Washington DC Mall area. Image is captured using Hyperspectral Digital Imagery Collection Experiment (HYDICE) sensor on August 23, 1995. Original image and detailed information of selected classes is given in following figure.

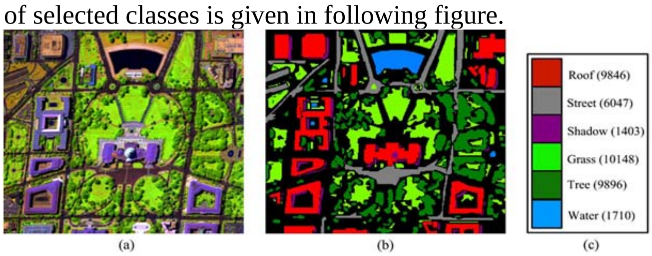

Fig. 2 (a)Original Image (b)Ground Truth (c)Map color of Ground Truth

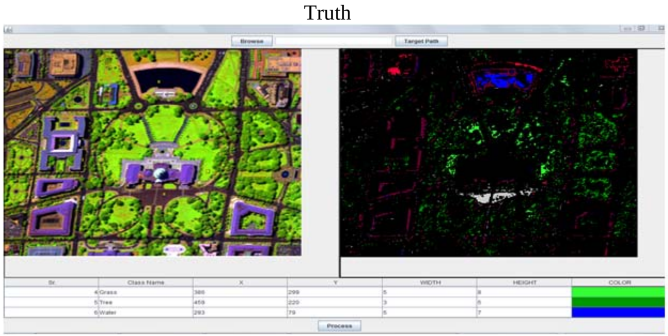

Fig. 3. Generated result

Performance system evaluated against execution time of hyperspectral image classification through bilayer graph based learning (existing system) and hyperspectral image classification through watershed algorithm.

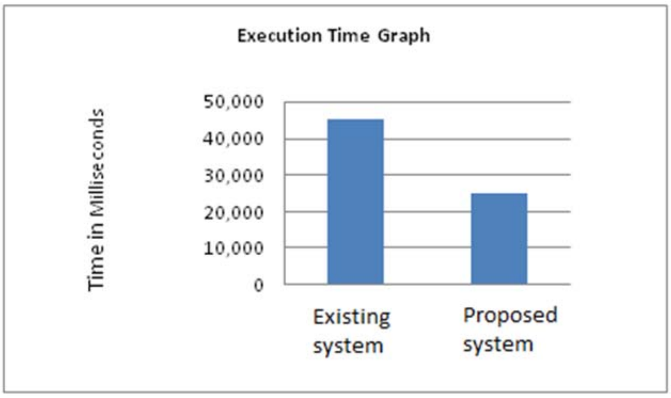

Fig. 4. Excution time graph

V. CONCLUSION

In this paper, we proposed a new framework to classify hypersectral image. In order to reduce the computational burden we segment the image with region based segmentation in this new proposed framework. In each region, we construct a simple graph to model pairwise relationship which are fed to second layer where hypergraph constructed and semisupervised learning conducted to get a classification map. Building hypergraph in a hierarchical way and semisupervised learning provides solutions to issues high dimensionality and working with limited training samples.

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