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Segmentation based Projected Clustering of Hyperspectral Images using Mutual Nearest Neighbour

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***Abstract*: In the field of remote sensing, (HP) hyper spectral images are one of the most important sources of information. Hyper spectral imagery contains hundreds of narrow spectral bands which are continuous and regularly spaced in the visible and infrared region of the Electromagnetic spectrum(EMS). Although hyper spectral imagery with its high spectral resolution provides an opportunity for more precise information extraction, the large number of bands available with the hyper spectral image leads to certain issues, typically attributed to the curse of dimensionality. Moreover, continual improvement in the sensor technology has led to an increase in spatial resolution of the hyper spectral imagery, which has a direct impact on the capability of the information extraction techniques.**

***Keywords*: HP (Hyper Spectral), EMS (Electromagnetic Spectrum)**

1. Introduction

For hyperspectral images an effective projected clustering method is proposed. This method assimilates segmentation, clustering, and local band selection within its framework.

Using k–means algorithm a segmented map of the hyperspectral image is obtained. In this subsequent stage, the obtained segments are considered as clusters and are merged by utilizing the mutual nearest neighbour information. It identifies the k significant clusters using a criterion based on entropy. The final cluster map is obtained by assigning all the remaining clusters to these k significant clusters. The clustering stages make use of multiple subspaces. They obtained by deploying a local band selection approach.

To test the performance of the proposed method, experiments are conducted over five hyperspectral images and is further compared with other clustering frameworks. The efficacy of the proposed method is confirmed by the experiments conducted over these images.

Hyperspectral imaging expands and improves capability of multispectral imaging taking advantage of hundreds of contiguous spectral bands to uncover materials that usually cannot be resolved by multispectral sensors. This area has been showing to be a fast growing one in remote sensing.

Collects and processes information of Hyperspectral Images from across the electromagnetic spectrum. To get the spectrum for each pixel in the image of a scene, with the purpose of finding objects, identifying materials, or detecting processes is the goal of hyperspectral imaging. There are two general branches of spectral imagers. To read images over time push broom and the related whisk broom scanners are used, and snapshot hyperspectral imaging, which uses a staring array to generate an image in an instant. The human eye sees visible light color in mostly three bands. They are,

- long wavelengths
- perceived as red, medium wavelengths
- perceived as green, and short wavelengths perceived as blue

A Spectral imaging divides the spectrum into many more bands. The technique of dividing images into bands can be extended beyond the visible. In Hyperspectral Imaging (HI) the recorded spectra have fine wavelength resolution and cover a wide range of wavelengths. It measures continuous spectral bands, as opposed to multispectral imaging which measures spaced spectral bands.

For applications in astronomy agriculture, molecular biology, biomedical imaging, geosciences, physics, and surveillance the engineers build hyperspectral sensors and processing systems, using a vast portion of the electromagnetic spectrum the Hyperspectral sensors look at objects. Some objects leave unique 'fingerprints' in the electromagnetic spectrum are called spectral signatures, these 'fingerprints' enable identification of the materials which make up a scanned object.

2. Block diagram

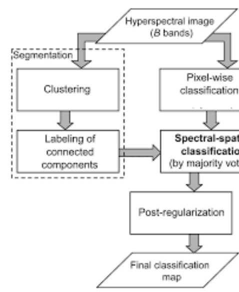

Fig. 1. Block diagram of segmentation-based projected clustering of hyperspectral images

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A. Related work

- Xia et al. presented a rapid clustering method for SAR images by embedding an MRF model in the clustering space and by using graph cuts to search for data clusters optimal in the sense of the maximum a posteriori (MAP)criterion.
- Palubinskas et al. introduced the concept of a global classification of remote sensing images in large archives,
- Palubinskas et al. introduced the concept of a global classification of remote sensing images in large archives, e.g., covering the whole globe. The classification is realized through a two-step procedure: 1) unsupervised clustering and2) supervised hierarchical classification. Features, derived from different and non-commensurable models, are combined using an extended k-means clustering algorithm and supervised hierarchical Bayesian networks incorporating any available prior information.
- Liu & Setiono proposed a feature subset-based feature selection method namely consistencybased feature subset selection (COFS). This method uses the class consistency as an evaluation metric in order to select the significant feature subset from the given dataset. These methods are the filter-based methods since they do not use the supervised learning algorithm to validate the subsets and they use the statistical measure for evaluating the feature subsets.

B. Proposed system

- The proposed clustering framework is termed as PCMNN (Projected Clustering using MNN).
- PCMNN integrates segmentation, clustering and local band selection within its framework.
- Segmentation is achieved by applying KM algorithm over the image. For performing clustering, a novel two step projected clustering technique is proposed.
- In the first step, the technique makes use of MNN information to perform clustering. In the second step, the obtained cluster map is refined by fixing the number of clusters equal to k.

Advantages of proposed system

- The primary advantage to hyperspectral imaging is that, because an entire spectrum is acquired at each point, the operator needs no prior knowledge of the sample, and postprocessing allows all available information from the dataset to be mined.
- Hyperspectral imaging can also take advantage of the spatial relationships among the different spectra in a neighbourhood, allowing more elaborate spectral-spatial models for a more accurate segmentation and classification of the image.

C. Modules

1. Segmentation
2. Mutual Nearest Neighbour
3. Assign
4. Local Band Selection

D. Experimental results

1) Segmentation

One of the ways to include spatial information is to perform image segmentation. In PCMNN framework, KM algorithm is used to perform image segmentation.

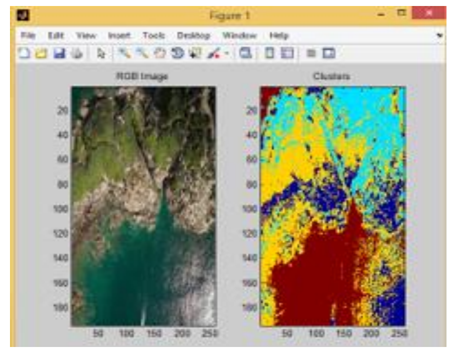

Fig. 2. Segmentation using k-mean

2) Mutual Nearest Neighbour

This stage takes two input parameters, which are segmentation map obtained from the previous stage and the number of bands in the subspace (l). The segmentation map is converted to a cluster map, by considering each segment as a cluster. These clusters are now merged in the feature space on the basis of MNN information. MNN is a stronger and more restrictive variant of nearest neighbour (NN) concept. The use of MNN results in a more tighter neighbourhood than the usual NN. The motivation behind using MNN are simplicity, independent of the processing order and no assumption about the shape of the clusters. The MNN in the context of clustering can be defined as follows. Let there be two clusters C1 and C2. If C1 ’s

NN is C2 and C2 ’s NN is C1 , then it can be said that C1 and C2 are MNN cluster pair. For any given iteration, PCMNN first identifies all MNN cluster pairs and then merges them. Subsequently, the cluster map is also updated.

To identify all the MNN cluster pairs, initially, NN of each cluster is obtained. The NN of a cluster is determined by calculating the Euclidean distance between the cluster’s centroids, measured in the subspace of a cluster. The subspace for each cluster.

3) Assign

In this stage, the cluster map obtained from the previous stage is further refined by executing a two step procedure. In the first step, k significant clusters are identified and then in the second step, all the remaining non-significant clusters are assigned to these k clusters.

To measure the significance of a cluster, a criterion based on entropy is used. Using the criterion a value for each cluster is computed. On the basis of the values obtained from this criterion, the k clusters having the least values are pronounced as significant. The criterion is a combination of entropy and cluster size. Entropy is a statistical measure of randomness, which can be used to describe the information content of a cluster. In a case of well-formed clusters entropy is low.

4) Local Band Selection

The local band selection approach proposed is used in this study. It is basically a band prioritization approach.

The approach accounts for both relevancy (Z) and redundancy (δ) among the bands while obtaining the subspace for each cluster.

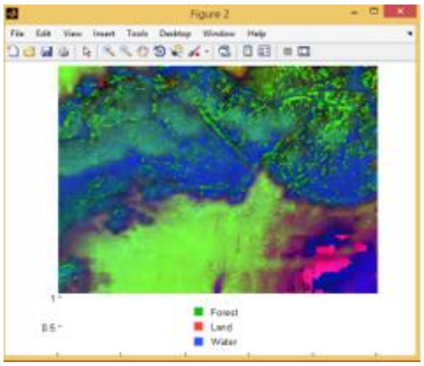

Fig. 3. Local band selection

3. Conclusion

In this paper, the field of remote sensing, hyper spectral images are one of the most important sources of information.

Hyper spectral imagery contains hundreds of narrow spectral bands which are continuous and regularly spaced in the visible and infrared region of the Electromagnetic spectrum.

Although hyper spectral imagery with its high spectral resolution provides an opportunity for more precise information extraction, the large number of bands available with the hyper spectral image leads to certain issues, typically attributed to the curse of dimensionality.

Moreover, continual improvement in the sensor technology has led to an increase in spatial resolution of the hyper spectral imagery, which has a direct impact on the capability of the information extraction techniques. We have proved a recent variant of K-means, to hyperspectral image analysis, in particular implementation, which has been shown to obtain good processing results in hyperspectral image analysis when compared with other popular K-means implementations.

As future work, we are planning on using the Yinyang K-means in conjunction with other techniques for hyperspectral image classification (e.g. supervised and semi-supervised techniques) with the aim of improving the obtained classification results.

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