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A NOVEL APPROACH FOR HYPERSPECTRAL IMAGE SEGMENTATION USING BINARY PARTITION TREE

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ABSTRACT

In this paper, we are doing the segmentation of hyperspectral image using the binary partition tree. Hyper spectral imaging has enabled the characterization of regions based on their spectral properties. Segmentation is the process of partitioning a digital image into multiple segments (sets of pixels, also known as super pixels). The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze. Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images. The work presented here proposes a new Binary Partition Tree pruning strategy aimed at the segmentation of hyper spectral images. The Binary Partition Tree is a region-based representation of images that involves a reduced the number of elementary primitive and therefore allows us to define robust and efficient segmentation algorithm. Here, the regions contained in the Binary Partition Tree branches are studied by recursive spectral graph partitioning. The goal is to remove subtrees composed of nodes which are considered to be similar. To this end, affinity matrices on the tree branches are computed using a new distance-based measure. Hyper spectral imaging has enabled the characterization of regions based on their spectral properties. This has lead to the use of such images in a growing number of applications, such as remote sensing, food safety, healthcare or medical research. Hence, a great deal of research is invested in the field of hyper spectral image segmentation. The number of wavelengths per spectrum and pixel per image as well as the complexity of handling spatial and spectral correlation explain why this approach is still a largely open research issue. The proposed work focuses on the problem of image segmentation and provides the better results.

KEYWORDS: Hyperspectral imaging, Binary Partition Tree, segmentation, graph partitioning.

INTRODUCTION

Hyperspectral imaging is part of a class of techniques commonly referred to as spectral_imaging or spectral analysis. Hyperspectral imaging is related to multispectral__imaging. The distinction between hyper- and multi-spectral is sometimes based on an arbitrary "number of bands" or on the type of measurement, depending on what is appropriate to the purpose. Multispectral imaging deals with several images at discrete and somewhat narrow bands. Being "discrete and somewhat narrow" is what distinguishes multispectral in the visible from color photography. A multispectral sensor may have many bands covering the spectrum from the visible to the long wave infrared. Multispectral images do not produce the "spectrum" of an object. Land sat is an excellent example. Hyperspectral deals with imaging narrow spectral bands over a continuous spectral range, and produce the spectra of all pixels in the scene. So a sensor with only 20 bands can also be hyperspectral when it covers the range from 500 to 700 nm with 20 bands each 10 nm wide. (While a sensor with 20 discrete bands covering the VIS, NIR, SWIR, MWIR, and LWIR would be considered multispectral.)'Ultra spectral' could be reserved for interferometer type imaging sensors with a very fine spectral resolution. These sensors often have (but not necessarily) a low spatial_resolution of several pixels only, a restriction imposed by the high data rate.

This had led to the use of such images in a growing number of applications, such as remote sensing, food safety, healthcare or medical research. Hence, a great deal of research is invested in the field of hyper spectral image segmentation. The number of wavelengths per spectrum and pixel per image as well as the complexity of handling spatial and spectral correlation explain why this approach is still a largely open research issue. Recently, an abstraction from the pixel-spectrum-based representation has been proposed using Binary Partition trees (BPT) [1]. This representation [2] stores a hierarchical region-based representation in a tree structure. This provides a

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hierarchy of regions at different levels of resolution to cover a wide range of applications. This generic representation, independently from its construction, can be used in many different applications such as segmentation [3], classification [1], and indexing, filtering, compression or object recognition. This work focuses on the problem of image segmentation by processing an already constructed BPT. The processing of the BPT consists in the analysis of all the different BPT branches and in the pruning of some of these branches.

The analysis proposed here is based on the construction of the affinity matrices using the similarity measure used in the BPT construction. The BPT pruning for hyper spectral segmentation is also explained here. From an image containing n pixels, a BPT generates a tree structure containing 2n-1 nodes. In this tree representation, three types of nodes can be found: Firstly, leaves nodes representing the original image pixels, secondly, the root node representing the entire image support and finally, the remaining tree nodes representing image regions formed by the merging of their two child nodes corresponding to two adjacent regions. A possible way to construct a BPT is to use an iterative region merging algorithm that merges, at each step, the pair of most similar neighboring regions.

The BPT is then built by keeping track of the merging steps. Fig. 1 shows an example of BPT construction starting from an original partition involving 4 regions. In the sequel, this initial partition will be the partition of individual pixels.

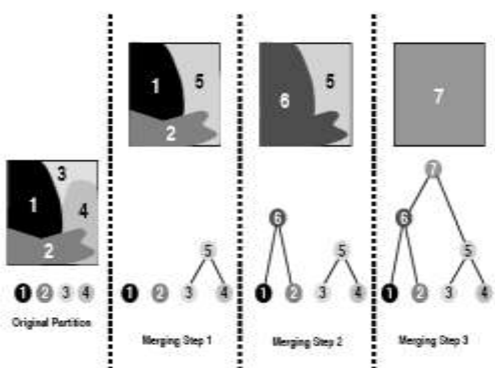

Fig.1. Construction of Binary Partition Tree

The creation of BPT relies on two important notions. The first one is the region model *MR* which specifies how regions are represented and how to model the union of two regions. The second notion is the merging criterion O (Ri;Rj), which defines the similarity between neighboring regions and hence determines the order in which regions are merged.

The work which is proposed here makes use of the Binary Partition Tree for performing the segmentation of the hyperspectral images. As we know that various methods are available for performing the image segmentation of the color images, but these methods are not much more efficient when applied on the hyperspectral images. Here in this work we are going to make use of one of the concept from data structures which are called as the binary partition tree for performing the segmentation of the hyperspectral images which provides better results as compared to the results that are obtained from other segmentation methods.

RELATED WORK

S. Valero *et al.* [1] introduced a new hierarchical structure representation for such images using binary partition trees (BPT). Based on region merging techniques using statistical measures, this region-based representation reduces the number of elementary primitives and allows a more robust filtering, segmentation, classification or information retrieval. To demonstrate BPT capabilities, I am going to discuss the construction of BPT in the specific framework of hyper spectral data. I have proposed a pruning strategy in order to perform a classification. Labelling each BPT node with SVM classifiers outputs, a pruning decision based on an impurity measure is addressed.

Hyper spectral imaging segmentation has been an active research area over the past few years. Despite the growing interest, some factors such as high spectrum variability are still significant issues. P. Salembier *et al.* [7] proposed a method to deal with segmentation through the use of Binary Partition Trees (BPTs). BPTs are suggested as a new representation of hyper spectral data representation generated by a merging process. Different hyper spectral region models and similarity metrics defining the merging orders are presented and analyzed. The resulting merging sequence is stored in a BPT structure which enables image regions to be represented at different resolution levels. The segmentation is performed through an intelligent pruning of the BPT that selects regions to form the final partition.

The most significant recent breakthrough in remote sensing has been the development of hyper spectral sensors and software to analyze the resulting image data. Fifteen years ago only spectral remote sensing experts had access to hyper spectral images or software tools to take advantage of such images.

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Over the past decade hyper spectral image analysis has matured into one of the most powerful and fastest growing technologies in the field of remote sensing. The "hyper" in hyper spectral means "over" as in "too many" and refers to the large number of measured wavelength bands. Hyper spectral images are spectrally over determined, which means that they provide ample spectral information to identify and distinguish spectrally unique materials. Hyper spectral imagery provides the potential for more accurate and detailed information extraction than possible with any other type of remotely sensed data. S. Valero *et al.* [2] reviewed some relevant spectral concepts, discussed the definition of hyper spectral versus multispectral, review some recent applications of hyper spectral image analysis, and summarize image-processing techniques commonly applied to hyper spectral imagery.

H. Ling *et al.* [4] presented a new histogram distance family, the Quadratic-Chi (QC). QC members are quadratic-Form distances with a cross-bin χ^2 -like normalization. The cross-bin χ^2 -like normalization reduces the effect of large bins having undo influence. Normalization was shown to be helpful in many cases, where the χ^2 histogram distance outperformed the L2 norm. However, χ^2 is sensitive to quantization effects, such as caused by light changes, shape deformations etc. The Quadratic-Form part of QC members takes care of cross-bin relationships (*e.g.* red and orange), alleviating the quantization problem. He has presented two new cross bin histogram distance properties: *Similarity-Matrix-Quantization-Invariance* and *Sparseness-Invariance* and show that QC distances have these properties. He also showed that experimentally they boost performance. QC distances computation time complexity is linear in the number of non-zero entries in the bin-similarity matrix and histograms and it can easily be parallelized. The results for image retrieval using the Scale Invariant Feature Transform (SIFT) and color image descriptors are obtained. In addition, he presents results for shape classification using Shape Context (SC) and Inner Distance Shape Context (IDSC). He has shown that the new QC members outperform state of the art distances for these tasks, while having a short running time.

ANALYSIS & PROBLEM DEFINITION

In Image processing, segmentation refers to the process of partitioning a digital image into multiple segments (sets of pixels, also known as super pixels). The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze. Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images. More precisely, image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain visual characteristics.

The result of image segmentation is a set of segments that collectively cover the entire image, or a set of contours extracted from the image (see edge detection). Each of the pixels in a region is similar with respect to some characteristic or computed property, such as color, intensity, or texture. Adjacent regions are significantly different with respect to the same characteristic(s).When applied to a stack of images, typical in Medical imaging, the resulting contours after image segmentation can be used to create 3D reconstructions with the help of interpolation algorithms like Marching cubes. Several general-purpose algorithms and techniques have been developed for image segmentation. Since there is no general solution to the image segmentation problem, these techniques often have to be combined with domain knowledge in order to effectively solve an image segmentation problem for a problem domain.

As we know that the hyperspectral images are very difficult to analyze as they contain few such intensity components which are not visible by human eye. In order to make those images easier for analysis and decision making we have proposed this work. The proposed work focuses on the problem of hyperspectral image segmentation and resolves it using one of the techniques of data structures which is called as the Binary Partition Tree (BPT). Here in this work we are going to process an already constructed BPT while performing the segmentation. The simplest method of image segmentation is called the thresholding method. This method is based on a clip-level (or a threshold value) to turn a gray-scale image into a binary image. The key of this method is to select the threshold value (or values when multiple-levels are selected). Several popular methods are used in industry including the maximum entropy method, Otsu's method (maximum variance), and et al. k-means clustering can also be used. Graph partitioning methods can effectively be used for image segmentation. In these methods, the image is modeled as a weighted, undirected graph. Usually a pixel or a group of pixels are associated with nodes and edge weights define the (dis)similarity between the neighborhood pixels. The graph (image) is then

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partitioned according to a criterion designed to model "good" clusters. Each partition of the nodes (pixels) output from these algorithms are considered an object segment in the image.

CONSTRUCTING BPT & FLOW DESIGN

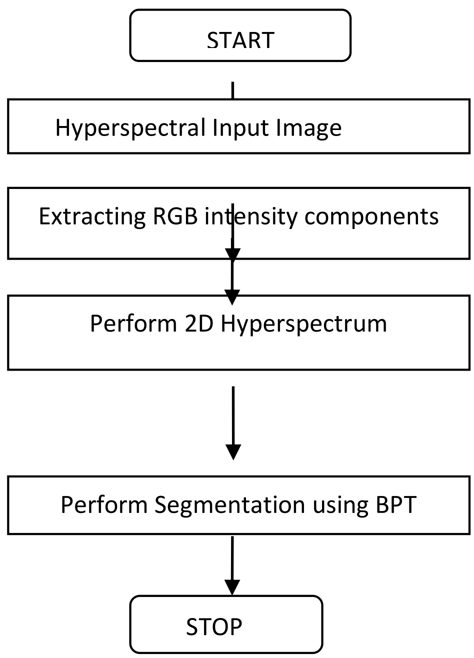

Fig.2 Flow of BPT

4.1 Extracting RGB Intensity Components:

The algorithm ***for*** performing 2D Hyperspectrum is described as follows.

Algorithm:

Step 1. Read the input image into the variable 'img'.

Step 2. Extract the RED, GREEN and BLUE intensity components from the input image.

img (: , : , 1) →Red intensity
img(: , : , 2) →Green intensity
img(: , : , 3) →Blue intensity

4.2 Performing 2D Hyperspectrum

The algorithm ***for*** performing 2D Hyperspectrum is described as follows.

Algorithm:

Step 1: Enter the spectral width.

Step 2: Determine the total number of hyperspectral component layers.

Step 3: For each value of the gray level process every pixel of the image.

Step 4: If the pixel value is greater then or equal to gray level and less than or equal to the sum of gray level and spectral width assign that pixel the least value of gray level.

Step 5: Repeat the above step for all the hyperspectral components.

Step 6: Now summing up all the images that are obtained for each component, we get

hyper_image (: , : , 2)→Green intensity
hyper_image (: , : , 3)→Blue intensity
hyper_image(: , : , 1)→Red intensity

Step 7: Now again summing up all the above images to obtained the spectral segmented image.

4.3 Constructing Binary Partition Tree

The algorithm ***for*** performing 2D Hyperspectrum is described as follows.

Algorithm:

Step 1: Read the Max_tree_depth and construct the binary tree and determine the base pixel.

Step 2: For each pixel check whether it suffices to the image tree.

Step 3: If the pixel value is greater than or equal to gray level and less than or equal to the sum of gray level and spectral width left child has been found.

Step 4: If the pixel value is greater than or equal to the difference between the base pixel value and spectral width and less than the base pixel value Right child has been found.

Step 5: Repeat the above step till found pixel equals to total number of pixel.

Step 6: Now, the images which are obtained by performing step 5 are:

bin_image(: , : , 1)→Red intensity
bin_image(: , : , 2)→Green intensity
bin_image(: , : , 3)→Blue intensity

Here initially an hyperspectral image is considered as an input. In the first module we are going to extract the RGB intensity components from the input image. This means that the input image is now divided into three images, first is consisting of only RED intensity components, second is consisting of only GREEN intensity components and third is consisting of only BLUE intensity components.

Now the second module processes these three images which are obtained from the first module using the Histogram based segmentation method. Again here we are going to obtained the three images i.e RGB intensity images. Thus we are going to merge those three images to obtain the hyperspectral segmented image using the histogram based segmentation method.

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Now the third module processes these three images which are obtained from the Second module using the concept of data structure which is called as the Binary Partition Tree. Again here we are going to obtained the three images i.e RGB intensity images. Thus we are going to merge those three images to obtain the hyperspectral segmented image using the Binary Partition Tree method.

RESULT & DISCUSSION

The following is the hyperspectral image which was taken in a laboratory by illuminating the room by reddish color light for the research work. Figure 3 Example of Hyperspectral image.

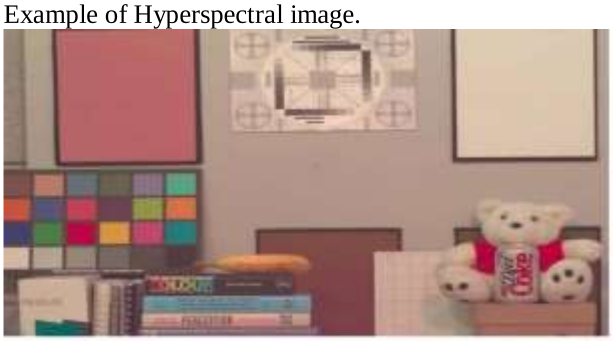

Fig.3. Example of Hyperspectral image

Extracting Rgb Intensity Components

As we know that the image consist of different RGB intensity values, now before applying segmentation on the image, first we need to divide the image into three parts. The first part contains only RED intensity pixels, the second part contains only GREEN intensity pixels and the third contains only Blue intensity pixels. fig 4 shows Probability of occurrence of RED intensity pixel in original image.

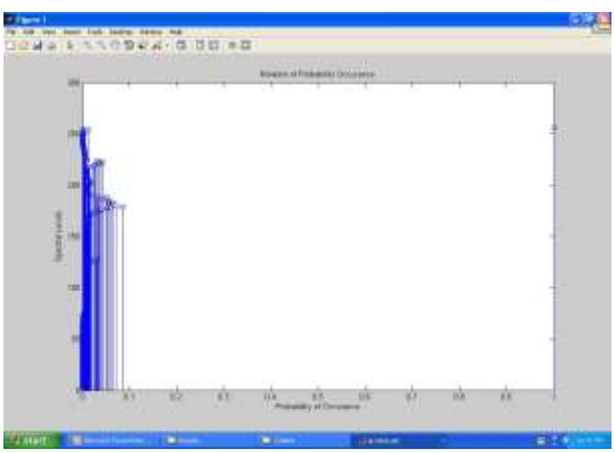

Fig.4. Probability of occurrence of RED intensity pixel in original image.

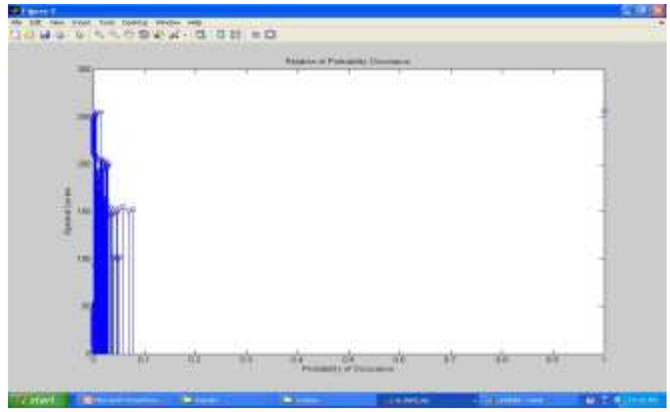

Fig.5. Probability of occurrence of GREEN intensity pixel in original image.

Fig.6. Probability of occurrence of BLUE intensity pixel in original image.

Applying 2d Hyperspectrum

The following is the output which is obtained after performing Histogram based Segmentation on the original image.The original hyperspectral image was first of all converted into the three distinct images each of them were consisting of RED, GREEN and BLUE intensity pixels. These three images were considered as the input for performing the histogram based segmentation.

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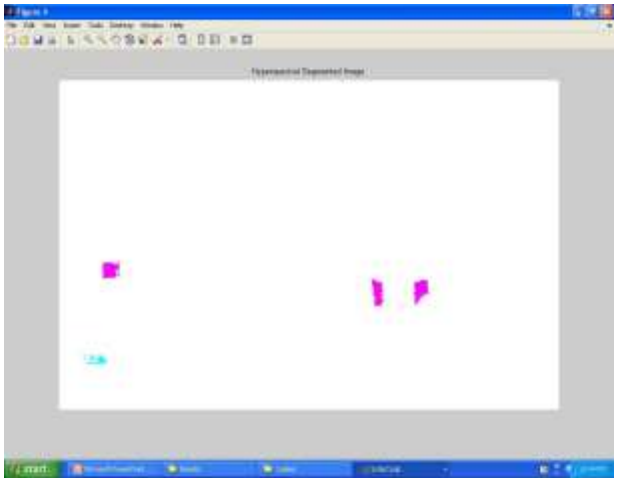

Fig. 7. HyperSpectral Segmented image using Histogram Method

Constructing Binary Partition Tree

The following is the output which is obtained after performing the Segmentation with the help of Binary Partition Tree on the three distinct images each of them were consisting of RED, GREEN and BLUE intensity pixels respectively. These three images were considered as the input for performing the Segmentation with the help of Binary Partition Tree.

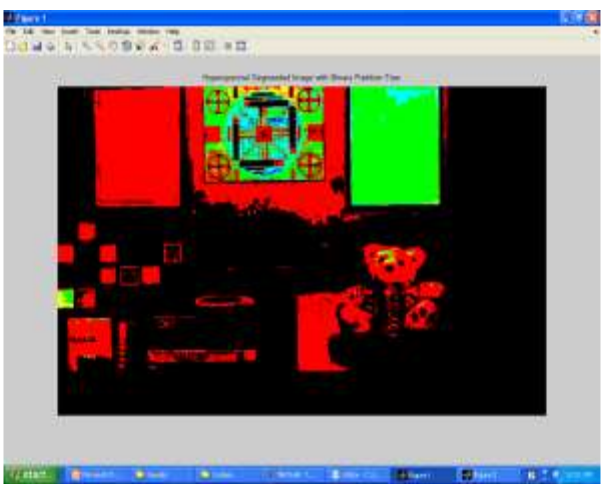

Fig.8.HyperSpectral Segmented image using BPT

Comparisons

The following Screenshot shows the comparison between the results that are obtained after performing the segmentation on the hyperspectral image using Histogram based method and using BPT. Various dataset are tested over the proposed work as follows.

TEST CASE

Fig.9. HyperSpectral image

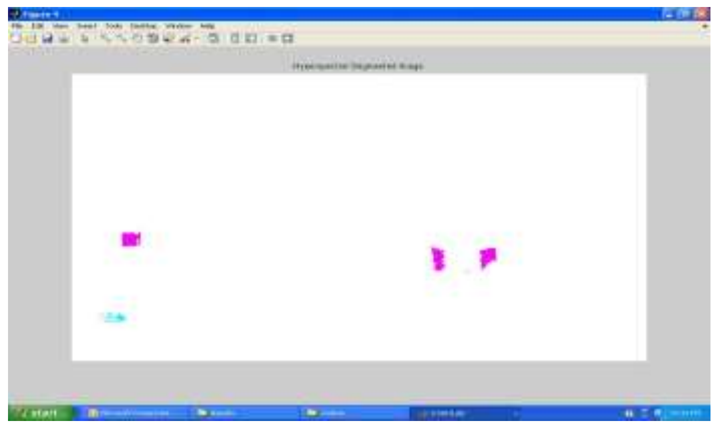

Fig.10. Segmented image using Histogram method

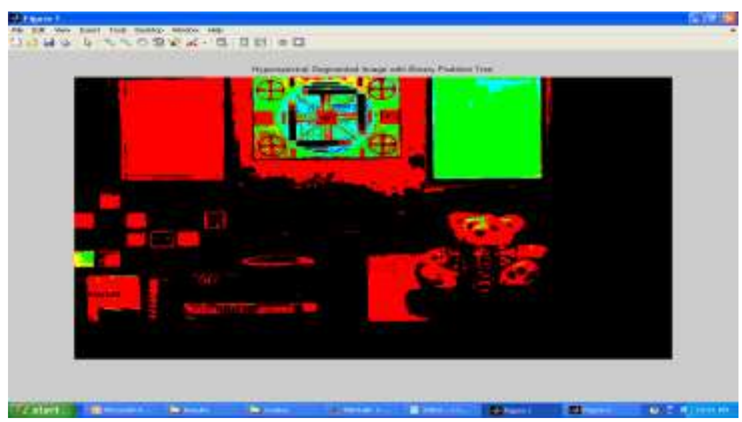

Fig.11. Segmented image using BPT

CONCLUSION & FUTURE WORK

Many parameters in hyper spectral segmentation remains to be investigated. To find better hyperspectral image segmentation method and to find better segmented image are in great demand. Future work will be conducted for improving the merging criterion given that information between bands is not

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introduced in our similarity measure. New techniques are currently being studied to improve the accuracy and the robustness of the segmentation results. From Experimental results we can say that Algorithm provides higher quality segmentation for the hyperspectral images. The Algorithm which has been proposed here is very efficient in determining and segmenting the pixels that are not visible by human eye. The segmented image is more informative as it preserves more fine details of the image compare to histogram based segmentation.

REFERENCES

1. S. Valero, P. Salembier, and J. Chanussot, "New hyperspectral data representation using binary partition tree," in Proc.of IGARSS10, Honolulu, Hawaii, USA, 2010.
2. S. Valero, P. Salembier, and J. Chanussot, "Comparison of merging orders and pruning strategies for binary partition tree in hyperspectral data," in Proc.of ICIP10, Hong Kong, 2010.
3. F. Calderero and F. Marques, "Region merging techniques using information theory statistical measures," IEEE Trans. Image Processing, 2010, vol. 19, pp. 1567–586.B.
4. H. Ling and K. Okada, "Diffusion distance for histogram comparison,"Proc. of CVPR, 2006.
5. J. Cardoso and L. Corte-Real, "Toward a generic evaluation of image segmen-tation," in IEEE Trans. Image Processing, 2005,vol. 14, pp. 1773–1782.
6. J. A. Gualtieri and J.C. Tilton, "Hierarchical segmentation of hyperspectral data," AVIRIS Earth Science and Applications Workshop Proceedings, 2002, pp. 5–8.
7. P. Salembier and L. Garrido, "Binary partition tree as an efficient representation for image processing, segmentation, and information retrieval," in IEEE Trans. Image Processing, 2000, vol. 9, pp. 561–576.
8. J.Shi and J.Malik, "Normalized cuts and image segmentation,"Proc. of CVPR, 1997.
9. C.M. Cuadras, A. Arenas, and J. Fortiana, "Some computational aspects of a distance-based model for prediction," in Communications in Statistics: Simulation and Computation,1996, vol. 25, pp. 593–609.
10. T.F. Cox and M.A.Cox, "Multidimensional scaling,"K. Fernandez and A.Morineau (Ed.),Chapman & Hal, 1994.
11. E. Cramer and W.A. Nicewander, "Some symmetric, invariant measures of multi-variate association," in Psychometrika, 1979,vol. 44, pp. 43–54.