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Structure Representation for Hyper spectral Images Using Binary Classification

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Abstract

Binary Partition Trees are hierarchical region-based representations of images. They define a reduced set of regions that covers the image support and that spans various levels of resolution. They are attractive for object detection as they tremendously reduce the search space. In this paper, several issues related to the use of BPT for object detection are studied. Concerning the tree construction, we analyze the compromise between computational complexity reduction and accuracy. This will lead us to define two parts in the BPT: one providing accuracy and one representing the Search space for the object detection task. The optimal exploitation of the information provided by hyperspectral images requires the development of advanced image processing tools. This paper introduces a new hierarchical structure representation for such images using binary partition trees. 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, we first discuss the construction of BPT in the specific framework of hyperspectral data. We then propose a pruning strategy in order to perform a classification. Labeling each BPT node with SVM classifiers outputs, a pruning decision based on an impurity measure is addressed. Experimental results on two different hyperspectral data sets have demonstrated the good performances of a BPT-based representation

Keywords : Hyperspectral imaging, Binary classification, segmentation, BPT Pruning, Region model

1. INTRODUCTION

Recent advances in remote sensing and geographic information has led the way for the development of hyperspectral sensors which produce a data cube of hundreds of contiguous waveband images. Therefore, each pixel is represented by a spectrum related to the light absorbing and/or scattering properties of the spatial region that it represents. Given the wide range of real-life applications, great deal of research is invested in the field of hyperspectral image segmentation. The segmentation of these images is a key step in their analysis. Unfortunately, hyperspectral image processing is still a difficult endeavor due to the huge amount of data involved. Consequently, most of the standard segmentation methods fail.

In the literature, different segmentation algorithms based on morphological profiles, end member extraction, Markov random fields, Bayesian segmentation and hierarchical segmentation have been proposed. The goal of segmentation (in particular for all the algorithms mentioned before) is to compute a partition from a pixel-based representation of the image.

This approach has two drawbacks: 1) The segmentation cannot be generic and also reliable. In fact, it has to depend on the application. 2) The initial pixel-based representation is too low level which implies that the segmentation algorithm is quite complex or not very robust. To tackle these issues, we would like to define a new data representation which represents a first abstraction from the pixel-based representation and that is multiscale to be able to cover a wide range of applications.

Binary Partition Tree (BPT) is one example of such representations. Having a rather generic construction (more or less application independent), they can be interpreted as a set of hierarchical regions stored in a tree structure. Note that from the tree representation, many partitions can be extracted for various applications. The processing of BPT will then involve an application dependant pruning strategy.

Hence, we propose BPT as a new region-based hierarchical representation for hyperspectral images. In the case of remote sensing hyperspectral data, different pruning's can be suitable for filtering, classification and segmentation purposes. As a first instance, we present here a pruning strategy aiming at a classification of the image[1]. The organization of this paper is given as follows: section 2 gives goals for hyperspectral image visualization and statistics of hi data description in section 3. Section 4 gives the color display strategy. Section 5 gives a brief introduction on BPT, explaining the details of its construction. The BPT pruning for classification is discussed in section 6. Experimental results are shown in section 7. Finally, conclusions are drawn in section 8.

2. GOALS FOR HYPERSPECTRAL IMAGE VISUALIZATION

We propose the following design goals for displaying hyperspectral imagery. Not all goals will be important for all tasks, and it may not be possible to achieve all goals simultaneously. However, each of these goals would increase the effective transmission of information. In Sections III and IV, we present visualization solutions and show how they satisfy these goals in the following sections.

1) Consistent Rendering: Any given spectrum is always displayed as the same color value so that it can be easily recognized across images. This goal also facilitates comparison between different images. There is a further advantage if the rendered colors correspond to an existing color-association system. This constraint may be loosened to allow luminance scaling of the display image, which would result in a spectra being consistently displayed as the same hue and saturation.

2) Edge Preservation: Edges (at all spatial resolutions) of the original hyperspectral image are represented faithfully in the visualization. We discuss objective metrics for this goal in Section IV. A sub goal is the discriminability of different spectra in the visualization.

3) Computational ease: The visualization can be rendered quickly, enabling real-time interactivity.

4) Equal-energy white point: A pixel with the same reflectance value for each spectral band appears as a shade of gray. Thus, lack of color saturation is related to how closely an object resembles a gray body diffuse reflector.

5) Smallest effective differences: Visual distinctions are no larger than needed to effectively show relative differences. According to Tufte, who is a proponent of this design goal for general visualizations, minimal distinctions reduce visual clutter, and using smallest effective differences helps in designing secondary and structural elements such as arrows, pointer lines, highlights, legends, etc.

6) Appropriate preattentive features: The visualization minimizes preattentive features of the image that distract the viewer without reason. For example, a small bright saturated color region on a background of a different color will "pop-out" at the viewer and attract attention [2].

7) Natural palette: Visualizations use a palette and spatial distribution of colors that is consistent with natural imagery. This goal is partly based on the assumption that humans are well-designed to interpret natural scenes, and partly based on the misinterpretation caused by strongly saturated colors. In particular, large regions of strongly saturated colors rarely appear in nature, and have long been eschewed by design experts as confusing and distracting. In fact, strong background coloration can induce perceived differences in smaller color regions. These simultaneous contrast effects can make it difficult to accurately judge quantitative differences between colors. For example, two small squares of the same color will actually look increasingly different if viewed against two backgrounds with strong differences in color.

Conversely, two small squares of different colors can look the same when viewed against a background that strongly differs from the foreground. These simultaneous contrast effects are well-studied visual phenomena, and their effect in maps can be explored on-line with Cynthia Brewer's Color Brewer software (www.colorbrewer.org). Large regions of saturated color may also induce temporal chromatic adaption, where after staring at one part of the image other parts of the image then appear to be different colors due to the afterimage formed.

8) Wavelength Shift Invariance: All wavelengths are accorded equal weight. This allows the visualization method to work equally well for any number of spectral bands, in any spectral range. This makes a visualization method easily adaptable to spectral zooming, spectral panning, or new instrumentation. A basic requirement is that a monochromatic spike at any wavelength is displayed with the same luminance [3]. A further desired feature is that the perceived difference in a color property (such as hue) between two rendered monochromatic Spectra depends only on the change in wavelength.

These goals are consistent with goals for scientific visualization proposed by other researchers. For example, Tyo et al. propose "anthropometric optimality" which they describe as "information should be presented in a way that maximizes usefulness to the human observer."

Our goals try to achieve this by taking into account human visual properties, such as our goals of a natural palette, appropriate preattentive features, equal-energy white-point, consistent rendering, and edge preservation. The goal of consistent rendering, or at least relative consistency with respect to luminance, satisfies the most common natural variation captured by Tyo et al.'s goal of "ecological invariance," that "representations remain qualitatively similar over natural variation." Robertson and Callaghan argue that hyperspectral image displays should communicate data "as effectively and unambiguously as possible." The above goals aim to support this larger goal.

3. STATISTICS OF HI DATA DESCRIPTION

Airborne hyperspectral imagery data collected by the HYDICE3 sensor at the Indian Army which provides Grounds on 24 August 2005 were used in this analysis. HYDICE collects calibrated (after processing) spectral radiance data in 210 wavelengths spanning 0.4 to 2.5 is in nominally 10 nm wide bands [5]. Figure 1 shows a single band (A =0.565 ,am) image of the Run 07 data collected at 9:27 AM local time under clear conditions from an altitude of 3 km. The spatial resolution of the imagery is approximately 1.5 meters.

In examining the statistical properties of the data, several groupings, or classes, were considered. Three regions are identified in the white boxes in Figure 1 describing three classes that were selected by their spatial proximity. In the lower right is a "Grass" region, the middle top is a "Tree" region, and on the left is a "mixed" region. These regions define the pixels selected for three of the classes considered. Also considered were two classes resulting from a supervised classification process performed to isolate spectrally similar (not necessarily spatially adjacent) pixels. Data from two classes selected from this analysis were labeled "Class 2 Grass" and "Class 9 Tree". Table 1 summarizes the classes analyzed and their sample sizes (number of pixels).

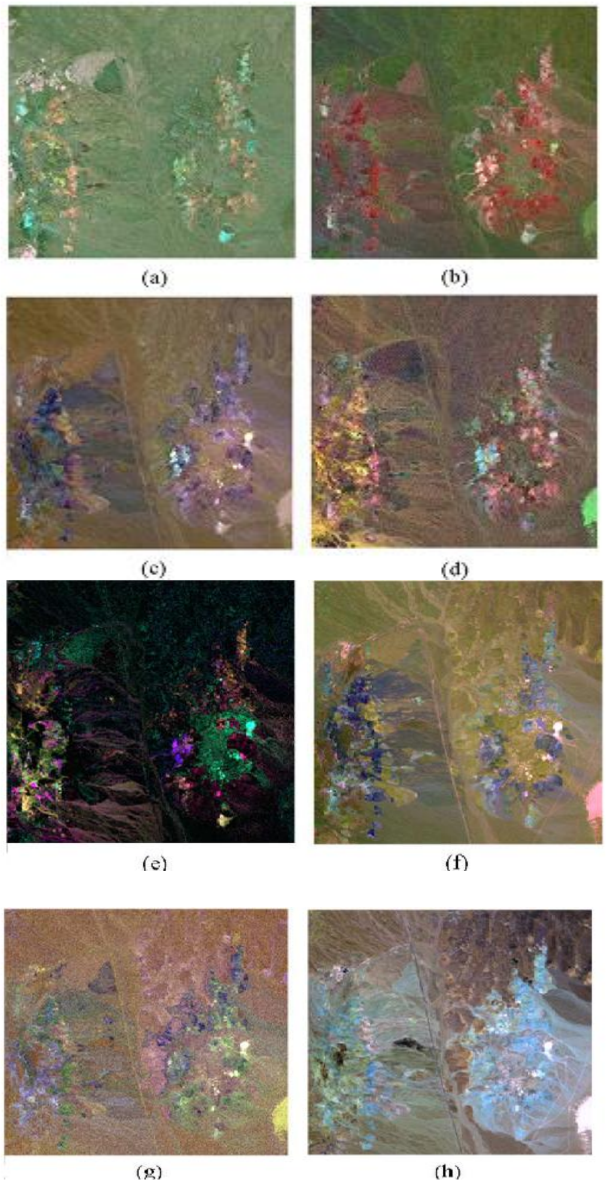
TABLE 1. CLASSES SELECTED FOR STATISTICAL ANALYSIS.

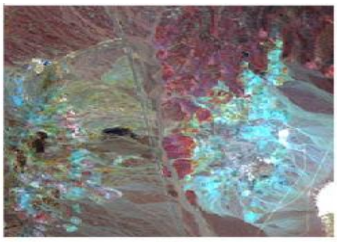
Class name	Selection Technique	Sample Size
Grass S	partially adjacent	7,760
Tree	Spatially adjacent	8,232
Mixed	Spatially adjacent	7,590
Class 2	Grass Supervised	27,351
Class 9	Tree Supervised	25,872

4. COLOR DISPLAY STRATEGIES

Assume that q DEs are used to generate a color display. In general, q and p are not equal; they are equal when a supervised classification result is used for visualization. The detailed steps for generating a color display include color selection, color assignment, display element adjustment, and color display reproduction.

- Perception-Based Distinctive Color Selection
- B.Color Assignment Considering Display Element Similarity
- Display Element Adjustment
- Color Display Reproduction
- Evaluation on Visual Interpretation





(i)

FIG. 1. COLOR DISPLAY USING DIFFERENT METHODS

(a) CLDA. (b) LDA. (c) INAPCA. (d) ICA. (e) UFCLU. (f) NAPCA. (g) PCA. (h) CMF. (i) TBC.

5. CONSTRUCTION OF THE BPT

Binary Partition Tree (BPT) is a hierarchical representation of a set of regions obtained from an initial partition. The tree leaves correspond the regions of the initial partition and the remaining tree nodes represent regions formed by the merging of two children regions. The root node represents the entire image support. The tree construction is performed by keeping track of merging steps of an iterative region merging algorithm (see Fig. 1). The creation of BPT implies two important notions. On one hand, the merging criterion O(Ri,Rj) between two adjacent regions Ri and Rj, on the other hand, the region modelMRi. The merging criterion defines the similarity of neighboring regions and hence determines the order in which regions are going to be merged. The region model specifies how regions are represented and how to model the union of two regions. Nevertheless, the definition of O (Ri, Rj) as a similarity measure between two hyperspectral regions nodes is not an easy issue.

In the literature, some distances such as Spectral Angle Mapper or Spectral Information Divergence have been proposed to measure spectral similarity. However, their use as O(Ri,Rj) is not straightforward as each region is made of several pixels and therefore several spectra. To overcome this problem, past approaches have assumed that MRi is a constant, representing the regions by their mean spectrum. With this approach, the interclass spectral variability induced by natural variations, noise and mixed pixels is overlooked. In order to take into account this spectral variability within regions, we propose to model each band of the region spectrum by its probability density function.

5.1. Region Model

Working with N bands, the region model consists of N histograms representing for each band the empirical distribute on of the pixels belonging to the region [7]. Consequently, the region model MRi is given by

MRi = {P1Ri, P2 Ri, ..., PNRi} (1)

Where Pk Ri is the empirical distribution of the region Ri in the band k which is formed by

PkRi = {PkRi (a1)PkRi(a2), ...Pk Ri(a|χ|) (2)

Being ai the possible values of the pixels in each band k. We must remark that this region model can also be defined when tree leaves are single pixels by exploiting the image self-similarity. Indeed, the probability density function for individual pixels can be estimated and the precise modeling of the pixels pdf is important in order to get very precise region contours.

5.2. Merging criterion: Bhattacharyya coefficient

For each band k of each region R, the model PkR is an empirical discrete probability distribution. Accordingly, the Bhattacharyya coefficient can be used to measure the similarity between two adjacent regions Ri and Rj of a given band k. Theorically, this measure is defined by:

$$BC\,(PkRi,\ PkRj) = -\log\Big(\sum_{j=1}^{|\chi|} PRi(k)(aj)\ 1/2PRj(k)(aj)\ 1/2\Big) \quad (3)$$

Existing a perfect overlap between both probability distributions, the Bhattacharyya coefficient will be 0. Consequently, a merging criterion of a pair of adjacent regions can be defined as the minimum sum of the N dissimilarity measures obtained for the different bands.

$$O(R_i, R_j) = \underset{R_i, R_j}{\mathrm{argmin}} \sum_{k=0}^{N-1} BC(P_k R_i, P_k R_j) \quad (4)$$

Experimentally, we have observed that the criterion of Eq. 4 does not assure that the areas of the regions tend to increase as the number of regions into the partition decreases. Then, in order to avoid small and meaningless regions into the generated partitions, the merging of very small regions has to be favored. To this goal we introduce a regularization term based on the size of the regions.

$$O(R_i,R_j) = \min(\sqrt{NR_i}, \sqrt{NR_{ij}})O(R_i,R_j) \quad (5)$$

Note that we propose to use the square root of the minimum area.

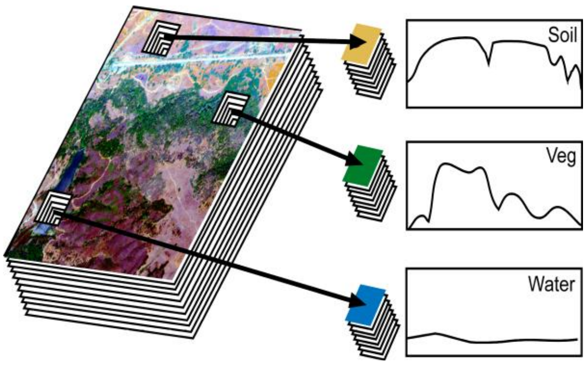


Fig. 2. Example of BPT construction

The concept of hyperspectral imagery: Image measurements are made at many narrow contiguous wavelength bands, resulting in a complete spectrum for each pixel.

To conclude this section, we must let us mention that the merging criterion defined by Eq. 4 simply adds the contribution of the various bands without exploiting their mutual information. Future works will analyze how this mutual information between bands can be used in the merging criterion.

6. BPT PRUNING

In this section, we discuss an example of tree processing for a classification application. The processing can be seen as a tree pruning step the goal of which is to remove sub trees composed of nodes belonging to the same class. To perform this task, we analyze the tree starting from the leaves and moving along the branches to select the nodes of largest area that involve pixels belonging to a unique class. As a first step, we measure specific region descriptors for each node Ri along the tree structure. These values are used to compute an increasing cost C associated to each BPT node. The increasingness of C along the branches guarantees that removing nodes having a cost lower than given threshold leads to a pruning.

The choice of region descriptors is determined by the application. In our case, the BPT pruning is focused on the hyperspectral data classification. Hence, we propose a pruning strategy populating the nodes with the density probability function of belonging to each class. Such a task can be achieved using a multi-class classifier output. Here, we use Support Vector Machine as a classifier which has demonstrated its advantages in high dimensional data. We note that being supervised, SVM needs firstly to construct a model to be able to classify the data. Then, we start constructing the model by training the SVM classifier using some leaves nodes according to the available ground truth. After the model construction, modeling each Ri by its mean spectrum, all nodes are populated by their class probability estimation CpRi and their predicted class ClassRi. Using CpRi values, we define an increasing iterative cost C along tree branches using a node impurity measure. The impurity of a node is interpreted by how mixed is the node, that is, the proportion of elements of different classes in the same region. To measure that, we propose a popular impurity function such as the entropy. Therefore, merging Ri at level l, the cost associated to Ri is computed using the following equation:

$$C(R_i) = C' - \sum_{t=0}^{N_c} C_{pR_i}(t) \log(C_{pR_i}(t)) \quad (6)$$

Where Nc is the number of classes and C_ is the maximum cumulative cost until the l − 1 branch level. It should be noticed that measuring the sum of all the impurities, a maximum threshold λ should be set to determine the last pure node. Thus, a node Ri is removed if C(Ri) < λ and if all its ancestors also satisfy this condition. After tree pruning, we construct the classification map by selecting the lower nodes of the resulting pruned tree. Regions contained in these nodes are labeled by the ClassRi which has been assigned by the SVM classifier in the tree population.

6.1 Pruning Decision

The pruning of a sub-tree Ts hanging from a node R consists in deciding if all its descendants can be replaced by R. This is done by the function φR which compares the misclassification rate at node R with the misclassification rate corresponding to the set of leaf nodes of the sub-tree Ts. In this example, the misclassification rate associated with the node Ri should be compared with the error associated to the 3 leaves Rleaves i= {l1, l2, l3} contained in Ts . Mathematically, the function defining the pruning function φR is given by

$$\phi_R(R_i) = \mathcal{MR}(R_i) - \overline{\mathcal{MR}(R_i^{leaves})} \quad (4)$$

The aim is to detect when φR is higher than an allowed threshold α. Considering a node Ri , if the cost function φR(Ri) < α, the subtree hanging from Ri can be pruned and replaced by Ri . Contrarily, if φR (Ri) > α, the node Ri cannot be a leaf in the pruned BPT. Note that the value determines the size of the pruned BPT [8]. When α is small, the penalty term is small, so the size of the pruned tree will be large. Contrarily, as α increase, the pruned BPT has fewer and fewer nodes.

7. EXPERIMENTAL RESULTS

7.1. Experiment with AVIRIS Indian Pines

In our first experiment, Indian Pines AVIRIS hyperspectral data containing 200 spectral bands having a spatial dimension of 145 X 145 pixels is used. The whole image is formed by 16 different classes having an available ground truth. Before constructing BPT as detailed in Section 2, some parameters such as the number of bins Nbins used to represent PkR should be set. In our case, having different ranges of values in each channel, we set Nbins as the minimum range difference found in the image (Nbins=46). Once the BPT has been created, we train the SVM classifier selecting randomly 30% of samples for each class from the reference data. After that, CpR and ClassR values are assigned to each node to perform the pruning task.

In this pruning step, we should set λ in order to define the maximum impurity cost allowed along BPT branches. After some experimental tests, we set λ=20. Fig. 3 compares the obtained results using the BPT pruning against a classical SVM pixel classification. The same training samples are used for both classification methods.

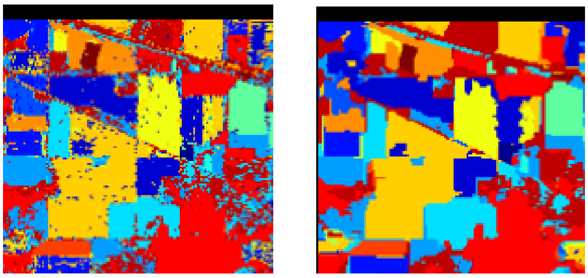


FIG. 3. OBTAINED CLASSIFICATION MAP. LEFT: SVM RESULT. RIGHT: PRUNING BPT RESULT

Looking at BPT pruning results, we observe that the classification map is formed by quite homogeneous regions. In particular, the BPT nodes selection according to the proposed pruning criterion provides a less noisy classification. The obtained results also corroborate the BPT performances since extracted nodes reflect semantic real-world regions of the image. We should remark that Indian Pines has a high spectra variability due to its low spatial resolution.Table-1 illustrates the class-specific and the global classification accuracies. Observing these results, we verify that the proposed BPT classification improves the classification accuracies for almost all the classes.

TABLE 2. CLASS SPECIFICALLY ACCURACY IN PERCENTAGE

Class	Simple SVM	Pruned BPT
1	86.11	94.44
2	88.39	93.41
3	83.45	89.03
4	77.56	80.77
5	95.18	92.77
6	67.72	98.43
7	95.30	100
Overall	87.67	94.52

7.2. Experiment with ROSIS-03 over the Anna University, India

In this second experiment, data from the ROSIS-03 optical sensor over the Anna University is presented. The image is formed by 103 denoised channels possessing 610 X 340 pixels. In this work, due to space limitations, only the top-down corner of this image is considered. For this example, we should increase Nbins to 100 considering that this second data has a smaller spatial resolution (1.3 m per pixel) [9]. Although the merging criterion is not strongly dependent of the Nbins, it is better to take it into account. Fig. shows the results obtained after applying BPT pruning.

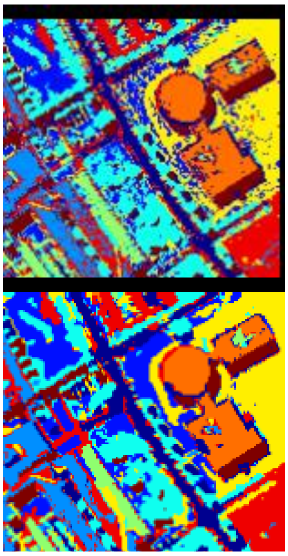


FIG. 4. OBTAINED CLASSIFICATION MAP. LEFT: SVM RESULT. RIGHT: PRUNING BPT RESULT

It can be observed that, using the BPT, a better classification map is also obtained for this second data set. Despite of the improvement, some noise is still present in the results. This implies that our pruning criterion can be improved. Regarding the global accuracy, the simple SVM classifier reaches 90.68 % whereas our proposed BPT pruning achieves 95.19%. It should be observed that BPT pruning improves the classification accuracy preserving most of the edges and shapes.

8. CONCLUSIONS

In this work, Binary Partition Trees have been proposed as a new representation for hyperspectral images. Obtained through a recursive region merging algorithm, they can be interpreted as a new region-based and hierarchical representation of the hyperspectral data. The main advantage of BPT is that it can be considered as a generic representation. Hence, it can be constructed once and used for many applications.

Many tree processing techniques can be formulated as pruning strategies.
Concerning the BPT construction, a solution for the problem of the spectra variability for clustering hyperspectral data has been proposed using statistical region models. BPT

enables the extraction of a hierarchically structured set of regions representing a semantic content of the image.
As a first example of BPT processing, we have proposed and illustrated a pruning strategy to classify the hyperspectral data. Experimental results have shown that the proposed method improves the classification accuracies of a classical SVM, providing classification maps with a reduced amount of noise.

Future work will be conducted for improving the merging criterion given that information between bands is not introduced in our similarity measure. Regarding the pruning strategy, new techniques are currently being studied to improve the accuracy and the robustness of the segmentation results.

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9. REFERENCES

[1] M. Pesaresi, J.A. Benediktsson, and K. Arnason, “Classification and feature extraction for remote sensing”, IEEE Trans. Geoscience and Remote Sensing, 2003, vol. 41, pp. 19401949.

[2] A. Plaza, J.A.Benediktsson, J. Boardman, J. Brazile, L. Bruzzone, G. Camps-Valls, J. Chanussot, M. Fauvel, P. Gamba, A. Gualtieri, J. Tilton and G. Trianni.“Advanced Processing of Hyperspectral Images”, Remote Sensing of Environment, DOI: 10.1016/j.rse.2007.07.028, 2009.

[3] J.L. Marroquin, E.A. Santana, S. Botello “Hidden Markov Measure Field Models for Image Segmentation”, IEEE Trans. on Pattern Analysis and Machine Intelligence, 2003, vol.25(11), pp. 13801387.

[4] J. Li, J.M. Bioucas-Dias and A. Plaza, “Semi-supervised hyperspectral image segmentation”, IEEE GRSS Workshop on Hyperspectral Image-WHISPERS’2009, Grenoble 2009.

[5] J. A. Gualtieri and J.C. Tilton,“ Hierarchical Segmentation of Hyperspectral Data”, 2002 AVIRIS Earth Science and Applications Workshop Proceedings, 2002, pp 58.

[6] P. Salembier and L. Garrido, “ Binary partition tree as an efficient representation for image processing, segmentation, and information retrieval” IEEE Trans. Image Processing, 2000, vol. 9, no. 4, pp. 561576,

[7] F. Calderero and F. Marques,“ General region merging approaches based on information theory statistical measures”, in Proc.of ICIP 2008, San Diego (CA), pp. 3016- 3019

[8] M. Dimicolli and P. Salembier,“ Hierarchical regionbased representation for segmentation and filtering with depth in single images”, in ICIP 2009, November 2009, Cairo, EGYPT.

[9] G. M. Johnson and M. D. Fairchild, Digital Color Imaging. Boca Raton, FL: CRC, 2003, ch. 2, pp. 141–148.

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