HYPERSPECTRAL IMAGE SEGMENTATION USING RECURSIVE MERGING ALGORITHM

Aditya P.Bakshi [st]
M.E 2nd Year Computer Engineering
Sipna's College of Engineering & Technology,
Amravati, India

Prof. Vijaya K.Shandilya
Associate Professor, CSE department
Sipna's College of Engineering & Technology,
Amravati, India

Abstract: 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 (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, we then propose a pruning strategy in order to perform a classification. Labeling each BPT node with SVM classi.ers 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 Partition Tree, segmentation, classification, filtering.*

I.   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 pro.les [1], end member extraction [2], Markov random fields [3], Bayesian segmentation [4] and hierarchical segmentation [5] 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 de.ne 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.

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 [6] for hyperspectral images. In the case of remote sensing hyperspectral data, different pruning 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. The organization of

this paper is given as follows: Section 2 gives a brief introduction on BPT, explaining the details of its construction. The BPT pruning for classification is discussed in section 3. Experimental results are shown in section 4. Finally, conclusions are drawn in section 5.

II.   CONSTRUCTION OF 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 model MRi. 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 Map per 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 [5] 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 [7].
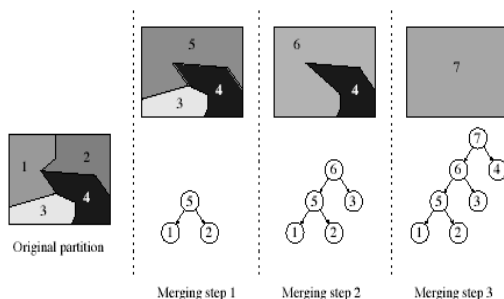

Fig. 1. Example of BPT construction

A) Region Model:

Working with *N* bands, the region model consists of N histograms representing for each band the empirical distribution of the pixels belonging to the region. Consequently, the region model *MRi* is given by

$$M_{Ri} = \{P_{Ri}^1, P_{Ri}^2, ..., P_{Ri}^N\} \quad (1)$$

Where *PRi* is the empirical distribution of the region *Ri*
the band *k* which is formed by

$$P_{Ri}^k = \{P_{Ri}^k(a_1)P_{Ri}^k(a_2), ...P_{Ri}^k(a_{|\chi|})\} \quad (2)$$

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 exploit-ting 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 [8].

B) Merging Criterion:

For each band *k* of each region *R*, the model *Pk R* is an empirical discrete probability distribution. Accordingly, the
coefficient [7] 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:

$$BC(P_{Ri}^k, P_{Rj}^k) = -\log\left(\sum_{j=1}^{|\chi|} P_{Ri(k)}(a_j)^{\frac{1}{2}} P_{Rj(k)}(a_j)^{\frac{1}{2}}\right) \quad (3)$$

Existing a perfect overlap between both probability distri-butions, the coefficient will be 0. Consequently, a merging criterion of a pair of adjacent regions can be de.ned as the *minimum* sum of the *N* dissimilarity measures obtained for the different bands.

$$O(R_i, R_j) = \operatorname*{argmin}_{Ri,Rj} \sum_{k=0}^{N-1} BC(P_{Ri}^k, P_{Rj}^k) \quad (4)$$

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.

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

Note that we propose to use the square root of the *minimum* area. To conclude this section, we must let us mention that the merging criterion de.ned 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.

III. 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 mea-sure a specific region descriptors for each node R_i 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 demostrated 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, modelling each R_i by its mean spectrum, all nodes are populated by their class probability estimation CpR_i and their predicted class $Class\ R_i$ .Using CpR_i values, we de.ne 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 R_i at level l, the cost associated to R_i is computed using the following equation:

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

where N_c 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 $ё$ should be set to determine the last pure node.
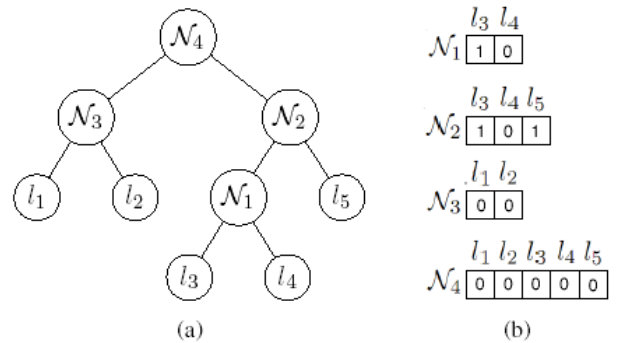

Fig:2 (a) BPT decision (b) Node decision.

Tree Branch B as a connected graph:

Let P_B the set of N_B BPT nodes in the branch B forming a partition of the image. Given a leaf l_0, a local pruning of B regarding l_0 consists in deciding which nodes belonging to P_B should be removed with l_0. To answer this question, we propose to represent each PB space as a weighted undirected graph G, where each edge is formed between every pair of BPT nodes in B. Fig. 3(a) illustrates the branch example of the leaf l_3 in Fig. 2. For this example, the graph interpretation corresponds to Fig. 3(b). Having a N_B possible regions to be merged with a leaf, the idea is to study the similarities/dissimilarities between these regions to assure a cut bipartitioning the set P_B into two disjoint non-empty sets (A; B). In the resulting space, l_0 A and such that similarity among nodes in A is high and similarity across A and B is low.

(a) BPT branch $\mathcal{B}$ (b) G according $\mathcal{B}$
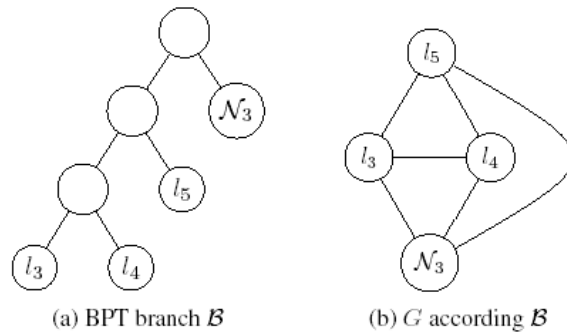
Fig:3 Example of P_B Space.

The graph G is weighted by w_{ij}, which measures the Similarity of an edge linking a pair of nodes Ni and Nj. These values form a matrix W and are given , where d is the distance between regions and controls the size of the neighborhood.

$$w_{ij} = \begin{cases} e^{-\frac{d(\mathcal{N}_i, \mathcal{N}_j)}{\sigma}} & \text{if } i \neq j, \\ 0 & \text{otherwise} \end{cases}$$

(7)

Let D be the diagonal matrix whose values in the diagonal
are the total connection from each node i to all its neighbor nodes. The algorithm for each li is given by

1. NB=hanging nodes from Li until the root
2. **while** NB > 2 and the end is not true **do**
3.   Compute the Laplacian matrix relating Li with all their possible NB.
4. Compute the graph cut level k according to closer BPT nodes on the branch having the same sign that E(Li).
5. Compute N cuts between the first nodes arriving to level k and the remaining NB
6. **if** Ncut < maximum allowed Ncut **then**
7.   Lcut is equal to k
8. **else**
9. the end is true
10. **end if**
11. Next Laplacian matrix to study is given by the hanging nodes until level k, then NB=k
12. **end while**

VI. CONCLUSION

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 represent-ation of the hyper spectral 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. 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.

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