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HYPERSPECTRAL IMAGE SEGMENTATION USING A NEW SPECTRAL MIXTURE-BASED BINARY PARTITION TREE REPRESENTATION

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ABSTRACT

The Binary Partition Tree (BPT) is a hierarchical region-based representation of an image in a tree structure. BPT allows users to explore the image at different segmentation scales, from fine partitions close to the leaves to coarser partitions close to the root. Often, the tree is pruned so the leaves of the resulting pruned tree conform an optimal partition given some optimality criterion. Here, we propose a novel BPT construction approach and pruning strategy for hyperspectral images based on spectral unmixing concepts. The proposed methodology exploits the local unmixing of the regions to find the partition achieving a global minimum reconstruction error. We successfully tested the proposed approach on the well-known Cuprite hyperspectral image collected by NASA Jet Propulsion Laboratory's Airborne Visible/Infrared Imaging Spectrometer (AVIRIS). This scene is considered as a standard benchmark to validate spectral unmixing algorithms.

Index Terms— Binary Partition Trees, hyperspectral images, spectral unmixing, segmentation

1. INTRODUCTION

Hyperspectral unsupervised segmentation allows to explore and understand the contents of hyperspectral images without any a-priori knowledge. Thus, it is an important application that have been scarcely investigated. Watershed segmentation provides an oversegmented partition map, while clustering methods such as K-NN require of the number of clusters as an input. On the other hand, hierarchical segmentation using trees provides a flexible approach to remotely sensed image interpretation.

The Binary Partition Tree (BPT) is a hierarchical region-based representation of an image in a tree structure [1]. In the BPT literature [1, 2], two region models are commonly used for hyperspectral images: the first order parametric region model, which represents a region by its mean spectrum, and the non-parametric statistical region model, which models a region by its set of histograms (one histogram per spectral band). Both types of region models have their non-exhaustive associated family of merging criteria [2]. Often, the BPT is pruned to achieve a more compact representation where the leaves of the pruned tree represent an optimal partition for some kind of application. Many pruning strategies have already been investigated in the BPT literature [1, 2, 3] to achieve a classical segmentation or to improve a further classification operation. In this work we introduce for the first time in the literature the use of spectral unmixing for the construction and merging of BPT hyperspectral representation. In the linear mixing model [4] a hyperspectral image can be seen as the result of the linear combination of the pure spectral signatures of spectrally pure material, named endmembers, with a fractional abundance matrix. The unmixing process corresponds to the inverse problem: given a hyperspectral image find the endmembers and their per-pixel abundances.

Our contribution is two-fold. On one hand, we propose a region model based on the endmembers induced from the region by means of some endmembers induction algorithm (EIA), and a merging criterion based on the spectral similarity between two regions. On the other hand, we also propose two novel pruning optimizing criteria based on the average and maximum spectral mixture reconstruction error. The final result is an optimal segmentation of the hyperspectral scene in terms of spectral unmixing quality.

The remainder of the paper is organized as follows. In sections 2 and 3 we briefly overview the construction and pruning of BPT and the spectral unmixing topics respectively. In section 4 we introduce the proposed BPT construction and pruning by means of hyperspectral unmixing. Then, we provide the experimental methodology and results obtained from the AVIRIS Cuprite scene in section 5. Finally, we give some conclusions in section 6.

2. BINARY PARTITION TREE

In the BPT representation, the leaf nodes correspond to the initial partition of the image, which can be the set of pixels, or a coarser segmentation map. From this initial partition, an iterative merging algorithm is applied until only one region remains, which is represented by the root node (the whole image). All the nodes between the leaves and the root corre-

spond to the merging of two children regions.

Two notions are of prime importance when defining a BPT: the *region model* $\mathcal{M}_\mathcal{R}$ which specifies how a region $\mathcal{R}$ is modelled, and the *merging criterion* $\mathcal{O}(\mathcal{M}_{\mathcal{R}_i}, \mathcal{M}_{\mathcal{R}_j})$, which is a distance measure between the region models of two regions $\mathcal{R}_i$ and $\mathcal{R}_j$. Each merging iteration involves the search of the two neighbouring regions which achieve the lowest pair-wise distance among all the pairs of neighbouring regions in the current segmentation map. Those two regions are consequently merged.

The pruning step follows the construction of the BPT. If the construction of the BPT is generic once the region model and merging criterion have been defined, the pruning of the BPT is application dependant. Consequently, different pruning strategies are very likely to lead to different results. In this operation, the branches of the tree are pruned so the new leaves correspond to the regions achieving the most meaningful segmentation in the image with respect to the desired task.

3. SPECTRAL UNMIXING

Let $\mathbf{E} = [\mathbf{e}_1, \ldots, \mathbf{e}_m]$ be the pure endmember signatures (normally corresponding to macroscopic objects in scene, such as water, soil, vegetation,…) where each $\mathbf{e}_i \in \mathbb{R}^q$ is a q-dimensional vector. Then, the hyperspectral signature $\mathbf{r}$ at each pixel in the image is defined by the expression:

$$\mathbf{r} = \mathbf{s} + \mathbf{n} = \sum_{i=1}^m \mathbf{e}_i \phi_i + \mathbf{n}, \qquad (1)$$

where $\mathbf{r}$ is given by the sum of the pixel's signal $\mathbf{s}$ and an independent additive noise component $\mathbf{n}$; and, ϕ is the m-dimensional vector of fractional per-pixel abundances at the given pixel subject to constraints: $\phi_i \geq 0, \forall i = 1, \ldots, m$, and $\sum_{i=1}^m \phi_i = 1$. This equation can be extended to the full image as $\mathbf{H} = \mathbf{E}\boldsymbol{\Phi} + \boldsymbol{\eta}$, where $\mathbf{H}$ is the hyperspectral image, $\boldsymbol{\Phi}$ is a matrix of fractional abundances and $\boldsymbol{\eta}$ is independent additive noise.

Once the set of endmembers, $\mathbf{E}$, has been induced, their corresponding abundances can be estimated by Full-Constrained Least Squares Unmixing (FCSLU). The quality of the unmixing, the estimated $\hat{\mathbf{E}}$ and $\hat{\boldsymbol{\Phi}}$, at a given pixel $\mathbf{r}$ can be measured by the Root Mean Squared Error (RMSE) of the original hyperspectral signature with respect to the reconstructed one, $\hat{\mathbf{r}} = \sum_{i=1}^m \hat{\mathbf{e}}_\mathbf{i} \hat{\phi}_i$:

$$\epsilon(\mathbf{r}, \hat{\mathbf{r}}) = \sqrt{\frac{1}{q} \sum_{j=1}^q (r_j - \hat{r}_j)^2}. \qquad (2)$$

4. BPT CONSTRUCTION AND PRUNING BY MEANS OF HYPERSPECTRAL UNMIXING

In this section, we introduce the adaptation of the BPT algorithm for hyperspectral unmixing purposes by defining a region model and merging criterion based on the induced endmembers, and two pruning strategies based on the optimization of the spectral reconstruction error.

4.1. Initial Partition

First of all, the initial partition of the image is obtained by a Watershed segmentation of the original data [5]. First, we calculate the supremum of the component-wise morphological gradient from the original image, and then we apply a classical Watershed onto this gradient map. Finally, we set all the resulting border pixels to their respective most similar connected regions.

4.2. A novel region model and merging criterion

We propose to use the following region model for the construction of the tree: for each region $\mathcal{R}$, its virtual dimensionality δ is computed using the Hyperspectral Signal Subspace Estimation (Hysime) algorithm [6]. If the region is too small to estimate δ accurately, that is if $\delta = 0$ or $\delta > N_\mathcal{R}$, being $N_\mathcal{R}$ the number of pixels in the region, then its region model $\mathcal{M}_\mathcal{R}$ is set to the mean spectrum of the region. Otherwise, the Vertex Component Analysis (VCA) algorithm [7] is run over the $N_\mathcal{R}$ pixels of the region, and a set of δ endmembers $\mathbf{E}_\mathcal{R} = [\mathbf{e}_1, \ldots, \mathbf{e}_\delta]$ is generated. In any case, the FCLSU is then conducted and the fractional abundances are estimated. Each pixel finally has its RMSE computed according to (2). To overcome the stochastic part of the VCA algorithm, the previously described procedure is run 20 times for each region, and the unmixing result with the smallest average RMSE among the 20 trials is retained.

The merging criterion between two regions $\mathcal{R}_i$ and $\mathcal{R}_j$ is given by the spectral dissimilarity between the set of endmembers of the two regions [8]:

$$\mathcal{O}\left(\mathcal{R}_i, \mathcal{R}_j\right) = s\left(\mathbf{E}_i, \mathbf{E}_j\right) = \|\mathbf{m}_r\| + \|\mathbf{m}_c\|, \qquad (3)$$

where $\|\mathbf{m}_r\|$ and $\|\mathbf{m}_c\|$ are respectively the Euclidean norms of the vectors of row and column minimal values of the between endmembers distance matrix $D_{i,j} = [d_{kl}]$, $k = 1, \ldots, \delta_i$, $l = 1, \ldots, \delta_j$, and d_{kl} is the angular distance between endmembers $\mathbf{e}_k$ and $\mathbf{e}_l$. Once two regions merge into a new one, the spectral unmixing process is run again for the new resulting region.

4.3. A novel pruning strategy for optimal segmentation

We present now two new pruning strategies based on the minimization of the average and the maximum RMSE of the unmixing process. Let $\mathcal{P}$ be a partition of the image (a pruning of the BPT) and Ω be the set of all possible partitions. Then the partition minimizing the overall average RMSE is defined as

$$\mathcal{P}^\star_{\text{mean}} = \arg\min_{\mathcal{P} \in \Omega} \frac{1}{N} \sum_{\mathcal{R}_i \in \mathcal{P}} \sum_{\mathbf{r} \in \mathcal{R}_i} \epsilon_{\mathcal{R}_i}(\mathbf{r}, \hat{\mathbf{r}}), \qquad (4)$$

(a) Average RMSE results using mBPT   (b) Average RMSE results using uBPT

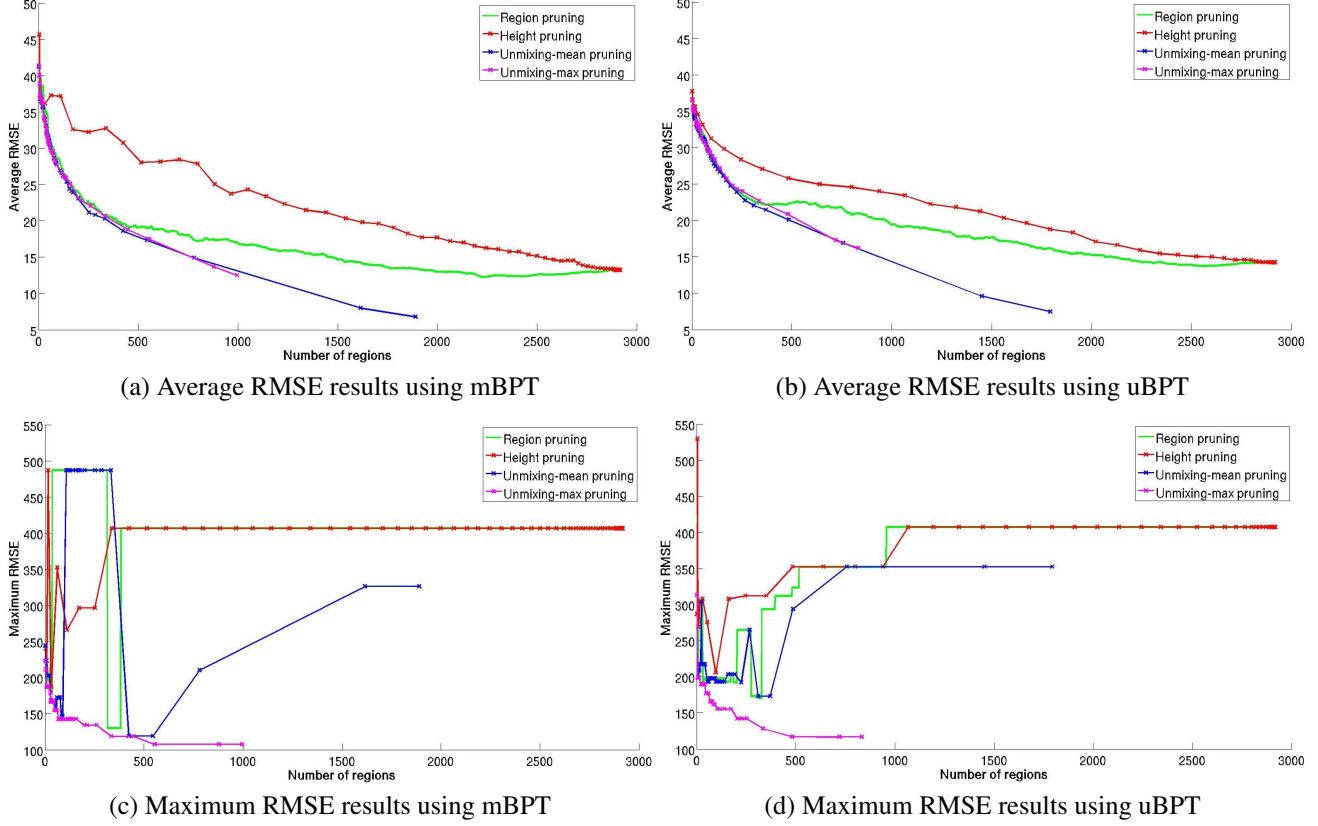(c) Maximum RMSE results using mBPT   (d) Maximum RMSE results using uBPT

Fig. 1. Results comparing the four pruning criteria.

where N is the number of pixels in the image and $\epsilon_{\mathcal{R}_i}(\mathbf{r}, \hat{\mathbf{r}})$ is the RMSE (2) for the pixel $\mathbf{r}$ given the unmixing obtained for region $\mathcal{R}_i$. Similarly, the partition minimizing the overall maximum RMSE is defined as

$$\mathcal{P}^\star_{\max} = \arg \min_{\mathcal{P} \in \Omega} \max_{\mathbf{r}} \epsilon_{\mathcal{R}_i}(\mathbf{r}, \hat{\mathbf{r}}), \forall \mathcal{R}_i \in \mathcal{P}. \quad (5)$$

Although the pruning strategies proposed above make use of the unmixing results, it is not mandatory to build the tree using the methodology proposed in section 4.2. It is possible to use, for instance, a region model based on the mean spectrum of the region and its corresponding merging criterion, and then prune the tree using the proposed pruning strategy based on (4) or (5).

5. EXPERIMENTAL METHODOLOGY AND RESULTS

5.1. Methodology

We tested the proposed approach over the well-known Cuprite hyperspectral scene [9]. The scene was taken by the NASA's AVIRIS sensor and covers the Cuprite mining district in western Nevada, USA. Given the watershed segmentation of the Cuprite scene, we built two independent BPTs, a first one using the mean region model and the spectral distance as merg-

ing criterion, denoted as mBPT; and a second one following the unmixing approach proposed in section 4.2, denoted as uBPT. In both cases, we applied different pruning strategies and compared the resulting partitions in terms of average and maximum RMSE. The *region pruning* strategy traverses the tree using an inverse order to its construction, pruning it once the number of regions in the partition reaches some given value. The *height pruning* stage prunes the tree at some given height. Finally, we applied as well the two proposed pruning strategies, the *unmixing-mean pruning* (4) and the *unmixing-max pruning* (5). For the region and height pruning strategies we made an exhaustive search of the whole partition sets obtained by them. For the unmixing-based pruning strategies we constrained the valid partitions to those with regions having a minimum size.

5.2. Results

Figure 1 shows the result of applying the four pruning criteria to the mBPT (fig.1a and 1c) and the uBPT (fig.1b and 1d). Each point in the plots represents a partition obtained by each of the pruning strategies over the corresponding BPT. In order to compare them, we plot the average RMSE (top row) and the maximum RMSE (bottom row) with respect to the number of regions contained in each partition. We can see that the four
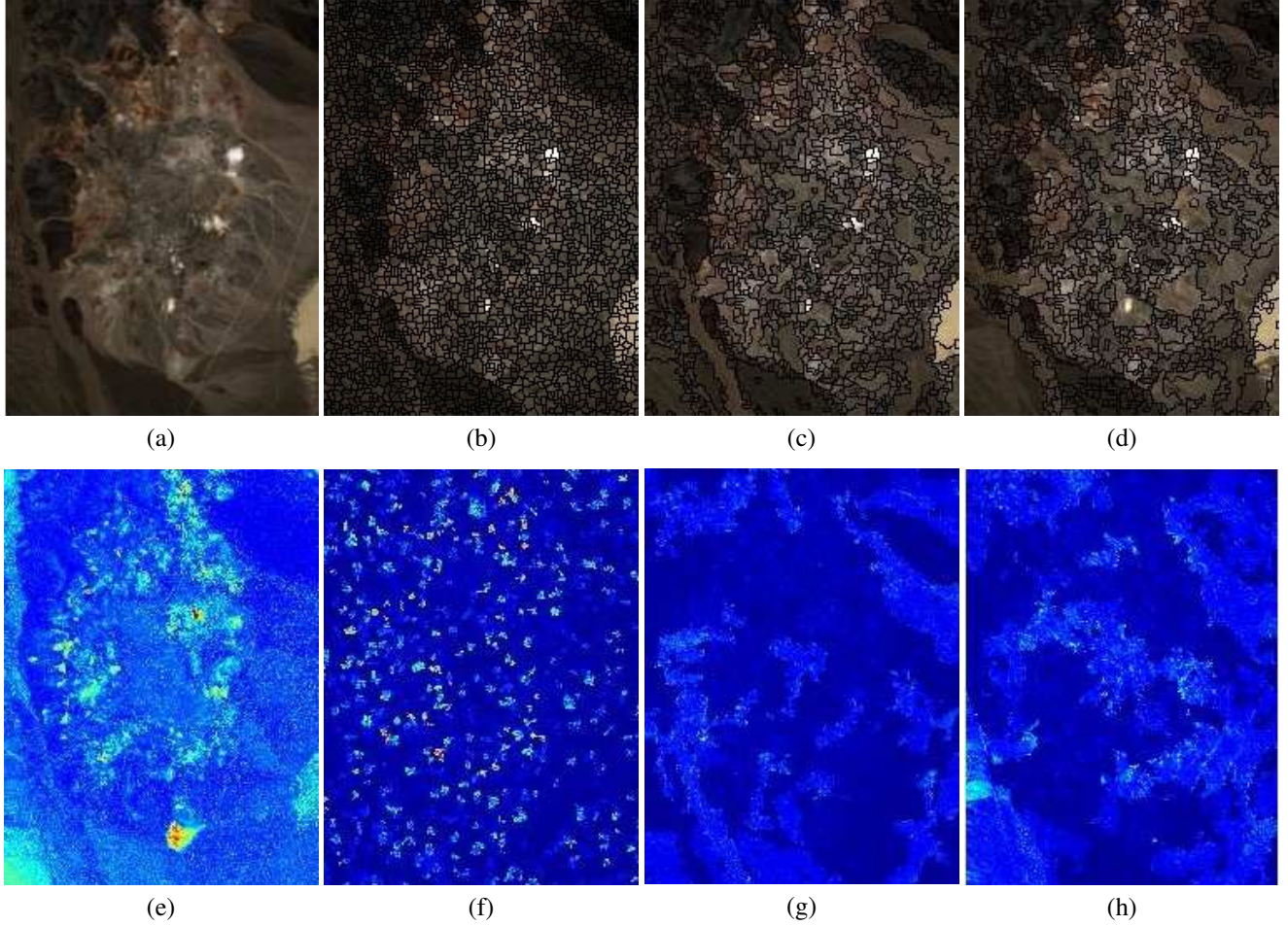
Fig. 2. Segmentation (top row) and corresponding RMSE maps (bottom row) for: (a)(e) the original image, (b)(f) the watershed segmentation, and the unmixin-max pruning using (c)(g) the mBPT and (d)(h) the uBPT.

criteria have a quasi-decreasing behaviour in terms of average RMSE as the number of regions in the partition increases, out-performing the proposed unmixing-based pruning approaches to the other two. The behaviour in terms of maximum RMSE is quite different, being the unmixing-max pruning criterion the only one that approximates to a decreasing function. The other three pruning approaches have multiple local minima, with none of them outperforming the unmixing-max pruning for the same number of regions. Overall, we can conclude that the unmixing-max pruning strategy is the best criterion to find an optimal partition in terms of unmixing reconstruction.

Figure 2 shows the segmentations (top) and the RMSE maps (bottom) given the optimal partitions obtained by unmixing-max pruning strategy without region size con-straints over both the mBPT and uBPT, compared to the original image and the partition obtained by the watershed segmentation. Watershed segmentation shows an overseg-mented map, while the unmixing-max pruning partitions show more balanced segmentation maps. RMSE images

are equally scaled on the range $[0, 200]$ (from blue pixels to red ones) so they could be fairly compared. The maximum RMSE values for the original, leaves, unmixing-max mBPT and unmixing-max uBPT respectively are: 223.68, 406.53, 107.51 and 116.66; and analogously, the average RMSE values are: 41.37, 13.26, 12.50 and 16.23; which can be considered quite low in terms of overall reconstruction errors.

6. CONCLUSIONS

We have provided novel construction and pruning strategies to build a BPT representation from a hyperspectral image that exploits the results of a spectral unmixing process. We have also given experimental evidence that minimizing the maxi-mum RMSE of the image is a good criterion to find an op-timal partition in terms of the unmixing results quality. Fur-ther work will focus on exploring the BPT representation and pruning in terms of the quality of the obtained spectral signa-tures in order to find an optimal spectral representation.

Acknowledgements

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