A COMPARISON STUDY BETWEEN WINDOWING AND BINARY PARTITION TREES FOR HYPERSPECTRAL IMAGE INFORMATION MINING

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Outline

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Image Information Mining (IIM) implies the collection, storage and exploitation of large image databases.

- Rapid increase of hyperspectral data collection.
- Major issue in remote sensing community.
- IIM for remote sensing data exploitation has not provided a satisfactory response.
- Active open field.

Hyperspectral Image Information Mining

A new challenge.

- Several hyperspectral EO and AO missions have been scheduled for the incoming years (EnMAP, PRISMA, MUSE, and so on...).
- Large amounts of data will be collected and stored.
- High spectral dimensionality of data is an additional challenge for hyperspectral IIM.

Scenes windowing (patches).

- Divide the scene in rectangular windows (patches).
- Could provoke the split of spectrally homogeneous areas.
  - Presence of objects of interest in correspondence to windows borders.
  - The fixed size of the windows does not adapt well to the scale of the objects.
- Solution : overlapping windows -> data redundancy.

Alternative : tree representations.

- Hierarchical region-based representation of images.
- First level of abstraction with regard to the raw pixelwise information.
- Atomize the image into homogeneous components and embed multiple nested segmentations.
- Interactive image content exploration.

Goal

Use of BPT for hyperspectral local spectral unmixing.

> We are particularly interested in storing the information resulting of local spectral unmixing processes running over a large real hyperspectral scene.

> We show that under similar conditions BPT allows a better storage of the unmixing information in terms of reconstruction error.

Outline

BPT representation

- The leaf nodes correspond to the initial partition of the image : the set of pixels or a coarser segmentation map.
- The root node represents the whole image.
- Iterative merging algorithm from leafs to the root.
- All the nodes between the leaves and the root correspond to the merging of two children regions.

BPT representation

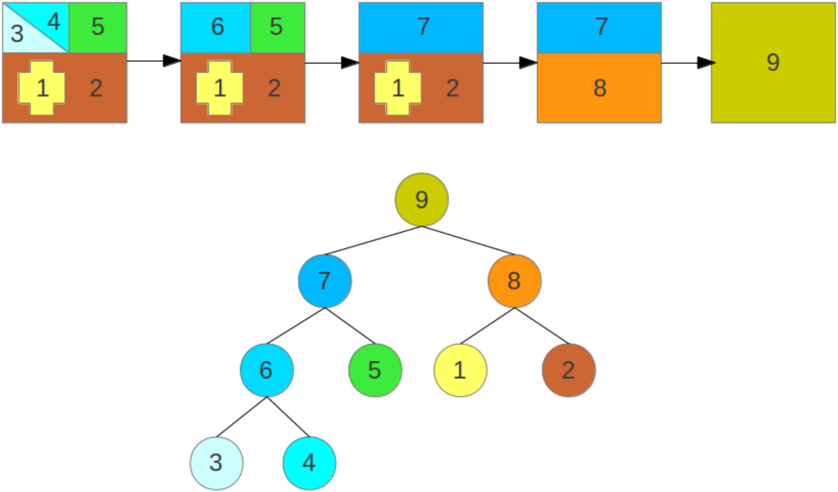

FIGURE: Construction of the Binary Partition Tree.

Region model and merging criterion

Two important notions

- The region model, $\mathcal{M}_{\mathcal{R}}$, specifies how a region $\mathcal{R}$ is modelled.
- The merging criterion, $\mathcal{O}(\mathcal{M}_{\mathcal{R}_i}, \mathcal{M}_{\mathcal{R}_j})$, is a distance measure between two adjacent region models : $\mathcal{R}_i$ and $\mathcal{R}_j$.

Hyperspectral region model and merging criterion

- Region model : First-order parametric model [1] (region spectral average).
- Merging criterion : Spectral angle distance.

[1] S. Valero, P. Salembier, and J. Chanussot, "Hyperspectral image representation and processing with binary partition trees," IEEE Transactions on Image Processing, vol. 22, no. 4, pp. 1430-1443, 2013.

Algorithm

- Set the initial partition (leaf nodes) : pixels or a coarser segmentation (e.g., watershed).
- In each iteration :
  - Search for the two neighbouring regions with lowest pair-wise distance among all the pairs of neighbouring regions in the current partition.
  - Those two regions are consequently merged : calculate the region model of the new region.
  - The partition is updated : remove the merged regions and add the new one.

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Linear mixing model

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

- Hyperspectral pixel ($\mathbf{r}$) : pixel's signal ($\mathbf{s}$) plus an independent additive noise component ($\mathbf{n}$).
- Pure endmember signatures : $\mathbf{E} = [\mathbf{e}_1, \ldots, \mathbf{e}_m]$.
- Fractional per-pixel abundances : ϕ subject to positivity and sum-to-one constraints : $\phi_i \geq 0, \forall i = 1, \ldots, m$, and $\sum_{i=1}^{m} \phi_i = 1$.

Spectral unmixing implementation

Endmember induction and fractional abundances estimation

- Endmembers induction ($\hat{\mathbf{E}}$) : Vertex Component Analysis (VCA) [2].
- Abundances estimation ($\hat{\mathbf{\Phi}}$) : Full-Constrained Least Squares Unmixing (FCLSU).
- Reconstruction error (RMSE) :

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

where $\hat{\mathbf{r}} = \sum_{i=1}^{m} \hat{\mathbf{e}}_{\mathbf{i}} \hat{\phi}_i$.

[2] J.M.P. Nascimento and J.M. Bioucas Dias, "Vertex component analysis : a fast algorithm to unmix hyperspectral data," IEEE Transactions on Geoscience and Remote Sensing, vol. 43, no. 4, pp. 898-910, 2005.

BPT pruning

- Achieve a more compact representation.
- Application dependant.
- 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.

BPT pruning

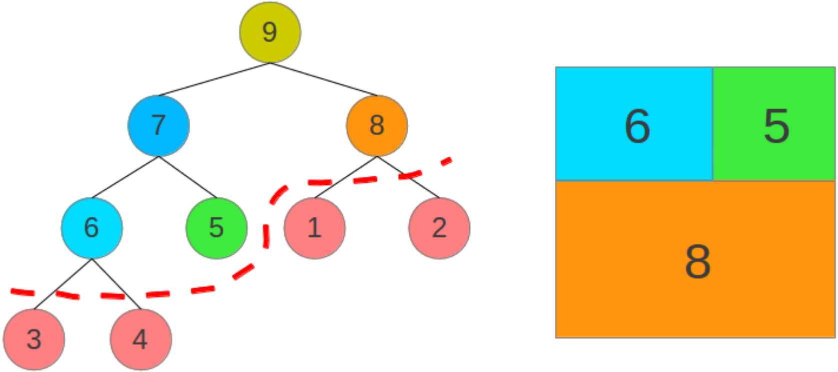

FIGURE: Pruning of the Binary Partition Tree.

BPT pruning for local spectral unmixing

- Optimal partition in terms of unmixing reconstruction error[3] :

$$\mathcal{P}^{\star}_{\max} = \arg \min_{\mathcal{P}\in\Omega} \max_{\mathbf{r}} \epsilon_{\mathcal{R}_i}\left(\mathbf{r}, \hat{\mathbf{r}}\right), \forall \mathcal{R} \in \mathcal{P} \tag{3}$$

- Minimum spatial size constraint :

$$\Omega = \{\mathcal{P}\}, \text{s.t. } \forall \mathcal{P} \in \Omega,\ \forall \mathcal{R} \in \mathcal{P},\ |\mathcal{R}| \geq c, \tag{4}$$

  where $|\mathcal{R}|$ denotes the cardinality (number of pixels) of region $\mathcal{R}$ and $c \geq 0$ is a threshold on the region size.

- If $c = 0$, the term (4) has no effect and the pruning criterion is considered to be unconstrained.

[3] M.A. Veganzones, G. Tochon, M. Dalla Mura, A. Plaza, and J. Chanussot, "On the use of binary partition trees for hyperspectral unmixing," IEEE 2013 International Conference on Image Processing (ICIP).

Outline

Dataset

Pavia university hyperspectral dataset

> Collected by the ROSIS-03 sensor over the facilities of the University of Pavia in Italy.

> Spatial size of 610x340 pixels with a spatial resolution of 1.3 m per pixel, and 103 spectral bands comprised in the range of 430-860 nm.

> Urban area : buildings, parking lots, roads and other typical human-made constructions, together with trees, green areas and bare soil.

Experimental methodology : flowchart

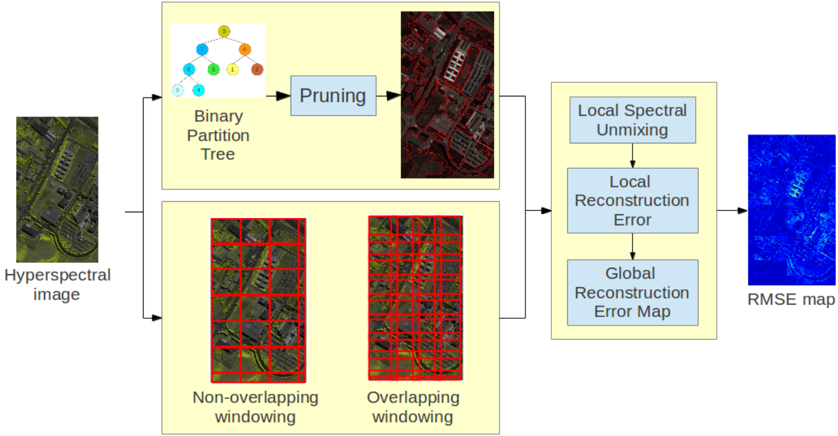

FIGURE: Proposed methodology flowchart.

Windowing

- We cut the Pavia University scene in patches using a non-overlapping windowing of increasing sizes : 16x16, 32x32, 64x64, 128x128 and 192x192.
- We also cut the scene using an overlapping windowing with increasing overlapping rate : 3, 5, 10, 20 and 30 respectively.

BPT representation

- We obtain a BPT representation of Pavia University.
- We found an optimal partition by pruning the BPT representation with minimum size threshold values, c, in the range [0,5000].

Spectral unmixing

- The unmixing results have been obtained by the VCA endmember induction algorithm and the FCLSU unmixing algorithm.
- As the VCA is an stochastic algorithm, we run it 20 times for each patch/node, keeping the results of the one achieving the minimum average Root Mean Squared Error ($\mathrm{R\hat{M}SE}$) :

$$\mathrm{R\hat{M}SE} = \sum_{i=1}^{N} \epsilon(\mathbf{r}_i, \hat{\mathbf{r}}_i). \tag{5}$$

Results I

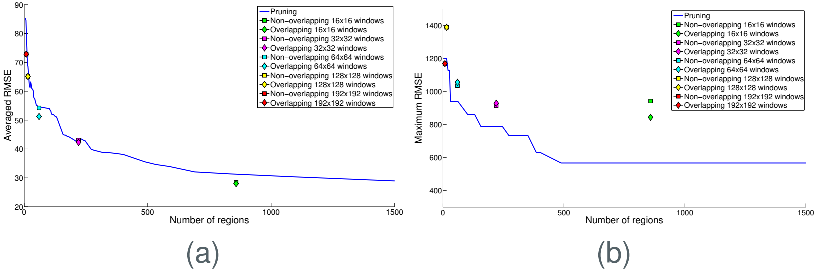

FIGURE: (a) Averaged and (b) maximum RMSE errors for the Pavia University scene, using the windowing and pruning approaches.

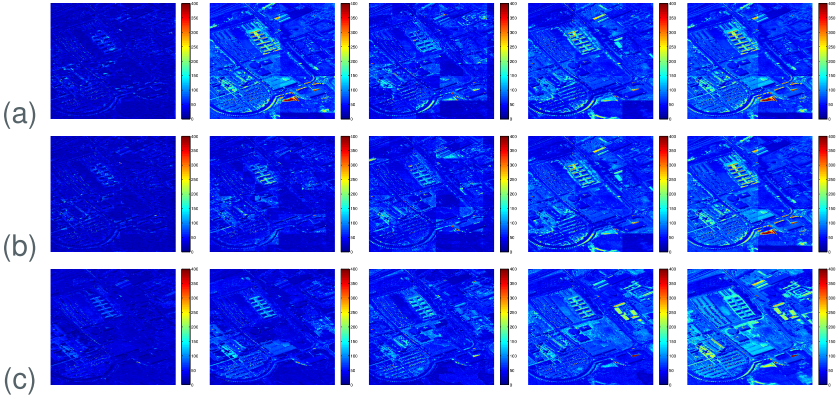

FIGURE: RMSE maps of the Pavia University scene using : (a) Non-overlapping windowing, (b) overlapping windowing and (c) pruning. Columns from left to right indicate an increasing window size.

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Conclusions I

- We propose to store the spectral unmixing information of large hyperspectral data using an optimal partition obtained by pruning a BPT representation.
- Instead of the traditional windowing patching, either with or without overlapping.
- We compared both approaches in terms of the reconstruction error using the real Pavia University hyperspectral scene.

Conclusions II

- We have shown that the pruning approach outperforms the windowing in terms of maximum RMSE, and is similar in terms of averaged RMSE.
- Solves the undesired splitting effects of the windowing (more visually appealing).
- Further work will focus on the role of the spectral information, the endmembers obtained by the unmixing process, in the BPT representation.

Thanks

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