# Hierarchical approach for neonate cerebellum segmentation from MRI

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#### **Abstract**

Morphometric analysis of brain structures is of high interest for premature neonates, in particular for defining predictive neurodevelopment biomarkers. This requires beforehand, the correct segmentation of structures of interest from MR images. Such segmentation is however complex, due to the resolution and properties of data. In this context, we investigate the potential of hierarchical image models, and more precisely the binary partition tree, as a way of developing efficient, interactive and user-friendly 3D segmentation methods. In particular, we experiment the relevance of texture features for defining the hierarchy of partitions constituting the final segmentation space. This is one of the first uses of binary partition trees for 3D segmentation of medical images. Experiments are carried out on 19 MR images for cerebellum segmentation purpose.

#### Introduction

Each year, about 15 million babies are born premature. A part of them will develop cerebral palsy while others will experiment troubles in cognitive performance or behavioral issues. This motivates an active clinical research devoted to find a correlation between early life cerebellar anatomy and neurodevelopmental disorders. In this context, Magnetic Resonance Imaging (MRI) provides an efficient way of observing the newborn brain in a safe fashion. MR images of newborns are of lower quality than with adults (lower resolution, a decreased signal-to-noise ratio, possible artifacts, partial volume effects). Methods aimed at segmenting the whole brain, cerebral tissues, or specific structures (e.g., cortex, ventricles, hippocampus), but none focused on the cerebellum [3]. Cerebellum segmentation from neonate MR images is a difficult task, both in an automated and in a manual way. We consider hierarchical image models, the Binary Partition Tree (BPT, for brief) to model the image in a multiscale way, from fine anatomical structures to larger classes of tissues.

#### **Main Objectives**

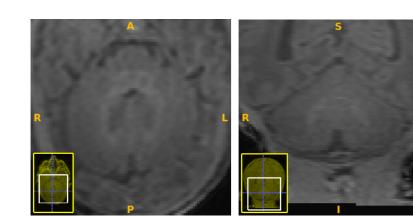
We propose a 2 step method:

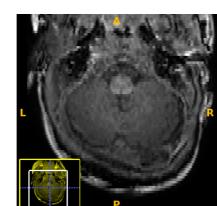
- 1. Supervoxel calcultaion: to reduce space and time complexity
- 2. BPT construction using different region descriptor based on texture

We propose a way of assessing the relevance of a promopartition and a BPT with respect to ground-truth via respectivly a discordance evaluation and a Pareto front paradigm.

# **Materials and Methods**

We worked on two MRI datasets: the Neonatal Brain Atlas (ALBERTs<sup>1</sup>), and the French Epirmex<sup>2</sup> dataset. ALBERTs data have a resolution of  $0.82 \times 0.82 \times 1.60$  mm, and dimensions  $155 \times 155 \times 189$  voxels. Epirmex data have a resolution of  $3 \times 3 \times 3$  mm, and dimensions  $560 \times 560 \times 90$  voxels.





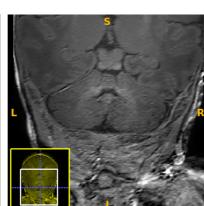


Figure 1: Examples of MR images. Two left: Epirmex. Two right: ALBERTs.

### **Initial partitioning: Waterpixels**

We considered the waterpixels [2], namely a superpixel approach that applies a seeded watershed on a mixed gradient / distance, saliency map. More precisely, we developed a 3D version of this 2D superpixel model, namely the watervoxels [1], in order to allow for a relevant partitioning of an MR image. The main two parameters of waterpixels are the density of seeds (that determines the number of elements of the partition  $\Lambda$ ) and the trade-off between the gradient map and the distance map.

### **Features for BPT construction**

The construction of a BPT requires to choose features involved in the definition of the region model (M), and a merging criterion (O) for assessing the relevance of merging two nodes / regions.

### Region model and merging criterion

Working with co-occurence matrix ind third direction and define as:

$$\mathcal{M}_{\mathbf{e}_i}(v, w) = \frac{1}{|\Omega|} \left| \left\{ x \in \Omega \mid I(x) = v \land I(x + \mathbf{e}_i) = w \right\} \right| \tag{1}$$

Using the homogeneity (H), contrast (C) and entropy (E) indices, as texture information:

$$H = \sum_{i=1}^{3} \sum_{v \in V} \sum_{w \in V} \frac{M_{\mathbf{e}_i}(v, w)}{1 + |v - w|}$$
(2)

$$C = \sum_{i=1}^{3} \sum_{v \in V} \sum_{w \in V} |v - w|^2 \cdot M_{\mathbf{e}_i(v, w)}$$
(3)

$$E = -\sum_{i=1}^{3} \sum_{v \in V} \sum_{w \in V} (v - w) \cdot \log(M_{\mathbf{e}_i}(v, w))$$

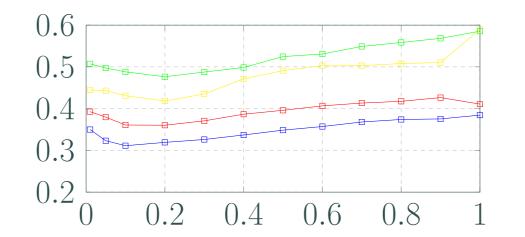
$$\tag{4}$$

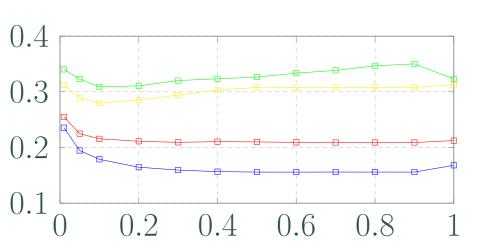
Merging criterion define as absolute difference of feature values between both regions

#### Results

#### Watervoxel partition: Parameter setting

For a given partition  $\Lambda$  of the image support  $\Omega$ , we define the associated error  $\delta$  based on a measure called discordance, introduced in [5]. For the ground-truth segmentation  $C \subset \Omega$  of the cerebellum, and the partition  $\Lambda \subset 2^{\Omega}$ , we use the DICE.

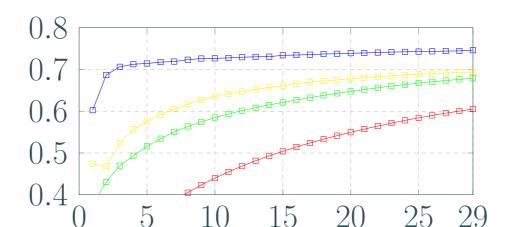


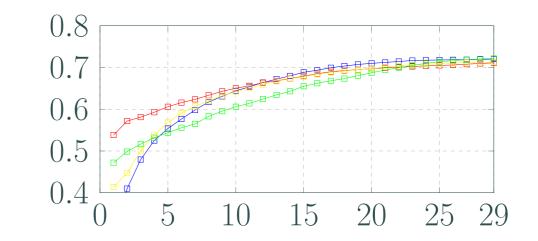


**Figure 2:** Discordance  $\delta$  (y-axis) depending on the trade-off parameter  $\alpha$  between the gradient map and the distance map (x-axis), for various densities d. Left: Epirmex dataset. In blue:  $d=2,32.10^{-3}$  (initial Voronoi cells of  $12\times12\times3$  voxels). In red:  $d=1,11.10^{-3}$  ( $15\times15\times4$  voxels). In yellow:  $d=5,54.10^{-4}$  ( $19\times19\times5$  voxels). In green:  $d=3,15.10^{-5}$  ( $23\times23\times6$  voxels). Right: ALBERTs dataset. In blue:  $d=1,56.10^{-2}$  (initial Voronoi cells of  $4\times4\times4$  voxels). In red:  $d=8,00.10^{-3}$  ( $5\times5\times5$  voxels). In yellow:  $d=2,92.10^{-3}$  ( $7\times7\times7$  voxels). In green:  $d=1,95.10^{-3}$  ( $8\times8\times8$  voxels).

#### **Segmentation / BPT evaluation**

The quality of a cut  $\mathcal{C}$  / segmentation  $\mathcal{S}$  is characterized from two points of view. First,  $\mathcal{S}$  has to fit at best the target (here the cerebellum C), i.e. it should maximize a quality measure [4]. Here, we consider the Dice index, defined as :  $D(\mathcal{S}, C) = \frac{2|\mathcal{S} \cap C|}{|\mathcal{S}| + |C|}$  Second,  $\mathcal{C}$  should contain a minimal set of nodes.





**Figure 3:** Pareto front (Dice D in y-coordinate vs. size of the cut |C| in x-coordinate) for the BPTs constructed with the four texture features  $\mu$  (in blue), H (in red), C (in yellow) and E (in green). The results are obtained by averaging the Dice values over the datasets Left: Epirmex dataset. Right: ALBERTs dataset.

### **Conclusions**

- Resolution of the MR images has a strong influence on the relevance of using texture features for BPT construction
- For Epirmex data, due to a low resolution, texture features are not able to guide the BPT construction process better than the standard mean feature  $(\mu)$ .
- In the case of ALBERTs, i.e. with MR images of higher resolution, one can observe that Homogeneity (H) provides better results than the standard mean feature  $(\mu)$  up to cuts of 10 nodes.

### **Forthcoming Research**

We will experiment various paradigms of gradient, in order to improve the ability of the watervoxel preprocessing to provide initial partitions with greater voxel sizes. We will investigate BPTs built from several features, instead of one. This will allow us to couple texture features, but also to mix them with prior knowledge modeled by atlases. Further works will also consist of developing visualization / interaction paradigms to allow a medical expert to easily navigate within a BPT, and observe / define in real time the segmentation associated to a given cut in 3D MR images.

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