Automatic Brain Segmentation Method based on Supervoxels

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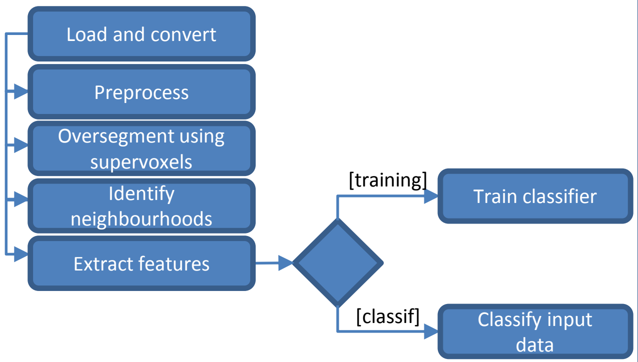
Motivation and goal

Goal:
- Segment human brain MR volume into white matter (WM), grey matter (GM) and cerebrospinal fluid (CSF).

Motivation:
- Segmentation quality directly influences diagnostics.
- Manual segmentation is extremely time-consuming even if performed by experienced radiologists.
- Examples of segmentation use cases: regional brain volume estimation in Multiple Sclerosis, tumor volume measurement, brain change analysis, surgical planning, etc.

Method overview



Preprocessing

Main goals of preprocessing in our method are to ***increase success rate of supervoxel classification*** and to ***decrease computational complexity*** of training and classification. Therefore we perform two preprocessing steps:
- Incorporate **prior knowledge** that supervoxels that have average intensity below 2 (before normalization) belong to background.
- **Remove skull, eyes and other non-brain tissues** using BET [1] (Fig. 1) preserving brain voxels.

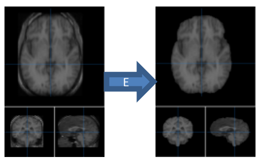


Figure 1. Skull stripping performed by BET

BET has two main parameters – Intensity threshold (IT) and Threshold gradient. We adjusted IT to maximize equation (1) and minimize inequality (2).

$$s = 1 - \frac{|NONBRAIN - REMOVED|}{|NONBRAIN|} \quad (1)$$

$$0.0075 \leq \frac{|REMOVED \cap BRAIN|}{|BRAIN|} \quad (2)$$

Oversegmentation and supervoxels

- **SLIC** algorithm [2] with supervoxel **size 120** and **compactness 6**
- Oversegmentation success rate is defined in equation (3)

$$s = \frac{1}{N} \sum_{s \in SV} \frac{major(s)}{size(s)} \quad (3)$$

- Oversegmentation success is higher for smaller supervoxels. Nevertheless, small supervoxels contain only limited information.

Features extraction

Features are based on intensity and position of supervoxel:
- Normalized intensity histogram of voxels in supervoxel.
- Normalized intensity histogram of neighbouring supervoxels.
- Normalized Euclidean distance of supervoxel centroid from the brain centre.
- Angle between supervoxel centroid and brain centre in XY, XZ and YZ plane.

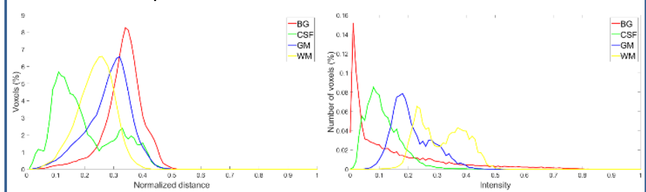


Figure 4. Left - distribution of normalized Euclidean distances of supervoxels of individual tissues from brain centre. Right – normalized intensity histogram of individual tissues.

Classification

- Each supervoxel is assigned to either BG, CSF, GM or WM.
- We train multilayer perceptron (MLP) with two hidden layers, sigmoidal activation function and Levenberg–Marquardt training function.
- In training process, we do not include supervoxels having less than 87% voxels from single class.
- Supervoxels with mean intensity <= 2 are a priori background.

Results, conclusion and future work

- IBSR-18 dataset, all supervoxels divided in ratio 80:20 (train:test)
- Results are promising and clearly comparable to state-of-the-art (Tab. I)

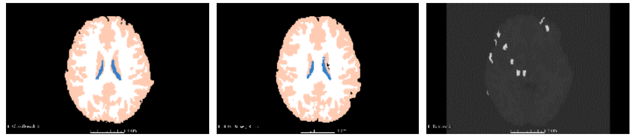
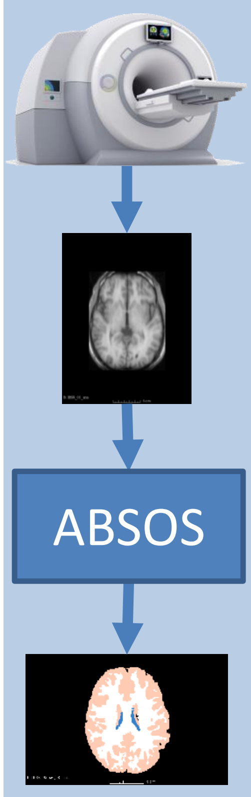


Figure 5. Segmentation result and areas with low MLP excitation rate

Tissue	CSF	GM	WM
DSC	0.67	0.86	0.85
SITDS (DSC)	0.67	0.86	0.89

Table I. Comparison with current state-of-the-art method SITDS [3]

Conclusion and future work:
- In this work we propose a fully automatic method for segmentation of brain from MR images.
- Supervoxels with higher oversegmentation error have higher standard deviation and lower MLP excitation rate. In future work we are going to use this information to identify potentially oversegmented and/or misclassified supervoxels and either split them into smaller supervoxels or use some other segmentation technique, e.g. majority voting using non-rigidly registered atlases. Next option is to use and evaluate performance of another oversegmentation algorithm.



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[1] S. M. Smith, "Fast robust automated brain extraction," Human brain mapping, vol. 17, no. 3, pp. 143–155, 2002.
[2] R. Achanta, A. Shaji, K. Smith, A. Lucchi, P. Fua, and S. Susstrunk, "Slic superpixels," Tech. Rep., 2010.
[3] Y. Kong, Y. Deng, and Q. Dai, "Discriminative clustering and feature selection for brain mri segmentation," IEEE Signal Processing Letters, vol. 22, no. 5, pp. 573–577, May 2015.