Automatic Brain Segmentation Method based on Supervoxels

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***Abstract*—In this work, we present a fully automatic brain segmentation method based on supervoxels (ABSOS). We propose novel features used for classification, that are based on distance and angle in different planes between supervoxel and brain centre. These novel features are combined with other prominent features.**

The presented method is based on machine learning and incorporates also a skull stripping (cranium removing) in the preprocessing step. Neural network - multilayer perceptron (MLP) was trained for the classification process. In this paper we also present thorough analysis, which supports choice of rather small supervoxels, preferring homogeneity over compactness, and value of intensity threshold parameter used in preprocessing for skull stripping. In order to decrease computational complexity and increase segmentation performance we incorporate prior knowledge of typical background intensities acquired in analysis of subjects.

***Keywords*—Supervoxel, brain mri segmentation, IBSR, positional feature, supervoxel classification, WM, GM, CSF.**

I. Introduction

In radiology and neurology, segmentation of brain tissues into cerebrospinal fluid (CSF), grey matter (GM) and white matter (WM) is an important part of clinical diagnostics as it allows to extract and examine only tissues of interest. Brain segmentation is often used as a preprocessing step in medical image processing pipeline.

Input images acquired by magnetic resonance (MR) devices suffer from specific kinds of noise (e.g. periodical noise or partial volume) or other distortion. Moreover, inhomogeneity in magnetic field produced by MR causes intensity inhomogeneity where the intensity level of a single tissue class varies gradually over the extent of the image [1].

In recent years, techniques based on oversegmentation using superpixels or supervoxels have grown in importance. Supervoxels are segments in 3D space which are expected to create homogeneous regions of a given size and, despite this, the supervoxel edges should follow the natural intensity gradients in data. Supervoxels can be characterized by different kinds of statistic-based features including those based on intensity, texture, shape and position in MR volume.

In this paper, we propose a method for segmentation of brain tissue from MR image stack and its classification into four classes: {WM, GM, CSF, BG}. The proposed method, ABSOS, is a fully automatic and based on supervoxels. Supervoxels are classified using the MPL neural network and they are described by set of features $fsv = \{$*Normalised intensity histogram, Normalised intensity histogram of voxels in neighbouring supervoxels, Normalized Euclidean distance from brain centre, Angles between supervoxel centroid and brain centre*$\}$.

A. Segmentation in 3D medical imaging

Segmentation of medical volumes can be performed in two different ways: either directly in three-dimensional space or slice-by-slice, assigning a class label to each pixel in a slice.

Used similarity metrics could be based on intensity, brightness or colour and also could be extended by more complex metrics which are based on neighbouring voxels. In [2] authors use average intensity of neighbouring pixels, differences of maximum brightness values and differences of five minimum brightness values. In some cases, mutual distance of voxels is important, especially if voxels from the same class are positioned in some specific location (e.g. location of thalamus relatively to the centre of brain).

B. Oversegmentation and supervoxels

In medical imaging, a common volume consists of millions of voxels. Oversegmentation using supervoxel reduces the redundance in the data and decreases the computational complexity by several orders of magnitude. Another benefit is that supervoxels can be easily described by a set of statistical features [3].

In addition to qualities of supervoxels defined in [4] we also find homogeneity of a supervoxel important. In other words, intra-supervoxel variance should be minimized.

II. Related work

Almost twenty years ago authors in [5] proposed an adaptive algorithm using knowledge of tissue intensities and EM for MRI data segmentation. Since then, an appreciable amount of brain segmentation methods has been proposed. Methods are based on different segmentation techniques, such as thresholding [6], region-growing [7], edge based techniques, atlases [8] or active contour [9]. With increase of computational performance more advanced and computationally expensive techniques could be used, such as Markov Random Field (MRF) or Self-Organizing Map (SOM). From another perspective, segmentation methods and techniques can be based on statistics, prior knowledge (e.g. intensity distribution) or on their combination [10].

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In [3], Lucchi et al. segmented mitochondria in electron microscopy image stacks. The authors first over-segmented 3D data and then merge these groupings (supervoxels) according to their similarity. Intensity histograms of voxels and neighbouring supervoxels were chosen as similarity criteria.

Authors in [11] used intensity histogram in combination with features that described texture and shape of a supervoxel, creating a feature vector with length 228.

Combination of prior information of relative overlap between tissue intensity distributions in MRI, spatial information and probabilistic atlas maps is the base of [10]. Authors observed that the overlap between tissue pairs is relatively stable among MR volumes and that the overlap extent differs among tissue pairs. This prior knowledge in combination with adaptive tissue priors initialized by probabilistic atlases is used in Bayesian decision theory framework. Authors in [2] segmented T2 MR images into CSF, GM, WM. Authors based their method on 1-D SOM and Adaptive Resonance Theory (ART). In this method brightness difference of brain tissues is widely used. Authors claim that brightness of pixels is the most informative property. As a feature vector not the brightness of individual pixel is used, but characteristics of whole neighbourhood of pixel, called block. Four features were proposed: brightness, average brightness in block, difference of maximum and difference of minimum.

In [9] authors incorporate region-based active contour/surface model for MR brain segmentation. Method balances between global and local intensity information. If the segment contour is close to boundary, local intensity term grows in importance. When the contour reaches boundary, it stops there. Method is evaluated on standard Brain Web[12] dataset. Authors claim promising results - Jaccard similarity coefficients for CSF, GM and WM are 0.77, 0.79 and 0.87.

Especially in last few years, many segmentation methods using oversegmentation to superpixels or supervoxels have been presented [3], [11], [13]. In May 2015 Kong et al. [11] published "SITDS", a supervised method for brain segmentation from MRI. Supervoxels obtained using SLIC were used as the unit of segmentation. "SITDS" incorporates discriminative clustering, which handles intra-class variability in order to maximize the margin among clusters and a set of initial labels. The goal of the method is to assign a label to every supervoxel. Algorithm is initialized by k-means. Next, labels are iteratively re-assigned, maximizing mutual information between labels and supervoxels.

III. Method overview

In this paper we propose ABSOS, a method for segmentation of brain tissue from MR image stack and its classification into four classes: {WM, GM, CSF, BG}. The method is divided into two main phases – Training phase and Classification phase. Both phases start with the same five steps: Data loading and conversion, Preprocessing, Oversegmentation, Identification of neighbourhoods and Features extraction. Then Training phase continues with Training of MLP and Classification phase with Classification.

TABLE I: Intensity threshold (IT) influence on BET.

IT	Missing brain vox. (%)	Remaining non-brain vox. (%)
0.3	0.5254	2.4595
0.4	1.5555	1.4548
0.5	3.9954	0.5473
0.6	7.9358	0.2109

A. Data description

There are two dataset that are commonly used for this evaluation of performance of brain segmentation methods, IBSR[14] (real world examinations) and Brain Web [12] (synthetized). In this paper we use IBSR dataset for evaluation.

IV. Preprocessing

As volumes in IBSR-18 vary in dynamic range, all data are normalized into interval [0,1] using quantile normalization. In order to avoid the usage of noisy values in normalization process, we consider all values above $Q_{0.99999}$ equal 1.

Main goals of preprocessing in our method are to increase success rate of supervoxel classification and to decrease computational complexity of training and classification. We incorporate prior knowledge that supervoxels that have average intensity below 2 (before normalization) belong to background. Removal of skull, eyes and other non-brain tissues can dramatically decrease time needed for training and classification, too. In [6] authors proposed Brain extraction tool (BET) for this purpose]. We use a BET plugin[1] in Multiimage Analysis GUI application (Mango)[2]. This implementation has two main parameters – Intensity threshold and Threshold gradient. There are two main requirements that we lay on this step:

- Remove significant number of non-brain voxels from processed volume (maximize eq. (1))
- Must not remove more than 0.75% of voxels belonging to brain (eq. (2))

If we remove every voxel from volume, we will maximize the equation (1), which would obviously lead to volume consisting only of one segment. Therefore, we set the second requirement, which satisfaction guarantees that after this preprocessing step almost all brain voxels stay in the preprocessed volume.

$$s = 1 - \frac{|NONBRAIN - REMOVED|}{|NONBRAIN|} \tag{1}$$

$$0.0075 \leq \frac{|REMOVED \cap BRAIN|}{|BRAIN|} \tag{2}$$

We thoroughly evaluated influence of Intensity threshold (Threshold gradient is set to default value). Based on evaluation results (Table I) we decided to use BET with intensity threshold equal 0.3.

[1] http://rii.uthscsa.edu/mango/plugin_jbet.html
[2] MangoHomepage:http://rii.uthscsa.edu/mango/

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V. Oversegmentation using supervoxels

To oversegment image into supervoxels, we decided to use SLIC algorithm proposed in [15] and compared SLIC to other state-of-the-art superpixel and supervoxel algorithms in [4].

Supervoxels, represented by statistical data of included voxels, in its nature resist to noise better than single voxels. In [9] authors also use neighbouring pixels to describe single pixel, but they do it in 2D space. Our approach models supervoxel in context of 3D neighbourhoods.

In ideal case a supervoxel should contain only voxels belonging to the same tissue. Success rate of supervoxelization in terms of homogeneity of supervoxels can be expressed by following equation:

$$success = \frac{1}{N}\sum_{s\in 1}^{N}\frac{major(s)}{size(s)} \tag{3}$$

where N is number of supervoxels, $size(s)$ is size of the supervoxel s, $major(s)$ is number of voxels that belong to the most occurring class in a supervoxel s. We have also evaluated eq. (3) corresponding to the classes, because the number of supervoxels belonging to background was much higher than the number of supervoxels belonging to other classes {WM, GM, CSF}.

SLIC allows to set desired size and compactness of supervoxels. The outcomes of our analysis were used for the parameters setting. For compactness equal to 6 at fixed supervoxel size reaches the success rate defined in eq. (3) its maximum. We adopted this value and used it in oversegmentation procedure. Although very small supervoxels maximize 3, we decided to use supervoxel size 120 in order to balance oversegmentation success rate and amount of information in supervoxel. In our method supervoxel S1 and S2 is considered a neighbour of S2 if at least one voxel from S1 is in 8-neighbourhood with at least one voxel from S2 in a single slice of volume.

VI. Features extraction

In case of supervoxel we can characterize its neighbours much more descriptive than in case of a voxel. We propose to describe supervoxel with following features:

- Normalized intensity histogram of voxels in supervoxel (24 bins)
- Normalized intensity histogram of all voxels in neighbouring supervoxels (24 bins)
- Normalized Euclidean distance of supervoxel centroid from the centre of the brain
- Angle between supervoxel centroid and brain centre in XY, XZ and YZ plane

If a supervoxel is surrounded by supervoxels with intensity histograms typical to some class (e.g. GM) it is a good chance that the supervoxel will also belong to the same class. On the other hand if, intensity histogram of neighbours contains intensities from all classes it is clear that the classified supervoxel lies on the boundary of some tissue.

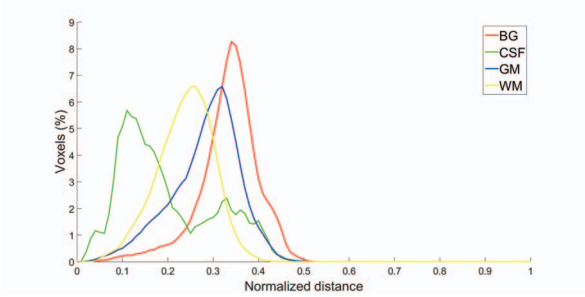

Figure 1: Distribution of normalized Euclidean distances of supervoxels of individual classes from brain centre. Supervoxels having mean intensity equal to 0 are ignored.

Normalized Euclidean distance of supervoxel centroid from the centre of the brain, is based on morphology of brain. Outer boundary of GM and CSF is typically the most distant from the centre of the brain. On the other hand, some structures belonging to CSF are closer to centre. Distributions of normalized distances between centroids of supervoxels and brain centre can be seen in Fig. 1. Distance is calculated as:

$$dist = \frac{\sqrt{(x_s - x_b)^2 + (y_s - y_b)^2 - (z_s - z_b)^2}}{norm} \tag{4}$$

$norm$ denotes normalization term equal to:

$$norm = \sqrt{(\frac{max(x)}{2})^2 + (\frac{max(y)}{2})^2 + (\frac{max(z)}{2})^2} \tag{5}$$

x_s, y_s and z_s are coordinates of supervoxel, x_b, y_b and z_b are coordinates of brain centre, $norm$ is normalization term and $max(x/y/z)$ is maximal coordinate in MR image in a particular direction.

Many supervoxels belonging to different classes have similar distance from brain centre. Therefore, we added three angles between the centroid of supervoxel and brain centre (in XY, XZ and YZ plane). In combination with the distance from brain centre, position of supervoxel is described much more precisely and uniquely.

VII. Classification

Each supervoxel is assigned to either BG, CSF, GM or WM. In training phase, we train multilayer perceptron (MLP) with two hidden layers, sigmoidal activation function and Levenberg–Marquardt training function. A significant number of supervoxels consists of voxels from even more than two different classes. In training process, we do not include supervoxels having less than 87% voxels from single class and in overall classification we do not include supervoxels having mean intensity equal less than 2 (a priori background).

VIII. Results

For training, classification and evaluation purposes, we took supervoxels from all subjects in IBSR-18 and split them to training set and testing set (80:20). Proposed method is compared with the current state-of-the-art method SITDS [11] using the same evaluation metrics – DSC. The authors compared SITDS using the IBSR-18 with other state-of-the-art

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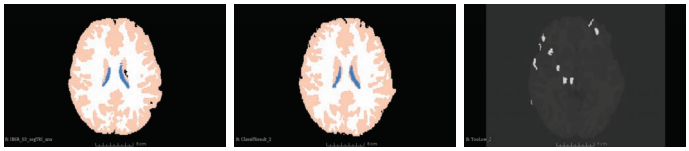

(a) Ground truth (b) ABSOS segmentation (c) Low MLP excitation

Figure 2: Segmentation result. (c) highlights supervoxels that excited MLP in rate lower than 0.9.

methods and reported the best results. We thoroughly evaluated performance of proposed method for every tissue individually (Table II) and conclude that our results are clearly comparable to those of current state-of-the-art methods.

TABLE II: Performance comparison of ABSOS measured using Dice similarity coefficient (DSC).

Tissue	**CSF**	**GM**	**WM**
DSC	0.67	0.86	0.85

Performance of proposed method can be increased even more. In classification evaluation we observed that misclassified supervoxels tend to have bigger standard deviation, lower percentage of major class voxels and lower MLP excitation rate (Table III). Therefore, we can identify missclassified supervoxels, split them and classify individually. We assume that such supervoxels will be more homogeneous.

TABLE III: Correctly classified supervoxels have greater MLP excitation and major class percentage. Contrary, intensity standard deviation is lower among them.

	Intens. stand. dev.	**Major class perc.**	**MLP excit. rate**
Correct	8.1692	92.67%	0.9883
Missclass	10.0361	72.50%	0.8964

We also trained second MLP using all supervoxels from subjects 3-15 of IBSR-18. Subsequently, we segmented subject 3 from IBSR-18. Results can be seen in Fig. 2.

IX. Conclusion

In this paper we propose a fully automatic method for segmentation of brain from MR images, ABSOS. Supervoxels are classified into four classes {BG, CSF, GM, WM} and they are described by set of features *fsv* = {*Normalised intensity histogram, Normalised intensity histogram of voxels in neighbouring supervoxels, Normalized Euclidean distance from brain centre, Angles between supervoxel centroid and brain centre*}. As shown in Table II, our results are promising in context of current state-of-the-art methods and proposed method (as is) is going to be subject of further research.

Supervoxels with higher oversegmentation error (which tend to be misclassified, too) have higher standard deviation and lower MLP excitation rate. We are going to use this information to identify potentially oversegmented and/or misclassified supervoxels and either split them into smaller supervoxels (which will be classified individually) 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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