Automated Tissue Segmentation in Cranial MR Imaging

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Introduction

Magnetic resonance imaging is currently a widely applied technique for visualization of the human brain. MR images offer a large utility in diagnosis and treatment of brain diseases. In addition to the detection of abnormalities, an increasing interest is seen in quantitative determination of intracranial lesions (WMLs) (i.e. volume rather than number of white matter lesions), cerebro-spinal fluid (for atrophy research), white matter (WM) and gray matter (GM). Therefore, accurate segmentation of different brain tissues and pathologies is of high importance for many studies. In this study we propose a new method for segmentation of five types of brain tissue simultaneously: WM, GM, cerebro-spinal fluid without ventricles (CSF), ventricles (VENT) and WML. The method is fully automatic, and based on the K-Nearest Neighbor (KNN) classification technique using multi-spectral information.

Methods

The algorithm uses two types of regular MRI-scans: T1-weighted inversion recovery (IR) and Fluid Attenuation Inversion Recovery (FLAIR) scans. Ten patients with arterial vascular disease were included in this study. Manual segmentations of the five tissue types were used for the learning of the system and considered as gold standard. Two preprocessing steps were performed on the data: (1) Rigid registration[1] (intra patient) and (2) the generation of a brain mask by the brain extraction tool[2], dilated by three voxels in x an y direction. Voxels were classified by the KNN-classification method (K=100), which generated five probabilistic segmentations (probability maps), which indicated per voxel the probability being one of the tissue classes, with two types of features: (1) Voxel intensity values of the two different scans, (2) spatial features: coordinates x, y and z. Binary segmentations were generated by applying thresholds to the probability maps. Evaluation was performed by comparison of the segmentations with the manual segmentations. The similarity index[3] (SI) over the binary segmentations was calculated, as well as the probabilistic similarity index (PSI) over the probability map. The SI and the PSI are defined by:

$$\mathrm{SI} = \frac{2\times(Ref \cap Seg)}{Ref + Seg} \qquad \text{and:} \qquad \mathrm{PSI} = \frac{2\times\sum \mathrm{P}_{x,\,gs\,=\,i}}{\sum 1_{x,\,gs\,=\,i} + \sum \mathrm{P}_x},$$

with: Ref: the area the tissue type in the reference (gold standard), Seg: the segmentation area, $\sum \mathrm{P}_{x,\,gs\,=\,i}$: Sum over all voxel probabilities, where in the gold standard (= manual segmentation) the voxel value = i (i = 1, 2, 3, 4 or 5); $\sum 1_{x,\,gs\,=\,i}$: Sum over all voxels with voxel value i in the gold standard; $\sum \mathrm{P}_x$: Sum over all probabilities in the probability map of tissue type i.

Results

Figure 1 shows an example image of the classification result. Figure 2 shows the ROC-curves for the segmentations of the five tissue types, with thresholds running from 0 to 1. Table 1 shows the sensitivity, specificity and SI of the binary segmentations, and the PSI of the probabilistic segmentations.

Discussion

KNN-classification, combining spatial information with voxel intensities, offers a strong and flexible technique for segmentation of brain tissue in MR imaging. It provides the opportunity to segment different tissue types simultaneously with highly accurate results. This study has shown that the IR and FLAIR images together are well suitable for the segmentation of WM, GM, CSF, VENT and WML. Apparently, the gray matter-white matter separation in the IR, and the tissue and lesion discriminating quality of the FLAIR form an proper combination for segmentation of different tissue types. In conclusion, KNN-classification provides a convenient multi-spectral technique to segment different brain tissue types, using a limited number of different MR images. The proposed method is fully automated and straightforward, in the sense that little preprocessing and no postprocessing steps are incorporated. Therefore, it is suitable for brain segmentation problems in a large and longitudinal population studies.

Table 1. Similarity measures of the segmentations of different tissue types

Tissue type	Sensitivity	Specificity	SI	PSI
WM	0.924	0.920	0.892	0.852
GM	0.878	0.918	0.832	0.769
CSF	0.875	0.958	0.842	0.764
VENT	0.902	0.998	0.909	0.849
WML	0.815	0.999	0.808	0.717

REFERENCES: *[1] F Maes, et al. IEEE Trans. Med. Imaging **16:** 187-198 (1997); [2] SM Smith, et al. Human Brain Mapping **17:** 143-155 (2002); [3] LR Dice. Ecology **26:** 297-302 (1945).*

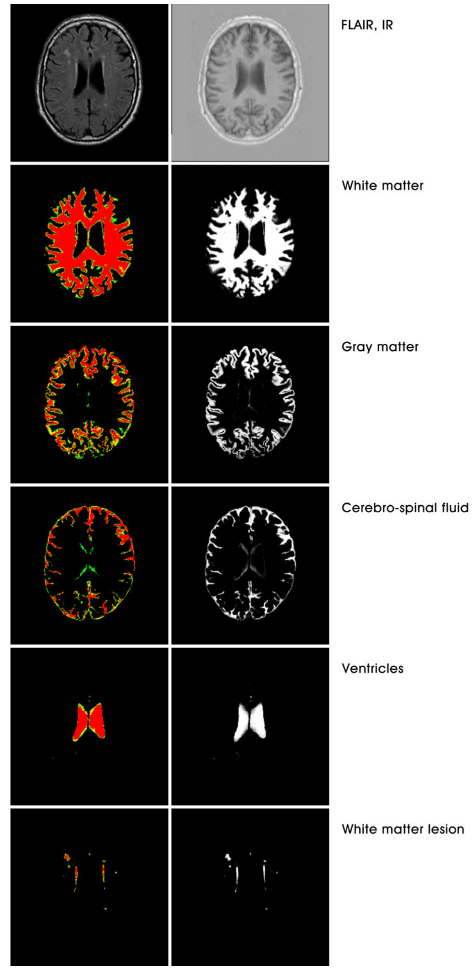

Figure 1: Classification of five tissue types; left image: black: probability (p) <= 0.3, green: 0.3 < p <= 0.5, yellow: 0.5 < p <= 0.8, red: 0.8 < p <= 1; right: gray levels indicate probability running from 0 (black) to 1 (white).

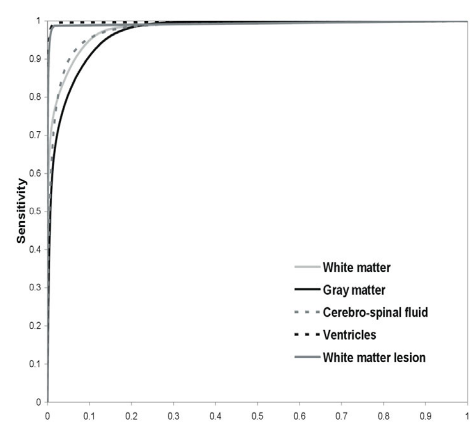

Figure 2: ROC-curves of five tissue types for thresholds running from 0 to 1
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