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FUZZY MODELING OF KNOWLEDGE FOR MRI BRAIN STRUCTURE SEGMENTATION

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ABSTRACT

In this paper, we propose a novel automatic method based on fuzzy modeling of knowledge to segment brain structures in MRI (Magnetic Resonance Imaging) images. The segmentation is achieved by the region-wise classification using GAs (Genetic Algorithms), followed by the voxel-wise refinement using parallel region growing. To improve the accuracy of the labeling, we introduce a fuzzy model of ROI (Regions Of Interest) by analogy with the electrostatic potential distribution, to represent more appropriately knowledge of shape, distance and reaction between structures, and to estimate more reliably the statistical moments. This modeling is also used in the design of the fitness function of GAs, and the criteria of the region growing. The performance of our proposed method has been quantitatively validated by 4 indexes with respect to manually segmented images.

1. INTRODUCTION

Segmentation of neuroanatomic structures in MRI (Magnetic Resonance Imaging) brain images, is an indispensable prerequisite for quantitative morphometric analysis, 3-D volume visualization, and measurements of the correlationship between brain structures and functions, particularly in clinical investigations, such as pathology, diagnosis, therapy and surgery planning [1]. However, this segmentation is complicated by the difficulties due to overlapping intensities between different structures (e.g., intensities of caudate, thalamus, and putamen), anatomical variabilities in shape, size, and orientation of structures, partial volume effect, as well as noise perturbations, intensity inhomogeneities, and low contrast in images.

Two important strategies reported in recent years are: the registration-segmentation paradigm [2, 3], and the shape model-based segmentation [4, 5, 6]. The performance of the first strategy over-relies on the accuracy of image registration, suffering from insufficient precision in the transformation, and from anatomical variabilities (for instance, in intensity, orientation, scale, shape, size and position). Furthermore, the one-to-one mapping does not always exist for registration [2]. The performance of the second strategy is spoilt by the mismatching between a geometric model and the MRI gray level data.

Our aim is to develop a novel automatic method to segment precisely and reliably neuroanatomic brain structures of interest, using fuzzy modeling of knowledge derived from the Talairach atlas [7]. The Talairach atlas is well-accepted in medical image processing, owing to its contribution to the delineation and labeling of numerous neuroanatomic brain structures (see Fig.1(a) with a sample image).

2. PROPOSED METHOD

2.1. Outline

The outline of our method is:

– first, to pre-process MRI images with skull removal, noise suppression by anisotropic filtering, and intensity inhomogeneity correction; then to oversegment images into three brain tissues: cerebrospinal fluid (CSF), gray matter (GM), and white matter (WM) using fuzzy Markov random field (MRF) [8].

– second, to indicate the coarse location of neuroanatomic structures by registering, and thus superimposing the atlas onto the images.

– third, to classify those regions obtained from oversegmention in the first part into brain structures using genetic algorithms (GAs), followed by a voxel-wise refinement using parallel region growing; the region growing is guided by the obtained knowledge.

The third part is the backbone of this work, in which we devised a fuzzy model of regions of interest (ROI) to represent structural knowledge from the atlas, to facilitate a reliable estimation of the statistical distribution, to design the objective function of GAs, and to guide the region growing.

2.2. Fuzzy model of ROI

After registering and superimposing the Talairach atlas onto the MRI images to be segmented, we construct a fuzzy model of the ROI from the registered atlas (see Fig.1(b)), to quantitatively represent the potential of any voxel x belonging to a given brain structure s ($s \in [1, N]$, where N is the number of structures of interest). The fuzzy model is constructed by analogy with the electrostatic potential distribution in the vicinity of hollow structures with uniform surface charge density, to represent the distance and the interaction between different brain structures. The construction is comprised of two stages.

First, we consider each structure as an isolated conductor in the electrical equilibrium, i.e., all the charges are distributed on its 3-D outer surface, which is equipotential. The electrical potential, produced by one brain structure at voxel x located outside any equipotential structure, can be expressed as

$$p_s(x) = \frac{1}{4\pi\varepsilon_0} \int_{S_s} \frac{\zeta(x'_s)}{|x - x'_s|} dS' \,, \tag{1}$$

where ε_0 is a constant of vacuum permitivity, s denotes the considered brain structure in the registered atlas, S_s is its 3-D outer surface, and $\zeta(x'_s)$ denotes the charge density at point x'_s on S_s. To simplify our fuzzy model, we presume an uniform $\zeta(x'_s)$. Thus, equation (1) can be rewritten as

$$p_s(x) = \sum_{x'_s \in S_s} 1/d(x, x'_s) \,, \tag{2}$$

where $d(x, x'_s)$ is a 3-D distance from x to x'_s. To make the computation practical, we ignore the surface voxels that are farther than 5 slices from x. In this way, all the electrical potentials $p_s(x)$, $s \in [1, N]$, corresponding to different brain structures are obtained.

Second, we treat the ROI of a brain structure s as a fuzzy set. Using the electrical potentials obtained above, we design the fuzzy membership function $\mu_s(x)$ of this ROI on the basis of favoring the larger electrical potential as

$$\mu_s(x) = p_s(x) / \sum_{j=1}^{N} p_j(x) \,, \tag{3}$$

Obviously, $\forall\ x$ in the ROI, $\sum_{s=1}^{N} \mu_s(x) = 1$.

2.3. Statistical moment estimation

Using fuzzy MRF oversegmentation, we obtain plenty of regions along with three fuzzy membership values for each region; every three values represent the degrees of the corresponding region belonging to three different brain tissues (CSF, GM and WM). Firstly, we select some regions to assemble a set Ω_s; those selected regions should have large intersection areas with the brain structure s in the registered Talairach atlas, and high degrees of fuzzy membership to brain tissues, e.g., high membership to GM while regarding s as caudate, and putamen. It is reasonable to regard Ω_s as the set of those regions reliably belonging to s.

Secondly, the statistical mean M_s and variance σ_s^2 are chosen to describe the intensity of the brain structure s. With the help of the fuzzy model of the ROI and Ω_s, we can estimate M_s and σ_s^2 with a higher precision as

$$M_s = \frac{1}{\mathcal{Z}} \sum_{x \in \Omega_s} \mu_s(x) f(x) \,, \tag{4}$$

$$\sigma_s^2 = \frac{1}{\mathcal{Z}} \sum_{x \in \Omega_s} \mu_s(x) [f(x) - M_s]^2 \,, \tag{5}$$

where $\mathcal{Z} = \sum_{x \in \Omega_s} \mu_s(x)$, and $f(x)$ is the intensity of the voxel x.

2.4. Region-wise classification using GAs

GAs are stochastic search methods, by analogy with some mechanisms of evolution in nature, conducted by an objective function which is referred as fitness function in GAs related references. GAs are widely applied in optimization, in artificial intelligence, as well as in brain structures labeling [9, 5]. Preliminarily, we define a set Ω_t of the oversegmented regions which possibly coresond to one of the brain structures:

$$\Omega_t = \{\text{region } r \mid \exists \text{ structure } s, \sum_{x \in r} \mu_s(x) > t\} \,, \tag{6}$$

where t is an empirical threshold. Ω_t embraces not only the elements of all the Ω_s, but also the regions without significantly high possibility to be a constituent of any brain structure of interest, i.e., $\Omega_t \supset (\bigcup_{s \in [1,N]} \Omega_s)$. Then, we design the fitness function as the sum of two items, using our fuzzy model and the statistical mean estimated above.

The first item measures the average fuzzy membership value of all the voxels in Ω_t after classifying each voxel into a certain brain structure:

$$Fit_1 = \frac{1}{N_1} \sum_{r \in \Omega_t} \sum_{x \in r} \mu_{s_r}(x) \,, \tag{7}$$

where s_r is the corresponding structure s labeled to the region r. $N_1 = \sum_{r \in \Omega_t} n_r$ is a normalization coefficient, where n_r represents the number of voxels in the region r. This item relates to the correct classification rate if we take the registered atlas as a template of the correct classification.

The second item measures the correlation of intensity between regions and the corresponding structures:

$$Fit_2 = \frac{1}{N_1} \sum_{r \in \Omega_t} n_r \left[1.0 - \left(\frac{|m_r - M_{s_r}|}{I_{max} - I_{min}} \right)^{\alpha} \right] \,, \tag{8}$$

where m_r is the mean of region r, and M_{s_r} denotes the mean of the structure s_r as estimated in equation (4) and (5). I_{max} (I_{min}) is the maximum (minimum) intensity of the images. The exponent α adjusts the influence of intensity disparity.

2.5. Voxel-wise refinement

The use of only region-wise classification is no doubt coarse and insufficient to achieve an accurate segmentation of neuroanatomic structures, because the foregoing oversegmentation suffers significantly from the overlap of intensity ranges among different structures like caudate, thalamus and putamen. However, after region-wise classification, the majority of voxels has been correctly labeled; these voxels can be preserved as seeds for refinement. In this context, we choose a parallel region growing algorithm to achieve voxel-wise refinement, guided by the structural and statistical knowledge obtained.

Region growing techniques are often hampered by two difficulties: selection of reliable seeds, and predetermination of appropriate growing criteria. Here, firstly we use conditional morphological erosion to remove the voxels unqualified of being seeds; then we define criteria of region growing as follows:

A voxel x is allowed to "grow" into the same structure s with certain seeds if it satisfies the following requirements: a) its value of membership $\mu_s(x)$ in fuzzy model of ROI is above an empirical threshold; b) its intensity $f(x)$ lies in the statistical range determined by the mean M_s and the variance σ_s^2 which are estimated reliably by equation (4) and (5).

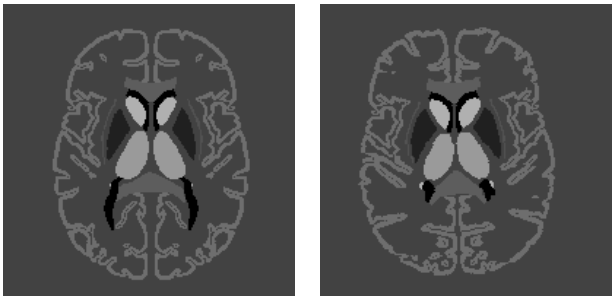
3. RESULTS, VALIDATION, AND CONCLUSION

The subjects in our study were scanned with a GE Signa 1.5 Tesla scanner, employing a T1-weighted SPGR sequence. We employ four different indexes (false positive ratio γ_{fp}^s, false negative ratio γ_{fn}^s, similarity index ρ^s [10], and Kappa statistic κ^s [10]) as quantitative measures to validate the accuracy and reliability of our method, compared to the manually segmented result considered as "ground truth". Four important neuroanatomic structures are segmented. They are clearly visible close to the center of Fig.1: the brightest one is caudate, the second brightest one is thalamus, the darkest one is ventricle, and the second darkest one is putamen). The fuzzy model of the ROIs of these four structures are shown in Fig.2 with respect to Fig.1(b). The quantitative validation results are shown in Table 1. One sample image of the original MRI data and the corresponding segmentation result using our method are shown in Fig.3(a), and 3(b) respectively.

From Table 1, we deduce that almost all the false ratios are less than 10% (except γ_{fp}^s for caudate due to its smaller size), and all the similarity indexes and Kappa statistics are higher than 90%. The results show that our segmentation method is promising for quantitative analysis of brain neuroanatomic structures.

	γ_{fp}^s	γ_{fn}^s	ρ^s	κ^s
Ventricle	0.070	0.018	0.982	0.957
Caudate	0.112	0.086	0.914	0.902
Thalamus	0.090	0.063	0.937	0.924
Putamen	0.083	0.049	0.951	0.934

Table 1. Quantitative validation results with false positive ratio, false negative ratio, similarity index, and Kappa statistic.



(a) Talairach atlas (b) registered Talairach atlas

Fig. 1. Sample images of Talairach atlas and its registered result onto the MRI images to be segmented.

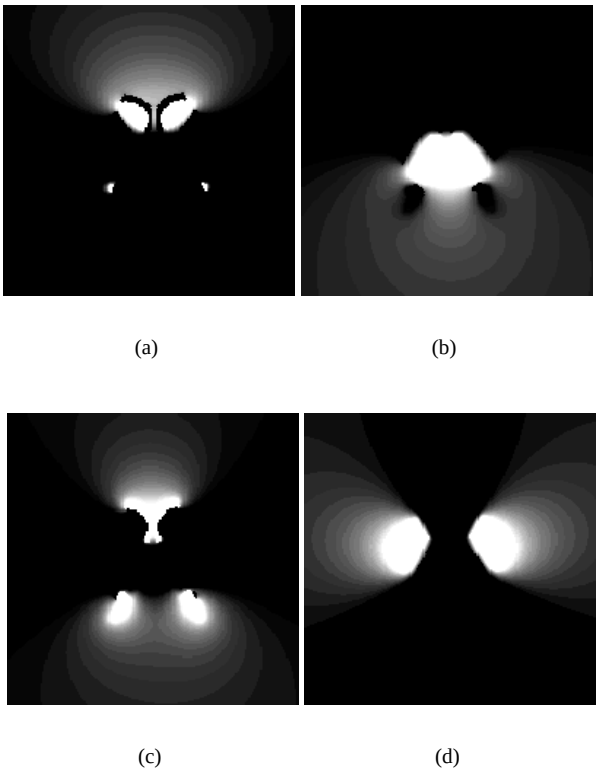
4. REFERENCES

[1] L.P. Clarke, R.P. Velthuizen, M.A. Camacho, J.J. Heine, M. Vaidyanathan, L.O. Hall, R.W. Thatcher, and M.L. Silbiger, "MRI segmentation: methods and application," *Magnetic Resonance Imaging*, vol. 13, no. 3, pp. 343–368, 1995.

[2] D.L. Collins and A.C. Evans, "Animal: automatic nonlinear image matching and anatomical labeling," in *Brain Warping*, A. Toga, Ed., pp. 133–142. Academic Press, 1999.

[3] M. Chen, T. Kanade, D. Pomerleau, and J. Schneider, "3-D deformable registration of medical images using a statistical atlas," Tech. Rep. CMU-RI-TR-98-35, Robotics Institute, Carnegie Mellon University, December 1998.

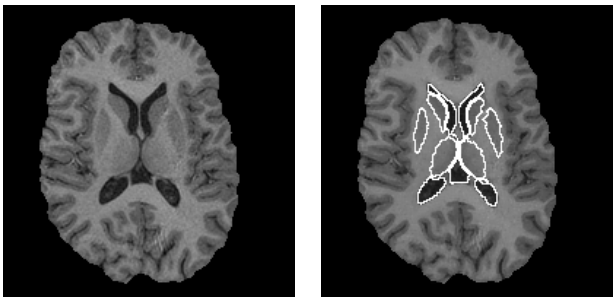
[4] L.H. Staib, A. Chakraborty, and J.S. Duncan, "An integrated approach for locating neuroanatomical struc-



(a) (b)

(c) (d)

Fig. 2. Fuzzy model of the ROI: the potential fields corresponding to Fig.1(b) with respect to (a) caudate; (b) thalamus; (c) ventricle; (d) putamen.



(a) original MRI image (b) final segmentation result

Fig. 3. Sample image of MRI images and its segmentation result by our method.

ture from MRI," *International Journal of Pattern Recognition and Artificial Intelligence*, vol. 11, no. 8, pp. 1247–1269, 1997.

[5] T.F. Cootes, A. Hill, C.J. Taylor, and J.Haslam, "The use of active shape models for locating structures in medical images," *Image and Vision Computing*, vol. 12, no. 6, pp. 355–366, 1994.

[6] N. Duta and M. Sonka, "Segmentation and interpretation of MR brain images: an improved active shape model," *IEEE Transactions on Medical Imaging*, vol. 17, no. 6, pp. 1049–1062, 1998.

[7] J. Talairach and P.Tournoux, *Co-Planar Stereotaxic Atlas of the Human Brain*, Thieme Medical, New York, 1988.

[8] F. Salzenstein and W. Pieczynski, "Parameter estimation in hidden fuzzy markov random fields and image segmentation," *Graphical Models and Image Processing*, vol. 59, no. 4, pp. 205–220, 1997.

[9] M. Sonka, S.K. Tadikonda, and S.M. Collins, "Knowledge-based interpretation of MR brain images," *IEEE Transactions on Medical Imaging*, vol. 15, no. 4, pp. 443–452, 1996.

[10] A.P. Zijdenbos, B.M. Dawant, R.A. Margolin, and A.C. Palmer, "Morphometric analysis of white matter lesions in MR images: method and validation," *IEEE Transactions on Medical Imaging*, vol. 13, no. 4, pp. 716–724, 1994.