Fuzzy Knowledge-based Recognition of Internal Structures of the head

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Résumé - Nous proposons une méthode basée sur la connaissance a priori pour la segmentation et la reconnaissance des formes des structures internes du cerveau en IRM. Les connaissances sur les formes des structures et les distances entre elles, provenant de l'atlas de Talairach, sont modélisées par un champ flou en utilisant une analogie avec la distribution du potentiel d'électrostatique. Une sur-segmentation est d'abord effectuée sur le cerveau pour obtenir des régions homogènes. La reconnaissance des structures est ensuite obtenue par la classification des régions utilisant un algorithme génétique, suivie par un affinement au niveau du pixel. Les connaissances floues modélisées sont utilisées dans ces deux étapes. La performance de la méthode proposée est validée par référence aux résultats manuels en utilisant 4 indices de quantification.

Abstract *– We propose a knowledge-based method for segmenting and recognizing internal brain structures viewed by MRI (Magnetic Resonance Imaging). The knowledge about shapes of the structures and relative distances between them, derived from Talairach stereotaxic atlas, is fuzzified by analogy with the electrostatic potential distribution. The brain is firstly over-segmented. Then the recognition of the cerebral structures is achieved by the region-wise labeling using GAs (Genetic Algorithms), followed by a voxel-wise amendment using parallel region growing. The fuzzy knowledge is used both to design the fitness function of GAs, and to conduct the region growing. The performance of our proposed method has been quantitatively validated by 4 indexes with respect to manually labeled images.*

1. Introduction

Automated labeling of structures is complicated, facing difficulties due to overlapping intensities, anatomical variability in shape, size, and orientation, partial volume effects, as well as noise perturbations, intensity inhomogeneities, and low contrast in images. Therefore, it is needed to supplement domain knowledge, to achieve labeling like what radiologists do. In recent years, many reports have been published in this direction in terms of atlas-based (model-based, or knowledge-based) segmentation of neuroanatomical structures .

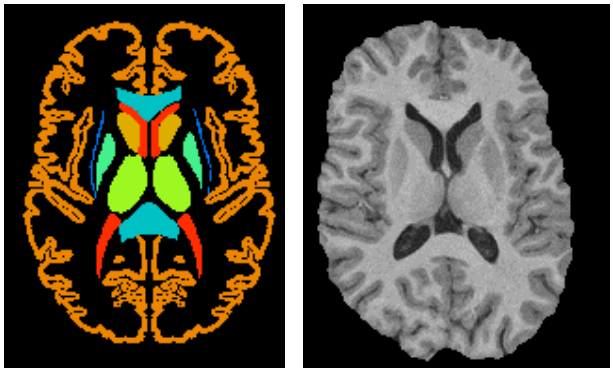
One intuitive strategy to use knowledge for labeling, named as registration-segmentation paradigm by Collins et al. [1] , is to register and transfer labels of a pre-labeled atlas onto the MRI images to be segmented. The performance of this strategy over-relies on the accuracy of the registration employed, which suffers from the limited degrees of freedom of the transformations, and from anatomical inter-individual variability (in orientation, shape, size, and position). Another important strategy is to integrate statistical knowledge of intensity and position into a shape model, and to locate the structures which match the model. Staib et al. [2] used a gradient-based parametric deformable shape model, integrating region information and prior probability knowledge about mean shape and variation of the structures. Gonzalez Ballester et al. [3] guided the segmentation by statistical shape knowledge built from data sets of pre-labeled structures. Several researchers used ASM (Active Shape Models) to label brain structures [4][5]. ASM are parametric deformable models of shape and appearance of flexible objects, which restrict the possible deformation using shape template and intensity model, both generated through statistics of training sets.

Besides the two strategies aforementioned, the use of the fuzzy sets theory to represent structural information has been introduced by I.Bloch [6][7]. From these fuzzy sets, the atlas-based recognition using fuzzy fusion is proposed [8]. The recognition is carried out sequentially on one structure at a time. The information got from the atlas is updated after the recognition of each structure in order to guide the next one. Inversely to this method, our method use a parallel process.

The contribution of this paper is twofold. First, the structural knowledge from the Talairach stereotaxic atlas is modeled with fuzzy sets. The fuzzification is carried out by analogy with the electrostatic potential distribution in the vicinity of hollow structures with uniform surface charge density. Second, the fuzzy sets obtained for each structure are used to search the optimal labels from over-segmented regions using GAs (Genetic Algorithms).

2. Fuzzification of the knowledge

The Talairach atlas is well-accepted in medical image processing, owing to its contribution to the delineation and labeling of numerous brain neuroanatomical structures (one sample slice of this atlas is shown in FIG 1.a). Although it indicates approximate shape, position and relationship of the brain structures, it is far from the real brain (FIG 1.b). Therefore, we use fuzzy sets to model the imprecision and the uncertainty of the structure information.



(a) (b)

FIG. 1 (a) one sample slice of Talairach atlas: putamen (1), ventricle (2), thalamus (3) and caudate (4), (b) one slice of MRI brain volume.

We define the degree of fuzziness to represent the degree of belonging to one structure. Since our recognition process searches for the structures in parallel, the interactions between different structures have to be taken into account. We propose a model which is constructed by analogy with the electrostatic potential distribution in the vicinity of conducting objects. The potential of any point relative to one structure is in fact influenced by all structures. More precisely, any structure s ($s \in \lfloor 1, N \rfloor$) is considered as an isolated conductor in the electrical equilibrium, i.e. all the charges are distributed on its 3-D outer surface S_S. The electrostatic potential at voxel x located outside any structure can be expressed as:

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

where ε_0 is a constant of vacuum permitivity, $\zeta(x')$ denotes the charge density at point x' on S_S. If $\zeta(x')$ is considered as an uniform distribution, the equation (1) can be simplified as:

$$p_s(x) = \sum_1^{n_S} \frac{1}{d(x, v_i^s)} \tag{2}$$

where n_S denotes the number of voxels v_i^S (i=1, ...,n_S) on the surface of the structure s in the atlas T_V, and $d(x,v_i^S)$ is a distance from x to v_i^S. The potential distribution of the structure s is firstly normalized by its maximal value to guaranty $p_s(x) \in [0,1]$. The fuzzy membership value related to the structure s is than defined by:

$$\mu_s(x) = \begin{cases} p_j^{\max}(x) & \text{if } j = s \\ p_s(x)\left(p_s(x) / p_j^{\max}(x)\right) & \text{if } j \neq s \end{cases} \tag{3}$$

where $p_j^{\max}(x) = \sup_{i \in [1,N]}(p_i(x))$. The structure j has the maximal potential value.

3. Recognition method

We propose a coarse-to-fine strategy to achieve the brain structure recognition, based on both the fuzzy structural knowledge from the Talairach stereotaxic atlas, and on the information from the MRI images.

Two datasets were made available in our method. One is the Talairach stereotaxic atlas T_O ; another one is a volume of MRI images V_T, which have been registered into the stereotaxic coordinates system using MPItool[1] software package. The volume V_T is used as a registration template. To obtain the coarse location of brain structures in a new volume MRI V_O , the AIR software package developed by Woods et al. [9] is used to register the prepared registration template V_T onto V_O. A matrix of mapping parameters is thus obtained. T_O is resampled using this matrix, and the resampled result T_V can be superimposed automatically onto V_O. This resampled Talairach atlas is then fuzzified by the way described in the previous section.

3.1 Over-segmentation with fuzzy MRF

We expect the over-segmentation to fulfill the following requirements: 1) not to result in tremendous redundant regions like those generated by the watershed algorithm, thus to be able to reduce the computation complexity of the following GAs in searching optimal labeling of regions; 2) to segment brain tissues like GM (Gray Matter) and CSF (Cerebro-Spinal Fluid), which contain most of the important neuroanatomical structures; 3) to describe partial volume effects quantitatively; and 4) to decrease the information loss before labeling. In this context, we applied a scheme using the combination of partial volume modeling [10] and fuzzy MRF (Markov Random Fields) [11], which can generate regions of pure tissues: GM, WM (White Matter),and CSF, and also mixtures of these pure tissues. The fuzzy MRF models simultaneously "pure" voxels using Dirac functions, and "mixed" voxels using Lebesgue measure. Moreover, fuzzy MRF can preserve information through fuzzy membership of voxels belonging to a given class, as well as statistical context information through MRF. It is justified for our requirements.

3.2 Estimation of statistical moments

The statistical mean M_S and variance σ_s^2 of each structure s are chosen to describe the intensity of the structure, and estimated from a set Ω_S which includes regions reliably belonging to s. Using a fuzzy MRF segmentation, over-segmented regions are obtained along with their fuzzy membership values to different tissues (CSF, GM and WM). The regions classified into Ω_S should have large intersection areas with *s* in the registered Talairach atlas T_V, and high values of fuzzy membership to brain tissues, e.g. high membership to GM while regarding s as caudate, and putamen, and membership to CSF while regarding *s* as ventricle. With the help of the fuzzy model of ROI and the set Ω_S, we can estimate the mean M_S and variance σ_s^2 with a higher precision. The way of estimation can be written as follows:

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

[1]MPItool, version 2.58, Advanced Tomo Vision GmbH. http://www.atv-gmbh.de/mpitoolh/

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

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

1.3 Region-wise recognition using Gas

GAs are stochastic search methods which use analogy with some mechanisms of evolution in nature. They are used widely in optimization, artificial intelligence, involving brain structures labeling, conducted by an objective function which is referred as fitness function in GAs related references [12][13]. The most application-dependent component of GAs is the fitness function, which affects significantly the performance and computation complexity of GAs.

Our fitness function has been designed as the multiplication of two items, based on the fuzzy model of ROI and the statistical mean estimated above. The first item relates to intersected shapes with the same label between the atlas T_V and images V_o , as :

$$Fit_1 = \frac{1}{N_1}\sum_{x=1}^{n_r}\mu_s^r(x) \quad (6)$$

where μ_s^r is the membership value corresponding to the structure s in the region r. $N_1 = \sum_{r=1}^{n_t} n_r$ is a normalization coefficient, where n_r represents the amount of voxels in the region r .

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

$$Fit_2 = [1-(\frac{|m_r - M_s^r|}{I_{\max}-I_{\min}})^2] \quad (7)$$

where m_r is the mean of region r , and M_s^r denotes the mean of the structure s in the region r, which are estimated in equations (5). I_{max} (I_{min}) is the maximum (minimum) intensity of the images.

1.4 Voxel-wise amendment conducted by knowledge

The only use of region-wise labeling is no doubt coarse and insufficient to achieve an accurate labeling of neuroanatomical structures, because the over-segmentation suffers significantly from the overlap of intensity ranges among different structures like caudate, thalamus and putamen.

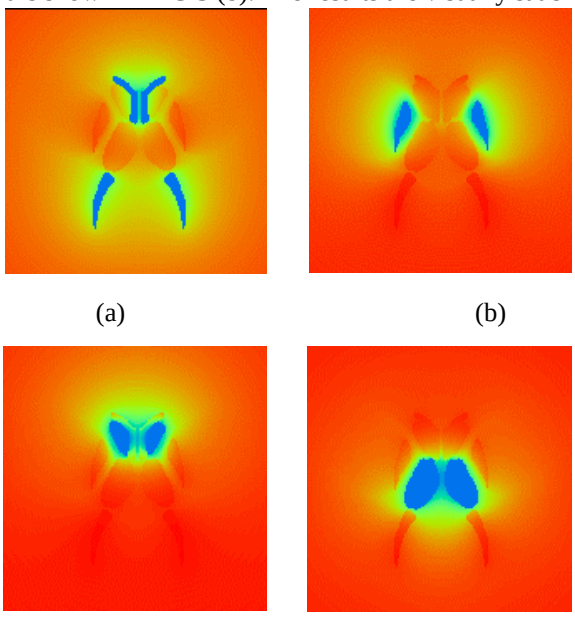
However, after the region-wise labeling, the majority of voxels has been correctly labeled, and can be considered as seeds for refinement. In this context, we choose a parallel region growing algorithm to achieve voxel-wise amendment, conducted by the structural and statistical knowledge formerly obtained. In this procedure, we make the different structures grow simultaneously, to avoid one structure to grow into another one located in its proximity and whose intensity is overlapping.

Some of the knowledge applied are derived from the atlas T_v, such as shape, spatial position, and distance information represented by the fuzzy sets. Some others are derived from the MRI images V_O and its over-segmented version, such as the statistical moments

4. Results and quantitative validation

In this study, the subjects were scanned with a GE Signa 1.5 Tesla scanner, employing a T1-weighted SPGR pulse sequence. The parameters of the SPGR sequence were TR=30ms, TE=7ms, flip angle=40°, image size= 256x256x124 voxels, and voxel size =0.94x0.94x1.2 mm3.

The performance of the method is demonstrated by labeling four important neuroanatomical structures: caudate, thalamus, ventricle and putamen. These four structures are clearly visible close to the center of the axial Talairach atlas (see FIG 1.a). The fuzzification of the Talairach atlas is carried out by the method described in section 2. The slice of index 67 is shown in FIG 2 to illustrate the four obtained fuzzy sets corresponding to the four main structures. The over-segmentation applied to the MRI dataset generates 2878 regions in the slice shown in FIG 1 (b). The result of this sample image is shown in FIG 3 (a). The volume rendering result is shown in FIG 3 (b). The results are visually satisfied.

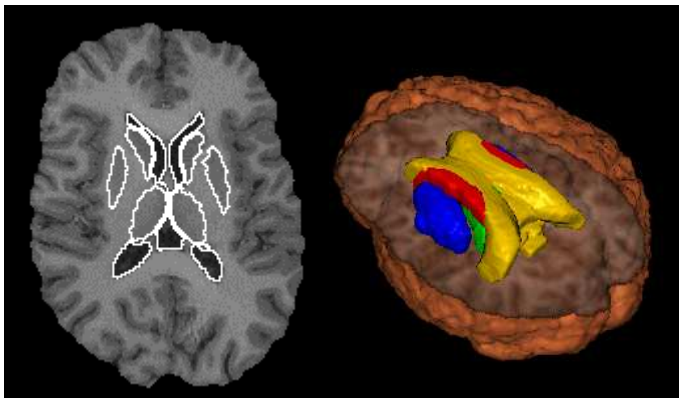


(a) (b) (c) (d)

FIG. 2 Fuzzy sets derived from the Talaraich atlas (corresponding to FIG 1(a)): (a) ventricle; (b) putamen; (c) caudate; (d) thalamus.

The quantitative validation is carried out by comparing the results obtained by our method denoted as L_a, with the "ground truth" obtained manually denoted as L_g. Seven images were chosen randomly for the comparison. Two indices of quantitative measures were calculated from the statistical moments of distance histogram [14]. In fact, we calculated the distance of any contour voxel x_s of the structure s in L_a to the corresponding contour of s in L_g: the distance histogram, revealing the spatial distribution of recognition errors, is built from the superimposition of L_a onto the distance map of L_g, from which some characteristics are extracted, such as mean, standard deviation (SD). The

two other indices measured are the false positive ratio representing the error due to the misrecognition of the structure s (γ_{fp}^{s}) , and false negative representing the error due to the loss of desired voxels of s (γ_{fn}^{s}). The results obtained by these four indices are shown in Table 1. At first sight, it appears that the mean discrepancy between L_g and L_a is always less than 1 voxel, which is quite satisfactory. The low SD indicates that the labeling errors are peakwise, which entails a concentration of labeling errors around 1 voxel. We can also deduce that almost all the false ratios are less than 10% (except γ_{fp}^{s} for caudate due to its smaller size).



(a) (b)

FIG. 3 Recognition results. (a) The four obtained structures superimposed to the original MRI image (FIG 1(a)). (b) Volume rendering of the 4 recognized structures .

TAB. 1: Quantitative validation results with statistical moments of distance histogram and with false positive and false negative ratios.

	Means	SD	γ_{fp}^{s}	γ_{fn}^{s}
Ventricule	-0.890	0.482	0.07.	0.018
Thalamus	-0.801	0.908	0.090	0.063
Putamen	-0.819	0.651	0.083	0.049
Caudate	-0.598	1.422	0.112	0.086

5. Conclusion

An automatic, knowledge-based method to segment and recognize brain neuroanatomical structures (ventricle, caudate, thalamus and putamen) from MRI images has been developed. The structural knowledge derived from Talairach stereotaxic atlas is fuzzified to represent the impression and uncertain information for guiding the recognition process. Quantitative validation has also been performed to demonstrate the performance of the proposed method, with manually labeled images considered as “ground truth” using 4 quantitative indices. The results show that this method is promising for quantitative analysis of brain neuroanatomical structures. The direction of knowledge integration is certainly worthy of further investigation in image segmentation and recognition.

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