Segmentation of the striatum using data fusion

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Abstract: **This article proposes a new segmentation scheme to detect cerebral structures in MRI acquisitions using numerical information contained in the image and expert knowledge brought by a specialist. This process is divided in three steps: first, information contained in the MR image is extracted using a fuzzy clustering algorithm, and theoretical information concerning the structure to segment is modeled using possibility theory. Information fusion is then processed, followed by a decision step ending the structure segmentation. Heads of caudate nuclei and putamens are segmented using this method. Results are promising and validation is performed using both numerical indexes and assessment by an expert. This method can be applied to any cerebral structure in an MR image, provided that it can be described in terms of shape, direction and distance by an expert and that the contrast and resolution of the MRI are sufficient.**

Keywords: **Striatum segmentation, MRI, data fusion.**

INTRODUCTION

Cerebral structures segmentation in medical imaging has numerous clinical applications. It can provide assistance tools for pathologies forecast [1] and follow up [2]. It can also be used as an help to surgery and radiotherapy [3] or to obtain an anatomical reference for functional studies [4].

Various segmentation methods are inventoried in literature, many of them requiring an operator intervention. For example, region growing [5] for tumors detection or deformable contours [6,7] for hippocampus segmentation need to be initialized. In [8,9] interactive methods using mathematical morphology are proposed; other methods (*e.g.* neural networks [10] or a modified k-nearest neighbors rule [11]) require a learning step. Finally, some segmentation methods are fully automatic. For example those using data fusion to aggregate information stemming from images (numerical data) [12], or theoretical knowledge and numerical data [3,13]. Géraud [14], in particular, proposes a segmentation method using anatomical knowledge and information extracted from an atlas.

In this article, we propose to mimic the way the clinician looks for a cerebral structure in an MRI using an automatic segmentation method. He synthesizes the information brought by the image and his own knowledge (shape, matter, distance, direction) to locate the structure. The segmentation scheme is divided in three steps: first the representation of numerical (image) and contextual (expert) information in the same theoretical frame, then its fusion and last the decision step.

MATERIAL AND METHODS

1- MR Images

Fifteen MR images (3D SPGR T_1-weighted images, using a GE 1.5 Tesla with a head coil, La Pitié Salpêtrière, Paris) have been acquired, coded using a 256×256 matrix (0.85×0.85×1.5 mm^3 voxels) and saved in 128×128 format (2×2×2 mm^3 voxels). The studied subjects were 48.9 ± 8.2.

2- Cerebral structures of interest

The method is illustrated with the segmentation of putamens (P) and heads of caudate nuclei (HCN). These structures are affected by numerous diseases such like Parkinson’s disease or schizophrenia.

Caudate nuclei (CN) are gray matter coma-shaped structures coiling up the thalami and going down behind them. The HCN is ovoid, rather bulky and bulges into the lateral wall of the lateral ventricles (LV) frontal horn. P are pyramidal-shaped gray matter structures and constitute the side part of the lenticular nuclei. P and CN carry out, among others, motor functions. Fig. 1 shows these structures of interest.

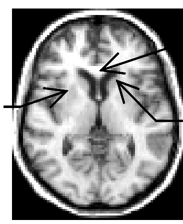

Fig. 1 View of the structures of interest on a T1-weighted MRI

Theoretical knowledge concerning these structures has been collected from an expert and represented within the same theoretical framework. It has then been fused in order to segment P and HCN in MR images.

3- Possibility theory and data fusion

Data fusion in medical imaging

Data fusion is defined here as an aggregation of conflicting, ambiguous, supplementary and/or redundant information, allowing more accurate or less uncertain data interpretation. Fusion has to manage uncertainties and inaccuracies, like a specialist does while observing several medical images, to avoid inconsistencies.

Possibility theory

Information treated in medical imaging is often inaccurate (“HCN is close to LV frontal horn”) and uncertain (*e.g.* noise in MR acquisitions). Possibility theory has been introduced by Zadeh in 1978 [15] and developed by Dubois and Prade [16] to allow inaccuracy and uncertainty treatment in a non-probabilistic way. This is why possibility theory seems us to be well adapted to medical data representation.

4- Modeling and fusion of information

While modeling information, possibility theory allows taking into account the fact that shape and volume of the structures vary from one subject to another according to his age, sex and pathologies. It is possible to segment structures of interest using reference structures which can easily be spotted (called *landmarks*). Information was provided by an expert (Dr Marie-Odile Habert, La Pitié Salpêtrière, Paris, France) in

0-7803-7211-5/01$10.00©2001 IEEE

Report Documentation Page

Report Date	Report Type	Dates Covered (from... to)
25OCT2001	N/A	-

Title and Subtitle Segmentation of the striatum using data fusion	**Contract Number**
	Grant Number
	Program Element Number
Author(s)	**Project Number**
	Task Number
	Work Unit Number
Performing Organization Name(s) and Address(es) ERIM, Faculty of medicine, Place Henri Dunant, 63001 CLERMONT-FERRAND, FRANCE	**Performing Organization Report Number**
Sponsoring/Monitoring Agency Name(s) and Address(es) US Army Research, Development & Standardization Group (UK) PSC 802 Box 15 FPO AE 09499-1500	**Sponsor/Monitor's Acronym(s)**
	Sponsor/Monitor's Report Number(s)

Distribution/Availability Statement
Approved for public release, distribution unlimited

Supplementary Notes
Papers from the 23rd Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 25-28 October 2001, held in Istanbul, Turkey. See also ADM001351 for entire conference on cd-rom., The original document contains color images.

Abstract

Subject Terms

Report Classification unclassified	**Classification of this page** unclassified
Classification of Abstract unclassified	**Limitation of Abstract** UU

Number of Pages
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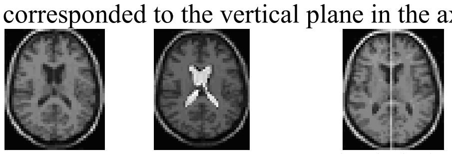
addition to data extracted from the MRI. Each piece of information has been modeled as a fuzzy map to be fused.

Numerical information extracted from MRI

Five tissue classes (background, cerebrospinal fluid (CSF), white matter, gray matter and subcutaneous fat) were extracted from the MR image using a possibilistic clustering algorithm on voxels wavelet coefficients [18]. This algorithm created five fuzzy "matter maps" in which one voxel gray level represented its membership to the considered tissue.

Segmentation of the landmarks

Fuzzy maps were then used to segment the anatomical landmarks. The frontal horn of LV and the inter-hemispheric plane (Fig. 2) are the landmarks used to model contextual information. LV were extracted from a binary CSF map (obtained by thresholding the fuzzy CSF map) using mathematical morphology operations. The rough location of the inter-hemispheric plane was then calculated by maximizing Pearson's correlation coefficient between the two halves of the image. The patients were supposed to be always placed in the MR scan so that the inter-hemispheric plane roughly corresponded to the vertical plane in the axial slices.

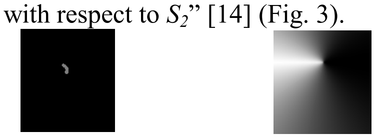


MRI LV Inter-hemispheric plane

Fig. 2 Results of landmarks segmentation on an axial slice

Information concerning directions

We had to model by a fuzzy set a vague sentence like "the structure S_1 is in the direction D with respect to S_2" where S_2 was an already segmented structure. D was represented in spherical coordinates and we used fuzzy mathematical morphology [19] to obtain a fuzzy map in which one voxel gray level represented its membership to the domain "in direction D with respect to S_2" [14] (Fig. 3).

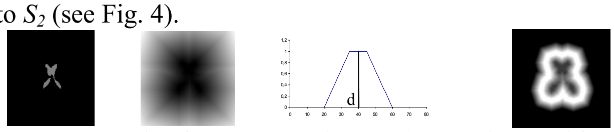


Frontal horn of the left LV "Rather on the left of the frontal horn of the left LV"

Fig. 3 Example of fuzzy direction map

Information concerning distances

The piece of information to be modeled here was a vague sentence like "the structure S_1 is at distance $F(d)$ from S_2" where $F(d)$ was a linguistic modifier (*"almost"*, *"inferior to"*, *"superior to"*) applied to distance d. We used the method described in [3] to create the fuzzy distance map with respect to S_2 (see Fig. 4).



LV Chamfer map "Almost at *d*" "Almost at d from LV"

Fig. 4 Example for distance modeling

Representation of shape information

To create a fuzzy model of structure shapes, we used a binary segmentation of P and HCN on 14 co-registered MR images. In this model (Fig. 5), one voxel gray level represented its frequency of appearance in the considered structure. During the segmentation process, this map was roughly registered on the MRI and fused with the other fuzzy maps.

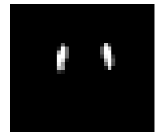


Fig. 5 Example of fuzzy shape map

Data fusion and decision step

Fusion allows extracting redundancies, complementarities and ambiguities from data. Here, we illustrate data fusion by the aggregation of information resulting of two sources (it can be applied with n sources [16,17]). This information is represented by memberships concerning events on a given voxel. Data aggregation is performed with a binary operator managing conflicts and redundancies. In [17], a review and classification of fusion operators is proposed.

For the fusion step, we used two operators which can easily be extended to the n sources case: *max* (complementary information) and *min* (redundant information) operators. The fusion step resulted in a fuzzy map in which gray levels were the memberships to the required structure with respect to the whole set of numerical and contextual data. The last step was the decision step. Only surest voxels were conserved: we used an α-cut to eliminate voxels having a membership inferior to 0.8 (empirically determined threshold).

The whole fusion process is summarized in Fig. 6.

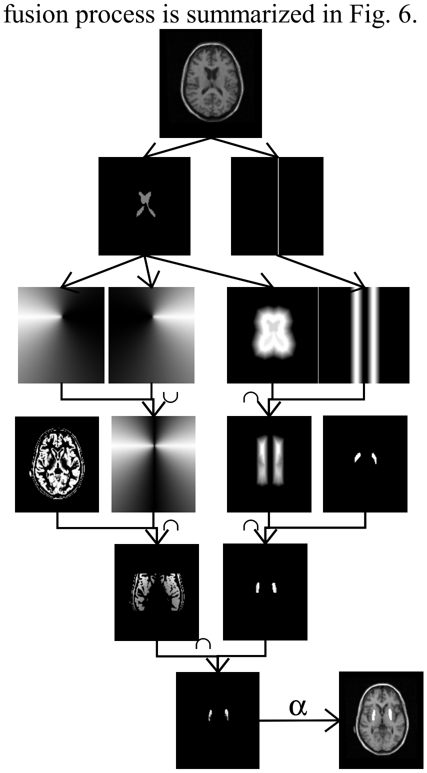


Fig. 6 Data fusion process for putamens segmentation

Quantitative indexes for the validation of the method

P and HCN have been manually segmented on each image we had automatically processed. The efficiency of the method was evaluated by comparison with manual segmentation, using three numerical indexes [22].

The first one is a similarity index computed from the relative error in volume estimation (the reference volume was the expert's one):

$$I1 = 1 - \frac{|V_T - V_C|}{V_T},$$

where V_T (resp. V_C) is the expert-segmented (resp. automatically-segmented) volume.

The second index is a spatial accuracy term, assessing the relative overlapping of the computed structure S_C with respect to the reference one S_T:

$$I2 = \frac{Card(S_T \cap S_C)}{Card(S_T)}$$

The last index is a mean distance (in millimeters) from the segmented structure to the manually expert one:

$$I3 = \frac{\sum_{P_C \in S_C} \min_{P_T \in S_T} \|P_C P_T\|}{Card(S_C)}$$

Where $\|.\|$ denotes the Euclidean norm and P_C (resp. P_T) is a generic point of S_C (resp. S_T).

RESULTS

The fusion process was implemented on a compatible PC (AMD K7 700 MHz) using C language and an image processing library developed in our laboratory [20]. HCN were segmented in about 45 seconds and P in approximately 55 seconds. This program is now being transferred on clinical image processing consoles using the MIRAGE system (SEGAMI Corporation)

1- Segmentation of the putamens

According to our expert P are "two gray matter pyramidal structures, at approximately 28 mm of the LV, 72mm of the inter-hemispheric plane and in slightly posterior direction (left and right) with regard to the frontal horn of LV". Fig. 7 shows the P segmented on the slices of interest and superimposed in the MRI.

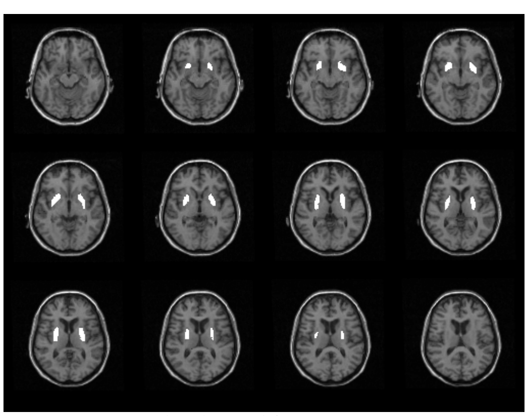


Fig. 7 Results obtained for putamens segmentation

2- Segmentation of the heads of caudate nuclei

HCN are described as "Two gray matter egg-shaped structures, stuck on the frontal horn of the LV, and partially forming their outer limit" (see segmentation results on Fig. 8)

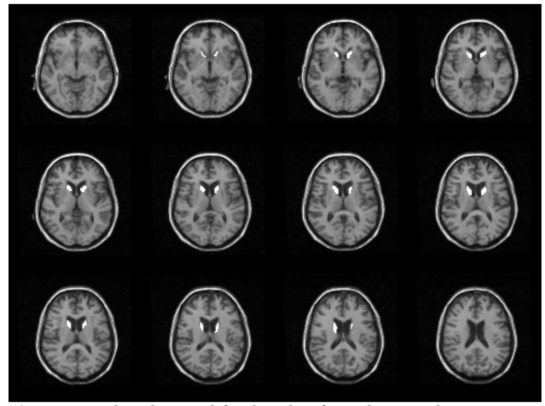


Fig. 8 Results obtained for heads of caudate nuclei segmentation

The quantitative evaluation of the method is presented with averaged indexes. The mean similarity index $\overline{I1}$ for the left P (resp. right) was 0.94±0.03 (resp. 0.93±0.03) and 0.92±0.02 (resp. 0.90±0.04) for the left (resp. right) HCN. The mean spatial accuracy index, $\overline{I2}$, was 0.88±0.03 (resp. 0.88±0.04) for the left (resp. right) P and 0.85±0.06 (resp. 0.84±0.05) for the left (resp. right) HNC. Finally, the distance between manual and automatic outlines did not overtake 2mm for 90% of the considered structures, the worst result observed giving a 3mm distance.

3- Volumes of the structures of interest

Table 1 presents the mean volumes obtained for the automatically segmented structures.

TABLE 1
MEAN VOLUME AND STANDARD DEVIATION FOR THE SEGMENTED STRUCTURES

	Mean volume (mm^3)	Standard deviation
Left (resp. right) P	3837,71 (4138,29)	10,9% (8,5%)
Left (resp. right) HCN	1992,57 (1995,43)	14,4% (12,5%)

DISCUSSION

The fusion process proposed here successfully segmented the P and HCN in 14 out of 15 MR images. The last image could not be automatically treated due to problems for the creation of tissue maps. For the 14 segmented images, contours were visually assessed by an expert. The mean similarity index indicates that the volume estimation agrees with that of the expert. The large value of the mean spatial accuracy index moreover confirms a good overlap between the structures. Finally, low distance indexes suggest that the shapes of the segmented structures are quite close to the ones delineated by the expert. The results are good enough to confirm the similarity between the reference and the segmented structures. We now intend to compute these indexes with regard to other experts (management of inter-operator variability).

Cerebral structures volumes depend on many parameters: acquisition protocol, segmentation method, age and sex of the subject. Consequently, there is no absolute reference for comparisons. However, volume estimations are consistent with the ones published by Schultz *et al* [2] (total volume: 7720mm^3±5.6% for P and 5940mm^3±5.4% for CN on healthy subjects) and Harris *et al* (total volume: 7670mm^3±12% for P and 4010mm^3±12.7% for HCN on young patients suffering from Huntington disease). Gunning-Dixon *et al* [23] propose a study of striatum volume according to healthy subjects age, and sex. Mean volumes obtained are 4360mm^3±14% (resp. 4020mm^3±14.9%) for the right (resp. left) P and 3340mm^3±15.6% (resp. 3430mm^3±15.7%) for the right (resp. left) HCN. The authors also detect a right asymmetry of 8.2% between the P which is observed here too (7.5%).

The segmentation method described here automatically reproduces the way a clinician proceeds to identify a cerebral structure. The use of fuzzy maps allows the management of possible inaccuracies in the representation of some knowledge, the collection of different pieces of information correcting these inaccuracies. It also allows the management of uncertainty and redundancy. Finally, it is easy to add new knowledge, *e.g.* information stemming from other image acquisitions, in the fusion process.

Our process relies on the idea to establish anatomical references for quantitative studies concerning pathologies like Parkinson's disease. Indeed, MR acquisitions are used for such studies to locate regions of interest in SPECT images. The segmentation process we propose here is much faster than manual segmentation and allows using the patient himself as anatomical reference. The use of a standard shape as anatomical reference for a pathological case supposes that the pathology doesn't affect the shape and volume of the considered cerebral structure, which is not always true.

CONCLUSION

A new automatic method using data fusion for cerebral structures segmentation has been proposed. This method successfully segmented the heads of caudate nuclei and the putamens on 14 clinical MR acquisitions. Quantitative indexes used to evaluate the method indicate a low error rate both for spatial location and volume evaluation. This method can be extended to any structure segmentation provided that it can be described by spatial, shape and matter information and that contrast and resolution of the MRI are sufficient. Automatic cerebral structures segmentation opens wide perspectives both for an help to diagnosis and for assistance to surgery.

ACKNOWLEDGMENT

Authors would like to thank Dr Marie-Odile Habert for her expertise and her analyze of the results.

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