# AUTOMATIC SEGMENTATION OF THE ENCEPHALIC PARENCHYMA USING FUZZY TECHNIQUES

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*Abstract*-**This work shows an automatic, fast and reproducible algorithm to segment the encephalic parenchyma in magnetic resonance (MR) images. The algorithm has been implemented following a rule-based schema in which a fuzzy analysis of MR images information has been introduced to deal with the vagueness associated to the images. The obtention of a fuzzy result helps to determine the accuracy of the classification. The evaluation of the results is based on the use of quality indexes, which allow the comparison with previous works.**

***Keywords* - MR, brain, labeled segmentation, image processing, fuzzy techniques.**

## I. INTRODUCTION

Magnetic resonance imaging (MRI) has become the imaging method of choice for examination of disorders of the central nervous system [1][2]. Together with diagnostic applications of MRI, its role in research studies must be emphasized. In some of them is necessary a further analysis or post-processing of the information obtained in the explorations. Many of the computer-assisted tasks introduced in brain analysis require segmentation of the whole brain, either because the whole brain is the region of interest (ROI), as in atrophy studies, or because this segmentation makes easier a further analysis. Nevertheless, this segmentation is difficult due to the complexity of MR images and the different characteristics observed in a study. This complexity is based on factors like noise, non-homogeneities, number of structures, and morphologic dependencies of these structures with the location and the orientation of the slices. All them are a handicap to segment the whole brain with solutions based on automatic algorithms.

Several techniques have been considered with the aim to achieve automatic solutions in the segmentation of the brain. Examples of them are the application of knowledge-based classification algorithms [3], the use of automatic thresholds [4][5], the refinement of brain contours [6][7], the isolation of brain tissues based on statistical methods [8][9], the use of region-growing algorithms [10], the application of neural networks [11], and the introduction of fuzzy techniques in the segmentation process [12][13][14]. Nevertheless, obtaining optimal and full automatic segmentation is a difficult task and most of the results of previous works are sensitive to factors as non-homogeneities, misclassifications, the presence of disjoint regions or the excessive computational cost.

Since MR brain studies can be acquired using different sequences, different weighted images (PD, T2, T1) must be considered. Each weighted image introduces different problems in the segmentation process according with the tissue contrast introduced by the sequence. Then, a right selection of weighted images, based on morphological properties, is essential to obtain good results. T1-weighted images provide a high degree of morphological information, and show good contrast of parenchyma region with regard to cerebrospinal fluid (CSF).

Moreover, an important factor to consider in the segmentation process is the uncertainty of MR images. This uncertainty depends on the own features of each image, and the presence of noise or magnetic field non-homogeneities. In this way, the brain segmentation is conditioned by the vagueness observed in the different regions to analyze.

In this work, we propose a fuzzy rule-based algorithm to segment the encephalic parenchyma in T1-weighted images. The introduction of a fuzzy analysis of the information aids to treat better the uncertainty associated to MR images. The assessment of the results has considered different quality criteria to evaluate them and to compare with other works.

## II. METHODOLOGY

The structure of the algorithm is oriented to obtain the solution from low-level perception features, considering a final validation procedure in order to refine the result. The algorithm has been designed following a rule-based schema to make easier its implementation.

In T1-weighted images, according with their perception features, the brain has been divided in four classes, which are subregions of the encephalic parenchyma and CSF. These classes have been described in the following way:

1) Normal Appearing White Matter (NAWM): region observed in the images with light gray level and quite homogeneous texture.
2) Remainder parenchyma (RP): pixels included in this region are those observed with medium-dark gray level and slight homogeneous texture. This region is the complementary to NAWM in the encephalic parenchyma including gray matter and the lesions or regions where gray level alterations on normal values are appreciated
3) Wide fluid regions (WFR): wide regions observed with dark gray level and quite homogeneous texture. Pixels included in this region basically belong to the ventricular region.
4) Narrow fluid regions (NFR): narrow regions observed with dark gray level and slight

# Report Documentation Page

| Report Date | Report Type | Dates Covered (from... to) |
|---|---|---|
| 25 Oct 2001 | N/A | - |

| | |
|---|---|
| **Title and Subtitle**<br>Automatic Segmentation of the Encephalic Parenchyma Using Fuzzy Techniques | **Contract Number** |
| | **Grant Number** |
| | **Program Element Number** |
| **Author(s)** | **Project Number** |
| | **Task Number** |
| | **Work Unit Number** |
| **Performing Organization Name(s) and Address(es)**<br>Unitat de RM Vall D'Hebron Institut de Diagnostic per la Imatge Barcelona, Spain | **Performing Organization Report Number** |
| **Sponsoring/Monitoring Agency Name(s) and Address(es)**<br>US Army Research, Development & Standardization Group (UK) PSC 803 Box 15 FPO AE 09499-1500 | **Sponsor/Monitor's Acronym(s)** |
| | **Sponsor/Monitor's Report Number(s)** |
| **Distribution/Availability Statement**<br>Approved for public release, distribution unlimited | |
| **Supplementary Notes**<br>Papers from 23rd Annual International Conference of the IEEE Engineering in Medicine and Biology Society, October 25-28, 2001, held in Istanbul, Turkey. See also ADM001351 for entire conference on cd-rom. | |
| **Abstract** | |
| **Subject Terms** | |
| **Report Classification**<br>unclassified | **Classification of this page**<br>unclassified |
| **Classification of Abstract**<br>unclassified | **Limitation of Abstract**<br>UU |
| **Number of Pages**<br>4 | |

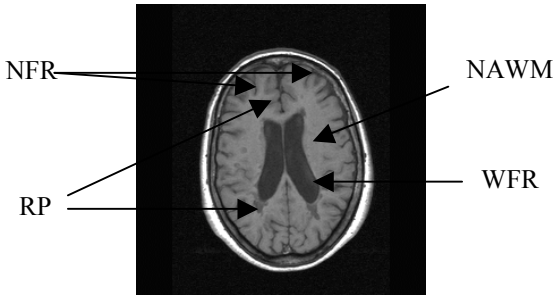


Fig. 1. Some localizations of the different classes in a T1-weighted image.

homogeneous texture. This region is basically determined by the subarachnoid spaces.

According with the previous descriptions, the following features are considered:

1) Gray level: light, medium-dark and dark.
2) Texture: quite homogeneous and slight homogeneous.

Previous descriptions can be formulated by means of the fuzzy rules:

1) A pixel belongs to the NAWM class if its gray level is light and its texture is quite homogeneous.
2) A pixel belongs to the RP class if its gray level is medium-dark and its texture is slight homogeneous.
3) A pixel belongs to the WFR class if its gray level is dark and its texture is quite homogeneous.
4) A pixel belongs to the NFR class if its gray level is dark and its texture is slight homogeneous.

The implementation of a fuzzy system based on these four rules requires the definition of the antecedent fuzzy sets:

1) $f_{\text{light gl}}$ : fuzzy set associated to the feature light gray level.
2) $f_{\text{medium-dark gl}}$ : fuzzy set associated to the feature medium-dark gray level.
3) $f_{\text{dark gl}}$ : fuzzy set associated to the feature dark gray level.
4) $f_{\text{QH t}}$ : fuzzy set associated to the feature quite homogeneous texture.
5) $f_{\text{SH t}}$ : fuzzy set associated to the feature slight homogeneous texture.

Membership functions of these fuzzy sets are defined from probability density and distribution functions. The aggregation of the antecedent fuzzy sets allows obtaining the consequent fuzzy sets ($f_{\text{NAWM}}$, $f_{\text{RP}}$, $f_{\text{WRF}}$, $f_{\text{NRF}}$).

In order to obtain the probability density functions, we have considered 72 images of 2 multiple sclerosis (MS) patients. These images are axial slices acquired using a T1-weighted spin-echo sequence (TR/TE/NEX 667/14/1, FA 70°, FOV 250 mm, Thickness 3mm) in a 1.5 T Magnetom Vision MR System (Siemens, Erlangen, Germany). These images have been manually segmented to obtain the 3 data sets associated to gray level (light, medium-dark and dark) and the 2 associated to texture (quite and slight homogeneous). In this way, we have obtained the 5 subsets of the design set, each one of them associated to each one of the antecedent fuzzy sets.

The evaluation of the features has been performed using the following operators:

1) The evaluation of a value associated to gray level is performed by means of the minimum gray level value in a 3x3 window (8-neighborhood of the central pixel).
2) The evaluation of a value associated to texture is performed by means of the threshold to get 25 pixels in which the gray level differences are greater than this threshold inside a 7x7 window.

The membership functions to the five antecedent fuzzy sets ($f_{\text{light gl}}$, $f_{\text{medium-dark gl}}$, $f_{\text{dark gl}}$, $f_{\text{QH t}}$, $f_{\text{SH t}}$) are determined from their probability density function (p.d.f.) [15]. For each subset of the design set, the values of the design set are evaluated with the considered operators, and a p.d.f. is obtained. Then, each p.d.f. allows obtaining the membership degree to the corresponding antecedent fuzzy set.

The membership functions to the consequent fuzzy sets are obtained by aggregation of the antecedent fuzzy sets according with the fuzzy rules previously described and considering the minimum as aggregation function.

In the defuzzification process, each pixel is classified according with the membership degree to the fuzzy set associated to each class. The membership degree to each fuzzy set allows labeling each pixel under one of the four defined classes. This labeling is based on the greatest value among the membership degrees associated to the four consequent fuzzy sets. Pixels belonging to NAWM class are right classified while some misclassifications are observed in pixels belonging to the other three classes. In addition, external structures to the encephalic parenchyma are also misclassifications because they were not initially removed.

In order to reduce misclassifications and to remove external structures a validation procedure must be introduced in the algorithm. This validation procedure considers to reduce the number of misclassifications the rule: ‘a pixel classified under RP class belongs to encephalic parenchyma if it is located very close and contiguous to pixels classified under NAWM class, it has strong membership degree to RP class or its probability of belonging to NAWM class is higher than to WFR or NFR classes’.

Then, the encephalic parenchyma is determined by those pixels classified under NAWM class and those classified under RP class according with the third previous rule. The implementation of this rule has been performed in the following way:

1) A pixel classified under RP class is close enough and contiguous to NAWM class pixels if its distance to

the closest pixel initially classified under NAWM class is not greater than 2 pixels. Its implementation consists on applying morphological dilation using a circular structuring element of radius 2.

2) A pixel classified under RP class has strong membership degree to this class if its membership degree to $f_{RP}$ is higher than or equal to 0.75.
3) A pixel classified under RP class has higher possibility of belonging to NAWM class than WFR or NFR classes when its membership degree to NAWM is greater than to WFR or NFR fuzzy sets.

The isolation of the encephalic parenchyma has been performed dividing the different slices in two groups separated by a automated selected reference slice located upper the presence of eyes, in which the encephalic parenchyma appears as a single region with high enough size clearly differentiated of external structures. The isolation procedure is based on the application of erosion and dilation morphological operators and the analysis of the connectivity according with the complexity observed on the reference, upper or lower slices.

## III. Results

The designed algorithm has been tested over a test set of 230 MR images from 5 patients and 138 MR images from 3 healthy volunteers. Images of the test and design sets were acquired using the same sequence. Its analysis has been performed on a SGI Octane workstation with a 270 MHz R12000 processor that spends about 5 minutes to segment the whole encephalic parenchyma in 46 T1-weighted images (2 minutes in the first stage, and 3 minutes in the validation).

Figure 2 is a sample of the segmentation results, in which the contour of the segmented regions is represented by white lines surrounding these regions.

The quality of these results has been evaluated considering qualitative and quantitative criteria. Qualitative analysis is based on the visual inspection by different neuroradiologists. And, quantitative assessment considers:

1) The similarity degree between the proposed automatic segmentation and the result obtained by different operators using semi-automated and manual tools included in Dispimage software (UCLH, UK).
2) The study of reproducibility for scan-rescan.

### *A. Qualitative analysis*

The proposed algorithm achieves an accurate enough encephalic parenchyma segmentation for volume measurement purposes, bearing in mind the reproducibility introduced by the automatic segmentation. In addition, it is important to emphasize the good NAWM estimation obtained using this algorithm.

### *B. Analysis of similarity*

Two indexes have been considered to evaluate the similarity between automatic and manual segmentations in three patients and three healthy volunteers. These indexes considers a binary segmentation as a set R containing the pixels belonging to the classification, yielding that the similarity between two segmentations $R_1$ and $R_2$ is given by a real number $S \in [0,1]$ defined by

$$S=2\,|R1\cap R2|/(|R1|+|R2|) \quad (1)$$

$$S'=(R1\cap R2)/(R1\cup R2) \quad (2)$$

Both indexes take high values, nearly all of S values higher than 0.9 and S' values around to 0.9 in all cases. In patients, mean values of S and S' are around 0.93 and 0.89 respectively for automatic/manual comparison, while that in the comparison of manual traces take mean values of 0.953 and 0.912 respectively. In healthy volunteers it can observe a slight increase of these values of about 1-2%. Standard deviations are in the same range in all measures, keeping on below 0.026.

### *C. Reproducibility analysis*

Reproducibility was assessed for scan-rescan (i.e. imaging the subject twice and segmenting encephalic parenchyma from separate acquisitions). 4 MS patients were selected to represent a range of parenchyma measures. Each subject was scanned, removed from the magnet, and after a break not lower than 15 minutes repositioned and rescanned. The images were post-processed and brain parenchyma volumes were obtained from each scan. The coefficient of variation ($\sigma$/mean) observed was 0.65%.

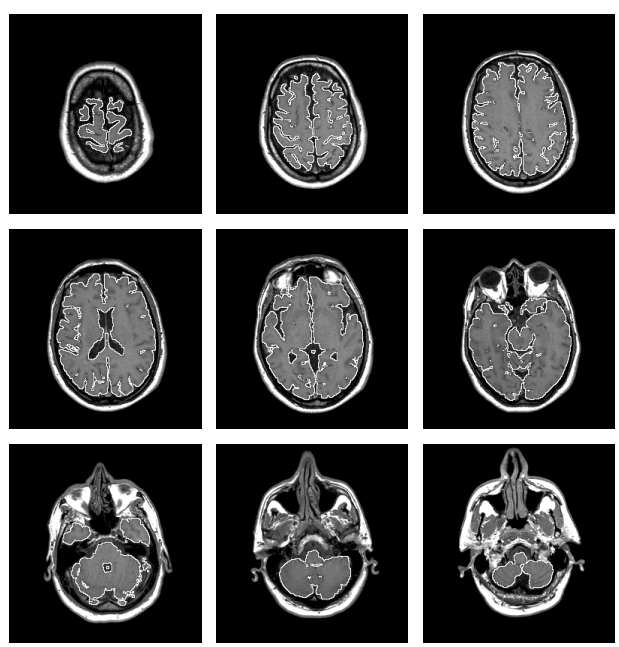

Fig. 2 Sample of obtained results for different slices.

## IV. Discussion

The segmentation, that this algorithm achieves, is accurate in most of slices. Nevertheless, some regions can be affected by non-critical misclassification problems, usually located on end slices or periphery regions. These misclassifications do not mean important reductions in the size of these regions. Sometimes misclassifications are due to the presence of flow artifacts such as around the fourth ventricle. The inclusion of external regions is very infrequent, only in locations such as orbital fat could be partial and small misclassifications.

The use of quality criteria helps to compare with other works. To make this comparison we must corrected the differences that manual methodology introduces. In this way, we have equaled the values of the similarity indexes related to the comparison of manual segmentations, and from this new value we have corrected the value of the indexes for automatic/manual comparisons. Then, we have observed that the corrected values of the similarity indexes obtained in this work are in the same range of values that the obtained in other works [4][7] using the same indexes. The comparison with the work [7] shows that the values of S are the same range, and it is important to emphasize that our segmentation also excludes CSF regions. In the comparison with the work [4], S' values are also in the same range, but our algorithm takes advantage of the local fuzzy analysis to improve its robustness in presence of non-homogeneities.

The reproducibility of the algorithm allows applying it to brain volume measurements. In addition the computational cost is one of the lowest in this kind of algorithms [4][5][7], and clearly lower in relation to a manual segmentation.

## V. Conclusion

By means of the application of fuzzy techniques we have designed a fast, reproducible and fully automatic approach to segment the encephalic parenchyma on T1-weighted images. This algorithm achieves a good NAWM estimation and an accurate segmentation of the encephalic parenchyma. And, the analysis of the results, based on different quality indexes, shows high enough quality to use the designed algorithm instead of manual or semi-automatic algorithms, allowing its application to quantitative studies [16].

Finally, it is important to emphasize that this algorithm gives information about the accuracy in the classification of pixels. In this way, the study of the continuity in the fuzzy information helps to evaluate and improve the results.

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