AUTOMATIC SEGMENTATION OF MULTIPLE SCLEROSIS LESIONS FROM MRI SLICES

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ABSTRACT

We present, in the scope of this article, a contribution to the automatic extraction of Multiple Sclerosis (MS) lesions from MRI images (Magnetic Resonance Imaging). Our method is entirely automatic[1][2]. It is based on three steps : first, brain segmentation, then construction of Talairach atlas thanks to the determination of the CA-CP, VCA, and the interhemispheric plans, and finally the extraction of MS lesions by statistic analysis. Thus, the results we have obtained are close to 100%, even if some mistakes, linked to unexpected movements of the patient, can occur during the acquisition.

1 INTRODUCTION

The MRI allows to determine the cerebral lesions precisely and to relate them more closely to clinical data. Numerous neurologic studies have proved that the size and localisation of the lesion do not necessary reveal behaviour troubles. Nonetheless, they give a superficial piece of information. Our final objective is to improve the localisation of the ischemy zones through an automatic detection but firstly we validate our method on patients who are affected by MS lesions. So as to do that, we carry out a resizing of the brain in the Talairach atlas [6], to have a common system of reference for each patient. Then, we propose a method capable of segmenting lesions automatically. Eventually, a multivaried statistic analysis will enable us to determine the lesion's effective area, in the Talairach atlas, according to a precise clinical syndrome.

The MS lesions appear in hypersignal in protons density σ. In order to detect them, it is necessary to find a way of suppressing the environment exterior to the brain (dome of the skull, eyeball, subcutaneous fatty tissues) and so avoid any mistake during the detection. First, we present the Expectation Maximisation (EM) segmentation [3][4] to obtain the brain, then, the Talairach atlas' construction and finally the MS lesions extraction method. For each step we will specify the originality of our approaches. Our method of brain segmentation is characterised by a *more geometrical approach* of the segmentation problems. This has allowed us to correct mistakes linked to the statistic processing of the EM algorithm on the axial slices of the skull.

The first results we propose have been obtained after the study of 28 patients' clinical folders and are superior to 95 % in each case. The 5% left are linked to some patients' excessive agitation.

2 EM SEGMENTATION

2.1 Suppression of the noise

In order to suppress the background noise, we have used the EM segmentation on the histogram's image. This approach assumes that the image is a combination of uncertain fields. The EM segmentation is a robust method that allows, whatever the acquisition conditions of a patient's skull MRI slices, to determine an optimal threshold so as to suppress an image's background noise. The EM algorithm is iterative and can be analysed into 3 steps.

The first step is the initialisation of the a priori probabilities, averages and classes' variances. We thus can calculate :

$$\pi_k^{m=0} = \frac{1}{K} \quad \text{and} \quad \theta_k^{m=0} = (\mu_k^0, \sigma_k^0)$$

Then, we estimate the a posteriori probabilities $t_k^m(x_i)$ for the x_i pixel belonging to the k class at the mth iteration.

$$t_k^m = \frac{\pi_k^m f\left(x_i / \theta_k^m\right)}{\sum_{p=1}^{K} \pi_p^m f\left(x_i / \theta_p^m\right)}$$

We can recalculate, for the m+1 iteration, the a priori probabilities, the averages and each classes' variances as follows:

Classes' apriori Probabilities :

$$\pi_k^{m+1} = \frac{1}{n} \sum_{i=1}^{n} t_k^m\left(x_i\right)$$

Classes' average :

$$\mu_k^{m+1} = \frac{\sum_{i=1}^{n} x_i t_k^m(x_i)}{\sum_{i=1}^{n} t_k^m(x_i)}$$

Classes' variances :

$$\left(\sigma_k^{m+1}\right)^2 = \frac{\sum_{i=1}^{n} \left(x_i - \mu_k^{m+1}\right)\left(x_i - \mu_k^{m+1}\right)^t t_k^m(x_i)}{\sum_{i=1}^{n} t_k^m(x_i)}$$

When the algorithm converges, we apply the Bayes rule which attributes a k class to each pixel as follows :

$$k(x_i) = Arg\left[\max\left\{\pi_k f\left(x_i/\theta_k\right)\right\}\right] \text{ with } 1 \le k \le K$$

After the classification operation in the initial image (fig 1), we separate the information from the noise (fig 2) and we eliminate it thanks to morphological (fig 3) operators.

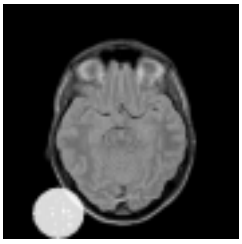


Fig 1 : initial image

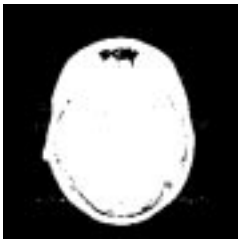


Fig 2 : image after segmentation

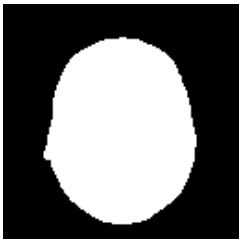


Fig 3 : mask after filling

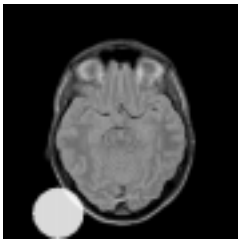


Fig 4 :after suppression the background noise

3 SEGMENTATION OF THE BRAIN

After the suppression of the background noise, the second step consists in segmenting the brain while suppressing the undesirable regions and those exterior to the brain such as fat, the eyes...

Note :

For the EM segmentation to function in the best possible conditions, it appeared necessary to delimit the interest zone corresponding to the skull. That allows us to have a better repartition of the classes.

The result of the segmentation of a patient's skull MRI images into 3 classes are given fig 5. Then, we carry out a double thresholding in order to suppress the classes corresponding to the air, eyes and skull (fig. 6). At the close of this operation, we obtain the all brain. We will then apply different treatments so as to delimit the brain's region we are looking for.

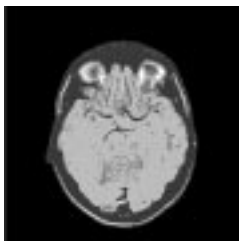


Fig 5 :The 3 classes obtained by EM segmentation

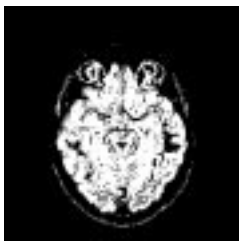


Fig 6 : image after a double thresholding

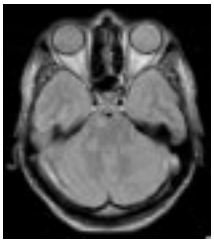
4 THE FLOOD FILL

The segmentation into 3 classes and double thresholding allow a first suppression of the regions exterior to the brain. The results obtained, although good, however remain inadequate in the region corresponding to the cerebellum as shown below (fig. 7).

The brain is, of course, not related to the eyes or subcutaneous fat. It is thus possible to save the brain while suppressing the undesirable parts. We have fixed our choice on a recursive filling method : the Flood Fill algorithm.

Note

Over 28 patients' clinical folders, we have noticed that, in axial slices, the brain is situated at the centre of the image. That has allowed us to automate the process through the creation of a germ whose level of grey's value is given for a pixel belonging to the centre of the image.



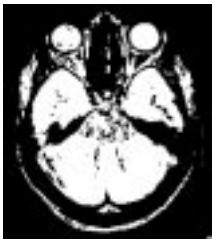


Fig 7 :slice near the cerebellum

The suppression of the undesirable regions, such as the eyes and the skull, is more and more increasingly difficult when it comes to deal with the MRI slices representing the cerebellum.

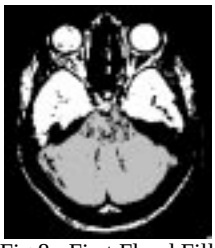


Fig 8 : First Flood Fill

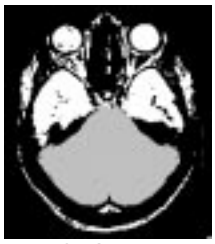


Fig 9 : Symmetry

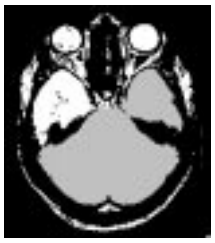


Fig 10 : Second Flood Fill

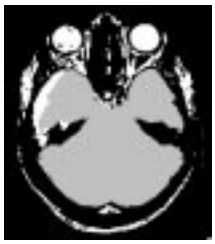


Fig 11 : Symmetry

We propose to use the fact that the brain is relatively symmetrical. Thus, by taking the symmetrical figure of this mask and by adding it to the mask we have obtained after the first filling, we can save the disjoint parts of the brain.

The Flood Fills (fig 8,9,10,11) and the successive symmetries thus allow us to finally obtain the mask of the brain (in grey fig. 12). By applying this mask, we can thus save the brain (fig. 13).

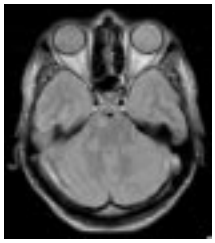


Fig 12 : initial image

Fig 13 : final brain mask

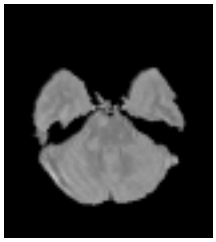


Fig 14 : brain

Notes :

Over the 28 files treated, our method has proved its reliability and robustness. Nevertheless, problems appear in the brain's first MRI slices.

The fat and brain have very similar levels of grey (fig. 15). It is thus necessary, so as to obtain a correct mask of the brain, to use some of the skull's geometry continuity properties to avoid segmentation artefacts. We propose the following solution :

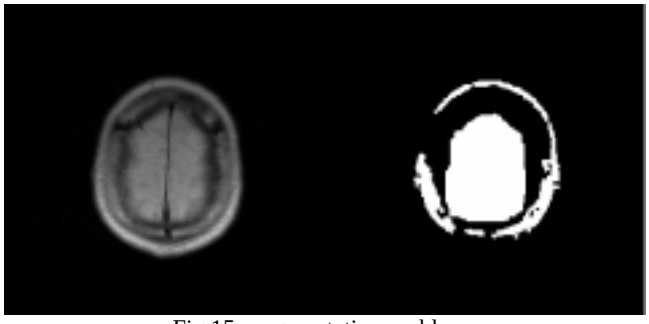


Fig 15 : segmentation problem

In order to correct the mistakes, we suppose (fig 16) that there only are a few variations from one slice to the following or the previous.

However, the slicing must be thin enough so as to allow distinction between the skull and the brain and, thus, to avoid problems linked to partial volumes.

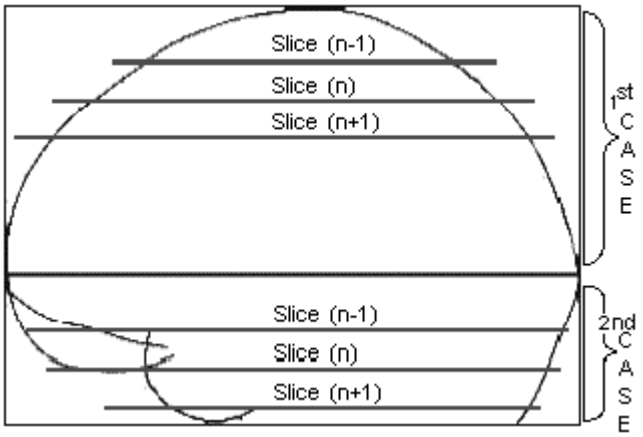


Fig 16 : Geometrical approach

In the first case :

- the (n-1) slice is smaller than the (n) slice.
- the (n+1) slice is bigger than the (n) slice.

In the second case :

- the (n-1) slice is bigger than the (n) slice.
- the (n+1) slice is smaller than the (n) slice.

A simple comparison between the height of the slices is thus enough to determine if a mask of the brain is erroneous.

Then, a LOGICAL AND, between the (n) slice and the (n+1) slice for example, allows to correct the possible mistakes.

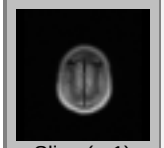
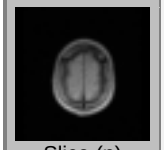
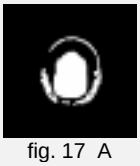
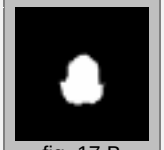
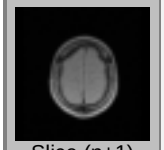
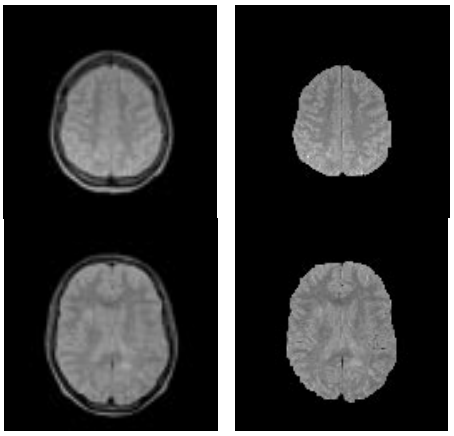
Brain slices	Mask after segmentation	Mask after mistakes correction	Final Image
 Slice (n-1)			
 Slice (n)	 fig. 17 A	 fig. 17 B	
 Slice (n+1)			

Fig 17A. : This mask is false : the slice n>n-1, whereas the slice n>n+1.

Fig 17B : AND between the (n) slice mask and the (n+1) slice mask.

4.1 Segmentation Results

Our brain segmentation (fig 18) method is characterised by a more geometrical approach of the segmentation problems. That has allowed to correct mistakes linked to the statistic treatment of the EM algorithm on the skull's axial slices.



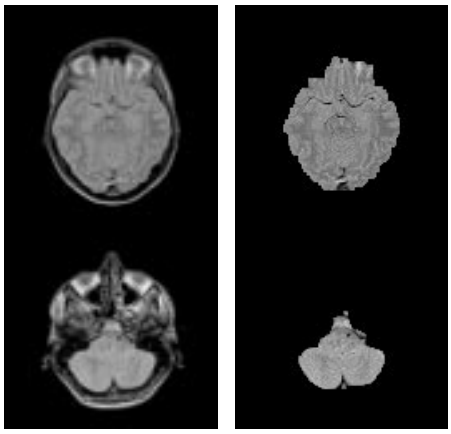


Fig 18: brain segmentation results

After the thresholding process, we will describe the method used to separate the MS lesions from the brain.

4.2 Resizing in the Talairach atlas

In order to localise the automatic extraction of MS lesions in the brain, we use the Talairach atlas (fig 19) which constitute the only reference marks system. This atlas allows an identification and analysis of the cerebral structures.

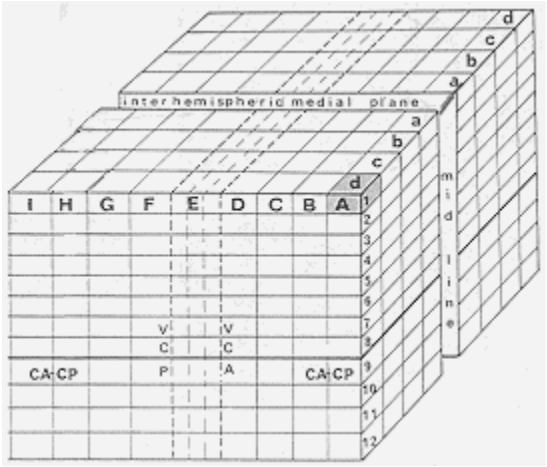


Fig 19 : Talairach atlas

In order to resize the brain in the Talairach atlas, we must detect the CA-CP, VCA, interhemispheric plans.
The CA-CP and the VCA plan are perpendicular. Thus, in order to detect them, we must find the maximum euclidian distance in each plan. Then, we must use the axial and coronal slices to determine the interhemispheric plan (fig 20). We can only see the interhemispheric axis in the brain top axial slices. To extract this line we apply a Sobel filter, morphological filters and thresholding (fig 21).

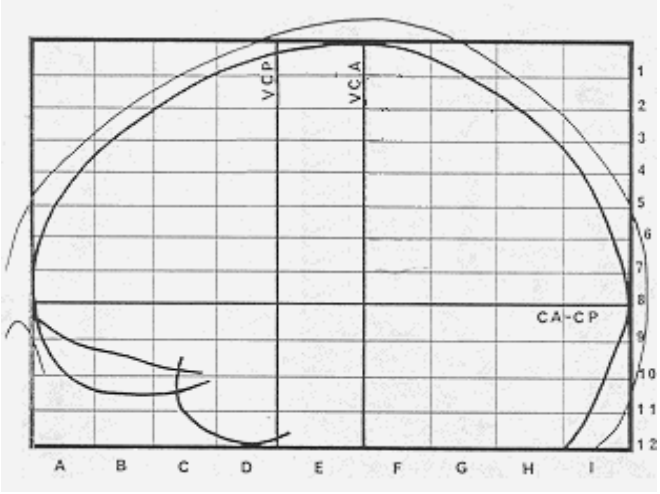


Fig 20 : CA-CP, VCA plans in the interhemispheric plan

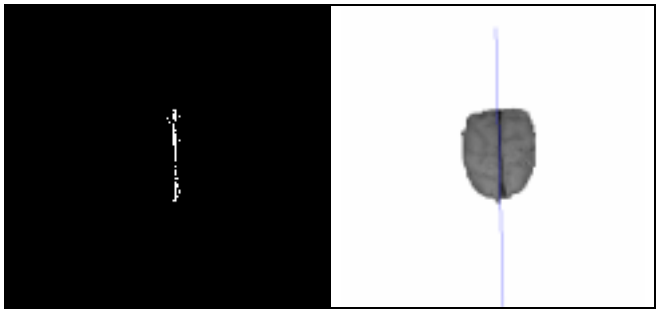


Fig 21 : determination of the interhemispheric plan

To obtain the equation of this axis we propose to calculate the linear regression coefficients on every axial slice. We thus take these coefficients mean value. From this line equation, we can compute the rotation angle, which is to be apply to each axial slice. We repeat these operations in the coronal plane, built from the axial slices.
This method is useful when it comes to correct the inclinaison of the patient's head in the coil during the acquisition. Then, we normalise the brain so as to help neurologists in the interpretation of cognitive troubles.

5 EXTRACTION AND LOCALISATION OF THE MS LESION IN THE NORMALISED BRAIN

The extraction is built in two steps. First, we approximately delineate the MS lesions thanks to a thresholding.

We study each voxel of the Talairach atlas. We compute the mean value Ξ and the variance σ in this voxel. Each pixel of this voxel is compared to $\Xi+3\sigma$, and is ranked as a lesion if its value is superior to $\Xi+3\sigma$.

Finally, we can improve the results thanks to the correlation between the T2 and PD acquisition.

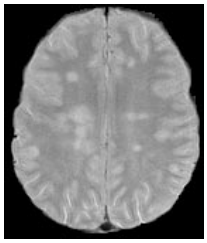


Fig 22 : Proton density slice

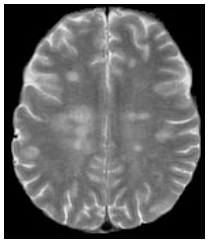


Fig 23 : T2 slice

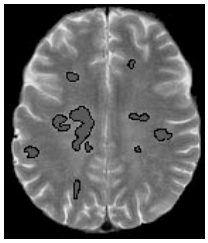


Fig 24 : the MS lesions

6 RESULTS

Our method is relatively quick and entirely automatic. By working on T2 and PD ponderated brain slices made every 5mm and whose size is 512x512 pixels, the segmentation of a patient's brain and the correction of mistakes take about 6 minutes on a Pentium 100 Mhz fitted out with 32 Mo of RAM. As for the localisation of the MS lesions in the Talairach atlas takes about 4 minutes (fig 22,23,24). These different techniques we have here described only make up the first part of our work in the scope of the cerebral ischemic lesions segmentation study, which we lead together with Lilles's Centre Régional Hospitalier Universitaire Neurology and Neuroradiology services. At the present time, the data multivaried statistic analysis is being tested on patients suffering from speech troubles.

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