Symbolic Knowledge and Fuzzy Logic in Automatic Segmentation of MRI Images

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Abstract— **We present, in the scope of this article, a contribution to the automatic segmentation of the encephalon. The standard segmentation algorithms cannot efficiently compensate the heterogeneity of intensity, which is a common artifact in magnetic resonance images (MRI). They don't either make use of the knowledge of the medical experts. With the increasing resolution of the brain images manual segmentation becomes a time consuming and a non-reusable task. So, an automatic and accurate segmentation technique is essential to correctly identify the three main tissues of human brain that are White Matter (WM), Gray Matter (GM), and Cerebrospinal Fluid (CSF). An accurate segmentation of brain tissues is also crucial for most of medical imaging applications such as diagnosis, localization of pathology, study of anatomical structures, treatment planning, and computer assisted surgery. We propose an automatic segmentation method that benefits both from a classic approach and from a fuzzy framework that makes use of expert physicians' knowledge. The experts' knowledge provides symbolic informations that are used to improve the segmentation results. So, the goal of our method is to automatically identify the brain structures, such as white matter, gray matter, and cerebrospinal fluid. For this work we have used T1-weighted magnetic resonance images (MRI) of the brain.**

1. Introduction

Tissue segmentation is a necessary step in most of medical imaging applications. However, the segmentation of voxels in brain structures is a difficult task because of artifacts existing into the images. Among the medical imaging modalities, magnetic resonance imaging (MRI) has the best tissue contrast. This is why we use this modality although it is not free of additive noise and other imaging artifacts. It is very difficult and almost impossible to obtain a correct automatic segmentation based only on colorimetric informations. Therefore, it is necessary to use other informations such as atlases, phantoms or experts' knowledge so as to improve the operation of segmentation. But the use of an atlas or a phantom increases the cost substantially, because they are built from a database of normal patients. And it is possible that a ill patient had been included into the database by mistake and this can produce an inaccurate phantom and incorrect segmentation results. Another approach is based on the use of the experts' knowledge. The atlases or phantoms give static informations, but the brain structures vary from a patient to another. The rules induced from the experts' knowledge allow a dynamic treatment of the informations. For all these reasons we have chosen to study this second approach. In order to provide a model of the experts' knowledge, the symbolic informations have to be formulated relatively to the gray levels existing into the images, the distance and the orientation relations between the typical structures of the brain. And to implement the use of symbolic informations, we chose the concept of fuzzy logic and in this purpose we had to establish the corresponding membership functions and a set of appropriated rules. Our method begins with the determination of an initial and coarse segmentation of the brain structures (CSF, GM, and WM) by the use of histogram thresholding. Then, the accurate segmentation is performed thanks to our fuzzy system. The main advantage of our approach is that it needs neither a phantom (or an atlas) nor a model and furthermore it is entirely automatic. The paper is organized in four main parts. The first section presents some related works about the segmentation of brain structures.

In the next section the different steps of our approach are developed. The third part focuses on the results that we have obtained . Finally, the paper ends with a conclusion.

2. Related works

The automatic segmentation of cerebral MRI is a hard problem due to the complex brain organisation. The existing segmentation methods are based on different concepts as the classification, the histogram analysis, the use of deformable models, the automatic or supervised training, or the knowledge based approaches. The classical approaches in structures detection provide an incomplete and ambiguous segmentation. Among these classic approaches we find probabilistic models as Generalized Expectation Maximization (GEM) [15], Modified Fuzzy C-Mean in [18], Adapted Fuzzy C-Mean (AFCM) [23]. To overcome these difficulties, [14] has proposed a new approach called Adaptative Fuzzy C-Mean with contextual constraints. This method gives better results, but it doesn't use symbolic informations. Other approaches using active contours and deformable models have been presented by Davatzikos et al [11], [10], [22], [24] and [1]. These approaches don't give stable results and can be very slow for noisy images. Other autors [4] use phantoms, atlases or models to detect the brain tissues. These classic approaches provide partial and not reliable results. Other methods, called parametric methods, model the searched structures. These methods are dynamic, adaptative and independent of an anatomical model (in opposition to atlases and phantoms). There are two major kinds of parametric methods, the ones based on training and the ones based on experts' knowledge. Wilburn et al [25] and Chiou et al [10] use a training approach by neural network to build a specific model of a knowledge. The drawbacks of such methods lie in the difficulty of conception and implementation. [2] introduces a method that associate the *Empirical Procedures* and the *Anatomical Knowledge*. Other parametric approaches such as [27] to improve the empirical methods add a model of knowledge *a priori* obtained from a set of training steps. The approaches proposed by Dou et al [13] and Hata [17] are guided by the knowledge determined from the modelling of the fuzzy attributes of the different searched structures (size, gray levels, information about position and directional relations). The main interest of these approaches is the ability to make use of knowledge models so as to control the segmentation process. The results are generally more efficient than the ones obtained with the empirical approach. However, the complexity of the model makes tough the cooperation with the experts. Another rule-based method is described in [19]. Recently, Barra et al [3] and Bloch et al [8], [7] have introduced two methods based on the theory of data fusion in image processing. These two approaches use symbolic informations given by an expert and fuzzy logic to model the uncertainty inherent in every linguistic description. These methods give good results, nevertheless, the theory of data fusion is difficult to implement and we chose a simpler way to perform the initialization step for our approach.

3. Our works

Actually, the better way to discriminate one brain structure from the other ones is to take into account the experts' knowledge. The strength of knowledge-based systems is the ability to perform *coarse-to-fine* operations. Instead of attempting to achieve the segmentation in only one step an incremental refinement is applied. The easily identifiable tissues are first located and labeled then the others tissues are sought out. We present in the next section our method both based on a classic pre-treatment step and a fuzzy logic system which models the symbolic knowledge.

3.1. Pretreatment

The centering of the images is a necessary preliminary task so as to consider the same reference center for all the slices during the next steps. The method that we use to center all the images is rather simple but gives good results. We first calculate the center of gravity of all the pixel that are not considered as part of the background of the image. The same process is applied on every image and the center of gravity is obtained by averaging all these results. Then, the pixels of the current image are translated relatively to this center of gravity in order to correctly put in place the points, relatively to the center of the significative pixels of the image. The distribution of the gray levels in an image varies according to the acquisition mode (T1 or T2), and even the tissue of the patient. Thus, another pretreatment is necessary, in order to facilitate the automatic parameters setting. The used method is that of the histogram expansion. Let us consider X_{min} and X_{max}, respectively the minimum value and the maximum value of each slice, after the expansion we obtain for each pixel:

$$X = 255(\frac{X - X_{min}}{X_{max} - X_{min}})$$

After these two treatments, we can apply our segmentation method.

3.2. Initialization

Our objective is to improve the identification of the brain structures corresponding with GM, WM and CSF. But the contrast obtained between the various components of the human brain in medical imaging is not significant enough and this can generate unexpected errors during the image interpretation. In order to determine the thresholds, and so to identify the components of the brain, we use the colorimetric informations given by the histogram obtained after the pretreatment step. Then, the thresholds are determined by the use of the method of the ascent of gradient. As we use neither an atlas nor a phantom, we need an initialization step. During this step we want to be sure that the areas associated with a brain tissue (GM, WM, and CSF) are correctly identified even if these areas correspond only with a part of the image. This step is very crucial as it ensures that the following automatic treatment gives good results.

The ascent of gradient can be described as follows: Let us consider $x_i \in [0..255]$ the abscisse of the histogram which represents a pixel value, and $f(x_i)$ the number of identical pixels in the whole image.

1) for each x_i
2) continue if $f(x_{i-1}) \geq f(x_{i-1})$ or $f(x_i) \geq f(x_{i+1}))$
3) else stop: x_i is a peak
4) restart from 1 of the next point of x_i

For the valley detection, the algorithm is:

1) for each x_i
2) continue if $f(x_{i-1}) \leq f(x_{i-1})$ or $f(x_i) \leq f(x_{i+1}))$
3) else stop: x_i is a valley
4) restart from 1 of the next point of x_i

Because this methods detects too many valleys and peaks, a filtering step of the histogram is necessary. A minimal distance between the near peaks (and valleys) is established, then the most relevant ones are kept until remain only two valleys and three peaks. After the filtering step, we obtain the histogram as shown in the figure 1. The result of this initialisation operation is far from being satisfactory because this step doesn't take into account of the topology. Some pixels are associated with a wrong structure because their colorimetric information is in contradiction with the topology. The two black triangles in the figure 4 represent the ambiguous pixels that still have to be classified. The problem arises from the proximity between the gray level of the pixels and a considered threshold value, and also from the lack of informations about the topology. On the one hand some pixels corresponding to the CSF structure are combined with the GM structure, and on the other hand some pixels corresponding to the WM structure are combined with the orbital cavity and the cranial bone.

As shown in the initialization step, we can use the threshold values to properly associate some areas with the CSF and the GM structures. Then, we can seek for the other brain structures, as the WM ones. The following properties are considered:

- The WM is situated around or partly inside the GM
- The WM and the GM are not far from the center of the brain
- The WM and the GM are separated from the cranial bone by the CSF
- The CSF is all around the WM and the GM

To get the coarse segmentation of the structures (CSF, GM and WM), we use the histogram obtained from the application of the threshold algorithm. Each structure corresponds with a peak

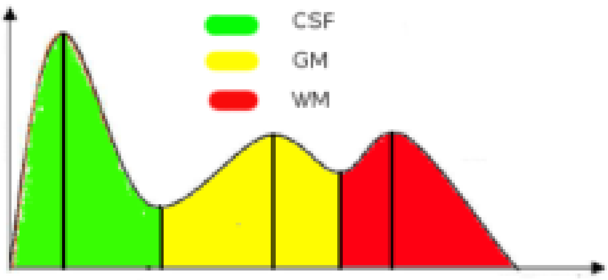

Fig. 1. Histogram obtained after filtering

of the histogram. In particular, we only calculate the threshold corresponding with the gray matter (GM) in order to build a correct reference that will be used during the next steps of our approach. Since the threshold algorithm gives several corresponding areas for the GM, it is then necessary to look for the good area. So, we calculate the connected components to these areas and we keep the nearest to the center of the image. See the figures 2 and 3. In the following sections of this paper, we propose a method based on the experts' knowledge to provide a better classification of the ambiguous pixels.

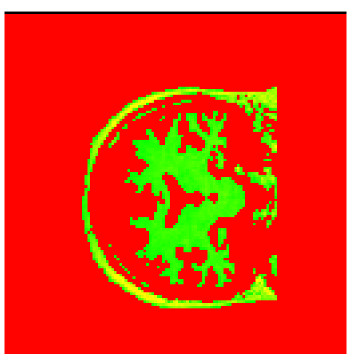

Fig. 2. GM after the histogram filtering

3.3. Definition of our fuzzy system

Our approach is based on the fuzzy logic in order to take into account symbolic informations about the brain anatomy. Fuzzy Logic was initiated in 1965 by L.A. Zadeh in [26]. Other authors as [6] use this concept in brain segmentation. D. Dubois et al [12] have exposed new perspectives on the reasoning with fuzzy rules. Basically, the fuzzy Logic is a multivalued logic which allows

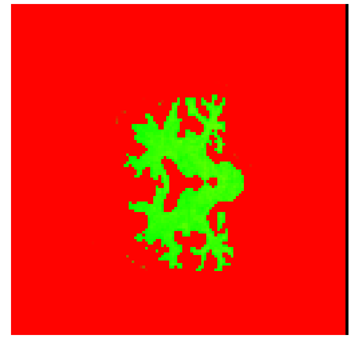

Fig. 3. GM after determination of the connected components

intermediate values to be continuously defined. Experts' knowledge can be formulated in a natural way using linguistic variables, which are then symbolized by the mean of fuzzy sets. Linguistic rules are described in the fuzzy system by: an antecedent block (between *if* and *then*) and a consequent block (following *then*). For example, *if a pixel is black and far from center of the brain then it is probably part of the background.*

The fuzzy system is decomposed into the three following steps:

- the fuzzification converts the numerical input values (gray levels) into fuzzy variables by application of the membership function,
- the fuzzy inference evaluates and applies the linguistics rules; the inputs are logically combined using an operator (for example the *and* operator) and produce output fuzzy values,
- the defuzzification converts the output values, which are fuzzy values, in numerical values.

In this works, we have used a classic trapezoidal function as membership function. With this function we obtain a better correspondence between the fuzzy distances and the expected brain structures. Our reference gray level is the one corresponding with the GM structure. We want to calculate a *distance map* that indicates the *distance* between the GM gray level and the one of the others pixels of the image. The use of the fuzzy logic allows us to obtain a better association between pixels and brain structures. This is done according to not only the colorimetric distances, but also the symbolic informations and the GM threshold.

3.3.1. Directional representation

Let us consider two areas, respectively characterized by two sets of points $A = a_1, ..., a_n$ and $B = b_1, ..., b_m$. The relative position of the two areas is evaluated by calculating the relative position (directional relation) of each pair of points a_i et b_j $\forall\ i = 1..n\ and\ j = 1..m$. The angle-histogram H_{AB} is related to a variable θ which represents the number of pairs $(a, b) \in A \times B$ that verify $(\vec{i}, \vec{a_i b_j}) = \theta$

$$H_{AB} = cardinal \left\{ (a_i, b_j) / (\vec{i}, \vec{a_i b_j}) = \theta \right\}$$

where

$$(\vec{i}, \vec{a_i b_j}) = \arctan \frac{Y_{B_j} - Y_{A_i}}{X_{B_j} - X_{A_i}}$$

The histogram of force is an extension of the angle histogram. This kind of histogram takes account of the metric information in addition to the angular information. It is defined by:

$$H_F^r(\theta) = \sum_{(a,b) \in A \times B, (\vec{i}, \vec{a_i b_j}) = \theta} f_r(\| \vec{i}, \vec{a_i b_j} \|$$

where

$$f_r(d) = \frac{1}{d^r}$$

H_F^r is the H_{AB} weighted by $f_r(d) = \frac{1}{d^r}$ and it represents the pair of points $\forall\ (a_i, b_j) \in A \times B$ in the direction θ at the distance d.
The angle histogram and the histogram of force allow the representation of the linguistics variables (such as *on the left*, *on the right*, *above* and *below*) by:

$$Rel(A, B) = \left(\int_{-\pi}^{+\pi} H_{AB}^N(\theta) (f_{rel}(\theta)^p) d\theta \right)^{\frac{1}{p}} \quad (1)$$

where

$$H_{AB}^N = \frac{H_{AB}}{\int_{-\pi}^{+\pi} H_{AB}^N(\theta) d\theta}$$

$f_{rel}(\theta)$ is the function described in (2) and defined by:

$$f_{rel} = \begin{cases} 1 & if \quad |\theta| < a \star \frac{\pi}{2} \\ \frac{\pi}{2} - |\theta| & if \quad a \star \frac{\pi}{2} < |\theta| < \frac{\pi}{2} \\ 0 & otherwise \end{cases} \quad (2)$$

The histogram of force provides the metric information but it is not directly transposable with the concept of fuzzy logic, because it gives a result relatively to two related variables that are *geometric distance* and *angular distance*. This result corresponds with a planar surface, thereby, we chose to use these two variables as follows:

- the geometric distance and the colorimetric distance are both used to define the fuzzy connection between pixels,
- the geometric distance and angular distance are both used to calculate the relative position of two areas (or pixels).

3.3.2. Fuzzy geometric distance

To determine the *fuzzy geometric distance* we use the geometric distance and the fuzzy variables: *very near*, *near* and *far* characterized by the trapezoidal membership functions, as shown in the figure 4.

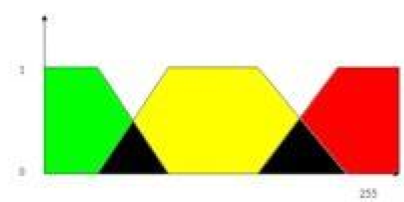

Fig. 4. Green: Very Near; Yellow: Near; Red: Far

The following membership functions, corresponding with the fuzzy geometric distance, are identical to the membership functions shown in the figure 4 and are called:

- DVN : very near distance
- DN : near distance
- DF : far distance

3.3.3. Fuzzy colorimetric distance

The *fuzzy colorimetric distance* is based on the same model, but it is defined in the color space. It uses the distance between two pixel in the space color (gray levels) and the membership functions as shown in the figure 4.

- CVN : very near color
- CN : near color
- CF : far color

3.3.4. Fuzzy connection

The simple combination of the two fuzzy distances (geometric and colorimetric) cannot provide a total order between the pixels. So, we introduce our concept of *fuzzy connection* based on the two distances and on the rules given by the experts (by application of the fuzzy operator *and*). Thus, there are nine possible combinations: two fuzzy connections (two membership functions (geometrical and colorimetric distances) and three fuzzy variables (very near, near, and far)).

3.3.5. Fuzzy colorimetric value

The space color is fuzzified by using the three similar trapezoidal membership functions: *black*, *gray* and *white* (figure 5).

- BL : black (like Very Near)
- GR : gray (like Near)
- WH : white (like Far)

3.3.6. Fuzzy structure value and fuzzy noisy structure value

They are characterized by the membership functions defined by three similar trapezoidal functions (figure 4):

- OCSF : Output CSF
- OGM : Output GM
- OWM : Output WM

The fuzzy noisy structure value is characterized by:

- NCSF : Noisy CSF
- NGM : Noisy GM
- NWM : Noisy WM

These two fonctions provide two outputs, one for the structure value and one for the noisy structure value.

3.3.7. Distance transformation

Let us consider an area A (a part of the image) that contains n pixels $p_i, i = 1..n$.The distance transformation, called D(A, image) where A belongs to the image, is the set, for every pixel of the image, of the minimum distance between this pixel and all the pixels of A.

$$D(A, image) = min_{p_i \in A}\{d(p, p_i)\}, \forall p \in image$$

d is any distance (colorimetric or geometric).

3.4. Workflow

The fuzzy system that we have defined contains three inputs and two outputs. The inputs are: *the fuzzy geometric distance, the fuzzy colorimetric distance, and the fuzzy colorimetric value*. The fuzzy outputs correspond to a structure value (CSF, WM, and GM) and a noisy structure (NCSF, NGM and NWM). Theoretically, there are 125 possible cases (3 fuzzy variables for 5 membership functions) associated with the three inputs and the two outputs.
The first input (colorimetric value) is directly obtained from the gray level of the pixels. To obtain the geometric and colorimetric distances, we use the results of the first step (figure 3). This result allows to build the distance map (for the color space and the geometric space). The calculus of the distance map uses the distance transformation as described before, and the reference area that is the GM obtained after the initialization step. We apply the fuzzy system and we obtain the two values, as said before. The distance map provides distance values and the membership functions are used to obtain the corresponding fuzzy geometric distances. However, we want to associate to every pixel only one structure. So, we keep the maximum of the two fuzzy output values because it corresponds to the searched structure value.

In our implementation, the rules can be dynamically added from the interface and this is done without recompilation. A rule is described in our fuzzy system by five values : the first three values represent the inputs corresponding to the fuzzy variables (respectively associated to the three membership functions: colorimetric information, colorimetric distance, and geometrical distance) and the two last values represent the activated outputs, one value among (OCSF, OGM, OWM) and one value among (NCSF, NGM, NWM). The ”–” symbol represents an unactivated output (i.e.

without an associated rule). If the two outputs are activated then the OR operator is used (maximum of the outputs). An example of rule, given by an expert, is: *if a pixel is black and very near to the GM structure then it belongs to the CSF structure*. This rule is described by *BL* || *CVN* || *DVN* || *OCSF* || – (the first line in the next tabular). There is an unactivated output (the noisy one) because experts are sure that such values correspond with a searched structure.. Note that the reference used to build our distance map is the GM obtained from the first step.
The next table shows the rules associated with the GM structure as reference. However, the rules change to according to the reference.

IN1	**IN2**	**IN3**	**OUT1**	**OUT2**
BL	CVN	DVN	OCSF	–
BL	CN	DVN	OCSF	NCSF
BL	CN	DN	OGM	NCSF
BL	CVN	DN	OGM	–
WH	CVN	DVN	OWM	–
WH	CVN	DN	OWM	NWM
WH	CN	CVN	OWM	NGM
WH	CN	DF	–	NWM
WH	CF	DF	–	NWM
GR	CVN	DVN	OGM	–
GR	CN	DVN	OGM	–
GR	CVN	DVN	OGM	NGM
GR	DN	DN	OWM	NGM

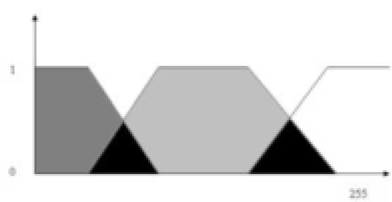

Fig. 5. Black: CSF; Gray Matter: GM; White Matter: WM

From the previous definitions, our fuzzy system consists in:

- evaluation of the input values by the way of the membership functions associated with each fuzzy variable,
- evaluation of the rules corresponding with the symbolic knowledge,
- application of the defuzzification step.

4. Results

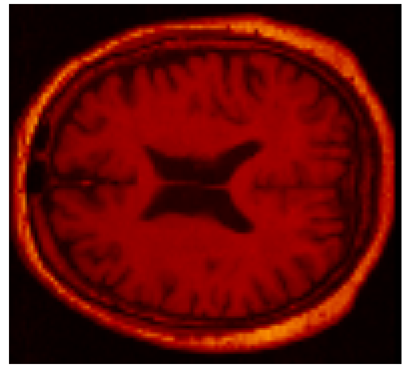

Fig. 6. Brain image before segmentation (1)

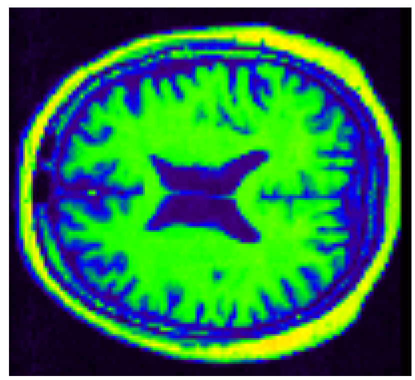

Fig. 7. Brain image before segmentation (2)

In this section, we present some results of application of our approach with real MRI data. The three first images represent the input images of brain (fig 6, fig 7, and fig 8 with a resolution of 128*128). The three last ones are the results (with an uniform color mask) corresponding to the three searched structures (CSF, GM and WM) (fig 9, fig 10, and fig 11 with a resolution of 128*128). The brain images that we used in the experimentation have been given by the *Toulouse Medical Imaging Research Group*.
We show in the results that we obtain the characterization of the three searched tissues. The parts that don't correspond with the brain tissues (like the bones) have been correctly removed. However, we observe that the results are not fully satisfactory because some areas are not associated with the right structure. The segmentation of the GM and the WM is globally correct, except at the border of the brain structures. Some other

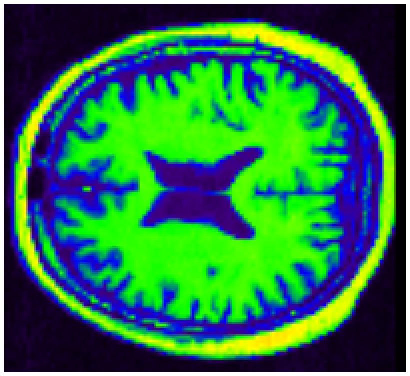

Fig. 8. Brain image before segmentation (3)

problems arise from not searched structures (like the ventricular cavities) that correspond with not any rules.
These results can be strongly improved by the use of the contribution of the neighbors. In image segmentation, the information brought by the neighborhood is primordial to decrease or at contrary to increase the uncertainty. The geometric distance and the angular distance (obtain from the angle histogram) are used to build directional relation. Using the expression (1), we can calculate the directional relation between the GM and the 8 neighbors of the current pixel. It is also possible to use the membership function presented by Matsakis in [21] to calculate the fuzzy relation between two areas. The angle between two areas is defined in (1).

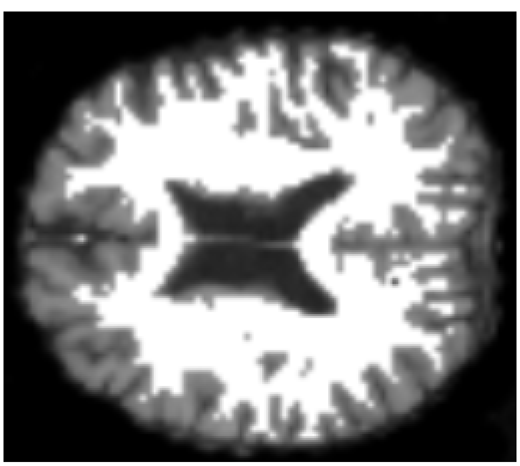

Fig. 9. The three structures after segmentation (1)

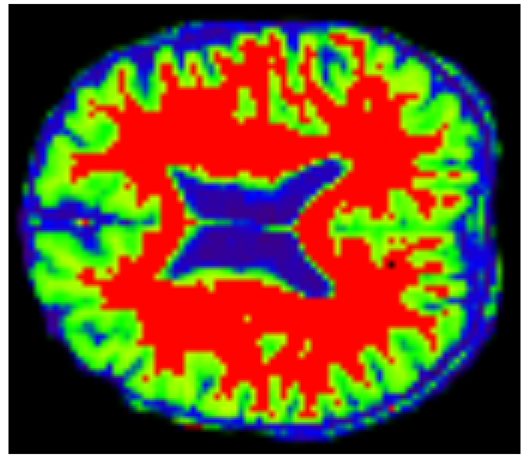

Fig. 10. The three structures after segmentation (2)

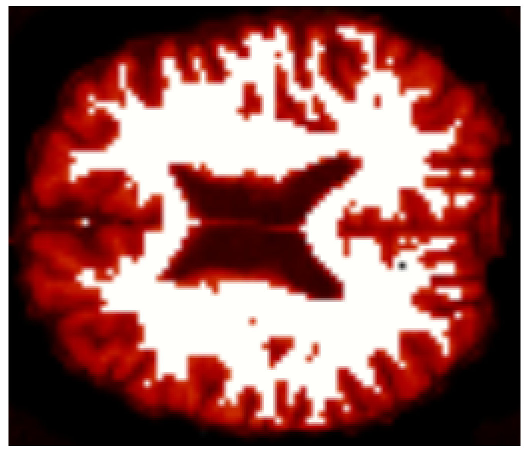

Fig. 11. The three structures after segmentation (3)

5. Conclusion and future works

We have presented an automatic method for CSF, GM and WM segmentation of the MR brain images. Our approach is based both on the expert's knowledge and a fuzzy framework.
The first results show the potential and the quality of our model but some improvements are necessary to obtain more accurate results. Our future works will concentrate on:

- segmentation of the other brain tissues, such as thalamus and ventricular system,
- establishment of more precise and therefore more complex rules,
- consideration of the neighborhood.

The *Toulouse Medical Imaging Research Group* provided to us the set of brain images used to test our model. The collaboration with

this research team has also allowed us to obtain informations in order to define the applied rules. The exchange of informations with experts will allow us to improve our model and to verify the correctness of our results.

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