Improvement of brain lesions detection using information fusion approach

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Abstract

Automatic segmentation of brain lesions such as multiple sclerosis in MRI images is a complex operation. One of main difficulties is to optimize the dilemma between the false positives and false negatives present in the segmented image. We propose here a new approach to this problem. The idea is to exploit the complementary results from different segmentation algorithms as well as the a priori knowledge to reduce false positives. The method starts with modeling inaccuracy about the borders of the segmented regions. The logic rules are then defined in order to combine the white matter image and lesions within the framework of evidence theory. The results show that brain lesions detection is substantially improved using this data fusion approach.

Keywords

Data fusion, image segmentation, evidence theory, MRI, multiple sclerosis.

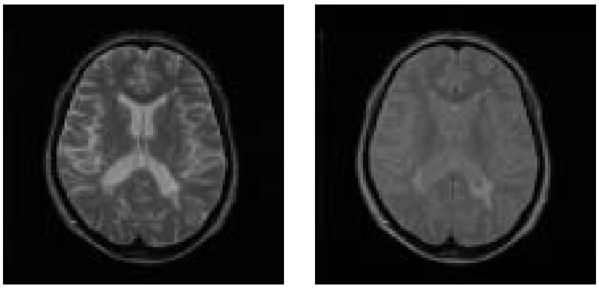
1 Introduction

Magnetic resonance imaging (MRI) is nowadays a popular reference technique for the diagnosis and monitoring of many brain lesions such as multiple sclerosis (MS) [1]. In this field, automatic segmentation of MR brain images plays a primordial role in the quantitative analysis of MS lesions [2]. In spite of much work reported in the literature [3], algorithms of automatic segmentation are not yet sufficiently precise and reliable for routine clinic utilization. This is due to several difficulties : a) the field inhomogeneities create the situation in which two voxels corresponding to the same tissue appear in the image in different manners ; b)the actual transition between different brain tissues is, from a physiological point of view, not precise in nature ; c)the partial volume effect yields mixture of several tissues in the same voxel. Add to that the difficulties specific to MS lesions. For instance, the number, shape, size, and contrast of MS lesions are very variable ; their borders can be fuzzy. To detect MS lesions, existing methods consist in privileging either segmentation of brain tissues by regarding MS as pathological tissue, or segmentation of lesions only. These two kinds of approaches have their advantages and shortcomings. Our idea here is to exploit their complementarities in order to achieve a more precise and robust detection of MS lesions. To do that, we use the results, yielded respectively by a MS lesion segmentation algorithm and a brain tissue segmentation algorithm, as two information sources. A third source is also considered that stems from the fact that MS lesions occur mainly in white matter, often near the ventricle. The evidence theory is then used to fuse the three information sources to obtain final detection of MS lesions.

2 Segmentation of MS lesions and tissues in MRI

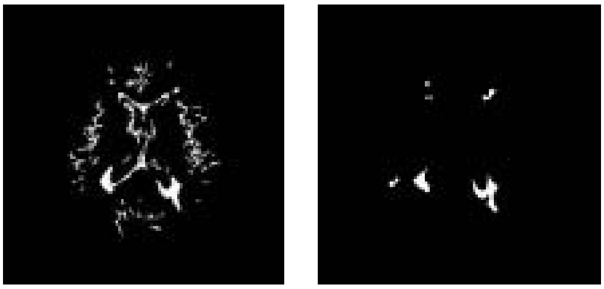
Figure 1 shows a typical pair of MR brain images corresponding to the same slice of brain. Algorithms of brain tissue segmentation aim, loosely speaking, to partition the image into main regions representing respectively white matter (WM), gray matter(GM) and cerebrospinal fluid (CSF). In contrast, algorithms of MS lesions segmentation aim only to bring out the objects in the image, which represent the lesions.

Both lesion and tissue segmentation algorithms used here were developed in our laboratory. The lesion segmentation algorithm is based on fuzzy C means (FCM) clustering [4]. It can be decomposed in five steps : a) enhancement of the contrast of the PD image, b) fuzzy clustering of the image's gray levels, c) second segmentation of image regions (corresponding to lesions and/or CSF) obtained in a) and b), d) identification of lesions cluster using gray-level information from T2 image, e) elimination of objets smaller than 3 pixels and objects touching the brain contour. An example



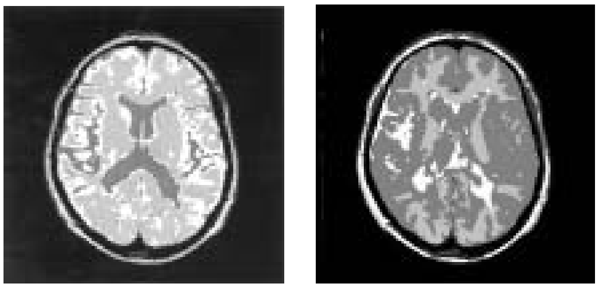
T2 image PD image

FIG. 1 – Brain MR images



Automatic segmentation Manual segmentation

FIG. 2 – Segmentation of MS lesions



segmented T2 image segmented PD image

FIG. 3 – Segmentation of brain tissues

of the segmented lesions using such an algorithm is shown in 2. The method presents the particularity of enabling the detection of all objects susceptible of lesions. The shortcoming is that there exist false positives in the segmented image, in comparison with segmentation manually done by medical expert.

The brain tissue segmentation is based on a statistical model including Bayesian distribution for brain tissues intensities and Gibbs Random Fields (GRF)-based spatial contiguity constraints [5]. The algorithm is unsupervised (i.e. the intensity-based signatures of brain tissues and the spatial hyperparameters of the underlying GRF are derived from the data) and adaptive (achieved through varying the size of neighborhoods used in estimating intensity characteristics). It does not require initialization and classifies data in any number of tissue classes. With this algorithm, two segmented images are obtained that correspond to T2 and PD images, respectively. Each of them contains four classes non-labeled, which should represent four tissues (WM, GM, CSF and skin). Fig. 3 illustrates an example of the segmented tissues using such an algorithm. Since the two images correspond to the same physical slice of brain, it is evident that the segmentation of the tissues was not perfect, and that it is necessary to label the obtained objects.

3 Information sources

In order to improve the segmentation of brain lesions, especially to reduce the false positives, we propose to use simultaneously information coming from different sources, such as MR images, medical experts and statistical a priori knowledge. The information sources are as follows :

Lesions segmentation : the segmentation process gives a binary mask of the potential lesions, with a large number of false positives, but not many false negatives.

Expert knowledge : medical experts know that 95% of MS lesions are in WM, so, a lesion found outside WM would be not a lesion. If a binary mask of WM is given, it is possible to combine the lesion and WM masks to decrease the number of false positives.

Tissues segmentation : the algorithm gives two segmented images (T2 and PD images) into four unlabeled classes. Some of these classes may correspond more or less to WM, but this is not sure. So, it is necessary to identify them.

Statistical knowledge : In order to label the segmented regions, it is possible to use a brain atlas such as that developed at Mc Connel Brain Imaging Center of the Mc Gill university of Montréal [6], where tissues are described by a probability image. This atlas is used here to automatically identify the segmented regions.

4 Modeling of information sources

4.1 Model of the confidence on the masks

The masks coming from the lesion and tissue segmentation algorithms are binary images. We choose to quantify the quality of these masks by modeling the confidence on the borders of their regions through the use of the basic belief assignment of evidence in the belief theory developed initially by Dempster and Shafer (DS) [7]. This theory permits to model the doubt between two hypothesis of a frame or space of discernment by assigning a mass of evidence to the union of these two hypotheses.

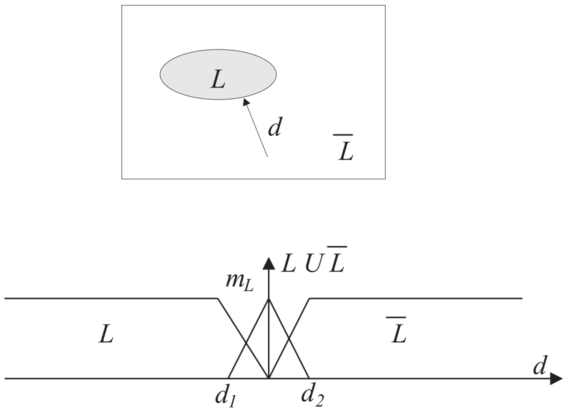


FIG. 4 – Definition of the basic belief assignment as a function of distance to the border

The basic belief assignment of mass m defined on the power of the space of discernment Ω of hypotheses H_i is :

$$\begin{array}{rccc} m: & 2^{\Omega} & \rightarrow & [0,1] \\ & A & \mapsto & m(A) \end{array} \quad (1)$$

$$\begin{array}{l} \sum_{A \subset \Omega} m(A) = 1 \\ m(\emptyset) = 0 \end{array} \quad (2)$$

where A is a set of hypotheses H_i.
The space of discernment of the lesions mask is $\Omega_L = \{L, \overline{L}\}$ where L means "lesions" and $\overline{L}$ means "non-lesion". The space of discernment of the white matter is $\Omega_{WB} = \{WM, \overline{WM}\}$ where WM means "white matter" and $\overline{WM}$ means "non white matter".
It is assumed that a pixel near a border of a region does not belong to this region with total certainty. The doubt or uncertainty near the border is modeled by a basic belief assignment m_L for the mask of lesions and m_{WM} for the mask of white matter, computed from the Euclidean distance d of the pixel to the border. Evidence m_L is represented In Fig. 4 as a function of distance. The sign $\cup$ means logical OR.

$$\begin{array}{l} m_L^d(L) \\ m_L^d(\overline{L}) \\ m_L^d(L \cup \overline{L}) \end{array}$$

The basic belief assignment for white matter is similar.

4.2 Determination of the white matter mask

As mentioned before, the brain tissue segmentation gives two segmented images, in which there are four tissue classes, but we do not know which is WM mask. In order to identify the WM mask without losing any information, we have evaluated all the 16 possible conjunctive combinations (2 images with 4 classes lead to 2^4 possible masks). In a heuristic manner, three masks have been identified as WM masks with the aid of the brain atlas presented in Section 3, and they are combined using disjunctive combination (OR logic) to produce the final WM mask.

	L	$\overline{L}$
WM	L	$\overline{L}$
$\overline{WM}$	$\overline{L}$	$\overline{L}$

TAB. 1 – Logical combination rules

	L	$\overline{L}$	$L \cup \overline{L}$
WM	L	$\overline{L}$	$L \cup \overline{L}$
$\overline{WM}$	$\overline{L}$	$\overline{L}$	$\overline{L}$
$WM \cup \overline{WM}$	$L \cup \overline{L}$	$\overline{L}$	$L \cup \overline{L}$

TAB. 2 – Extended logical rules of combination

4.3 Combination rules between lesions and white matter

Following the medical experts' knowledge, MS lesions generally appear in white matter. This means that the lesions outside the WM mask are false positives. The logical table 1 describes this rule.
Due to inaccuracy, doubt may exist concerning the belonging of a pixel to a region. This doubt is modeled by a basic belief assignment on the whole space of discernment. To calculate all the possible combinations of information on lesions and WM, we construct table 2 which is an extension of the logical table 1, and a function f defined by :

$$f: 2^{\Omega_L} \times 2^{\Omega_{WM}} \rightarrow 2^{\Omega_L} \quad (3)$$

Given the lesion and WM masks, two basic belief assignment m_L and m_{WM} are then available. They are combined to yield a new one m'_L taking into account all the available information :

$$m'_L(A) = \sum_{A=f(B,C)} m_L(B).m_{WM}(C) \quad (4)$$

5 Fusion architecture

The global fusion structure is shown in Fig. 5.
The masks obtained from the brain tissue segmentation algorithm are decomposed, then identified and labeled with the aid of brain atlas, yielding the final WM mask. The following step is then to fuse the lesion and WM masks. For each pixel, two basic belief assignments m_L and m_{WM} are determined and combined to get a new one m'_L. A new lesion mask is finally obtained from the combined m'_L. Fig. 6 shows the final detection of lesions. For comparison, manual segmentation by a medical expert is also given. Note that medical experts always over-evaluate the area of lesions.
The results show that a large number of important false positives have been eliminated, only a small number of false positives still remaining. Note that after

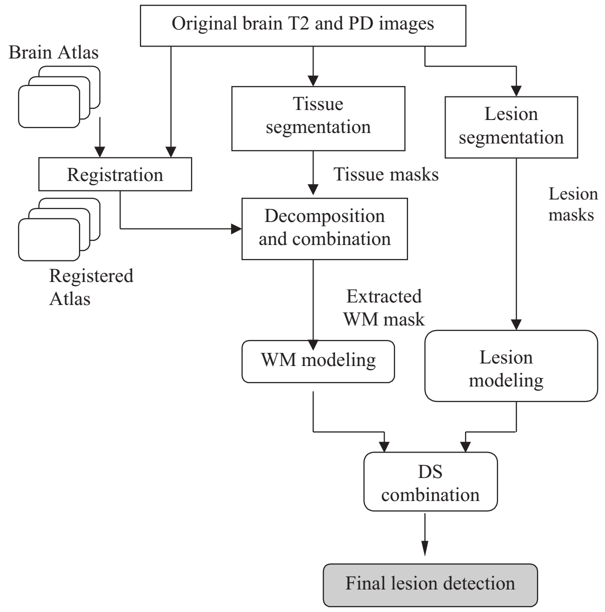


FIG. 5 – Global fusion architecture

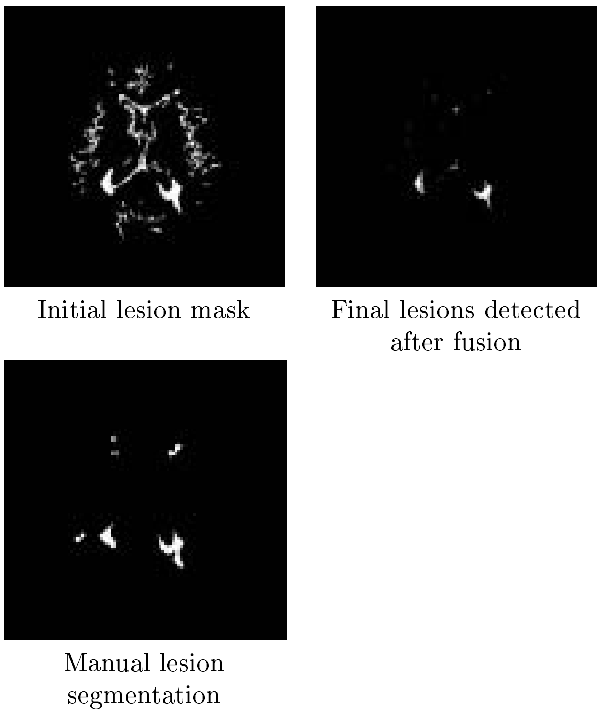


FIG. 6 – MS lesions detection after data fusion

fusion process, small false negatives were introduced. This is due to the fact that the eliminated small lesions were not present in the original lesion mask. It is worthy to note that the lesion detection is more accurate using data fusion based method than using manual segmentation.

6 Conclusion

We have proposed a new approach for improving the detection of brain MS lesions, by fusing the segmented images coming from two other algorithms, the one is lesion oriented and the other brain tissue oriented. The obtained results show that a good performance in lesion detection can be achieved without requiring that the two segmentation algorithms used should be powerful, the only condition being that they give complementary information (no false negatives in one image, and good detection of WM in the other image, for example).

7 Acknowledgement

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