Automatic Segmentation Approach based Possibility Theory for the Classification of Brain Tissues

Lamiche Chaabane
Department of Computer Science
University of M'sila Algeria
lamiche07@gmail.com

Moussaoui Abdelouahab
Department of Computer Science
University of Setif
moussaoui.abdel@gmail.com

***Abstract*—The paper presents a study and an evaluation of a novel unsupervised segmentation technique based aggregation approach and some possibility theory concepts. Information provided by different sources of MR images is extracted and modeled separately in each one using MPFCM (Modified Possibilistic Fuzzy C-Means) algorithm, extracted data obtained are combined with an operator which can managing the uncertainty and ambiguity in the images and the final segmented image is constructed in decision step. The efficiency of the proposed method is demonstrated by segmentation experiments using simulated MR Images.**

Keywords— Aggregation, possibility theory, segmentation, MPFCM; MR images.

Introduction

Magnetic resonance (MR) imaging has been widely applied in biological research and diagnostics, primarily because of its excellent soft tissues contrast, non-invasive character, high spatial resolution and easy slice selection at any orientation. In many applications, its segmentation plays an important role on the following sides : (a) identifying anatomical areas of interest for diagnosis, treatment, or surgery planning paradigms; (b) preprocessing for multimodality image registration ; and (c) improved correlation of anatomical areas of interest with localized functional metrics [1].

Fully automatic brain tissue classification from magnetic resonance images (MRI) is of great importance for research and clinical study of much neurological pathology. The accurate segmentation of MR images into different tissue classes, especially gray matter (GM), white matter (WM) and cerebrospinal fluid (CSF), is an important task.

In medical imaging field, segmenting MR images has been found a quite hard problem due to the existence of image noise, partial volume effects, the presence of smoothly varying intensity inhomogeneity, and large amounts of data to be processed. To handle these difficulties, a large number of approaches have been studied, including fuzzy logic methods [3], neural networks [4], Markov random field methods with the maximum expectation [5], statistical methods [5], and data fusion methods [6], to name a few.

Here the evaluation of the full automatic segmentation of the human brain tissues using a multispectral aggregation approach is presented. This approach consists of the computation of fuzzy tissue maps extracted from each of three modalities of MR images T1, T2 and PD as an information source, the creation of fuzzy maps by a combination operator and a segmented image is computed in decision step.

The reminder of this paper is organized as follows : In section II, some previous related works are briefly cited. Section III summarize fuzzy clustering with the MPFCM algorithm. In section IV, we describe the principals of possibility theory reasoning. Section V describes the proposed process. Simulation results are introduced in Section VI. Conclusion is given in Section VII.

Related Works

A brief review of some related works in the field of fuzzy information fusion is presented in this section. Waltz [11] presented three basic levels of image data fusion : pixel level, feature level and decision level, which correspond to three processing architectures. I. Bloch [2] have outlined some features of Dempster-Shafer evidence theory, which can very useful for medical image fusion for classification, segmentation or recognition purposes. Examples were provided to show its ability to take into account a large variety of situations. Registration-based methods are considered as pixel-level fusion, such as MRI-PET (position emission tomography) data fusion[12]. Some techniques of knowledge-based segmentation can be considered as the feature-level fusion such as the methods proposed in [16].

Some belief functions, uncertainty theory, Dempster-Shafer theory are often used for decision-level fusion such as in [14]. In [17], I. Bloch proposed an unified framework of information fusion in the medical field based on the fuzzy sets, allow to represent and to process the numerical data as well as symbolic systems.

V. Barra and J. Y. Boire [9] have described a general framework of the fusion of anatomical and functional medical images. The aim of their work is to fuse anatomical and functional information coming from medical imaging, the fusion process is performed in possibilistic logic frame, which allows for the management of uncertainty and imprecision inherent to the images. A new class of operators based on information theory and the whole process is finally illustrated in two clinical cases : the study of Alzheimer's disease by MR/SPECT fusion and the study of epilepsy with MR/PET/SPECT. The obtained results was very encouraging.

V. Barra and J. Y. Boire [15] proposed a new scheme of information fusion to segment intern cerebral structures. The information is provided by MR images and expert knowledge, and consists of constitution, morphological and topological characteristics of tissues. The fusion of multimodality images is used in [13]. In [8], the authors have presented a framework of fuzzy information fusion to automatically segment tumor areas of human brain from multispectral magnetic resonance imaging (MRI); in this approach three fuzzy models are introduced to represent tumor features for different MR image sequences and the fuzzy region growing is used to improve the fused result.

Maria del C. and al [10] proposed a new multispectral MRI data fusion technique for white matter lesion segmentation, in that a method is described and comparison with thresholding in FLAIR images is illustrated. Recently, The authors in [19] have presented a new framework of fuzzy information fusion using T2-weighted and proton density (PD) images to improve the brain tissue segmentation.

The MPFCM Algorithm Clustering

Clustering is the partitioning of unlabeled data set $X=\{x_1, x_2, x_3, \ldots, x_n\}\in\Re^p$ into 1<c<n classes, by assigning labels to the vectors in X. A cluster contains similar patterns placed together. One of the most widely used clustering methods is the MPFCM (Modified Possibilistic Fuzzy C-Means) algorithm [20]. The MPFCM algorithm uses both the information of pixels and their neighborhoods, membership and typicality for classification. The MPFCM clustering algorithm minimizes the objective function :

$$J(U,T,V,X)=\sum_{i=1}^{C}\sum_{k=1}^{N}(au_{ik}^{m}+bt_{ik}^{\eta})D_{ik}+\sum_{i=1}^{C}\gamma_i\sum_{k=1}^{N}(1-t_{ik})^{\eta}$$
$$+\beta\sum_{i=1}^{C}\sum_{k=1}^{N}(au_{ik}^{m}+bt_{ik}^{\eta})S_{ik} \qquad (1)$$

where m>1 is the weighting exponent, $\lambda\in[3,5]$ is the typicality exponent D_{jk} is the Euclidean distance between data x_j and cluster center v_i, $S_{ik}=\sum_{w=1}^{n_w}\|x_w-v_i\|$ where xw is a neighbor pixel of xk in a window around x_k and n_w is the number of neighbors in this window., $[U]_{CxN}$ is the fuzzy matrix where $\forall k, \sum_{i=1}^{C}u_{ik}\le 1$. $[T]_{CxN}$ is the typicality matrix where $\forall k, t_{ik}\le 1$, a>0, b>0 are user defined constants and the parameter γ_i is given by :

$$\gamma_i=\frac{\sum_{k=1}^{N}D_{ik}}{\sum_{k=1}^{N}u_{ik}^{m}}, K>1$$

The minimization of objective function $J(U,T,V,X)$ can be brought by an iterative process in which updating of membership degrees u_{ij} , typicality degrees t_{ij} and the cluster centers are done for each iteration by :

$$u_{ik}=\sum_{j=1}^{C}\left(\frac{D_{ik}+\beta S_{ik})}{D_{jk}+\beta S_{jk})}\right)^{1/(1-m)}. \qquad (2)$$

$$t_{ik}=\frac{1}{1+(\frac{b}{\gamma_i}D_{ik}+\beta S_{ik})^{1/(\eta-1)}}. \qquad (3)$$

$$v_i=\frac{\sum_{k=1}^{N}(au_{ik}^{m}+bt_{ik}^{\eta})(x_k+\beta R_k)}{(1+\alpha)\sum_{k=1}^{N}(au_{ik}^{m}+bt_{ik}^{\eta})}. \qquad (4)$$

where : α and β are a given values and :

$$R_k=\sum_{w=1}^{n_w}x_w. \qquad (5)$$

The algorithm of the MPFCM consists then of the reiterated application of (2), (3) and (4) until stability of the solutions.

The Possibility Theory

Possibilistic logic was introduced by Zadeh (1978) following its former works in fuzzy logic (Zadeh, 1965) in order to simultaneously represent imprecise and uncertain knowledge. In fuzzy set theory, a fuzzy measure is a representation of the uncertainty, giving for each subset Y of the universe of discourse *X* a coefficient in [0,1] assessing the degree of certitude for the realization of the event *Y*. In possibilistic logic, this fuzzy measure is modeled as a measure of possibility Π satisfying:

$$\Pi(X)=1 \quad et \quad \Pi(\phi)=0$$

$$(\forall(Y_i))\Pi(\cup_i Y_i) \;=\; \operatorname*{Sup}_i \;\Pi(Y_i)$$

An event Y is completely possible if $\Pi(Y)=1$ and is impossible if $\Pi(Y)=0$. Zadeh showed that Π could completely be defined from the assessment of the certitude on each singleton of *X*. Such a definition relies on the definition of a distribution of possibility π satisfying :

$$\pi : X \rightarrow [0,1]$$
$$x \rightarrow \pi(x) / \operatorname*{Sup}_x\{\pi(x)=1\}$$

Fuzzy sets F can then be represented by distributions of possibility, from the definition of their characteristic function μ_F : $(\forall x \in X)\mu_F(x) = \pi(x)$

Distributions of possibility can mathematically be related to probabilities, and they moreover offer the capability to declare the ignorance about an event. Considering such an event A (e.g., voxel v belongs to tissue T, (where v is at the interface between two tissues), the probabilities would assign $P(A) = P(\overline{A}) = 0.5$, whereas the possibility theory allows fully possible $\Pi(A) = \Pi(\overline{A}) = 1$. We chose to model all the information using distributions of possibility, and equivalently we represented this information using fuzzy sets [21].

The three-steps fusion can be therefore described as :

- Modeling of information in a common theoretical frame ;
- The extracted information is then aggregated with a fusion operator *F*. This operator must affirm redundancy and manage the complementarities and conflicts.
- In the decision step, we pass from information provided by the sources to the choice of a decision.

Proposed Method

Modeling Step

Particularly, in our study this step consists in the creation of WM, GM, CSF and background (BG) fuzzy maps for both T1, T2 and PD images using the MPFCM algorithm.

Fusion Step

In this step, If $\pi_T^{T1}(v)$, $\pi_T^{T2}(v)$ $\pi_T^{PD}(v)$ are the memberships of a voxel *v* to tissue *T* resulting from step 1 then a fusion operator *F* combine these values to generate a new membership value and can managing the existing ambiguity and redundancy. The possibility theory propose a wide range of operators for the combination of memberships [7]. I. Bloch [18] classified these operators in three classes defined as: Context independent and constant behavior operators (CICB), Context independent and variable behavior operators (CIVB) and Context dependent operators (CD). For our MR images fusion, we chose a context-based conjunctive operator because in the medical context, both images were supposed to be almost everywhere concordant, except near boundaries between tissues and in pathologic areas. In addition, the context-based behavior allowed to take into account these ambiguous but diagnosis–relevant areas. Then we retained an operator of this class, this one is introduced in [18]:

If $\pi_T^{T1}(v)$, $\pi_T^{T2}(v)$ and $\pi_T^{PD}(v)$ are the gray-levels possibility distributions of tissue *T* extracted from T_{T1}, T_{T2} and T_{PD} fuzzy maps respectively and *F* design the fusion operator, then the fused possibility distribution is defined for any gray level *v* as :

$$\pi_T(v) = \max\left(\frac{\min(\pi_T^{I_i}(v), \pi_T^{I_j}(v))}{h}, 1-h)\right)$$

Where I_i, I_j $\in$ {T1,T2,PD}, and h is a measure of agreement between $\pi_T^{I_i}$ and $\pi_T^{I_j}$:

$$h = 1 - \sum_{v \in \mathrm{Im}\,age} \left|\pi_T^{I_i}(v) - \pi_T^{I_j}(v)\right| / \left|\mathrm{Im}\,age\right|$$

Decision Step

A segmented image was finally obtained using the four maps computed in step 2 by assigning to the tissue *T* any voxel for which it had the greatest degree of membership.

The general algorithm using for fusion process is :

General algorithm
Modeling of the image
For a **in** {I_i,I_j} **do**
MPFCM (a)
End For
Fusion
Possibilistic fusion
Decision
Segmented image

Three models of fusion are generated by this algorithm : T1/T2 fusion, T1/PD fusion and T2/PD fusion.

Simulated Results

Brainweb provides simulated brain datasets which contains a set of realistic MRIs created using an MRI simulator. In this section, T1-weighted, T2-weighted and PD-weighted brain MR images with a slice thickness of 1 mm, and a volume size of 217x181x181 are employed to investigate the proposed method. These images are obtained from the Brainweb Simulated Brain Database at the McConnell Brain Imaging Centre of the Montreal Neurological Institute(MNI), McGill University.

To compare the performance of these three models of fusion produced by F operator, we compute different coefficients reflecting how well two segmented volumes match. We use a different performance measures :

$$Overlap(Ovrl) = \frac{TP}{TP + FN + FP}.$$

$$Similarity\,(SI) = \frac{2.TP}{2.TP + FN + FP}.$$

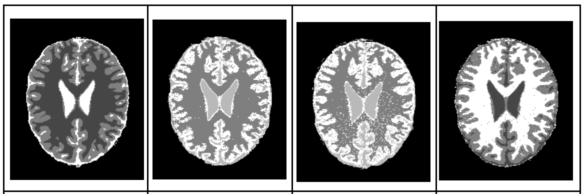
where *TP* and *FP* for true positive and false positive (voxels correctly and incorrectly classified as brain tissue). *TN* and *FN* for true negative and false negative, which were defined as the number of voxels correctly and incorrectly classified as non-brain tissue by the automated algorithm. The comparative results are presented in table 1 below :

COMPARATIVE SESULTS

	T1/T2 Fusion			**T1/PD Fusion**			**T2/PD Fusion**		
	CSF	***WM***	***GM***	***CSF***	***WM***	***GM***	***CSF***	***WM***	***GM***
Overl.	**0.88**	**0.92**	**0.87**	0.74	0.85	0.82	0.70	0.88	0.72
SI	**0.96**	**0.95**	**0.90**	0.88	0.90	0.86	0.81	0.90	0.83

The results in Table 1 show considerable improvement for all tissues using T1/T2 fusion than T1/PD and T2/PD models.

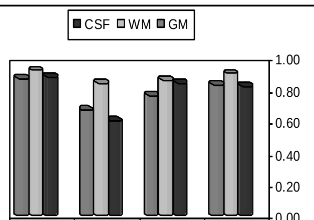
The results obtained on fusion T1/T2 are compared to the results obtained with a fuzzy segmentation computed by the algorithm of classification MPFCM on the T1 image alone, T2 image alone and the PD image alone. An example of segmentation result for the slice 95 of Brainweb is presented in figure 1 below:



(a) (b) (c) (d)

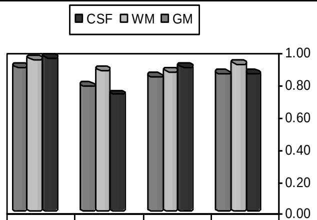
(a) T1 segmeneted with MPFCM algorithm. (b) T2 segmeneted with MPFCM algorithm. (c) PD segmeneted with MPFCM algorithm. (d) Image of T1/T2 fusion with F operator.

The results for each one of the segmentation for all tissues CSF, WM and GM are reported in figures 2 and 3 below :



	Fusion T1/T2	PD alone	T2 alone	T1 alone
CSF	0.88	0.60	0.84	0.82
WM	0.92	0.84	0.86	0.90
GM	0.87	0.67	0.76	0.83

Overlap measurment for different segmentations with 3% noise.



	Fusion T1/T2	PD alone	T2 alone	T1 alone
CSF	0.96	0.73	0.90	0.86
WM	0.95	0.88	0.87	0.92
GM	0.90	0.78	0.84	0.86

Similarity measurment for different segmentations with 3% noise.

The graphics of figures 2 and 3 underline the advantages of the multispectral fusion images within the fuzzy possibilistic framework to improve the segmentation results clearly. Indeed all measurement values obtained with fusion of T1 and T2 images for CSF, WM and GM tissues are greater than ones obtained when to taking into account of only one weighting in MR image segmentation.

Conclusion

In this paper, a study and an evaluation of a novel technique for a brain MRI segmentation based on a fusion approach and possibility theory concepts are discussed. In the proposed method the pixel intensity, its neighborhood, memberships and typicality are used in the modeling step to generate data to fusion step. This method offers a considerable improvement in brain MRI segmentation and demonstrate the superior capabilities of fusion approach compared to the taking into account of only one weighting in MR image segmentation.

As a perspective of this work other more robust algorithms or hybrid algorithms to modeling a data are desired. In addition, we can integrate other numerical, symbolic information, experts' knowledge or images coming from other imaging devices in order to improve the segmentation of the MR images or to detect anomalies in the pathological images.

REFERENCES

[1] L. P. Clark, R.P. Velthijizen, M. A. Camacho, and J. J. Heine, “MRI Segmentation methods and applications,” Magnetic Resonance Imaging, vol. 13, pp. 343–368, 1995.

[2] I. Bloch, “Some aspects of Dempster-Shafer evidence theory for classification of multi-modality medical images taking partial volume effect into account,” Pattern Recognition Letters, vol. 17, pp. 905–919, 1996.

[3] Y. Hata, S. Kobashi, and S. Hirano, “Automated segmentation of human brain MR images aided by fuzzy information granulation and fuzzy inference”, IEEE Trans. SMC, Part C, vol. 30, pp. 381–395, 2000.

[4] D. Goldberg-Zimring, A. Achiron, and S. Miron, “Automated detection and characterization of multiple sclerosis lesions in brain MR images”, Magnetic Resonance Imaging, vol. 16 pp. 311–318,1998.

[5] K. Van Leemput, F. Maes, D. Vandermeulen, and P. Suetens, “Automated model-based tissue classification of

MR images of the brain", IEEE Trans. Medical Imaging, vol. 18, pp. 897–908, 1999.

[6] Y. Wang, T. Adali, J. Xuan, and Z. Szabo. "Magnetic resonance image analysis by information theoretic criteria and stochastic models", IEEE Trans, Information Technology in Biomedicine, vol. 5, pp. 150-158, 2001.

[7] I. Bloch, and H. Maitre, "Data fusion in 2D and 3D image processing: An overview," X Brazilian symposium on computer graphics and image processing, Brazil, pp. 127–134, 1997.

[8] W. Dou, S. Ruan, Y. Chen, D. Bloyet, J. M. Constans, "A framwork of fuzzy information fusion for the segmentation of brain tumor tissues on MR images," Image and vision Computing, vol. 25, pp. 164–171, 2007

[9] V. Barra and J. Y. Boire, "A General Framework for the Fusion of Anatomical and Functional Medical Images," NeuroImage, vol. 13**,** 410–424, 2001.

[10] D. C. Maria, H. Valdés, J. F. Karen, M. C. Francesca, M. W. Joanna, "New multispectral MRI data fusion technique for white matter lesion segmentation: method and comparison with thresholding in FLAIR images," Eur Radiol, vol. 20, 1684–1691, 2010.

[11] E.D Waltz, the principals and practice of image and spatial data fusion in : Davis L, Hall, James llinas (Eds), Proceedings of the Eight National Data Fusion Conference ,(Dalls, TX. March 15-17, 1995) Handbook of Multisensor Data Fusion, CRC pess, West Bam Beach, FL,1995, pp. 257–278. (p4–1–4–18).

[12] F. Behloul, M. Janier, P. Croisille, C. Poirier, A. Boudraa, R. Unterreiner, J. C. Mason, D. Revel, "Automatic assessment of myocardial viability based on PET-MRI data fusion," Eng. Med. Biol. Mag., Proc. 20th Ann. Int. Conf. IEEE, vol. 1, pp. 492–495, 1998.

[13] M. Aguilar, R. Joshua, "New fusion of multi-modality volumetric medical imagery," ISIF, pp. 1206–1212, 2002.

[14] E. Lefevre, P. Vannoorenberghe, O. Colot, "About the use of Dempster-Shafer theory for color image segmentation," First international conference on color in graphics and image processing, Saint-Etienne, France, 2000.

[15] V.Barra, and J-Y Boire, "Automatic segmentation of subcortical brain structures in MR images using information fusion," IEEE Trans. on Med. Imaging., vol. 20, n7, pp. 549–558, 2001.

[16] M. C. Clarck, L.O. Hall, D.B. Goldgof, R Velthuizen, F.R. Murtagh, M.S. Silbiger, "Automatic tumor segmentation using knowledge-based techniques," IEEE Trans. Med. Imaging, vol. 17, pp. 187–201, 1998.

[17] I. Bloch, "Fusion of numerical and structural image information in medical imaging in the framework of fuzzy sets," Fuzzy Systems in Medicine, ed. par P. Szczepaniak et al., pp. 429–447, Springer Verlag, 2000.

[18] I. Bloch, "Information combination operators for data fusion : A Comparative Review with Classification," IEEE Transactions en systems, Man. and Cybernitics, vol. 1, pp. 52–67, 1996.

[19] C.Lamiche, A.Moussaoui, "Improvement of brain tissue segmentation using information fusion approach", International Journal of Advanced Computer Science and Applications, vol 2, n6, pp. 84–90, 2011.

[20] H. Khotanlou, "3D brain tumors and internal brain structures segmentation in MR images," Thèse de Doctorat, Ecole Nationale Supérieure des Télécommunications, ParisTech, 2008.

[21] D. Dubois and H. Prade, "Combination of information in the framwork of possibility theory," In Data Fusion in Robotics and Machine Intelligence, M. Al Abidi et al., Eds. New York : Academic, 1992.