NEW TRENDS IN MATHEMATICAL SCIENCES
Vol. 2, No. 2, 2014, p134-140
ISSN 2147-5520 - www.ntmsci.com

A cooperative method to improve segmentation of brain MR images

Lamiche Chaabane[1], Moussaoui Abdelouahab[2]

[1,2]Department of Computer Science, University of M'sila, Algeria
E- mail: [1]Lamiche07@gmail.com, [2]Moussaoui.abdel@gmail.com

Abstract: In this paper, we present a fully unsupervised segmentation process of magnetic resonance image (MRI) of the brain using a data fusion technique and some of ideas of the possibility theory context. The fusion methodology is decomposed into three fundamental phases. We modeling information coming from T2 and PD weighted images in a common framework, in this step an hybridization between FCM and PCM algorithms is retained. In the second phase an operator of fusion is used to combine then this information. Finally, an image of fusion is generated when a decision rule is applied. Some results are presented and discussed using a set of simulated MR image.

Keywords: Fusion, Possibility theory, Segmentation, FPCM, MR images

1. Introduction

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 in homogeneity, and large amounts of data to be processed. To handle these difficulties, a large number of approaches have been studied, including fuzzy logic methods [1], neural networks [2], Markov random field methods with the maximum expectation [3], statistical methods [3], and data fusion methods [4], to name a few.

In recent years, the need for data fusion in medical image processing increases in relation to the increase of acquisition techniques such as magnetic resonance imaging (MRI), tomography(CT), the newer positron emission tomography (PET) and a functional modality SPECT. These techniques are more and more jointly used to give access to a better knowledge [5].

As one typical data fusion problem, the segmentation of multispectral brain MR images aims at achieving improved segmentation performance by taking advantage of redundancy and complementariness in information provided by multiple sources. There have existed many data fusion methodologies, which are capable of reasoning under various types of uncertainty. Typical ones include probability theory based approaches, possibility theory based approaches, and Dempster-Shafer evidence theory based approaches [5].

Traditionally probabilities theory was the primary model used to deal with uncertainty problems, but they suffer from drawbacks. Whereas the Dempster-Shafer theory also allows to representing these two natures of information using functions of mass but the set of operators used by this theory is very restricted.

Alternative to this approach is the possibility theory where uncertainty and imprecision are easily modeled and it allows to combining information coming from various sources by the use a wide range of available combination operators [5].

In this work we aim to improve the segmentation of the human brain tissues using a multispectral fusion approach. This approach consists of the computation of fuzzy tissue maps in each of tow modalities of MR images namely 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. This paper is organized as follows: In section II, we summarize the main ideas of FCM algorithm. In section III, we introduce the principals of possibility theory reasoning. Section IV outlined the fusion process methodology. Steps of our proposed method are described in section V. Section VI presents some experimental results. Finally, conclusion and perspectives of our work are suggested in section VII.

2. The FCM Algorithm Clustering

Clustering is a process of finding groups in unlabeled dataset based on a similarity measure between the data patterns (elements). A cluster contains similar patterns placed together. The fuzzy clustering technique generates fuzzy partitions of the data instead of hard partitions. Therefore, data patterns may belong to several clusters, having different membership values with different clusters. The membership value of data pattern to a cluster denotes similarity between the given data pattern to the cluster. Given a set of N data patterns $X = \{x_1, x_2 x_3, \dots, x_n\}$ the Fuzzy C-Means (FCM) clustering algorithm minimizes the objective function [26][27]:

$$J(B,U,X) = \sum_{i=1}^{C}\sum_{j=1}^{N} u_{ij}^{m} d^2(x_j, b_i) \tag{1}$$

Where x_j is the $j-$th P-dimensional data vector, b_i is the center of cluster i, u_{ij} is the degree of membership of x_j in the $j-$th cluster, m is the weighting exponent $d^2(x_j, b_i)$ is the Euclidean distance between data x_j and cluster center b_i.

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

$$u_{ij} = \left[\sum_{k=1}^{C}\left(\frac{d^2(x_j, b_i)}{d^2(x_j, b_k)}\right)^{2/(m-1)}\right]^{-1} \tag{2}$$

$$b_i = \frac{\sum_{k=1}^{N} u_{ij}^{m} x_k}{\sum_{k=1}^{N} u_{ik}^{m}} \tag{3}$$

where

$$\forall i \in \{1..C\}, \forall j \in \{1..N\} \begin{cases} u_{ij} \in [0,1] \\ 0 < \sum_{j=1}^{N} u_{ij} < N \end{cases} \tag{4}$$

$$\forall j \in \{1..N\} \sum_{j=1}^{C} u_{ij} = 1. \tag{5}$$

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

3. 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:

$$\Pi(\mathrm{X}) = 1 \; et \; \Pi(\phi) = 0$$

$$(\forall(Y_i))\Pi\left(\bigcup_i Y_i\right) = \underset{i}{Sup}\,\Pi(Y_i)$$

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:

$$\pi: X \rightarrow [0,1]$$

$$x \rightarrow \pi(x)/\underset{x}{Sup}\{\pi(x) = 1\}$$

Fuzzy sets F can then be represented by distributions of possibility, from the definition of their characteristic function

$$\mu_F: (\forall x \in X)\mu_F(x) = \pi(x)$$

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 $P(A) = P(A) = 0.5$, whereas the possibility theory allows fully possible $\Pi(A) = \Pi(A) = 1$. We chose to model all the information using distributions of possibility, and equivalently we represented this information using fuzzy sets.

The literature classically distinguishes three modes for combination of uncertainty and imprecise information in a possibility theory framework:

The conjunction: gather the operators of t-norms (fuzzy intersection), this mode of combination must be used if measurements are coherent, i.e. without conflict.

The compromise: gather the median operator and some average operators, it must be used when measurements are in partial conflict.

The Disjunction: gather the operators of t-conorms (fuzzy union), it must be used when measurements are in disaccord, i.e. in severe conflict.

4. The Fusion Process Steps

A general information fusion problem can be stated in the following terms: given l sources S_1, $S_2, \ldots, S_1$ representing heterogeneous data on the observed phenomenon, take a decision d_i on an element x, where x is higher level object extracted from information, and d_i belongs to a decision space $D = \{d_1, d_2, d_3, \ldots, d_n\}$. In numerical fusion methods, the information relating x to each possible decision d_i according to each source S_j, is represented as a number M_{ij}, having different properties and different meanings depending on the mathematical fusion framework. In the centralized scheme, the measures related to each possible decision i and provided by all sources are combined in a global evaluation of this decision, taking the form, for each $i: F(M_{i1}, M_{i2}, M_{i3}, \ldots, M_{in})$, where F is a fusion operator. Then a decision is taken from the set of $M_i, 1 \leq i \leq n$ in this scheme, no intermediate decision is taken and the final decision is issued at the end of the processing chain. In decentralized scheme decisions at intermediate steps are taken with partial information only, which usually require a difficult control or arbitration step to diminish contradictions and conflicts [5]. The three-steps fusion can be therefore described as:

Modeling of information in a common theoretical frame to manage vague, ambiguous knowledge and information imperfection. In addition, in this step the M_{ij} values are estimated according to the chosen mathematical framework.

Combination: the information is then aggregated with a fusion operator F. This operator must affirm redundancy and manage the complementarities and conflicts.

Decision: it is the ultimate step of the fusion, which makes it possible to pass from information provided by the sources to the choice of a decision d_i.

5. Proposed Method

According to the data fusion process, our method consists on three steps below:

A. Modeling Step

In the framework of possibility theory and fuzzy sets [7], the M_{ij}'s represent membership degrees to a fuzzy set or possibility distribution π , taking the form for each decision d_i and source S_i: $M_{ij} = \pi_j(d_i)$. Particularly, in our study this step consists in the creation of WM, GM, CSF and background (BG) fuzzy maps for both T2 and PD images using the FPCM algorithm then $u_{ij} = \pi_j(d_i)$.

B. Fusion Step

For the aggregation step in the fusion process, the advantages of possibility theory rely in the variety of combination operators, which must affirm redundancy and manage the complementarities. And may deal with heterogeneous information. It is particular interest to note that, unlike other data fusion theories like Bayesian or Dempster-Shafer combination, possibility theory provides a great flexibility in the choice of the operator, that can be adapted to any situation at hand [4]. If $\pi_T^{T2}(v)$ and $\pi_T^{PD}(v)$ 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 [8].

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 [8]:

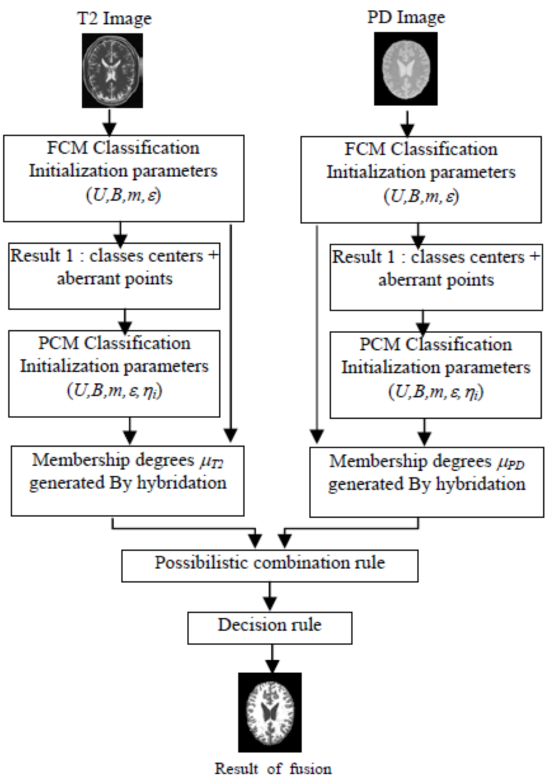
If $\pi_T^{T2}(v)$ and $\pi_T^{PD}(v)$ are the gray-levels possibility distributions of tissue T extracted from T2 and PD fuzzy maps respectively and F design the fusion operator, then the fused possibility distribution is defined for any gray level v as:

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

where $I_i, I_j \in \{\mathrm{T2}, \mathrm{PD}\}$ and h is a measure of agreement between $\pi_T^{I_i}$ and $\pi_T^{I_j}$: $h = 1 - \sum_{v \in Image}\left|\pi_T^{I_i}(v) - \pi_T^{I_j}(v)\right| / |Image|$

C. 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 (i.e maximum of possibility rule) [5].



It should be noted that the stability of this approach depend to the stability of the algorithm used in the modeling step [8].

6. Experimental Results

Since the ground truth of segmentation for real MR images is not usually available, it is impossible to evaluate the segmentation performance quantitatively, but only visually. However, Brainweb[1] provides a simulated brain database including a set of realistic MRI data volumes produced by an MRI simulator. These data enable us to evaluate the performance of various image analysis methods in a setting where the truth is known.

To have tests under realistic conditions, one volume was generated with a thickness of 1 mm and a level of noise of 3%. We fixed at 20% the parameter of heterogeneity.

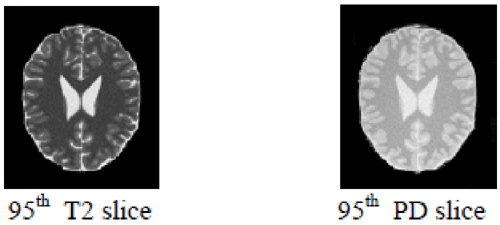


Figure 1. Simulated T2 and PD images illustrate the fusion

The different segmentations are showing in figure 2 below:

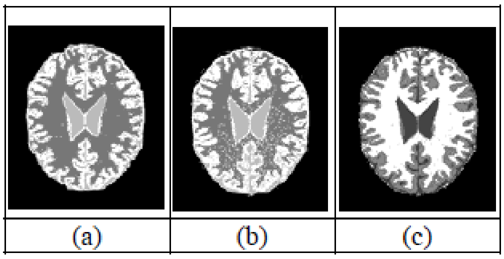


Figure 2. (a) T2 segmented with FCM algorithm (c) PD segmented with FCM algorithm (d) Image of fusion

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 stand for true positive and false positive, which were defined as the number of voxels correctly and incorrectly classified as brain tissue by the automated algorithm. TN and FN stand 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:

Table 1. Comparative results

	T2/PD Fusion			**PD alone**			**T2 alone**		
	CSF	WM	GM	CSF	WM	GM	CSF	WM	GM
Ovrl.	**0.90**	**0.93**	**0.92**	0.58	0.76	0.70	0.67	0.90	0.83
Si.	**0.94**	**0.96**	**0.95**	0.78	0.83	0.80	0.83	0.92	0.86

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

---

[1] www.bic.mni.mcgill.ca/brainweb.

Finally, we have also compared the performance of our proposed algorithm to that of well-known methods and other published reports that have recently been applied on brain tissue segmentation on Brainweb datasets for the segmentation of MR images in CSF, WM and GM tissues. They are summarized in table 2, these include the proposed work in [9] and the published approach of fusion in [10]. The results are reported in table 2 below using Accuracy coefficient [9], and Dice coefficient [11].

Table 2. Results on Brainweb phantom images for nine methods and the approach we propose

		Inu. / Noise	20% 0%	3%	5%
Measurement	Approach				
Accuracy coefficient (%)	Published work in [9] (FDS1)	Min Acc.	-	95.95	-
		$\overline{Acc}$	-	96.95	-
		Max Acc.	-	97.51	-
	Published work in [9] (FDS2)	Min Acc.	-	96.11	-
		$\overline{Acc}$	-	97.04	-
		Max Acc.	-	97.58	-
Dice coefficient	Published work in [10]	CSF	0.87	0.85	0.83
		WM	0.96	0.95	0.88
		GM	0.90	0.88	0.78
Dice coefficient	Our proposed aproach	CSF	**0.96**	**0.94**	**0.91**
		WM	**0.97**	**0.96**	**0.93**
		GM	**0.96**	**0.95**	**0.90**
Accuracy coefficient (%)	Our proposed aproach	Min Acc.	-	**97.09**	-
		$\overline{Acc}$	-	**97.16**	-
		Max Acc.	-	**97.86**	-
'-' that means no result is given in this case on the reference					

The methods compared in table 2 have been run on images which have 0%, 3% and 5% of noise, 20% of intensity inhomogeneity (Inu.) and voxel size of 1mm3.

Regarding the performance of the fusion based methods, the proposed evidential fusion approach described in [9] is the worst (in terms of average accuracy $\overline{Acc}$, minimum accuracy Min acc. And maximum accuracy Max acc.) and the published work in [10] is the next worst, because the first one use focal elements and masses to represent data and the Dempster-Shafer rule to combine evidence. And in the second one, the data is modeled by the FCM algorithm, that is considered poorly to classify the pixels when they are situated very far to cluster centers. However, our approach is close to those proposed in [9] and [10]. Results of comparison show clearly the potential interest of our approach for magnetic resonance imaging (MRI) brain segmentation.

7. Conclusion

In this paper, a new multispectral fusion approach for the segmentation of MR images is discussed. We outlined in here some features of possibility theory context, which can be very useful for medical images fusion. And which constitute advantages over classical theories. The results reported in this paper show 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, the cooperation of the algorithms of classification to modeling a data is desired. In fusion step, further studies to construct other adaptive operators is necessary. In addition, we can integrate other numerical, symbolic information, experts' knowledge or images coming from other imaging devices include computer tomography (CT), the newer positron emission tomography (PET) or a major functional modality SPECT in order to improve the segmentation of the MR images or to detect anomalies in the pathological images.

References

[1] 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, vol. 30, 1998, pp. 381–395.

[2] 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, 1998, pp.311–318.

[3] 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, 1999, pp.897–908.

[4] Y. Wang, T. Adali, J. Xuan, and Z. Szabo, "Magnetic resonance image analysis by information theoretic criteria and stochastic models," IEEE Trans, Infor. Tech. in Biom., vol. 5, 2001, pp.150–158.

[5] I. Bloch, and H. Maitre, "data fusion in 2D and 3D image processing: an overview," In Proceedings of the X Brazilian symposium on computer graphics and image processing, Brazil, 1997, pp.127–134.

[6] C. Bezdek, J. Keller, R. Krishnapuram, and N. R. Pal Fuzzy Models and Algorithms for Pattern Recognition and Image Processing, Kluwer Academic, TA 1650, F89. 1999.
[7] D. Dubois, and H. Prade, Fuzzy Sets and Systems: Theory and Application, New-York: Academic Press, 1980.
[8] I. Bloch, ‘‘Information combination operators for data fusion: a comparative review with classification’’, IEEE Transactions en systems, Man. and Cybernitics, vol. 1, 1996, pp.52–67.
[9] J. Z. Hongwei, and O. Basir, “Adaptive Fuzzy Evidential Reasoning for Automated Brain Tissue Segmentation,” In Proceedings of the 7th International Conference of Information Fusion. Stockholm, Sweden, 2004.
[10] C. Lamiche, and A. Moussaoui, “Improvement of brain tissue segmentation using information fusion approach,” Int. Jou. of Advan. Comp. Sci. and Applications, vol. 2, 2011, pp.84–90.
[11] L. R. Dice, “Measures of the Amount of Ecologic Association Between Species,” Ecology, vol. 26, 1945, pp.297–302.