Three Models Based Data Fusion Approach for the Segmentation of MR Images : A Comparative Study

Lamiche Chaabane[1] and Moussaoui Abdelouahab[2]

[1] **Department of Computer Science, University of M'sila, City Ichbilia, M'sila, Algeria**

[2] **Department of Computer Science, University of Setif, Setif, Algeria**

Abstract

In this paper, we propose an automatic segmentation technique of multispectral magnetic resonance image (MRI) of the brain using three models based data fusion approach through the framework of the possibility theory. The fusion process is decomposed into three fundamental phases. Firstly, we modeling information extracted from the various images in a common framework, in this step the retained formalism is FPCM algorithm . in the second phase an operator of fusion is used to combine then this information by taking account redundancies and complementarities of data. We build a Synthetic information to exploit the fusion results in the last phase. Some results are presented and discussed.

Keywords: *Fusion; Possibility Theory; Segmentation; FPCM; MRI.*

1. Introduction

Segmentation is a process of partitioning an image space into some non-overlapping meaningful homogeneous regions. In general, these regions will have a strong correlation with the objects in the image. The success of an image analysis system depends on the quality of segmentation. In the analysis of medical images for computer-aided diagnosis and therapy, segmentation is often required as a preliminary processing task. Medical image segmentation is a complex and challenging task due to the intrinsically imprecise nature of the images[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. Moreover, regional volume calculations may bring even more useful diagnostic information. Among them, the quantization of gray and white matter volumes may be of major interest in neurodegenerative disorders such as Alzheimer disease, in movement disorders such as Parkinson or Parkinson related syndrome, in white matter metabolic or inflammatory disease, in congenital brain malformations or perinatal brain damage, or in post traumatic syndrome.

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.

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[7]. 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 [7]. 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 [7].

In this work we aim to evaluate the segmentation of the human brain tissues using a models based data fusion approach. This approach consists of the computation of fuzzy tissue maps in each of three modalities of MR images namely 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.

This paper is organized as follows : In section 2, some previous related works are briefly cited. Section 3 summarize fuzzy clustering with the FPCM algorithm. In section 4, we describe the principals of possibility theory reasoning. Section 5 outlined the fusion process. Steps of fusion in medical image processing are illustrated in section 6. Section 7 present some experimental results. We finally provide main conclusions and discuss further works in Section 8.

2. Previous 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.

3. The FPCM Algorithm Clustering

Clustering is a process of finding groups in unlabeled dataset based on a similarity measure between the data patterns (elements) [17]. A cluster contains similar patterns placed together. One of the most widely used clustering methods is the FPCM algorithm. The FPCM algorithm solves the noise sensitivity defect of Fuzzy C-Means algorithm and overcomes the problem of coincident clusters of Possibilistic C-means algorithm. Given a set of N data patterns $X=\{x_1, x_2, x_3, \dots, x_n\}$ the fuzzy Possibilistic C-Means (FPCM) clustering algorithm minimizes the objective function :

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

Where x_j is the j-th P-dimensional data vector, b_i is the center of cluster i, $m>1$ is the weighting exponent, $\lambda\in[3,5]$ is the typicality exponent, $d^2(x_j,b_i)$ is the Euclidean distance between data x_j and cluster center b_i, $[U]_{CxN}$ is the fuzzy matrix and $[T]_{CxN}$ is the typicality matrix.

The minimization of objective function $J(B,U,T,X)$ 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 :

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

$$t_{ij} = \left[\sum_{k=1}^{C} \left(\frac{d^2(x_j, b_i)}{d^2(x_j, b_k)} \right)^{2/(\lambda-1)} \right]^{-1}. \quad (3)$$

$$b_i = \frac{\sum_{k=1}^{N} (u_{ik}^m + t_{ik}^\lambda) x_k}{\sum_{k=1}^{N} (u_{ik}^m + t_{ik}^\lambda)}. \quad (4)$$

where :

$$\forall i \in \{1..C\}, \quad \forall j \in \{1..N\} \quad \begin{cases} u_{ij} \in [0,1] \\ 0 < \sum_{i=1}^{N} u_{ij} < N \end{cases}. \quad (5)$$

$$\forall j \in \{1..N\} \quad \sum_{i=1}^{C} u_{ij} = 1 \cdot \quad (6)$$

$$\forall i \in \{1..C\} \quad \sum_{j=1}^{N} t_{ij} = 1 \cdot \quad (7)$$

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

4. 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:

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

$$(\forall (Y_i)) \Pi(\bigcup_i Y_i) = \sup_i \Pi(Y_i)$$

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 :

$$\pi : X \to [0,1]$$
$$x \to \pi(x) / \sup_x \{\pi(x) = 1\}$$

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.

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.

5. The Fusion Process and Type of Architectures

A general information fusion problem can be stated in the following terms : given *l* sources $S_1, S_2, \ldots S_l$ 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 $D=\{d_1, d_2, d_3, \ldots, d_n\}$ (or set of hypotheses). 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 : $M_i = F(M_{i1}, M_{i2}, M_{i3}, \ldots, M_{in})$, 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 [7][9].

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.

6. Data Fusion in Image Processing Using Possibility Theory

6.1 Modeling Step

In the framework of possibility theory and fuzzy sets, 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 T1, T2 and PD images using the FPCM algorithm then $u_{ij} = \pi_j(d_i)$

6.2 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 [6]. 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. 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);

- 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 :

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

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

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

6.3 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)[7].

The general algorithm using for fusion process can be summarized as follows :

IJCSI International Journal of Computer Science Issues, Vol. 9, Issue 5, No 2, September 2012
ISSN (Online): 1694-0814
www.IJCSI.org

General algorithm

Modeling of the image

For a **in** $\{I_i, I_j\}$ **do**

FPCM (a) { *Computation of membership degrees for both images I_i , I_j where $i \neq j$* }

End For

Fusion

Possibilistic fusion {*Between each class of I_i image and the same one of I_j image using F operator*}

Decision

Segmented image {*maximum of possibility rule*}

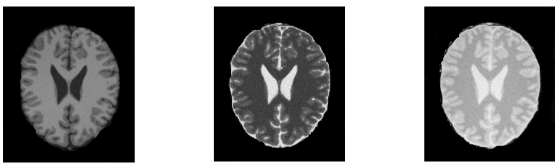
It should be noted that the stability of this algorithm depend to the stability of the algorithm used in the modeling step. In addition three fusion models are produced : T1/T2 fusion, T1/PD fusion and T2/PD fusion.

7. 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.

The fuzzy maps results on a noisy 95th brain only slice are shown in figure 1. This noisy slice was segmented into four clusters: background, CSF, white matter, and gray matter using FPCM algorithm, however the background was neglected from the viewing results.



95th T1 slice 95th T2 slice 95th PD slice

(a)

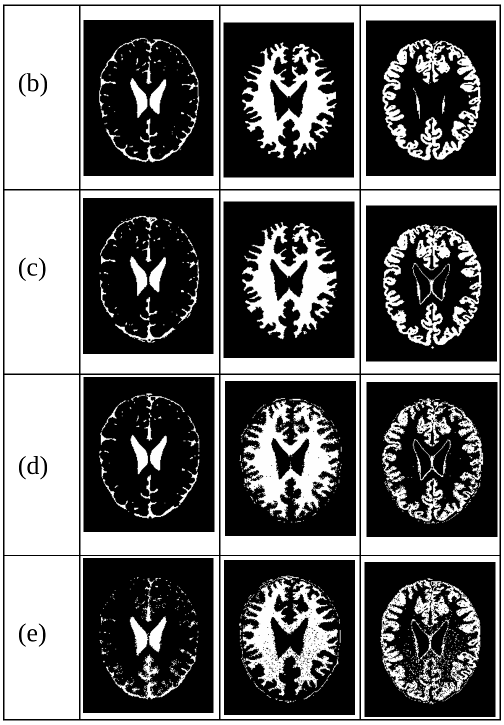


Fig. 1 (a) Simulated T1, T2 and PD images illustrate the fusion. (b) Discrete anatomical model. (c) Fuzzy maps of CSF, WM and GM obtained by FPCM for T1 image. (d) Fuzzy maps of CSF, WM and GM obtained by FPCM for T2 image. (e) Fuzzy maps of CSF, WM and GM obtained by FPCM for PD image.

The fused maps produced in fusion step are presented in figure 2 below :

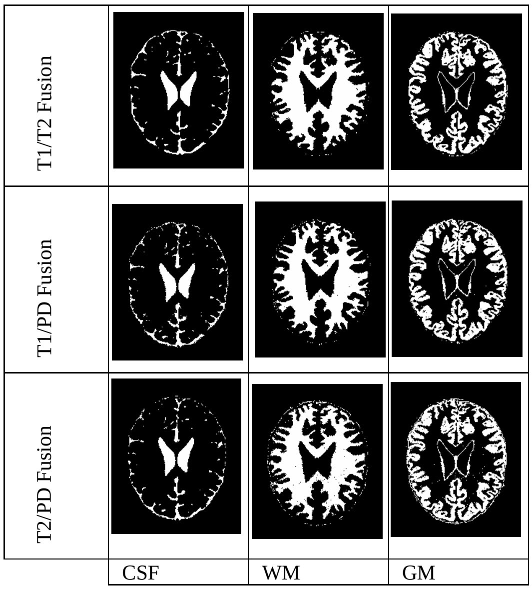


Fig. 2 Results of proposed process.

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

The WM fused map obtained with T1/T2 fusion is strongly improved compared to that obtained by the T1/PD fusion and the T2/PD fusion.

Information in GM fused map with F operator is reinforced in area of agreement (mainly in the cortex). And the fusion showed a significant improvement and reduces the effect of noise in images particularly with T1/T2 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 :

Table1: Comparative results

	T1/T2 Fusion			T1/PD Fusion			T2/PD Fusion		
	CSF	***WM***	***GM***	***CSF***	***WM***	***GM***	***CSF***	***WM***	***GM***
Overl.	**0.84**	**0.93**	**0.87**	0.74	0.87	0.80	0.71	0.90	0.76
SI	**0.92**	**0.96**	**0.93**	0.84	0.91	0.89	0.83	0.92	0.86

The results in Table 1 show considerable improvement for all tissues using T1/T2 fusion than T1/PD and T2/PD models. To validate the interest of fusion produced by F operator in terms of segmentation of the cerebral tissues, we compared the results obtained on fusion T1/T2 with a fuzzy segmentation computed by the algorithm of classification FPCM 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 3 below:

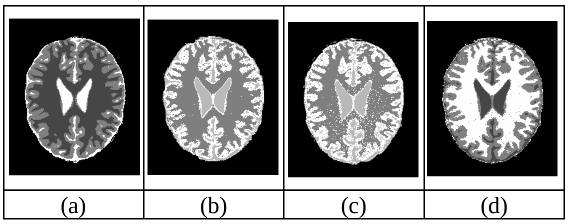


Fig. 3 (a) T1 Segmented with FPCM algorithm. (b) T2 segmeneted with FPCM algorithm. (c) PD segmeneted with FPCM algorithm. (d) Image of T1/T2 fusion with F operator.

The results for each one of the segmentation for all tissues CSF, WM and GM are reported in figures 4 and 5 below :

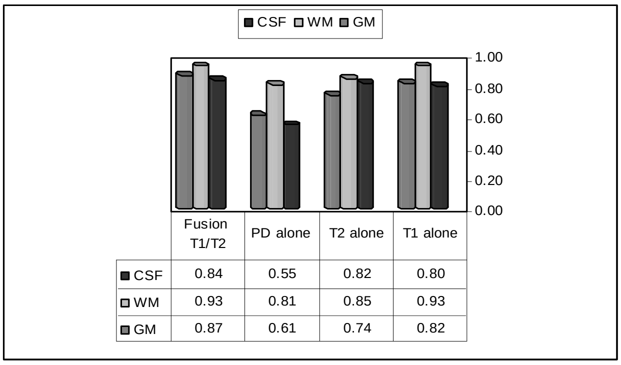


Fig. 4 Overlap measurement for different segmentations with 3% noise.

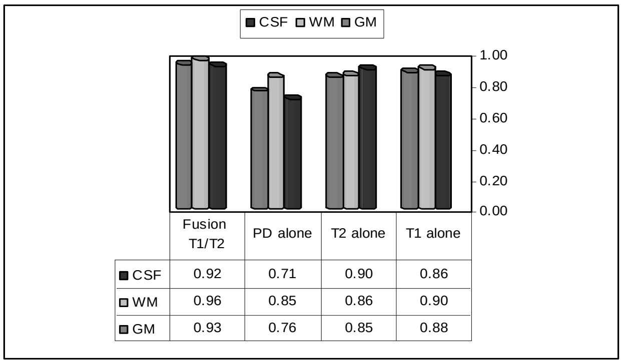


Fig. 5 Similarity measurement for different segmentations with 3% noise.

The graphics of figures 4 and 5 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.

Finally, our approach was compared with our earlier published work [Lamiche and Moussaoui (2011)] and the published work in [Ibrahim et al. (2006)] on the same dataset of MR images. The results are reported in table 2 below :

Table 2: Comparative results using similarity measurement (Dice coefficient)

Brain 1020								
Our earlier work in [19]			**Ibrahim et al. [20]**			**Proposed approach**		
CSF	*WM*	*GM*	*CSF*	*WM*	*GM*	*CSF*	*WM*	*GM*
0.87	0.96	0.90	-	-	-	**0.93**	**0.97**	**0.93**
Brain 1320								
Our earlier work in [19]			**Ibrahim et al. [20]**			**Proposed approach**		
CSF	*WM*	*GM*	*CSF*	*WM*	*GM*	*CSF*	*WM*	*GM*
0.85	0.95	0.88	-	77.2	82.8	**0.92**	**0.96**	**0.93**
Brain 1520								
Our earlier work in [19]			**Ibrahim et al. [20]**			**Proposed approach**		
CSF	*WM*	*GM*	*CSF*	*WM*	*GM*	*CSF*	*WM*	*GM*
0.83	0.88	0.78	-	-	-	**0.92**	**0.94**	**0.91**

The similarity coefficients obtained with the fusion method were better for all tissues than those resulting from an approach proposed in [Lamiche and Moussaoui (2011)] and in [Ibrahim et al. (2006)]. For example, the gray matter (GM) was strongly improved by our new proposed approach. The improvement of CSF similarity was about 7% for different noise levels, in addition the white matter (WM) was moved to 1% at 6% if the noise level augmented to 5%. Then quantitative performance comparison illustrated in table 3 clearly demonstrated the superiority of the proposed fusion model.

8. Conclusion

In this paper, a study and an evaluation of the segmentation of MR images with multispectral fusion approach are 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. Our study 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 to modeling a data are desired. In addition, we can integrate other numerical, symbolic information, experts' knowledge or images coming from other imaging devices include such as CT, 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.

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Lamiche Chaabane received his computer science engineer degree in 1997 from the Department of Computer Science from Ferhat Abbas University, Algeria. He also received a Magister degree in Computer Science in 2006 from University of M'sila. He has 5 years experience in teaching. His areas of interests include data mining and warehousing, artificial intelligence, image processing and operational research. His current research interests include the data mining techniques and medical image analysis.

Moussaoui Abdelouahab received his BSc in Computer Science in 1990 from the Department of Computer Science from the University of Science and Technology of Houari Boumedienne (USTHB), Algeria. He also received a MSc in Space Engineering in 1991 from University of Science and Technology of Oran (USTO). He received also a MSc degree in Machine Learning from Reims University (France) since 1992 and Master's degree in Computer Science in 1995 from University of Sidi Bel-abbes, Algeria and PhD degree in Computer Science from Ferhat Abbas University, Algeria. He is IEEE Member and AJIT, IJMMIA & IJSC Referee. Actually, he is a professor in computer science in the university of Setif (Algeria) and His researches are in the areas of clustering algorithms and multivariate image classification applications. His current research interests include the fuzzy neuronal network and non parametric classification using unsupervised knowledge system applied to biomedical image segmentation. He also works from a long time on pattern recognition’s algorithm, complex data mining and medical image analysis.