Segmentation of MR Brain Images using a Data Fusion Approach

Lamiche Chaabane
Department of Computer Science
University of M'sila
Algeria

Moussaoui Abdelouahab
Department of Computer Science
University of Setif
Algeria

ABSTRACT
The goal of this work is to evaluate the segmentation of MR images using the multispectral fusion approach in the possibility theory context. The process of fusion consists of three steps : (1) information extraction, (2) information combination, and (3) decision step. Information provided by T2-weighted and PD-weighted images is extracted and modeled separately in each one using fuzzy logic, fuzzy maps 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. Some results are presented and discussed.

General Terms
Image Processing, Data Fusion, Pattern Recognition.

Keywords
Fusion; possibility theory; segmentation; MR images.

1. INTRODUCTION
Image segmentation is an important step in image analysis and pattern recognition. It is the first essential partitioning an image into some non-intersecting regions such that each region is homogeneous, but the union of any two adjacent regions is not. It is can be seen as an unsupervised classification problem. It supposes that it is possible to group in one cluster pixels belonging to one same region. We suppose therefore that : (a) all pixels belonging to a region are affected to only one cluster. (b) pixels belonging to a cluster can form several and no adjacent regions in the image[1].

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 multi-modality 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 multispectral fusion approach. This one consists of the computation of fuzzy tissue maps in each of two 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 2, some previous related works are briefly cited. Section 3 summarize the FPCM algorithm. In Section 4, we describe the possibility theory concepts. Section 5 outlined the fusion process methodology. Steps of fusion in medical image processing are illustrated in section 6. Section 7 shows computational results using simulated data. Finally, Section 8 contains conclusions and addresses future work.

2. 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 [28] 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 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 [26]:

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

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 :

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

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

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

Where :

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

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

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

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

4. THE POSSIBILITY THEORY CONCEPTS

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:

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

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

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 :

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

$$x \to \pi(x) / \mathop{Sup}_x\{\pi(x)=1\}$$

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 $P(A)=P(\overline{A})=0.5$, 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 [23].

5. THE FUSION PROCESS

A general information fusion problem can be stated in the following terms : given l sources S_1, S_2,…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

6.1 Modeling Step

In the framework of possibility theory and fuzzy sets [18][19][20], 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 $u_{ij} = \pi_j(d_i)$

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 [21][22][23]. 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 $\pi_T^{T2}(v)$, $\pi_T^{PD}(v)$ are the memberships of a voxel v to tissue T resulting from step 1 then a fusion operator F generate a new membership value $\pi_T(v) = F(\pi_T^{T2}(v), {}_T^{PD}(v))$ and can managing the existing ambiguity and redundancy. The possibility theory propose a wide range of operators for the combination of memberships.

I. Bloch [25] 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 [21]. 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 [23][24][25]:

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

FOP:

$$\pi_T(v) = \max\left(\frac{\min(\pi_T^{T2}(v), \pi_T^{PD}(v))}{h}, \min(\max(\pi_T^{T2}(v), \pi_T^{PD}(v)), 1-h)\right)$$

Where h is a measure of agreement between π_T^{T2} and π_T^{PD} :

$$h = 1 - \sum_{v \in \mathrm{Image}} \left|\pi_T^{T2}(v) - \pi_T^{PD}(v)\right| / \left|\mathrm{Image}\right|$$

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][24].
The general algorithm using for fusion process can be summarized as follows :

General algorithm

Modeling of the image
    For i **in** {T2,PD} **do**
        FPCM (i) {*Computation of membership degrees for both images T2 and PD*}
    End For
Fusion
    Possibilistic fusion {*Between each class of T2 image and the same one of PD image using FOP 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[26].

7. COMPUTATIONAL 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 [27].

to have tests under realistic conditions, three volumes was generated with a thickness of 1 mm and a level of noise of 0%, 3% and 5%. We fixed at 20% the parameter of heterogeneity.

The fuzzy maps results on a noisy 95th brain only slice are shown in figures 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 simulated T2 slice   95th simulated PD slice

(a)

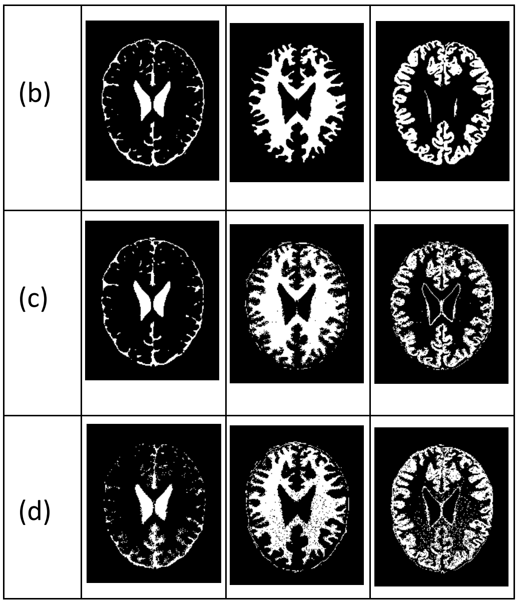


Figure 1 : (a) Simulated T2, PD images illustrate the fusion. (b) Disctret anatomical model. (c) Fuzzy maps of CSF, WM and GM obtained by FPCM for T2 image. (d) Fuzzy maps of CSF, WM and GM obtained by FPCM for PD image.

The fused maps produced in fusion step using FOP operator and the final segmentation obtained after decision step are presented in figure 2 below :

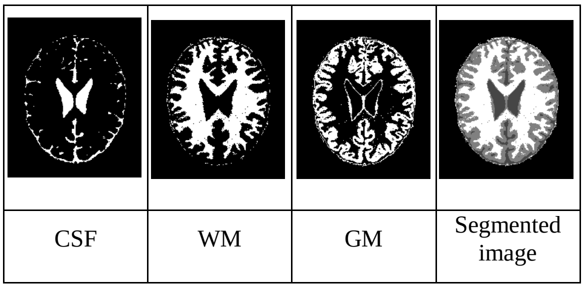


Figure 2 : Results of proposed process.

The WM fused map is strongly improved compared to that obtained by the T2 only and the PD only.

Information in GM fused map with FOP 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.

To validate the interest of fusion produced by operator FOP in terms of segmentation of the cerebral tissues, we compared the results obtained on fusion T2/PD with a fuzzy segmentation computed by the algorithm of classification FPCM on the 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:

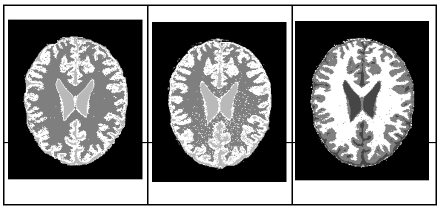
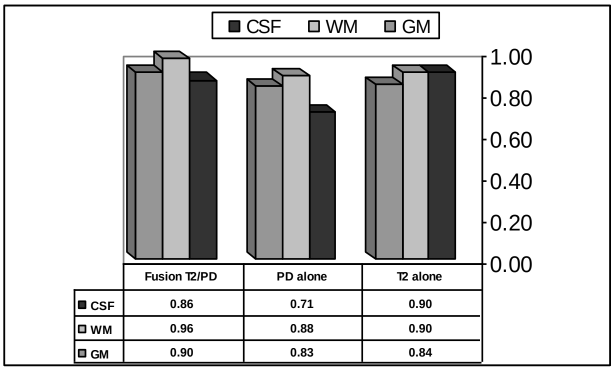


Figure 3 : (a) T2 segmeneted with FPCM algorithm. (b) PD segmeneted with FPCM algorithm. (d) Image of fusion with FOP operator.

To compare the performance of these various final segmentations, we use the DSC[2] coefficient. Which measures the overlap between two segmentations S1 and S2 defined as :

$$DSC(S1, S2) = 2.card(S1 \cap S2) / card(S1 + S2)$$

The results for each one of the segmentation for all tissues CSF, WM and GM are reported in figures 4, 5 and 6 below :



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

[2] Dice Similarity Coefficient.

Figure 4 : DSC measurment for different segmentations with 0% noise.

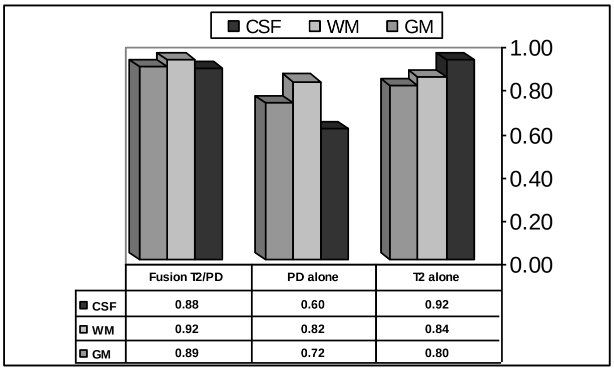


Figure 5: DSC measurment for different segmentations with 3% noise

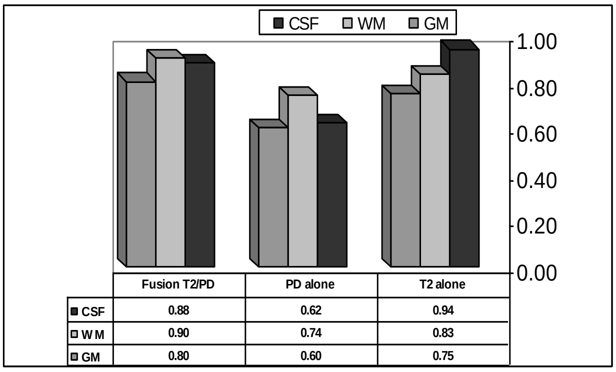


Figure 6: DSC measurement for different segmentations with 5% noise

The graphics of figures 4, 5 and 6 underline the advantages of the multispectral fusion images within the fuzzy possibilistic framework to improve the segmentation results clearly. Indeed all DSC values obtained with fusion of T2 and PD images for WM and GM tissues are greater than ones obtained when to taking into account of only one weighting in MR image segmentation.

8. CONCLUSION

In this paper, a study and an evaluation of the segmentation of MR images with multispectral fusion approach using an adaptive operator are presented. 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 adaptive operators or 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 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.

9. ACKNOWLEDGMENTS

The authors thank the reviewers for their valuable comments and suggestions that helped us to make the paper in its present form.

10. REFERENCES

[1] Gonzalez, R. C. and Woods, R. E. 1992. Digital Image Processing, Addison-Wesley.

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

[3] Hata, Y., Kobashi, S., and Hirano, S. 2000. Automated segmentation of human brain mr images aided by fuzzy information granulation and fuzzy inference. IEEE Trans. SMC 30, 381-395.

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

[5] Van Leemput, K., Maes, F., Vandermeulen, D., and Suetens, P. 1999. Automated model-based tissue classification of mr images of the brain. IEEE Trans. Medical Imaging 18, 897-908.

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

[7] Bloch, I., and Maitre, H. 1997. Data fusion in 2D and 3D image processing: an overview. In proceedings of the X Brazilian symposium on computer graphics and image processing, Brazil, 127-134.

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

[9] Barra, V. and Boire, J. Y. 2001. A general framework for the fusion of anatomical and functional medical images. NeuroImage 13**,** 410-424.

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

[11] Waltz, E. D. 1995. The principals and practice of image and spatial data fusion. In Proceedings of the Eight National Data Fusion Conference. Dalls, 257–278.

[12] Behloul, F., Janier, M., Croisille, P., Poirier, C., Boudraa, A., Unterreiner R., Mason J. C., and Revel D. 1998. Automatic assessment of myocardial viability based on pet-mri data fusion. In Proceedings of the 20th Ann. Int. Conf. IEEE 1, 492-495.

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

[14] Lefevre, E., Vannoorenberghe, P., and Colot, O. 2000. About the use of Dempster-Shafer theory for color image segmentation. In First International Conference on Color in Graphics and Image Processing, Saint-Etienne, France.

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

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

[17] Bloch, I. 2000. Fusion of numerical and structural image information in medical imaging in the framework of fuzzy sets. In Fuzzy Systems in Medicine, P. Szczepaniak et al.

[18] Zadeh, L. A. 1965. Fuzzy sets. Information and Control 8, 338-353.

[19] Zadeh, L. A. 1978. Fuzzy sets as a basic for a theory of possibility. Int. Jour. of Fuzzy Sets and Systems 1, 3-28.

[20] Dubois, D. and Prade, H. 1980. Fuzzy Sets and Systems: Theory and Application. Academic Press, New-York.

[21] Dubois, D. and Prade, H. 1985. A Review of Fuzzy Set Aggregation Connectives. Information Sciences 36, 85-121.

[22] Yager, R. R. 1991. Connectives and Quantifiers in Fuzzy Sets. Int. Jour. of Fuzzy sets and systems 40, 39-75.

[23] Dubois, D. and Prade, H. 1992. Combination of information in the framework of possibility theory. In Data Fusion in Robotics and Machine Intelligence, M. AL Abidi et al.

[24] Barra, V. 2000. Fusion d'Images 3D du Cerveau : Etude de Modèles et Applications. Thèse de doctorat, Université d’Auvergne.

[25] Bloch, I. 1996. Information combination operators for data fusion : a comparative review with classification. IEEE Transactions in systems, Man. and Cybernitics 1, 52-67.

[26] Bezdek, J. C., Keller, J., Krishnapuram, R., and Pal, N. R. 1999. Fuzzy Models and Algorithms for Pattern Recognition and Image Processing. Kluwer Academic, TA 1650.F89.

[27] Cocosco, C. A., Kollokian, V., Kwan, R. K. S., and Evans, A. C. 1997. BrainWeb: Online interface to a 3D MRI simulated brain database. NeuroImage 5, S425.

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