Fuzzy Segmentation of MR Brain Real Images Using Modalities Fusion

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Abstract— With the development of acquisition image techniques, more data coming from different sources of image become available. Multi-modality image fusion seeks to combine information from different images to obtain more inferences than can be derived from a single modality. The main aim of this work is to improve cerebral IRM real images segmentation by fusion of modalities (T1, T2 and DP) using Fuzzy C-Means approach (FCM). The evaluation of adopted approaches was compared using four criteria which are: the standard deviation (STD), entropy of information (IE), the coefficient of correlation (CC) and the space frequency (SF). The experimental results on MR brain real images prove that the adopted scenarios of fusion approaches are more accurate and robust than the standard FCM approach.

Keywords-component; Data fusion, Segmentation, Fuzzy C-Means, MR images.

I. INTRODUCTION

In last decades, biomedical and medical image processing have become one of the most challenging fields of image processing and pattern recognition. Brain segmentation consists of separating the different tissues: gray matter (GM), white matter (WM), cerebrospinal fluid (CSF) and probably abnormal (tumor) tissue.

The aim of segmentation of MR Brain images is to: Study anatomical structure, Identify region of interest: locate tumor, …, others abnormalities, measure tissue size (to follow the evolution of tumor) and help in treatment planning prior to radiation therapy (radiation dose calculation).

However, the segmentation of MR Brain images has remained a challenge in image segmentation. And this is due to partial volume effects, motion (patient movement, blood circulation and respiration), the existence of image noise, the presence of smoothly varying intensity in-homogeneity, the fact that different anatomical structures may share the same tissue contrast and large amounts of data to be processed. For these and others many approaches have been studied, including Methods based edge [1][2][3], methods based region [4][5], Methods based on thresholding [6][7], methods based artificial neural networks [8], data fusion methods [9], Markov random field methods [10] and hybrid Methods [11][12][13].

In fuzzy segmentation, the image pixel values can belong to more than one segment, and associated with each of the points are membership grades that indicate the degree to which the data points belong to different segments.

Segmentation process also helps to find region of interest in a particular image. The main goal is to make image more simple and meaningful. Fuzzy C-Means (FCM) is a supervised fuzzy classification algorithm. Resulting from the C-means algorithm (C-means), it introduces the concept of fuzzy set in the class definition: each point in the data set for each cluster with a certain degree, and all clusters are characterized by their center of gravity.

The data fusion, in imaging, is used mainly on radar images, satellite images, and aerial images. Recently, it is also applied in medical image. The increasing diversity of the medical image acquisition techniques motivated recent years much research aimed at developing models increasingly effective data fusion. Indeed, medical imaging, it may happen that no images available alone does not contain sufficient information. On the other hand the medical community entrusts each image type to an expert who has a partial diagnosis of the modality of his specialty and specialists exchange experiences and this confrontation comes the final diagnosis.

In this paper, our contribution is mainly to propose an architecture of a information fusion system guided by the prior knowledge and based on Fuzzy C-Means approach to segment human MR real Brain images.

The organisation of the paper is as follows. In section 2 the Fuzzy C-Means approach of segmentation is reviewed and in section 3 describes briefly data fusion. Section 4 present a complete description of proposed segmenting approach using data fusion, where each step of the algorithm is developed in detail. Section 5 illustrates the obtained experimental results and discussions and section 6 concludes this paper.

II. FUZZY C-MEANS TECHNIQUE [14]

Modeling inaccuracy is done by considering gradual boundaries instead of clear borders between classes. The uncertainty is expressed by the fact that a pixel has attributes that assign a class than another. So, Fuzzy clustering assigns not a pixel a label on a single class, but its degree of membership in each class. These values indicate the
uncertainty of a pixel belonging to a region and are called membership degrees. The membership degree $s$ in the interval $[0, 1]$ and the obtained classes are not necessarily disjoint. In this case, the data $X_j$ are not assigned to a single class, but many through degrees of membership $U_{ij}$ of the vector $X_j$ to class $i$. The purpose of classification algorithms is not only calculating cluster centers $b_i$ but all degrees of membership vectors to classes. If $U_{ij}$ is the membership degree of $X_j$ to class $i$, the matrix $U(C \times N, C$ number of cluster and $N$ is the data size) is called fuzzy $C$-partitions matrix if and only if it satisfies the conditions (1) and (2):

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

$$\forall i \in [1, C], \sum_{j=1}^{N} u_{ij} = 1 \quad (2)$$

The objective function to minimize $J$ and the solutions $b_i$, $U_{ij}$, of the problem of the FCM are described by the following formulas:

$$J(B, U, X) = \sum_{i=1}^{C} \sum_{j=1}^{N} (U_{ij})^m d^2(x_j, b_i) \quad (3)$$

$$b_i = \frac{\sum_{j=1}^{N} (u_{ij})^m X_j}{\sum_{j=1}^{N} (u_{ij})^m} \quad (4)$$

$$u_{ij} = \left[ \frac{\sum_{k=1}^{C} \left( \frac{d^2(x_j, b_k)}{d^2(x_j, b_i)} \right)^{\frac{1}{m-1}}}{C} \right]^{-\frac{1}{m-1}} \quad (5)$$

with the variable $m$ is the fuzzification coefficient which takes values in the interval $[0, +\infty [$. The FCM algorithm stops when the partition becomes stable.

Like other unsupervised classification algorithms, it uses a criterion minimization of intra-class distances and maximizing inter-class distances, but gives a degree of membership of each class for each pixel. This algorithm requires prior knowledge of the number of clusters and generates classes through an iterative process by minimizing an objective function. Thus, it allows to obtaining a fuzzy partition of the image by providing each pixel with a membership degree (between 0 and 1) to a given class. The cluster which is associated with a pixel is one whose degree of membership is the highest.

The main steps of the Fuzzy C-means algorithm are:

1. Input the image $X_j$: $j = 1..N$, $N$: size of image.
2. Set the parameters of the algorithm: $C$: number of cluster, $m$: fuzzy coefficient, $\varepsilon$: convergence error.
3. Initialize the membership matrix $U$ with random values in the range $[0, 1]$.
4. Update the centers $b_i$ using the equation (4) and evaluation of the objective function $\mathcal{J}_{old}$ using the formula (3).
5. Update the membership matrix $U$ using the equation (5) and evaluation of the objective function $\mathcal{J}_{new}$ using the formula (3).
6. Repeat steps 4 and 5 until satisfaction of the stopping criterion which is written: $| \mathcal{J}_{old} - \mathcal{J}_{new} | \leq \varepsilon$.
7. The outputs are the membership matrix $U$ and the centers $b_i$.

III. DATA FUSION

Information fusion is to combine information (often imperfect and heterogeneous) from multiple sources to obtain better complete global information, to improve decision making and make better act. The terms "information" (numeric or symbolic) and "sources" cover many possibilities. In the same way, the notion of improvement depends wholly on the application.

Information fusion has evolved considerably in recent years in various fields, especially in vision and robotics, information sources have increased (sensors, a priori information, generic knowledge ... etc.). In general, each source of information is imperfect, it is important to combine several to get a better understanding of the all of the system. MRI is a powerful tool to improve clinical diagnosis because it can provide various information in the form of image intensities related to the anatomy through a variety of excitation sequences (for example: T1, T2, and PD).

The proposed fusion involves the aggregation MR images from different acquisition techniques. Data to be combined are so homogeneous, and depending on the type of image acquisition will provide more or less pronounced contrast between tissues or between parenchyma and pathology. One of the main interests of the fusion will be to exploit in particular the complementarity between the different images. Many applications can benefit from this technique. These include:

**The detection of tumour regions:**

MRI provides easy assess tumour extension, especially when contrast media are used. With certain acquisition techniques, the specificity is also greater in some cases to distinguish between tumor and oedema. The whole point is going to reside in a combination of these techniques with a more anatomical acquisition (weighted T1 type) to measure the tumor extension.

**Quantification of brain tissue volumes**

Because of its anatomical accuracy and variety of acquisition techniques, MRI is used to assess the distribution of different brain tissues following several contrasts. The volume quantification of these tissues is clinically fundamental to the study of many pathologies that affect the white matter, gray matter or cerebrospinal fluid, or simply for the measurement of volumes in healthy subjects.

Information fusion can be doing at three conceptual levels corresponding to three types of information:
• Data fusion: it is essentially to marry low-level information such as primitives, in order to make information less noisy than that obtained with a single source of information.
• Decision fusion: it performs the combination of sophisticated information (numeric or symbolic) that can be considered as proposals for a decision.
• Models fusion: in this case, different approaches are set apart to fill imperfections affecting each of them independently.

A general information fusion problem can be stated in the following terms: given L sources S1, S2, ..., SL representing heterogeneous data on the observed phenomenon, take a decision di on an element x, where x is a higher level object extracted from information, and D1 belongs to a decision space D={d1, d2, d3, ..., dn} (or set of hypotheses). In numerical fusion methods, the information relating x to each possible decision di according to each source Sj is represented as a number Mij 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: Mi = F(Mi1, Mi2, Mi3, ..., Min), where F is a fusion operator. Then a decision is taken from the set of Mi, 1 ≤ i ≤ 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 [15][16].

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 Mij 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 di.[17]

I. Bloch [18] classified these operators in three classes defined as:
- Context independent and constant behaviour operators (CICB);
- Context independent and variable behaviour operators (CIVB);
- Context dependent operators (CD).

IV. METHODOLOGY

Segmentation of brain images can separate different brain structures and detect possible pathologies, namely brain tumors. A good segmentation helps the doctor for making a final decision before his surgery. The main applications of the segmentation are morphometry, functional mapping and surface or volume visualization. Morphometry is the quantitative measurement of the positions, shapes and sizes of brain structures. It requires prior segmentation of these structures, and can identify, understand and follow the progression of diseases such as Alzheimer's or different tumors.

The figure 1 shows the implementation of the proposed approach with its various stages:

![Diagram of the various steps of the analysis system MRI images.](image)

**A. Acquisition:**

MR Brain images are obtained by a Magnetic resonance imaging (MRI). Examination performed on a machine of high field 1.5 T according to the sequences:
- Axial and Sagittal TI
- Axial T2 * Flair and diffusion.
- Coronal T2.
- Examination with and without gadolinium injection.

These MRI images are of different sections (axial, sagittal, and coronal) of healthy and pathological subjects. They are grouped into several sections.

**B. IRM Database:**

The format of images is the format DICOM (Digital Imaging and Communication in Medicine). This latter is a file used by most of the manufacturers of medical imaging; this standard was issued by the ACR (American College of Radiology) in association with the NEMA (National Electrical Manufacturers Association). The DICOM format is a file containing the image and patient data compressed (patient name, exam type, hospital, examination date, type of acquisition...etc.). To validate our segmentation algorithms, we use a real database. These images are encoded in the DICOM format size 256x256 pixels. These images are grouped into several sections. Each image DICOM used has the following details:

- **Format** : ‘DICOM’
- **Color Type** : ‘grayscale’
- **Modality** : ‘MR’
- **Manufacturer** : ‘GE MEDICAL SYSTEMS’
- **Institution Name** : ‘Medical Imaging Center of M’sila (DR S. F. Ghadbane)’
- **Study Description** : ‘CEREBRAL’
- **Series Description** : ‘FL:A/3-pl T2* FGRE S’
- **Slice Thickness** : 5
- **Repetition time** : 55.500
- **Magnetic Field Strength** : 15000
- **Echo Time** : 2.1000
- **Spacing Between Slices** : 10
- **Spatial Resolution** : 1.8750
- **Flip Angle** : 0

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The modality T1 is used to distinguish the different tissues such as: gray matter (GM), white matter (WM) and cerebrospinal fluid (CSF). However, The T2 modality do not allow to distinguish the GM from WM but highlight lesions and CSF.

C. Segmentation

Normally MR Brain image can be classified in three classes: gray matter (GM), white matter (WM), cerebrospinal fluid (CSF). Each region has a certain gray level, for the T1 modality, the WM region has the gray level which tend to white one, the CSF region has the gray level which tend to black one and the grey level of GM region is between the both. The process of segmentation is done with FCM using modalities fusion to separating the different tissues of MR Brain images.

For our MR images fusion, context-based conjunctive operators are chosen 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 behaviour allowed to taking into account these ambiguous but diagnosis–relevant areas. Then we retained four operators of this class, three of them are introduced in [18][19][20]:

- **OP1:** $\pi_T (v) = \min (\pi_{T1} (v), \pi_{T2} (v)) +1-h$ (4)
- **OP2:** $\pi_T (v) = \min \left( \frac{\min (\pi_{T1} (v), \pi_{T2} (v))}{h}, 1-h \right)$ (5)
- **OP3:** $\pi_T (v) = \min (1, \frac{\min (\pi_{T1} (v), \pi_{T2} (v))}{h} +1-h)$ (6)

with:

- $h=1-\Sigma_{v \in \text{image}} |\pi_{T1} (v) - \pi_{T2} (v) |/|\text{Image}|$ (7)
- **OP4:** $\pi_T (v) = \frac{\pi_{T1} (v) \pi_{T2} (v)}{2}$ (8)

The general algorithm for the FCM using modalities fusion approach can be formulated as follows:

1. Set the parameters of the algorithm: C: number of cluster, $\varepsilon$: convergence error.
2. For each image of section j: Xj: j=1...SC, which SC is the section number.
3. Segmentation of each image section of each modality (T1, T2, PD) using FCM provide posteriori-probabilities membership Rjt, t=(T1, T2, PD), which t is the modality.
4. Use one operator fusion OP(t1,t2) then the output is membership matrix Rj.
5. Assign all pixels to clusters by using the maximum membership value of every pixel.

D. Evaluation:

In addition to visual analysis, a quantitative evaluation is used on the above experimental results by different fusion algorithms. The selected quantitative criterions are standard deviation (SD), entropy (EN), spatial frequency (SF) and coefficient correlations (CC).

**Standard deviation (SD):** standard deviation is the square root of the variance, the variance of an image reflects the degree of dispersion among the grayscale values and the average value of gray levels. The larger the value is, the better fusion results are obtained.

\[
SD = \sqrt{\frac{\sum_{i=1}^{N} \sum_{j=1}^{M} F(i,j)^2}{M}}
\] (9)

**Entropy (EN):** Entropy can effectively reflect the amount of information in certain image. The larger the value is, the better fusion results are obtained [21]:

\[
EN = \sum_{i=1}^{L-1} P_i(i) \log_2 P_i(i)
\] (10)

where $P_{i \mu}$ is the normalized histogram of the fused image to be evaluated, L is the maximum gray level for a pixel in the image.

**Spatial frequency (SF):** Spatial frequency can be used to measure the overall activity and clarity level of an image. Larger SF value denotes better fusion result [21]:

\[
SF = \sqrt{RF^2 + CF^2}
\] (11)

With

\[
RF = \sqrt{\frac{1}{M(N-1)} \sum_{i=0}^{M-1} \sum_{j=0}^{N-2} (F(i,j+1) - F(i,j))^2}
\] (12)

And

\[
CF = \sqrt{\frac{1}{N(M-1)} \sum_{i=0}^{M-2} \sum_{j=0}^{N-1} (F(i+1,j) - F(i,j))^2}
\] (13)

**Coefficient correlation (CC):** Coefficient correlation can show similarity in the small structures between the original and reconstructed images. Higher value of correlation means that more information is preserved [21]:

\[
CC = \frac{\sum_{i=1}^{M} \sum_{j=1}^{N} (x_{i,j} - \mu(A))(x'_{i,j} - \mu(B))}{\sqrt{\sum_{i=1}^{M} \sum_{j=1}^{N} (x_{i,j} - \mu(A))^2(x'_{i,j} - \mu(B))^2}}
\] (14)

where $\mu(A)$ and $\mu(B)$ are the mean value of the corresponding dataset.

V. Experimental Results

The proposed approach Fuzzy c-means using modalities fusion have been tested on real MR brain images to certify their efficiency. It was acquired in medical imaging center of MSila (DR S. F. Ghadbane). These MRI images are of different sections (axial, sagittal, and coronal) of healthy and pathological subjects of size (256×256). These images are grouped into 26 sections. The format of images is the format DICOM (Digital Imaging and size Communications in Medicine).

Examples of real images MRI present in this paper are extracted on axial sections of three modalities (T1, T2 and PD). The healthy images are segmented in four parts (c=4): background, white matter WM, gray matter GM and
cerebrospinal fluid CSF. For tumoral subject, the images are segmented in five classes: background, WM, GM, CSF and the tumor. Standard deviation (SD), entropy (EN), spatial frequency (SF) and coefficient correlations (CC) are used to compare the performance of the adopted techniques for segmentation of MR brain images.

To evaluate the performance of the proposed approach, two slices are presented for each adopted fusion operator and each fusion system. And obtained results are compared to those of FCM. The two slices are: slice 16 from the healthy subject (Figure 2) and slice 22 from the tumor one (Figure 4) with three modalities (T1, T2 and PD). Figure 2, 3, 4 and 5 present for each example the segmented image using the FCM and FCM using system fusion ((T1, T2) (T1, PD), (T2, PD) and (T1, T2, PD)) with each operator (OP1, OP2, OP3 and OP4). Tables I, II, III, IV and V present for each example and for FCM and FCM using system fusion with each operator the detailed quantitative evaluation: (standard deviation (SD), entropy (EN), spatial frequency (SF) and coefficient correlations (CC)).

<table>
<thead>
<tr>
<th></th>
<th>T1</th>
<th>T2</th>
<th>PD</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Original</strong></td>
<td><img src="image1" alt="Image" /></td>
<td><img src="image2" alt="Image" /></td>
<td><img src="image3" alt="Image" /></td>
</tr>
<tr>
<td><strong>FCM</strong></td>
<td><img src="image4" alt="Image" /></td>
<td><img src="image5" alt="Image" /></td>
<td><img src="image6" alt="Image" /></td>
</tr>
</tbody>
</table>

Fig. 2. Slice 16 from healthy MR brain images and corresponding segmented image using FCM algorithm for c=4.

<table>
<thead>
<tr>
<th></th>
<th>T1</th>
<th>T2</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Original</strong></td>
<td><img src="image7" alt="Image" /></td>
<td><img src="image8" alt="Image" /></td>
</tr>
<tr>
<td><strong>FCM</strong></td>
<td><img src="image9" alt="Image" /></td>
<td><img src="image10" alt="Image" /></td>
</tr>
</tbody>
</table>

Fig. 4. Slice 22 from tumor MR brain images and corresponding segmented image using FCM algorithm for c=5.

<table>
<thead>
<tr>
<th></th>
<th>CC</th>
<th>EN</th>
<th>SF</th>
<th>STD</th>
</tr>
</thead>
<tbody>
<tr>
<td>T1</td>
<td>-0.718</td>
<td>1.360</td>
<td>7.329</td>
<td>6.868</td>
</tr>
<tr>
<td>T2</td>
<td>-0.672</td>
<td>1.291</td>
<td>6.420</td>
<td>7.090</td>
</tr>
<tr>
<td>DP</td>
<td>0.259</td>
<td>1.494</td>
<td>10.703</td>
<td>4.889</td>
</tr>
</tbody>
</table>

Table I. Experimental results using FCM for the slice 16 from healthy MR brain.

<table>
<thead>
<tr>
<th></th>
<th>CC</th>
<th>STD</th>
<th>SF</th>
<th>EN</th>
</tr>
</thead>
<tbody>
<tr>
<td>Op1</td>
<td>T1</td>
<td>-0.329</td>
<td>12.121</td>
<td>58.603</td>
</tr>
<tr>
<td></td>
<td>T2</td>
<td>-0.297</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Op2</td>
<td>T1</td>
<td>-0.329</td>
<td>12.121</td>
<td>58.603</td>
</tr>
<tr>
<td></td>
<td>T2</td>
<td>-0.297</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Op3</td>
<td>T1</td>
<td>0.448</td>
<td>13.656</td>
<td>71.660</td>
</tr>
<tr>
<td></td>
<td>T2</td>
<td>0.410</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Op4</td>
<td>T1</td>
<td>0.040</td>
<td>11.125</td>
<td>61.253</td>
</tr>
<tr>
<td></td>
<td>T2</td>
<td>0.019</td>
<td></td>
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</table>

Table II. Experimental results using FCM with the four fusion operator and the fusion system (T1, T2) for the slice 16 from healthy MR brain.
Table I and IV show that modality T2 provide the best segmentation. The use of modalities fusion has improved segmentation in terms of evaluation criteria (Table II, III and V). Segmentation by modalities fusion depends on modalities themselves and the used fusion operator: for example for the min operator (OP1) the best combination is T1 with T2.

The fusion using the three modalities with the operator min (OP1) offer the best segmentation with a rate of correlation $CC= 0.137$, 0.189 and 0.180 standard deviation $STD= 10.948$ spatial frequency $SF= 78.135$ and information entropy $EN= 1.640$. The segmentation using the third operator provide white matter and CSF) by using of Fuzzy c-means with modalities fusion approach. This aggregation was performed by fusion operators that model doctor daily analysis confronted heterogeneous clinical data. The proposed approach Fuzzy c-means using data fusion has been tested on real MR brain images (healthy and pathological) to certify their efficiency. Experimental results show that: modalities fusion improves the segmentation of brain images. The fusion operators min and mean are the best for the segmentation of brain images and can deliver satisfactory performance to separating the different parts of an MR brain real image. Further research is needed to improve the proposed approach. At level of modeling we would like to integrate other numeric or symbolic information to increase the mass of available knowledge and at the combination one to design adaptive fusion operators for the combination of data in the medical field.

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