Multimodal (MRI/PET) Fusion of Cerebral Images in Multiresolution Domain

W. Aribi*, A. Khalfallah and M. S. Bouhlel
Sciences of Electronic, Technologies of Information and Telecommunication (SETIT)
University of Sfax, Biotechnology High Institute of Sfax
Sfax, Tunisia
*Email: aribi_walid [AT] yahoo.fr

N. Elkadri
Unit of Research in Biophysics, Medicine Faculty of Tunis, Tunisia

Abstract— **As a result of the development of imaging techniques and information technology, it is possible to have several heterogeneous data. The fusion an anatomic imaging such as the magnetic resonance imagery (MRI) and functional imaging type such as the positron emission tomography (PET), made it possible to lead to a greater complementarities of data.**
In this work, we present a comparative study of fusion techniques in the transformed domain of the images. The results obtained showed that the best combination is the simultaneous use of the method of fusion DWT and the technique of classification K-Means.

Keywords—Fusion of images; MRI; PET; cerebral images; multiresolution; pyramidal decomposition; segmentation; classification; k-means, Fuzzy C-Means; Maximisation Estimate.

I. Introduction

The applied medical evolved considerably these last years, essentially by the technical revolution of the medical imagery.

Indeed, techniques of visualization not only have become richer of information, but also play an indispensable role before any therapeutic decision. In this study, we are interested in the medical image fusion. The fusion of information consists of combining the descended information of several sources in order to improve the decision making.

Algorithms of image fusion developed until now can be classified into three primary categories: methods of optimization, transformed domain and spatial domain.

The idea developed in this paper is based on the application of multi resolution approaches of anatomical multimodal images' fusion (MRI: Magnetic Resonance Imagery) and functional (PET: Positron Emission Tomography), then making the segmentation by different techniques, for a better classification of the cerebral tissue. Two facts motivated this choice. The human visual system is mainly sensitive to the change of the local contrast. The MRI and the PET are currently the best techniques of anatomical and functional imagery, respectively of the human brain.

In the first section, we are going to present the different techniques of fusion. The following section will present the comparative study of these techniques. Finally, we are going to conclude by our findings and discuss them.

II. Materiel and methods

A. Algorithms of medical image fusion in the multiresolution domain

The pyramidal multiresolution transformation divides the image using multiple resolutions and different scales while preserving the initial data. A pyramid is a sequence of images in which every level is a filtered and a sampled copy of the predecessor [1, 7].

The lowest level of the pyramid has the same scale of the original image and contains information of higher resolution.

Pyramidal multiresolution representations contain some descriptive information concerning contours, gradients, and the contrast in the image.

The process of pyramidal decomposition is based on two fundamental and important functions which are REDUCE and EXPAND [1, 2].

The images filtering are assured by a discrete low pass filter of order 5. This filter's characteristics are determined by the coefficients a, b and c. They are called Kernel coefficients.

In fact, this filter is defined by the discrete function w(m) where w(m) = [c, b, a, b, c]. It obeys the four following constraints [2]:

- Symmetric $w(m) = w(-m)$ (1)
- Separable $w(m,n) = w(m)w(n)$ (2)
- Normalization $\sum w(m) = 1$ (3)
- equal contribution $a + 2c = 2b$ (4)

The fact that the filter is at the same time symmetrical (equation 1) and separable (equation 2) allows the number of arithmetic operations to decrease the required operations of filtering in REDUCE and EXPAND during a complete convolution using a 5x5 filter.

The REDUCE operation essentially consists in filtering then decimating the even elements by a factor of 2 [3]. Graphically, the REDUCE operation can be represented in dimension 1D and it is shown the following diagram:

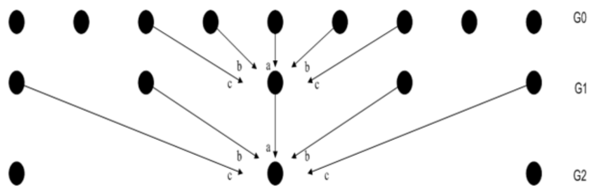


Fig. 1. The REDUCE operation in dimension 1D

The value of the targeted point is equal to the sum of the points of the other extremities multiplied by their respective weights [2].

To do an operation of filtering on an image, we can convolve its matrix with a discrete filter and decimate to a factor of 2 as presented in the following equation:

$$G_l(i,j) = \left[G_{l-1}(i,j) * w(i,j)\right]_{\downarrow 2} \qquad (5)$$

With G: Gaussian of level *l*, w: the function of the filter.

Thus, the REDUCE operation can be represented by the equation (6) or by the equation (7):

$$G_l(i,j) = REDUCE_{2D}\left[G_{l-1}(i,j)\right] \qquad (6)$$

$$\Rightarrow G_l = REDUCE_{2D}\left[G_{l-1}\right] \qquad (7)$$

The pyramid of Gauss consists in applying the REDUCE operation successively on the initial image. Thus, one can express the Gaussian of l level of the I image.

The REDUCE operation on an image can be represented by the successive application of REDUCE in 1D.

We apply the REDUCE operation initially on columns of the initial image. Then, we apply it again on lines.

The EXPAND operation is the inverse of REDUCE. It consists in dilating by zero interpolation and to filter thereafter [2]. It is represented in 1D in figure 2:

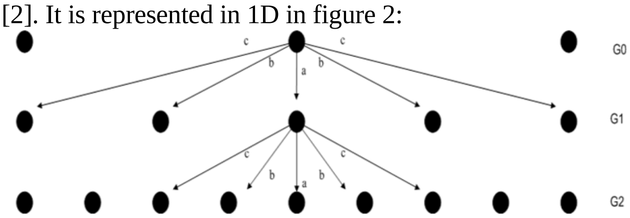


Fig. 2. The EXPAND operation in dimension 1D

The EXPAND function in 2D can be defined mathematically by the equation (8):

$$G_l(i,j) = 4 \sum_{m=-2}^{2} \sum_{m=-2}^{2} w(m,n) G_{l-1}\left(\frac{i+m}{2}, \frac{j+n}{2}\right) \qquad (8)$$

It is based on dilation by zero interpolation followed by a convolution with w (m, n).

In terms of convolution, the EXPAND function in 2D can be defined by the equation (9):

$$G_l(i,j) = 4\left(\left[G_{l-1}(i,j)\right]_{\uparrow 2} * w(i,j)\right) \qquad (9)$$

To simplify the expression, one often notes the EXPAND function by the equation (10) or by the equation (11):

$$G_l(i,j) = EXPAND_{2D}\left[G_{l-1}(i,j)\right] \qquad (10)$$

$$\Rightarrow G_l = EXPAND_{2D}\left[G_{l-1}\right] \qquad (11)$$

We apply the EXPAND operation initially on columns of the initial picture. Thereafter, we apply it again on lines.

1) Algorithm of Laplacian pyramid

The technique of the Laplacian pyramid has been developed by Burt and Adelson for the compression of image.

The approach of a fusion selection includes the three following stages[2]:

- Every image is decomposed into pyramidal multiresolution representation at level l.
- The pyramidal Laplacian decomposition at level l follows the following equation:

$$L_i = G_i - EXPAND_{2D}(G_{i+1}) \quad with\ 1 \le i < l-1 \ \ et\ \ L_l = G_l \qquad (12)$$

With L_i and G_i are respectively Laplacian and Gaussian pyramidal decomposition at level *i*.

- A combined pyramid is constructed from the Laplacian pyramids of source images.

An inverse pyramidal transformation is applied to the combined pyramid to get the fused image.

2) Algorithm of Filter-Subtract-decimate pyramid (FSD)

The calculation of the Laplace FSD pyramid consists to add all Laplace oriented pyramids in order to get an exact reconstruction of the Laplace FSD pyramid [1].

3) Algorithm of Gradient (GRAD) pyramid

The decomposition and the recomposition of pyramidal gradient require the following steps [4]:

- Calculation of Gaussian from the initial image;
- Calculation of gradients oriented pyramids from the pyramid Gaussian;
- Calculation of the Laplace oriented pyramids;
- Calculation of Laplace FSD pyramid;
- Transformation of the Laplace FSD pyramid in low pass Laplace pyramids;
- Recombination of the image from the pyramid of Laplace.

4) Algorithm of Pyramid Ratio (RATIO)

The Pyramidal Ratio decomposition is similar to the pyramidal Laplacian decomposition. The only difference between these two techniques is summarized in the replacement of the difference operator (equation 12) by a division operator at the calculation of the intermediate decompositions (equation 13). So, the equation of the transformation pyramidal RATIO can be written as follows:

$$R_i = \frac{G_i}{EXPAND_{2D}(G_{i-1})} \tag{13}$$

Where $1 \leq i < l$ et $R_l = G_l$

The report of the low pass pyramid RATIO algorithm reveals the relative importance of model segments types based on their local values of light and contrast [5].

All entered images are decomposed in light and dark tasks with the decreasing resolution levels (pyramids). The image in every level of the pyramid is essentially between two successive levels of the Gaussian pyramid [6]. The image on each level of the pyramid is primarily the ratio of two successive levels of the Gaussian pyramid [6].

5) Algorithm of morphological pyramid

The normal filtering techniques, as in the pyramid Laplacian, change usually the details of the shape and the exact location of the objects in the image [6].

The morphological algorithms of pyramid (Morph) tackle this issue by removing details of image without any negative effect or adding any distortion [8].

The main difference between the Morph and the Laplacian lies in the use of the morphological pyramids, while being based on a different filtering method: it employs a filtering method which is based on the definition and the extraction of form, instead of the pyramids of Laplacian with the simple low-pass and high-pass filters [6].

The morphological filters are sequences of morphological operations; moreover, they have special properties like the respect of the forms in the image [8].

Once that it is filtered, a morphological pyramid can be reconstituted by a specific sampling method. This process is similar to the Laplacian technique. Once the pyramids are formed, a decision rule is applied and an image is formed. The fused image is developed by the opposite transform of the pyramid.

6) Algorithm of contrast pyramidal

The contrast pyramid fusion algorithm is similar to the pyramid RATIO fusion algorithm. The contrast (the first fundamental form) is defined by the RATIO of the difference between the luminance in a certain site in a zone of the image and the luminance of the local origin [9].

Luminance is defined as the quantitative measure of luminosity that's to say the amount of energy of visible light at a point on a surface in a given direction. Each level Ri is a RATIO of two successive levels in the Gaussian pyramid.

The contrast of luminance is defined with:

$$C = (L - L_b) / L_b = \frac{L}{L_b} - I \tag{14}$$

Where L indicates luminance on a certain site in a zone of the image, Lb represents the luminance of the local origin, and I (i, j) = 1 for all i,j.

If C_i is defined by:

$$C_i = G_i / EXPAND[G_{i+1}] - I \tag{15}$$

We have:

$$R_i = C_i + I \tag{16}$$

For these reasons, we refer to sequence Ri like the RATIO or the pyramid of contrast.

The pyramid RATIO is a complete representation of the original image. G0 can be found by reversing the steps exactly used in the construction of the pyramid:

$$R_i = \frac{G_i}{EXPAND_{2D}(G_{i-1})} \tag{17}$$

$$\text{Where } 0 < i < l-1 \text{ et } R_i = G_i$$

For example, in the case of the fusion of two input images A and B, to find an output image C and with the maximum value absolute of contrast, we have a criterion of selection, for any I, J, and L, defines as follows:

$$RC_l(i,j) = \begin{cases} RA_l(i,j), & \text{si } |RA_l(i,j) - 1| > |RB_l(i,j) - 1| \\ RB_l(i,j), & \text{otherwise} \end{cases} \tag{18}$$

Where RA and RB represent the RATIO of pyramid for the two sources images and RC is the RATIO of output image.

7) Fusion by Discrete Wavelet Transform (DWT)

The concept of multiresolution analysis, as introduced by Stephan Mallat, results from the pyramidal algorithms [10, 11].

There exist many wavelets described in the literature (Morlet, Hâar, Daubechies, etc...) used in coding, denoising or signal analysis [13].

Daubechies showed that it is only the wavelet orthogonal and symmetrical corresponding to a bench of filters to finite impulsionelle response [14].

The analysis multiresolution of an image is applied to several levels. At each level, geometrical dimensions of the image are reduced by a factor of 2, using a set of orthogonal filters whose characteristics are determined by the family of wavelets used in [15].

The result resides then at four small images, one representing the reduction of the image source (approximation) and the three others containing information of spatial high frequencies information lost during the reduction (details).

The transition from one level to another is done by dividing the reduced image (approximation); there are then 4 times fewer points to treat. One applied technique is called multiresolution analysis discrete wavelet transform.

Fusion multi-scales by the transform in wavelets combine for each level the coefficients of decomposition of two or several images sources following fusion operators [16].

Thereafter, a transform reverses will be applied to the resulting coefficients in order to obtain the fusion image [17].

Initially, the two input images are decomposed in the field of the wavelet approximations (low frequency information) and details (high frequency information) horizontal, vertical and diagonal. Then, and according to the rules of fusion, these coefficients are used to build the details as well as the approximations of the output image by applying the transformed opposite one (W^{-1}).

8) Algorithm of transform of wavelets discrete invariant per shift

The shift invariant discrete wavelet (SiDWT) is a prolongation of the DWT but uses different algorithms and approaches. Indeed, SiDWT makes it possible to improve the stability and the temporal uniformity of image [18]. The difference is the elimination of the operation of sampling of the DWT. This causes the failure of the shift invariant of DWT. The elimination of the sampling stage shift invariant restored invariant with the SIDWT. However, this also makes the SIDWT less effective than DWT [19, 20].

The algorithm employed to produce SiDWT is the wavelet of Hâar [19]. The wavelet of Hâar: this one is simplest of the wavelets, defined on the interval [0, 1]. The wavelet of Hâar is the function H constant per pieces which is worth:

$$H(x)= \begin{cases} 1 & \text{if } x\in [0, ½[\\ -1 & \text{if } x\in]½, 1] \\ 0 & \text{otherwise} \end{cases} \tag{19}$$

For N = 1, it has built an orthogonal base orthonormal basis of functions defined by equation 2:

$$\begin{cases} h_n(x) = 2^{j/2}.h(2^j x - k) \\ with \\ n = 2^j x + k,\ j \geq 0, 0 \leq k \leq 2^j \end{cases} \tag{20}$$

$h_n(x)$: can be also written by the equation (21):

$$h_n(x) = 2^{j/2}.h(2^j x - k) = \frac{1}{\sqrt{2^{-j}}} h(\frac{x - k2^{-j}}{2^{-j}}) \tag{21}$$

The process of fusion in the case of SiDWT is identical to that in the case of fusion DWT: The initial images are decomposed by shift invariant discrete wavelet transform (SiDWT). At each step the image is decomposed into a recorded sequence of wavelets WI(n) and a function scale SI(n) which is useful for the next decomposition [20].

$$w_i(n) = \sum_k g(2^i.k).s_i(n-k) \tag{22}$$

$$s_{i+1}(n) = \sum_k h(2^i.k).s_i(n-k) \tag{23}$$

Obtaining the fused image by opposite SiDWT is similar to that by DWT. It is done by a convolution between the invariant discrete wavelets by shift and the function scale by using the appropriate reconstruction filters [17].

$$s_i(n) = \sum_k \tilde{h}(2^i.n - k).s_{i+1}(n) + \sum_k \tilde{g}(2^i.n - k).w_{i+1}(n) \tag{24}$$

B. Application of fusion algorithms

For the weighted cerebral MRI in T2, three structures have relatively homogeneous intensity. These structures constitute the three components of the image: the Gray matter, the white matter and the cerebrospinal fluid. On the other hand, the MRI imagery brings the main thing of the anatomical information. However, it remains a little precise for the positioning of the deep cerebral structures of the gray matter.

The PET is an exam of imagery that permits to get function images in a metabolic scale of organs, tissues or cells [23]. The PET imagery permits to correct the class of GM. Thus, the fused image should theoretically make this class clearer.

We used two bases. Each one has 25 images of MRI types (weighted in T2) and PET of a normal human brain. The generated images are constituted of several cuts of dimension 256 x 256 and coded in 8 bits.

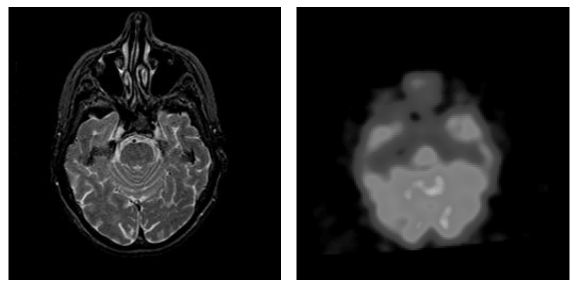
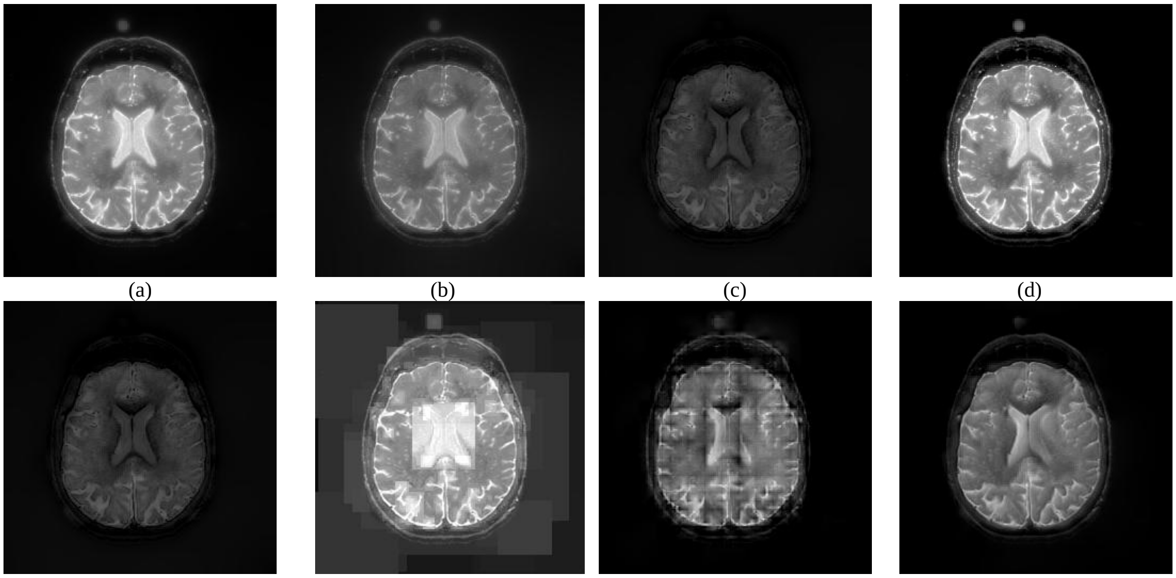

MRI Image PET Image

Fig. 3. Initial images for (MRI/PET) fusion

During this assessment study of these fusion techniques we used the same parameters:

- The level of pyramid in 6,
- Low pass combination: mean (I1, I2),
- High pass combination: maximum selection.

Results of every fusion method are presented in figure 4 on one same level of brain cut.



(e) (f) (g) (h)

Fig. 4. Rresults of (MRI/PET) images fusion by : (a) Laplacian ; (b) FSD ; (c) Gradient ; (d) RATIO ; (e) Morph ; (f) Contrast ; (g) DWT ; (h) SiDWT

After the application of different methods of fusion on anatomical and functional (MRI/PET) cuts, we are going to compare one result with the method that proposed segmentation.

C. Algorithms of segmentation

1) K-Means

The classification of tissues is clinically essential to the numerous studies of pathologies that affect the gray matter, the white matter or Cerebrospinal fluid [24]. In our case, it is used for the classification in the healthy topics.

Results of classification by the K-Means method are a group of clusters that are compact and clearly separated.

The K-Means algorithm is the most used algorithm of classification because of its simplicity in implementation. This method partitions data of an image in K classes. It is an iterative algorithm that orders the pixels according to their level of gray in K classes [25]. The pixel is affected in the class for which the distance of its pixel center is minimal. Every element of the image is assigned to a class and one alone among the proposed [26, 27].

The main steps of K-Means algorithm are:

- Random choice of the initial position of K classes
- (Re-) to affect objects to a class following criteria of distance minimization
- Once all objects are placed, recalculate K centroïdes
- Reiterate steps (2) and (3) until no reallocation is made.

The image elements classification is made in an iterative manner while alternating the step of classification and the step of centers up-dating until the stabilization of the segmentation.

2) Fuzzy C-Means

Fuzzy C-Means (FCM) is an algorithm of fuzzy unsupervised classification. Resulting from the algorithm of the K-Means, it introduces the notion of the blurry group in the definition of the classes: each point in the whole data belongs to each cluster with a certain degree, and all the clusters are characterized by their centre of gravity.

Like the other algorithms of unsupervised classification, it uses a criterion of minimization of the intra-class distances and of maximization of the inter class distances, but by giving a certain degree of membership to each class for each pixel [28]. This algorithm requires the preliminary knowledge of the number of clusters and generates the classes by an iterative process by minimizing an objective function.

Thus, it makes it possible to obtain a fuzzy partition of the image by giving to each pixel a degree of membership (ranging between 0 and 1) to a given class. The cluster, to which a pixel is associated, has the highest degree of membership.

3) Estimation Maximisation

Algorithm EM is an iterative algorithm much used for the research of the parameter carrying out the maximum of probability. The maximum of probability is reached by the calculation of a factor of probability V (X, I) suitable for each one of Gaussian I and pixels X which will allow each iteration to recalculate the parameters of Gaussian [29].

The criterion of stopping the algorithm is either a maximum number of iterations to limit the computing time, or an error lower than (ε) between two successive approximations (Ề(x)). It is easily applied because it is based on the calculation of the complete data. In fact, the Estimation stage uses only the expectation on the conditional distribution of the complete data to each iteration, while the Maximization stage does not require, for its part, more than the estimation of the maximum of probability of the complete data to each iteration. In spite of its advantages, algorithm EM has some limits: it is sensitive at the stage of initialization and it does not allow choosing the number of classes automatically [30].

4) Choice of the parameters of the algorithms used

To segment cerebral tissue in the fusion images (MRI/PET), the various parameters should be defined controlling these algorithms, namely the number of classes C, the initialization of the algorithm and finally the value of the parameter m [31].

Our objective consists in segmenting the cerebral image fusion in three classes, which carries out us to fix the number of class to be identified at 3 corresponding to the three principal present components in the brain (white matter, gray matter and cerebrospinal fluid).

Several strategies were proposed in the literature for initialization of the algorithm. The simplest consists in asking an expert to determine areas of interest representative of the centers of the classes. All the algorithms used (K-Means, Fuzzy C-Means and Maximization Estimation), constitute an adequate manner to initialize the data.

Concerning the choice of the fuzzy factor, there is no method to optimize this parameter in general. A value included in the interval [1.5, 3] is generally accepted and Tucker suggests in his theorem [33] taking to be sure of the algorithm convergence.

The fuzzy factor m interferes on two characteristics of the algorithm: the speed of convergence decrease with the increase in m, at the same time the contribution of each element in the calculation of the centers of the class's decreases. In our work we chose m equal to 1.5 for to ensure a rapid calculation.

The threshold of convergence has no remarkable influence only on the number of iterations. The higher the value of (ε) goes, the number of iterations decreases [33].

5) Results

During this study we had resorted to the unsupervised method that consists in judging our results by medical experts in the field. These physicians are going to compare results of segmentation of source images and fused images by the different fusion techniques in order to evaluate performances of these techniques for the classification of the cerebral images. To illustrate these elements, we segmented the different fused (MRI/PET) cuts in three classes and we represented the possible associated distributions (figure 5, 6 and 7).

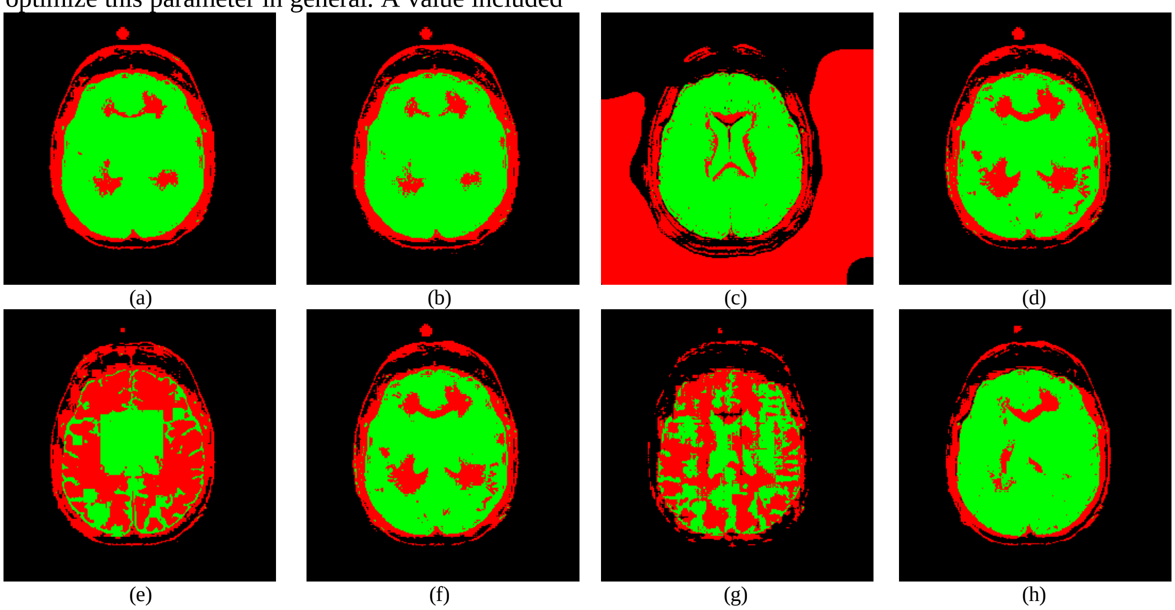


Fig. 5. Classification by K-Means of MRI/PET fusion images by: (a) Laplacian ; (b) FSD ; (c) Gradient ; (d) RATIO ; (e) Morph ; (f) Contrast ; (g) DWT ; (h) SiDWT

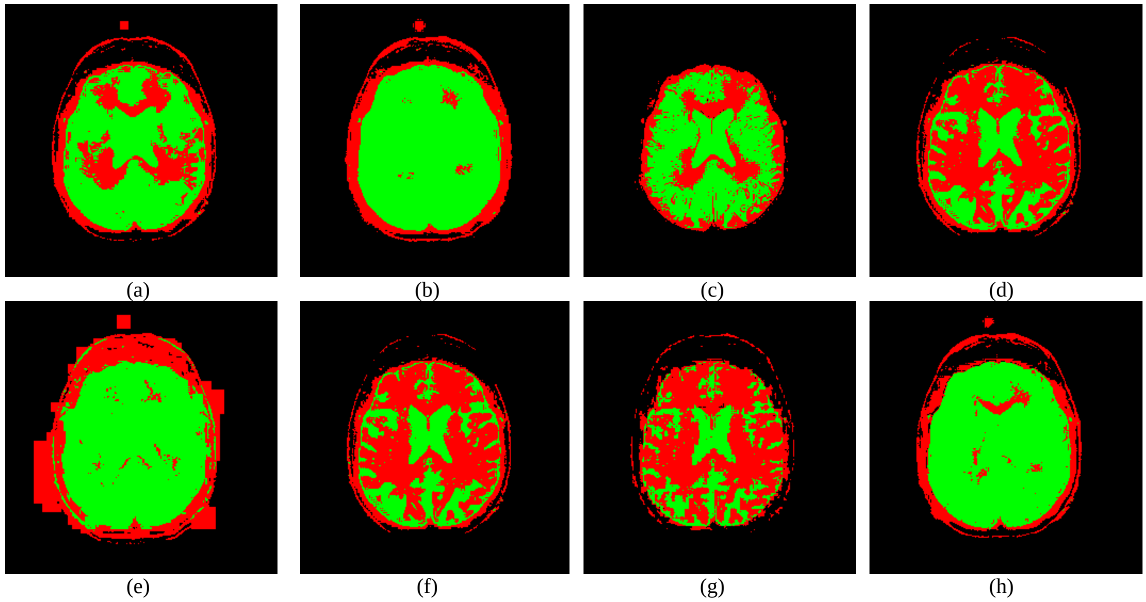


Fig. 6. Classification by Fuzzy C-Means of MRI/PET fusion images by: (a) Laplacian ; (b) FSD ; (c) Gradient ; (d) RATIO ; (e) Morph ; (f) Contrast ; (g) DWT ; (h) SiDWT

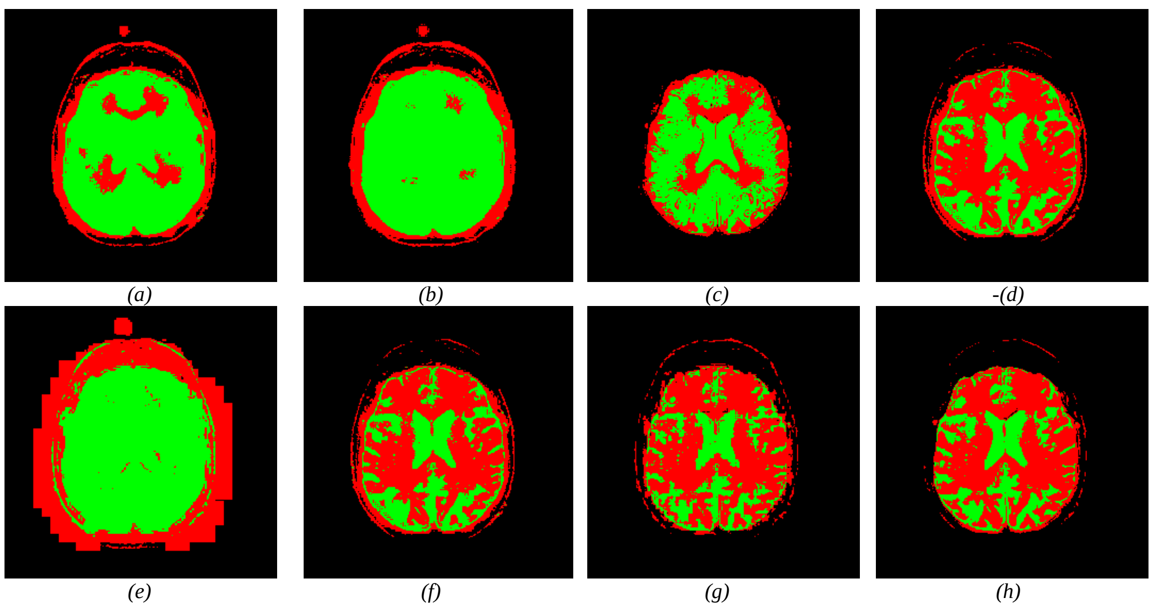


Fig. 7. Classification by Maximization Estimate of MRI/PET fusion images by: (a) Laplacian ; (b) FSD ; (c) Gradient ; (d) RATIO ; (e) Morph ; (f) Contrast ; (g) DWT ; (h) SiDWT

III. Medical appraisal

Results of the application of the eight pyramidal techniques (Laplacian, FSD, gradient, ratio, Morph, Contrast, DWT et SiDWT) in the 25 cuts of MRI and PET have been evaluated by an expert according to the following criteria: the differentiation of sides between tissues (GM, WM, CSF), the anatomical structure visualization, the function visualization, correspondence with the MRI and PET information and the presence of artifacts.

Techniques based on the Laplacian and the Gradients are clearly not satisfying. The technique of FSD is insufficient in the cutoff between GM and WM that is a main objective of this work. The technique of RATIO is more satisfying but presents a lot of artefact.

- The results were evaluated by an expert according to following criteria's [34, 35],
- Differentiation of the edges between tissue (GM/WM) noted from 0 to 2 since it is the goal of our work,
- Differentiation of the edges between tissue (GM/CSF) noted from 0 to 1,
- Similarity of information to MRI noted from 0 to 1,
- Similarity of information to PET noted from 0 to 1,

- The presence of artefact noted from 0 to -1.

Tables 1, 2 and 3 respectively contain the means of the results of classification of the images fusion (MRI/PET) by the methods fuzzy C-Means and Maximization Estimate.

TABLE I. RESULTS OF CLASSIFICATION BY THE K-MEANS METHOD OF FUSION IMAGES (MRI/PET) : (A) LAPLACIAN ; (B) FSD ; (C) GRADIENT ; (D) RATIO ; (E) MORPH ; (F) CONTRAST ; (G) DWT ; (H) SIDWT

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	Mean
Border GM/WM (0/2)	0.25	0.19	0.25	0.31	0.13	0.25	0.31	0.25	
Border GM/CSF (0/1)	0.13	0.13	0.19	0.13	0.19	0.13	0.25	0.19	
Similarity to MRI (0/1)	0.25	0.19	0.44	0.50	0.63	0.31	0.38	0.19	
Similarity to PET (0/1)	0.50	0.50	0.63	0.56	0.38	0.44	0.13	0.31	
Artefact (-1/0)	-0.06	-0.06	-0.56	0.00	-0.56	0.00	0.00	0.00	
Total	1.31	1.13	1.19	1.69	0.88	1.38	1.38	1.19	1.27

TABLE II. RESULTS OF CLASSIFICATION BY THE FUZZY C-MEANS METHOD OF FUSION IMAGES (MRI/PET) : (A) LAPLACIAN ; (B) FSD ; (C) GRADIENT ; (D) RATIO ; (E) MORPH ; (F) CONTRAST ; (G) DWT ; (H) SIDWT

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	Mean
Border GM/WM (0/2)	0.25	0.06	0.31	0.13	0.06	0.13	0.13	0.06	
Border GM/CSF (0/1)	0.00	0.00	0.19	0.19	0.38	0.38	0.19	0.19	
Similarity to MRI (0/1)	0.25	0.25	0.50	0.50	0.50	0.67	0.50	0.50	
Similarity to PET (0/1)	0.56	0.31	0.31	0.44	0.06	0.25	0.44	0.13	
Artefact (-1/0)	0.00	0.00	0.00	0.00	-0.44	0.00	0.00	0.00	
Total	1.31	0.69	1.57	1.32	0.57	1.45	1.33	0.89	1.14

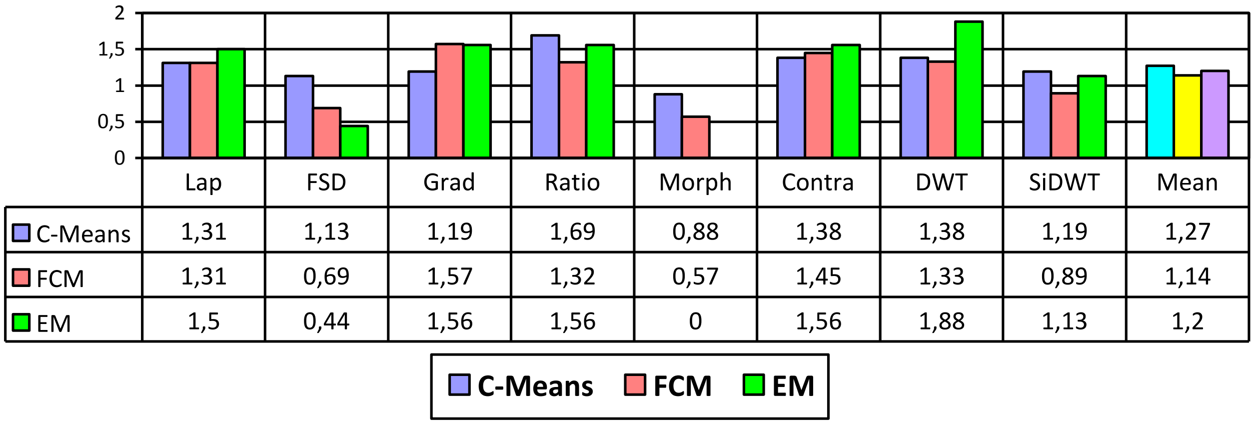
TABLE III. RESULTS OF CLASSIFICATION BY THE ESTIMATION MAXIMIZATION METHOD OF FUSION IMAGES (MRI/PET): (A) LAPLACIAN ; (B) FSD ; (C) GRADIENT ; (D) RATIO ; (E) MORPH ; (F) CONTRAST ; (G) DWT ; (H) SIDWT

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	Mean
Border GM/WM (0/2)	0.38	0.06	0.31	0.25	0.00	0.19	0.31	0.19	
Border GM/CSF (0/1)	0.00	0.00	0.13	0.25	0.19	0.38	0.25	0.19	
Similarity to MRI (0/1)	0.31	0.13	0.31	0.50	0.38	0.63	0.50	0.38	
Similarity to PET (0/1)	0.44	0.19	0.50	0.31	0.00	0.19	0.50	0.19	
Artefact (-1/0)	0.00	0.00	0.00	0.00	-0.56	0.00	0.00	0.00	
Total	1.50	0.44	1.56	1.56	0.00	1.56	1.88	1.13	1.20

The results of classification by method FCM (table 5) show that the fusion of images (MRI/PET) with DWT technique works best with an mean equal to 1,33. In the same way, the results of classification by method EM, on the fused images (MRI/PET) show that the technique which can be used is that of DWT with an mean of 1,88.

Figure 11 is a synthesis in the form of histogram of the performances of the various combinations classification methods and image fusion. This suggests that the overall performance of each fusion method is low since the best mean is 1,5. In addition, the best results are obtained following the combination of the method of fusion DWT and the technique of classification EM what is translated by a mean equalizes to 1, 88.

Based on these results, we proposed a process of fusion then a classification of cerebral structures, while being based on the simultaneous choice of the method of fusion and that of classification which gives the best result.



	Lap	FSD	Grad	Ratio	Morph	Contra	DWT	SiDWT	Mean
C-Means	1,31	1,13	1,19	1,69	0,88	1,38	1,38	1,19	1,27
FCM	1,31	0,69	1,57	1,32	0,57	1,45	1,33	0,89	1,14
EM	1,5	0,44	1,56	1,56	0	1,56	1,88	1,13	1,2

Fig. 8. Evaluation of the various methods of Classification of images C-Means, FCM: Fuzzy C-Means and EM: Maximization Estimate

IV. Discussion

The multimodal's image fusion must at least permit to bring new information that modes don't bring separately, while respecting a compatible treatment time with its clinic utilization [37].

The goal of the present work is the improvement of performances of the MRI essentially in the cutoff between GM and WM. Our experiments facilitate well the performance evaluation of the described algorithms of classification. In fact, the expert examines images (MRI/PET) fused, it takes into account simultaneously his own theoretical notes as well as the information provided by the images in order to carry out his diagnosis. We were able to evaluate the fusion of the images MRI and PET of a holy brain by two techniques of wavelets DWT and SiDWT combined with two techniques of classification.

After the evaluations quantitative and semi quantitative, it would seem that fusion by DWT combined with classification by EM is the most interesting to delimit cerebral tissue. Generally, to evaluate the quality of a segmentation of image one compares it with the image of phantom, or the image obtained by a technique of reference [27, 30]. We could use neither one nor the other. We called upon the calculation of the variances for the quantitative evaluation and with an expertise for the semi-quantitative evaluation.

The interpretation of the new visual representations was difficult even for the experts. It can be more, by the habituation with the old representations which constitute, at least initially, the basic references. This difficulty would explain overall dissatisfaction of the expert with respect to all the combinations in spite of their objective wealth of information. The results obtained show that the segmentation by EM gives better results after fusion with technique DWT and SiDWT. Fusion by SiDWT has more temporal stability, but it takes more time [18].

The combination between DWT like method of fusion and EM as method of classification seems most efficient according to the medical expertise. It should however be recalled that the DWT is constraining in the sense that it requires images (MRI and PET in our study) of the same sizes. The boundary problems of cerebral tissue with the two variant of the technique multiresolution employed seems to probably come from the weak space resolution of the PET.

The best identified technique (DWT-EM) could be improved by a preliminary pretreatment of the images, the choice of an area of interest and the zoom. Moreover, instead of using simple filters, it would be more interesting to employ methods of filtering which respect better the forms in the image.

The application located on an increased area would be more effective especially to delimit central structures of the brain or a cerebral lesion (tumor, hematoma, etc). However, the classic method is made in the reverse (PET/MRI) way. That is the localization of the hyperactive or little active structures of cuts of PET on cuts of the MRI. The MRI cuts present a good contrast between the cerebral structures of different tissue compositions and a better spatial resolution (about 1 mm) that the PET (about 4 mms). Problems of tissue cutoff with the four variants of the pyramidal employed technique presumably from the spatial resolution of the relatively weak PET.

A previous treatment of these images (by a filter) seems necessary. Besides, instead of using low pass filters and a simple band pass, it would be more interesting to use methods of filtering that respect better the shapes in the image.

The number of classes is probably insufficient. Four or five classes would permit a better differentiation of tissues. But they would remain the problem of the automation of the correspondence with the real biologic nature of tissues.

V. Conclusion

In this study, we proposed a process of classification technique of cerebral tissue that represents one the most important research ways.

This work didn't permit to affirm the utility of the application of the pyramidal techniques in the help of the interpretation of multimodales images (MRI/PET) that are and merged in the healthy human brain. It permitted to clear two susceptible techniques of the being after modifications of parameters and/or the association to other filters that are techniques of FSD and especially of ratio. For the segmentation, the increase of the number of classes would probably give better results.

To replace the mental gait of information fusion is a complicated and risky task. Even with a technique almost perfect an effort of training of the utilization of the new «source » of information is always necessary for the clinician.

Finally, our method appears reproducible and can be spread to all cerebral structures, provided that the treated image has contrast criteria and a correct resolution.

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