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Image Segmentation Techniques Based on Fuzzy C-Means and Otsu, Applied to the Brain MRI in Tumor Detection

Azzeddine Riahi

IMC Laboratory, Department of Physics, Chouaib Doukkali University, Faculty of Sciences, PO Box 20, postcode 24000, El Jadida, Morocco

www.ijcseonline.org

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***Abstract*—** Visual information is the richest probably different existing information sources in our daily lives. The extraction of this information by processing systems and image analysis has attracted growing interest. The image processing is a process involving several stages, that it was born from the need to replace the human observer by the machine. He works in many fields such as medicine. A must in all image analysis process is the segmentation. By providing a compact description of the image, more exploitable than all the pixels, the image segmentation facilitates automatic interpretation of an image similar to human interpretation. Indeed, she was inspired by the human visual perception system that uses the concept of similarity and difference in order to locate and delineate the objects in an image. It can be defined as following: the image segmentation is a low-level process of creating a partition of the image into subsets called regions in a way that no region is empty; the intersection between the two regions is empty and covers all regions throughout the image. A region is a set of connected pixels having common properties that differentiate the pixels neighboring regions. This task although fluently although raised by the human visual system, is actually complex and remains a challenge for the image processing community despite several decades of research. Thus, several segmentation methods have been proposed in the literature, and can be classified into three major approaches: Approach area, Approach contour, cooperative approach. This article studies the problem of segmentation of MRI brain images. We worked precisely on cooperating more automatic classifiers to exploit complementarities between different methods or operators and increase the strength of the segmentation process. Our approach focuses on the FCM algorithm (Fuzzy c-means), the sum of degrees of membership of an individual given to all possible classes being 1. To make the algorithm robust to inaccuracies and ambiguous data that can considerably affect on the classes centers, we introduce the notion of ambiguity rejection.

Keywords— Segmentation, C-means, MRI brain, thresholding, Otsu

I .Introduction:

Among the challenges of image processing, the automation of the interpretation of biomedical images is certainly the most studied in recent years. Conventionally, an automatic image processing system consists of two levels. The first is devoted to digital processing in a broad sense, such as coding operations, improvement or restoration. The second level is dedicated to the symbolic image analysis operations, such as description, recognition or interpretation, in order to extract information **[1]**.

Image segmentation is the most important operation in an image processing system, because it is located at the joint between the processing and analysis of images. Therefore, great interest is given to the development of dedicated methods and algorithms. Moreover, it is, in recent years, an important focus of research. This is the result of several factors: the diversity of images, the complexity of the problem, the evolution of computing machines and evaluation of enough empirical results.

Indeed, this operation allows the transition of a representation in light intensity (grayscale) to a symbolic representation (pixels belonging to different area classes) **[2].** The advantage of the segmentation is to partition an image into homogeneous regions in the sense of an already fixed criterion. Many segmentation criteria exist; Following the scope and type of processed images, the criterion will take into account the gray level, texture, color, movement, or even the distance. The advantage of having homogeneous regions is to provide simplified data which facilitate the task of a pattern recognition system, or other system details extractions, who directs image classification.

From an algorithmic perspective the segmentation is to assign to each pixel of the image a label referring to a particular region. This classification of pixels may be performed in supervised mode or unsupervised mode. In the first case, the number of regions and their characteristics are provided by the user, the segmentation is performed by determining, for each site, the class whose properties are similar to those seen best in this site. In the second case, the problem is more complex because the information needed to pixel classification process must be provided automatically. Hence the difficulty of this type of approach. The segmentation thus defined is a broad field, where many approaches are used **[3]**.

All approaches of segmentation are designed to extract visual cues. After years of research on the optimal method, the researches concluded that there was no ideal segmentation and sufficient sole criterion for segmenting all images. Indeed, the unicity of the segmentation of an image does not exist in most cases. A good segmentation method is the one that will come to a better understanding of the segmented image.

The segmentation of this brain MRI features are compared to other areas of application of the segmentation .These features are primarily related to noise, the inhomogeneity of the patient's frequency radio itself, the effect of volume part which is found when a pixel having a gray level is actually a mixture of two or more tissue.

The objective of our work is to develop a cooperative segmentation method that takes into account, both the blurred and possibilist appearance while introducing the concept of ambiguity rejection to optimize the positioning of the cluster centers.

The rest of the paper is divided into four parts .The second part is devoted to the study of different segmentation methods such as thresholding, parametric and non-parametric methods, adaptive thresholding, segmentation by classification and segmentation methods based based regions and contours. The third part is dedicated to the fuzzy c-means algorithm, its principle and its variants .The simulations and test results are the subject of Part IV .The conclusions are in the last part.

II. Image segmentation methods:

Several classifications of segmentation methods have been proposed in various research works dedicated to image processing **[4]**. We decided on the following classification:

1. Thresholding:

Thresholding is the most common segmentation technique for extracting the searched details of the background image. The advantages of this technique are its ease of implementation and its effectiveness in real-time systems (Cocquerez, et al., 1995). This technique is based on the assumption that the details can be distinguished by their gray level. The optimal threshold is the one that separates the details together, or different details of the bottom. The objective of this technique is to find the optimal threshold automatically **[5]**.

Thresholding works on classifying, according to the number of classes, the different pixels of an image, based on its gray level histogram. In other words, segmentation of an image into N classes is to search N-1 thresholds **[6]**.

Let f be the original image and g the segmented image, the classification of each pixel is defined by:

$$g(x, y) = k \quad \text{if} \quad T_k \le f(x, y) < T_{k+1} \quad \text{for} \quad k = 0, ..., m \qquad \textbf{(1)}$$

Where x, y are the pixel coordinates, m is the number of classes and $T_0, ..., T_{m+1}$ are different segmentation thresholds. For example, in the case of a simple threshold (also referred to as binarization) (m = 2), the values assigned to the pixels are 0 or 1**[7]**. Furthermore, a threshold is said part if the values assigned to the pixels are 0 or f (x, y), which allows to see the image grayscale values of the pixels belonging to class A.

The manual thresholding of an image consists of four steps:

- Observation of the histogram of the image,
- Choice of thresholds in the valleys,
- Defining classes of regions by color slots,
- Classification of pixels.

Optimal thresholding segmentation therefore requires an optimal location of segmentation thresholds in the histogram, which makes it a more complex segmentation operation. To solve this problem of optimal thresholds, a multitude of methods have been developed **[8]**.

In the literature, several classifications of thresholding methods have been proposed, but most authors classify thresholding methods into two classes: the parametric methods and nonparametric methods. Nonparametric methods have a reputation for being robust methods; they are based on the optimization of one or more criteria without the parameters estimation; the best known of these is the method of Otsu. Parametric methods are based on the assumption that the probability densities of the gray levels of the different classes are Gaussian, the optimal thresholds are then at the intersection of this last **[9]**.

2. Nonparametric methods:

By definition, methods used to find the optimal threshold segmentation without any parameter estimation. Generally these methods are based on statistical optimization criteria. The two reference methods in this class are the method of Otsu and method of Kapur **[10]**. Most techniques are then issued based on one of the two principles.

2.1 The Otsu's method and its variants:

Otsu describes three possible discriminating criteria: intra-class variance, the interclass variance and the total variance. The three criteria are equivalent and, depending on the situation, one of them may be selected **[11]**. Due to the simplicity of the implementation of the interclass variance, it has been often maximizes for segmenting images. In this method, the calculation of the different criteria is based on the probability density of the various pixels of the image, which is obtained by normalizing the histogram of the image **[12]**:

$$p_i = \frac{h(i)}{\sum_{j=0}^{L-1} h(j)} \quad \textbf{(2)} \qquad \text{With} \quad p_i \geq 0$$

$$\sum_{i=0}^{L-1} p_i = 1 \quad \textbf{(3)}$$

Where $h(i)$ is the number of occurrences of the gray level pixel $i \in [0, L-1]$ where L is the total number of gray levels.

In the case of binarization, the optimal threshold t^* is the one which maximizes the ratio of the interclass variance to the total variance **[13]**:

$$t^* = Arg_{th} \max \frac{\sigma^2{}_B{}^{(t)}}{\sigma^2{}_T} \quad \textbf{(4)}$$

Where the interclass variance is defined by:

$$\sigma^2{}_B{}^{(t)} = P_t(P_t - 1)(\mu_1 - \mu_0)^2 \quad \textbf{(5)}$$

And

$$\sigma^2{}_T = \sum_{i=1}^{L-1} P_i (i - \mu_T)^2 \quad \textbf{(6)}$$

Where

$$\mu_0 = \sum_{i=1}^{t} i.\frac{P_i}{P_t} \qquad \mu_1 = \sum_{i=t+1}^{L-1} i.\frac{P_i}{1-P_t}$$

$$\mu_T = \mu_0 + \mu_1 \quad \textbf{(7)}$$

$$P_t = \sum_{i=0}^{t} P_i \qquad 1 - P_t = \sum_{i=t+1}^{L-1} P_i \quad \textbf{(8)}$$

As the total variance associated to an image histogram is constant, the problem consists to maximizing the interclass variance.

As the method of Otsu consist to group pixels into two classes, its effectiveness is proven only when one type of object to segment is present in the image. At the end, the complete segmentation is done by grouping all the segmented objects. Among the problems of the method of Otsu, there is the unicity of the threshold that maximizes the criterion, this criterion is defined by **[14]**:

$$t^* = Arg\max_{0 \leq t \leq L} \left\{ (1-\lambda_t)\left(P_t \mu_1^2(t) + (1-P_t)\mu_2^2(t)\right) \right\} \quad \textbf{(9)}$$

Where λ_t is the lower probability of occurrence in the histogram .The change against the item Otsu is summed up in the introduction of the λ_t coefficient.

These methods have been applied in many fields, especially in biomedical applications, such as real-time segmentation of radiological images, segmentation of microscopic images, and segmentation of MRI images.

2.2 The entropic thresholding:

The entropic thresholding is a technique derived from information theory. The thresholds are determined so as to maximize entropy of the resulting cutting of the histogram into classes **[15]**. Indeed, the entropy measures the amount of information carried by a group. For a fixed number of thresholds, the aim is that the resulting classes carries the maximum information **[16]**.

2.2. a Thresholding based entropy in one dimension:

The entropic thresholding is based on the principle of maximizing the total Shannon entropy. In the case of segmentation of an image into two classes (A and B), the method assumes that the objects and the background have two independent probability densities. The optimal segmentation threshold is one that maximizes the total entropy of the partitioned image. Probability densities of the two classes (A and B) are defined by **[17]**:

$$ClassA : \frac{p_1}{p_t}, \frac{p_2}{p_t}, ..., \frac{p_t}{p_t} \quad \textbf{(10)}$$

$$ClassB : \frac{p_{t+1}}{1-p_t}, \frac{p_{t+2}}{1-p_t}, ..., \frac{p_L}{1-P_t} \quad \textbf{(11)}$$

Where L is the total number of gray levels and the cumulative probability Pt defined in (8).

The entropy of the two classes A and B are defined by **[18]**:

$$H_A(t) = -\sum_{i=1}^{t} \frac{p_i}{p_t} \log_2 \frac{p_i}{p_t} \quad \textbf{(12)}$$

$$H_B(t) = -\sum_{i=t+1}^{L} \frac{p_i}{1-p_t} \log_2 \frac{p_i}{1-p_t} \quad \textbf{(13)}$$

And the total entropy is:

$$H_T(t) = H_A(t) + H_B(t) \quad \textbf{(14)}$$

The first problem with this method is that the Shannon entropy is undefined for probability densities including zero probability. A new definition of entropy is proposed based on a exponential gain information **[19]**:

$$H_T(t) = -\sum_{i=1}^{t} \frac{p_i}{p_t} e^{1-\frac{pi}{pt}} - \sum_{i=t+1}^{L} \frac{pi}{1-P_t} e^{1-\frac{p_i}{1-p_t}}$$

(15)

In summary, entropic thresholding problem can be formulated as:

$$t^* = Arg\max_{1 \le t \le L} \{H_T(t)\} \quad \textbf{(16)}$$

This approach has opened the field to use further steps for better information segment images.

2.2.b Entropy two-dimensional:

The motivation for the implementation of the entropic thresholding to solve the problem of selection thresholds is in the success of this method in many cases of applications, such as restoring images or target recognition **[20]**. The principle of maximum entropy based on the probability distribution that maximizes the Shannon entropy. Several examples of applications have demonstrated the efficacy of entropy in two dimensions compared to classical Shannon entropy, entropy to a dimension **[21]**.

3. Parametric methods:

The parametric methods of image segmentation assume that the different image classes follows a certain function of probability density **[22]**. Generally, these probability density functions (pdfs) are assumed to follow a Gaussian model. Starting from an approximation of the histogram of the image by a linear combination of Gaussian, optimum thresholds are at the intersection of these lasts [**23**]. In this part, we will present the basic principle of these methods, running in two stages, the first is to estimate the parameters and the second is to find the segmentation thresholds **[24]**.

3.1 Approximation of the histogram by probability density functions:

For a multimodal histogram h (x) of a given image, where x is the value in the scale of gray levels, the most used technique to find the optimal segmentation threshold is to rebuild the image histogram as the sum of probability density functions (pdf) **[25]**. In case these pdfs are Gaussian, the histogram model can then be written:

$$h(x) = \sum_{i=1}^{d} \frac{P_i}{\sqrt{2\pi\sigma_i}} e\left[-\frac{(x-\mu_i)^2}{\sigma_i^2}\right] \quad \textbf{(17)}$$

Where Pi is the prior probability, μ_i the average and σ_i variance of the i mode **[26]**.

For a given histogram, optimal parameters are those that minimize the reconstruction mean square error:

$$J = \frac{1}{L} \sum_{i=0}^{L-1} \left[h(i) - h(\Theta, i)\right]^2 \quad \textbf{(18)}$$

Where J is the objective function to minimize

$$\Theta = \{P_i, \mu_i, \sigma_i; j = 1, 2, ..., d\} \quad \textbf{(19)}$$

$i \in [0, L-1]$, L denotes the total number of gray levels present in the original image **[27]**.

3.2 Calculating segmentation thresholds:

In the bimodal case d = 2, the optimal threshold is determined by minimizing the probability of error during assignment of a gray level x to the first class, knowing that it belongs to the second class **[28]**:

$$E(t) = P_1 \int_{-\infty}^{t} p_2(x)dx + P_2 \int_{t}^{+\infty} p_1(x)dx \quad \textbf{(20)}$$

Where t is the threshold, p_i (x) is the probability density function mode i and P_i are the amplitudes of the Gaussian point μ_i.

3.3 Algorithm expectation-maximization:

We consider the case of an approximation of an image histogram by a combination of Gaussian .The problem is how to estimate the parameters of the different (Θ) Gaussian approaching the histogram at it best.

For example, in the case of two classes, that is to say a histogram approached by two Gaussian, the vector of parameters to estimate $\Theta = \{P_1, \mu_1, \sigma_1, P_2, \mu_2, \sigma_2\}$ is associated with two classes (object and background). This estimate is in the sense of maximizing the maximum likelihood criterion $L(X \mid \Theta)$, defined by **[29]**:

$$\Theta^* = Arg\ \max_\Theta \{L(X|\Theta)\} \quad \textbf{(21)}$$

$$L(X|\Theta) = \sum_{x=0}^{L-1} h(x) \log\left[p(x|\Theta)\right] \quad \textbf{(22)}$$

4. Adaptive thresholding:

In the case where the background of the image is not uniform (changes in brightness), the global thresholding fails to extract the objects **[30]**. To overcome this difficulty, the most practical solution used is based on the application of an adaptive thresholding which consists in segmenting the image with different thresholds, which vary depending on the pixel position. The basic principle consists in dividing the image into sub predefined sizes of images, and applying a global thresholding technique to each of these sub-images **[31]**.

5. Classification Segmentation:

Since the image is essentially characterized by its histogram, most classification methods ("clustering") apply without any major difficulty to image segmentation. These methods can also be classified as parametric segmentation methods **[32]**.

In case the number of classes is already known, then we speak of supervised classification; otherwise, it's an unsupervised classification. Among the most used methods in image segmentation algorithm of mobile centers (K-means) algorithm [**33**].

The algorithm of mobile centers (K-means) is the simplest classification technique. This technique use as a criterion for evaluating a score mean squared distance. The principle of the algorithm is as follows:

Let a scatterplot (a picture) that we want partitioned into K classes. We set **[34]**:

$x_j^{(i)}$ The pixel j belonging to the class i,

y_i The centroid of the class i,

L_i The number of points of class i,

$d(x_j^{(i)}, y_i)$ The distance (measure of distortion) between $x_j^{(i)}$ and y_i; in the case of K means clustering algorithm, is the Euclidean distance.

D_i The overall distance of class i:

$$D_i = \sum_{j=1}^{L_i} d(x_j^{(i)}, y_i) \quad \textbf{(23)}$$

D The overall distortion to the set of vectors.

$$D = \sum_{i=1}^{K} D_i \quad \textbf{(24)}$$

The optimal classification is one that minimizes the total distortion D. The optimization procedure must take into account the following assumptions **[35]**:

- For a specific set of centroids, classification that minimizes D is one for which every pixel is assigned to the class whose centroid is the closest.
- For a given classification, if any, for each class i pixel y_i which minimizes the total distance of class D_i.

1. Select number of k classes.

2. Define a random classification C: Choose k centroids y_i randomly in space D grayscale [0, L-1].

3. While the intraclass inertia is not stable do

3.1. Allocate each gray level to the class whose center is the closest.

3.2 $C \leftarrow C'$

End While

4. Display the resulting classification.

Algorithm 1: Mobile centers Algorithm (K means).

6. Segmentation methods based regions:

Segmentation methods "based regions" or processing areas are designed to decompose the image into a set of connected regions according to a criterion of homogeneity. These methods are used, in particular, in the case where the histogram of the image is multimodal **[36]**. With the concept of connectivity used in these methods, segmentation obtained is better than the methods of thresholding.

The mathematical formulation of the problem of segmenting an image into different homogeneous regions according to a homogeneity criterion H is shown below.

Let $X_1,....,X_n$ regions of the image I, they must comply with the following assumptions **[37]**:

- $\cup_{i=1}^{i=n} X_i = I$ and $\forall i \neq j, X_i \cap X_j = \varnothing$
- $\forall i, X_i$ is associated
- $\forall i, H\left[X_i\right]$ is true the region X_i is said to be homogeneous.
- $\forall\left(X_i, X_j\right)$ Adjacent regions, $H\left[X_i, X_j\right]$ is false.

The choice of the criterion of homogeneity in these methods is essential for proper operation. This choice depends on the problem being treated and the type of images. From a statistical standpoint, the variance *Var* gray levels in a region X can be used as a criterion of homogeneity (H) **[38]**:

$$Var = \frac{1}{N}\sum_{(x,y)\in X}\left[I(x,y) - \frac{1}{N}\sum_{(x,y)\in X} I(x,y)\right]^2 \qquad \textbf{(25)}$$

7. Methods based segmentation edges:

Edge detection in an image is a much studied problem in the field of image processing and analyzing. In general, a contour is defined as the location of significant change information "gray level". Therefore, finding the contours in an image returns to evaluate the variation of the gray level in every pixel of the image **[39]**.

So segmentation methods based on edge approaches aim to find the scene of large variations in the gray level. A large number of methods has been developed. These methods rely on the detection of discontinuities in the image and can be divided into three classes: derivates methods, analytical methods and methods based on active contours **[40]**.

III. Fuzzy C-means:

The FCM algorithm is a method of unsupervised classification, very popular and very powerful compared to other methods such as K-means algorithm or neural networks .It has been widely used for image segmentation.

Despite this, the FCM algorithm suffers from certain drawbacks such as sensitivity to noise, the form of classes that is spherical, the need to know the number of classes and the dependence of its results to boot **[41]**. To overcome these drawbacks several variants of FCM, that we described, have been proposed.

1. Fuzzy C-means algorithm:

Fuzzy C-means clustering is an algorithm derived from the K-means algorithm. His contribution in relation to the latter is the introduction of the concept of fuzzy, to take into account the inaccuracy of the data. Developed by Bezdek in 1981 as a result of work of Dunn, the FCM algorithm is a fuzzy reallocation algorithm, wherein the classes are represented by prototypes or centers of gravity **[42]**. Its application therefore provides for each observation to classify a degree of membership between 0 and 1 to each class, thereby producing a fuzzy partition. As with most of the other partition by classification algorithms, FCM is based on minimizing a criterion in an iterative process **[43]**.

1.1 Principle of the algorithm:

Let $X = \{X_1, X_2, ..., X_i, ..., X_N\}$ be a set of N observations to be classified in classes K, $X_i\left(i = 1, 2, ..., N\right)$ each observation can be represented by a set of attributes D: $X_i = \left(X_{i1}, X_{i2}, ..., X_{ij}, ..., X_{iD}\right)^T$ .The K classes are represented by a vector of the centers of classes $V = \{V_1, V_2, ..., V_k, ..., V_K\}$ or $v_k = \left(v_{k1}, v_{k2}, ..., v_{kD}\right)^T$ is the center of the class k. Each case X_i is defined by its degree of membership in the class k μ_{ki} as $\mu_{ki} \in [01]$

We can then define a partition matrix $U = \left[\mu_{ki}\right]$ of dimension $\left(K \times N\right)$. The FCM algorithm is to partition the N observations in K classes to minimize the similarity of observations within each class .It results in minimizing the following objective function **[44]**:

$$J_{FCM}(U,V)=\sum_{k=1}^{K}\sum_{i=1}^{N}\mu_{ki}{}^{m}d^{2}(X_i,v_k) \quad \textbf{(26)}$$

In the following constraints:

$$0<\sum_{i=1}^{N}\mu_{ki}<N \quad \textbf{(27)}$$

$$\sum_{k=1}^{K}\mu_{ki}=1 \quad \textbf{(28)}$$

m: is the fuzzification factor or fuzzy factor such as $1<m<\infty$

$d(x_i,v_k)=\|x_i-v_k\|$ is the distance separating observation i and the center of the k class.

Usually the distance used is Euclidean: $d(X_i,v_k)=\sqrt{\sum_{j}^{D}(x_{ij}-v_{kj})}^{2}$

The first constraint ensures that no class should be empty and the second is a normalization constraint ensuring that the sum of the degrees of membership of each observation to all classes equals 1.

The fuzzy partitioning is performed by an iterative optimization of the objective function given by equation (26) .With update degrees of membership of the centers μ_{ki} and Class v_k as in the case of K-means algorithm.

Updating the following formulas are obtained by the introduction of a Lagrange multiplier associated with the λ normalization constraint given in equation (28).

By applying the Lagrangian with respect to X_i, we will have **[45]**:

$$L(X_i)=\sum_{k=1}^{K}\mu_{ki}{}^{m}\|X_i-v_k\|^2+\lambda\left(\sum_{k=1}^{K}\mu_{ki}-1\right),$$
$$\lambda>0 \quad \textbf{(29)}$$

The minimization of the Lagrangian with respect to degrees of membership and μ_{ki} Lagrange coefficient λ gives us:

$$\frac{\partial L(X_i)}{\partial\mu_{ki}}=0\Rightarrow m\left(\mu_{ki}{}^{m-1}\right)\|X_i-v_k\|^2+\lambda=0 \quad \textbf{(30)}$$

$$\frac{\partial L(X_i)}{\partial\lambda}=0\Rightarrow\sum_{k=1}^{K}\mu_{ki}-1=0\Rightarrow\sum_{k=1}^{K}\mu_{ki}=1 \quad \textbf{(31)}$$

From equation **(30)**, we deduce:

$$\mu_{ki}=\left(\frac{-\lambda}{m}\right)^{\frac{1}{m-1}}\left(\frac{1}{\|X_i-v_k\|^2}\right)^{\frac{1}{m-1}} \quad \textbf{(32)}$$

And from equation **(31)** and **(32)** we obtain:

$$\left(\frac{-\lambda}{m}\right)^{\frac{1}{m-1}}\sum_{l=1}^{K}\left(\frac{1}{\|X_i-v_l\|^2}\right)^{\frac{1}{m-1}}=1 \quad \textbf{(33)}$$

$$\Leftrightarrow\left(\frac{-\lambda}{m}\right)^{\frac{1}{m-1}}=\frac{1}{\sum_{l=1}^{K}\left(\frac{1}{\|X_i-v_l\|^2}\right)^{\frac{1}{m-1}}} \quad \textbf{(34)}$$

$$\Leftrightarrow\left(\frac{-\lambda}{m}\right)=\frac{1}{\sum_{l=1}^{K}\left(\frac{1}{\|X_i-v_l\|^2}\right)} \quad \textbf{(35)}$$

By replacing equation **(35)** into equation **(32)** we obtain:

$$\mu_{ki}=\sum_{l=1}^{K}\left(\frac{\|X_i-v_k\|}{\|X_i-v_l\|}\right)^{\frac{-2}{m-1}} \quad \textbf{(36)}$$

The update formula degrees of membership.

The minimization of the Lagrangian relative to the variable v_k represents the center of the k class, is written as follows **[44]**:

$$\frac{\partial L(X_i)}{\partial v_k}=0\Leftrightarrow\sum_{i=1}^{N}2\|X_i-v_k\|\mu_{ki}{}^{m}=0 \quad \textbf{(37)}$$

$$\Leftrightarrow\sum_{i=1}^{N}\mu_{ki}{}^{m}X_i-\sum_{i=1}^{N}\mu_{ki}{}^{m}v_k=0 \quad \textbf{(38)}$$

Hence the update formula of class centers:

$$V_k = \frac{\sum_{i=1}^{N} \mu_{ki}{}^{m} X_i}{\sum_{i=1}^{N} \mu_{ki}{}^{m}} \quad \textbf{(39)}$$

1. Set the parameters:

a : The number of class K.

b : The threshold ξ representing the convergence error.

c: The blur level m, usually taken equal to 2.

2. Initialize the centers of K classes randomly.

3. Updating the matrix U degrees of membership by (36)

4. Updating the vector V of cluster centers by formula (39)

5. Repeat steps 3 and 4 until satisfaction of stopping criterion: $\|V^{(t)} - V^{(t+1)}\| < \xi$, t is the tth iteration.

Algorithm 2: (Fuzzy c-means) FCM Algorithm

1.2 FCM algorithm Disadvantages:

The FCM algorithm has been extensively studied and has been used in many fields (medical image segmentation, geological and satellite). However this algorithm which requires knowledge of the number of classes is not robust towards the noise introduced by the imprecision of attributes and its effectiveness depends heavily on the initialization step of the centers of classes because the iterative process can easily provide a locally optimal solution **[46]**. Moreover, it is based on the Euclidean distance in the measurement of similarity between an observation and the center of a class which makes it usable for detecting spherical classes. To avoid these disadvantages therefore improve the classification results, several modifications were made to the standard algorithm and are presented as FCM variants. Those presented after taking into account the problem of noise and that of the distance **[47]**.

2. FCM algorithm variants:

Many variations have been thus proposed; they are either to change the functional to be minimized, or set to another distance or are still to change the influence of fuzzy factor. We have thus organized into three categories **[41]**:

- Variant according the distance.
- Variant according the objective function.
- Variant according the fuzzification.

2.1 Variant according the distance:

The standard version of previously described FCM uses the Euclidean distance. However this distance gives good results when the classes are spherical in shape and having the same size, or where they have well separated **[48]**. But in reality the classes can have any geometrical shapes and sizes. Thus, several variations of the FCM using other distances have been proposed.

2.2 Variant according the objective function:

Other variants FCM directly affect the objective function to improve the results of the classification especially in the presence of noise. These generally introduce another term in the objective function of the standard FCM algorithm **[49]**.

2.3 Variant according the fuzzification:

Another class of variants FCM relates to the modification of the influence of fuzzy factor. FCM algorithm variants have been proposed to improve the performance of FCM and avoid its disadvantages include its susceptibility to noise and spherical shapes classes. We classified these variants into three categories. In the first, the Euclidian distance is used by the relevant standard is replaced by another type of distance to detect classes of any shape. In the second category, information is introduced in the objective function as an additional term in order to take noise into account. The third category modifies the influence of fuzzy factor **[50]**.

Some of these methods have been developed in the general context, that is to say, to classify multidimensional data, others have been developed specifically for image segmentation in gray or color.

IV .Simulation and analysis of results:

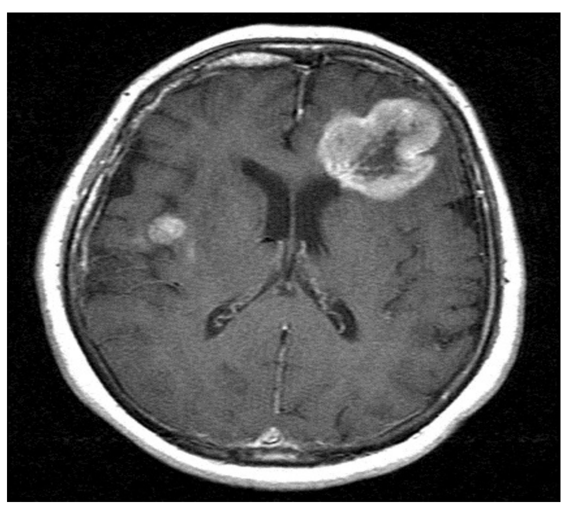

Figure 1: Original image MRI of a brain.

The classification is a mental activity that occurs frequently in everyday life, in many disciplines. Articles on classification involve either new technologies or versions adapted to a very specific problem. It is obvious that none of these techniques can claim a universal efficiency.

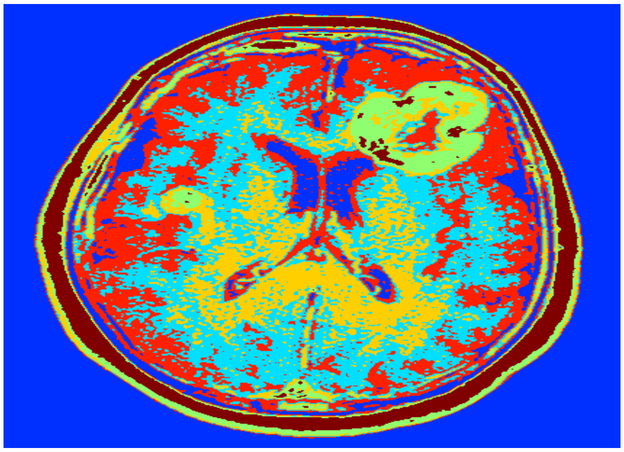

Figure 2: Segmented image of the brain with MRI tumor location.

Indeed, the objects are often listed relating to the categories or classes to which they are supposed to belong. This membership is usually vague time when uncertainty was represented by a logic called fuzzy logic.

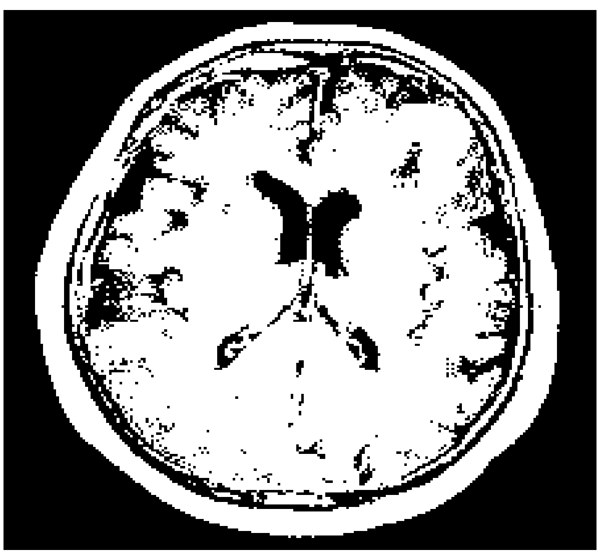

Figure 3: Segmentation of the original image of a brain MRI using Otsu thresholding, level = 0.286275.

These notions of uncertainty and imprecision are included in the image processing field; particularly MRI images that are not sharp in nature, they are a 2D representation of a 3D volume leading to an uncertainty due to a superposition of different signals. Membership of an object or vector is not limited to a single class, but shared with other classes which take into account overlapping partitions is the case of fuzzy classification, or C-Average algorithm or (FCM) is the most used. When the set of points to classify become wider, the calculating time of FCM algorithm is incremented in a fast way and the result is not good.

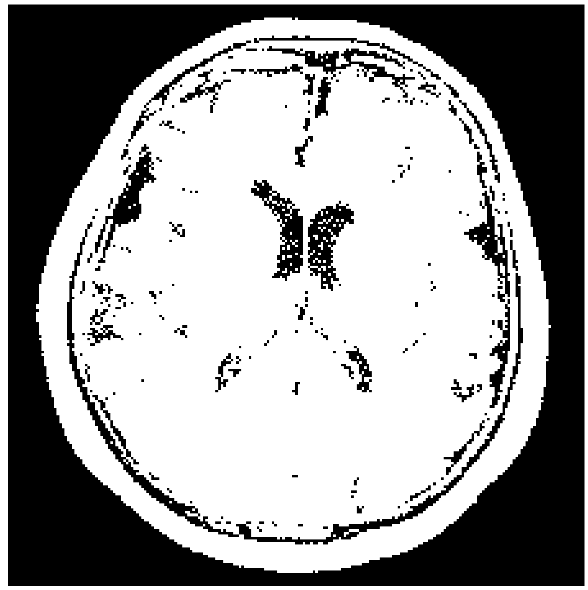

Figure 4: Segmentation by FCM algorithm for image 1, fcm 0, level = 0.205882.

For this variant of this algorithm was then developed in order to increase performance. These improved versions are often dedicated to particular applications. In the case of works of MRI images are performed to accelerate FCM.

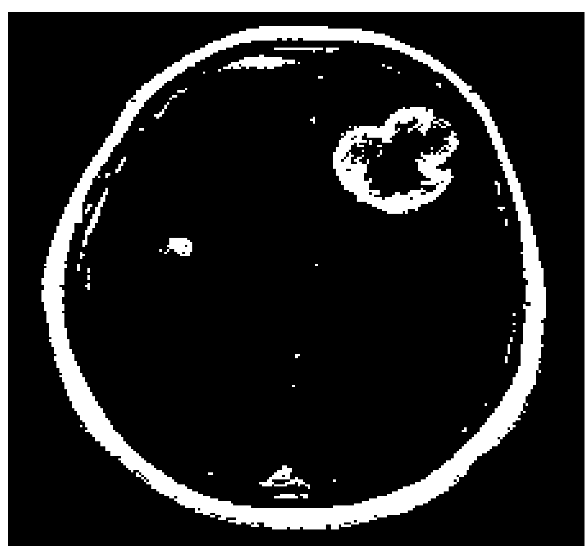

Figure 5: Segmentation by FCM algorithm for image 1, fcm 1 level = 0.64598.

Classification is the process that brings together objects into subsets while maintaining a sense in the context of a particular problem. Subsets obtained represent an organization, or a representation of the set of objects. The term k-means is a classification method of classifying an object in a single class, and minimize the intra-class inertia.

Figure 6: Image 1 segmentation result with a sigma = 0.5

The algorithm has the following properties: exact C-Means or HCM (Hard Means C) is independent of the data classes. The number of groups to be created is controlled by the user. It is to create a number of data groups such that each group is as compact as possible and the groups are the most distant from each other. The contribution of the algorithm Fuzzy C-Means (FCM) compared to the HCM algorithm is the introduction of the concept of fuzzy, allows the sharing of a picture point between several classes. Thus it facilitates the classification of sets of overlapping and non-acute points. FCM performs iterative optimization by evaluating approximate minimum of a function of error:

Figure 7: Image 1 segmentation result with a sigma = 1

We tested the segmentations Fuzzy C-means and K Means on a series of MRI brain images. After treatment of used features, we observed that, in general, the studied algorithms allows a good segmentation. However, images with defects (reflection, dark part, fuzzy,…) give a result that looks visually correct, but does not allow a good detection of characters.

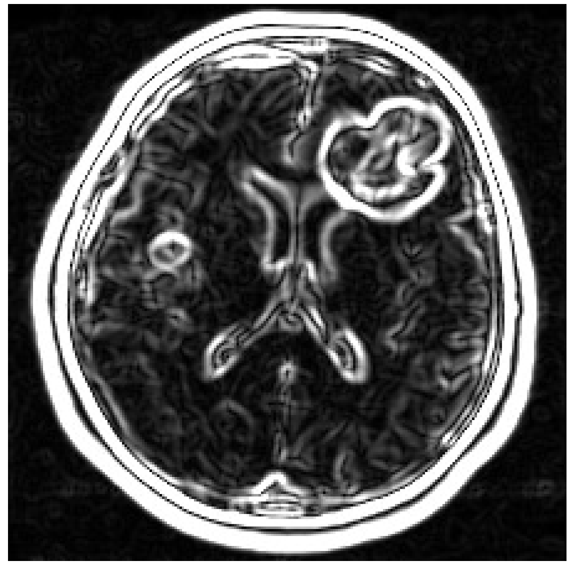

Figure 8: Image 1 segmentation result with a sigma = 1.5

We found that both algorithms require prior knowledge of the number of clusters to be determined, making it impossible, any process automation. By their iterative nature, they are not effective when the number of clusters becomes important.

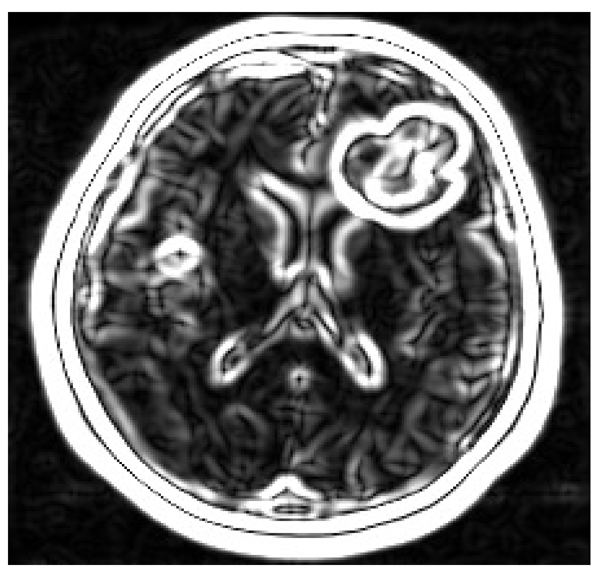

Figure 9: Image 1 segmentation result with a sigma = 2

We can therefore conclude that the Fuzzy C Means and K-means algorithms are effective for the detection of characters, but are not appropriate for images that have a large number of objects. From a perspective computation time, FCM appears to be more effective for high-resolution images while k-means is more suited to low-resolution images.

V .Conclusion:

The work presented in this paper relates to the field of image processing and more precisely that of the image segmentation based on the Fuzzy C-Means algorithm and its variants. We have presented in this paper an exhaustive number of these variants that have been proposed in the literature to address the problem of noise sensitivity of conventional FCM algorithm. These lasts trying to change or minimize the functional, or define another metric or change the influence of fuzzy factor. We presented in this paper the results of image segmentation textured fuzzy classification, based on Fuzzy C-means algorithm and its variants. A series of tests was carried out on an image to show the contribution of each method compared to the conventional FCM algorithm. To test the noise sensitivity of the algorithm, we test the noisy image with Gaussian noise variance equal 0.5, 1.0, 1.5 and 2.0 of the number of gray levels.

References:

[1]''Image segmentation '', chapter 10, https: //courses. cs.washington. edu/courses/ cse576/book /ch10.pdf.,Page No (1-51),March 2000.

[2] Rajeshwar Dass, 2Priyanka, 3Swapna Devi,'' Image Segmentation Techniques'', ISSN : 2230-7109 (Online) | ISSN : 2230-9543 (Print), International Journal of Electronics & Communication Technology, IJECT Vol. 3, Issue 1,Page No (66-70) ,Jan. - March 2012.

[3] Anna Blasiak,'' A Comparison of Image Segmentation Methods'', Senior Thesis in Computer Science Middlebury College, Page No (53-79), May 2007.

[4]''Segmentation'',Chapter 10, http://www.cs.uu.nl /docs /vakken /ibv/reader/chapter10.pdf, Page No (24-69).

[5] A. M. Khan, Ravi. S,'' Image Segmentation Methods: A Comparative Study'', International Journal of Soft Computing and Engineering (IJSCE), ISSN: 2231-2307, Volume-3, Issue-4, Page No (1-9),September 2013.

[6] Vinay Lowanshi, Shweta Shrivastava,'' Two Tier Architecture for Content Based Image Retrieval Using Modified SVM and knn-GA'', International Journal of Computer Sciences and Engineering, Volume-2Issue-10,Page No (41-45),2014.

[7]Bryan S.Morse ,''Thresholding'', Brigham Young University, 2000, http:// homepages .inf.ed.ac .uk/rbf/ CVonline/LOCAL_COPIES/MORSE/threshold.pdf, Page No (1-23).

[8] Mehmet Sezgin, Bulent Sankur,'' Survey over image thresholding techniques and quantitative performance evaluation'', Journal of Electronic Imaging 13(1), 146–165, Page No (1-18), (January 2004).

[9] S. Jansi, P. Subashini,'' Optimized Adaptive Thresholding based Edge Detection Method for MRI Brain Images'', International Journal of Computer Applications (0975 – 8887) Volume 51– No.20, Page No (1-8) ,August 2012.

[10] ''nonparametric methods'', contaminated sites statistical applications guidance document no. 12-5,Page No(1-4),April 2001.

[11] Junmo Kim_, John W. Fisher III_, Anthony Yezzi, Jr., Mujdat Cetin_, and Alan S. Willsky,'' nonparametric methods for image segmentation using information theory and curve evolution'', this paper appeared in Proceedings of the 2002 IEEE International Conference on Image Processing, Rochester, NY, Page No(1-4),September 2002.

[12] Ahmed Elgammal ,Dept of Computer Science,Rutgers University,'' CS 534: Computer Vision Segmentation III Statistical Nonparametric Methods for Segmentation'', http://www.cs.rutgers.edu/~elgammal/classes/cs534/lectures/Segmentation3_meanshift.pdf., Page No(4-14).

[13] Junmo Kim, *Member, IEEE*, John W. Fisher, III, *Member, IEEE*, Anthony Yezzi, *Member, IEEE*, Müjdat Çetin, *Member, IEEE*, and Alan S. Willsky, *Fellow, IEEE,''* A Nonparametric Statistical Method for Image Segmentation Using Information Theory and Curve Evolution'', IEEE Transactions On Image Processing, Vol. 14, NO. 10, Page No (1-17),OCTOBER 2005.

[14] DongjuLiu, JianYu,'' Otsu method and K-means'', Ninth International Conference on Hybrid Intelligent Systems, 978-0-7695-3745-0/09 $25.00 © 2009 IEEE DOI 10.1109/HIS.2009.74,Page No (344-349), 2009.

[15] Julie DELON, Agnès DESOLNEUX, José-Luis LISANI, Ana-Belén PETRO,'' A non parametric approach for histogram Segmentation'', http://desolneux .perso.math.cnrs. fr/ papers /DDLP_HistIP_07.pdf., Page No (1-9).

[16] Giovanna Menardi , ''a Nonparametric Clustering Method For Image Segmentation'', http:// convegni.unica.it/cla dag2015 /files /2015 /10/Menardi.pdf.,Page No (1-4).

[17] Yaoyong Liu, Shuguang Li,'' Two-Dimensional Arimoto Entropy Image Thresholding based on Ellipsoid Region Search Strategy'', 978-1-4244-7874-3/10/$26.00 © IEEE,Page No(1-4), 2010 .

[18] Ahmad Adel Abu Shareha, Mandava Rajeswari, Dhanesh Ramachandram,'' Textured Renyi Entropy for Image Thresholding'', Fifth International Conference on Computer Graphics, Imaging and Visualisation, DOI 10.1109/CGIV.2008.48 ,978-0-7695-3359_9/08 $25.00 © IEEE ,Page No (185-192),2008 .

[19] Yang Xiao , Zhiguo Cao , Junsong Yuan,'' Entropic image thresholding based on GLGM histogram '',

Pattern Recognition Letters 40 (2014), Elsevier , Page No (47–55),2014 .

[20] Prasanna K. Sahoo, Gurdial Arora,'' A thresholding method based on two-dimensional Renyi's entropy'', Pattern Recognition 37 1149 – 1161, 0031-3203/$30.00 ? 2003 Pattern Recognition Society. Published by Elsevier Ltd. All rights reserved, doi: 10.1016/ j. patcog. 2003.10.008, Page No (1149-1161),(2004).

[21] Mohamed. A. El-Sayed, S. Abdel-Khalek, and Eman Abdel-Aziz,'' Study of Efficient Technique Based On 2D Tsallis Entropy For Image Thresholding'', International Journal on Computer Science and Engineering (IJCSE), ISSN : 0975-3397 Vol. 3 No. 9 ,Page No (3125-3138),September 2011.

[22] Martin Lindquist,'' Statistical Methods in functional MRI'', Overview of fMRI Data Analysis, 04/02/13.Page No (1-8),2013.

[23] Alexei A. S amsn o v ,Ros,s T. Whiti kerE.ug,e ne G. Kholmovki'Chi,i s R. Johnson', ''Parametric Method for Correction of Intensity Inhomogeneity in MRI Data'', © Proc. Intl. Soc. Mag. Reson. Med. 10 (2002).

[24] Amy herlihy,Lada Krasnosselskaia,Agilent technologies, Yarnton , ''MRI methods for collecting and analyzing parametric maps of the mouse brain at 7T '', Page No(1-8),2012.

[25] Vitali Zagorodnov, *Member, IEEE*, and Arridhana Ciptadi, *Student Member, IEEE,* Component Analysis Approach to Estimation of Tissue Intensity Distributions of 3D Images'', IEEE TRANSACTIONS ON MEDICAL IMAGING, VOL. 30, NO. 3,Page No(838-848) ,MARCH 2011.

[26] Jan-Philip Bergeest, Florian Jager,'' A Comparison of Five Methods for Signal Intensity Standardization in MRI'',Springer,Page No(36-40) ,2008.

[27] Florian Jäger and Joachim Hornegger, *Member, IEEE,''* Nonrigid Registration of Joint Histograms for Intensity Standardization in Magnetic Resonance Imaging'', IEEE TRANSACTIONS ON MEDICAL IMAGING, VOL. 28, NO. 1,Page No(137-149) ,JANUARY 2009.

[28] Francisco J. Galdames, Fabrice Jaillet, Claudio A. Perez,'' An Accurate Skull Stripping Method Based on Simplex Meshes and Histogram Analysis in Magnetic Resonance Images' ,http://liris.cnrs.fr/Documents/Liris-5295.pdf. , Page No(1-17).

[29] Eugene Weinstein,''Expectation –Maximization Algorithm and applications'', Courant Institute of Mathematical Sciences,Page No(1-31) ,Nov 14th, 2006.

[30] Derek Bradley, Gerhard Roth,'' Adaptive Thresholding Using the Integral Image'', Page No (1-6), 2007.

[31] T .Romen Singh,Sudipta Roy,O.Imocha Singh,Tejmani Sinam, Kh .Manglem Singh,'' A New Local Adaptive Thresholding Technique in Binarization'', IJCSI International Journal of Computer Science Issues, Vol. 8, Issue 6, No 2, Page No(271-277) ,November 2011 ISSN (Online): 1694-0814 www.IJCSI.org,2011.

[32] F. P. Kressler , M. Franzen , K. Steinnocher,'' SEGMENTATION BASED CLASSIFICATION OF AERIAL IMAGES AND ITS POTENTIAL TO SUPPORT THE UPDATE OF EXISTING LAND USE DATA BASES'', Page No (1-6),Sep 29, 2014.

[33] Azzeddine Riahi ,''MRI Image Segmentation by K-Means Clustering Method and Detection of Lesions'', International Journal of Science and Research (IJSR) ISSN (Online): 2319-7064, Volume 4 Issue 6, Page No(2484-2492),June 2015

[34] Emre Akbas and Narendra Ahuja,'' Low-level Image Segmentation Based Scene Classification'', International Conference on Pattern Recognition, 1051-4651/10 $26.00 © 2010 IEEE ,DOI 10.1109/ICPR.2010.884,Page No(3623-3626),2010.

[35] Xiaofeng Ren and Jitendra Malik,'' Learning a Classification Model for Segmentation'', http://ttic.uchicago.edu/~xren/publication/xren_iccv03_discrim.pdf.,Page No (1-8).

[36] Chap. 7 — Region Segmentation, Computação Visual e-Multimédia http://www.di .ubi.pt /~agomes/cvm/teoricas/07-regionsegmentation.pdf. , Page No (1-32).

[37] Stephen Gould,Tianshi Gao,Daphne Koller,'' Region-based Segmentation and Object Detection'', http://ai.stanford.edu/~koller/Papers/Gould+al:NIPS09.pdf., Page No (1-9).

[38] Bryan S. Morse, ''Lecture 18: Segmentation (Region Based)'', Brigham Young University, Page No (1-6), March 3, 2000.

[39] Yu-Hsiang Wang,'' Tutorial: Image Segmentation'', Graduate Institute of Communication Engineering National Taiwan University, Taipei, Taiwan, ROC, http:// disp.ee.ntu.edu.tw/meeting/%E6%98%B1%E7%B %94/ Segmentation %20tutorial.pdf. , Page No (1-36).

[40] YI-WEI YU andJUNG-WA WANG,'' Image Segmentation Based on Region Growing and Edge Detection'', 0-7803-5731-0/99$$10.00 01999 IEEE, Page No (798-803),1999.

[41] Yinghua Lu, TinghuaiMa, Changhong Yin, Xiaoyu Xie, Wei Tian and ShuiMing Zhong,'' Implementation of the Fuzzy C-Means Clustering Algorithm in Meteorological Data'', International Journal of Database Theory and Application Vol.6, No.6 (2013), pp.1-18 http://dx.doi.org/10.14257/ijdta.2013.6.6.01, ISSN: 2005-4270 IJDTA Copyright 2013 SERSC,Page No(1-18),2013.

[42] Subhagata Chattopadhyay, Dilip Kumar Pratihar, Sanjib Chandra De Sarkar'' A COMPARATIVE STUDY OF FUZZY C-MEANS ALGORITHM AND ENTROPY-BASED FUZZY CLUSTERING ALGORITHMS'', Computing and Informatics, Vol. 30, 2011, 701–720, Page No (701-720) ,2012.

[43] Soumi Ghosh, Sanjay Kumar Dubey,'' Comparative Analysis of K-Means and Fuzzy C-Means Algorithms'', www.ijacsa.thesai.org, ((IJACSA)

International Journal of Advanced Computer Science and Applications, Vol. 4, No.4,Page No (35-39), 2013.

[44] S. Ramathilaga, James Jiunn-Yin Leu, Yueh-Min Huang,'' Adapted Mean Variable Distance to Fuzzy-Cmeans for Effective Image Clustering'', First International Conference on Robot, Vision and Signal Processing, 978-0-7695-4581-3/11 $26.00 © 2011 IEEE ,DOI 10.1109 /RVSP.2011.58,Page No(48-51),2011.

[45]chapter4''FUZZY CLUSTERING'' https: //homes. di.unimi.it /valenti/ Slide Corsi/Bioinformatica05/Fuzzy-Clustering-lecture-Babuska.pdf. ,Page No(55-71).

[46] Xiao Ying Wang, Jon Garibaldi, Turhan Ozen,'' Application of the Fuzzy C-Means Clustering Method on the Analysis of non Preprocessed FTIR Data for Cancer Diagnosis'',2003, http://ima.ac.uk/papers/wang2003.pdf., Page No (1-6).

[47] Keh-Shih Chuang , Hong-Long Tzeng , Sharon Chen , Jay Wu , Tzong-Jer Chen,'' Fuzzy c-means clustering with spatial information for image segmentation'', 0895-6111/$ - see front matter q 2005 Published by Elsevier Ltd,doi:10.1016/j.compmedimag.2005.10.001,Page No (9-15),2005.

[48] Tina Geweniger, Dietlind Zühlkeand Barbara Hammer and Thomas Villmann,'' Median Variant of Fuzzy c-Means'', ESANN'2009 proceedings, European Symposium on Artificial Neural Networks - Advances in Computational Intelligence and Learning. Bruges (Belgium), 22-24 April 2009, d-side publi, ISBN 2-930307-09-9, Page No (523-528), 2009.

[49] Stelios Krinidis and Vassilios Chatzis,'' A Robust Fuzzy Local Information C-means ClusteringAlgorithm'', http://infoman.teikav.edu.gr/~stkrini/pdfFiles/journals /2010_TIP.pdf. ,2010. , Page No (2-11),2010.

[50] Mathias Bank and Friedhelm Schwenker,'' Fuzzification of Agglomerative Hierarchical Crisp Clustering Algorithms'', Springer, Page No (1-8), 2012.

Author profile:

Professor Azzeddine Riahi received his PhD in Nuclear Physics in 1987 CENBG at the University of Bordeaux, France, he graduated in Nuclear Medicine, he is a professor the upper education at University Chouaib Doukkali since 1988, he holds a doctoral degree in atomic physics from UCD, he is currently Director of laboratory Instrumentation, Measurement and Control (IMC).