Detection of Brain Tumor in Medical Images

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***Abstract*— This paper introduces an efficient detection of brain tumor from cerebral MRI images. The methodology consists of three steps: enhancement, segmentation and classification. To improve the quality of images and limit the risk of distinct regions fusion in the segmentation phase an enhancement process is applied. We adopt mathematical morphology to increase the contrast in MRI images. Then we apply Wavelet Transform in the segmentation process to decompose MRI images. At last, the k-means algorithm is implemented to extract the suspicious regions or tumors. Some of experimental results on brain images show the feasibility and the performance of the proposed approach.**

***Keywords*— cerebral MRI images, mathematical morphology, Wavelet Transform, k-means, tumor.**

I. INTRODUCTION

In the last decades, we have been observed a dynamic growth in the number of research works conducted in the region of cerebral cancer diagnosis. Many university centres [1] are focused on the issue because of the fact that cerebral cancer is spreading among the world population. For example in the US, nearly 3000 children are diagnosed with brain tumors. Almost half will die within five years, making it the most fatal cancer among children [2]. It's associated with neurological disabilities, retardation and psychological problems and increased risk of death. Despite over all increases in incidences and death from cerebral cancer in the general world population; Africans are more likely than other patients to die of the disease. In Tunisia, for instance, the cancers mortality is responsible for 14.8% of deaths among the elderly. They represent the second leading cause of death after cardiovascular diseases [3]. Due to its negative effects on affected people, the cancer diseases constitutes a high burden on national economy and a source of suffering for the family as well as the society [3].

To identify a tumor, a patient will undergo several tests. Most commonly Computed Tomography (CT) and Magnetic Resonance Imaging (MRI) are used to locate brain tumor. The information obtained will influence the treatment a patient will receive. Perhaps the most widely used clinical diagnostic and research technique is MRI. It's an efficient medical imagery tool that has different methods (T1,T2, ARM, …) having each particular property and an effective way that enables to clarify the various tissues and to obtain a 2D, 3D and even 4D sight (3D+T) of a part of the body, in particular of the brain. It's based on the principal of nuclear magnetic resonance (NMR). Due to various sequences various tissues with high contrast can be observed [4].

Actually, many medical imagery diagnosis systems have to face the problem of cells and their nuclei separation from the rest of the image content [5]. As the process of separation is very important, much attention in the construction of the expert diagnosis system has to be paid to the segmentation stage.

Segmentation is a crucial step in image processing tasks. In literature, there are different definitions of segmentation Haralick, Zhang and Freixenet [6] summarize the segmentation definitions found in literature. From general point of view segmentation is the partitioning of an image into a set of homogeneous and significant regions having a single label and common or similar properties. Many algorithms were thus proposed during the last decades. They are based on various approaches: contour, region and texture.

In the image processing analysis, segmentation is preceded by a pre-treatment step called enhancement. In fact the enhancement step is needed to improve the quality of images since the majority of images dealt with have low contrast. The contrast correction is conducted for each color channel separately resulting in an image being better defined for later stages of the presented hybrid segmentation methods [1].

The segmentation phase is also followed by a post-treatment step known as classification which ensures the tumor extraction. The classification of medical images is a fundamental step in different applications such as psychology, biology, medicine. Due to the high variability of medical image data it's important to use appropriate models in the classification process. A large variety of methods for classification of medical images is discussed in the literature.

Sonka and Fitzpatrick in [7] provide a review of classification methods ranging from computer vision through statistical approaches to machine learning.

In the last decade, there has been a major development in machine learning based classification. These advances which prove to be useful for biomedical image analysis include support vector machine, kernel principal component analysis, independent component analysis, bagging and boosting techniques.

Classification algorithms are categorised into supervised and unsupervised; although each category has its basic principals and properties. Both categories have a common objective which is the detection and extraction of tumor.

The remainder of the paper is organized as follows. In section 2, we present a description of the proposed method of automatic tumor detection from cerebral images. The suggested method consists of three steps: the first step is the enhancement process applied by mathematic morphology. The second step is the image segmentation based on wavelet transform. The last one is the extraction of localised tumor applied by an unsupervised k-means classification method. Experimental results are reported in section 3. Finally concluding remarks are drawn in section 4.

II. THE PROPOSED METHOD

The principal of proposed method to detect the tumor automatically from the cerebral images, is summarized in figure 1.

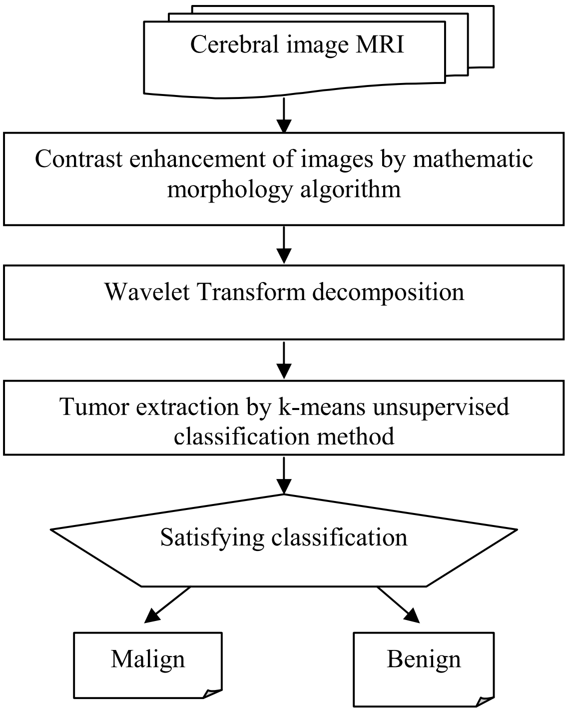


Figure 1. Steps of the proposed algorithm

The method is composed of three main steps: the enhancement phase, the decomposition of cerebral images suspects zones or tumors and the extraction of localized tumor.

The decision stage (not developed in this paper) is composed by classification disease whether the tumor is benign or malign.

A. Enhancement

Image enhancement has been applied successfully to different fields such as medical, industry and military fields [8]. Enhancement in medical imaging is the use algorithms to make image clearer and to ensure optimum presentation of all digital computer processing. It proves to be useful and important to the medicine diagnosis. This may aid interpretation by humans or computers. Enhancement aims at improving the quality of a given image. It can be accomplished by removing noise, enhancing contrast, emphasizing edges and modifying shapes. Figure 2 illustrates the enhancement process.

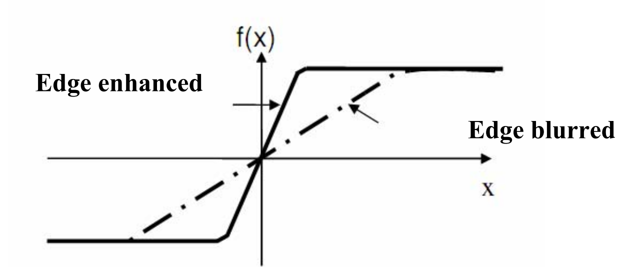


Figure 2. The enhancement process

The computerized enhancement techniques have been widely applied in the field of radiology, where the subjective quality of images is important for human interpretation and diagnosis. Many general purpose tools for accomplishing enhancement have been developed and applied to medical images [9]. They include histogram modification, mean filters, Gaussian filters, linear shift invariant filters and morphological filters. More recently, multiscale techniques have sparked the interest of researchers for contrast enhancement of images especially wavelet transform. For contrast enhancement based on mathematical morphology theory there are two methods: the first is Top-Hat which deals with images after the segmentation process. This algorithm enhances the edges of the segmented region of interest. The second algorithm deals with the contrast of the original image to enhance the segmentation process.

Here, we consider the second morphological contrast enhancement algorithm. A detailed theory of mathematical morphology is provided in [10]. Experimentally, we found that structuring element as a disk of radius 30 yields the best performance of the morphological algorithm. To increase the contrast enhancement, we convolve the resulting image with the following 3x3 Gaussian low-pass filter described in Equation (1)[10]:

$$\text{LPGF}=\begin{pmatrix} 0.0071 & 0.0835 & 0.0071 \\ 0.0835 & 0.9859 & 0.0835 \\ 0.0071 & 0.0835 & 0.0071 \end{pmatrix} \quad (1)$$

B. Segmentation

After pre-processing phase, we adopt a segmentation algorithm. The basic aim of segmentation is the partitioning of an image into homogeneous regions (spatially connected groups of pixels called classes, or subsets) with respect to one or more characteristics or features; such that the union of any two neighs boring regions yields a heterogeneous. Medical image segmentation is a promising field and imposes constraints related to the concept of time, the great number of implied data and the richness of image concerning the complexity of the organ's anatomy, the patient's position of catching image. All these medical images characteristics add more difficulties to the problem of image segmentation and make the construction of a general model more complex. This explains the variety of segmentation methods appeared in the last years. In literature there exist two major classes of segmentation techniques: edge based segmentation approach and region based segmentation approach.

Edge approach looks for limits between regions with different characteristics. Its aims at finding object boundaries and segmenting regions enclosed by the contours. Edge based techniques include Roberts, Prewitt, Robinson, Kirsch, Laplacian and Frein-Chen filters [11]. They prove to be computationally fast and don't require prior information about the image content. However a drawback of the edge approach is that the edges do not enclose the object completely.

In region-based techniques, segmentation is applied by identifying all pixels that belong to the object based on the intensity of pixels. Their aim is the regions satisfying a given homogeneity criterion. They include region growing, watershed algorithm and thresholding [12].

More recently, with the application of a spatial-frequency image analysis, multiscale techniques have sparked the interest of researchers for segmentation of images especially wavelet transform. The wavelet transform is the decomposition of an image into a family of functions called a wavelet family $\Psi_{a,b}(t)$ "Equation (2)", in which all of the basis wavelets are derived from scaling and translation of a single function called the mother wavelet $\Psi(t)$ "Equation (3)".

$$C_{a,b} = \int_{-\infty}^{+\infty} x(t)\Psi_{a,b}(t)dt \quad (2)$$

$$\Psi_{a,b}(t) = \frac{1}{\sqrt{a}}\Psi\left(\frac{t-b}{a}\right) \text{ With } a \neq 0 \quad (3)$$

Figure 3 presents some wavelet examples. There exist many types of mother wavelets and associated wavelets. They include Haar, Daubechies, Symmlet, Coiflet and biorthogonal.

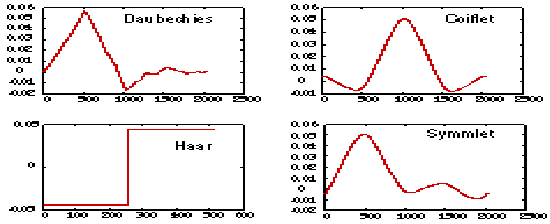


Figure 3. Example of classical wavelets

Mallat [13] shows that wavelet transform is implemented by using two quadrature mirror filters H (low-pass) and G (high-pass) (figure 4).

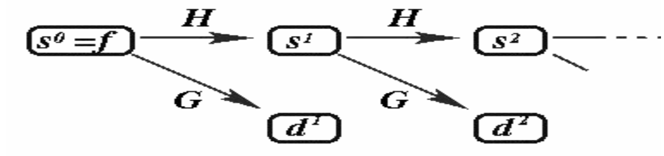


Figure 4. Signal decomposition into detail and approximation

The decomposition implemented by these two filters is applied at first line by line and then column by column. At each level, four sub-images are generated.

Wavelet transform represents an image at different resolution levels. At resolution j, it provides an approximation of the original image I_j and three detail of image $\mathbf{D}_2^V$, $\mathbf{D}_2^H$, $\mathbf{D}_2^D$. Each of these details images privileges a particular orientation: horizontal, vertical and diagonal, and preserves the lost information during their passage from j-1 to j. Figure 5 illustrated a decomposition of image at two levels. Morlet and Grossman [14] showed the wavelet coefficients resulting from this transformation contain the information concerning the original image for different scales. Wavelet coefficients represent the degree of correlation or similarity between the image and the mother wavelet at the particular scale and translation. Thus the set of all wavelet coefficients gives the wavelet domain representation of the image.

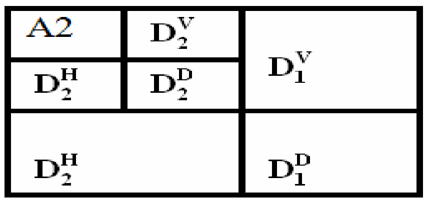


Figure 5. Sub-images generated at two lavels

Baarir [15] shows that the wavelet choice varies according to the application. In some cases, Haar is the most suitable wavelet. In other cases the number of null moments imposes the wavelet choice.

Here we consider Daubechies wavelet for detection and segmentation of tumors. Sahbani and al [14], applied several tests with different wavelet types and come to conclude that Daubechies wavelet is the best type in image application. In this research we realised many tests and they conclusion is that the Daubechies Wavelet Db2 gives more optimal results.

C. *Classification*

Classification is a frequent notion in our current life and a useful tool to regroup heterogeneous elements into a small number of classes comprising the most homogeneous elements. Most classification methods have been applied in various contexts such as object recognition, registration, segmentation and feature extraction, resulting in further advances to answer the demands and requirements of the clinical application domain. Classification results depend upon the number of classes opted by the user. Hence to have a good classification quality it's important to choose an exact number of classes K.

In the literature, there exist two types of classification algorithms: unsupervised clustering algorithms and basic supervised classifiers. K-nearest neighbour, maximum likelihood, neural networks and Parzen window classifiers [16] are among the supervised classification algorithms. The supervised classification uses a priori knowledge or information to determine the data structure. Its inconvenient is the lack of robustness and precision as it requires manual intervention in the apprenticing phase. In contrast unsupervised classification extracts the structure of the data from the data itself without the expert intervention.

Unsupervised classification, being automatic and based on clustering algorithms, seeks to partition n objects into K groups. They include K-means, Mean Shift, PCM and Fuzzy K-means FCM. Unsupervised classification is an important technique for automatic analysis of several brain dementias. Basically there are two types of unsupervised classification algorithms: one type is based on the analysis of physical scattering properties. Another type is based on statistical properties. Additionally several interesting combinations of these two types of classification approches have been found [17].

Undoubtedly, each approach has its advantages and its inconvenient. Many attempts have been made to improve the performance of these algorithms. The C-means, for instance incorporates a fuzzy criterion function and Krishna suggested using genetic algorithm [18]. However most of these improvements on the C-means algorithms are computationally demanding.

Here we implement the K-means unsupervised classification algorithm for tumor extraction. Being the most widely used technique, the K-means partitions the data set D containing n items into a user specified number of clusters K. the clusters C are initialized by selecting K items randomly from D and then the n items are arbitrarily assigned to cluster 0: the application of this algorithm consists of two steps: At first each item is assigned to its closest cluster center. Then each cluster centroid is updated to be the mean of its constituent items. Iterations continue until no item assignments change. Table 1 shows a brief outline of the K-means clustering algorithm.

TABLE I. A BRIEF OUTLINE OF K-MEANS ALGORITHM

Algorithm K-means
1: **Inputs:** data set D, number of clusters k 2: **Outputs:** clusters C = {cj , j = 1 . . . k} 3: Let n = |D|. 4: Initialize k clusters with randomly chosen d ∈ D. 5: Assign all items to cluster 0, ai = 0, i = 1 . . . n. 6: **repeat** 7: Assign each d ∈ D to its closest cluster in C. 8: Update each cluster c_j as mean of { $d_i \backslash a_i$ = j}. 9: **until** A does not change

K-means algorithm uses an all or nothing procedure, that is, $w_{ij} = 1$ if the data sample x_j belongs to cluster $w_{ij} = 0$. It uses a squared error function criterion: witch is the where K is the number of clusters, n the number of data in the sample x_i, $\ldots, x_n$ and m_i the cluster centroid defined as "Equation (4)":

$$m_i = \frac{\sum_{j=1}^{n} w_{ij} x_j}{\sum_{j=1}^{n} w_{ij}}, \forall i \tag{4}$$

The membership function w_{ij} indicates whether the data point x_j belongs to a cluster w_i and satisfies the following constraints "Equation (5)":

$$\sum_{i=1}^{k} w_{ij} = 1, \forall j \qquad 0 < \sum_{j=1}^{n} w_{ij} < n, \forall i \tag{5}$$

K-means algorithm also uses a criterion function based on the measure of distance such as the Euclidean distance which favours the hypersherical cluster. The criterion function to be minimized is defined by "Equation (6)":

$$J = \sum_{i=1}^{k} \sum_{j=1}^{n} w_{ij} \left\| x_j - m_i \right\|^2 \tag{6}$$

Other measures of similarity or distance will reinforce the choice of other cluster geometry. The initial choice of cluster geometry and measure of similarity or distance affects the way in which the algorithm converges behaves.

III. RESULTS

A. *Quantitative evaluation*

The proposed algorithm is applied to MRI brain tumor images. The evaluation of the performance is evaluated by tree indexed errors.

The first measure is PSNR (Peak-Signal-to-Noise-Ratio). It is defined by "Equation (7) and "Equation (8)":

$$\text{PSNR}=20 \log_{10}(\frac{256}{E}) \tag{7}$$

$$E=\sqrt{\frac{1}{mn}\sum_{i}(r_i-d_i)^2} \quad (8)$$

Where E is the root-mean-square-error, mn is the number of pixels in the image, and r, d denotes the original and the denoised image respectively.

The second measure is Contrast Improvement Index (CII), which is defined as follows "Equation (9)":

$$CII=\frac{C_{enhanced}}{C_{original}} \quad (9)$$

Where, $C_{enhanced}$ and $C_{original}$ are the contrasts for the processed and original images, respectively. The contrast C of an image is defined by the following form "Equation (10)":

$$C=\frac{g-d}{g+d} \quad (10)$$

Where, g is the mean gray-level value of the foreground, and d is the mean gray-level value of the background.

The third measure is MSAD (Multiple Scan Dose) defined by "Equation (11), Equation (12) and Equation (13)":

$$MSAD=\frac{1}{p}.CTDI \quad (11)$$

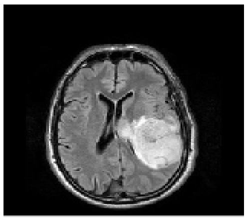
$$CTDI=\frac{1}{N.h_{col}}.\int_{-\infty}^{+\infty}D(z).dz \quad (12)$$

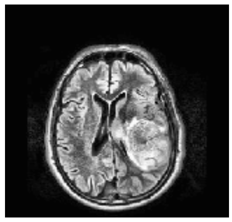
$$p=\frac{TF}{N.h_{col}} \quad (13)$$

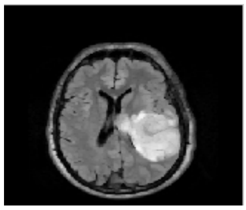
Where CTDI is the Computed Tomography Dose Index, D(z) is the value of the dose at a given location z, $N.h_{col}$ is the nominal value of the total collimation (beam width) that is used for data acquisition, TF is the Table Feed and p is the pitch factor.

B. *Experimental results*

The application of the proposed method is illustrated in the following steps for in MRI brain tumor (figure 6 (a)). Three enhancement algorithms are applied, the well known contrast-limited adaptive histogram equalization algorithm (CLAHE) [19] (figure 6 (b)), Beghdadi one [20] (figure 6 (c))and Mathematic Morphology (figure 6 (d)).


(a) original image


(b) CLAHE


(c) Beghdadi

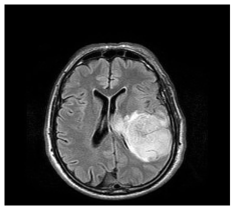

(d) Mathematic Morphology

Figure 6. Enhancement results

TABLE II. CONTRAST IMPROVEMENT INDEX (CII)

	CLAHE	Beghdadi	Mathematic Morphology
Image	0.8172	0.9997	1.5073

Table 2 shows a comparative study of the different algorithms using a CII factor and demonstrates that the Mathematic Morphology is the better.

From the figure 6 (d), the visual perception confirms a clearer tumor better than the original one figure 6 (a).

The enhanced image is decomposed by wavelet Transform at level 2. Figure7 gives a such decomposition.

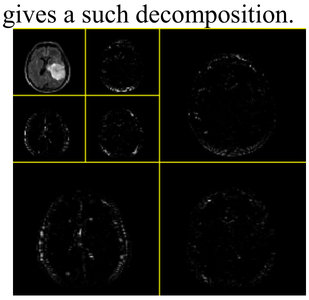
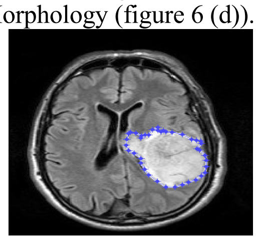


Figure 7. Wavelet decomposition of figure 6 (d)

The figure 7 shows the segmentation results where the approximation 2 (A2) preserve the qualitative and quantitative tumor.


(a) expert selection


(b) the mask of expert selection

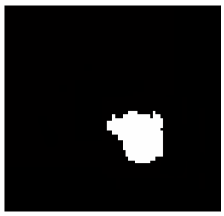

(c) K-means selection

Figure 8. Classification results

The extraction of the tumor from segmentation result is accomplished manually (expert method) of figure 8 (a), the mask corresponded (figure 8 (b)). The automatic extraction of the tumor is made by k-means method, the result is shown in figure 8 (c)

To validate this idea, we compare the performance of the expert's result with the K-means one and we conclude that the PSNR value is 21.6272, this value seems to be acceptable. The same can be said for the MASD. MSAD value equals 17.7768.

Figure 9. Masks error.

The error between the located tumor in the figure 87 (b) and 8 (c) is presented in the figure 9.
Visual inspection demonstrates the good performance of the proposed method of extraction.

IV. CONCLUSION

In this paper, an efficient detection of brain tumor has been introduced. It's based on mathematical morphology, wavelet transform and K-means technique. The algorithm reduces the extraction steps through enhancement the contrast in tumor image by processing the mathematical morphology. The segmentation and the localisation of suspicious regions are performed by applying the wavelet transforms. Finally K-means algorithm is implemented to extract the tumor. Results are presented, using a real image of brain tumor as illustrative example, which indicate significant concordance, comparing with expert result. Although the performances of proposed algorithm has been demonstrated.

The tumor extraction paves the way for the expert to decide the degree of malignancy or aggressiveness of a brain tumor. However, it isn't always easy to classify a brain tumor as "benign" or "malignant" as many factors other than the pathological features contribute to the outcome. This will be the subject of future research.

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