An Enhanced Implementation of Brain Tumor Detection Based on Statistical Features and F-Transform

Nemir Ahmed Al-Azzawi, Mohannad Kadhim Sabir
Biomedical Engineering Department, University of Baghdad,
Al-Jadriah, P.O.Box 47187, Baghdad, Iraq.
dr.azzawi@kecbu.uobaghdad.edu.iq

***Abstract*—Brain tumor is an abnormal growth of cells inside brain, which may be cancerous or non-cancerous. This paper describes the proposed approach for detection and extraction brain tumor from MRI scan images. Brain tumor need be detected, diagnosed and estimated in earliest stage. The classification involves classification of images into normal and tumor detected. The medical difficulties become serious if tumor is detected at the later stage. Asymmetry of brain is used for detection of abnormality. Statistical Features were extracted from the detected tumor texture using three kinds of features. The difference between the two halves in that row can judge each data as normal or with suspicious tumors. After detecting the tumor, the segmentation based on F-transform (Fuzzy-Transform) and morphological operations are performed to delineating brain tumor boundaries and calculate the area of the tumor. The F-transform is an excellent method to extract the salient edges. Experimental results on brain MR images succeed an average accuracy of 96 % and precision of 95% using the proposed algorithm.**

***Index Terms*—MRI; Image Segmentation; Brain Tumor; F-transform (Fuzzy-Transform); Edge Detection.**

I. INTRODUCTION

Automated MRI brain tumor detection provides suitable information for medical diagnosis and surgical planning. Nevertheless, it is a challenging task due to the complication of tumor characteristics in images, such as sizes, shapes, locations and intensities. Image segmentation and detection are dynamic method to resolve the medical problem of the various diseases [1, 2]. Imaging of the brain tumor can be done by computer tomography (CT) scan, magnetic resonance image (MRI) scan, Ultrasound, etc. Conventional MR imaging is the typical procedure for diagnosis, treatment planning with higher sensitivity compared to other modalities. In this paper, MRI scan is employed to implement the system. Several methods have been proposed for brain tumors detection and hence, could diagnosed and detected more efficiently such as deformable model [3], fuzzy connectedness [4] and particle swarm optimization algorithm [5]. Most of the earlier described effort falls into the category of pattern recognition methods [6, 7]. The key issue of successful pattern recognition methods is to extract effective features. Intensity-based statistical features are the best method and have been commonly used [8]. Nevertheless, due to the complexity of the pathology in human brain and the high quality required by clinical diagnosis, only intensity features cannot achieve acceptable result. Dubravko et al [9] proposed the rule based approach to label the abnormal regions such as calcification, hemorrhage and stroke lesion. Some other examples are modified texture based region growing and cellular automata edge detection [7], neural network algorithm [6], watershed and edge detection [10] and Fuzzy C Means Algorithm [11]. Asymmetry of brain is used for detection of abnormality [12]. The most generally used grading scheme today has been introduced by the world health organization (WHO) [13, 14].

Symmetry analysis of grey level can be used to detect the existence of tumor [15]. The problem of edge detection is one of the most attractive problems for the image processing community due to various important applications. Canny edge detection is commonly used to generate features for image segmentation to handle the accurate feature extraction [16-18]. The F-transform [19, 20] is an efficient intelligent method to handle uncertain information. It represents those natural phenomena which we observe in our real lives. Daňková and Valášek [21] shows that the F-transform technique is a promising and efficient method for feature and edge extraction. Mathematical morphology is developed from set theory. It was introduced by Matheron and extended to image analysis by Serra [22]. Morphological image analysis can be used to perform image filtering, image segmentation, and measurement operations [23]. The medical images contain object boundaries and shadows and noise. Therefore, they could be difficult to separate the exact edge from noise. Mathematical morphology is solved this issue. Several researchers have proposed techniques for medical image segmentation based on morphological operation [24-26].

In this paper, we improve an algorithm for the brain tumor detection and segmentation in order to overcome the accuracy and computational problems. There are two main stages carried out for proposed algorithm. First stage is based on study of asymmetry of the brain. A healthy human brain is roughly symmetrical bilaterally with respect to the midsagittal plane, so we use symmetry analysis of grey levels to detect the existence of tumor. The second stage is segmentation based on edge detection. We introduce an edge detection based on F-transform model which captures the silent edges. After edge extraction, a morphological operation was adopted for the final stage to show only tumor. The algorithm has been tried on a number of patients MRI data of brain tumor images. The experimental results show the efficiency and accuracy of the algorithm.

II. F-TRANSFORM

The original inspiration for the F-transform (an shortened name for the fuzzy transform) came from fuzzy modeling Perfilieva [19, 20]. The purpose was to show that, equally to conventional transforms (Fourier and wavelet). Let *u* be represented by the discrete function $u : P \to \mathrm{R}$ of two variables, where $P = \{(i, j) \mid i = 1, \ldots, N, j = 1, \ldots, M\}$ is an $N \times M$ array of pixels, and R is the set of reals. If *(i, j)* $\in P$ is a pixel, then *u(i, j)* represents its intensity range. Moreover, let fuzzy sets $A_k \times B_l$, *k=1, . . . , n, l=1, . . . , m,* where $0 < n \le N$, $0 < m \le M$ set up a fuzzy partition of *[1, N]×[1, M]*. The F-transform of *u* corresponds *u* to the matrix $F[u]_{nm}$ of F-transform components:

$$F[u]_{nm} = \begin{pmatrix} F[u]_{11} & \cdots & F[u]_{1m} \\ \vdots & \vdots & \vdots \\ F[u]_{n1} & \cdots & F[u]_{nm} \end{pmatrix} \quad (1)$$

Every component $F[u]_{kl}$ is a local mean value of u over a carry set of the respective fuzzy set $A_k \times B_l$. The membership functions of the respective fuzzy sets in a fuzzy partition are called basic functions. The (direct) F-transform of u (with respect to the chosen partition) is an image of the mapping $F[u]$: {A_1, . . . , A_n }×{ B_1, …, B_m }$\to \mathrm{R}$ defined by:

$$F[u](A_k \times B_l) = \frac{\sum_{i=1}^{N}\sum_{j=1}^{M} u(i,j)A_k(i)B_l(j)}{\sum_{i=1}^{N}\sum_{j=1}^{M} A_k(i)B_l(j)} \quad (2)$$

where k = 1, . . . , n, l = 1, . . . , m. The value $F[u](A_k \times B_l)$ is called an F-transform component of u and is denoted by $F[u]_{kl}$. We currently set up two extreme fuzzy partitions of [1, N] that will be used in the following.

Largest partition: The largest partition of [1, N]×[1, M] contains just one fuzzy set, $A_1 \times B_1$, such that for all (x, y)∈[1, N]×[1, M], ($A_1 \times B_1$)(x, y)=1. The respective F-transform component $F[u]_{11}$ and the respective inverse F-transform u_{11}.

Finest partition: The finest partition of [1, N] × [1, M] is established by N× M fuzzy sets $A_k \times B_l$, such that for all k=1, . . . , N, and l=1, . . . , M. The respective F-transform components $F[u]_{kl}$, k=1, . . . , N, l=1, . . . , M, and the respective inverse F-transform u_{NM}. The inverse F-transform of u is a function on P, which is represented by the following inversion formula:

$$u_{nm}(i,j) = \sum_{i=1}^{n}\sum_{j=1}^{m} F[u]_{kl} A_k(i) B_l(j) \quad (3)$$

where i = 1, . . . , N, j = 1, . . . , M. It can be made known that the inverse F-transform, u_{nm} approximates the original function u on the domain P. The proof can be found in [19, 27, 28]. The F-transform technique, leading to one-level or higher-level decomposition of an image; here we explain the technical details of these decompositions. The one level decomposition is as the following representation of u on P:

$$u(x,y) = u_{nm}(x,y) + e(x,y) \quad (4)$$

$$e(x,y) = u(x,y) - u_{nm}(x,y), \forall (x,y) \in P \quad (5)$$

where 0<n≤N, 0<m≤M and u_{nm} is the inverse F-transform of u and $e(x,y)$ is error function the respective residuum. If fuzzy sets $A_1,\ldots,A_n$ establish a fuzzy partition of [1, N] and $B_1,\ldots,B_m$ do the same for [1, M] then the Cartesian product {A_1, . . . , A_n }×{ B_1, …, B_m }of these fuzzy partitions is the set of all fuzzy sets $A_k \times B_l$, k = 1, . . . , n, l = 1, . . . , m and $h = \frac{N-1}{n-1}$ a distance between nodes $x_1, \ldots, x_n \in [1, N]$, where $x_1 = 1$, $x_k = x_1 + (k-1)h, k = 1,\ldots,n$. The membership function $A_k \times B_l$: [1, N] × [1, M] → [0, 1] is equal to the product $A_k . B_l$ of the respective membership functions. The difference between an original function and its inverse F-transform works as a high-pass filter of the former. Therefore, the mentioned above difference can be used for the edge detection problem [21].

III. THE PROPOSED ALGORITHM

The proposed procedure for, primarily extracting the image that contains a tumor and determines its approximated location, from a sequence of bin's MRI images, is based on two stages. It is detecting stage and segmentation stage. The overview of proposed system is show in Figure 1. The analyzed abnormality of the brain based on symmetry investigation of image grey levels. To ensure that the brain image in the middle so that comparison can be properly done. Image registration technique employed is as [29]. Extraction of the midsagittal plane of the human cerebrum and separate the brain into the left and right hemispheres [30]. The detecting stage is comparing three statistical features for the two similar half of the brain. It has been found that there is a similarity between the two half of the brain [15]. The difference between these features for left part with respect to those of the right part will be an indication of tumor. Additionally, since this difference continues, at the same location, to the next image in the sequence will increase the percentage of that indication.

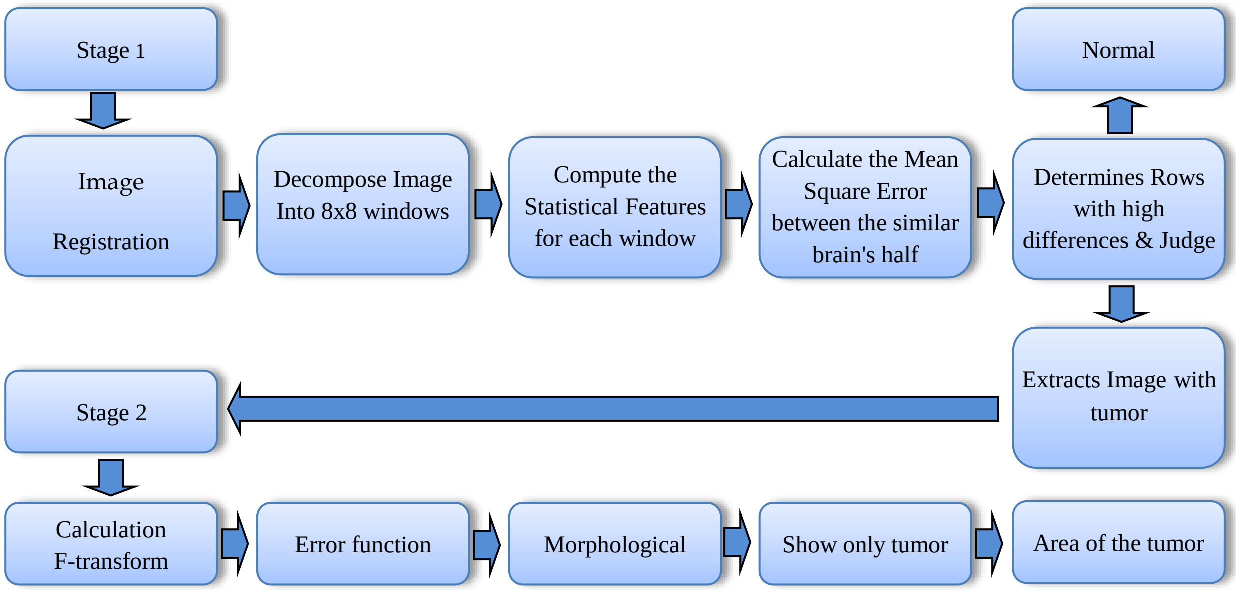

Figure 1:Block diagram of the proposed tumor detection

Figure 1 illustrates the block diagram of the proposed algorithm. Where, the first block will register the images, the second one decomposes the registered images into windows of 8x8 pixels. For each window, three statistical features (mean, energy, and entropy Equation (6)) are computed. Each of these features is normalized with respect to its maximum value in all windows. All rows of the resultant windowed image are divided into two equal half. For each row, the mean square error (MSE) is computed between the normalized features of each window in first half, with respect to its mirror window in the second half. Adding these MSE for each row will be a measure of the difference between the two half in that row. Judge each data as normal or with suspicious tumors according to the quantified similarity value as measure of the difference. The degree of asymmetry should be carefully considered as an indication of pathology. This indication will help the segmentation stage to extracts the tumor from the image.

$$\begin{aligned} \text{Mean} &= \frac{1}{64}\sum_{i=1}^{64} x(i) \\ \text{Energy} &= \frac{1}{64}\sum_{1}^{64} x^2(i) \\ \text{Entropy} &= -\sum_{i=1}^{256}\left(p(i)\log_2 p(i)\right) \end{aligned} \tag{6}$$

Image segmentation stage will divide the brain MRI scan image into few segments (sets of pixels, also known as super pixels). The idea of segmentation is to simplify or change the details of an image into something that is more meaningful and easier to analyze [31]. Image segmentation is commonly used to locate objects and boundaries (lines, curves, etc.) in images. Edge detection is used to find the boundaries of the object. Segmentation methods can also be applied to edges achieved from edge detectors [32]. The efficiency of many image-processing tasks depends on the perfection of detecting meaningful edges. In the proposed algorithm to detect the edge based on F-transform is used [21]. The two main purpose of using F-transform is to control the amount of detail, which appears in the edge image, and suppress noise.

Mathematical morphology is a methodology for image analysis that has been widely used in image analysis [23]. The fundamental of all simple morphological operators is to investigation the image under study with a structuring element. The structuring element is tiny binary images with a small matrix of pixels take a value of zero or one. The matrix dimensions identify the size of the structuring element. The pattern of ones and zeros specifies the figure of the structuring element. An origin of the structuring element is regularly one of its pixels, although normally the origin can be outside the structuring element. The primitives of morphological operations are erosion and dilation [33, 34]. Erosion and dilation are dual operations with respect to set complementation. In this paper, erosion is applied to detect the tumor. The erosion of B by A is given by the expression:

$$A \,!\, B = \left\{(i, j) : B_{(i,j)} \in A\right\} \tag{7}$$

where, A is the binary image, B is the structuring element and (i, j) is the center pixel of structuring element.

The stapes of segmentation is as follows:

1. Calculate $F[u]$ – the direct F-transform of image and calculate u_{nm} – the inverse F-transform using the components $F[u]$ by (3).
2. Calculate the error function $e(x) = |u(x) - u_{nm}(x)|$ for all $x \in P$. Rescale and round the values of e from [0, $max_{x\in P} e(x)$] the integers in [0, 255], which results in the new image e_r . Output: Image e_r . .
3. Computes a global threshold that can be used to convert an intensity image.
4. Compute the morphological operation as given in equation (7). The extracted region is then logically operated for extraction of massive region in given MRI image.
5. Show only tumor portion of the image by remove the small object area.

6. The area of the tumor region is calculated. The area of the tumor region is found by multiplying horizontal dimension, vertical dimension of the image with total number of pixel in the tumor region.

In Figure 2, shows the result of the proposed algorithm with final extracted brain tumor from MRI image.

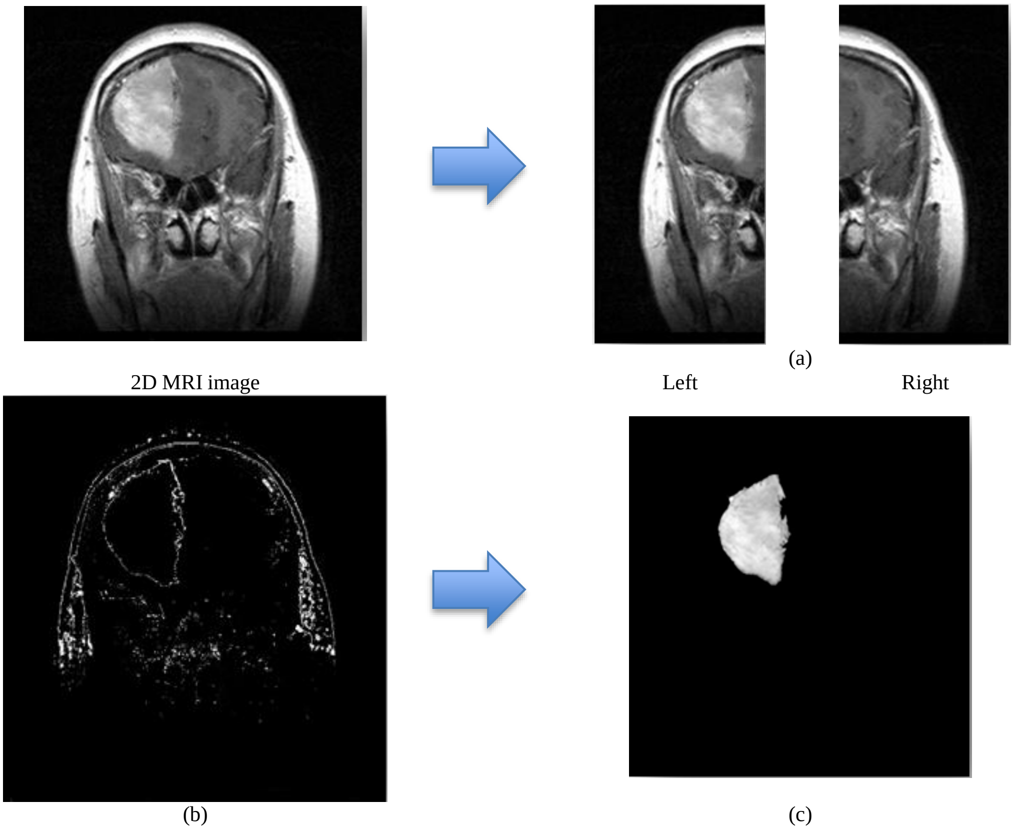

Figure 2: Proposed algorithm with final extracted brain tumor from MRI image. (a) MRI image and the midsagittal plane (b) Edge detection used threshold in percentage. (c) Final Result, show only tumor (The area is 324. 19 mm²)

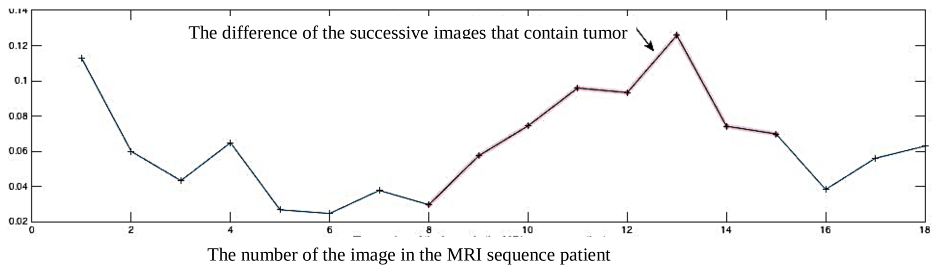

Figure 3: The total difference of all the horizontal windows of each Image of MRI sequence patient

IV. NUMERICAL EXPERIMENTS

The proposed algorithm has been implemented on MR images from 10 different patients with gliomas, provided by Hospital Universiti Sains Malaysia (HUSM) [35]. Each patient have 21 slices in coronal plain with 5 mm slice thickness. MR imaging was performed on GE Signa Horizon 1 Tesla scanner. Clinical MR, T1 image volumes were acquired with an echo time (TE) of 11 ms and a repetition time (TR) of 420 ms. Detection systems were implemented in MATLAB software package. The first stage (statistical feature), with input of brain image basic data from the scanning process, it gives immediate between (0.6-0.09 seconds on standard PC) information about brain normality. Figure 3, shows the total difference of all the horizontal windows of each image of MRI sequence patient.

The efficiency of any segmentation method is to be measured in terms of two factors: Accuracy, which denotes the degree to which the segmentation agrees with truth; Precision which represent repeatability of segmentation taking into account all subjective actions necessary to produce the result [36]. It can be used to determine the performance of the proposed algorithm. Accuracy is also used as a statistical measure of how well a binary classification test correctly identifies or excludes a condition. The possible outcomes of a two class prediction be represented as abnormal images correctly classified (ACC), normal images correctly classified (NCC), normal images classified as abnormal (NCA) and abnormal images classified as normal (ACN).

$$Accuracy = \frac{\sum ACC + \sum NCC}{\sum ACC + \sum NCC + \sum NCA + \sum ACN} \tag{8}$$

$$Precision = \frac{\sum ACC}{\sum ACC + \sum ACN} \quad (9)$$

Using these equations, we can analyze the performance of proposed algorithm. The results using proposed algorithm: accuracy: 96%, precision: 95%. According to these results it is shown that the proposed brain tumor detection is good. Therefore, the algorithm proposed in the paper is applicable in the medical image brain tumor detection.

V. CONCLUSIONS

This paper concerned with the difficult of automatically brain tumors detection and segmentation based on statically features and F-transform. The brain asymmetry analysis is performed using statistical features calculation. The experimental results show that proposed method is promising for detection of brain tumors. Results show that feature extraction is a valuable approach for brain tumors detection. The proposed algorithm can be used to process large brain image databases and provide quick outcomes in clinical setting. This kind of approach will help the diagnostics as a useful second opinion. Morphology operation provides an accurate analysis to be processed in all complementary individual algorithms. The performance of the decision system was calculated. The accuracy and precision of the detection system are 96% and 95% respectively. This method is very robust and accurate than the other existing methods. Along with the statistical features by including, neurotic properties and edema properties, the efficient system can be develop for detecting all kinds of glioma. The developed brain tumor detection system is expected to provide valuable diagnosis techniques for the physicians.

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