

Adaptive Technique Depending on Region Growing and Soft Clustering to Detect Tumors in Different Modalities of MRI Brain Images

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Abstract

Brain tumor is a very dangerous disease and life threatening, so early detection of the tumor is a vital task. Many techniques and algorithms are presented to enable doctors for fast and accurate diagnosis of tumors in MRI brain images. In this study, analytical study of Region Growing segmentation method with different threshold values ranged from 10 to 35, with steps of 5, is proposed. In addition, an adaptive technique is proposed, which is Region Growing based on the fuzzy clustering scheme to investigate the performance of this algorithm by implementing it on FCM clustered images. The adopted MRI images are of different modalities and different orientations to test the ability of the adaptive technique to segment different modalities of MRI images. The results showed that, utilizing different values of the threshold in proceeding of Region Growing algorithm produced different segmented images' properties. When the fine details of the processed images and their objects are the goal, low values of threshold must be adopted, while when isolating of the hole tumor regions is the goal, high values of threshold must be adopted. In addition, the results of the adaptive technique showed that Region Growing segmentation improved its performance and it could separate the consists of the tumor regions. The elapsed time of implementation is clearly reduced.

Keywords: Segmentation; Region Growing; FCM; MRI; Brain Tumors.

الخلاصة

تعتبر أورام الدماغ خطرة جدا ومهددة للحياة لذا فإن الكشف المبكر عن الورم يعتبر مهمة حيوية. لقد تم عرض العديد من التقنيات والخوارزميات لغرض تمكين الأطباء من التشخيص السريع والدقيق للأورام في صور الرنين المغناطيسي للدماغ. في هذا العمل تم اقتراح دراسة تحليلية لطريقة التجزئة باستخدام إنماء المناطق باستخدام قيم مختلفة للعتبة تتدرج من ١٠ إلى ٣٥ وبخطوات تساوي ٥. إضافة لذلك فقد تم تقديم تقنية مطورة وهي استخدام طريقة إنماء المناطق المستندة على العنقدة المضطربة لاختبار أداءها من خلال تنفيذ خوارزمية إنماء المناطق على الصور المقسمة باستخدام تقنية ال FCM علاوة على تنفيذها على صور الرنين المغناطيسية الأصلية الداخلة. إن الصور المتبناة في هذا العمل هي من أنماط مختلفة وباتجاهات مختلفة وذلك لاختبار مدى قابلية هذه التقنية المطورة لتقسيم الأنماط المختلفة من صور الرنين المغناطيسي. لقد بينت النتائج التي تم التوصل إليها من خلال هذه الدراسة إن استخدام قيم تعتیب مختلفة لخوارزمية إنماء المناطق قد أنتجت صور مقسمة مختلفة الخصائص, فعندما تكون التفاصيل الدقيقة للصورة ومكوناتها هو الهدف فيجب استخدام قيمة تعتیب منخفضة في حين إذا كان الهدف هو عزل منطقة الورم ككل فيجب تبني قيمة تعتیب عالية . إضافة إلى ذلك فإن نتائج التقنية المطورة قد بينت إن أداء خوارزمية إنماء المناطق قد تحسن, إذ تمكنت من فصل مكونات الورم. كما وأن الزمن اللازم لتنفيذ الخوارزمية قد انخفض بشكل واضح.

كلمات مفتاحية: التجزئة , إنماء المناطق, FCM, التصوير بالرنين المغناطيسي, أورام الدماغ.

Introduction

Region Growing segmentation algorithm is one of the region based segmentation methods. Region represents a set of connected pixels with similar properties. Region may correspond to object or part of an object. So for correct interpretation of any image, the image must be partition into regions and this partition is done depending on the intensity

(gray level values) of the pixels of this image (Gonzalez and Woods, 2002). The advantages of region growing method are that: it can correctly separate the regions that have the same predefined properties and it can provide the original images which have clear edges with good segmentation results. In addition, its concept is simple, all what it needs a small number of seed points to represent the wanted property, then grow the region. The desired seed points and the criteria can be determined. As well as, multiple criteria can be chosen at the same time [(Petrou and Bosdogianni, 2004) and (Pratt, 2007)]. There are many works in image segmentation utilizing region growing method to process medical images, as examples see: [(Wan and Higgins, 2000), (Law and Heng, 2000), (Ko S et. al., 2000), (Mancas et. al., 2004), (Muhammad et.al., 2012), (Ali et. al., 2014) and (Wafaa, 2014)].

Region Growing

Region Growing is classified as pixel based segmentation because it depends on selection of initial points called seed points. This algorithm involves examining the neighboring pixels of the seed points and determining which of the neighbors should be add to the region depending on predefined criteria such as gray values or color, and this process is iterated until every pixel must be belonged to a region. The basics of this algorithm can be explained as follows: Let R represents the entire image. Segmentation the region of this image may be viewed as a process that partitioning R into 'n' parts or subregions: $R_1, R_2, \dots, R_n$, such that (Gonzalez and Woods, 2002):

$$\bigcup_{i=1}^n R_i = R \quad (1)$$

, and it is controlled by set of rules which are:

- R_i is a connected region, where $i = 1, 2, 3, \dots, n$
- $R_i \cap R_j = \Phi$ for all i and j , where i not equal to j .
- $P(R_i) = TRUE$ for $i = 1, 2, \dots, n$
- $P(R_i \cup R_j) = FALSE$ for adjoint region R_i and R_j (i.e. i not equal to j).

Where $P(R_i)$ is a logical predicate over the points in set R_i and Φ is the null set. The rules described above mentions about continuity, one-to-one relationship, homogeneity and non-repeatability of the pixels after segmentation, respectively. The axioms above should satisfy the following conditions when seeded region growing method takes position in medical image (Gonzalez and Woods, 2002);

- The segmentation must be complete; i.e. every pixel must be assigned to a region.
- Condition requires; points in a region must be connected.
- Indicates that the regions must be disjoint.
- Deals with the properties that must be satisfied by the pixels in a segmented region i.e. $P(R_i) = TRUE$ if all pixels in R_i have the same intensity.
- Condition indicates that regions R_i and R_j are different in the sense of the predicate P .

Soft Clustering Scheme

Many clustering strategies had been presented, such as the hard clustering scheme and the soft (fuzzy) clustering scheme, each of them has its own special characteristics. Hard clustering method restricts each point of the image data set to exclusively just one

cluster, so the segmentation results are often very crisp (each pixel of the image belongs to exactly just one class). Segmentation of this approach is a difficult task when processed images that have limited spatial resolution, overlapping gray values and poor contrast. To overcome these difficulties the fuzzy set theory was proposed, which produces the idea of partial membership (probability) of belonging, that described by a membership function. Fuzzy clustering as a soft segmentation method has been widely studied and among the fuzzy clustering methods, Fuzzy C-Mean (FCM) algorithm is the most popular method used in image segmentation because it has robust characteristics for ambiguity and can retain much more information than hard segmentation methods (Yong Yang and Shuying Huang, 2007). Fuzzy clustering has been widely studied and successfully applied in image segmentation by many researchers like: [(Tolias and Pans, 1998), (Pham and Prince, 1999), (Noordam et.al., 2000), (Zhang et. al., 2003), (Yong Yang and Shuying Huang, 2007), (Khan and Ravi, 2013) and (Rabab et. al., 2015a)].

In FCM algorithm the data patterns may belong to several clusters, having different membership values with different clusters. The membership value of a data to a cluster denotes similarity between the given data pattern to the cluster.

Given a set of n data patterns $X = x_1, \dots, x_k, \dots, x_n$ FCM clustering algorithm is an iterative process to minimize the objective function $J_{FCM}(U, C)$ (Bezdec, 1981):

$$J_{FCM}(U, C) = \sum_{k=1}^n \sum_{i=1}^v (u_{ik})^m d^2(x_k, c_i) \quad (2)$$

Where: x_k is the k^{th} d-dimensional data vector, c_i the center of cluster i , u_{ik} is the degree of membership of x_k in the i^{th} cluster, m is the weighting exponent, it determines the degree of fuzziness of the final partition, $d(x_k, c_i)$ is the distance between data x_k and cluster center c_i and $d = \|x_k - c_i\|$,

U is $(v \times n)$ matrix i.e. $U = [u_{ik}]$, n is the number of data patterns, and v is the number of clusters. The minimization of the objective function $J_{FCM}(U, C)$ can be brought by an iterative process in which updating of degree of membership u_{ik} and the cluster centers, and these are done for each iteration (Bezdec, 1981):

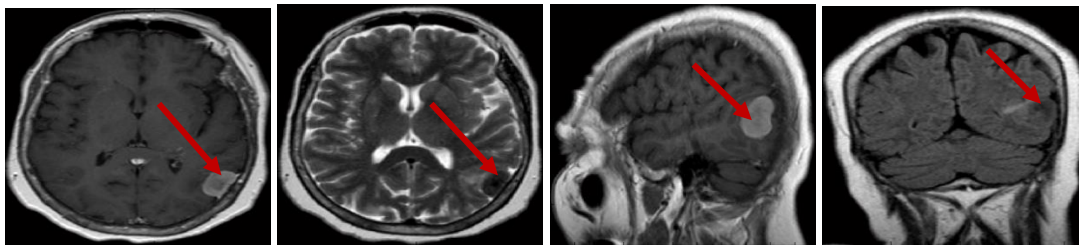
$$u_{ik} = \frac{1}{\sum_{j=1}^v \left(\frac{d_{ik}}{d_{jk}} \right)^{\frac{2}{m-1}}} \quad (3)$$

$$c_i = \frac{\sum_{k=1}^n (u_{ik})^m x_k}{\sum_{k=1}^n (u_{ik})^m} \quad (4)$$

Where for each i , u_{ik} satisfies: $u_{ik} \in [0,1], \forall k \sum_{i=1}^v u_{ik} = 1$ and $0 < \sum_{k=1}^n u_{ik} < n$ (Bezdec, 1981).

Experimental Materials and Datasets

The adopted images in this work were four MRI brain images of a patient with Mengioma Meningioma tumor. These images were acquired utilizing PHILIPS-9E9FE39 MRI scanning system, with static magnetic field of intensity equals 1.5T, in Al-Hilla surgical hospital in Iraq. The utilized images are of different modalities as shown in Fig.(1) and the necessary information of them are presented in Table (1).



Figure(1): The adopted input images :image1, image2, image3 and image4 from left to right respectively. The arrows refer to the abnormalities(tumors) in the images.

Table (1): The characteristics and information of the adopted images.

Image Name	Orientation	Modality	Slice Thickness	Pixel Spacing	Matrix Size
Image1	axial	T1W_SE	5 mm	0.89286 x 0.89286	224 x 224
Image2	axial	T2W_TSE	5 mm	0.89844 x 0.89844	256 x 256
Image3	sagittal	T1W_SE	5 mm	0.89286 x 0.89286	224 x 224
Image4	coronal	T2W_FLAIR	5 mm	0.89844 x 0.89844	256 x 256

Methodologies and Results

The proposed procedure of this work is summarized in the following block diagram:

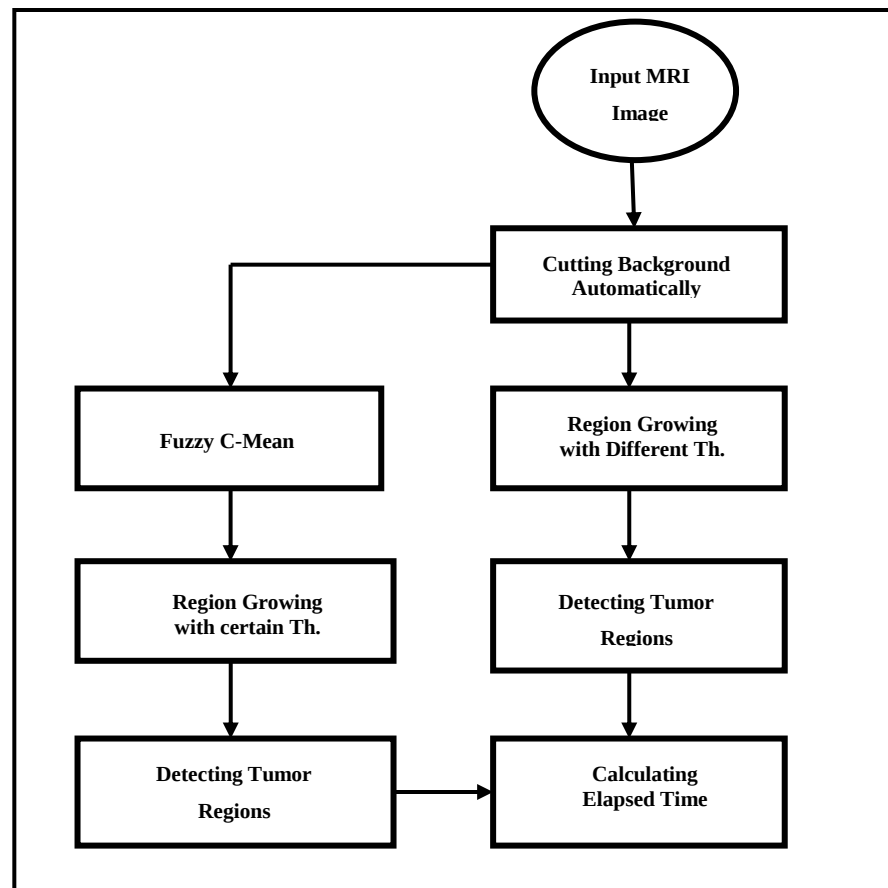
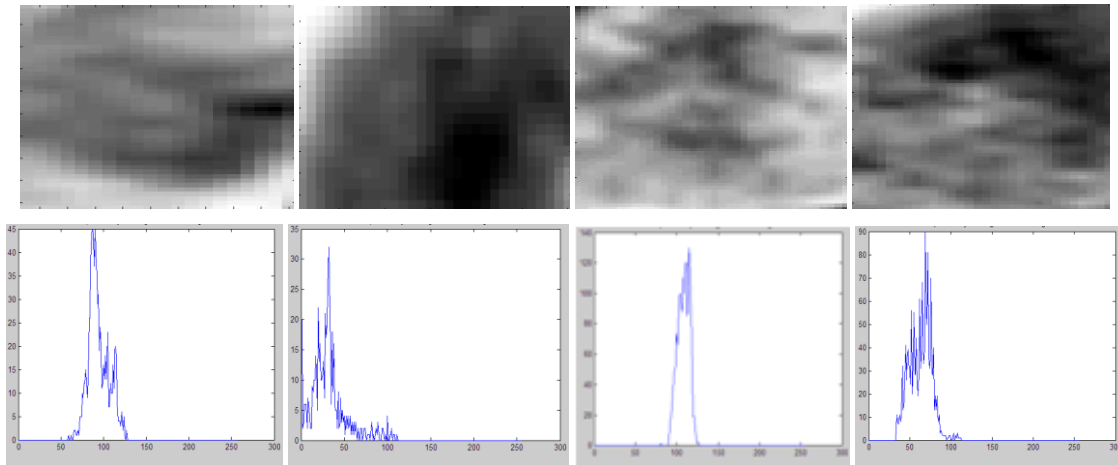


Figure (2): The block diagram of the proposed work.

1.Histogram of Tumor Regions

Before implementing the steps of this work, portions of the tumor regions were cut from the four adopted images as samples and the histogram of each of them was plotted to find out the intensity range of the tumor regions in the four images which are belonging to the four different modalities of MRI scanning as shown in Fig.(3).



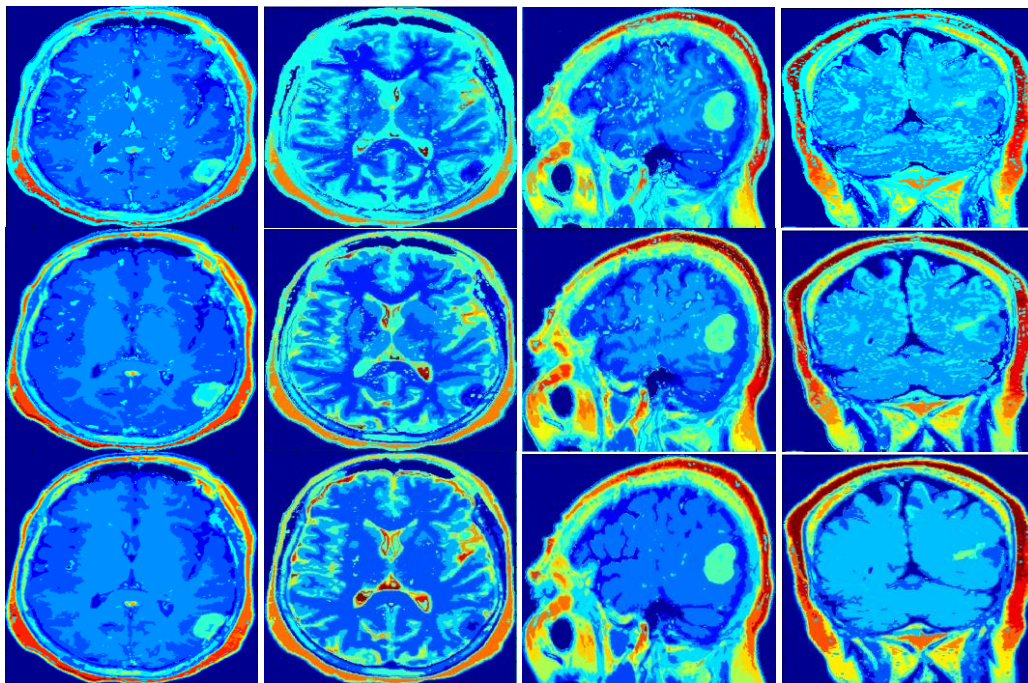
Figure(3): Extracted portions from the adopted images and the corresponding histogram of each of them: Image1, image2, image3 and image4 from left to right respectively.

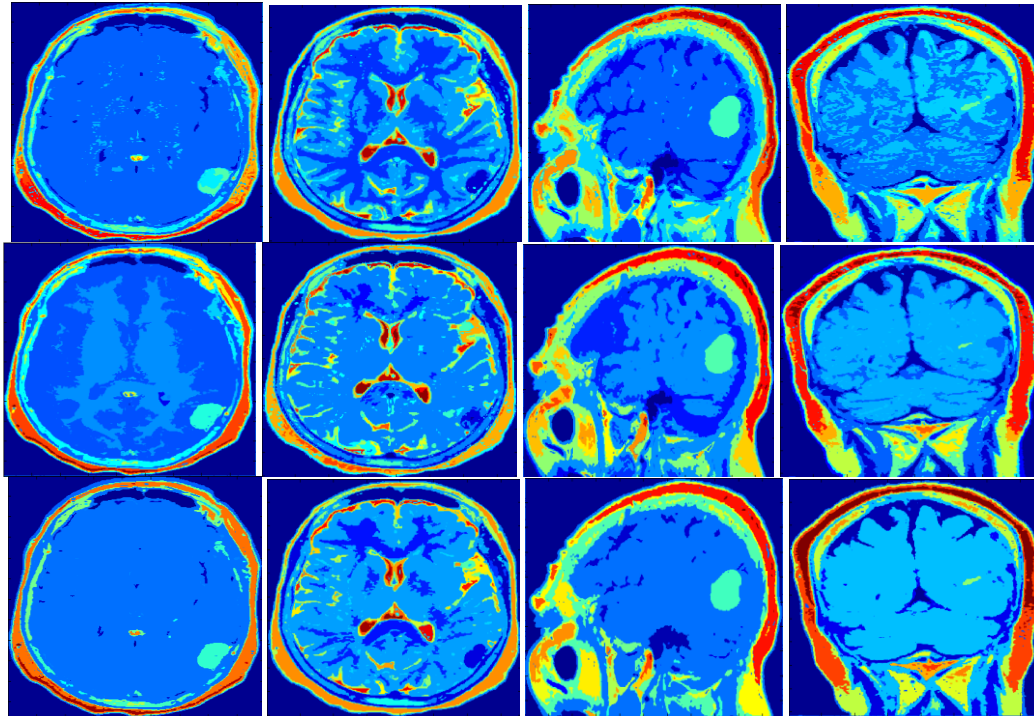
2.Cutting Background

The backgrounds of the input four images were cut automatically depending on the moment of the utilized images, for details see (Rabab et. al., 2015b).

3.Analysis Study of Region Growing Algorithm

Many threshold values were adopted to analysis the performance of region growing algorithm. These values of threshold are: 10, 15, 20, 25, 30 and 35, and the results of this step for the four images are presented in Fig.(4).





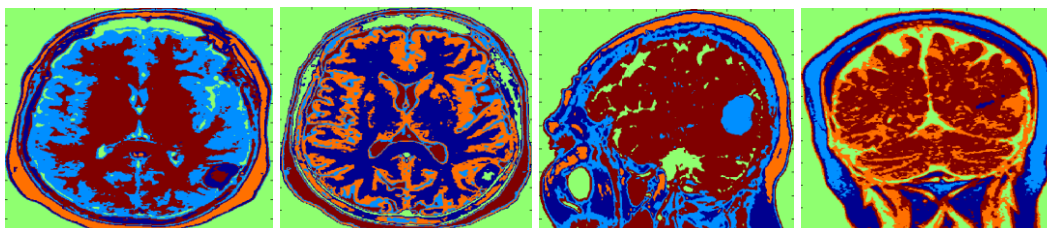
Figure(4): The results of implementing region growing algorithm on image1, image2, image3 and image4 from first to fourth column respectively with different values of threshold from 10 to 35 with steps of 5 from first to last row respectively.

By inspection Fig.(4), it is clear that utilizing different values of the threshold in proceeding of Region Growing algorithm produced different segmented images. When the fine details of the processed images and their objects are the goal, low values of threshold must be adopted, while when the isolating of the tumor regions is the goal, high values of the threshold must be adopted. This is obvious for the adopted image except the fourth one, since it has no contrast agent.

4.Region Growing Algorithm based on Fuzzy Clustering

In this stage of the study, an adaptive technique is proposed. Region growing segmentation algorithm was implemented on Fuzzy C-Mean clustered images, as well as the input MRI brain images, to investigate the performance of region growing method. FCM was implemented with five clusters since there are five different tissues: WM, GM, CSF, Skull and Tumors.

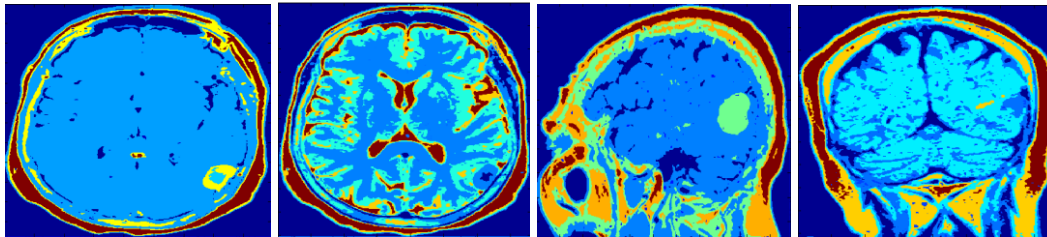
1-The results of applying FCM of the four images are shown in Fig.(5).



Figure(5): The results of implementing FCM on image1, image2, image3 and image4

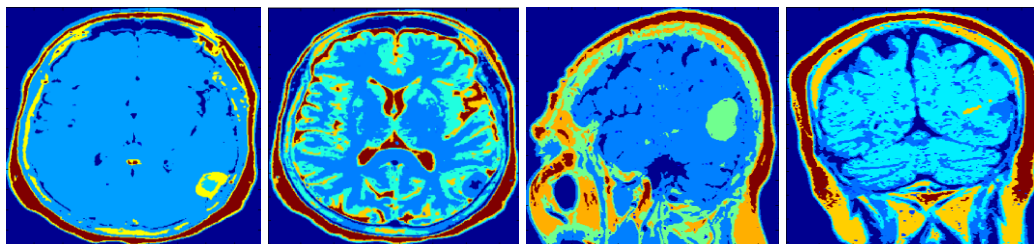
from left to right respectively.

2- Region growing algorithm was implemented with threshold values: 20, 25, 20 and 15 for image1, image2, image3 and image4 respectively, this algorithm was implemented on the resultant images of step 1 and the results are presented in Fig.(6).



Figure(6): The results of implementing Region Growing on the FCM clustered images of image1, image2, image3 and image4 from left to right respectively.

3. To compare the performance of Region Growing algorithm and Region Growing based on FCM clustering of the same threshold values, the resultant images of the two methods are demonstrated in Fig.(7).



Figure(7): A visual comparison of the results of implementing Region Growing(in first line) and Region Growing based on FCM clustered images (in second line) of the four images.

From Fig.(7), the resultant images of the Region Growing and the results of the adaptive technique showed that region growing segmentation improved its performance and presents the consists of the tumor regions (the center of the tumor and the surrounding region) especially in image1 and image 2. The second advantage of the adaptive technique is that, it increased the implementation speed of Region Growing algorithm and reduced the elapsed time as presented in Table (2).

Table (2): The elapsed time of implementing conventional Region Growing and adaptive Region Growing.

Image Name		Image1	Image2	Image3	Image4
Elapsed Time (sec)	Region Growing	380.2591	363.7379	345.4591	297.5431
	Region Growing based on Clustering	273.2921	260.1580	312.0098	213.8511

Conclusions

The results showed that, utilizing different values of the threshold in proceeding of Region Growing algorithm produced different segmented images. When the fine details of the processed images and their objects are the goal, low values of threshold must be adopted, while when the isolating of the tumor regions is the goal, high values of the threshold must be adopted. This is obvious for the adopted image except the fourth one, since it has no contrast agent. In addition, the results of the adaptive technique showed that region growing segmentation improved its performance and presents the consists of the tumor regions (the center of the tumor and the surrounding region) especially in image1 and image 2. The second advantage of the adaptive technique is that, it increased the implementation speed of Region Growing algorithm and it succeeded to reduce the elapsed time of implementation.

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