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Watershed Transform Based on Clustering Techniques to Extract Brain Tumors in MRI

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Abstract

In this work, watershed transform method was implemented to detect and extract tumors and abnormalities in MRI brain skull stripped images. An adaptive technique has been proposed to improve the performance of this method.Watershed transform algorithm based on clustering techniques: K-Means and FCM were implemented to reduce the oversegmentation problem. The K-Means and FCM clustered images were utilized as input images to the watershed algorithm as well as of the original image. The relative surface area of the extracted tumor region was calculated for each application. The results showed that watershed trnsform algorithm succeedeed to detect and extract the brain tumor regions very well according to the consult of a specialist doctor after viewing the resultant images. The adaptive technique, watershed based on clustered segmented image, improved the performance of the watershed transform and reduced the oversegmentation problem, and the utilizing of bilateral smoothing improves this result.

Keywords: Watershed transform, clustering, K-Means, FCM, MRI, Brain tumor.

استخدام تحويل الحد الفاصل المعتمد على تقنيات العنقدة لاستخراج أورام الدماغ في صور الرنين المغناطيسي

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الخلاصة

لقد تم في هذا العمل تطبيق تحويل الحد الفاصل (watershed) للكشف عن واستخراج الأورام والأنسجة غير الطبيعية في صور الرنين المغناطيسية للدماغ بعد إزالة عظام الجمجمة. وقد تم اقتراح تقنية مطورة لتحسين أداء هذه الطريقة، وهذه التقنية هي خوارزمية تحويل احد الفاصل المعتمدة على تقنيات العنقدة (K-Means and FCM) للحد من مشكلة oversegmentation. استخدمت الصور المقسمة باستخدام K-Means and FCM كصور داخلة بالإضافة إلى الصور الأصلية. كما تم حساب المساحة النسبية لمنطقة الورم المستخلصة لكل تطبيق. وأظهرت النتائج أن خوارزمية تحويل الحد الفاصل قد نجحت بالكشف عن واستخراج مناطق الورم بشكل جيد للغاية طبقا لاستشارة الطبيب المختص بعد عرض النتائج عليه. ان التقنية المطورة، تحويل الحد الفاصل المستند على الصور المقسمة باستخدام تقنيات العنقدة، قد حسنت من أداء تحويل watershed وقللت من مشكلة oversegmentation، كما وأن استخدام التنعيم بواسطة مرشح الثنائي قد ساهم في تحسين هذه النتيجة.

Introduction

Brain tumor is the most life-threatening disease, so accurate and speedy diagnosis is an urgent need. Medical imaging technology helps doctors to see the interior portions of the body for easy diagnosis. MRI technique is a powerful noninvasive technique that allows great contrast in soft tissues,

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high spatial resolution and has both anatomical and functional information in comparison with other kinds of medical imaging techniques. MRI is a tomographic imaging technique that taking many thin sliced images from many orientations and integrating them into a single image series.

Many segmentation approches are avaialble to solve varity of image processing problems. These approches can be divided into: boundary based techniques, region based techniques and statistical based techniques [1]. Watershed transform is a powerful tool for image segmentation; it is a region based approach of segmentation [2]. Watershed transform has many advantages: it is a simple intuitive method, it is always provides closed contours, that is very important in image segmentation, it is fast i.e. it requires low computation times in comparison with other segmentation methods and it produces a complete division of the image in separated regions even if the contrast is poor. The watershed transform has been widely used in many fields of image processing; one of them is medical image segmentation [3].

The watershed transform was initially presented by [4,5].They considered the gray scale images as topographic reliefs, each relief is flooded from its minima. When two lakes of water merge, a dam is built, the set of all dams define what so called watershed. Such representation of the watershed simulates the flooding process [3]. Other processes can be found in many literature such as [5,6]. However, using a standard morphological watershed transform on the original image or on its gradient, it is usually associated by oversegmentation of the resultant image. To decrease the oversegmentation, several approaches have been proposed likes watershed techniques based on markers [7], region merging methods [8], scale space approaches [9], methods based on partial differential equations for image de-noising or edge enhancement[10], wavelet techniques combined with a watershed transform [11]. Many other researchers widely studied and successfully applied watershed transform in image segmentation like [2, 3]. In this work, watershed transform is utilized for the first time to detect and extract the tumor regions in MR brain images. An adaptive technique, watershed transform based on clustered segmented images, is implemented to reduce the oversegmentation problem.

Watershed Transform

Briefly speaking, watershed in geography is a ridge that divides areas drained by different river systems. The geographical area draining into a river or reservoir is called a catchment basin. The watershed transform implements these ideas on gray scale image processing to help solving a variety problems of image segmentation [12].The concept of this method is based on visualizing an image in three dimensions: two of them represent the spatial coordinates and the third is the gray levels. According to such topographic interpretation, there are three types of points: (1) points belonging to a regional minimum, (2) points at which a drop of water, if placed at the location of any of these points of (1), would fall with certainty to asingle minimum, and (3) points at which water would be equally likely to fall tomore than one such minimum. For a particular regional minimum, the set of points that satisfying condition (2) is called the catchment basin (watershed) of the minimum. The points satisfying condithion (3) represent crest lines on the topographic surface and called watershed lines [13].Watershed transform can be implemented by applying flooding process. This flooding process can be achieved by using basic morphological operations. The algorithm of watershed transform is based on the concept of “immersion”. In this algorithm, each local minimum of a gray scale image, which can be regarded as a surface, has a hole and the surface is immersed out into water. Then, starting from the minima of the lowest intensity value, the water will progressively fill up different catchment basins of the image (surface). Conceptually, the algorithm then builds a dam to avoid a situation that the water coming from two or more different local minima to be merged. At the end of this immersion process, each local minimum is totally enclosed by dams corresponding to watersheds of the image (surface) [2]. There are three main methods of implementing watershed transform, which are: Distance transform approach, Gradient method and Marker controlled approach, for details see [13]. The three mentioned methods of applying watershed algorithm are implemented in this work, and the details are presented in [12].

Clustering Techniques

Clustering is a process that utilizing for segmenting and classifying objects in such a way that samples of the same group are more similar to each other than samples belonging to different groups. Many clustering schemes have been used, such as the hard clustering and the fuzzy clustering, each of them has its own characteristics. The hard clustering method restricts each point of the data set to exclusively just one cluster. Among this kind of clustering methods, K- Means, which is used clustering algorithm to partition data into certain number of clusters [14]. One of the fuzzy clustering methods, Fuzzy C-Mean (FCM) algorithm that is very popular method utilized in image segmentation because it has robust characteristics for ambiguity and can retain more information than hard segmentation methods. In FCM algorithm the data patterns may belong to more than one cluster, having different membership values. The membership value of a data to a cluster denotes similarity between the given data pattern to this cluster [15]. In this work, K-Means and FCM clustering techniques are implemented to segmented each of the adopted image into five clusters to detect and extract the tumor and abnormalities and to utilize the resultant segmented images as input to the watershed algorithm to reduce the oversegmentation of the resultant watershed segmented images, for more details about K-Means and FCM algorithms see [14, 15].

Skull Stripping Utilizing Active Contour Algorithm

In this part of the work, active contour was implemented to achieve skull stripping process to extract the fine brain tissue in order to avoid the interference between the intensity of the skull and the tumors. This process was applied with initialization element of circular shaped with radius of 50 pixels and with 1750 iteration. The size and position of the initialized element depends on the slice's shape and position, for details of the steps of this process see [16].

Smoothing (Bilateral Filtering)

The smoothing of the adopted images is achieved by utilizing bilateral filter to get rid of the noise in these images while maintain the edges of regions of interest and to avoid the blockness of the images' pixels. The size of the using bilateral filter window was 5x5 pixels and with sigma value of 15,these values were adopted after many experiments of different other values, for details see [17].

Experimental Materials

The experemental MRbrain images, that adopted in this work, are four sliced images of T2-weighted modality acquired from the internet website (*Whole Brain Atlas site)* for a patient with Metastatic Bronchogenic Carcinoma (malignant) tumor. Each of these images has size of 256 by 256 and spatial resolution (pixel spacing) equals (1mm, 1mm). The used samples possess good dis-connectivity between skull and brain tissues. Figure-1 shows the adopted MRI brain images.

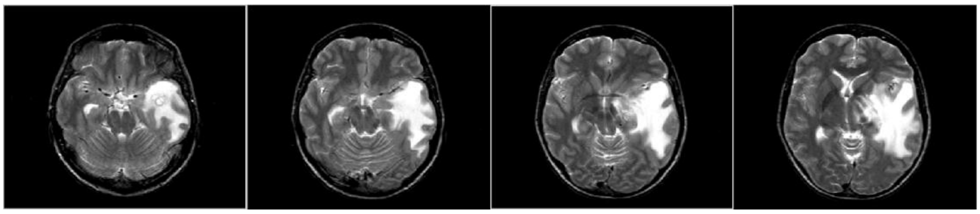


Figure 1- The adopted brain MRI images with Metastatic Bronchogenic Carcinoma tumor [Whole Brain Atlas website].

Experimental Results

The experiments of this work involved skull stripping followed by bilateral smoothing and then implementing watershed and watershed based on clustering segmented images as follows:

(I) Watershed Transform

1. Inputing brain MR image.
2. Skull stripping process utilizing active contour algorithm, and the results are shown in Figure-2.
3. Bilateral smoothing, and the results are shown in Figure-3.
4. Implementing watershed transform on the images of step 2 and 3 and the results of the steps of this process are shown in the Figure-3 and Figure-4.

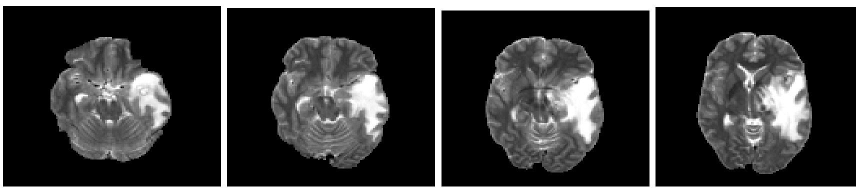


Figure 2-Thebrain MR images after skull stripping utilizing active contour algorithm.

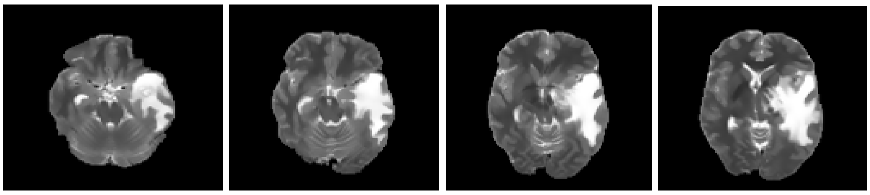


Figure 3-The brain MR images of figure 2 after bilateral smoothing.

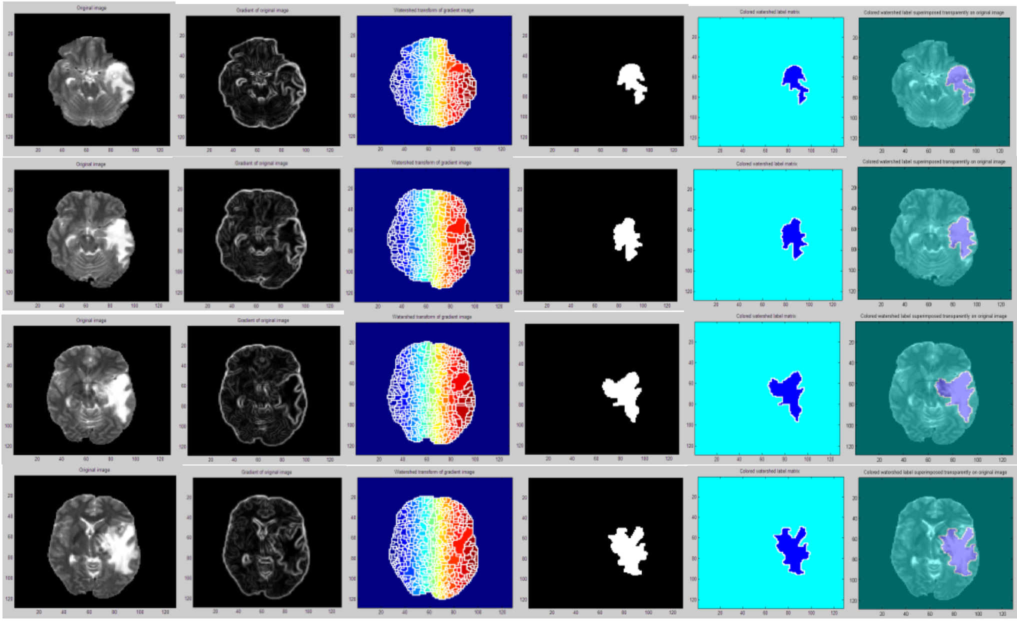


Figure 4-The steps of implementing watershed transform on brain MR images of Figure-2.

Figure-4 demonstrates the input skull stripped images, the gradient of them utilizing sobel filter, watershed transform of the gradient images, the detected tumor regions, color watershed label of the tumor regions and the color watershed label superimposed on the input images from first column to the last one respectively.

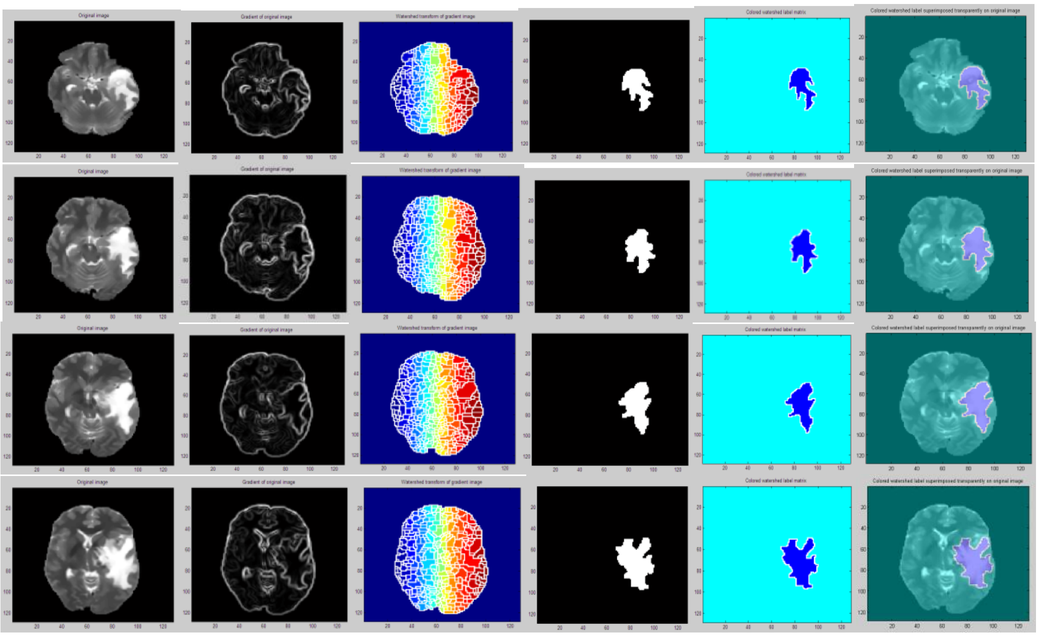


Figure 5-The steps of implementing watershed transform on bilateral smoothed brain MR images of Figure-3.

Figure-5 illustrates the input bilateral smoothed skull stripped images, the gradient of them utilizing sobel filter, watershed transform of the gradient images, the detected tumor regions, color watershed label of the tumor regions and the color watershed label superimposed on the input images from first column to the last one respectively.

(II) Watershed transform based on K-Means segmented images

1. Implementing K-Means clustering algorithm of five clusters on the images of step 2 and step 3 of part(I). The results of this step are shown in Figure-6 and Figure-7.

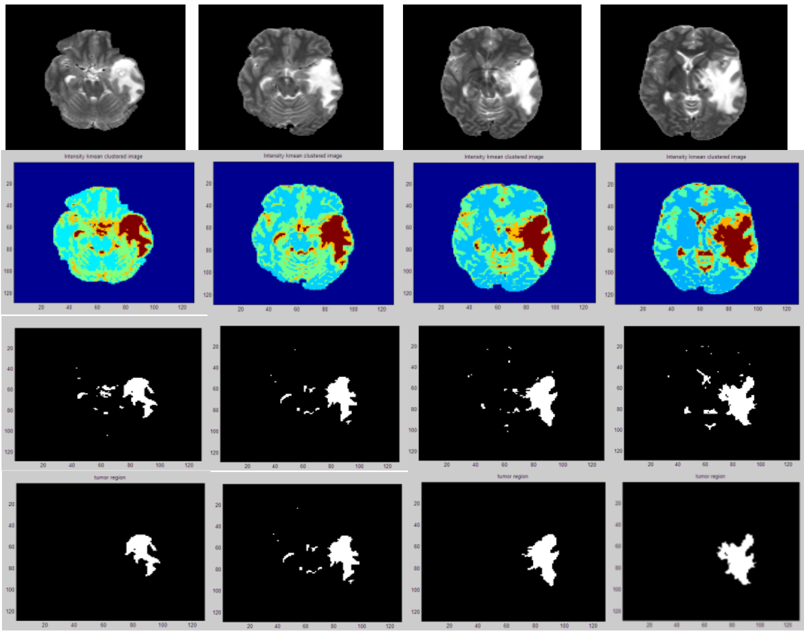


Figure 6-The steps of implementing K-Means clustering on brain MR images of figure 2 and extracting tumor regions.

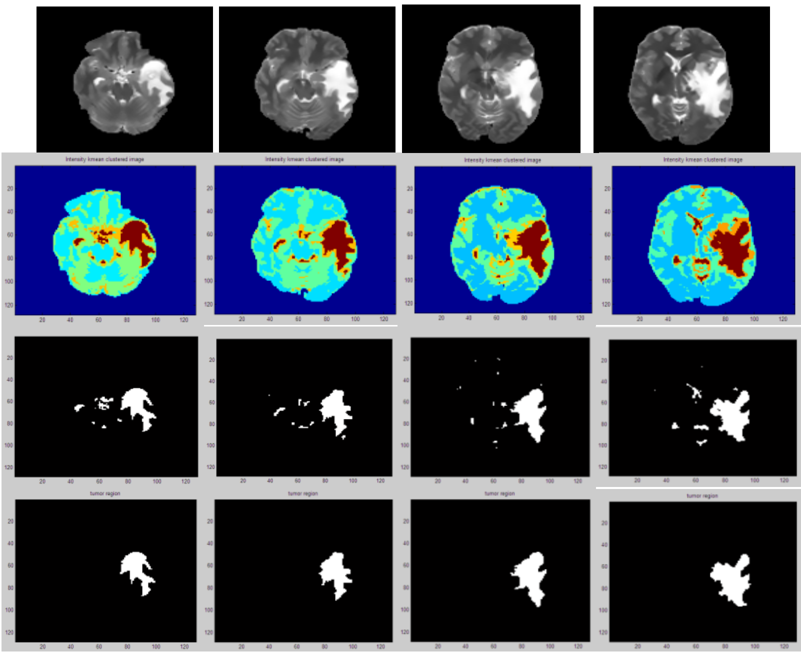


Figure 7-The steps of implementing K-Means clustering on bilateral smoothed brain MRI images and extracting tumor regions.

In Figure-6 and Figure-7, the results of implementing K-Means clustering into five clusters are presented. The input skull stripped images are presented in first row, while the clustered images and the cluster to which the tumor belongs are showed in the second and third rows respectively.

The extracted tumor regions are presented in the last row after removing the extra pixels by applying maximal region properties.

2. Implementing watershed transform on the K-Means clustered image for each of the images that results from the previous step. The results of this operation are shown in Figure-8 and Figure-9.

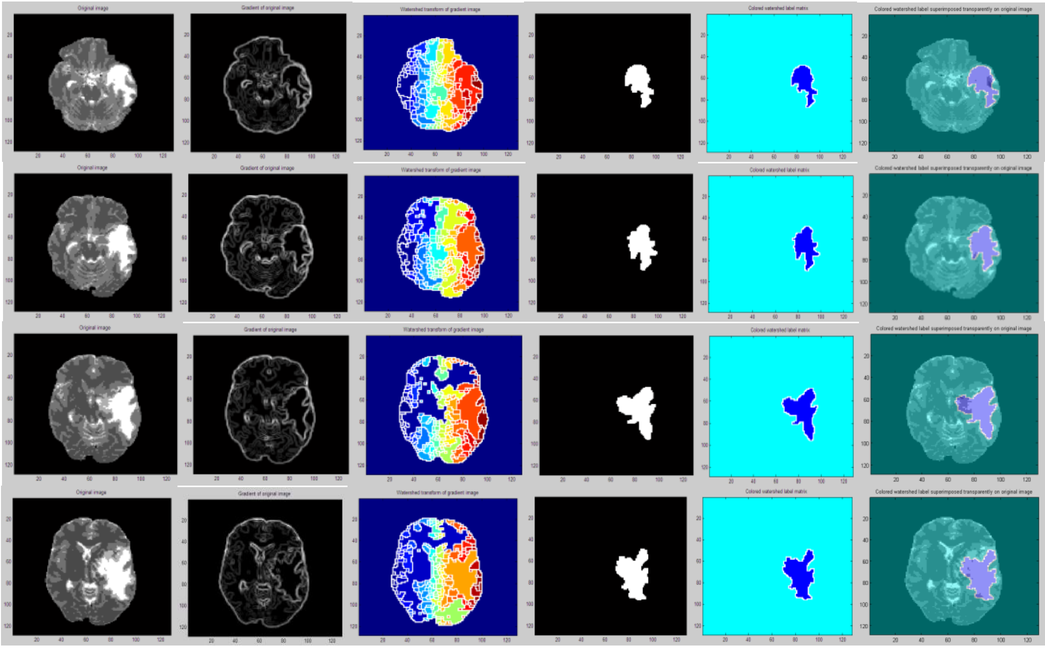


Figure 8-The steps of implementing watershed transform based on K-Means of brain MR images of Figure-2.

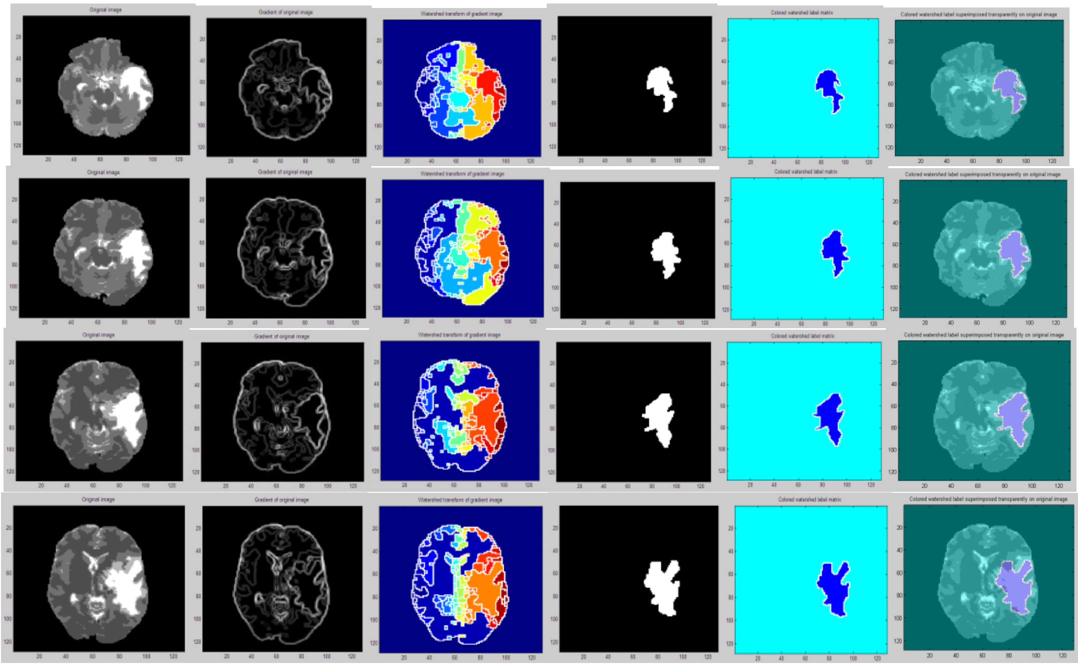


Figure 9- The steps of implementing watershed transform based on K-Means of bilateral smoothed brain MR images of Figure-3.

In Figure-8 and Figure-9, the first column shows the K-Means clustered images, the gradient of these images are presented in second column, watershed segmented images of the previous images are in third column. The detected tumor regions, color watershed label of the tumor regions and the color watershed label superimposed on the input images are in fourth, fifth and sixth columns respectively.

(III) Watershed transform based on FCM segmented image

1. Implementing FCM clustering algorithm of five clusters on the images of step 2 and step 3 of part (I). The results are shown in Figure-10 and Figure-11.

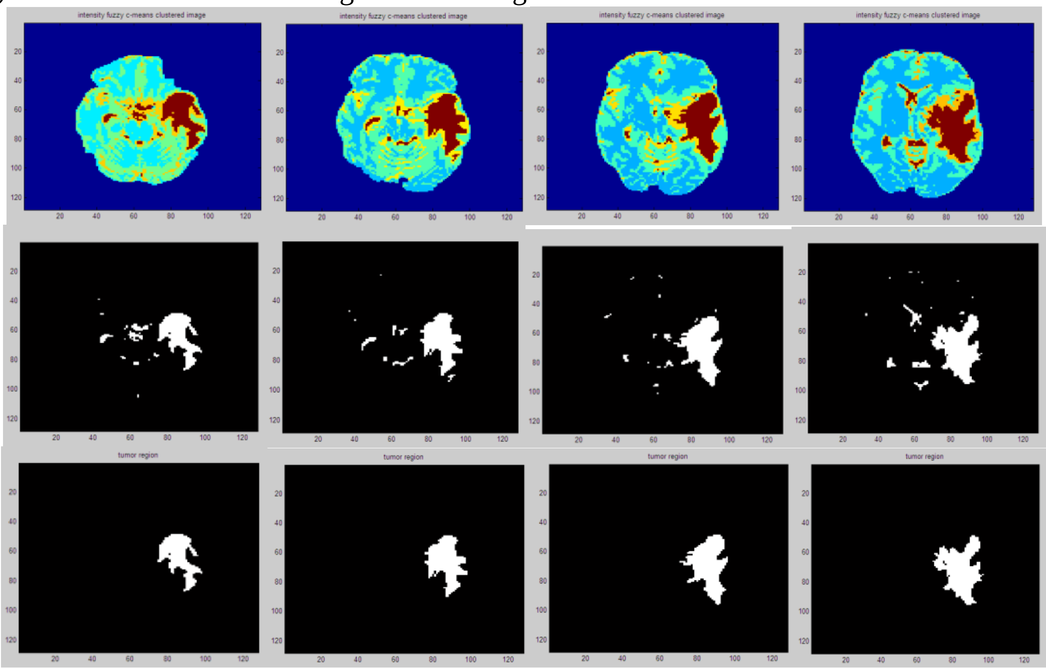


Figure 10-The steps of implementing FCM clustering on brain MR images of Figure-2.

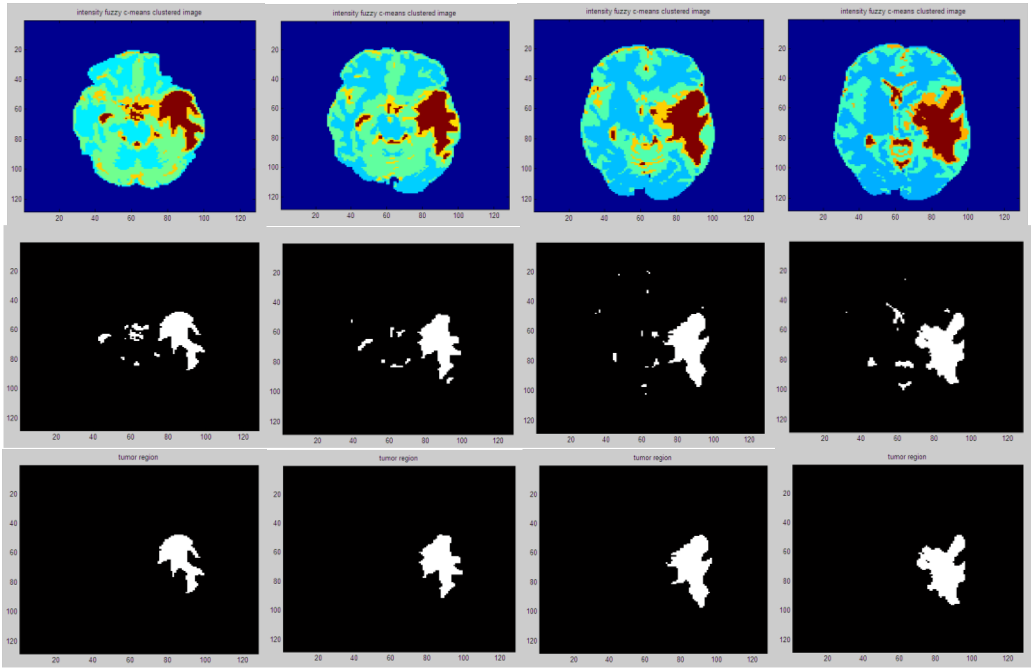


Figure 11-The steps of implementing FCM clustering on bilateral smoothed brain MRI images of Figure-3.

The Figure-10 and Figure-7 show the results of implementing FCM clustering into five clusters algorithm. The input skull stripped images are presented in first row, while the clustered images and the cluster to which the tumor belongs, are shown in the second and third rows respectively. The extracted tumor regions are presented in the last row after removing the extra pixels by applying maximal region properties.

2. Implementing watershed transform based on the FCM clustered image for each of the images results from the previous step. The results of this operation are shown in Figure-12 and Figure-13.

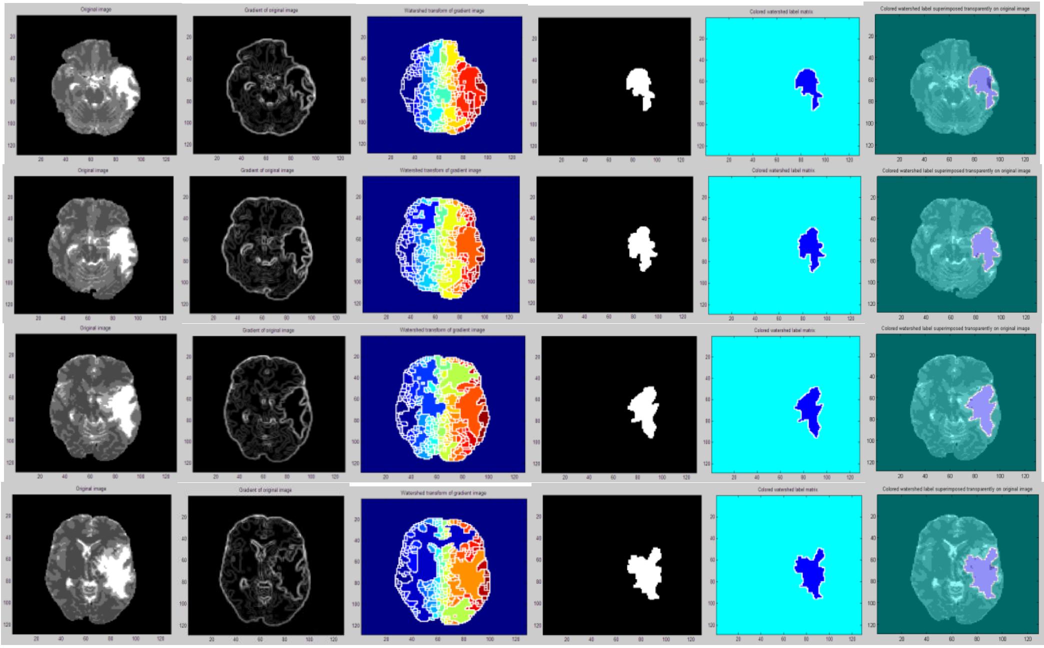


Figure 12-The steps of implementing watershed transform based on FCM of brain MR images of Figure-2.

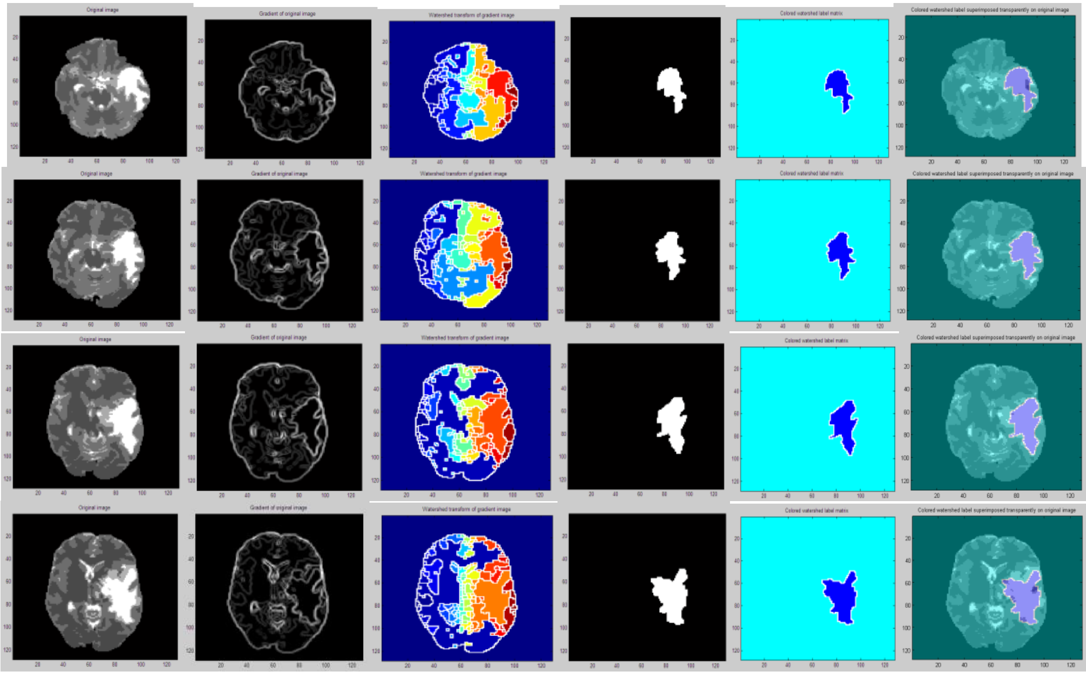


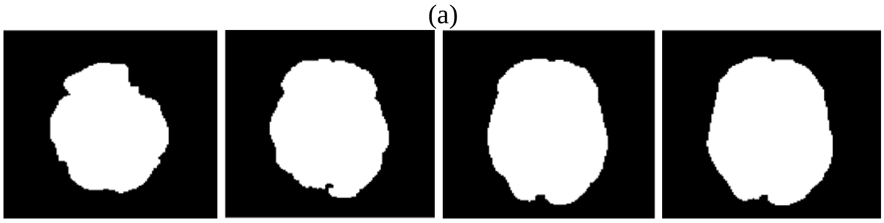
Figure 13-The steps of implementing watershed transform based on FCM of bilateral smoothed brain MR images of Figure-3.

In Figure-12 and Figure-13, the first column shows the FCM clustered images, the gradient of these images are presented in second column, watershed segmented images of the previous images are in third column. The detected tumor regions, color watershed label of the tumor regions and the color watershed label superimposed on the input images are in fourth, fifth and sixth columns respectively.

(IV) The Relative Surface Area

To calculate the relative surface area of the extracted tumor regions, the extracted tumor regions' area were calculated by adopting the binary images of each of them and the BW (binary) mask of the brain tissue of the adopted MR brain images of Figure-2 and Figure-3 was found by adopting a suitable threshold, as shown in Figure-14.The surface area of each of them was calculated depending on the spatial resolution of the utilized images which is (1mm x 1mm)/pixel.

(a)



(b)

Figure 14-The BW mask of brain tissue images of figure 2 and figure 3 in (a) and (b) respectively.

The values of the surface area are as were found to be: **4609, 5274, 5710** and **5870** mm^2 for the images of figure 14-a and **5079, 5809, 6273** and **6456** mm^2 for the images of Figure-14b. By adopting these values, the calculated relative surface areas of the extracted tumor regions are presented in Table-1.

Table 1- The relative surface area of the extracted tumor regions of the four images for the three proposed techniques.

Image Name	Relative Surface Area					
	Watershed		Watershed based on K-Means		Watershed based on FCM	
	Without Smoothing	With Bilateral Smoothing	Without Smoothing	With Bilateral Smoothing	Without Smoothing	With Bilateral Smoothing
Image1	0.1146	0.1132	0.1165	0.1083	0.1139	0.1107
Image2	0.1134	0.1090	0.1141	0.1048	0.1141	0.1057
Image3	0.1492	0.1199	0.1468	0.1197	0.1231	0.1189
Image4	0.1612	0.1530	0.1431	0.1417	0.1385	0.1394

Comparison of the Implemented Algorithms

1. To investigate the effect of bilateral smoothing on the input image of the applied algorithm, *visual comparisons* of the extracted tumor regions and colored watershed label superimposed transparently on the input image of the Figure-2 and Figure-3 are shown in Figure-15 and Figure-16 respectively.

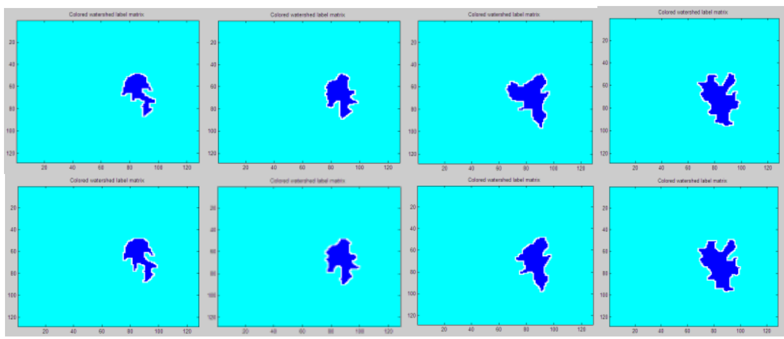


Figure 15- A visual comparison of extracted tumor regions' colored watershed of the input image of Figure-2 and Figure-3 in first and second row respectively.

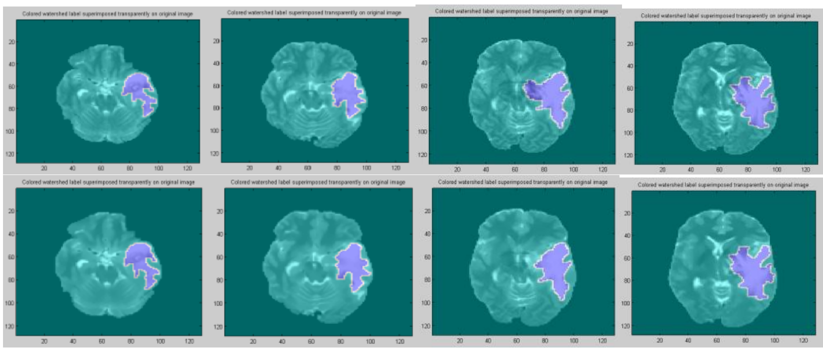


Figure 16- A visual comparison of colored watershed label superimposed transparently on the input image of the Figure-2 and Figure-3 in first and second row respectively.

2. To investigate the performance of watershed transform and watershed transform based on K-Means and FCM clustered images, *a visual comparison* of the extracted tumor regions and colored watershed label superimposed transparently on the input images of Figure-2 are shown in Figure-17 and Figure-18 respectively, while the results for the images of Figure-3are shown in Figure-19 and Figure-20.

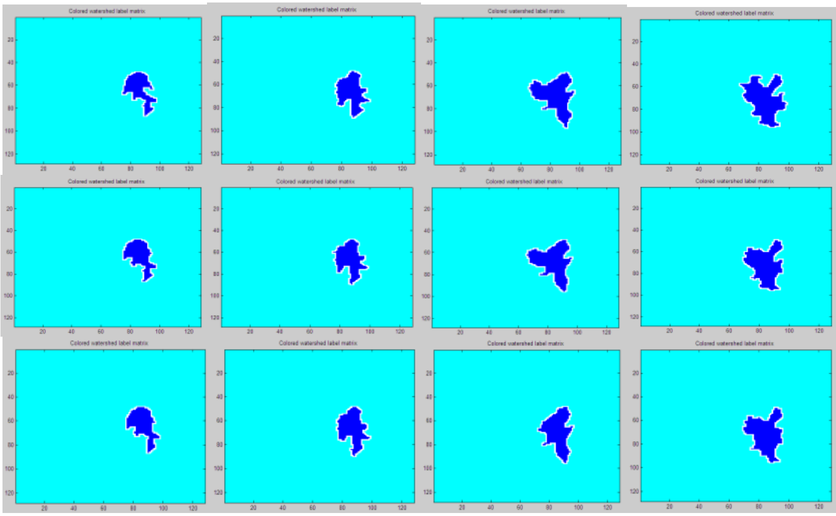


Figure 17- A visual comparison of extracted tumor regions by implementing watershed transform and watershed transform based on K-Means and FCM clustered images from first row to the last one for the brain MRI images of Figure-2.

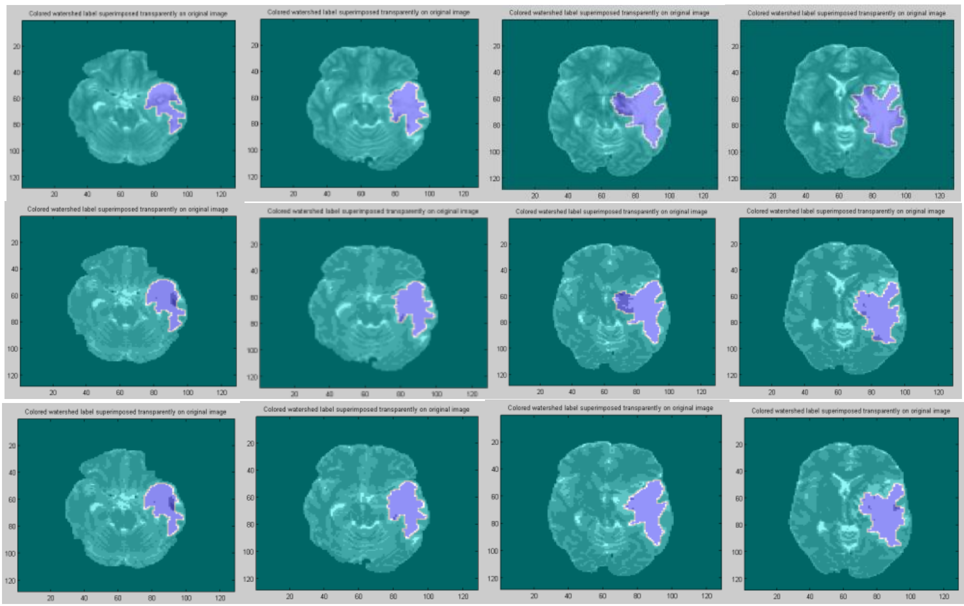


Figure 18- A visual comparison of watershed transform, watershed transform based on K-Means and FCM clustered images from first row to the last one for the brain MRI images of Figure-2.

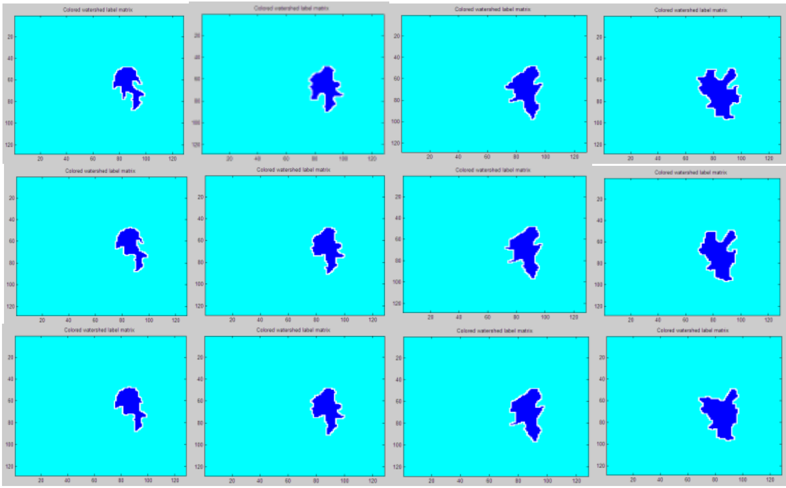


Figure 19- A visual comparison of extracted tumor regions by implementing watershed transform, watershed transform based on K-Means and FCM clustered images from first row to the last one for the bilateral smoothed MRI images of Figure-3.

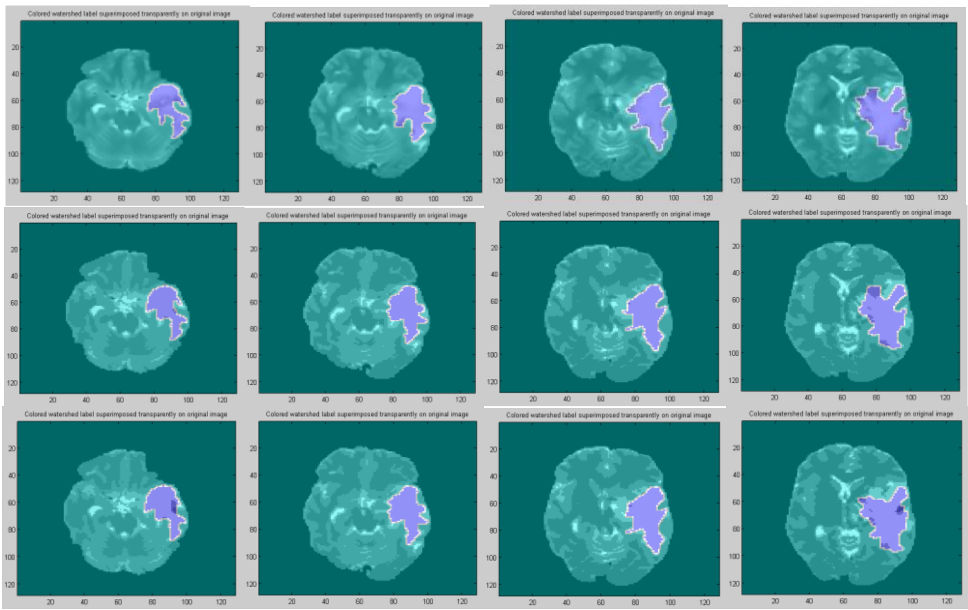


Figure 20- A visual comparison of watershed transform, watershed transform based on K-Means and FCM clustered images from first row to the last one for the bilateral smoothed MRI images of Figure-3.

Conclusions

In this work, watershed transform and two adaptive techniques: watershed based on K-Means clustered image and watershed based on FCM clustered image, have been adopted to *detect and extract the tumor regions from four MR brain sliced images after skull striping process for the first time*. By inspection of the watershed segmented resultant images in Figure-8, Figure-9, Figure-12 and Figure-13 and compare them with the results in Figure-4 and Figure-5, it is clear that the adaptive techniques reduced the oversegmentation problem, and the utilizing of bilateral filter has improved this result. The relative surface areas of the tumor regions were measured with respect to the brain tissue surface area for each of the four sliced images. The results of this work showed high quality performance of the proposed techniques according to consult of a specialist doctor in medical radio-therapy after viewing the resultant images, and it can adequately use to detect and extract the tumors and abnormalities in MR brain images. This work can be incorporated in studying the tumors as well as, it can be used for diagnosis, treatment planning, surgery and many other applications in this field.

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