Automatic Technique to Produce 3D Image for Brain Tumor Of MRI Images

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Abstract

In this research, three-dimensional images of brain tumors have been constructed from a series of Magnetic Resonance Images (MRIs) for successive T1-weighted slices, using a simple automatic technology. The MRIs are pre-processed through bilateral filtering to reduce noise and retaining the edges between brain tissues. Spatial enhancement technique is adopted to transform image gray levels by highlighting the band density of the region of interest (tumor) and expanding them into full range. Sobel edge detection is used by morphological operations to extract the tumor area of the image of each slice. The contour of the tumor area in each segmented slice is used to create 3D of the tumor. The relative size of the tumor then measured depending on brain tissue after stripping the skull. The result showed that the adopted technique can efficiently detect and extract the brain tumor from the consecutive slices which can be used to produce 3-D image of the tumor and to identify the tumor's location inside the skull.

Keywords : MRI; Brain Tumor; MRI Enhancement; Morphological Operations .

ألخلاصة

في هذا البحث، تم بناء صور ثلاثية الأبعاد لأورام المخ من سلسلة من صور الرنين المغناطيسي لشرائح T1 متعاقبة، وذلك باستخدام تكنولوجيا أوتوماتيكية بسيطة. تم معالجة صور الرنين المغناطيسي بعملية ثنائية للحد من الضوضاء والحفاظ على حواف بين أنسجة الدماغ. اعتمدت التقنية الإطار المكاني لتحويل مستويات الشدة في الصور من خلال تسليط الضوء على الفرق بين مستويات الشدة في منطقة الورم. استخدمت تقنية سوبيل للكشف عن الحافات وبعملية مورفولوجية لعزل منطقة الورم من الصورة لكل شريحة. تم استخدام مخطط الكفاف (المخطط الكونتوري) في منطقة الورم في كل شريحة لإنتاج صور ثلاثية الأبعاد للورم. تم قياس حجم الورم النسبي بعد تجريده من الأنسجة المحيطة و الجمجمة. أظهرت النتائج كفاءة التقنية المعتمدة في تحديد وعزل الورم في الدماغ من الشرائح المتتالية وإمكانية استخدامها لإنتاج صور ثلاثية الأبعاد لأورام المح وتحديد موقع الورم داخل الجمجمة.

1.Introduction

Magnetic resonance imaging (MRI) provides rich three dimensional (3D) information about the human soft tissue anatomy. It reveals fine details of anatomy, and yet is non invasive and does not require ionizing radiation such as x-rays. It is a highly flexible technique where contrast between one tissue and another in an image can be varied simply by varying the way the image is made. The rich anatomy information provided by MRI has made it an indispensable tool for medical diagnosis in recent years (Alan Wee-Chung Liew and Hong Yan, 2006). It also helped treatment centers to make keyhole surgeries for reaching the interior parts without really opening too much of the body. Image Processing techniques developed for analyzing the outputs of medical imaging systems can be utilized to identify the disease type and location easily. Tumor detection and extraction from brain medical images such as MRI required implementation of good segmentation and classification processes. The most widely applied segmentation technique is manual segmentation, which has several disadvantages: (i) *generally requires a high level of expertise,* (ii) *it is time and labor consuming, and* (iii) *it is subjective and therefore not reproducible*. Studies investigating inter and intra-patient variations in cerebral function or anatomy have repeatedly shown these shortcomings, which explains the demand for automated techniques (Rik Stokking, et al., 2000).

Numerous studies of brain segmentation have been proposed, many of which can be categorized into two classes, *region detection methods* and *boundary detection methods.* They can be divided into three categories: *classification based*, *region-based*, and *contour-based*. Most existing segmentation methods are usually dedicated only for specific objects (Hari Prasath et al, 2012). Other approaches involve: interactive segmentation tools (Vehkomäki et al., 1997), elastically fitting boundaries (Zhu, and Yan, ,1997), mathematical morphology (Gibbs et al., 1996), neural networks (Dickson and Thomas, 1997), or calculation of texture differences between normal and pathological tissue (Kjaer et al, 1995). Warfield.. et al. in (Warfield.. et al. ,1995,2000) combined elastic atlas registration with statistical classification (Nathan Moon et al., 2002). A few publications have proposed the segmentation of pathological brain images. Computer aided tumor detection was done using watershed segmentation (Angel Viji and Jayakumari, 2011). A texture based tumor detection and seeded region growing was performed by (Mukesh Kumar and Kamal K.Mehta, 2011). Comparison of several segmentation algorithms like mean-shift, K-Mean, fuzzy C-Mean and Otsu's method have been discussed by (Gajanayake, et al., 2009). From these initial studies, the Otsu's method, mean-shift segmentation algorithm, K-means, Fuzzy C-Means have performed well in segmenting a brain tumor from a 2D MRI (Angel Viji and Jayakumari, 2012).

In this work, an automatic and simple technique has been developed, based on a pre-process image enhancement, using a suitable methods to detect and extract the tumor region in three successive MRI T1-weighted slices. As the tumor region is delineated in the three slices, a 3-D image is constructed for this tumor. A skull stripping morphological based method is then implemented to extract the brain tissue in the slices images and measuring the surface area of the brain tissue, which then used to compute the relative volume of the tumor region.

3. Magnetic Resonance Imaging (MRI)

One of the methods used for the diagnosis of the tumor as innocuous or malignant was to raise a small amount of brain tissue and analyzed under a microscope to decide the type of tumor in the brain. Standard x-rays and computed tomography (CT) have also used in the diagnostic process. However, Magnetic resonance imaging (MRI) is generally more useful because it provides more detailed information about brain tumor composition, cellular structure, vascular supply, tumor type, position and size, making it an important tool for the effective diagnosis, treatment and monitoring of the disease. For this reason, MRI is the imaging study of choice for the diagnostic work up and, thereafter, for surgery and monitoring treatment outcomes (Guy M. McKhann, 2006) (Kadam D. Bet al., 2011) and (Lorena Tonarelli and Hons, 2012). MRI is an imaging technique based on the measurement of magnetic field vectors generated after an appropriate excitation with strong magnetic fields and radiofrequency pulses in the nuclei of hydrogen atoms present in water molecules of a patients tissues. Given that the content of water differs for each tissue, it is possible to quantify the differences of radiated magnetic energy, and have elements to identify each tissue. When specific magnetic vector components are measured under controlled conditions, different images can be acquired and information related to tissue contrast may be obtained, revealing details that can be missed in other measurements (Kadam D. Bet al., 2011).

4. Image Enhancement Methods

The principal objective of enhancement is to process an image so that the result is more suitable than the original image for a specific application. Image enhancement approaches fall into two broad categories ***spatial domain methods*** and ***frequency domain methods***. There is no general theory of image enhancement. When an image is processed for visual interpretation, the viewer is the ultimate judge of how well a particular method works. Visual evaluation of images quality is a highly subjective process, thus making the definition of a "*good image*" an elusive standard by which to compare algorithm performance. However, even in situations when a clear–cut criterion of performance can be imposed on the problem, a certain amount of trial and error usually is required before a particular image enhancement approach is selected (Gonzalez and Woods, 2002). In this work the spatial domain category is adopted which can easily expressed by: (Gonzalez and Woods, 2002)

$$g\,(x, y) = T\,[f(x, y)] \tag{1}$$

Where f is the input image, g is the output (processed) image, and T is an operator on f defined over a specified neighborhood about point (x, y).

The simplest form of the transformation operator T is when the neighborhood is of one pixel size. In this case, the value of g at (x, y) depends only on the intensity of f at that point, and T becomes an *intensity* or *gray-level* transformation function. These two terms are used interchangeably, when dealing with monochrome images. When dealing with color images, the term *intensity* is used to denote a color image component in certain color spaces, for more details see (Gonzalez and Woods, 2002) and (Gonzalez et al. , 2004) and . Figure (1) below show various pixel based mapping methods that can be used to improve image appearance by utilizing ***imadjust*** tool of *MatLab*.

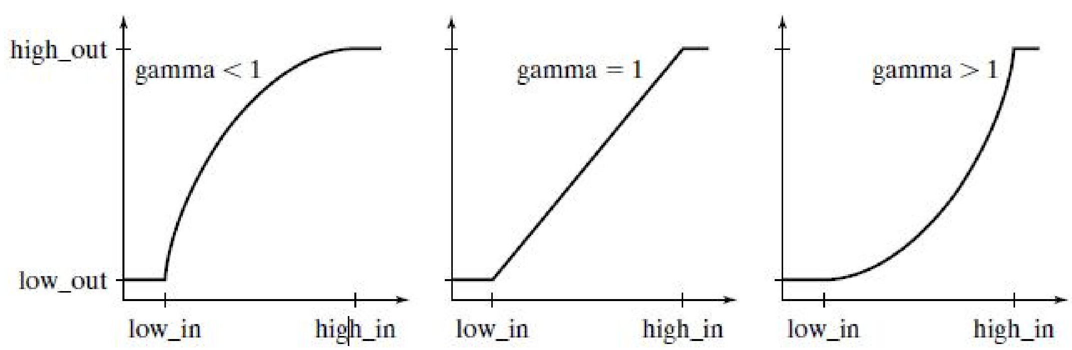

Figure (1) : Various mappings available in function imadjust tool of MatLab. (Gonzalez et al. , 2004)

In this work, this technique has been implemented to highlight the intensity of the tumor region.

5. Bilateral Filter

The bilateral filter that introduced by Manduchi *et al.*in1998 (Tomasi and Manduchi, 1998). It has been adopted to perform nonlinear smoothing to reduce the image noise and retaining the edge information. Nonlinear smoothing is performed by combining the geometric and intensity similarity of pixels. The filtering operation is given by; (Tomasi C. and Manduchi R.,1998),

$$I_b(x,y) = \frac{\sum_{n=-N}^{N}\sum_{m=-N}^{N} W(x,y,n,m)\ I_g(x-n,y-m)}{\sum_{n=-N}^{N}\sum_{m=-N}^{N} W(x,y,n,m)} \tag{2}$$

If $I_g(x , y)$ be a grayscale image having values in the range [0, 1] , $I_b(x, y)$ will be the bilateral filtered version of $I_g(x, y)$. This equation is simply a normalized weighted average of a neighborhood of $(2N + 1)\times (2N + 1)$ pixels around the pixel location (x, y).

The weight $W(x, y, n, m)$ is computed by multiplying the geometric weight factor, which is based on the Euclidean distance between the center pixel (x, y) and the $(x-n, y-m)$ pixel, and a weight factor that based on the grayscale intensity distance between the values at (x, y) and $(x - n, y - m)$. For discarding noise terms without disturbing object boundaries, the I_b function should be normalized by W(x, y, n, m).

6. Morphological Operations

Morphological operators have been used in the field of image processing and are preferred for their robust performance in preserving the shape of a signal, while suppressing the noise. Image morphology provides a way to incorporate neighborhood and distance information into algorithms. The basic idea in mathematical morphology is to convolve an image with a given mask (i.e. structuring element) and to binaries the result of the convolution using a given function. Choice of convolution mask and binarization function depends on the particular morphological operator being used. There are two basic morphological operators: erosion and dilation, opening and closing are two derived operations in terms of erosion and dilation.

1. **Dilation**: The dilation of a binary image can be expressed as :

$$X \oplus B = \{x : B_x \cap X \neq \emptyset\} \tag{3}$$

The dilation can be represented by the Minkowski sum of the two sets ***X*** and ***B*** :

$$X \oplus B = \cup_{x \in X} B_x \tag{4}$$

B_X represents the translation of the structuring element B to the point X.

2. **Erosion**: The erosion of X by B can be expressed as the set of points x where B_X can be positioned such that B is completely contained in X :

$$X \Theta B = \{x \setminus B_X \subset X\} \tag{5}$$

The erosion can be represented by the Minkowski difference of the two sets X and B :

$$X \Theta B = \bigcap_{b \subset B} X_b \tag{6}$$

3. Opening and Closing: The primitive operations of dilation and erosion are generally applied sequentially using a single structuring element. These combined operations are openings and closings. *The opening* consists of an erosion followed by a dilation and can be viewed as the union of all points in ***B*** everywhere that ***B*** is contained in ***X***. Opening is denoted in terms of the primitive operations of dilation and erosion as simply:

$$X^{op} = (X \Theta B) \oplus X\} \tag{7}$$

Closing reverses the order of operations such that ***X*** is first dilated and then eroded:

$$X^{cl} = (X \oplus B) \Theta B \tag{8}$$

These operations have been applied successfully to a broad variety of image processing analysis tasks (including shape recognition) encountered in diverse area such as biomedical image processing, for instance see (Serra J., 1982), (Gonzalez and Woods, 2002) and (Asma'a Al-Tamimy, 2005).

7. Skull Stripping

Skull stripping methods are classified into three types: *intensity based*, *morphology based* and *deformable model based*. Region based methods view brain regions as a group of connected pixel data sets. These regions will have muscles, cavities, skin, optic nerves, etc. The extraction of the brain region from the non-brain region is done by methods like region growing, watershed and mathematical morphological methods. Some previous works that performed skull stripping are: (Hohne, W.A., 1992), (Brummer et al. 1993), (Adams and Bischof, 1994), (Tsai et al. ,1995), (Lemieux et al. 1999), (Zu et al, 2002), (John et al., 2007), (Justice et al. 2007), (Acosta et al., 2008), (Somasundaram and Shankar, 2010) and (Somasundaram and Shankar, 2012). In this work many successive *morphological operations* have been implemented to strip the skull and get the brain tissue only.

8. Material and Datasets

The samples of images adopted in this work have been supplied by ***AL-HILLA SERGICAL HOSPITAL***. They have been obtained with 1.5 Tesla magnetic resonance**,** MRI device (PHILIPS). The used samples of MRI were three successive slices for T1-wieghted axial orientation (9,10, and 11) for a patient of an abnormal case. Each image has size equals to 618 ×1050 pixels per slice, from 1-20 slice with thickness of 5mm. The reason behind the selection of these images belongs to the distinguishable appearance of the tumor which is an important requirement in this work.

9. Experiments and Results

The proposed techniques is applied on images with tumor region of distinguishably high intensity.

Preprocessing Stage: This stage includes :

a- Automatically cutting the background of the images.
b- Implementing bilateral filter to smooth images.

Enhancement stage: In this stage, contrast adjustment has been, performed to expand the gray level of the input image from the range [0.4-0.7] to be in the full range [0 1] to highlight the *tumor region* within the image as a whole.

Morphological Operation: after converting the image into binary form by choosing threshold value (depending on the image intensity), many morphological operations have been applied using structural element of 'disk-shape' of 6-pixels diameter, these operations are:

a-Erosion: applied on the binary image.

b-Dilation: applied on the resultant image from the previous step. The dilated image then convolves with the input reduced intensity image (0.03 of its original intensity value).

Edge Detection: In this step, the Sobel operator is implemented on the resultant image from the previous steps, followed by filling process to represent the final image of the tumor. The results of the all steps mentioned above are illustrated in figures ***(2).***

Relative Volume Measurement

The relative volume of the tumor has been measured by computing the surface area of the tumor region in each slice's image and computing the surface area of the whole brain tissue in the corresponding slice after stripping the skull. Skull stripping step has been achieved by applying two morphological erosion operations on the binary image of the brain; the first erosion, using structuring element of shape rectangle of size 15×15 pixels, and the second with structuring element of shape disk with diameter equals 20 pixels. Dilation operation has been achieved on the eroded image with structuring element of shape disk with diameter equals15 pixels. The holes in the resultant image have been filled and the mask of the brain tissue has been gotten as shown in figure ***(4).***

The relative surface area for the tumor region in each slice has been computed depending on the surface area of the brain tissue mask,. By adding the resultant ratios, the relative volume of the tumor region has been calculated, the results are shown in table ***(1).***

The last step involves contouring the tumor region , construct the 3-D image for the tumor and determining the location of the tumor within the brain. The results of this step is illustrated in figures ***(4)***.

Table (1) : Illustrate the values of the surface area of the tumor region and the brain tissue mask in each slice, relative surface area and the relative volume of the tumor region within the brain tissue as a whole.

Slice number	Surface Area (pixel)		Relative Surface Area
	Tumor Region	Brain Mask	
9	**422**	**150062** 200222*	**0.0028** 0.0021*
10	**1731**	**146122** 199457*	**0.0118** 0.0087*
11	**2275**	**146072** 197704*	**0.0156** 0.0115*

Relative Volume	**0.0302** 0.0223*

* Represents the results when calculate the surface area relative to the whole brain mask without stripping the skull.

10. Conclusion

In this work, we have developed a fully automatic simple and efficient segmentation method for detecting and extracting the tumor region from three successive MRI T1-weighted slice images. The segmentation result is used to construct 3D image for the tumor region. The 3D tumor then inserted in 3D contour image of the brain. The relative size of the tumor has been measured with respect to brain size. This work showed that the proposed method can adequately used to detect and extract the brain tumor in MRI images, which can be incorporated in longitudinal studies, for analyzing the evolution of the tumors and their impact on surrounding structures, and they can be used for diagnosis, treatment planning, therapeutically monitoring, surgery and pathological brain modeling.

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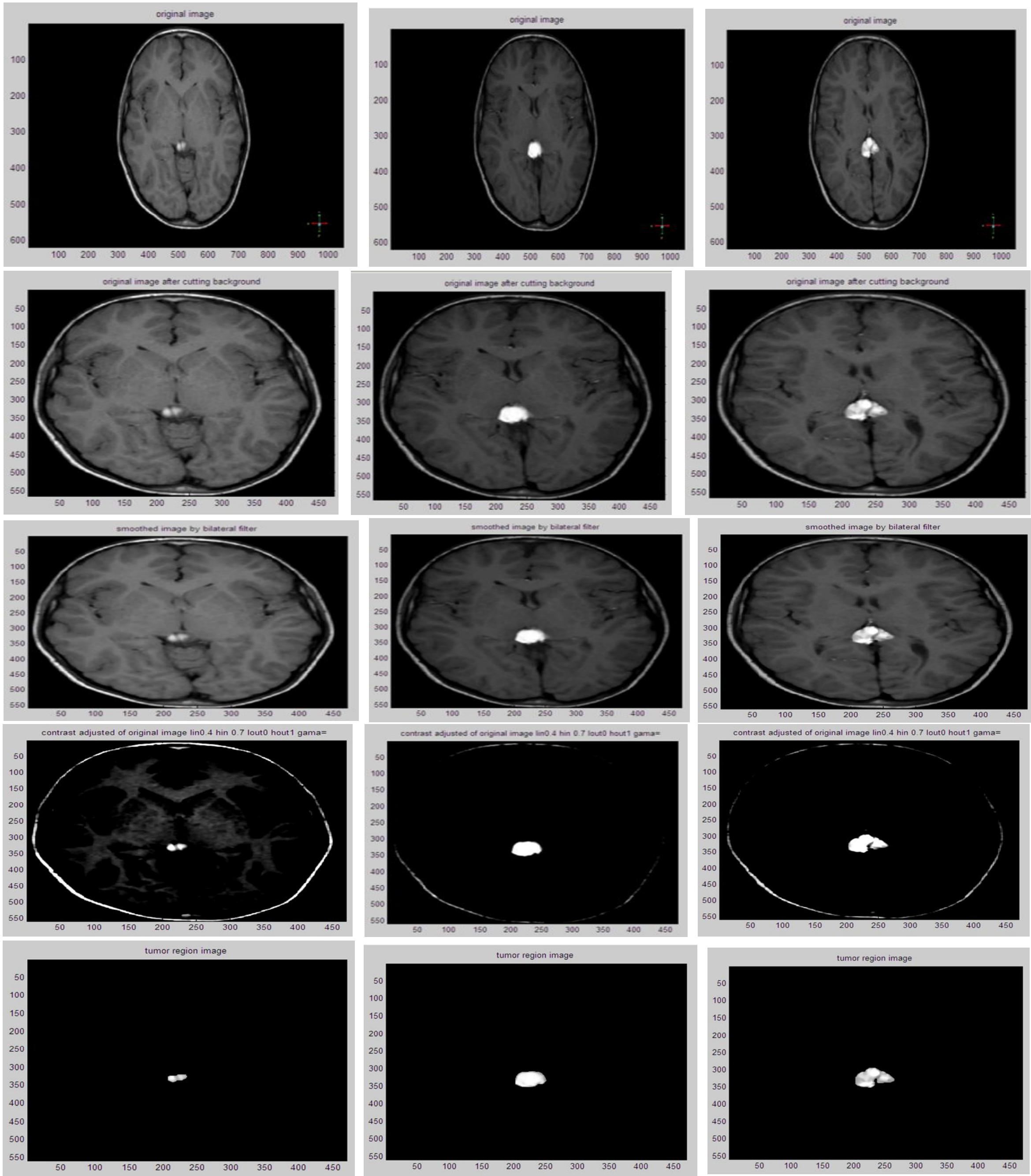


Figure (2): shows, in the first row, the input MRI images 9,10 & 11 slices from left to right; second row, background discarding for the images in the first row; third row, bilateral filtered images; fourth row, highlighting and expanding of the intensity band of the tumor region & the last row illustrates the image of the tumor region for the three slices' images.

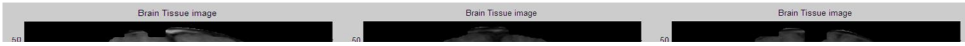
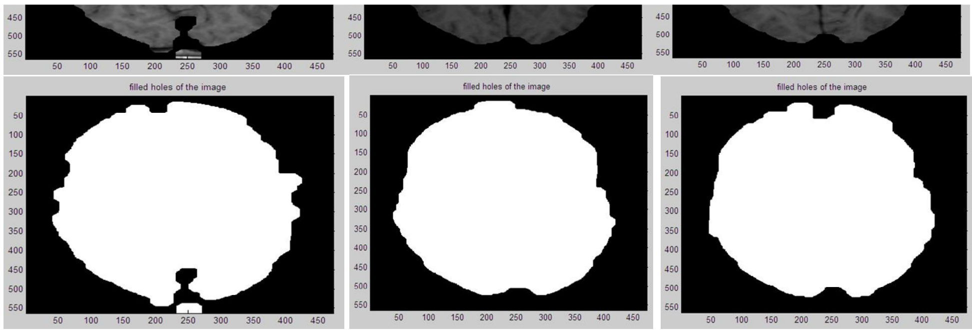
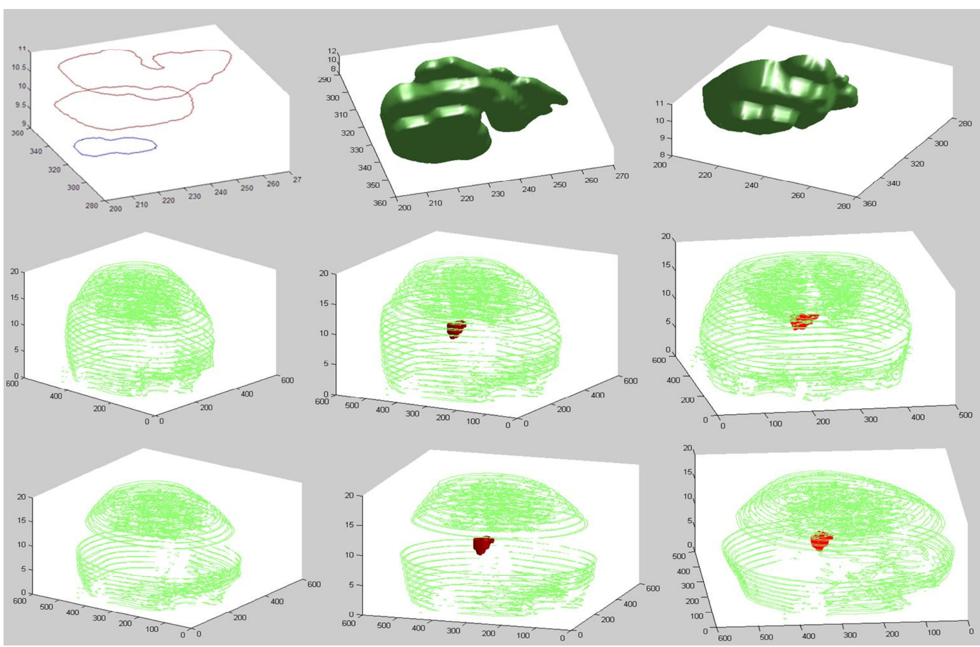


Figure (3): First row, shows the brain tissue after skull stripping using suitable morphological operations for the three slices' images from left to right 9,10, and 11. Second row shows the corresponding brain tissue mask for the three slices in the first row.



last row illustrates the image of the tumor region for the three slices' images.



Figure(4): The first row shows the contours of the tumor region for the three slices that contain the tumor(left image), the second and third image shows the 3-D image for the tumor region in different orientation. The second row shows 3-D image for the contours of the head as a whole without tumor (left image), and the location of the tumor (in red) within the brain in different orientation in the two other images. The third row shows the brain cutting contours(left image), the second and third image shows the tumor (in red) within the two cutting parts of the brain contours in different orientation.

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