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Review

Brain Tumor Detection from Medical Images: A Survey

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Abstract

Nowadays, medical image processing has been one of the most challenging emerging field. Magnetic resonance imaging (MRI) technique is now widely used to detect brain tumor. This survey provides different strategies to detect and extract the brain tumor signal. The strategy for detecting and extracting the brain tumor signals is based on the MRI scanned images of the cerebrum. These methods incorporate some noise removal functions, segmentations and morphological operations which are the fundamental concepts of image processing. Detection and extraction of tumor signal from MRI scanned images of the cerebrum are carried out by MATLAB.

Keywords: Medical images; Medical resonance imaging (MRI); Machine learning; Computer vision; Segmentation; Morphology

Introduction

In recent years, brain tumor has become one of the leading causes of death among children as well as in adults [1]. Some studies have showed that the number of people suffering and dying from brain tumor has increased to 300 per year during the last few decades [34]. Brain tumor is statically the second leading cause of child death [3]. Brain tumor is formed due to the abnormal cell growth in brain tissues. The real cause of most brain tumors is not well clarified yet. Brain tumors can be divided into two categories: (i) primary or metastatic tumor; and (ii) malignant or benign tumor. A metastatic brain tumor is defined as the cancer which is produced elsewhere and spread from any other part of the body to the brain. In this situation, brain goes into a disorder system. Clusters of nerve cells and neurons in the brain produce abnormal signals. Electrochemical impulses are generated by neurons generally. These electrochemical impulses then act on other neurons, glands and muscles to where thoughts, feelings and actions emerge. Due to the abnormality in the tissues, the normal activities get disturbed. It causes unusual sensations, emotions, behaviors, sometimes convulsions and spasms, and even loss of consciousness [29]. Therefore, how to realize quick location of brain tumor has become a great challenge.

Since Professor Weissleder at Harvard University promoted the concept of “molecular imaging” [5], molecular imaging technology has achieved great advances [6, 7]. Molecular imaging technology mainly applies high-affinity, high-targeted molecular imaging probes, which can recognize and bind the key molecular targets after entering into the human body, and give out visual, dynamic and real-time images, thus obtaining the quantitative and qualitative diagnosis or simultaneous targeted therapy of tumors at the molecular level [8-11]. A sign for the rapid development of molecular imaging technology is the publishing of *Towards Precision Medicine: Build Knowledge Networks in Biomedicine and New Disease Classification* in 2011, in which the concept of precision medicine was put forward. In 2015, the former U.S. President Obama suggested a “precision medicine” project. Precision medicine leads the way of future medicine, the significant tools of which are molecular imaging and translational medicine.

With the rapid development of molecular imaging technology, imaging diagnosis technology of brain tumor also has achieved great advances [12-16]. For example, a series of multifunctional nanoprobes were prepared and used for multimode imaging and simultaneous therapy of brain tumor [17-19]. For example, fluorescent imaging, magnetic resonance imaging (MRI), computer-assisted tomography (CT) and surface-enhanced raman spectroscopy (SERS) have been used for imaging different brain tumors [20-23]. However, there exists a big challenge dealing with these imaging informations captured by different methods

In this paper, we review the main advances in treatment of brain tumor imaging, the main strategies applied for color detection and shape detection of brain tumors, the prospects of application, and discuss the concepts, issues, approaches and challenges, with the aim of improving the development of imaging treatment of brain tumors.

Imaging Patterns and Treatment of Brain Tumors

Magnetic resonance imaging (MRI) is now being used to capture images of high quality and high efficiency. These images contained useful information on the sections of the human body. MR imaging is frequently used to obtain the images of the tumors, organs, joints and soft tissues. MR images provides such high resolutions where we can obtain the detailed anatomical information to examine the brain tumor, and to detect the development and abnormalities inside the brain, if any. There are several methodologies for the classification of MR images, which include fuzzy methods, neural networks, atlas methods, knowledge based techniques, shape methods and variation segmentation. MRI consists of T1 weighted, T2 weighted and PD (proton density) weighted images, and is processed by a system which integrates fuzzy based technique with multispectral analysis [24].

Pre-processing of MR images is the primary step in image analysis. Pre-processing steps include the image resize, image enhancement and removal of noise as well as reduction technique. There are some methods which are used to enhance the image quality, after which morphological operations are applied to detecting the tumor inside the brain which has been already captured through MR image. The morphological operations are basically applied on some assumptions about the size and shape of the tumor. In the end we mapped the tumor according to the original gray scale image with 255 intensity values. These values make it visible of the tumor in the image.

Up to date, in medical field to examine the internal structure of the body, MRI is one of the commonly used methods, which is being frequently used for the detection and visualization of the structure of the body. MRI examines the differences between the tissues and how the affected tissues are different from each other. MRI technique is much better as compared to the computed tomography (CT). It is widely used for the brain tumor detection and cancer imaging [25]. MRI, as the name suggests, it uses strong magnetic field to arrange the nuclear magnetization followed by changes of the alignment and radio frequency which can be detected by the scanner, whereas the CT uses ionizing radiation. The signal produced, can further be processed to get more information of the specific part of the body, especially the affected tissues. Due to diverse shapes, sizes and appearances of brain tumor, accurate measurement of brain tumor is quite difficult. 3D segmentation of image is playing a vital role in medical imaging before implementing object recognition. 3D image segmentation helps in automated diagnosis of brain diseases and helps in qualitative and quantitative analysis of images such as measuring the accurate size and volume of detected portion.

Treatment strategies of brain tumor images

According to Nagalkar and Asole [27], CT-Scan techniques are usually used for monitoring the images of damaged brain part. The images of the CT scans are shown in the form of gray scale images as the equipment for CT scans supports this form and an easy detection of tumor from the image can be achieved [28]. For example, in the parietal section of the head scanned by CT, the cerebrum part is shown in gray while the veins and arteries parts in creamy white. Any clotting that exists in the brain implying some kind of damages can be detected as dark gray in color. The process of extraction of parameters is basically like taking out information pixel by pixel then plotting them. For an image obtained by CT-Scan, tumor appears in white while damaged brain cells in black, so the binary values of the pixel showed will be 0 for damaged cells and 1 for tumor; which can be further checked and plotted by MATLAB [27]. The patient with damaged brain can be differentiated from normal patient by using this technique. In addition, tumor can

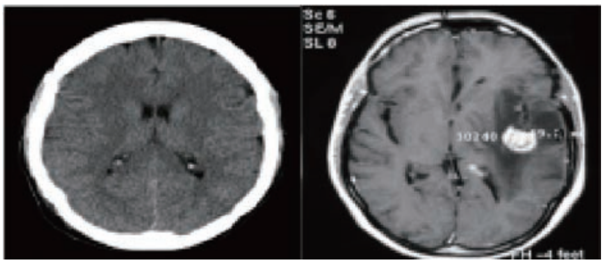

Fig. 1 Brain CT scan image of **(a)** a normal patient and **(b)** a tumor patient [27].

also be detected clearly based on the image results [27]. Fig. 1(a) shows the image of the a normal human being, whereas Fig. 1(b) indicates the CT scan of a patient suffering from brain tumor.

The technique mentioned above has been in used for a long time to determine the patient's response to treatment. For that reason, the radiologists have made series of cross sectional diameter measurements for indicator lesions purposes by using axial, incremental CT image data. Later, these measurements will be compared with the previous measurement scans [29]. Nevertheless, the measurement of lesion diameter does not represent the exact assessment of tumor size due to some factors such as:

(a) Irregular lesions: the lesions that grow other than sphere shape may not be adequately represented by diameters' changes;

(b) Different measurement between inter-observer and intra-observer: referred to the image selection used

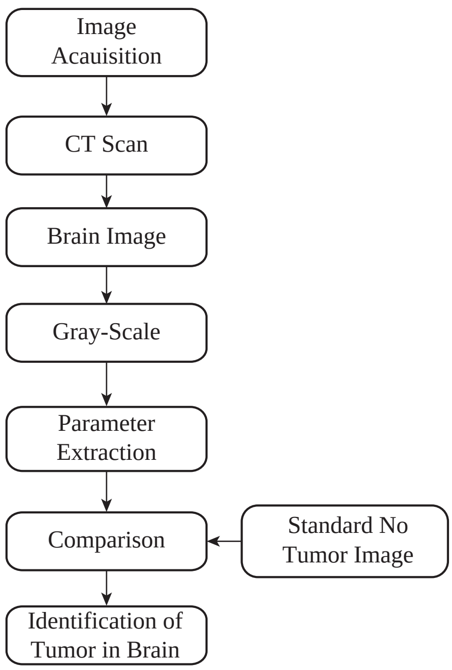

Fig. 2 Flowchart to determine the existence of tumor [27].

for the measurement and the location of lesion boundary; and

(c) Different levels of scanning results collected from various diagnoses: the lesions may not be captured exactly at the same spot from one diagnosis to another. Hence, it affects the lesion's image in which causes comparisons between examinations becoming more difficult.

On the other hand, with the ability to provide single breath-hold scans and overlapping reconstructions, the spiral CT is capable to improve the image lesions at reproducible levels from different diagnosis. Even so, these lesions' measurements are still a subjective task and yet open for variability as described in previous factors (a) and (b). What follows is a summary of several approaches to the problems involved in nodule detection. Therefore, the researchers have divided these approaches into two groups of methods:

(a) The process of detecting the pulmonary vasculature in order to help the detection of pulmonary nodules (if vasculature is successfully removed from the image, then only nodules should remain); and

(b) The process of detecting objects in the CT image volume to distinguish nodules from other structures.

Brain tumor extraction from MR images using MATLAB:

According to Patil and Bhalchnadra [29], their MATLAB algorithm is used to detect brain tumor. It involves two stages, the first of which comprises of preprocessing and segmentation. Morphological steps were applied in the second stage.

The structure of their algorithm is as follows:

1. Give MR image of brain as input;
2. Convert the image into the gray scale image;
3. Apply high pass filter for noise removal;
4. Apply median filter to enhance the quality of the image;
5. Compute threshold segmentation;
6. Compute wavelet segmentation;
7. Compute morphological operation; and
8. Final output will be a tumor region.

Dahab, Ghoniemy, & Selim [32] agreed with the technique mentioned above, where the main focus on image process lies in the format of MR image segmentation and detection algorithm are applied to get the region of the tumor. The MR image will first be converted into the gray scale type. One of the major parts is image segmentation, under which enhancement and smoothing adorn the gray scale MR images. According to Dahab, Ghoniemy, & Selim [32], most of MR images encounter Gaussian and Impulse noises. To remove the Gaussian noise the author proposes the use of Gaussian filter, then the use of linear filter to enhance the edges.

According to Dahab, Ghoniemy, & Selim [32] the equation of linear filter is

$$I_A(i,j) = I * A = \sum_{h=-\frac{n}{2}}^{\frac{n}{2}} \sum_{k=-\frac{m}{2}}^{\frac{m}{2}} A(h,k) I(i-h, j-k)$$

And for Gaussian filter

$$G_f(x,y) = \frac{1}{c} \exp\left[-\frac{[x^2+y^2]}{2\partial^2}\right.$$

The edge detecting module is the part of interest. It is used to determine the Region of Interests (ROIs) in the MR images. These ROIs can locate the tumor thus determining its existence and notifying people of its position in the MRI scanned images.

Whereas, in their paper Dina et al had proposed that the edge detection can be done by using canny edge detection technique. The canny optimal filter meets all three criteria above and can be effectively approximated using the first derivative of the Gaussian function.

Experimental results for the brain tumor extraction from MR images using MATLAB is given in Fig. 3. The image generated by Gaussian filter is set on the left while the one by average filter on the right, showing the latter provides as good results as the former.

In Fig. 4, canny edge detecting algorithm performs four steps to calculate the edge. At the first step it

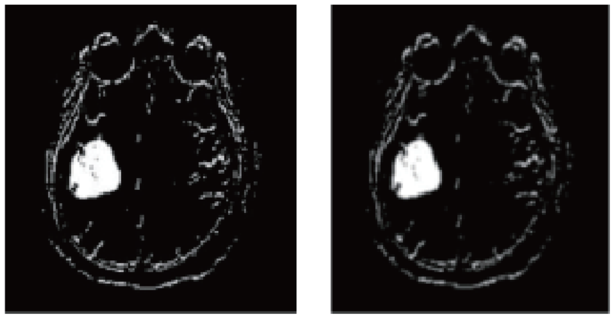

Fig. 3 (a) Result of Gaussian filter; and **(b)** result of average Filte [32].

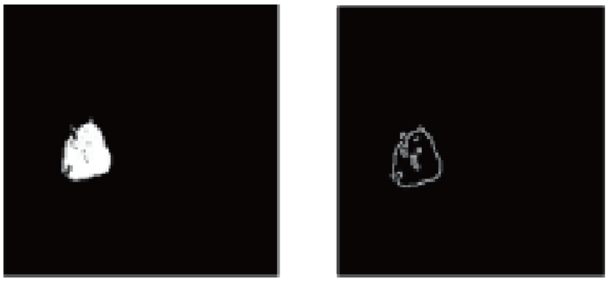

Fig. 4 (a) Edge detection; and **(b)** tumor detection using thresholding [32].

smoothens the image with a Gaussian optimization of the trade-off between noise filtering and edge localization. In the second step it computes the Gradient magnitude using approximations of partial derivatives 2 × 2 filters. In third step, thin edges get lucid by applying non-maxima suppression to the gradient magnitude. At last, we detect edges by double thresholding.

Improved edge detection algorithm for brain tumor segmentation

According to Aslam, Khan & Beg [33], who proposed an algorithm which can be used for edge detection for brain tumor segmentation. The proposed segmentation algorithm uses the following four steps and is based on automatic threshold calculations:

1. Finding gradient image using Sobel operator;
2. Calculate image dependent threshold iteratively;
3. Apply Closed contour algorithm; and
4. Object segmentation based on pixel intensity within closed contour.

Sobel operator uses a 3 × 3 mask. Given an image *f*(*x*, *y*), its gradients along *x* and *y* axis are calculated respectively by the following equations:

$$g_x = \frac{\partial f}{\partial x} = (z_7 + 2z_8 + z_9) - (z_1 + 2z_2 + z_3)$$

$$g_y = \frac{\partial f}{\partial y} = (z_3 + 2z_6 + z_9) - (z_1 + 2z_4 + z_7)$$

The gradient if image is defined as

$$\nabla f(x,y) = \frac{\delta f}{\delta x}\hat{\imath} + \frac{\delta f}{\delta y}\hat{\jmath} = g_x\hat{\imath} + g_y\hat{\jmath}$$

where *i* & *j* are unit vectors along *x* and *y* axes respectively. The magnitude of the gradient can be calculated by the following formula.

$$g(x,y) = |\nabla f(x,y)| = \sqrt{{g_x}^2 + {g_y}^2}$$

After finding the image gradient, the next step is to automatically find a threshold value so that edges can be determined. Once the final threshold is obtained, each pixel of gradient image *g*(*x*, *y*) is compared with Th, which is already calculated by applying the algorithm to find the threshold value. The pixels higher than the Th are considered as edge point and denoted as white pixels; otherwise they are denoted as black. The edge mapped image *E*(*x*, *y*), thus obtained is:

$$E(x,y) = \left[\begin{cases} 255 & \mathrm{g(x,y)} \geq \mathrm{Th} \\ 0 & \mathrm{otherwise} \end{cases}\right.$$

Therefore, a pixel at (*x*, *y*) having *g*(*x*, *y*) less than Th is called a background point; otherwise it is an edge point. After getting this, they used Closed Contour Algorithm. The method for Closed Contour Algorithm is described below.

They proposed an algorithm for closed region. The working principle is to find a seed pixel in each region then expand it to all eight connected neighbors. Scanning function is performed pixel by pixel to make sure there is no edge between the neighboring pixels. This procedure continues iteratively for neighbors, and it is a recursive procedure. At the same time, the algorithm also checks for the boundary of other regions by considering a 5×5 window around every pixel, where it stops if any pixel in the window is a boundary pixel. The proposed algorithm is presented below. Consider the image after thresholding as a two-dimensional matrix *E*(*i*, *j*) with 'h' rows and 'w' columns. The algorithm scans *E*(*i*, *j*) and segments it into r regions. Thereafter, it associates each pixel with one of the r (say) regions. Let Rk denote the kth region and initialize r with 0 in the main of closed-contour algorithm discussed below. Now the first pixel of a particular region Rr is known, and then more pixels of this region will be found. Thus a searching procedure called closed-contour Search (i_0, j_0) is developed (Fig. 5).

Fig. 6 shows the proposed algorithm for segmentation. By implementing this technique, we can enhance the edge detecting capability of MR images using Sobel operator. The number of false edges were generated by that purposed method are much less as compared to the conventional method. This results in better extraction of tumor than using conventional Sobel edge detecting method. Also this proposed method was found to be much superior when compared to other existing techniques in three dimensions as well.

In the future, we can improve efficiency of the closed contour algorithm by increasing the region

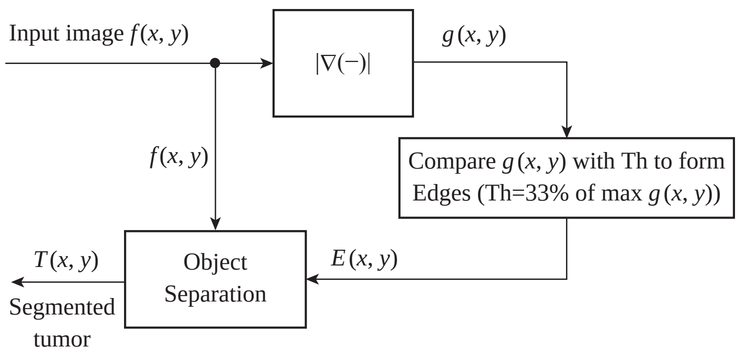

Fig. 5 Conventional algorithm [33].

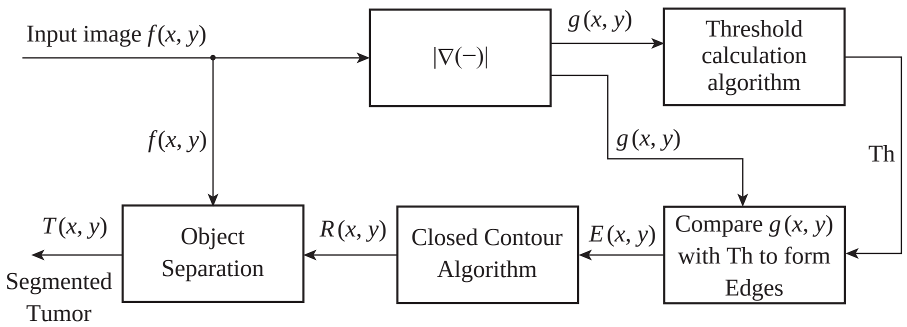

Fig. 6 Proposed method for segmentation [33].

area and decreasing the thickness of boundary lines of region of interest.

An efficient brain tumor detection algorithm using watershed & thresholding based segmentation

Mustaqeem, Javed, & Fatima [34] designed an efficient brain tumor detecting algorithm. This algorithm uses watershed & threshold values from the patient's MR images. The pie chart (Fig. 7) is indicating the rate of tumor diagnosis in the U.S., UK and India. As brain tumor detection is a very time consuming process, to tackle this issue, many segmentation techniques are developed by the image processing experts. Many of these techniques are not properly defined, though they are ad hoc techniques.

Some of the most common methods are:

(a) Amplitude threshold;

(b) Texture segmentation;

(c) Template matching; and

(d) Region growing segmentation.

Moftah, Hassanien, & Shoman [35] used K mean algorithm with connected component labeling. Clustering can be done with the help of object rendering process in 2D slices and then 3D patch is obtained.

Vasuda & Satheesh [36], proposed a technique to detect tumors from MR images suing fuzzy clustering technique. This algorithm uses fuzzy C-means but the major drawback of this algorithm is the computational time required. This paper also compares the FCM and improved version of FCM.

Experts working on tumor images often use three different types of algorithm. Some of the techniques are based on pixels, while some are based on the texture or structure of images. Gopal & Karnan [37] suggested an algorithm which used multi-scale image segmentation, based on fuzzy c-mean algorithm for the detection of brain tumor. Joshi, Rana, & Misra [38]

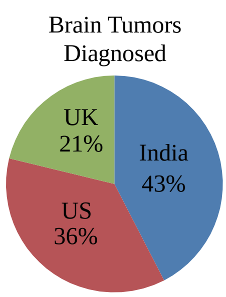

Fig. 7 Rate of tumor diagnosis per year [34].

suggested an improved technique for tumor detection, which used neuro fuzzy technique for the segmentation for the tumor detection.

Wu, Lin, & Chang [39] proposed an algorithm which uses a clustering technique(k-means) to detect the brain tumor in MR images. First of all they convert the gray scale images into color images and then by the help k means clustering.

Their research was to find out the brain tumour using Medical image techniques. The fundamental part of their research was the use of segmentation, which is the essential part of image processing. We distinguish foreground from background images. The segmentation in this research was done by using thershold segmentation, watershed segmentation and morphological operations. They wanted to locate brain tumour inside the scanned MR images. They found that by using their proposed method the results turned to be siginificantly efficeint. Experiments were done on several MR images and much better results were obtained.

As shown Fig. 8, the flow chart for the detection of brain tumor is divided into three parts. In the first step, MR image is taken as input. After attaining the image

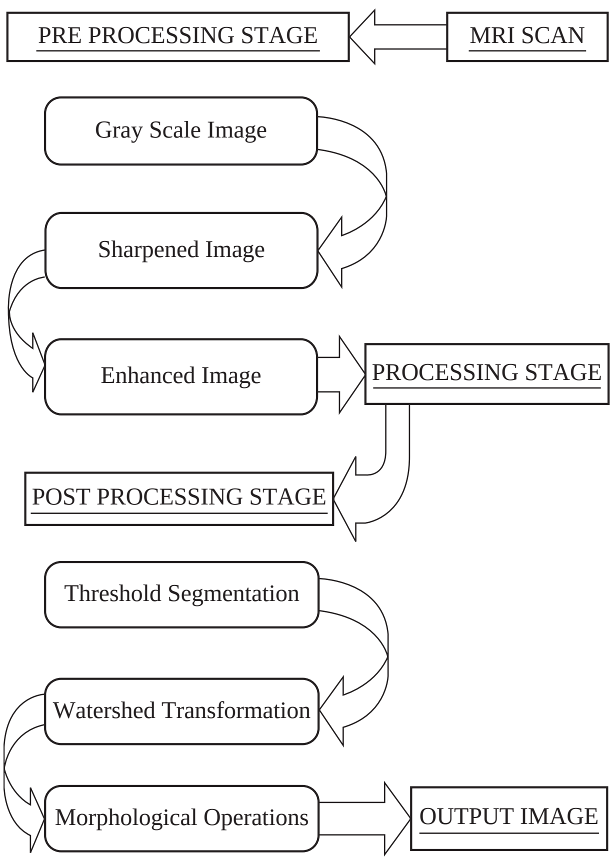

Fig. 8 Stages of tumor detection [34].

some pre processing steps were applied; these pre-processing steps are very necessary for better detection. If there was any pre-processing left unperformed, proper treatment would be impossible in the case and the detection would be affected. In the pre-processing stage, MR image is first converted into the gray scale type, then converted into the sharpened image, and further enhanced in terms of contrast and other features. Pre-processing stage stage is completed when enhanced images are obtained. After pre-processing stage is the post processing stage which also comprises of three steps. In the first step, threshold segmentation is performed, and it is the simplest method to find out the threshold value. The input image, which has already been converted into the gray image format will now be converted into binary image. The purpose of segmentation was to get the threshold value.

After threshold segmentation, watershed segmentation is performed. In watershed segmentation, those pixels with similar intensities joined together to form a group. In an image there are several pixels which will have same values, so watershed segmentation allows us to form groups of these pixels underlying the same intensities.

After converting the image into the binary format, some morphological operations are applied on the converted binary image. The purpose of the morphological operations is to separate the tumor part of the image. Now only the tumor portion of the image is visible, shown in white. This portion has the higher intensity than the other regions of the image.

Fig. 9 shows the results of the efficient brain tumor detection by image treatment. Fig. 9(a) shows the input image of the brain tumor in gray scale type. Fig 9(b) shows the result after the application of the thresholding segmentation. As shown in Fig. 9(c), this technique is called watershed segmentation which is applied on the resulted image obtained after threshold segmentation. Only the portion which contains tumor is highlighted here. The portions with the high intensity values are detected through threshold segmentation. These portions are marked through watershed segmentation methods. Fig. 9(d) & (e) show the treated images with morphological operations. Morphological operations were applied after the watershed segmentation and the obtained figures are quite prominent, which proves this technique to be very effective. Fig. 9(f) shows the result after imerode function was used for image treatment. This function is

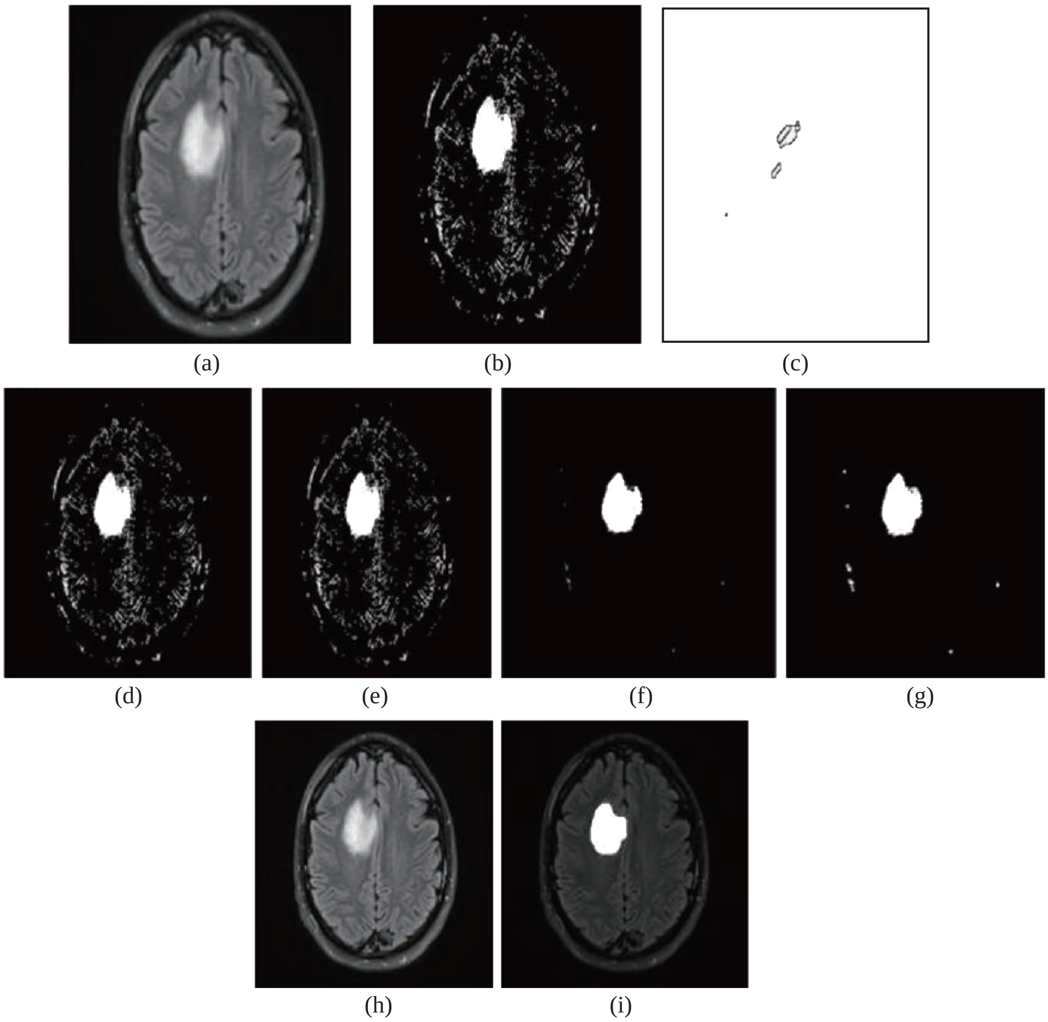

Fig. 9 Efficient brain tumor detection by image treatment. **(a)** Input brain tumor image; **(b)** image of brain tumor after thresholding segmentation; **(c)** results of the watershed segmentation treatment; **(d)** & **(e)** images after morphological operates were applied after the watershed segmentation; **(f)** image treated by using imerode function; **(g)** image treated by using imdilate function; **(h)** & **(i)** brain tumor images after image treatment [29].

used for the erosion of the image. Fig. 9(g) shows that the result after the imdiate function was used for image treatment. This function is used to filtrate the image. Fig. 9(h) & (i) show the final image of brain tumor after a series of image treatment, which are very clear.

Conclusions

In summary, three main processes have been used in determining the existence of brain tumor. Image segmentation, improved edge detection and efficient brain tumor detection using watershed & thresholding based segmentation. It can be generally concluded that the program will be interested in detecting damaged tissue with a certain intensity of brightness from its gray scale image. The thresholding will detect the damaged tissues. By the application of the image segmentation process, this research intends to use gray scale converted images of MRI or CT scans. A series of filters will be used including Gaussian, Linear and average filters to remove the noise. For the edge detecting process, the researchers intend to use a canny edge detector which is commonly used in such environments. Although imaging treatment of brain tumor has achieved great advances, there still exist some great challenges, especially with the fast development of molecular imaging technology, how to treat different patterns of images rapidly has become a challengeable problem. Further studies should focus on the integration technology development of multimode imaging technologies.

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