AN OPTIMAL SEGMENTATION METHOD FOR PROCESSING MEDICAL IMAGE TO DETECT THE BRAIN TUMOR

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Abstract: In the field of medical image processing, detection of brain tumor from computed tomography (CT) or magnetic resonance (MRI) scans is a difficult task due to complexity of the brain hence it is one of the top priority goals. In this article, we describe a new method which combines four different steps including smoothing, Sobel edge detection, connected component and finally region growing algorithms for locating and extracting the various lesions in the brain. The computational algorithm proposed method was implemented using Insight Toolkit (ITK) to process input image, Visualization Toolkit (VTK) to display and Qt software development framework to build user interface. The analysis results indicate that the proposed method automatically and efficiently detected the tumor region from the CT or MRI image of the brain. It is very clear for physicians to separate the abnormal from the normal surrounding tissue to get a real identification of related area; improving quality and accuracy of diagnosis, which would help to increase success possibility by early detection of tumor as well as reducing surgical planning time. This is an important step in calculating the correct dose of radiation therapy later.

Keywords: *Medical image, brain tumor, segmentation, ITK, VTK.*

1. INTRODUCTION

Brain tumors are known to be one of the main diseases leading to human death in the world. Clearly visible from CT, MRI images, there is overlap between the boundaries of the tumor in surrounding and tissue, the edges can be obscured by the structure of the skull, resulting in a lot of contrast to the background. Therefore, it is difficult to distinguish the boundary between normal and abnormal tissues. Removing the tumor without affecting the surrounding tissues is a big challenge for the doctors [1]. Early detection and treatment can increase the rate of survival for patients.There are many approaches used in many researches to differentiate biological tissue edges of brain images [2]. Up to now, there are many different algorithms that have been proposed and implemented. And each of the technique has its own advantage and disadvantage. However, there is no single approach that can generally solve the problem of segmentation for the large variety of image modalities existing today. Segmentation algorithms most effectively are obtained by customizing combinations of components carefully.

Our proposed method is based on the intensity of each pixel, that it would be easier to segregate the affected areas. An intensity image (grayscale image) can be treated as a data matrix, each element of the matrix corresponding to an image pixel and expressing its intensities within a certain range. The HU unit measures the attenuation of the X-ray beam in each projection in CT scan:

$$I / I_0 = e^{-\mu x} \tag{1}$$

Where: I_0 is the initial intensity of the X beam, I is the intensity of the beam at the detector, μ is the linear attenuation coefficient, and x is the thickness of the reconstruction matrix [3]. Because the thickness of the material along the X-ray beam transmitted through multiple pixels, the measurement is the sum of the attenuation of the individual pixels. The pixel value assigned to the image is called the HU or pixel intensity (Hounsfield unit). If μ is the average linear attenuation coefficient for the interest pixel and μ_w is the attenuation value of the water, the HU is calculated by [4]:

$$HU = (\mu - \mu_w) / \mu_w \quad (2)$$

The tissue density can vary considerably and many soft tissues have overlapping ranges between HU values so that HU values do not clearly distinguish between different types of soft tissues. This is explained by the attenuation of X-rays in low energy regions that depend on Compton scattering and photoelectric effect. Brain imaging consists of four regions i.e. white matter, gray matter, cerebrospinal fluid, and background [5]. These regions are called the clusters with pixels of different intensities. These regions have small boundaries and HU, so edge detection is difficult. However, the pixel intensity values in these regions are still different.

Many researches, softwares in the world today focus on the segmentation of medical images such as Slicer3D, Osirix [6, 7],... are either manual or semi-manual, takes a lot of processing time. Tumor detection is a long and time-consuming process. Location determination, characterization of the tumor depends much on the experience and skill of the doctor. Most of these segmentation works are manually done by hand. Manual segments are often inaccurate. Thus, the location of tumor is needed to determine automatically. In this paper, we use a region growing method for efficient segmentation with marking the region of interest (ROI) as well as the background in gray image. This process combines the basic approaches: smoothing, edge detection, and region growing segmentation. Here, we proposed mean smoothing in order to reduce the noises in CT, MRI images. Sobel algorithm is used for image segmentation. It uses the connected component as well to set proper boundaries between adjacent regions. The texture feature is extracted using region growing method. Hence, it is easy to implement and provides more stable results than using individual methods.

2. METHODOLOGY

2. 1. General description of proposed method

Brain tumors occur when abnormal cells develop in the brain affecting neighboring tissues. Image processing in medical diagnostics includes stages such as preprocessing, edge detection, segmentation and extraction of interest features [8]. Implementation procedure of algorithm is shown in Figure 1. Segmentation is a critical stage in the outcome of brain tumor extraction. Reliability, accuracy of the segmentation algorithm depends on indicators such as: threshold, position of seed point, number of iterations, multiplier. Properly adjusting these parameters will yield the desired tumor extraction results.

***Factors affecting image quality CT, MRI scan.**

Noise is a part of the information that creates the actual image. Noise affects image quality and reduces the effectiveness of subsequent processing methods. There are many causes of noise: due to insufficient photon to detector; the change in sensitivity of the detector, transmission error, the overlap of different tissues at the same slice; the movement of the patient; beam hardening phenomenon, the metal (which exceeds the maximum attenuation value that the CT can be reconstructed),.... There are 3 types of noise: additive noise, Gaussian noise, salt & pepper noise [9]. CT, MRI images are affected by Gaussian noise (due to the discrete nature of radiation) and salt & pepper noise (due to errors in data transmission, the error pixels are alternately carrying value of 0 or 1). Noise can be reduced by improving collimation, longer data acquisition time and circuit design, or applying image filters [10]. In this paper, the first step for image analyzing is to filter data.

2.2. Segmentation

2.2.1. Connected Component Labeling

Connected component is to divide the data into similar groups of objects. Each individual object is assigned a unique label. A region can be defined as a group of pixels where all the pixels in certain group defined by similar relationship. Basic approach is to start from a seed region (usually one or more pixels) that is considered inside the segmented object. The pixels neighboring this region are evaluated to check that they are part of the object. The minimum and maximum intensities of gray image are set 0 and 255 [4]. The factor which affects the outcome of Connected component algorithm is threshold value. In this paper, the influence of the threshold value to the segmented image quality was evaluated based on phantom.

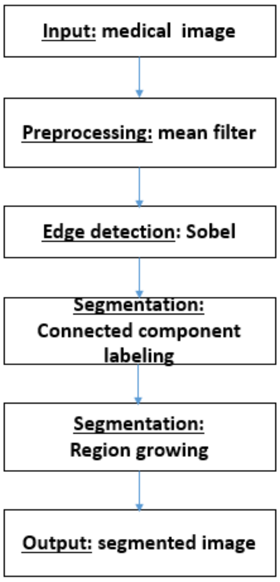


Figure 1: *Flowchart of the proposed method*

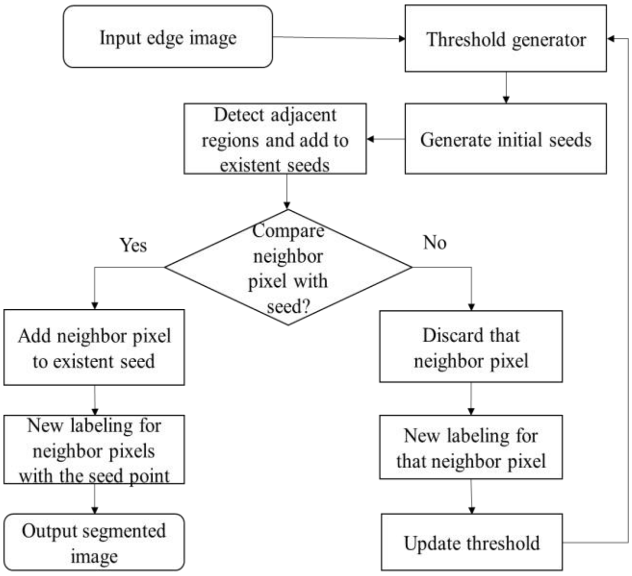


Figure 2: *Proposed image segmentation algorithm*

2.2.2. Region growing by Confidence Connected

This method is based on simple statistics of the current region. First, it calculates the average and standard deviation across a neighborhood (4, 8, 12,… connected) for a seed point. Pixels connected to seed point whose values are within the confidence interval are grouped. The algorithm completed its first iteration when no adjacent pixels are found satisfying the criteria. At that point, the mean and standard deviation of the intensity pixels are recalculated by all available pixels in the region. These 2 values determine a new intensity range that is used to visit existing neighbors and assess whether their intensity is within the range ($m \pm f\sigma$). The following equation describes the filter:

$$I(X) \in [m - f\sigma, m + f\sigma] \qquad (7)$$

Where m is the mean and σ is the standard deviation of the regional strength, *I(X)* is the intensity matrix of the input image, *f* is iterations and *X* is the location of the specific neighboring pixel being considered for inclusion in the area. Confidence connected requires three factors: intensity range f, the multiplier and the number of iterations. The recommended confidence multiplier is 2.5 for medical image in ITK [4]. The number of iterations is determined by the uniformity of the intensity of the segmented anatomical structure. High homogeneous region requires several iterations. In our problem, the number of iterations is 5 for all input images. A value greater than or less than 5 produces almost unchanged results for CT, MRI inputs. The output of this filter is a binary image with zero-valued pixels anywhere except the extracted region. The initialization algorithm requires the user to provide a seed-point. This point is placed in a typical area of segmented anatomical structure. The initial mean and standard deviation are defined by a small area around the seed. The size around the seed is defined as a rectangular area with 2r+1 pixels on the side (r is the radius of the original neighborhood) [4]. The size of neighborhood radius around seed point is set 3.

3. Results and discussion

3.1. Applying proposed method for Phantom Gamex 463

Initially, the proposed method was tested on the Phantom Gamex 463 (with standard area 9113 pixel). By tabulating the threshold values applied to Gamex's physical phantom, the article shows the threshold range for the area approximated to the given area of the phantom. The seed point for each type of tissue (corresponding to 3 holes representing air, bone and muscle) is determined automatically and gives the same result when the threshold values change. The seed point, threshold value calculated at this step is the reference for accurately extracting tumors without affecting surrounding healthy tissue. When the Minsize change is 20, 50, 100, 200 the number of components is also changed. But the number of components is still a linear function with the threshold when increasing the minsize. This proves that minsize does not affect the results of tumor extraction.

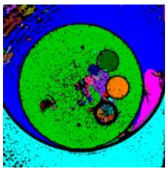
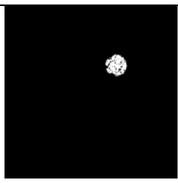
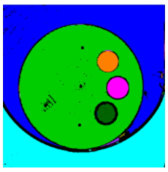
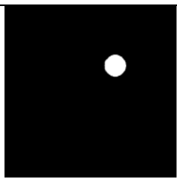
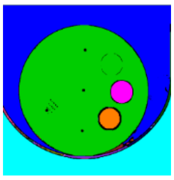
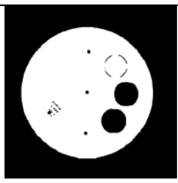
No.	**The output image**	**Threshold value**	**Extration output image**	**Caculated area (pixel)**
1		*7*		*7473*
2		***15***		***9098***
3		*31*		Unknown

Figure 3: Dependency of segmentation results on input threshold value with minsize= 20.

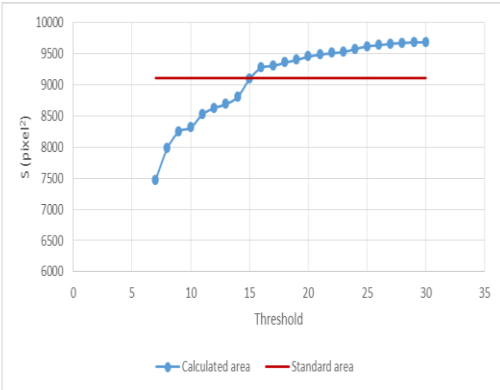


Figure 4: The graph shows the change of area by threshold.

Experimental results on the phantom with minsize =20 (or minsize =50, 100, 200) indicate that: With threshold values from 0 to 8: There are many objects that are detected excessively, cluttered and difficult to identify areas of interest. With threshold values from 5 to 8: only 2 holes corresponding to air and bone are detected, but the image appears more noise and objects are detected incorrectly; significant error. With threshold values from 9 to 13: all 3 areas of interest are detected; but affected by noise. Wide object edges cause big errors. With a threshold value of 14 to 30: all 3 holes correspond to air, bone tissue and soft tissue are clearly detected and not affected by surrounding areas. In particular, with a threshold value of 15, the boundary of the soft tissue hole is clear, smooth and unaffected by noise. With threshold value of 31 to 143: only 2 holes corresponding to air and bone are detected. With a threshold value of 144 to

221: only one hole corresponding to air is detected. And with a threshold value of 222 or higher: no holes are detected. The objects are completely submerged in the background.

From the results of Figure 3, 4 on Gamex phantom, with the threshold value of 15 is the optimal threshold position with all minsize values. This is a reliable threshold for extracting results of phantom in accordance with the actual standard area. The result of this threshold value is also used for segmentation with clinical images. The result of seed point value to determine the range of tumor extract were calculated as Table 1.

Table 1: *Results of seed points, area of 3 round holes extracted within the threshold range of 6 to 30.*

Seed point	d (mm)	R (mm)	d (px)	S (px^2)
(297,145)	28.96	14.48	108.72	9284
(328,227)	29.07	14.54	109.87	9480
(291,307)	28.85	14.43	107.91	9146

Calculate the area of the extracted object as a round hole with a diameter of 28.5 mm and a index of 122 HU. The background object is water with 0 HU index. The low HU difference is close to the brain tissue. The results of the three areas on the phantom are 9284 pixels^2, 9480 pixels^2, and 9146 pixels^2, roughly the same as the area recorded on the phantom 9113 pixels^2. Accurate rates are 98.12%, 95.96% and 99.64%, respectively.

3.2. Applying proposed method for brain images

Brain images containing tumors are soft tissues with a small HU index. Comparing with the phantom standard model, select the hole with the index is the soft tissue as a reference to perform segmentation and extract the object of interest. We collected this experimentation DICOM from hospitals in Vietnam and from the Brain Web dataset [11]. The threshold value of 15 is chosen as the optimal index for segmentation for brain images. In this paper, we show 4 typical results from four images corresponding to four patients (figure 5). The threshold selection problem is solved by maximizing the number of components connected to that threshold. We can see from the results of phantom analysis: the number of connected components is a threshold-dependent function. If the threshold is set too low, the objects are over-detected. Conversely, if the threshold is too high, the area of interest will be submerged in the background.

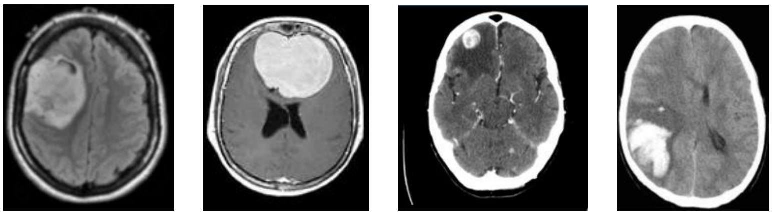


Figure 5: Raw input images

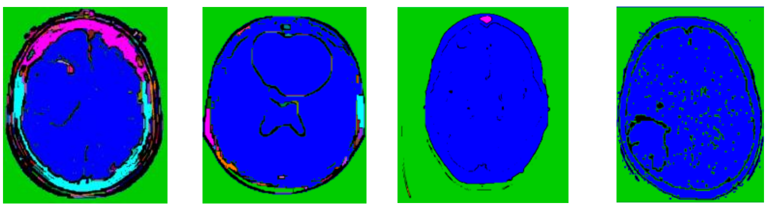


Figure 6: Connected component without using Sobel

The size of the square region set by the size of smallest tumor. It shows all types of nodules (large, small and medium size). The proposed is an automatic method and detected all of the nodules without human interference. We used some traditional preprocessing such as our references, especially Sobel method [12]. After applying the connected component filter, comparing figures 6 and 7, corresponding to using and without using Sobel edge detection algorithm. The results showed a clear effect in distinguishing lesions and surrounding areas: gray matter, white matter, and background are being completely segmented. After connected component, apply confidence connected transform, and author gained the region of interest from brain images in figure 8.

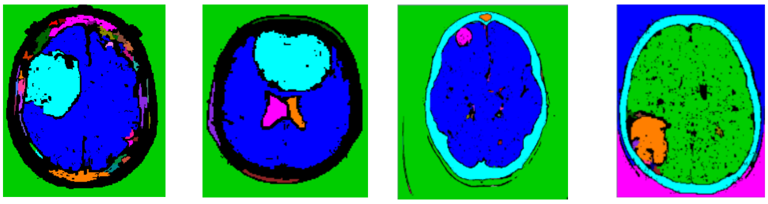


Figure 7: Connected component using Sobel

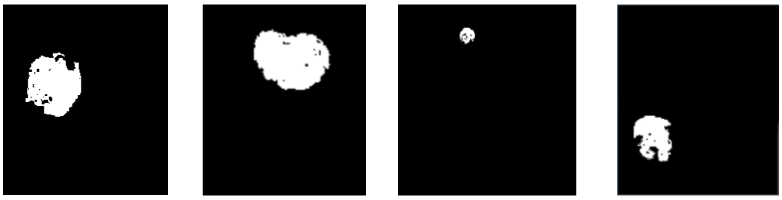


Figure 8: Segmented images after using region growing

The tumor portion of the brain image is visible, shown as white color. This section has the highest intensity compared to other areas of the image. Finally, the location of the tumor region has been determined based on pixel value of the tumor region. From the analysis results for phantom, we can see: The small threshold value, the greater the level of detailed segmentation, for Gamex phantom image, the objects of interest were clear. But for complex medical images, it was necessary to choose the value optimal threshold for extracting objects accurately in size. The tumor in Figure 8 with the optimal threshold value is 15 corresponding to the threshold value of the hole (soft tissue) of the phantom.The area of the tumor was calculated and compared with the results of the Slicer3D software, the accuracy shown in Table 2.

***Table 2:** Area of the extracted tumor*

Images	Original size (pixel)	Area in pixel	Area of tumor	Accuracy (%)
1	205x246	50430	10174	96.34
2	409x537	219633	32829	95.75
3	480x480	230400	1552	95.32
4	441x521	229761	9257	91.39

By experimenting on phantom samples and clinical medical images, the results obtained are highly accurate > 95.96%. This is a very useful result to distinguish abnormal areas for brain images with many purposes in surgery or treatment.

By using ITK with system configuration Inter(R) Core(TM) i5- 4210U, CPU 1.7GHz, 4GB RAM, 64 bit Windows 10, the proposed process has reduced the computational complexity.

3. CONCLUSION

The difficulty in brain tumors segmentation lies in their irregularities in terms of shape, size, and location. The purpose of this work is to separate the tumor region from the surrounding tissue by defining the boundaries between the regions. This process will reduce the complexity of a series of image segmentation algorithms. An automated algorithm based on regional development is proposed and verified in this study. Experimental results have confirmed its good performance in CT and MRI image segmentation. This is an important step in calculating the dose later.

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PHƯƠNG PHÁP PHÂN MẢNH TỐI ƯU ĐỂ PHÁT HIỆN KHỐI U NÃO TRONG HÌNH ẢNH Y TẾ

Tóm tắt: Trong lĩnh vực xử lý hình ảnh y tế, phát hiện khối u não từ chụp cắt lớp vi tính (CT) hoặc cộng hưởng từ (MRI) là một nhiệm vụ khó khăn và ưu tiên hàng đầu do sự phức tạp của não. Trong bài viết này, chúng tôi mô tả một phương pháp mới kết hợp bốn bước khác nhau bao gồm các thuật toán làm mịn ảnh, phát hiện cạnh Sobel, kết nối thành phần và phát triển vùng để xác định vị trí và trích xuất các tổn thương khác nhau trong não. Thuật toán tính toán đề xuất được thực hiện bằng 3 công cụ Insight Toolkit (ITK) để xử lý hình ảnh đầu vào, Visualization Toolkit (VTK) để hiển thị và khung ứng dụng đa nền tảng Qt để xây dựng giao diện người dùng. Kết quả thực nghiệm chỉ ra rằng phương pháp được đề xuất đã phát hiện tự động và hiệu quả vùng khối u từ hình ảnh CT hoặc MRI của não. Công cụ này có thể hỗ trợ cho các bác sĩ tách mô bất thường từ các mô xung quanh bình thường để có được một hình dung chính xác của khu vực quan tâm; cải thiện chất lượng và độ chính xác của chẩn đoán, tăng khả năng thành công bằng cách phát hiện sớm khối u cũng như giảm thời gian lên kế hoạch phẫu thuật. Đây là một bước quan trọng trong việc tính toán liều xạ trị chính xác về sau.

Từ khóa: Hình ảnh y tế, khối u não, phân mảnh, ITK, VTK