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

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Abstract. *In the field of medical physics, detection of brain tumors 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 of many recent researches. In this article, we describe a new method that 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 of the proposed method was implemented using Insight Toolkit (ITK). The analysis results indicate that the proposed method automatically and efficiently detected the tumor region from the CT or MRI image of the brain with an accuracy above 90%. This result is comparable to physician's manual practice in clinical and computational software in medicine. It is very clear for physicians to separate the abnormal from the normal surrounding tissue to get a real identification of related areas; 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 correctly calculating the dose in radiation therapy later.*

Keywords: medical image, brain tumour, segmentation, ITK.

Classification numbers: 87.57.nm, 87.57.N-, 87.61.Tg.

I. INTRODUCTION

Brain tumors are known to be one of the main diseases leading to human death in the world. They occur when abnormal cells develop in the brain affecting neighboring tissues. 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 doctor doctors [1]. Early detection and treatment can increase the rate of survival for patients.

There are many approaches used to differentiate biological tissue edges of brain images. Biji *et al.* [2] proposed a technique to detect tumors from MR images using fuzzy clustering and minimum error thresholding. This method shows how this technique overcomes the problem of over-segmentation with watershed algorithm, but the major drawback is the computational time required. Nandi *et al.* [3] have concluded that a set algorithms based on thresholding are a powerful tool for the detection of brain tumors in MRI images. The method proposed by Anam *et al.* [4] required a watershed algorithm for segmentation. The article goes into anatomical analysis of the brain and symptoms, damage caused by encephalopathy. The only downside is the over-segmentation leads to poor detection of significant areas with low contrast boundaries that commonly results in MRI brain images. M.C. Jobin Christ and R.M.S. Parvathi [5] introduced the method of the brain tumor detection that integrates K Means clustering with a marker-controlled watershed algorithm and integrates Fuzzy C Means clustering with marker-controlled watershed algorithm separately for medical image segmentation. The drawback of K-means clustering is that it requires multiple loops. Ahmed *et al.* [6] proposed the method for the detection and extraction of brain tumors from MRI images using K-means Clustering. This method is very effective, that is proven to be less time consuming and achieves maximum lossless data compression. But this approach causes fake edges on the image. Mohane S. *et al.* [7] proposed morphology method, the results are sensitive to noise, and the tumor region is approximately obtained. Up to now, many different algorithms have been proposed and implemented, and each has its own advantages and disadvantages. However, the methods mentioned above did not clearly state how to verify their method. Besides, there is no single approach that can generally solve the problem of segmentation for the large variety of image modalities existing today. To overcome the above disadvantages, this study proposes brain tumor segmentation method based on simple techniques in image processing. Segmentation algorithms are most effectively obtained by carefully customizing combinations of components.

Our proposed method is based on the intensity of each pixel to make it easier to segregate the affected areas. The Hounsfield unit (HU) measures the attenuation of the X-ray beam in each projection in CT scan. 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

$$HU = (\mu - \mu_{\mathrm{w}})/\mu_{\mathrm{w}} \tag{1}$$

The tissue density can vary considerably, and many soft tissues overlap in the range of HU values, so that HU values do not clearly distinguish between 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 [8]. These regions are called 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 [9], Osirix [10], etc. are either manual or semi-manual, which 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 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 by 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 to segment images. 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.

II. METHODS

II.1. General description of proposed method

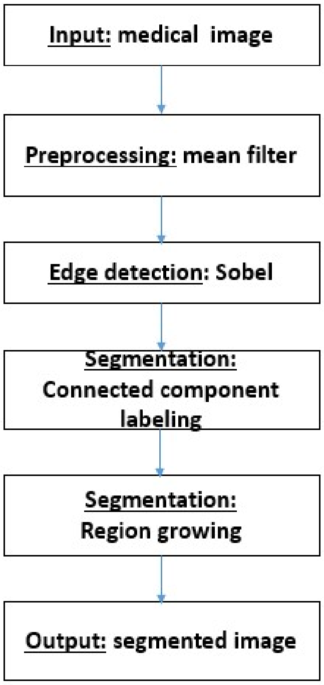


Fig. 1. Flowchart of the proposed method.

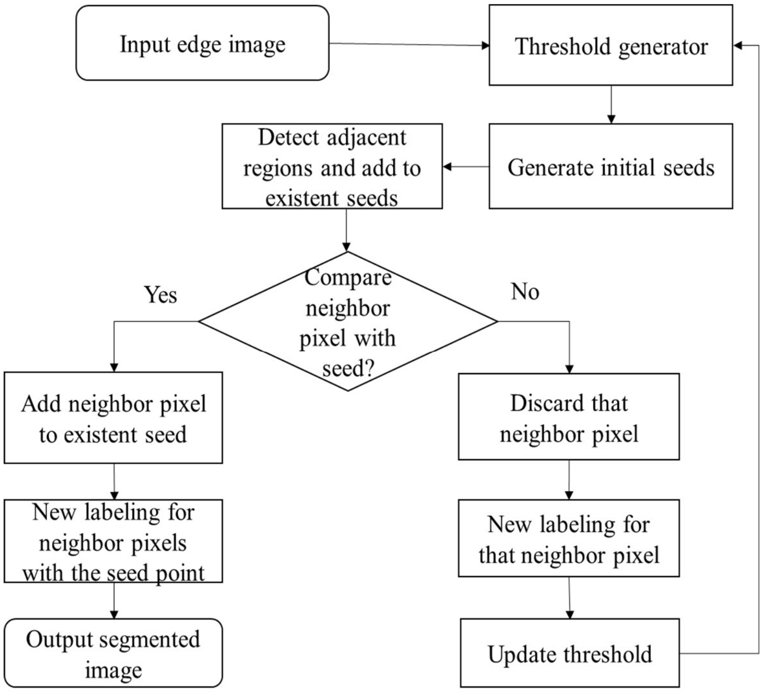


Fig. 2. Proposed image segmentation algorithm.

Image processing in medical diagnostics includes stages such as preprocessing, edge detection, segmentation and extraction of interest features. The implementation procedure of algorithm is shown in Fig. 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.

In the first step, the input image is pre-processed with mean filter to smooth and reduce the noises with the 3×3 square kernel. After being pre-processing, the image will be applied with an edge-detection algorithm to detect the boundary of the tumour.

The algorithmic abstract applies to an area of interest as follows:

```
• Set R to a region to be extracted (R contains only the seed point p).
• Set F to a region containing edge points of R (F consists of 8 neighbours of seed point p)
• WHILE F is not an empty matrix
FOR each pixel neighbour p* of p in F.
    - IF p* is similar to p
      Neighbour pixels of p* (not in R) are added to F.
    - ELSE
      Set p* is not similar pixel.
```

II.2. Factors affecting quality of CT, MRI scans

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 photons reach the 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, and salt & pepper noise. 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. In this paper, the first step for image analysis is to filter data. Image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain visual characteristics [11]. Its result is a set of segments that covered the entire image, or a set of contours extracted from the image. Edges are basically sharp intensity transitions, local to a region, in the images and mark the pixel as boundary element. Region-based method groups the pixels which share common characteristics to form homogeneous regions. In this work, Sobel edge detection is used to sharpen the brain image. This is a gradient-based segmentation technique and suitable for the images that have a large gray level.

II.3. Segmentation

Connected Component Labelling. 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 a certain group are defined by similar relationships. Basic approach is to start from a seed region (usually one or more pixels) that is considered inside the segmented object. The pixels neighbouring this region are evaluated to check if they are part of the object.

The minimum and maximum intensities of the gray image are set to 0 and 255. The factor which affects the outcome of Connected component algorithm is the threshold value. In this paper, the influence of the threshold value to the segmented image quality was evaluated based on phantom.

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 neighbour (4, 8, or 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 neighbours and assess whether their intensity is within the range ($m \pm f\sigma$). The following equation describes the filter:

$$I(X) \in [m - f\sigma, m + f\sigma] \tag{3}$$

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 neighbouring pixel being considered for inclusion in the area. Confidence connected requires three factors: the intensity range f, the multiplier and the number of iterations. The recommended confidence multiplier is 2.5 for medical image in ITK [12]. 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-value 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 neighbour). The size of neighbour radius around seed point is set 3.

III. RESULTS AND DISCUSSION

III.1. Applying proposed method for Phantom Gamex 463

Initially, the proposed method was tested on CT image of the Phantom Gamex 463 (with standard area 9113 pixel) from Kien Giang Cancer Hospital, Vietnam. 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 also changes. 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.

Experimental results on the phantom with minsize =20 (or minsize =50, 100, 200) indicate that:

- With threshold values from 0 to 5: There are many objects that are detected excessively, cluttered and difficult to identify areas of interest.

- With threshold values from 6 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.

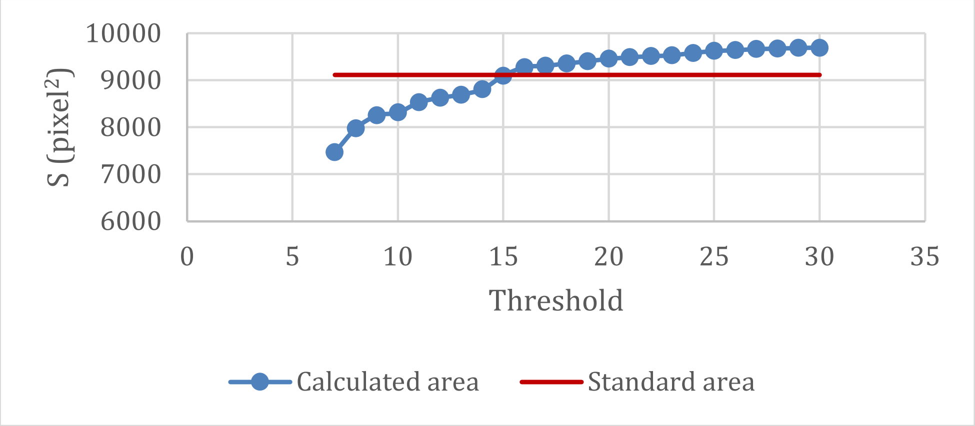


Fig. 3. The graph shows the change of area by threshold.

From the results of Table 1 and Fig. 3 on Gamex phantom, 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 tumour extract was calculated as Table 1 and Table 2.

Calculate the area of the extracted object as a round hole with a diameter of 28.5 mm. 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, 9480 pixels, and 9146 pixels, roughly the same as the area recorded on the phantom 9113 pixels. Accurate rates are 98.12%, 95.96% and 99.64%, respectively.

Table 1. Dependency of segmentation results on input threshold value with minsize = 20.

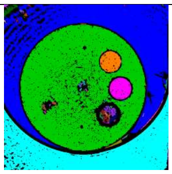
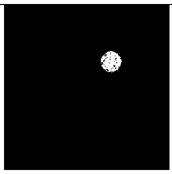
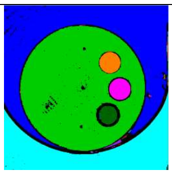
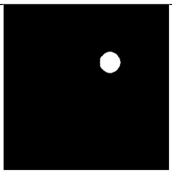
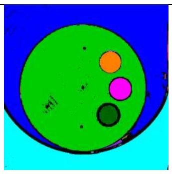
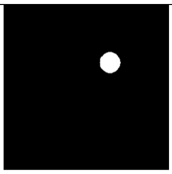
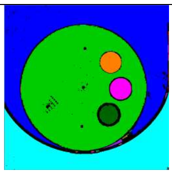
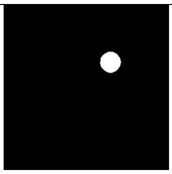
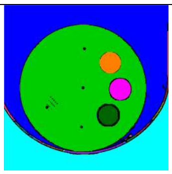
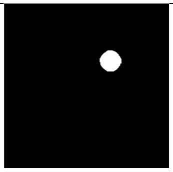
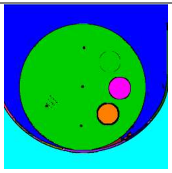
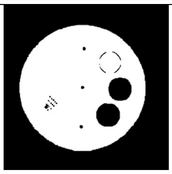
No.	The output image	Threshold value	Extraction output image	Calculated area (pixel)
1		*8*		*7979*
2		*14*		*8811*
3		*15*		*9098*
4		*16*		*9278*
5		*30*		*9689*
6		*31*		Unknown

Table 2. 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(pixel)**	**S(pixels)**
(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

III.2. Applying proposed method for brain images

Brain images containing tumours 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 54 CT images from Kien Giang Cancer Hospital, Vietnam and from the Brain Web dataset [13]. All procedures were approved by the Medical Ethics Committee of Kien Giang Cancer Hospital. 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 (Fig. 4). 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.

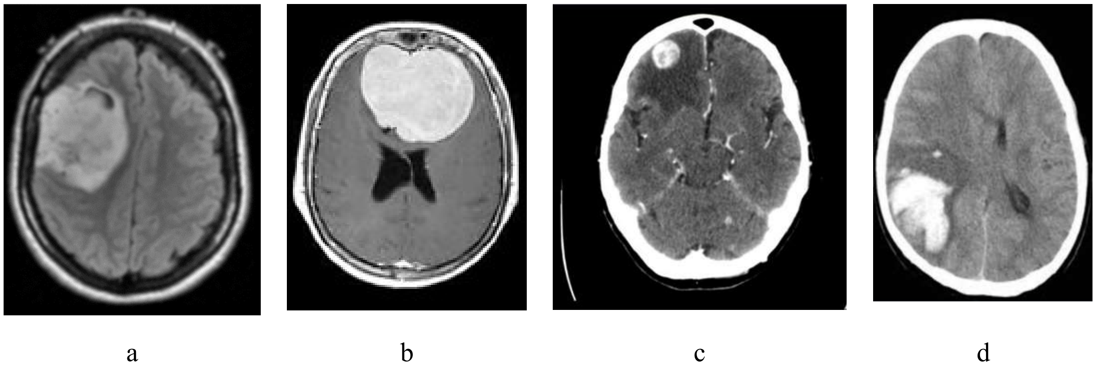

a b c d

Fig. 4. Raw input images.

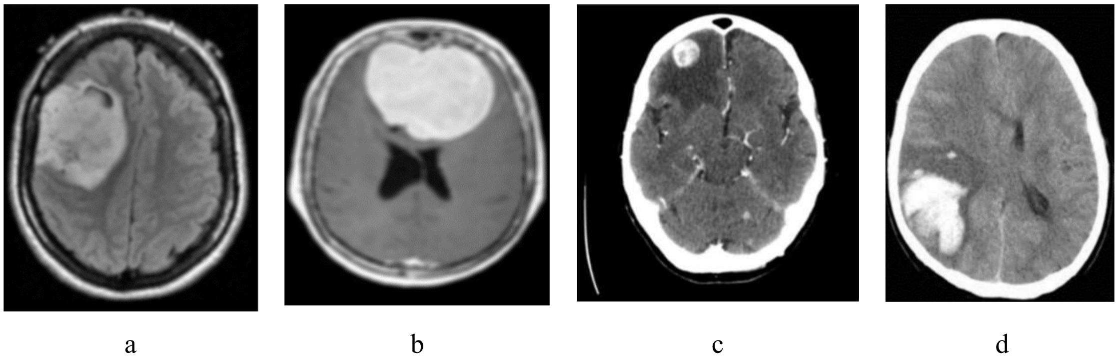

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Fig. 5. Pre-processing mean filter.

Sobel changes the pixel intensity distribution, improving signal-to-noise ratio, and enhancing visibility of the ROI's edges. We can see the edge markers is necessary for each ROI and

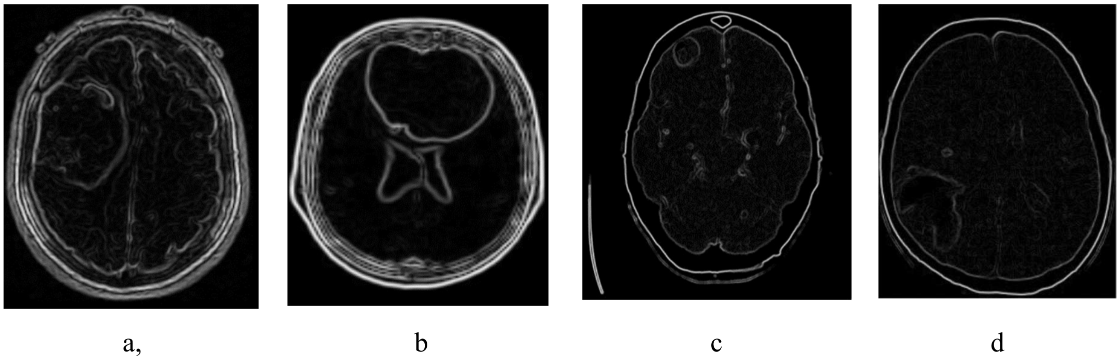

Fig. 6. Sobel edge detection.

background in medical image processing. The markers computation was done by using the Sobel edge detection operation technique to clean up the image and removing the small blemishes without affecting the overall shape of the segmented objects (Fig. 6). Making markers for background and ROI by Connected Component filter and output colour segmented image without calculating the gradient magnitude (Fig. 7). Making markers for background and ROI by Connected Component filter, output colour segmented image, and calculate the gradient magnitude (Fig. 8). It depends on the change in the grayscale of the area of interest that the threshold value changes accordingly.

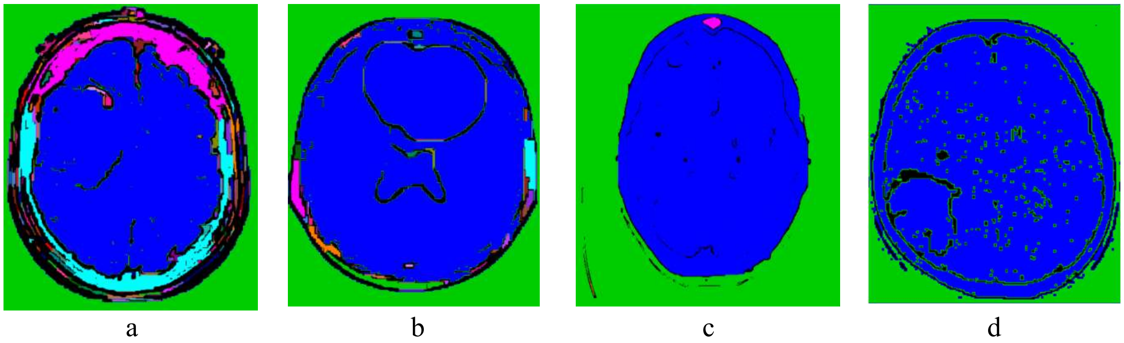

Fig. 7. Connected component without using Sobel.

The algorithm determines the number of suspected areas automatically and quantifies them. 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.

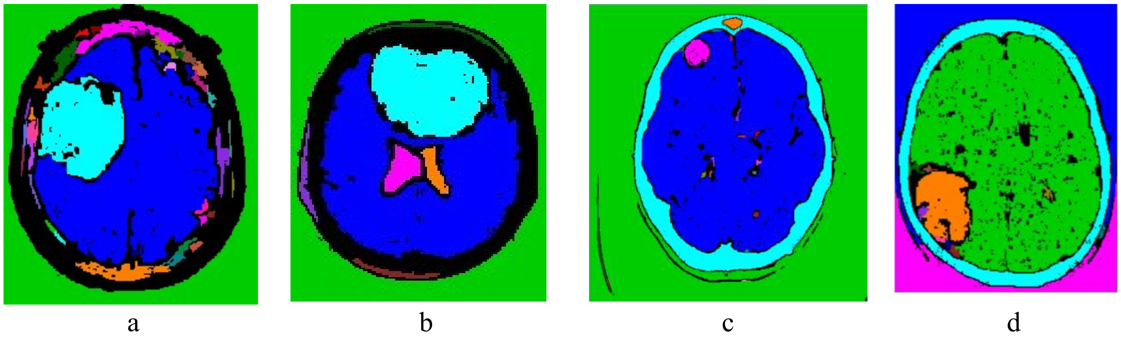

Fig. 8. Connected component using Sobel.

The tumour of the clinical image is clearly visible, shown in white. This part has the highest intensity compared to other areas of the image. Finally, the location of the tumour area was determined based on the pixel value of the tumour region.

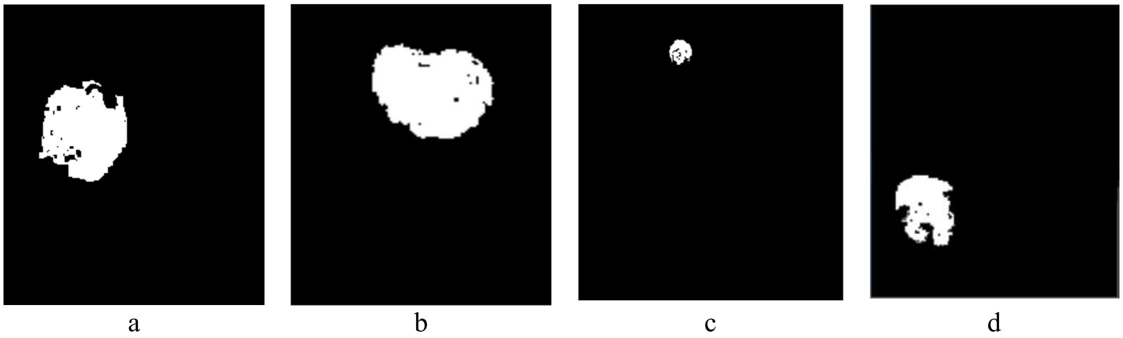

Fig. 9. Segmented images after using region growing.

The size of the square region is set by the size of the smallest tumour. It shows all types of nodules (large, small and medium size). The proposed is an automatic method and detected all the nodules without human interference. After applying the connected component filter, comparing Fig. 7 and Fig. 8, 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 we gained the region of interest from brain images in Fig. 9.

The tumour 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 tumour region has been determined based on pixel value of the tumour 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 tumour in Fig. 9 with the optimal threshold value is 15 corresponding to the threshold value of the hole (soft tissue) of the phantom. The area of the tumour was calculated and compared with the results of the Slicer3D software from taking a clinician, the accuracy shown in Table 3.

Table 3. Area of the extracted tumour.

Images	Original size (pixel)	Area in pixel	Area of tumor	Accuracy (%)
Image 1	205 x 246	50430	10174	96.34
Image 2	409 x 537	219633	32829	95.75
Image 3	480 x 480	230400	1552	95.32
Image 4	441 x 521	229761	9257	91.39

By experimenting with phantom samples and clinical medical images, the results obtained are highly accurate $> 91.39\%$. The average implementation time of the proposed method is about $\sim$1 minute for each case from the pre-processing step to final area calculation, significantly exceeding that in clinical practice by clinician (about $\sim$20 minutes). This is a very useful result to distinguish abnormal areas for brain images with many purposes in surgery or treatment.

The proposed method has higher accuracy and simpler implementation than the previously proposed methods [3–7]. Most methods mentioned above did not clearly state how to verify their method. The evaluation results by Nandi *et al.* [3] are subjective and the tumour area exists unwanted pieces around. In method by Haritha [7], the results only distinguish between the background (cerebrospinal fluid, white matter, and grey matter) and the foreground (brain tumour). The authors point out the polygon matrix that contains the tumor and calculate the qualitative parameters. The method of manually defining polygons proves that this research is not accurate and unreliable.

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.

IV. CONCLUSION

Medical image processing plays an important role in diagnosis and useful in many clinical applications. The difficulty in brain tumor segmentation lies in their irregularities in terms of shape, size, and location. Assisted diagnostic tools need to have high sensitivity with the ability to efficiently detect brain tumors. In this study, an automated algorithm based on regional development is proposed and verified to be over 90% accurate with CT and MRI brain segmentation. 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. Image segmentation not only takes a lot of time but also requires great user interaction, the proposed method has significantly reduced tumor detection and identification time compared with doctors in clinical practice, from more than 20 minutes to less than one minute. Using ITK, we showed the combination of edge and region growing algorithms are effective methods for brain image segmentation. This is an important step in planning the treatment with radiation therapy later. In the future, we will continue to do this research by collecting more data from different centers in Vietnam as well as applying advanced deep learning methods to brain tumor segmentation.

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