Brain Tumor Detection from Pre-Processed MR Images using Segmentation Techniques

Sarbani Datta
Student of Master of Bio-Medical Engineering
School of Bio-Science and Engineering,
Jadavpur University
Kolkata, India

Dr. Monisha Chakraborty
Assistant Professor
School of Bio-Science and Engineering,
Jadavpur University
Kolkata, India

ABSTRACT
Magnetic resonance imaging (MRI) has become a common way to study brain tumor. In this paper we pre-process the two-dimensional magnetic resonance images of brain and subsequently detect the tumor using edge detection technique and color based segmentation algorithm. Edge-based segmentation has been implemented using operators e.g. Sobel, Prewitt, Canny and Laplacian of Gaussian operators. The color-based segmentation method has been accomplished using K-means clustering algorithm. The color-based segmentation carefully selects the tumor from the pre-processed image as a clustering feature. The present work demonstrates that the method can successfully detect the brain tumor and thereby help the doctors for analyzing tumor size and region. The algorithms have been developed on MATLAB version 7.6.0 (R2008a) platform.

General Terms
Image Processing, Algorithms.

Keywords
magnetic resonance imaging; brain tumor; edge-based segmentation; color-based segmentation; K-means clustering.

1. INTRODUCTION
Magnetic resonance imaging (MRI) acts as an assistant diagnostic device for the doctors during disease diagnosis and treatment [1]. This imaging modality produces images of soft tissues. These acquired medical images show the internal structure, but the doctors want to know more than peer images, such as emphasizing the abnormal tissue, quantifying its size, depicting its shape, and so on [2]. If such tasks are covered by the doctors themselves, it may be inaccurate, time consuming and burden them heavily.

Thus, computer image processing plays an important role in radiology [3]. There are many computer-aided diagnosis systems which are implemented in disease monitoring, operation guiding, etc. [4]. Segmentation is an important process in medical image analysis and classification for radiological evaluation or computer-aided diagnosis [5]. The quantification is based on accurate segmentation. It is still not solved very well because of the complexity of the medical images. Therefore, the expert hand work for image segmentation is the best way for diagnosis. But it is tedious, time consuming and difficult for the doctors to handle [4, 5]. To reach the goal that can simulate the doctor's actions in the diagnosis, a system should implement the algorithm of segmentation which could provide the most precise result as possible. On the other hand, the system should adapt good interactive mechanism, such that segmentation could be under the user's control and give the feedback in the real time.

Image segmentation methods can be classified into three categories: edge-based methods, region-based methods [5], and pixel-based methods. K-means clustering is a key technique in pixel-based methods. Pixel-based methods based on K-means clustering are simple and the computational complexity is relatively low compared to other region-based or edge-based methods. The application is more practicable. Furthermore, K-means clustering is suitable for biomedical image segmentation as the number of clusters is usually known for images of particular regions of the human anatomy [6]. Many researchers have proposed K-means clustering segmentation [6, 7]. The improvements achieved by [6, 7] have been remarkable, but more computational complexity and extra software functionality are required.

This paper describes segmentation techniques to detect brain tumor from two-dimensional MR images. In this work, pre-processing algorithm has been applied on MR images of brain to enhance the contrast. Subsequently, image segmentation methods e.g. edge-based method and pixel-based method has been applied. The edge-based segmentation significantly detects the tumor. The pixel-based segmentation technique selects the tumor from the pre-processed image as a clustering feature. Low computation aspect has been maintained and resulted with a successful segmentation. Therefore, color-based K-means clustering segmentation on brain MR images for tumor detection has maintained efficiency. The experimental results confirm that the proposed method will help the doctors for diagnosis.

2. MATERIALS AND METHODS
2.1 Pre-Processing
Histogram equalization is a spatial domain image enhancement technique that modifies the distribution of the pixels to become more evenly distributed over the available pixel range [8]. In histogram processing, a histogram displays the distribution of the pixel intensity values, mimicking the probability density function (PDF) for a continuous function. An image that has a uniform PDF will have pixel values at all valid intensities. Therefore, it will show a high contrast image. Histogram equalization creates a uniform PDF or histogram [9]. This can be accomplished by performing a global equalization that considers all the pixels in the entire image or a local equalization that segments the image into regions.

Subtraction images may also cause enhancement of certain regions of an image. In contrast enhanced MR images, a mask image is used and subtracted from a contrast enhanced image to boost up the contrast [10].

2.2 Edge-based Segmentation

The edge detection process detects outline of an object and boundaries between objects and the background in the image. The basic edge detection operator shows a matrix area gradient operation that determines the level of variance between different pixels. The edge-detection operation is performed by forming a matrix centered on a pixel chosen as the center of the matrix area [11]. If the value of this matrix area is above a given threshold value, then the middle pixel is considered to be as an edge. Examples of gradient based edge detectors are Sobel, and Prewitt, operators. The gradient-based algorithms have kernel operators that calculate the strength of the slope in directions which are orthogonal to each other, commonly vertical and horizontal. Later, the different components of the slopes are combined to give the total value of the edge strength [12]. The first-order derivative of an intensity, f(x,y), of an image is the gradient. The gradient is defined as the vector as in (1).

$$\nabla f = \begin{bmatrix} G_x \\ G_y \end{bmatrix} = \begin{bmatrix} \partial f/\partial x \\ \partial f/\partial y \end{bmatrix} \quad (1)$$

The magnitude of the vector is given in (2).

$$\nabla f = \operatorname{mag}(\nabla f) = \left[G_x^2 + G_y^2\right]^{1/2} = \left\{\left(\partial f/\partial x\right)^2 + \left(\partial f/\partial y\right)^2\right\}^{1/2} \quad (2)$$

The gradient vector points in the direction of the maximum rate of change of the 2-D function, f(x,y), of an image. The angle at which this maximum rate of change occurs is mathematically shown in (3).

$$\alpha(x,y) = \tan^{-1}\left(G_y/G_x\right) \quad (3)$$

There are various approaches as mentioned in this section to determine the derivatives G_x and G_y digitally. The second-order derivatives of the intensity, f(x,y), of an image are computed using the Laplacian equation as given in (4).

$$\nabla^2 f(x,y) = \frac{\partial^2 f(x,y)}{\partial x^2} + \frac{\partial^2 f(x,y)}{\partial y^2} \quad (4)$$

2.2.1. *Sobel Operator*

The Sobel operator performs a 2-D spatial gradient measurement on an image. It is used to find the approximate absolute gradient magnitude at each point in an input grayscale image [12]. Fig 1 shows the 3x3 area representing the gray levels of an image. The operator consists of a pair of 3×3 convolution masks as shown in Fig 2. One mask is simply the other rotated by 90° [8, 11].

Z_1	Z_2	Z_3
Z_4	Z_5	Z_6
Z_7	Z_8	Z_9

Fig 1: Image neighborhood

Gx

-1	0	+1
-2	0	+2
-1	0	+1

Gy

+1	+2	+1
0	0	0
-1	-2	-1

Fig 2: Sobel convolution masks

The detector uses the masks to compute the first order derivatives G_x and G_y, as in (5).

$$G_x = Z_7+2Z_8+Z_9$$

$$G_y = Z_1+2Z_2+Z_3 \quad (5)$$

2.2.2. *Prewitt Operator*

The Prewitt operator as similar to the Sobel measures two components. The vertical edge component is calculated with kernel Gx and the horizontal edge component is calculated with kernel Gy, as shown in (6).

$$G_x = (Z_7+Z_8+Z_9)-(Z_1+Z_2+Z_3)$$

$$G_y = (Z_3+Z_6+Z_9)-(Z_1+Z_4+Z_7) \quad (6)$$

In the mentioned formulation, the difference between the first and third rows of the 3x3 image region as show in Fig 1 approximates the derivative in the x-direction, and the difference between the third and first columns approximates the derivative in the y-direction [8, 11]. The Prewitt masks as shown in Fig 3 are used to implement G_x and G_y.

G_x

-1	0	1
-1	0	1
-1	0	1

G_y

1	1	1
0	0	0
-1	-1	-1

Fig 3: Prewitt masks

2.2.3. *Canny Operator*

The Canny edge detection algorithm is known as an optimal edge detector based on a set of criteria which include finding the edges by minimizing the error rate, marking edges as closely as possible to the actual edges to maximize localization, and marking edges only once when a single edge exists for minimal response [13].

The first stage involves smoothing the image by convolving with a Gaussian filter. This is followed by computing the gradient of the image by feeding the smoothed image through a convolution operation with the derivative of the Gaussian in both the vertical and horizontal directions.

-1	0	+1
-2	0	+2
-1	0	+1

Gx

+1	+2	+1
0	0	0
-1	-2	-1

Gy

Fig 4: Canny convolution masks

2.2.4. Laplacian of Gaussian Operator

The Laplacian is a 2-D isotropic measure of the 2nd order derivative of an image. The Laplacian of an image highlights regions of rapid intensity change and is therefore often used for edge detection [11]. The Laplacian is applied to an image that has first been smoothed with Gaussian filter in order to reduce its sensitivity to noise. The operator takes a single graylevel image as input and produces another graylevel image as output.

0	1	0
1	−4	1
0	1	0

1	1	1
1	−8	1
1	1	1

−1	2	−1
2	−4	2
−1	2	−1

Fig 5: Laplacian of Gaussian kernels

The kernels that are mentioned in Fig 5 are used as discrete approximations to the Laplacian filter [11-12]. The 2-D Laplacian of Gaussian function centered on zero and with Gaussian standard deviation σ has the form as in (7).

$$\mathrm{LoG}(x,y) = -\frac{1}{\pi\sigma^4}\left[1-\frac{x^2+y^2}{2\sigma^4}\right]e^{-\frac{x^2+y^2}{2\sigma^2}} \qquad (7)$$

2.1 Pixel-based Segmentation

K-means is an extensively used clustering algorithm to partition data into *k* clusters [6]. Clustering is the process for grouping data points with similar feature vectors into a single cluster and for grouping data points with dissimilar feature vectors into different clusters. Let the feature vectors derived from *l* clustered data be X=(x_i |*i*=1,2,…,*l*). The generalized algorithm initiates k cluster centroids C=(c_j |*j*=1,2,…,*k*) by randomly selecting k feature vectors from X. Later, the feature vectors are grouped into k clusters using a selected distance measure such as Euclidean distance as in (8) so that

$$d = \left\|x_i - c_j\right\|. \qquad (8)$$

The next step is to recompute the cluster centroids based on their group members and then regroup the feature vectors according to the new cluster centroids. The clustering procedure stops only when all cluster centroids tend to converge [6, 7].

The block diagram of our developed algorithm is shown in Fig 6. The input brain MR images are taken from the websites e.g. braintumors.in, ncbi.nlm.nih.gov, and springerimages.com.

The algorithms are developed on MATLAB version 7.6.0(R2008a) in Microsoft Windows XP operating system, with the processor 2.16GHz and 1.96GB of RAM.

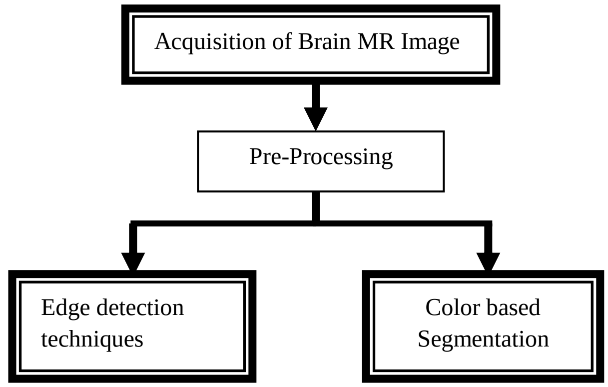

Fig 6: System Block Diagram

3. RESULTS AND DISCUSSION

Twenty brain MR images (160 x 202 resolutions) are used to evaluate the proposed algorithm. Initially, histogram equalization technique is performed. The original and the histogram equalized images are then converted to double precision images in order to perform the subtraction operation. Subtraction image is obtained by subtracting the original image from the histogram equalized image. Finally to get the pre-processed image, the subtracted image is been complemented as shown in Fig 9. Histogram equalization takes advantage of the neglected pixel values and provides better definition and more information for the doctors. Subtracted images boost up the result. Further, complement of the subtracted images provides a better means to assess the tumor region in the MR images.

Edge detection operators e.g. Sobel, Prewitt, Canny and Laplacian of Gaussian are used to perform on the complemented image. Edge-based segmentation on the processed MR image of brain has been shown in Fig 10 (a), Fig 10 (b), Fig 10 (c) and Fig 10 (d) respectively using the above mentioned operators. The developed algorithm automatically calculates the threshold for the images. Edge detection algorithms are able to detect the tumor region very well. The best algorithm among the Sobel, Prewitt, Canny and Laplacian of Gaussian is the Canny operator. This algorithm detects the tumor well to help the doctors for treatment plan making.

Color-based segmentation on the processed brain MR image has been shown in Fig 11. In this proposed method, we convert the pre-processed gray-level brain MR image into RGB color image first. The RGB color image is then been coarsely represented using 25 bins. Coarse representation uses the spatial information from a histogram based windowing process. K-means is been used to cluster the coarse image data. In each of the segmented images *k*=6 has been taken. As seen in Fig 11, the segmentation result identifies the tumor region significantly.

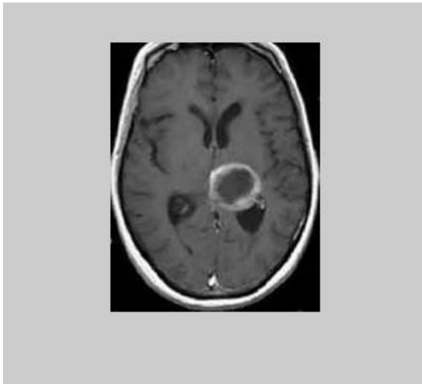

Fig 8: Original Image

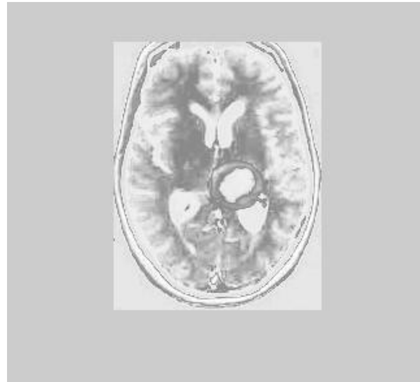

Fig 9: Pre-Processed Image

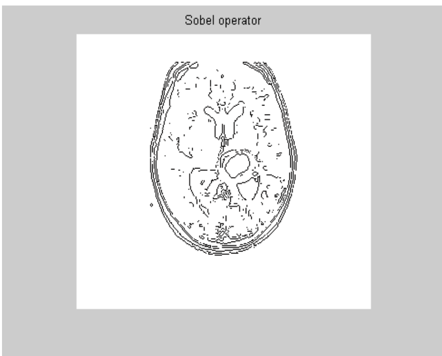

Fig 10(a): Sobel based edge detection

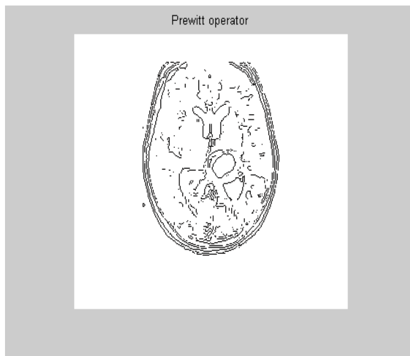

Fig 10(b): Prewitt based edge detection

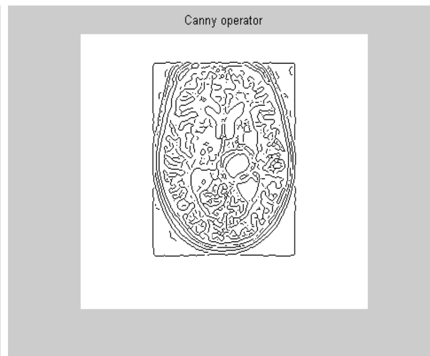

Fig 10(c): Canny based edge detection

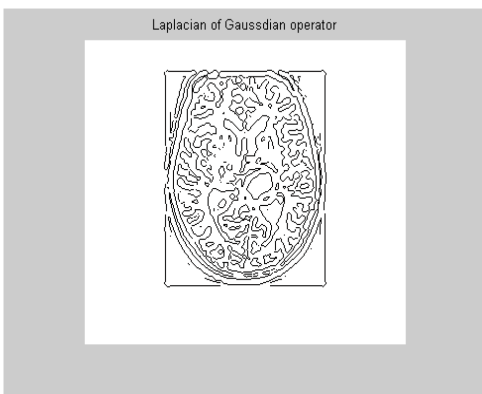

Fig10(d): Laplacian of Gaussian based edge detection

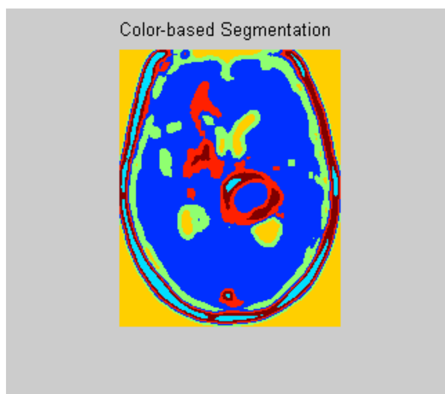

Fig 11: Color-based segmentation

4. CONCLUSION

In this paper color-based segmentation using K-means clustering for brain tumor detection is proposed. The developed algorithm shows better result than Canny based edge detection. The method will help the doctors for diagnosis in a better way by reducing the subjectivity and miss rate in brain MR images and thereby will enhance the tumor detection accuracy in less time.

5. ACKNOWLEDGMENTS

We would like to express our sincere thanks and deepest gratitude to all the members of the websites e. g. braintumors.in, ncbi.nlm.nih.gov, and springerimages.com, who provided the MR images showing brain tumor in their websites and without these images this work would not have been possible.

5. REFERENCES

[1] M.R.Kaus, S.K.Warfield, A.Nabavi, P.M.Black, F.A.Jolesz, and R.Kikinis, "Automated segmentation of MR images of brain tumors," Radiology, vol. 218, pp. 586-591, 2001.

[2] S.K.Bandyopadhyay and D.Saha, "Brain region extraction volume calculation," UNIASCIT, vol. 1, no. 1, pp. 44-48, 2011.

[3] T.Logeswari and M.Karnan, "An improved implementation of brain tumor detection using segmentation based on hierarchical self organizing map," Internatinal Journal of Computer Theory and Engineering, vol. 2, no. 4, pp. 1793-8201, August 2010.

[4] C.Sai, B.S.Manjunath, and R.Jagadeesan, "Automated segmentation of brain MR images," Pergamon, Pattern Recognition, vol. 28, no. 12, March 1995.

[5] C.S.Tsai and C.C.Chang, "An improvement to image segment based on human visual system for object-based coding", Fundamenta Informaticae, vol. 58, pp. 167–178, 2004.

[6] C.W.Chen, J.Luo, K.J.Parker, "Image segmentation via adaptive K-mean clustering and knowledge-based morphological operations with biomedical applications", IEEE Trans. on Medical Imaging, vol. 7, pp. 1673–1683, 1998.

[7] H.P.Ng, H.H.Ong, K.W.C.Foong, P.S.Goh and W.L.Nowinski, "Medical image segmentation using K-means clustering and improved watershed algorithm", IEEE Southwest Symposium on Image Analysis and Interpretation, pp. 61–65, 2006.

[8] R. C. Gonzalez and R. E. Woods, Digital Image Processing, Prentice Hall, pp. 711-791, (2001).

[9] Y.H.Hu, ECE 533 Image Processing Lecture Notes: Image Enhancement by Modifying Gray Scale of Individual Pixels, 2002-2003.

[10] M.Prince, T.M.Grist, and J.F.Debatin, *3D Contrast MR Angiography*, Springer-Verlag, NY, 1999.

[11] E.Nadernejad, S.Sharifzadeh,, and H. Hassanpour, "Edge detection techniques: evaluation and comparisons", Applied Mathematical Sciences, vol.2, pp. 1507-1520, 2008.

[12] A.A. Moustafa and Z.A. Alqadi, "A practical approach of selecting the edge detector parameters to achieve a good edge map of the gray image", J. Comput. Sci., vol. 5, pp. 355-362, 2009.

[13] J.Canny, "A computational approach to edge detection", *IEEE Trans.* Pattern Analysis and Machine Intalligence, vol. 8, pp.679-714, November 1986.