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A Comparative Analysis of Various Segmentation Techniques in Brain Tumor Image

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Abstract

Image segmentation is a very important step in image analysis, and performance evaluation of processed image data. Image segmentation is typically used to locate objects and boundaries in images. The brain has a particularly complicated structure and its precise segmentation is very important for detecting tumors and other tissues. Edge detection is one of the important aspects of image segmentation comes prior to feature extraction, extracting the shapes an image and image recognition system for analyzing images. In this paper we have discussed the different edge detection segmentation techniques using MRI brain tumor image were compared with each other and analyzed and find the most accurate using error measurement techniques.

Keyword: Image segmentation, Edge detection techniques, Root Mean Square Error.

1. INTRODUCTION

Image segmentation techniques play an important role in image recognition system. An edge and line detection technique highlights the boundaries and the outlines of the image by suppressing the background information. The main problem of quantifying different edge detectors is that there is no unique way of studying an image. Segmentation algorithms will be very helpful to evaluate the efficiency of image segmentation techniques.

Medical imaging techniques like Magnetic Resonance Imaging (MRI), Computerized Tomography (CT), Ultrasound (US) and Positron Emission Tomography (PET) are the tools used for extraction of vital information by medical field specialists. Thus, accurate segmentation which aid in image analysis and unerring diagnosis is of immense importance. Compared to other medical imaging techniques, Magnetic Resonance Imaging has the benefit of having excellent contrast between soft tissues. But, because of the convoluted nature of the regions of interest, accurate segmentation of these regions is still a challenging task. Since MR images are gray level images the segmentation algorithms used in this study are gray-level image segmentation algorithms. The resultant segmented images were analyzed to determine the most accurate image segmentation algorithm for the segmentation of a brain tumor

This paper presents a quantitative study of different edge detection techniques. Comparison is done on MRI Brain Tumor image to use Edge detecting techniques like Prewitt, Canny and Sobel were implemented and tested on brain tumor image from these fields. The characteristic used to measure the consistency of these edge detectors is $erms$, which is root mean square error between the input image and the output image. This measure allows a principled comparison between different results generated by the edge detectors.

This paper is organized a follows: section II is describes a literature review. Section III explains an image segmentation technique. Section IV describes the various edge detectors used in this paper. Section V presents the experimental results of brain tumor image. Section VI concludes the paper.

2. LITERATURE REVIEW

There are many algorithms used for image segmentation in that some algorithms segmented an image based on the object while some can segment automatically. There is a huge literature on segmentation dating back to decades, with applications in myriad areas. In this section, some of the related work is presented relevant to the approach of this paper. In threshold image segmentation [1] an image is segmented and simply sorted to object and background by setting a threshold. It is easy to get good results by threshold segmentation. However, if there is complex information in an image, the threshold algorithm is definitely not suitable. Edge detectors have been evaluated based on average risk [2]. It is the performance measure based on Bayesian decision theory. In this performance, edge detector is context dependent which makes it non-trivial. Edges are detected for the images in spatial domain and edge detectors are evaluated based on the relative frequencies of the edge detected pixels and edge differences.

The main goal of segmentation is to divide an image into parts having strong correlation with areas of interest an image. Segmentation can be classified as complete segmentation and partial segmentation. Complete segmentation results are a set of disjoint regions corresponding only with input image objects. Partial segmentation resultant regions do not correspond directly with input image [3]. Image segmentation is often treated as a pattern recognition problem since segmentation requires classification of pixels [4].

In medical imaging for analyzing anatomical structures ,pathological regions and dividing an entire image into sub regions such as the white matter (WM), gray matter (GM) and cerebrospinal fluid (CSF) spaces of the brain automated delineation of different image components are used [2, 4].

Graph-cuts are one of the emerging image segmentation techniques for brain tissue identification. It introduced for image analysis since the year 2001 through global energy minimization [3]. The efficient graph cuts algorithm performs optimal and accurate image segmentation with minimum cut and maximum flow. Image segmentation is crucial tool in image processing and used in several applications. For example, in medical imaging field it is used to surgical planning, locate tumors and other pathologies, assess tissue volumes, brain MRI segmentation, revise of anatomical structure etc [4]. Other practical applications of image segmentation are machine visualization, traffic control system; face and finger print recognition and locate objects in satellite images. Graph cuts technique for Image segmentation has uses cropping and colorization along with the multi-view image stitching, image reconstruction, n-dimensional image segmentation etc [5].

There are a number of techniques available to segment an image. Those techniques are not suitable for medical images because of complexity and inaccuracy. There are no standard image segmentation technique produce acceptable results for all imaging applications like MRI brain, brain cancer analysis etc.

3. IMAGE SEGMENTATION

Image Segmentation is the process of dividing an image into vital regions or objects [6]. The purpose of segmentation is to simplify the representation of an image is easier to analyze. Image segmentation is basically used to locate an objects and boundaries in images. Segmentation algorithms are based on the two basic properties of an image intensity values: discontinuity and similarity. The first step in image analysis is segment the image.

Segmentation divides an image into parts or objects. There are two techniques available in segmentation process, discontinuity detection technique and Similarity detection technique. In the first one is to partition an image based on rapid changes in gray-level image. The second technique is based on threshold and region growing. This paper discuses the discontinuity detection techniques using various Edge Detection method.

3.1 Edge Detectors

Edge detection is more common for detecting discontinuities in gray level and intensity values than detecting isolated points and thin lines because isolated points and thin lines so not occur frequently in most practical images. The boundary between two regions is edge with relatively distinct gray level properties. Here the transition between two regions is determined on gray level discontinuities alone. Such discontinuities are detected by using first and second order derivatives. The first-order derivative in image processing is the gradient defined as below. The gradient of an image *f(x,y)* at location *(x,y)* is the vector[5]:

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

The gradient vector points in the direction of maximum rate of change of f at *(x,y)*.
In edge detection techniques, an important parameter is the magnitude of this vector.

$$|\nabla f| = \sqrt{G_x{}^2 + G_y{}^2}$$

The gradient takes it's maximum rate of increase of *f(x,y)* per unit distance in the direction of f . To simplify computation, ignoring square root approximates this quantity.

$$|\nabla f| = |Gx| + |Gy|$$

The gradient vector points in the direction of the maximum rate of change of ∇f at coordinates (x, y). The angle at which the maximum rate of change occurs is $\alpha\,(x,) = tan^{-1}\left(\frac{G_y}{G_x}\right)$

4. EDGE DETECTION TECHNIQUES

4.1 Sobel Operators

The computation of the partial derivation in gradient may be approximated in digital images by using the Sobel operators. Sobel edge detector uses the masks as shown in the figure below to digitally approximate the first order derivatives

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

1	2	1
0	0	0
-1	-2	1

These two masks mutually with the equations:

$$|\nabla f| = \sqrt{G_X^{\ 2} + G_Y^{\ 2}}$$

$$|\nabla f| = |Gx| + |Gy|$$

are used to obtain the gradient magnitude of the image from the original.

4.2 Roberts Cross Edge Detector

The Roberts Cross operator performs a trouble free, speedy to compute, gradient measurement on an image. The most common usage of this operator, the input is grayscale image, as is the output. Pixel values at each point in the output are representing the estimated absolute magnitude of spatial gradient of the input image at that point.

1	0
0	-1

0	-1
-1	0

4.3 Prewitt Operator

The prewitt operator uses the same equations as the Sobel operator, except that the constant c = 1. The Prewitt operator measures two components are vertical and horizontal. The vertical edge component is calculated with kernel Gx and the horizontal edge component is calculated with kernel Gy. |Gx| + |Gy| give an indication of the intensity of the gradient in the current pixel.

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

G_x

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

G_y

4.4 Canny edge detector technique

Canny technique is very important method to find edges by isolating noise from the image before find edges of an image, without disturbing the features of the edges in an image and then applying the tendency to find the edges and the critical value for threshold.

The algorithm of canny edge detection technique is follows:

1. Convolve image f(r, c) with a Gaussian function to get smooth image f^(r, c).
   f^(r, c)=f(r,c)*G(r,c,6)
2. Apply first difference gradient operator to compute edge strength then edge magnitude and direction are obtain as before.
3. Apply non-maximal or critical suppression to the gradient magnitude.
4. Apply threshold to the non-maximal suppression image.

4.5 Laplacian Operator

The Laplacian of an image *f(x,y)* is a second order derivative defined as:

$$\nabla^2 f = \frac{\partial^2 f}{\partial x^2} + \frac{\partial^2 f}{\partial y^2}$$

The digital implementation of this operator is usually made through the mask below:

0	-1	0
-1	4	-1
0	-1	0

This operator is usually used to establish whether a pixel is on the dark or light of an edge.

4.6 Gradient Magnitude

This algorithm calculates the gradient magnitude of an image using the first derivatives (*Gx*, *Gy*, and *Gz* [3D]) of the Gaussian function at a user-defined standard deviation and convolving it with an image. The convolution of the Gaussian an image is a robust method of extracting edge information. By varying the standard deviation, a scale-space of an edges can easily constructed.[7][8][9]

4.7 Thresholding

Thresholding is one of the simplest image segmentation techniques. A threshold is chosen according to the application for which it is applied. If one particular image has light objects in the dark background, one way to extract the objects in the background is to select a threshold T that separates background and foreground objects [10]. The point for which $f(x,y) \geq T$ is called an object point; otherwise the point is called as background point.

$$g(x, y) = 1 \ if \ f \ x,y \geq T$$

$$0 \; if \; f \; x, < T$$

There are numerous ways of selecting threshold like visual inspection, trial and error but these methods consume a lot of time .The best way for choosing threshold automatically is given in the following procedure [11]:

1. Select an initial estimate for T. Generally it is the midpoint between the minimum and maximum intensity values of the image.
2. Segment the image using T. This will produce two groups of pixels: G1, consist of all pixels an image with intensity values ≥ T, and G2, consisting of pixels with values < T.
3. Then compute the average intensity values μ1 and μ2 for the pixels in regions G1 and G2.
4. Last step is computing a new threshold value:
5. T = 1/2 (μ1 + μ2)
6. Repeat the steps from 2 to 4 until the difference in T in successive iterations is smaller than a predefined parameter.

4.8 Gaussian filter

Gaussian filters are designed to give no overshoot to a step function input while minimizing the rise and reduce time. This behavior is closely connected to the Gaussian filter has the minimum possible group delay.

The one-dimensional Gaussian filter has an impulse response is given by

$$g(x)=\sqrt{\frac{\alpha}{\pi}}.e^{-\alpha x^2}$$

The standard deviation as parameter

$$g(x)=\frac{1}{\sqrt{2\pi\sigma}}.e^{-\frac{x2}{2\sigma^2}}$$

In two dimensions, it is the product of two such Gaussians is one per direction:

$$g(x,y)=\frac{1}{\sqrt{1\pi\sigma^2}}.e^{-\frac{x2+y2}{2\sigma^2}}$$

Where x is the distance from the origin of horizontal axis, y is the distance from the origin of vertical axis, and σ is the standard deviation of the Gaussian distribution.

4.9 Hough transform:

Hough transform, the points are linked by determining first if they lie on the curve of specified shape. Unlike the local analysis method, given on N points of an image is consideration. Suppose we want to detect the subset of these points that lie on the straight lines.

The Hough transform can be used to find features of shape in an image. It is generally used for finding straight lines or circles. The computational complexity of the method grows quickly with more complex shapes. Consider a point (xi, yi) in the image. The basic equation of a line is

y = ax + b.

There are infinitely lines pass through this point, but those lines are satisfy the condition

yi = axi + b For varying a and b.

We can rewrite this equation as b = -xia + yi And plot the variation of a and b.

5. EXPERIMENTAL RESULTS

In this section, the results are presented which are obtained by applying different edge detecting techniques like Prewitt, Canny, Sobel and Thresholding segmentation techniques. The error measure calculated using root mean square error techniques.

5.1 Root Mean Square Error

The Root mean square error ($erms$) is a measure, which calculates the average magnitude of the error. The equation for the $erms$ is given below. The difference between the forecast and corresponding observed values are each squared and then averaged. Finally, the square root of the average is taken. The $erms$ gives a relatively high weight to large errors. The input image is represented as f (x,y), output image f'(x,y) and the error with e(x,y).

$$e \; x,y = f' \; (x,y) - f(x,y)$$

The error between two images is

$$\sum_{x=0}^{m-1}\sum_{y=0}^{n-1}[f('x,y) - f(x,y)]$$

The rms error $erms$ between input and the output is given as

$$erms=1/[\sum_{x=0}^{m-1}\sum_{y=0}^{n-1}[f('x,y) - f(x,y)]^2]^{1/2}$$

The experiments were made on brain tumor image and one from each field is shown over here and the results are compared (Figure 1)

Medical images:

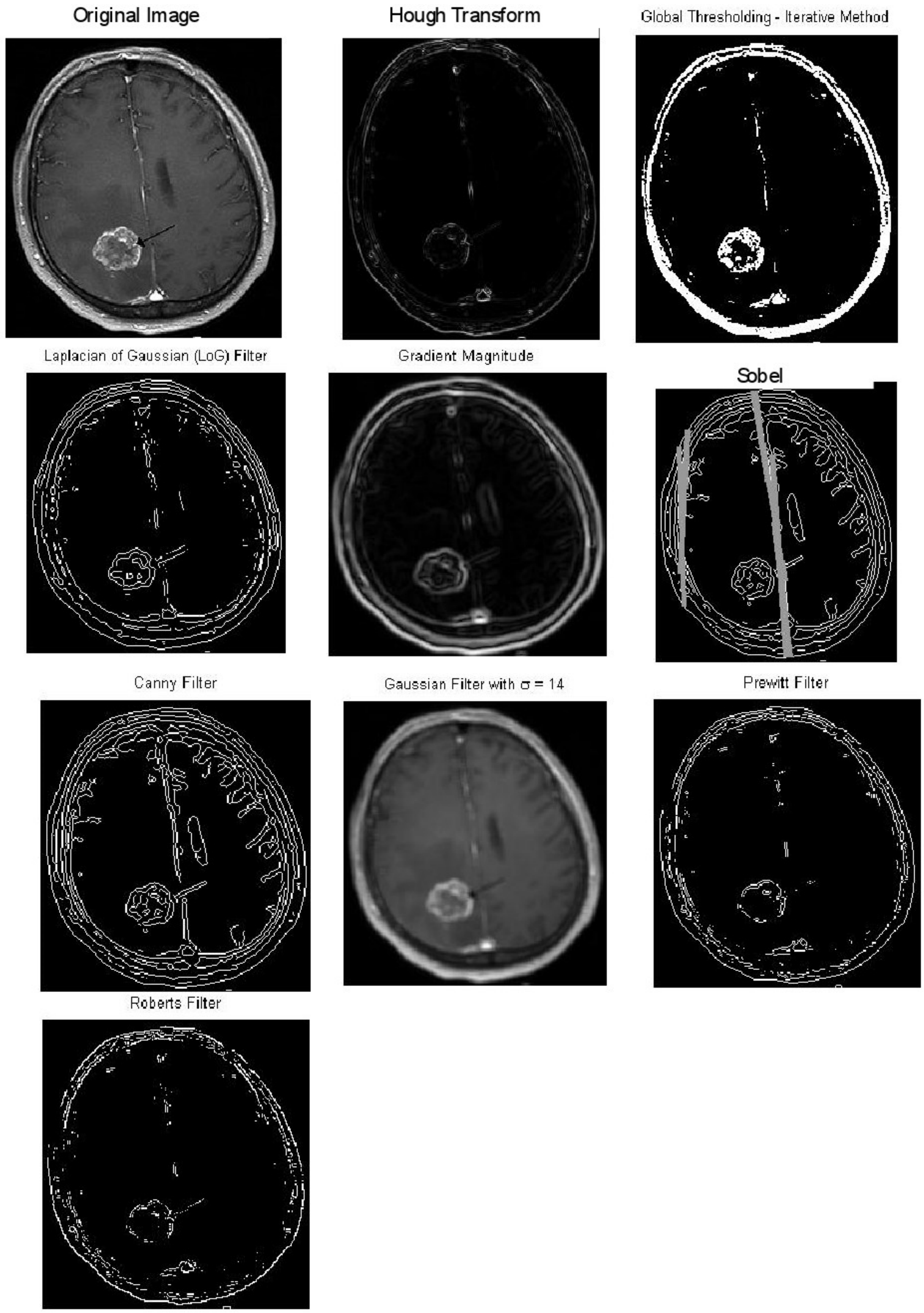

Figure. 1. Results of Various Edge Detection algorithms

These images taken over here were implemented over many other similar images to detect particular areas. As an example to the field are added in this section. Based on the application for the purpose we are analyzing the image is the idea behind getting the error between input and output. If that particular area is detected our purpose is solved and if not we need to use other detector which provides the best result with the least $erms$ as shown in Figure 2.

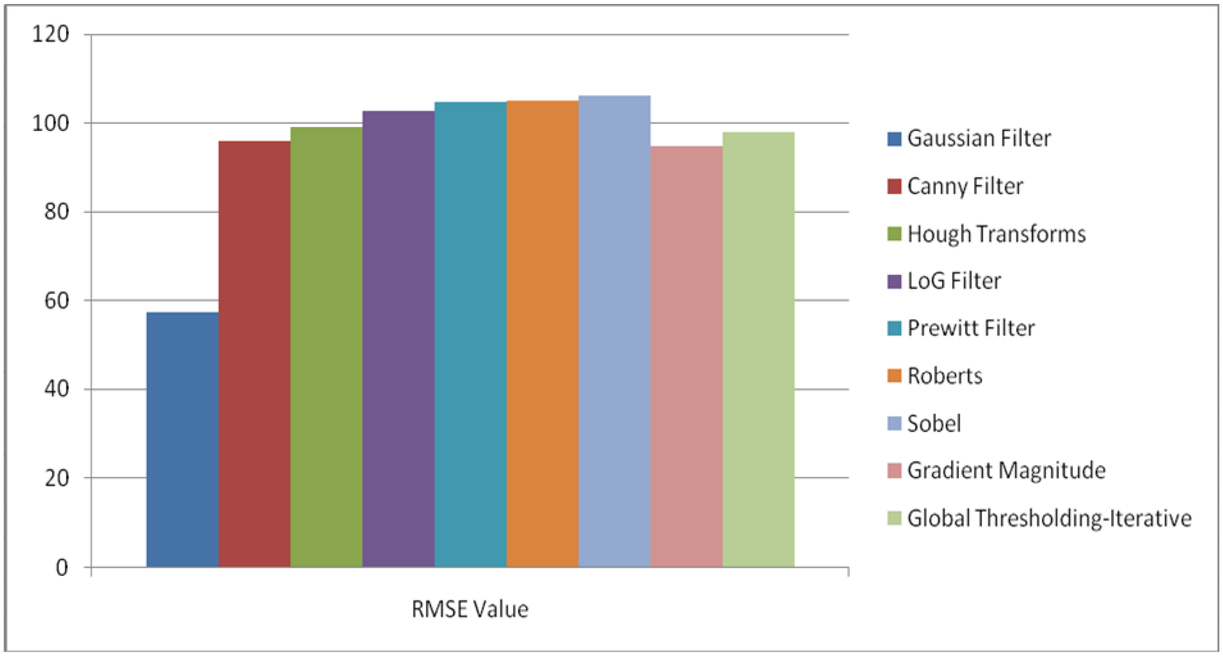

Figure 2: RMSE value for Various Image Segmentation Techniques

6. CONCLUSION

Image segmentation has become a very important task in today's scenario. Observation was made that different segmentation technique in medical brain tumor image to be analyzed. In this paper, the comparative studies applied by using several techniques of edge detection segment on the brain tumor original image. comparative study are explained & experiments are carried out for different techniques Gaussian Filter, Canny Edge Detector and Thresholding techniques respectively are the best techniques for edge. In the future work, the comparative study will be made by taking different clustering techniques used in brain image and find efficient Edge detector algorithm, measuring size of tumor.

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