PERFORMANCE ANALYSIS USING EDGE FOLLOWING TECHNIQUE AND CONTOUR SEGMENTATION FOR BRAIN TUMOR DETECTION

Malathi R, SAAS College, and Nadira Banu Kamal A R, TBAK College,
Ramanathapuram District, Tamil Nadu, India

***Abstract*—Brain tumors are composed of cells that exhibit unstrained growth in brain. Brain tumor detection is one of the challenging task in medical image processing. Since, brain tumors are intricate and tumors can be analyzed only by medical experts. Detecting the accurate boundary in brain images is a crucial task, so this analysis recommends a new edge following technique for correct boundary detection in brain images. The edge detection process serves to facilitate the scrutiny of images by intensely diminishing the amount of data to be processed, while at the same time conserving useful structural information about object boundaries. The canny edge detection algorithm can be used as an optimal edge detector based on a set of principle, which comprise finding the most edges by diminishing the error rate. Canny operator is an edge detection technique containing three processes, namely, edge detection, thresholding and edge thinning. Genetic Algorithm (GA) is type of evolutionary systems that simulates the process of natural selection over generations. In this paper, a genetic optimizer is used to predict a suitable threshold value to detect the edges of medical image. The main intent of this paper is to segment the tumor from brain image using the combination of canny operator and active contours. The performance of the proposed method have been tested in medical images, including brain MRIs, brain CT and brain ultrasound images. In this paper, the value of Hausdorff distance is minimized in the range of 0 to 2 and the level of accuracy is increased by 98%. Experimental results shows that the proposed contour segmentation performs very well and give better results, when compared with the existing methods.**

***Index Terms*— Boundary detection, Canny Operator, Contour segmentation, Edge detection, Genetic Algorithm (GA), Genetic Optimizer, Image segmentation.**

I. INTRODUCTION

Segmentation of images holds a crucial position in the field of image processing. The segmentation of an image involves the demarcation or partition of the image into regions of related attribute. In medical imaging, segmentation is important for feature extraction, image measurements and image display. Segmentation techniques can be split into classes in many ways, depending on the classification scheme. The most commonly used segmentation techniques can be categorized into two classes, i.e. edge based approaches and region based approaches. The method of edge based approaches is to detect the object boundaries by using an edge detection operator and then extract boundaries by using the edge information. Image edge detection significantly diminishes the amount of data and filters out incompetent information, while protecting the decisive anatomical properties in an image. On the other hand, region based approaches are based on affinity of regional image data.

A tumor is a mass of tissue that grows out of control of the normal forces that regulates growth. The multifaceted brain tumors can be split into two common categories depending on the tumors beginning, their enlargement prototype and malignancy. Primary brain tumors are tumors that take place commencing cells in the brain or commencing the wrapper of the brain. Edge detection associates to the action of determining and establishing sharp discontinuities in an image. The canny edge detection algorithm is familiar to many as the optimal edge detector. The edge detection method of canny operator is to find topical maximum value of the image gradient, the gradient is calculated by the derivative of the Gauss filter. The canny operator should satisfy the three judgment criteria: signal-to-noise ratio criterion, positioning accuracy criterion and single-edge response criterion.

Noise presented in the image can diminish the capacity of region growing large regions or may result as a fault edges. The proposed edge following technique is based on the vector image model and the edge map. The implied edge vector field is generated by averaging magnitudes and directions in the vector image. The edge map is derived from texture feature and the canny edge detection. The vector image model and the edge map are applied to select the best edges. Edge vectors of an image indicate the magnitudes and directions of edges, which from a vector stream flowing around an object. However, in an unclear image, the vectors derived from the edge vector field may distribute randomly in magnitude and direction.

Edge map is edges of objects in an image derived from texture and canny edge detection. It gives important information of the boundary of objects in the image that is exploited in a decision for edge following. The canny approach to edge detection is optimal for step edges corrupted by white Gaussian noise. This edge detector is assumed to be the output of a filter that diminishes the noise and locates the edges. The edge following technique is performed to find the boundaries of an object. In order to implement the canny edge detector algorithm, a sequence of steps must be followed. The initial step is to filter out any noise in the primitive image before trying to discover and identify any edges. And because

the Gaussian filter can be enumerated using a modest mask, it is used entirely in the canny algorithm.

Once a reasonable mask has been determined, the Gaussian smoothing can be operated using standard convolution methods. A convolution mask is generally much shorter than the definite image. As a result, the mask is slid over the image, manipulating a square of pixels at a time. An algorithmic approach is proposed to deal with noisy conditioned edge detection. The edge operator uses a random threshold which needed to be optimized to produce refined edges. Thus, a genetic optimizer is used to predict a suitable threshold value to detect the edges of medical image. These results provide a supporting structure to initialize the object boundary.In this paper, the proposed contour segmentation technique is compared with the Active Contour Models (ACM), Geodesic Active Contour models (GAC), Active Contours without Edges (ACWE), Gradient Vector Flow (GVF) and Vector Field Convolution (VFC).

The remaining part of the paper is organized as follows: Section II involves the works related to probable solutions for brain tumor detection and segmentation. Section III involves the description of the proposed method – Canny operator edge detection and Contour segmentation. Section IV involves the performance analysis of the proposed work. The paper is concluded in Section V.

II. Related Work

This section deals with the works related to the brain tumor detection and segmentation in medical images. *Somkantha, et al* [1] designed a new edge following technique for boundary detection in noisy images and applied it to object segmentation problem in medical images. The proposed technique was applied to detect the object boundaries in several types of noisy images where the ill-defined edges were encountered. *Yan, et al* [2] suggested a technique of edge detection based on the enhanced canny operator. In this paper, the traditional canny operator was improved in electing the variance of the Gaussian filter and the threshold, which overcomes the drawbacks of standard interventions in electing the variance of the Gaussian filter and the threshold. *Mustaqeem, et al* [3] implemented an efficient brain tumor detection algorithm using watershed and threshold based segmentation. This research was conducted to detect brain tumors using medical imaging techniques.

Gooya, et al [4] presented a method GLISTR for segmentation of gliomas in multi-modal MR images by joint registering the images to a probabilistic atlas of healthy individuals. The major contribution of the paper was the incorporation of a tumor growth model to adopt the normal atlas into the anatomy of the patient brain. *Parisot, et al* [5] contemplated a different approach for detection, segmentation and characterization of brain tumors. This technique exploits prior knowledge in the form of a sparse graph delineating the expected spatial positions of tumor classes. In this paper, implied a novel way to encode prior knowledge in tumor segmentation, making use of the fact that the tumors tend to appear in the brain in preferential locations. They combined an image based detection scheme with identification of the tumor's corresponding preferential location, which was associated with a specific spatial behavior.

Bauer, et al [8] determined a novel approach to adapt a healthy brain atlas to MR images of tumor patients. They presented a new method which makes use of sophisticated models of bio-physio mechanical tumor growth to adapt a general brain atlas to an individual tumor patient image.

III. Proposed Method

The objective of this paper is to find the exact boundary in the tumor image by using the refined edges. The suggested approach can detect the boundaries of objects in medical images using the information from the intensity gradient via the vector image model and the texture gradient via the edge map. The proposed boundary detection algorithm is used to detect the boundary of an object in an image. Boundary extraction algorithm consists of following three phases.

- Edge Vector gradient
- Edge mapping model
- Edge detection technique

A) Closed Contour Segmentation

The initial position of the classical contour model is calculated by the following steps:

Step 1: Calculate the average magnitude, distance between points.

Step 2: Calculate the density of the edge length map

$$L = \frac{D(x,y)}{max_{x,y} D(x,y)} \quad (4)$$

Step 3: Summation of average magnitude and density of edge length. By summing equation (4) and (5), initial position I (a, b) is obtained.

$$\text{Average magnitude P (x, y)} = \frac{1}{Pr} \sum_{(x,y)\in T} \sqrt{P_i(x,y)^2} + \sqrt{P_j}(x,y)^2 \quad (5)$$

$$\text{I (a, b)} = \frac{1}{2} P(x,y) + L(x,y) \quad (6)$$

Step 4: Closed loop contour is accomplished by thresholding the initial position of the map.

Edge detection methodology is performed on the filtered images. For edge detection, an inimitable procedure is applied by the modification of the original canny edge detection algorithm. After performing the filtering operation on the selected region, the edges in the region of the image are detected by the canny edge detector. In this method, the image is first smoothened by the Gaussian filter to reduce noise in the image. In this paper, the performance is evaluated in terms of Hausdorff distance, Jaccard, Dice, Accuracy, Sensitivity and Specificity.

IV. PERFORMANCE ANALYSIS

Edge detection and boundary detection plays an important role in image analysis. Boundaries are mainly used to detect the outline or shape of the object. Image segmentation is used to locate objects and boundaries in images.

1) Average Edge Vector Field

The edge following technique is performed to find the boundary of an object. The magnitude and direction of the average edge vector field give information of the boundary which flow around an object. In addition, the edge map gives information of edge which may be a part of object boundary. The average vector field is shown in Fig 3.

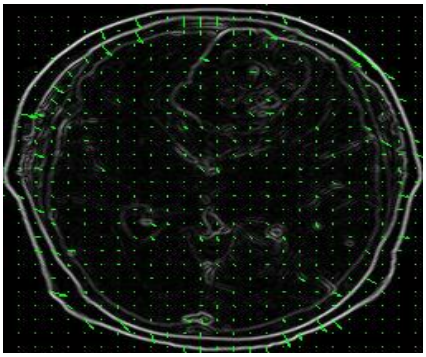

Fig 3. Average Edge Vector Field

2) Law's Texture

The edge map is derived from the law's texture feature and the canny edge detection. The texture features images of Law's texture are computed by convolving an input image with each of the masks. The law's texture is shown in Fig 4. The initial step of edge detection is to convolve the output image obtained from the law's texture with a Gaussian filter.

Fig 4. Law's Texture

3) Fitness Value Calculation

The fitness value calculation is shown in Fig 5. In this graph, the x – axis represents the generation and the y – axis represents the fitness value. This graph shows the Best and Mean fitness value as 0.1053 obtained by applying Genetic Algorithm (GA).

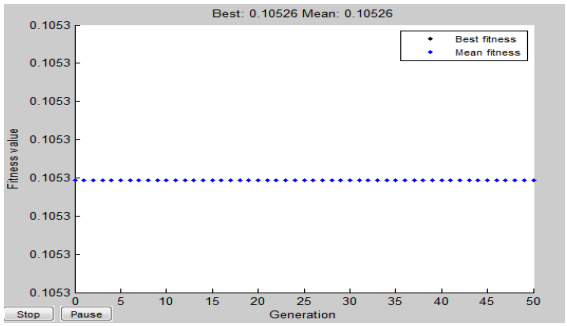

Fig 5. Fitness Value Calculation

4) Canny Edge

The Canny edge approach to edge detection is optimal for step edges corrupted by white Gaussian noise. This edge detector is assumed to be the output of a filter that diminishes the noise and locates the edges. Fig 6 illustrates the canny edge.

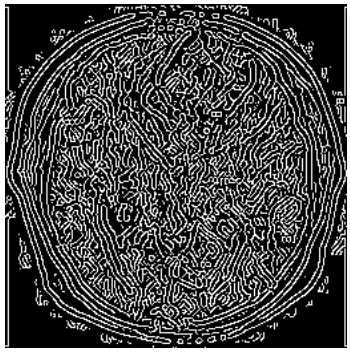

Fig 6. Canny Edge

5) Strong Edges

Edge pixels stronger than thehigh threshold are marked as strong. Strong edges are interpreted as certain edges and can immediately be included in the final edge image. Final edges are determined by suppressing all edges that are not connected to a very strong edge. Fig 7 shows the strong edges.

Fig 7. Strong Edges

6) Average Magnitude

Most edge following algorithms take into account the magnitude as primary information for edge following. However, the edge magnitude information is not efficient enough for searching the correct boundary of objects in noisy

images because it can be very weak in some contour areas. The magnitude and direction of the average edge vector field give information on the boundary which flows around an object.

Fig 8. Average Magnitude Validation analysis

Accuracy [26] is the proportion of correctly diagnosed cases from the total number of cases. Sensitivity measures the ability of the method to identify abnormal cases. Specificity measure the ability of the method to identify normal cases. The determination of the position and structure of the tumor is evaluated by using Jaccard index. The Jaccard and dice are the volumetric metrics. Table 2 shows the performance analysis of proposed method.

$$Jaccard = \frac{|X \cap Y|}{|X|+|Y|-|X \cap Y|} \quad (8)$$

$$Dice = 2\frac{|X \cap Y|}{|X|+|Y|} \quad (9)$$

Where, X represents the documents and Y represents the corresponding queries. Sensitivity, Specificity and accuracy are described in terms of TP, TN, FN and FP.

$$Specificity = \frac{TN}{(TN+FP)} = \frac{Number\ of\ true\ negative\ assessment}{Number\ of\ all\ negative\ assessment} \quad (10)$$

$$Accuracy = \frac{(TN+TP)}{(TN+TP+FN+FP)} = \frac{Number\ of\ true\ correct\ assessment}{Number\ of\ all\ assessment} \quad (10)$$

$$Sensitivity = \frac{TP}{(TP+FN)} = \frac{Number\ of\ true\ positive\ assessments}{Number\ of\ all\ positive\ assessments} \quad (11)$$

Where, TP – True Positive, TN – True Negative, FP – False Positive, FN – False Negative.

Table 2. Performance analysis of proposed method

Images	**Jaccard**	**Dice**	**Accuracy**	**Sensitivity**	**Specificity**
Brain MR images	83.71 %	90.13 %	96.48%	93.97 %	96.93%
Brain CT images	91.73 %	95.70 %	98.64%	95.20 %	99.29%
Brain ultra sound images	87.40 %	93.26 %	98.61%	93.08 %	99.25%

V. CONCLUSION

In this paper, a new edge following technique is designed for boundary detection and applied it to object segmentation problem in medical images. An edge is a property attached to an individual pixel and is calculated from the image function behavior in a neighborhood of the pixel. The purpose of edge detection in general is to significantly diminish the amount of data in an image, while preserving the structural properties to be used for further image processing.This edge following technique incorporates a vector image model and the edge map information. The proposed technique was applied to detect the object boundaries in several types of noisy images where the ill-defined edges were encountered.The proposed integrated image processing algorithm is based on a modified canny edge detection algorithm and implemented using MATLAB.

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