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Evaluating the Hausdorff Distance for Contour Segmentation of Brain Images

[1]Malathi, R. and [2]Dr. Nadirabanu Kamal, A.R.

[1]*Associate Professor, SAAS College, Department of Computer Science, Malathi R, Box.3030. Ramanathapuram, Tamil Nadu, India.,*
[2]*Professor, TBAK College for Women, Department of Computer Science, Nadirabanu Kamal A.R, Box.3030.Ramanathapuram,Tamil Nadu, India.*

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ABSTRACT

Background: Evaluating the hausdorff distance for contour segmentation of brain images. **Objective:** 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 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. **Results:** 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. The proposed edge detection technique for detecting the boundaries of the object using the information from intensity gradient using the vector model and texture gradient using the edge map. The results show that the technique achieves very well and yields better performance than the classical contour models. **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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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

Corresponding Author: Malathi R., Associate Professor, SAAS College, Department of Computer Science, Box.3030. Ramanathapuram, Tamil Nadu, India. SAAS College, Ramanathapuram, Tamil Nadu, India.
E-mail: Malathyrphd2014@hotmail.com

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.

Related work:

This section deals with the works related to the brain tumor detection and segmentation in medical images. *Somkantha, et al* (2011) 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* (2013) 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* (2012) 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 (2012) 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* (2012) 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.

Wang and Li (2012) presented a database of images segmented by human subjects along with an application for boundary detection. The images in this database are based on image pairs and this will greatly facilitate the algorithms combining depth information and other low level cues to detect boundaries or segment images. *Manikis, et al* (2011) suggested a novel framework for assessing tumor changes based on histogram analysis of temporal Magnetic Resonance Image (MRI) data. The proposed method detects the distribution of tumor and quantitative models its growth or shrinkage offering the potential to assist clinicians in objectively assessing subtle changes during therapy. *Bauer, et al* (2012) 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.

The suggested method offers the possibility to implicitly segment tumor-bearing brain images by atlas-based registration. *Kong, et al* (2011) designed a comprehensive structure to support classification of nuclei in digital microscopy images of diffuse gliomas. They developed an inclusive and standardized approach for delineating image analytical results and a competent database implementation with powerful query support. *Dou, et al* (2011) contemplated a data fusion method to perform an automatic segmentation of brain tumor. Brain tumor segmentation was an important technique in computer aided diagnosis. The objective of this paper was to find a simple information fusion strategy to project MRS information on MRI structure image.

Mondal, et al (2011) developed a novel technique for automatic localization of craniofacial structures based on the detected edges in the region of interest. Before the edge detection of the appropriate region, the region was filtered by an adaptive non local filter for noise removal by keeping the edge information undisturbed. The algorithm for the automated detection of craniofacial structures in 2D cephalogram images was developed in this work. *Gooya, et al* (2011) designed a deformable registration algorithm for glioma images with a normal atlas (template). An expectation maximization algorithm was used duringthe registration process to evaluate the spatial transformation and other parameters related to tumor simulations are optimized through asynchronous parallel pattern search (APPSPACK).

Roy, et al (2013) suggested an analysis on automated brain tumor detection and segmentation from MRI of brain. Brain tumor segmentation was a significant process to extract information from complex MRI of brain images. *Logeswari and Karnan* (2010) studied the performance of the MRI image in terms of weight vector, execution time and tumor pixels detection. A tumor was a mass of tissue that grows out of control of the normal forces that regulates growth. The convoluted brain tumors were scattered into two broad classes depending on the tumor's origin, their growth pattern and malignancy. *Roy and Bandyopadhyay* (2012) proposed an interactive segmentation method that enables users to quickly and efficiently segment tumors in MRI of brain. They implied a new method that in addition to area of the region and edge information uses a type of prior information also its symmetry analysis, which was more consistent with pathological cases. *Xavierarockiaraj, et al* (2012) proposed a paper for brain tumor detection using converted histogram thresholding-quadrant approach. In medical image processing, brain tumor detection was one of the challenging task, since brain images were complicated and tumors were analyzed only be expert physicians.

Balasubramanian, et al (2012) designed a new algorithm for segmentation of tumor images with automatic seed point selection to region growing segmentation. Tumor volume was an important diagnostic indicator in treatment planning and results assessment of brain tumor. *Kowar and Yadav* (2012) presented a novel technique for the detection of tumor in brain using segmentation and histogram thresholding. In this paper, a technique to detect presence of the brain based on thresholding technique has been developed. *Verma, et al* (2013) suggested the image processing techniques for the enhancement of brain tumor patterns. They intended a hybrid approach for classification of brain tissues in MRI based on Genetic Algorithm (GA). An enhanced information about brain tumor detection and segmentation was presented in this paper. *Taheri, et al* (2010) introduced a threshold based scheme that uses level sets for 3D tumor segmentation (TLS). In this scheme, the level set speed function was designed using a global threshold. This threshold was defined based on the idea of confidence intervals and iteratively updates throughout the evolution process.

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) Edge Mapping:

Edge map is edges of objects in an image derived from Law's 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. Edge based segmentation is described in terms of discontinuities in image attributes as Gray level, texture, color, etc. 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 edge following technique is performed to find the boundary of an object. Edge based segmentation is the most prevalent method based on detection of edges i.e. boundaries which separates distinct regions. The edge detection method is based on marking of discontinuities in gray level, color, etc. and often these edges represent boundaries between objects. This approach splits an image on the basis of boundaries.

B) Canny Edge Detector:

Canny is an extremely famous and effective edge detector. Edge detection by the method involves a number of steps mainly, (i) Noise removal (ii) Gradient computation (iii) Edge Tracking. The raw image is convolved with a Gaussian filter resulting into a slightly blurred version of the original image.

The canny algorithm can be used an optimal edge detector based on a set of principle which include finding the most edges by diminishing 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. The closed contours indicate a steep slope and two or more contour lines merging indicates a cliff. Figure 2 represents the process of the canny edge detection algorithm.

Algorithm I – Enhanced Boundary Detection Using Refined Edges

Step 1: Select Input Image.

Step 2: Compute gradient of the input image. From the resultant magnitude and direction of the edge vector, calculate the average magnitude and direction of edge vector field.

Step 3: Compute the edge map from the image derived from Law's Texture algorithm and GA optimized canny edge detection.

Step 4: Compute the closed contours for segmentation.

Step 5: Initialize the window of vertices.

Step 6: Compute the ration of the contour corresponding to the two line segments.

Step 7: Include the line segment according to the pixel depth.

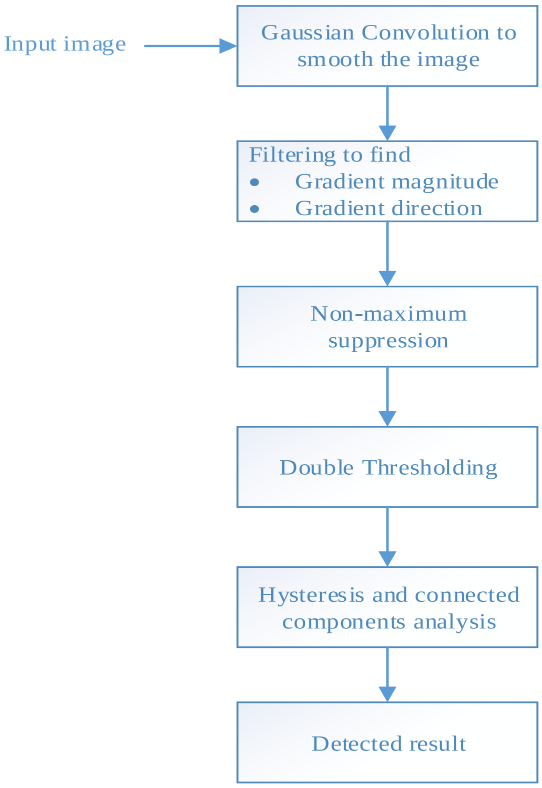

Fig. 1: Canny edge detection

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C) Optimized Canny Edge Detection:

Textural features of the image are essential from image segmentation and classification point of view. The intent of texture based segmentation method is to partition the image into regions having various texture properties, while in classification the objective is to classify the regions which have already been segmented by one or other method. Edge detection is used to determine the boundaries of the object. This gives the similarity present in the image. In this method to detect the edge canny filter is used. Five steps are followed in canny filter.

The steps of optimized canny edge detection are given below:

i. The texture feature image of Law's texture is enumerated by convolving an input image with each of the masks.

ii. A column vector namely L = $(1, 4, 6, 4, 1)^T$ and 2D – Mask l (i, j) is used.

iii. Convolve the input image with the generated texture mask.

D) GA Optimized Canny Edge Detection:

The steps of GA optimized canny edge detection are given below:

i. Smoothen the image to eliminate noise.

ii. Find the image gradient to highlight regions with great spatial derivatives.

iii. Track along these regions and suppress any pixel that is not at the maximum (Non-maximal suppression).

iv. A set of pre-trained thresholds are fed to Genetic Algorithm (GA) to find best threshold values for input image which in turn guides segmentation.

v. The pre-training is implemented through Support Vector Machine (SVM) classifier where the error rate is projected as a penalty function to satisfy the fitness criterion.

vi. Hysteresis uses two thresholds namely T1 (Low threshold) & T2 (High threshold) from GA. Where, M – Magnitude.

$$\text{Edge} = \begin{cases} 0, \; M < T_1 \\ 1, \; M > T_2 \\ 0, M \in \; T_1 \; and \; T_2 \end{cases} \tag{1}$$

E) Edge following procedure:

The magnitude and direction of the average edge vector field give information of the boundary which flows around an object. In addition, the edge map gives information of edge which may be a part of object boundary. Hence, both average edge vector field and edge map are exploited in the decision of the edge following technique. At the position (i, j) of an image, the successive positions of the edges are then calculated by 3 x 3 matrix.

Initialize the weight parameters α =0.6; β =0.2; ε= 0.2;

$$L_{i,j}(r,c) = \propto M_{ij}(r,c) + \beta D_{ij}(r,c) + \in E_{ij}(r,c) \;\; 0 \le r \le 2, 0 \le c \le 2 \tag{2}$$

$$P(i,j) = \frac{1}{2}\left(M(i,j) + L(i,j)\right) \tag{3}$$

Where,

M - Magnitude; D - Direction; E - Edge Map; $L_{i,j}$– Strong Edge; $M_{i.j}$, $D_{i,j}$, $E_{i,j}$ – 3 x 3 matrices; α, β ,ε – Weight Parameters; P – Initialization Position.

F) Contour Segmentation:

Segmentation is an essential process to extract information from complex medical images. The main objective of the image segmentation is to segregate an image into commonly exclusive and exhausted regions such that each region of interest is spatially contiguous and the pixels within the region are homogeneous with respect to a predefined criterion.The idea is that the contour of the tumor should be situated somewhere in between the boundary of the initial detection and the boundary of the tumor around tissues. This constraint also prevents the deformable model from leakage in the weak boundaries. Obtaining brain contours is usually the first step of a brain segmentation process. The contour approach and the regional approach are typical techniques used for the segmentation. The boundary detection problem is defined as an optimization process that seeks the boundary points to diminish an energy functional based on an active contour model. Figure 2 depicts the enhanced boundary detection using refined edges.

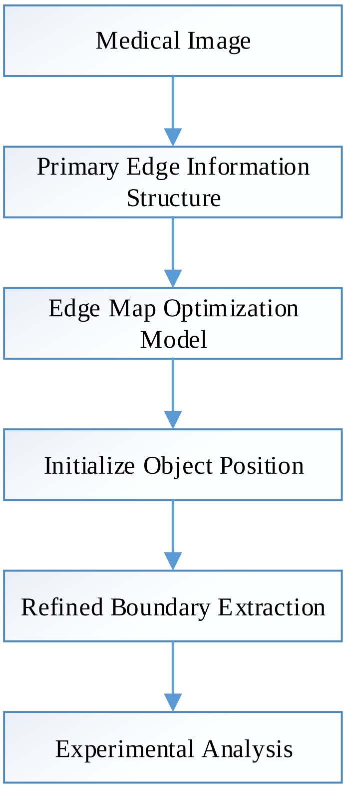

Fig. 2: Enhanced Boundary Detection using refined edges,

G) 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

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

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

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

I (a, b) $= \frac{1}{2}\ P(x,y) +\ L(x,y)$ (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. The edge points detected by the canny edge detection algorithm, the location of the candidate points and the magnitude of the entire pixel are selected. Boundary detection is different from what is classically referred to as edge detection. An edge is most often defined as an abrupt change in some low-level image features such as brightness, color and texture, while a boundary is a contour in the image indicating a change in pixel ownership from one object or surface to another. In this analysis, the proposed method is compared with various existing methods such as, ACM, GAC, ACWE, GVF and VFC snake models. When compared with the existing methods, the proposed method yields high accuracy, sensitivity and specificity.Jaccard and Dice are the metrics used to finding the relevancy level between two sets. In this paper, the performance is evaluated in terms of Hausdorff distance, Jaccard, Dice, Accuracy, Sensitivity and Specificity.

Performance analysis:

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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. The proposed edge detection technique for detecting the boundaries of the object using the information from intensity gradient using the vector model and texture gradient using the edge map. The results show that the technique achieves very well and yields better performance than the classical contour models.

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.

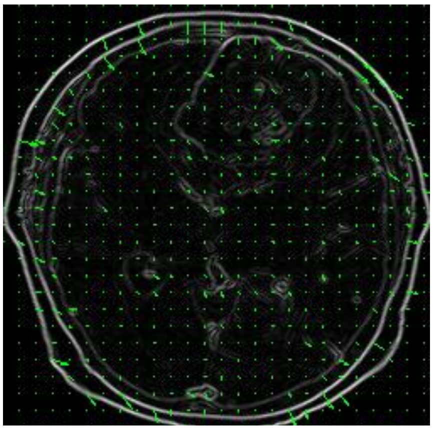

Fig. 3: Average Edge Vector Field.

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 5. The initial step of edge detection is to convolve the output image obtained from the law's texture with a Gaussian filter.

Fig. 5: Law's Texture.

3) Fitness Value Calculation:

The fitness value calculation is shown in Fig 6. 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).

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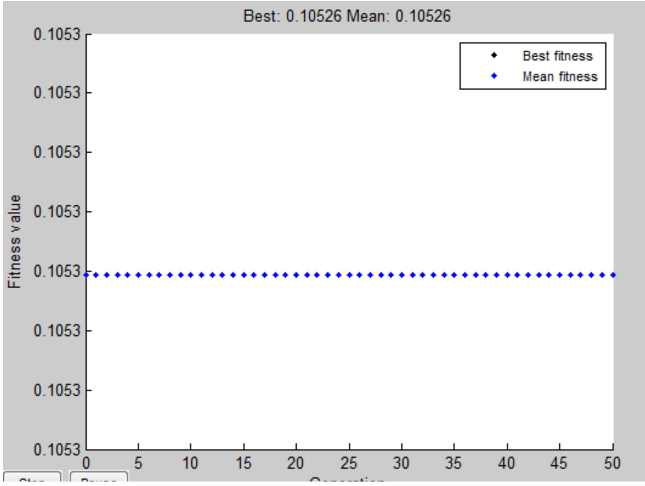

Fig. 6: Fitness Value Calculation.

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 7 illustrates the canny edge.

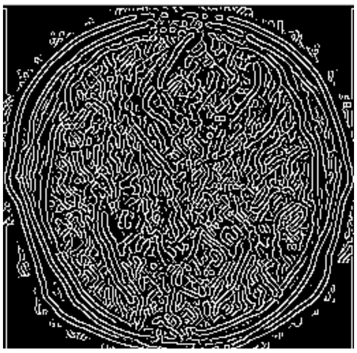

Fig. 7: Canny Edge.

5) Strong Edges:

Edge pixels stronger than the high 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 8 shows the strong edges.

Fig. 8: 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. In addition, the edge map gives information of edge which may be a part of object boundary. Hence, both average edge vector field and edge map are exploited in the decision of the edge following technique. The average magnitude in shown in Fig 9.

Fig. 9: Average Magnitude.

7) Contour Segmentation:

The last stage refines the segmentation. The analysis is based on cooperation between the region growing and the contour detection algorithm. After determining the suitable initial position, the proposed technique will follow edges along the object boundary until the closed loop contour is achieved. Fig 10 shows the contour segmentation.

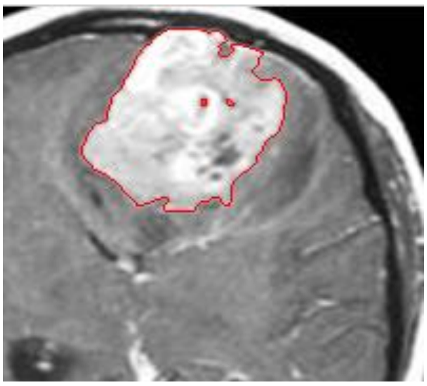

Fig. 10: Contour Segmentation.

8) Comparison Table for the proposed method and the existing method:

The Hausdorff distance is a mathematical construct to measure the "closeness" of two sets of points that are subsets of a metric space. Hausdorff distance [1] express a good position of the boundary of the tumor. Table 1 shows the comparison between the proposed method and the existing method. This distance measure is used to determine the degree of resemblance between the two objects. It is a generic technique to define a distance between two nonempty sets. The results shown in table 1 is the average results of all images in each type.

The Hausdorff distance between A and B, denoted by dH (A, B) is defined by,

$$dH\ (A,B) = maximum\ \{\sup dz(a,B), \sup dz\ (a,B), \sup dz\ (b,A\} \quad (12)$$

For all a in A, b in B,

$$dH\ (A,B) = \max(h(A,B), h(B,A)) \quad (13)$$

Where, $h\ (A,B) = maximum\ \left(minimum\ \left(d(a,b)\right)\right)$ and $d\ (a,b)$ is a L2 norm. A is the first point set and B is the second point set. A and B are the subsets of a metric space (Z, dZ).

The ACWF and GVF snake models provides better performance than the ACM and GAC models. The VFC model provides the best performance among the five snake models. The performance of the proposed technique is evaluated by comparing with the five existing methods, includes, Active Contour Model (ACM), Geodesic Active Contour (GAC), Active Contours without Edges (ACWE), Gradient Vector Flow (GVF) and Vector Field Convolution (VFC) snake models. The snake models have become popular particularly in boundary detection.

Active Contour Models (ACM) (2013) provide a unified solution to several image processing problems, includes, the detection of light and dark lines and edges. They are often used to segment spatial and temporal image sequences. Active Contours without Edges (ACWE) (2013) snake model is used to extract the contours. Gradient Vector Flow (GVF) [23]snakes is an extension of the well-known method snakes or active contours. The Geodesic Active Contour (GAC) (2014) for object segmentation allows to connect classical snakes based on energy minimization and geometric active contours based on the theory of the curve evolution. Vector Field Convolution (VFC) (2011) is calculated by convolving a vector field kernel with the edge map derived from the gray-level or binary image.

Table 1: Comparison table for Hausdorff distance.

Images	ACM		GAC		ACWE		GVF		VFC		Existing		Proposed	
	I1	I2	I1	I2	I1	I2	I1	I2	I1	I2	I1	I2	I1	I2
Brain MR images	6.62	7.90	5.84	6.77	6.37	6.53	6.93	7.11	5.86	6.26	5.31	5.34	1.41	1.41
Brain CT images	14.08	15.36	12.94	13.48	5.71	6.48	8.30	9.30	5.86	6.61	4.64	5.82	0.72	0.80
Brain ultra sound images	14.44	15.70	13.45	14.35	10.50	10.96	11.84	12.66	9.45	10.05	7.91	8.46	1.41	3

9) Validation analysis:

Accuracy (2011) 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.

$$Jaccard = \frac{|X \cap Y|}{|X|+|Y|-|X \cap Y|} \tag{6}$$

$$Dice = 2\frac{|X \cap Y|}{|X|+|Y|} \tag{7}$$

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.

$$Specificity = \frac{TN}{(TN+FP)} = \frac{Numbe\ r\ of\ true\ negative\ assessment}{Number\ of\ all\ negative\ assessment} \tag{9}$$

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

$$Sensitivity = \frac{TP}{(TP+FN)} = \frac{Number\ of\ true\ positive\ assessments}{Number\ of\ all\ positive\ asses\,sments} \tag{11}$$

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%

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.

The objective of segmentation is to cluster pixels into prominent image regions. In this paper, segmentation of gray level images is used to provide information such as anatomical structures and identifying the Region of interest i.e. locate tumor. However, simulation results using this algorithm to show its ability to accurately detect and identify the contour of the tumor. The edge detection process serves to facilitate the scrutiny of images by drastically diminishing the amount of data to be processed, while at the same time conserving useful structural information about object boundaries.

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