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Boundary Detection in Medical Images Using Edge Following Algorithm

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Abstract

This paper introduces a new edge following technique for boundary detection in noisy images. Utilization of the proposed technique is exhibited via its application to various types of medical images. Our proposed technique can detect the boundaries of objects in noisy images using the information from the intensity gradient via the vector image model and the texture gradient via the edge map. The performance and robustness of the technique have been tested to segment objects in synthetic noisy images and medical images including prostates in ultrasound images, left ventricles in cardiac magnetic resonance (MR) images, aortas in cardiovascular MR images, and knee joints in computerized tomography images. We compare the proposed segmentation technique with the active contour models (ACM), geodesic active contourmodels, active contours without edges, gradient vector flow snake models, and ACMs based on vector field convolution, by using the skilled doctors' opinions as the ground truths. The results show that our technique performs very well and yields better performance than the classical contour models. The proposed method is robust and applicable on various kinds of noisy images without prior knowledge of noise properties.

Introduction

Digital Image Processing

Digital image processing is the use of computer algorithms to perform image processing on digital images. Digital image processing has many advantages over analog image processing. It allows a much wider range of algorithms to be applied to the input data and can avoid problems such as the build-up of noise and signal distortion during processing. Since images are defined over two dimensions (perhaps more) digital image processing may be modeled in the form of Multidimensional Systems.

Image Segmentation

In computer vision, segmentation refers to the process of partitioning a digital image into multiple segments (sets of pixels, also known as super pixels). The goal of segmentation is to simply and/or change the representation of an image into something that is more meaningful and easier to analyze. Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.)in images. More precisely, 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.

The result of image segmentation is a set of segments that collectively cover the entire image, or a set of contours extracted from the image. Each of the pixels in a region is similar with respect to some characteristics or computed property, such as color, intensity, or texture. Adjacent regions are significantly different with respect to the same characteristics. When applied to a stack of images, typical in Medical imaging, the resulting contours after image segmentation can be used to create 3D reconstructions with the help of interpolation algorithms like marching cubes.

Image segmentation is an initial step before performing high-level tasks such as object recognition and understanding. Image segmentation is typically used to locate objects and boundaries in images. In medical imaging, segmentation is important for feature extraction, image measurements, and image display. In some applications it may be useful to extract boundaries of objects of interest from ultrasound images, microscopic images, magnetic resonance (MR) images, or computerized tomography (CT) images. Segmentation techniques can be divided into classes in many ways, depending on the classification scheme.

Segmentation Algorithms

Segmentation algorithms are based on one of two basic properties of intensity values discontinuity and similarity. First category is to partition an image based on abrupt changes in intensity, such as edges in an image. Second category is based on partitioning an image into regions that are similar according to predefined criteria.

Types Of Segmentation Technique

The most commonly used segmentation techniques can be categorized into two classes, i.e., edge-based approaches and region-based approaches.

- Edge-based approach
- Region-based approach

Edge detection operators

1st order: Roberts Cross, Prewitt, Sobel, Canny, Spacek

2nd Order: Laplacian, Marr-Hildreth

Currently, the canny operator is most commonly used, followed by Marr-Hildreth. Very many operators have been published but so far none have any significant advantage over the canny operator in general situations.

Literature Survey

Real Time Vessel Segmentation And Tracking For Ultrasound Imaging Applications

A method for vessel segmentation and tracking in ultrasound images using Kalman filters is presented. A modified Star-Kalman algorithm is used to determine vessel contours and ellipse parameters using an extended Kalman filter with an elliptical model. The parameters can be used to easily calculate the transverse vessel area which is of clinical use. A temporal Kalman filter is used for tracking the vessel center over several frames, using location measurements from a handheld sensitized ultrasound probe. The segmentation and tracking have been implemented in real-time and validated using simulated ultrasound data with known features and real data, for which expert segmentation was performed. Results indicate that mean errors between segmented contours and expert tracings are on the order of 1%-2% of the maximum feature dimension, and that the transverse cross-sectional vessel area as computed from estimated ellipse parameters a, b as determined by our algorithm is within 10% of that determined by experts. The location of the vessel center was tracked accurately for a range of speeds from 1.4 to 11.2 mm/s.

Source:

J. Guerrero, S. Nicolaou, B. A. Masri, J. A. McEwen and S. E. Salcudean.

Segmentation In Ultrasonic B-Mode Images Of Healthy Carotid Arteries Using Mixtures Of Nakagami Distributionsand Stochastics Optimization

The goal of this work is to perform a segmentation of the intimamedia thickness (IMT) of carotid arteries in view of computing various dynamical properties of that tissue, such as the elasticity distribution (elastogram). The echogenicity of a region of interest comprising the intimae-media layers, the lumen, and the adventitia in an ultrasonic *B*-mode image is modeled by a mixture of three Nakagami distributions. In a first step, we compute the maximum a posteriori estimator of the proposed model, using the expectation maximization (EM) algorithm. We then compute the optimal segmentation based on the estimated distributions as well as a statistical prior for disease-free IMT using a variant of the exploration/selection (ES) algorithm. Convergence of the ES algorithm to the optimal solution is assured asymptotically and is independent of the initial solution. In particular, our method is well suited to a semi-automatic context that requires minimal manual initialization. Tests of the proposed method on 30 sequences of ultrasonic *B*-mode images of presumably disease-free control subjects are reported. They suggest that the semi-automatic segmentations obtained by the proposed method are within the variability of the manual segmentations of two experts.

Source:

G. Cloutier, F. Destrempes, M.-F. Giroux, J. Meunier, and G. Soulez,

Edge Detection Techniques: Evaluations And Comparisons

Edge detection is one of the most commonly used operations in image analysis, and there are probably more algorithms in the literature for enhancing and detecting edges than any other single subject. The reason for this is that edges form the outline of an object. An edge is the boundary between an object and the background, and indicates the boundary between overlapping objects. This means that if the edges in an image can be identified accurately, all of the objects can be located and basic properties such as area, perimeter, and shape can be measured. Since computer vision involves the identification and classification of objects in an image, edge detections is an essential tool. In this paper, we have compared several techniques for edge detection in image processing . We consider various well-known measuring metrics used in image processing applied to standard images in this comparison.

Source:

E. Argyle

A Computational Approach To Edge Detection

This paper describes a computational approach to edge detection. The success of the approach depends on the definition of a comprehensive set of goals for the computation of edge points. These goals must be precise enough to delimit the desired behaviour of the detector while making minimal assumptions about the form of the solution. We define detection and localization criteria for a class of edges, and present mathematical forms for these criteria as functional on the operator impulse response. A third criterion is then added to ensure that the detector has only one response to- a single edge. We use the criteria in numerical optimization to derive detectors for several common image features, including step edges. On specialising the analysis to step edges, we find that there is a natural uncertainty principle between detection and localization performance, which are the two main goals. With this principle we derive a single operator shape which is optimal at any scale. The optimal detector has a simple approximate implementation in which edges are marked at maxima in gradient magnitude of a Gaussian-smoothed image. We extend this simple detector using operators of several widths to cope with different signal-to-noise ratio in the image. We present a general method, called feature synthesis, for the fine-to-coarse integration of information from operators at different scales. Finally we show that step edge detector performance improves considerably as the operator point spread function is extended along the edge. This detection scheme uses several elongated operators at each point, and the directional operator outputs are integrated with the gradient maximum detector.

Source:

J. F. Canny

Geodesic Active Contours

A novel scheme for the detection of object boundaries is presented. The technique is based on active contours evolving in time according to intrinsic geometric measures of the image. The evolving contours naturally split and merge, allowing the simultaneous detection of several objects and both interior and exterior boundaries. The proposed approach is based on the relation between active contours and the computation of geodesics or minimal distance curves. The minimal distance curve lays in a Riemannian space whose metric is defined by the image content. This geodesic approach for object segmentation allows to connect classical "snakes" based on energy minimization and geometric active contours based on the theory of curve evolution. Previous models of geometric active contours are improved, allowing stable boundary detection when their gradients suffer from large variations, including gaps. Formal results concerning existence, uniqueness, stability, and correctness of the evolution are presented as well. The scheme was implemented using an efficient algorithm for curve evolution. Experimental results of applying the scheme to real images including objects with holes and medical data imagery demonstrate its power. The results may be extended to 3D object segmentation as well.

Source:

V. Caselles, R. Kimmel, and G. Sapiro

Edge Detection

Edge detection is a problem of fundamental importance in image analysis. In typical images, edges characterize object boundaries and are therefore useful for segmentation, registration, and identification of objects in a scene. Edge detection of an image reduces significantly the amount of data and filters out information that may be regarded as less relevant, preserving the important structural properties of an image. A theory of edge detection is presented. The analysis proceeds in two parts: Intensity changes, which occur in a natural image over a wide range of scales, are detected separately at different scales. An appropriate filter for this purpose at a given scale is found to be the second derivative of a Gaussian. Intensity changes at a given scale are best detected by finding the zero values of image. The intensity changes discovered in each of the channels are represented by oriented primitives called zero-crossing segments.

Edge Detection- Fundamentals

Edge detection refers to the process of identifying and locating sharp discontinuities in an image. The discontinuities are abrupt changes in pixel intensity which characterize boundaries of objects in a scene. Classical methods of edge detection involve convolving the image with an operator, which is constructed to be sensitive to large gradients in the image while returning values of zero in uniform regions. This is an extremely large number of edge detection operators available, each designed to be sensitive to certain types of edges.

Variables involved in the selection of an edge detection operator are:

Edge Detection: The geometry of the operator determines a characteristic direction in which it is most sensitive to edges. Operators can be optimized to look for horizontal, vertical, or diagonal edges.

Noise level in environment: Edge detection is difficult in noisy images, since both the noise and the edges contain high-frequency content. Attempts to reduce the noise result in blurred and distorted edges. Operators used on noisy images are typically larger in scope, so they can average enough data to discount localized noisy pixels. This results in less accurate localization of the detected edges.

Edge Structure:

Effects such as refraction or poor focus can result in objects with boundaries defined by a gradual change in intensity. The operator needs to be chosen to be responsive to such a gradual change in those cases. Newer wavelet-based techniques actually characterize the nature of the transition for each edge in order to distinguish, for example, edges associated with hair are different from edges associated with a face. There are many ways to perform edge detection. However, the majority of different methods may be grouped into two categories:

Gradient:

The gradient method detects the edges by looking for the maximum and minimum in the first derivative of the image.

Laplacian

The Laplacian method searches for zero crossings in the second derivative of the image to find edges. An edge has the one-dimensional shape of a ramp and calculating the derivative of the image can highlight its location. Suppose we apply the following signal, with an edge shown by the jump in intensity as in fig 3.1.

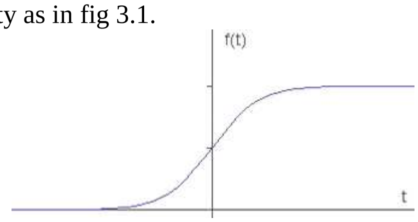


Fig 3.1 – Signal applied to edge detector.

The gradient obtained from the signal applied to the edge detector will be as in fig 3.2

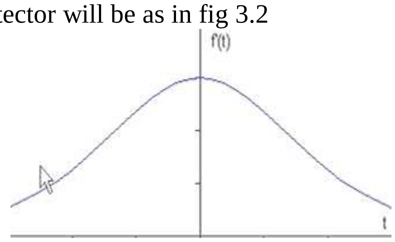


Fig 3.2 – Gradient first derivative of the applied signal.

This method of locating an edge is characteristic of the “gradient filter” family of edge detection filters as prescribed by the Sobels method. A pixel location is declared an edge location if the value of the gradient exceeds some threshold. As seen from the fig 2.2, edges will have higher pixel intensity values than those surrounding it. When a threshold is set, we can compare the gradient value to the threshold value and detect an edge whenever the threshold is exceeded. Further, when the first derivative is at a maximum, the second derivative will be zero, proving another alternative to find the location of an edge by locating the zeros in the second derivative. This method is known as the Laplacian and the second derivative of the signal is as seen in fig 3.3.

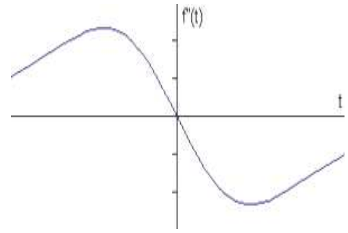


Fig 3.3 – Gradient second derivative of the applied signal.

The purpose of detecting sharp changes in image brightness is to capture important events and changes in properties of the world. It can be shown that under rather general assumptions for an image formation model, discontinuities in image brightness correspond to:

- Discontinuities in depth,
- Discontinuities in surface orientation,
- Changes in material properties and
- Variations in scene illumination.

In the ideal case, the result of applying an edge detector to an image may lead to a set of connected curves that indicate the boundaries of objects, the boundaries of surface markings as well curves that correspond to discontinuities in surface orientation. Thus, applying an edge detector to an image may significantly reduce the amount of data to be processed and may therefore filter out information that may be regarded as less relevant, while preserving the important structural properties of an image. However it is not always possible to recover the ideal edges from real life images of even moderate complexity.

Since edges extracted from non-trivial images are often hampered by fragmentation, meaning that the edge curves are not connected, missing edge segments as well as false edges may not correspond to interesting phenomena in the image - thus complicating the subsequent task of interpreting the image data. The edges from real life images are normally affected by one or several of the following effects:

- Focal blur caused by a finite depth-of-field and finite point spread function.
- Penumbral blur caused by shadows created by light sources of non-zero radius.
- Shading at a smooth object edge.
- Local speculations or inter-reflections in the vicinity of object edges.

Detection Of Edges In 1-Dimension

Single dimension edge detection has the following key steps:

- Reduction of noise effects.
- Measurement of magnitude change in the region.
- Discovery of peak changes

- Non-maximum suppression.
- Threshold.

We hope to find the peaks, because in the neighborhood of an edge, after smoothing (reduction of noise effects), there may be many pixels where the image is changing rapidly, but we merely want to identify one of them as the edge. Discrete convolution is performed by sampling the filter with two most important parameters:

- Normalize the sampled Gaussian, so that it sums to '1'.
- Wide filter utilization for capturing the Gaussian shape. (Heuristic filter modeling)
- Firstly, look for points where the magnitude of the derivative is bigger than at the two neighboring points. This is called non-maximum suppression and is equivalent to finding the place where the first derivative is a maximum.
- Secondly, look for peaks where the magnitude of the first derivative is above some threshold. This eliminates spurious edges.

Detection Of Edges In 2-Dimensions

Dual dimension edge detection follows up the same steps as single dimension except for a few mutations:

1 Reduction of noise effects:

This is similar to the single dimension, utilizing the Gaussian but in 2D. Decomposing 2D Gaussian into two 1D Gaussian improves the efficiency.

2 Measurement of magnitude change in the region:

In 1D, measurement of change with derivative is needed, unlike in 2D where change with gradient is needed. We can derive it with the help of partial

derivatives in x and y directions. The direction of the gradient provides the direction of maximum change. The magnitude of the gradient tells us how fast the image is changing if we move in that direction.

Edge Detection Phases

1 Smoothing

Suppress as much noise as possible, without destroying the true edges.

2 Enhancement

Apply a filter to enhance the quality of the edges in the image.

3 Detection

Determine which edge pixels should be discarded as noise and which should be retained.

4 Localization

Determine the exact location of an edge. Edge thinning and linking are usually required in this step.

Edge Detection Using Derivatives

Calculus describes changes of continuous functions using derivatives. An image is a 2D function, so operators describing edges are expressed using partial derivatives. Points which lie on an edge can be detected by:

- Detecting local maxima or minima of the first derivative.
- Detecting the zero-crossing of the second derivative.

To compute the derivative of a signal, we approximate the derivative by finite differences: Computing the 1st derivative:

Edge Detection Techniques

Edge detection aims at identifying points in a digital image at which the image brightness changes sharply or more formally has discontinuities. Following edge detectors are handy:

- Sobels Edge Detector - 3×3 gradient edge detector.
- Prewitt Edge Detector - 3×3 gradient edge detector.
- Canny Edge Detector - non-maximal suppression of local gradient magnitude.
- Zero Crossing Detector - edge detector using the Laplacian of Gaussian operator.

System Analysis and Design

Existing System

In recent years, there have been several new methods to solve the problem of boundary detection, e.g., active contour model (ACM), geodesic active contour (GAC) model, active contours without edges (ACWE), gradient vector flow (GVF) snake model, vector field convolution (VFC) snake model, etc. The snake models have become popular especially in boundary detection where the problem is more challenging due to the poor quality of the images. The ACMs also known as snakes are curves defined within an image domain that can be moved under the influence of the internal energy and external energy. The internal energy is designed to keep the model smooth during deformation. The external energy is designed to move the model toward an object boundary or other desired features within an image. However, the snake has weaknesses and limitations of small capture range and difficulties progressing into concave boundary regions. The GAC model is an extension of the ACM by taking into account of the geometric information of an image. An ACM based on curve evolution and level sets, namely the ACWE, can detect objects' boundaries that are not necessarily defined by gradient .The GVF is an ACM with a new external energy. This new external energy is computed as a diffusion of gray-level gradient vector

of a binary edge map derived from the image. The resultant field has a large capture range and forces active contours
into concave regions. VCF was applied as a new external energy of an ACM and proved to be better than the existing snake models. However, when an image is highly noisy and possesses a complex background, determining the correct boundaries of objects from the gradients is not easy. Most of the methods of snake models require a very accurate initial contour estimate of the object. The contour of snake models can converge to a wrong boundary if the initial contour is not close enough to the desired boundary. Though many algorithms for boundary detection have been developed to achieve good performance in field of image processing, most algorithms for detecting the correct boundaries of objects have difficulties in medical images in which ill defined edges are encountered. Medical images are often noisy and too complex to expect local, low level operations to generate perfect primitives. The complexity of medical images renders the correct boundary detection very difficult.

Proposed System

This paper proposes a new technique for boundary detection for ill-defined edges in noisy images using a novel edge following. The proposed edge following technique is based on the vector image model and the edge map. The vector image model provides a more complete description of an image by considering both directions and magnitudes of image edges. From the vector image model, a derivative-based edge operator is applied to yield the edge field. The proposed edge vector field is generated by averaging magnitudes and directions in the vector image. The edge map is derived from Law's texture feature and the canny edge detection. The vector image model and the edge map are applied to select the best edges.

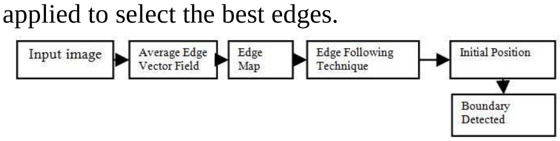


Fig 4.1 The Overall System Model

In the above figure, the overall system model is explained. First Average edge vector field is calculated. Then edge map is performed. Next step is edge following technique is performed and initial position of the system is calculated. Finally the boundary of the Image is detected.

SYSTEM MODULES

The proposed system development consists of the following modules:

1. Average Edge Vector field
2. Edge map
3. Edge following Technique
4. Initial Position
5. Boundary Detection

Boundary Extraction Algorithm

Average Edge Vector Field Model

We exploit the edge vector field to devise a new boundary extraction algorithm. Given an image *f*(*x*, *y*), the edge vector field is calculated according to the following equations:

$$\vec{e}(i,j) = 1/k(M_x(i,j)\vec{i} + M_y(i,j)\vec{j})$$

$$\vec{e}(i,j) \approx \frac{1}{k}\left(\frac{\partial f(x,y)}{\partial y}\vec{i} - \frac{\partial f(x,y)}{\partial x}\vec{j}\right)$$

$$K = \max_{\forall ij}\left(\sqrt{M_x(i,j)^2 + M_y(i,j)^2}\right)$$

Each component is the convolution between the image and the corresponding difference mask, i.e.,

$$M_x(i,j) = -G_y \times f(x,y) \approx \frac{\partial f(x,y)}{\partial y}$$

$$M_y(i,j) = G_x \times f(x,y) \approx -\frac{\partial f(x,y)}{\partial x}$$

Where G_x and G_y are the difference masks of the Gaussian weighted image moment vector operator in the *x* and *y* directions, respectively,

$$G_x(x,y) = \frac{1}{\sqrt{2\pi}\sigma}\left(\frac{x}{\sqrt{x^2+y^2}} exp\left(-\frac{x^2+y^2}{2\sigma^2}\right)\right)$$

$$G_y(x,y) = \frac{1}{\sqrt{2\pi}\sigma}\left(\frac{y}{\sqrt{x^2+y^2}} exp\left(-\frac{x^2+y^2}{2\sigma^2}\right)\right)$$

Edge vectors of an image indicate the magnitudes and directions of edges which form 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. Therefore, we extend the capability of the previous edge vector field by applying a local averaging operation where the value of each vector is replaced by the average of all the values in the local neighborhood, i.e.,

$$M(i,j) = \frac{1}{M_r}\sum_{(i,j)\in N}\sqrt{M_x(i,j)^2 + M_y(i,j)^2}$$

$$D(i,j) = \frac{1}{M_r}\sum_{(i,j)\in N}\tan^{-1}\frac{M_y(i,j)}{M_x(i,j)}$$

Where M_r is the total number of pixels in the neighborhood *N*. We apply a 3 × 3 window as the neighborhood *N* throughout our research. An example of the edge vector field and average edge vector field is displayed in Fig. 5.1. Fig. 5.1(b) and (c) shows the results of the edge vector field and average edge vector field of the original image in Fig. 5.2(a). From the result, we can see that our proposed edge vector field yields more descriptive vectors along the object edge than that of the original edge vector field.

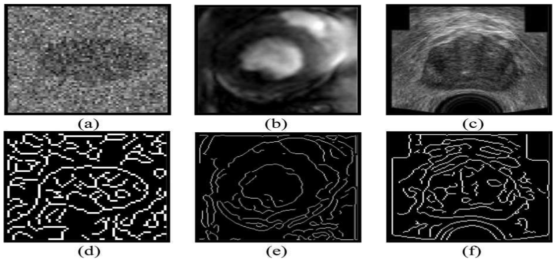


Fig. 5.2. (a) Synthetic noisy image. (b) Left ventricle in the MR image. (c) Prostate ultrasound image. (d)–(f) Corresponding edge maps derived from Law's texture and Canny edge detection.

This idea is exploited for the boundary extraction algorithm of objects in unclear images.

Edge Map

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

1 Law's Texture:

The texture feature images of Law's texture are computed by convolving an input image with each of the masks. Given a column vector *L*= (1, 4, 6, 4, 1) *T* , the 2-D mask *l*(*i*, *j*) used for texture discrimination in this research is generated by *L* × *LT* . The output image is obtained by convolving the input image with the texture mask.

2 Canny Edge Detection:

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 reduces the noise and locates the edges.

The first step of Canny edge detection is to convolve the output image obtained from the aforementioned Law's texture *t*(*i*, *j*) with a Gaussian filter.

The second step is to calculate the magnitude and direction of the gradient.

The third step is non maximal suppression to identify edges. The broad ridges in the magnitude must be thinned so that only the magnitudes at the points of the greatest local change remain.

The last step is the thresholding algorithm to detect and link edges.

The double threshold algorithm is used to detect and link edges. Edge map shows some important information of edge. This idea is exploited for extracting objects' boundaries in unclear images.

Edge Following Technique

The edge following technique is performed to find the boundary of an object. Most edge following algorithms take into account the edge 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.

This is exactly the reason why many edge following techniques fail to extract the correct boundary of objects in noisy images. To remedy the problem, we propose an edge following technique by using information from the average edge vector field and edge map. It gives more information for searching the boundary of objects and increases the probability of searching the correct boundary. 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 a 3 × 3 matrix

$$L_{ij}(r,c) = \alpha M_{ij}(r,c) + \beta D_{ij}(r,c) + \varepsilon E_{ij}(r,c)$$

$$0 \le r \le 2, 0 \le c \le 2$$

Where *α*, *β*, and *ε* are the weight parameters that control the edge to flow around an object. The larger value of an element in **L***ij* indicates the stronger edge in the corresponding direction. The 3 × 3 matrices M_{ij} , D_{ij} and E_{ij} are calculated as follows:

$$M_{ij}(r,c) = \frac{M(i+r-1, j+c-1)}{\max_{i,j} M(i,j)}$$

$$D_{ij}(r,c) = 1 - \frac{D(i,j) - D(i+r-1, j+c-1)}{\pi}$$

$$E_{ij}(r,c) = E(i+r-1, j+c-1),$$

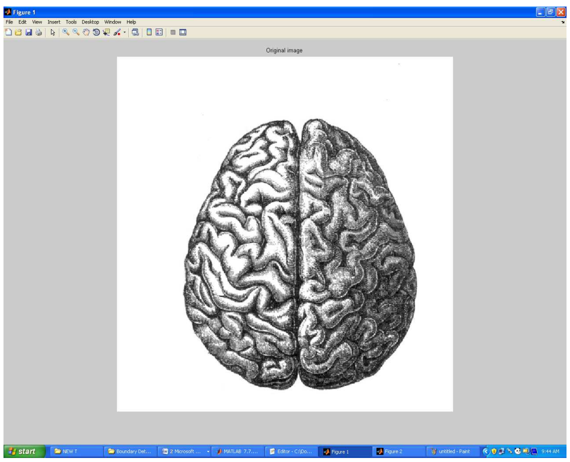
$$0 \le r \le 2, \qquad 0 \le c \le 2$$

Where *M* (*i*, *j*) and *D* (*i*, *j*) are the proposed average magnitude and direction of edge vector fields as shown in and. *E* (*i*, *j*) is the edge map from Law's texture and Canny edge detection. It should be noted that the value of each element in the matrices M_{ij} , D_{ij} , and E_{ij} are ranged between 0 and 1. Let **C***k*, *k* = 1, 2. . . 8, be the constraint masks of edge following to the next direction in object boundary as shown in Fig. 5.3. The constraint mask is selected by considering the direction of the vector model at a position (*i*, *j*). The mask which has a similarity in direction of vector is selected to suit the chosen constraint of edge following. The value of each element in each mask dictates the corresponding direction. At the position (*i*, *j*), the next direction of the edge following technique is selected as the direction that gives the maximum value of the element-wise multiplication results between L_{ij} and C_k . The next direction can be calculated by

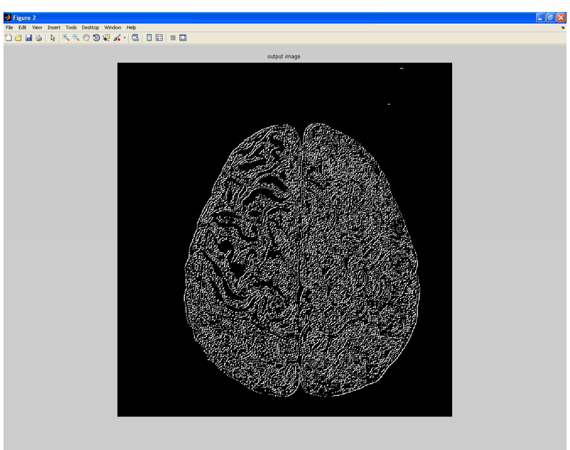
$$D_{i,j,opt} = \underset{k}{\arg\max} \sum_{r=0}^{2} \sum_{c=0}^{2} L_{ij}(r,c)C_k(r,c)$$

Where k =1, 2. . . 8 denote the eight directions as indicated by the arrows at the center of the masks shown in Fig.5. 3. The edge following is started from the initial position to end position.

Screen Shots



Original Image



Output Image Without Noise

Conclusion

In the existing methods like Active contour model (ACM), Geodesic active contour (GAC) model, Active contours without edges (ACWE), Gradient vector flow (GVF) snake model, Vector field convolution (VFC) snake model, when an image is highly noisy and possesses a complex background, determining the correct boundaries of an object from the gradients is not easy. The probability of error is also high and the initial position of the image should be known prior to detect the exact boundary of the object in the existing system. The five snake models require huge computation cost. To overcome these drawbacks a new method is implemented. In this proposed method a new edge following algorithm is used to improve the performance of the system and probability of error is reduced. This method does not require the knowledge about initial position of the image to detect the exact boundary of the object. The proposed edge following technique incorporates a vector image model and the edge map information. In future work, the proposed algorithm may be applied to noisy images and the performance may be studied for random noise, speckle noise, gaussian noise, salt and pepper noise.

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