BOUDARY DETECTION OF MEDICAL IMAGES USING EDGE FOLLOWING TECHNIQUE

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Abstract: In this paper we propose and advanced medical image boundary detection technique using edge following techniques in noisy medical images. Here we proposes an edge following technique using texture gradients and intensity gradient models. We are using edge map techniques to define the textures of image and vector image models for intensity models. Additionally we have adopted the concept of active contour model to identify the accurate boundaries of medical image. 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.

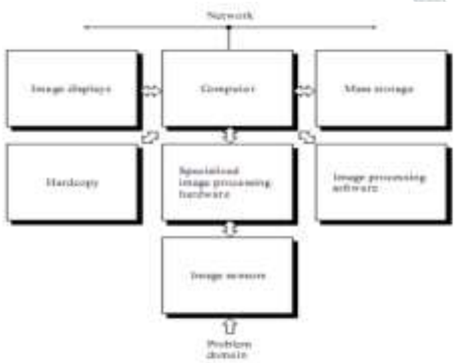
Digital Image

A digital image is a numeric Representation (normally binary) of A two dimensional image. Depending on whether the image resolution is fixed, it may be of vector or raster type. By itself, the term "digital image" usually refers to raster images or bitmapped images.

Raster

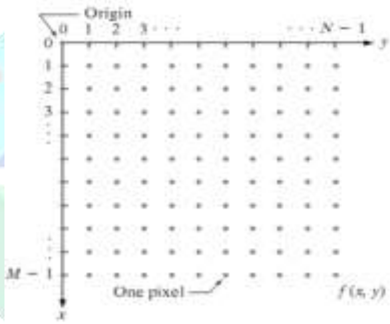
Raster images have a finite set of digital values, called *picture elements* or pixels. The digital image contains a fixed number of rows and columns of pixels. Pixels are the smallest individual element in an image, holding quantized values that represent the brightness of a given color at any specific point.

Components of an Image Processing System



As recently as the mid-1980s, numerous models of image processing systems being sold throughout the world were rather substantial peripheral devices that attached to equally substantial host computers. Late in the 1980s and early in the 1990s, the market shifted to image processing hardware in the form of single boards designed to be compatible with industry and hard buses and to fit into engineering workstation cabinets and personal computers. In addition to lowering costs, this market shift also served as a catalyst for a significant number of new companies whose specialty is the development of software written specifically for image processing. **Image representation and its properties**

We will use two principal ways to represent digital images. Assume that an image (x, y) is sampled so that the resulting digital image has M rows and N columns. The values of the coordinates (x, y) now become discrete quantities. For notational clarity and convenience, we shall use integer values for these discrete coordinates. Thus, the values of the coordinates at the origin are (x, y) = (0, 0). The next coordinate values along the first row of the image are represented as (x, y) = (0, 1). It is important to keep in mind that the notation (0, 1) is used to signify the second sample along the first row. It does not mean that these are the actual values of physical coordinates when the image was sampled. Figure shows the coordinate convention used.



The notation introduced in the preceding paragraph allows us to write the complete M*N digital image in the following compact matrix form:

$$f(x,y) = \begin{bmatrix} f(0,0) & f(0,1) & \cdots & f(0,N-1) \\ f(1,0) & f(1,1) & \cdots & f(1,N-1) \\ \vdots & \vdots & & \vdots \\ f(M-1,0) & f(M-1,1) & \cdots & f(M-1,N-1) \end{bmatrix}.$$

The right side of this equation is by definition a digital image. Each element of this matrix array is called an image element, picture element, pixel, or pixel

Cropping Images:

Cropping an image extracts a rectangular region of interest from the original image. This focuses the viewer's attention on a specific portion of the image and discards areas of the image that contain less useful information. Using image cropping in conjunction with image magnification allows you to zoom in on a specific portion of the image. This section describes how to exactly define the portion of the image you wish to extract to create a cropped image

Padding Images:

Image padding introduces new pixels around the edges of an image. The border provides space for annotations or acts as a boundary when using advanced filtering techniques. This exercise adds a 10-pixel border to left, right and bottom of the image and a 30-pixel border at the top allowing space for annotation. The diagonal lines in the following image represent the area that will be added to the original image. For an example of padding an image, complete the following steps.

Geometric Transform

Geometric image transformation functions use mathematical transformations to crop, pad, scale, rotate, transpose or otherwise alter an image array to produce a modified view of an image. The transformations described in this chapter are linear transformations. For a description of non-linear geometric transformations, When an image undergoes a geometric transformation, some or all of the pixels within the source image are relocated from their original spatial coordinates to a new position in the output image. When a relocated pixel does not map directly onto the centre of a pixel location, but falls somewhere in between the centers of pixel locations, the pixel's value is computed by sampling the values of the neighboring pixels. This resampling, also known as interpolation, affects the quality of the output image.

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Rotating Images:

The rotation operator performs a geometric transform which maps the position(x1,y1) of a picture element in an input image onto a position (x1,y1) in an output image by rotating it through a user-specified angle θ about an origin O . In most implementations, output locations (x2,y2) which are outside the boundary of the image are ignored. Rotation is most commonly used to improve the visual appearance of an image, although it can be useful as a pre-processor in applications where directional operators are involved.

Reflecting images:

The reflection operator geometrically transforms an image such that image elements, *i.e.* pixel values, located at position (x1,y1) in an original image are reflected about a user-specified image *axis* or image *point* into a new position (x2,y2) in a corresponding output image. Reflection is mainly used as an aid to image visualization, but may be used as a pre-processing operator in much the same way as rotation.

Local Pre-processing

Pre-processing is the name used for operations on images at the lowest level of abstraction both input and output are intensity images. These iconic images are usually of the same kind as the original data captured by the sensor, with an intensity image usually represented by a matrix or matrices; of image function values (brightness's). Pre-processing does not increase image information content. **Image restoration:**

Pre-processing methods that aim to suppress degradation using knowledge about its nature arc called image restoration. Most image restoration methods are based on convolution applied globally to the whole image.

Introduction to Image Segmentation

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 im age display. **Methods used for Segmentation**

Image segmentation is the grouping of a set of pixels that share similar characteristics, such as intensity and texture. In our study in segmenting the prostate, segmentation can be described as a procedure that separates the foreground of the image, which refers to the set of pixels that is mapped from structures inside the prostate, and the background. Segmentation techniques widely used can be classified into three categories: threshold techniques, edge-based techniques and model-based techniques. In the following, a brief introduction of these techniques is given, along with the pros and cons of each segmentation technique.

3.1.1. Threshold Techniques

This technique is very simple: Given an image A, which could be the original image itself or the image resulted after applying a transform operator on the original, if the grayscale value of the pixel $A[m,n]$ is lower than a preset threshold θ, the pixel will be classified as belonging to a predefined region.

Otherwise, the pixel falls into another region [29].

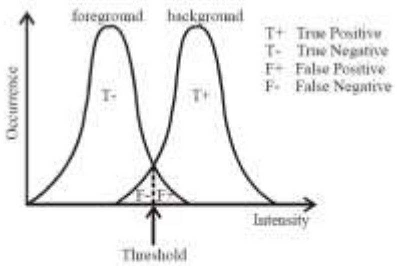


Figure 30 Distribution models of the foreground and the background

The most important issue in this technique is the choice of the threshold θ. Normally, distribution models associated with different regions, which describe the occurrence of a range of pixel value in the corresponding region, are established before the classification (see Figure 30). An appropriate choice of threshold is derived from these distribution models image have a high contrast in their intensities or other measurable features. However, as could be observed in Figure 30, if two distributions have a significant overlapping region, detection error (i.e., false positive and false negative shown in Figure 30) will be large. A partial solution to this problem may be to define the threshold to be a function of the position, based on pixel value distributions of different regions in the neighborhood of the position in question. This method is based on the idea that the local variations of the pixel values representing a particular type of tissue is smaller comparing to the variations in the whole image, and therefore, the standard deviation of the distributions decrease, reducing the overlapping area in different distribution. Also, the thresholding technique is sensitive to noise or intensity in homogeneity. As a result, regions will become disconnected, and a closed segment is often hard to obtain.

3.1.2. Edge-Based Techniques

Edge-based techniques find the edge of the desired object as opposed to finding the whole object in the threshold technique. This class of techniques finds the edge by locating regions where pixel values change significantly in a neighbourhood. Two widely used edge-detection techniques are the gradient-based procedure and the zero-crossing procedure. However, both the gradient-based method and the zero-crossing method are sensitive to undesirable fluctuations caused by noise. To reduce the impact of noise on the segmented contour, one needs to smooth the image. The smoothing filter should be chosen such that it is localized in the frequency domain and the spatial domain – it should be localized in frequency domain because it should act as a low-pass filter to suppress high-frequency noise, and it should be spatially localized because the location of the edge can not be precisely identified if the image is filtered by a wide filter. The Gaussian filter is very popular in this application because it has a minimum space-bandwidth product.

A) Gradient-Based Procedure

An abrupt change can be detected by finding the first derivative of a one-dimensional function or the gradient of a two-dimensional function. For example, in a one dimensional function, the edge can be located by finding the maximum of the first derivative (see Figure 31).

B) Zero-Crossing Procedure

An edge can also be found by locating the zero-crossing of the second derivative of a one-dimensional function or the Laplacian of an image (see Figure 31).

However, this approach has a significant drawback. Finding the zero-crossing of the second derivative of a function is equivalent to finding the inflection point, where the first derivative attains either a maximum or minimum. Sharp variation occurs at inflection point where the first derivative is at a local maximum (see Figure 31). On the other hand, slow variation occurs at inflection point where the first derivative is at a local minimum (see Figure 32). Solely using the zero-crossing technique, it is impossible to distinguish between these two kinds of inflection point, and therefore edge will be incorrectly located.

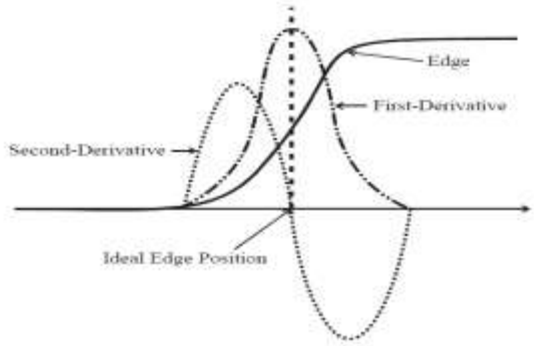


Figure 31 An edge structure and its first and second derivatives

1 Introduction to Image Edge Detection

Edge Detection

Edge detection is the name for a set of mathematical methods which aim at identifying points in a digital image at which the image brightness changes sharply or, more formally, has discontinuities. The points at which image brightness changes sharply are typically organized into a set of curved line segments termed edges. The same problem of finding discontinuities in 1D signal is known as step detection and the problem of finding signal discontinuities over time is known as change detection. Edge detection is a fundamental tool in image processing, machine vision and computer vision, particularly in the areas of feature detection and feature extraction.

Simple Edge Model

Although certain literature has considered the detection of ideal step edges, the edges obtained from natural images are usually not at all ideal step edges. Instead they 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

A number of researchers have used a Gaussian smoothed step edge (an error function) as the simplest extension of the ideal step edge model for modeling the effects of edge blur in practical applications.[4][5] Thus, a one-dimensional image f which has exactly one edge placed at $x = 0$ may be modeled as:

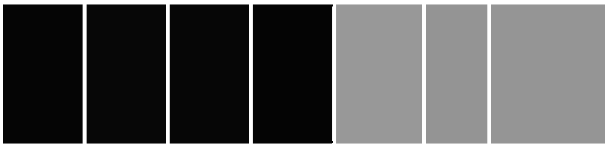
$$f(x) = \frac{I_r - I_l}{2}\left(\mathrm{erf}\left(\frac{x}{\sqrt{2}\sigma}\right) + 1\right) + I_l.$$

At the left side of the edge, the intensity is $I_l = \lim_{x \to -\infty} f(x)$, and right of the edge it is $I_r = \lim_{x \to \infty} f(x)$. The scale parameter σ is called the blur scale of the edge.

Why Edge Detection is a Non-Trivial Rask

To illustrate why edge detection is not a trivial task, consider the problem of detecting edges in the following one-dimensional signal. Here, we may intuitively say that there should be an edge between the 4th and 5th pixels.

5	7	6	4	152	148	149



If the intensity difference were smaller between the 4th and the 5th pixels and if the intensity differences between the adjacent neighboring pixels were higher, it would not be as easy to say that there should be an edge in the corresponding region. Moreover, one could argue that this case is one in which there are several edges.

Hence, to firmly state a specific threshold on how large the intensity change between two neighbouring pixels must be for us to say that there should be an edge between these pixels is not always simple.[4] Indeed, this is one of the reasons why edge detection may be a non-trivial problem unless the objects in the scene are particularly simple and the illumination conditions can be well controlled (see for example, the edges extracted from the image with the girl above).

Introduction to Medical Image Edge Detection

The edge of the image is one of the most fundamental and important features in the images ,it is showed that the mutation of local scope gray-scale, which refers to set of those pixels that have step changes in the around of the gray pixels[15]. Edge as primary extraction target and the diving line of the background can significantly reduce the information to deal, but retain the shape information of the objects in image. Edges help in identifying the outline of an object .The primary goal of edge detector is to output the edges required for further image-processing stages like detecting the object ,its shape ,size . **1.1 Problem definition**

*1.1.1*In medical images it is usually hard to segment and analysis the continuity and direction of some area in interest, we are going to suggest effectived results in the particular medical images.

2 Theoretical background

In the gray image, the existence of the edge is showed by the diversification of the gray value in the image. Treating the two dimensional image as a two dimensional signal in the space, so the edge can be regard as the performance of the high frequency components in the two dimensional signal. By designing the rational high-pass filter, edge information can be showed. But edges are the mutations of the gray valued between the adjacent pixels. Therefore the design of the high-pass filters, the airspace pixels involved by the filters should not be too much. So the general operator template are always 2*2, 3*3, 5*5 size. In the following analysis, understand the spatial differential operators is more appropriate high-pass filter to do the edge detection.

From the knowledge of the signal processing, the signal is equal to multiplying the signal in the frequency domain convolution in the airspace. The edge detection can be finished by the convolution of the spatial differential operators. Most of the edge detection techniques are

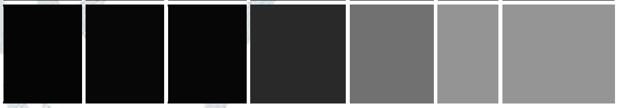
based on applying simple convolution masks to the entire image in order to compute the first-order or second-order derivative ,thus resulting in an edge. It is nothing but a calculation of differences in pixel values. [5]

Edge detection can be divided into two types .

First derivative method:

First-order based edge detection-the first order derivative at a pixel is used to decide the presence of an edge. The first order derivative is searched for the maximum or the minimum value and the pixel containing this value is considered an edge. An example of this is the Sobel edge detector [7] Gradient

5	7	6	41	113	148	149



corresponds to the first derivate, gradient operator is a derivative operator. For one continuous function f(x, y), its location gradient can be showed as a vector [3],

$$\nabla f(x,y)=[G_x \quad G_y]^T=\left[\frac{\partial f}{\partial x} \quad \frac{\partial f}{\partial y}\right]^T$$

This vector's gradient and direction angle are shown in the Equation 2

$$mag(\nabla f)=[G_x^2+G_y^2]^{1/2}$$

$$\varphi(x,y)=\arctan(G_y/G_x)$$

On the above the equation, the partial derivatives require to calculate the location of each pixel, in reality, it is commonly used the small area template convolution to do the approximate calculation. Not only the step edge, but also the roof edge , its first derivative has local Extremum. First calculate the an order difference of each pixel, take the appropriate threshold , when the first derivate of one point is bigger than threshold, it sets the points as the edge points.

Second Order Derivatives

Second-order based edge detection-the second order derivatives are used to decide the presence of an edge .The pixel that has its second order derivative as zero is considered an edge, that is, this method searches for zero-crossings .An example of this is the Laplace edge detector. For one continuous function f(x, y), its Laplace value be defined as Equation 3

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

2.1 Robert operator

The Roberts cross operator is used in image processing and computer vision for edge detection. It was one of the first edge detectors and was initially proposed by Lawrence Roberts in 1963.[1] As a differential operator, the idea behind the Roberts cross operator is to approximate the gradient of an image through discrete differentiation which is achieved by computing the sum of the squares of the differences between diagonally adjacent pixels.

BOUNDARY EXTRACTION ALGORITHM

A. Average Edge Vector Field Model

We exploit the edge vector field to devise a new boundary extraction algorithm [29]. Given an image $f(x, y)$, the edge vector field is calculated according to the following equations:

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

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

$$k = \max_{i,j}\left(\sqrt{M_x(i,j)^2 + M_y(i,j)^2}\right).$$

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 *Gx* and *Gy* are the difference masks of the Gaussian weighted image moment vector operator in the *x* and *y* directions, respectively, [29]

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

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

Edge vectors of an image indicate the magnitudes and directions

of edges which form a vector stream flowing around an object.

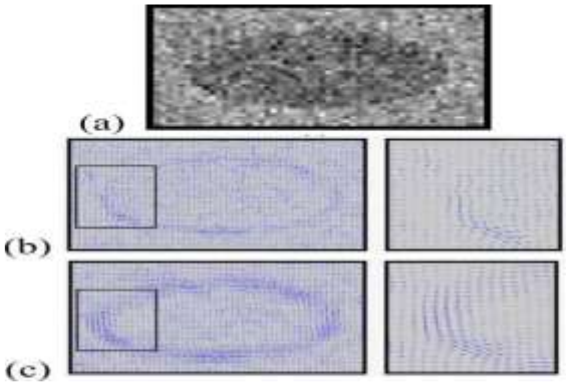


Fig. 1. (a) Original unclear image. (b) Result from the edge vector field and zoomed-in image. (c) Result from the proposed average edge vector field and zoomed-in image..

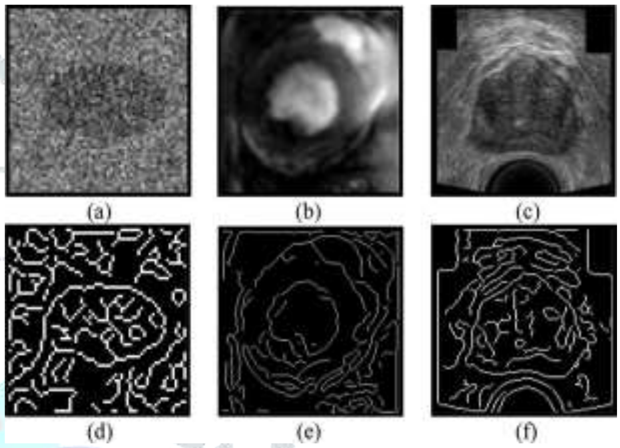


Fig. 2. (a) Synthetic noisy image. (b) Left ventricle in the MR image. (c) Prostate ultrasound image. (d)–(f) Corresponding edge maps derived from Law's texture and Canny edge detection This idea is exploited for the boundary extraction algorithm of objects in unclear images.

B. 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 $L \times LT$. 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. 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

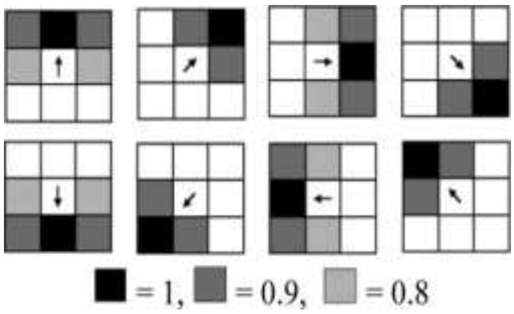


Fig. 3. Edge masks used for detecting of image edges (normal direction constraint).

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. The edge following is started from the initial position to end position.

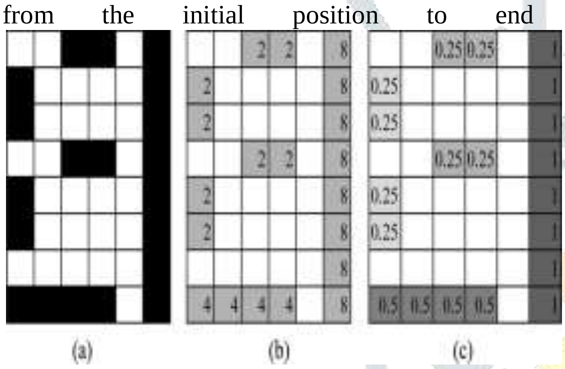
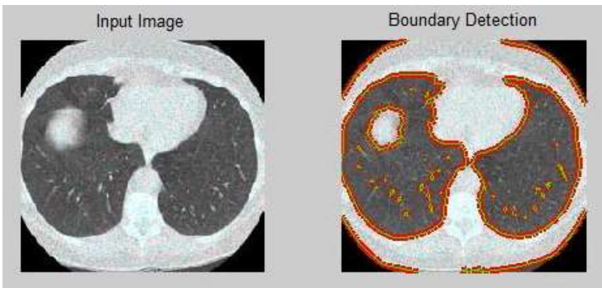
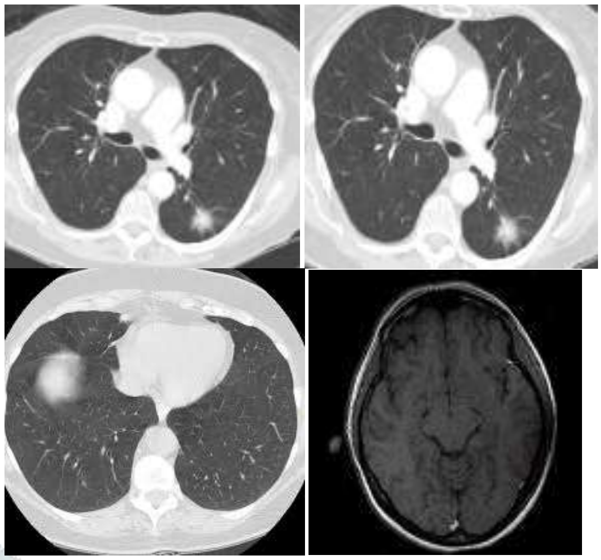


Fig. 4. (a) Edge map [$E(i, j)$]. (b) Results of counting the connected pixels [$C(i, j)$]. (c) Density of edge length [$L(i, j)$].

D. Initial Position

In this section, we present a technique for determining a good initial position of edge following that can be used for the boundary detection. The initial position problem is very important in the classical contour models.





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[1] J. Guerrero, S. E. Salcudean, J. A. McEwen, B. A. Masri, andS. Nicolaou, “Real-time vessel segmentation and tracking for ultrasoundimaging applications,” IEEE Trans. Med. Imag., vol. 26, no. 8, pp. 1079–1090, Aug. 2007.

[2] F. Destrempes, J. Meunier, M.-F. Giroux, G. Soulez, and G. Cloutier,“Segmentation in ultrasonic B-mode images of healthy carotid arteries using mixtures of Nakagami distributions and stochastic optimization,”IEEE Trans. Med. Imag., vol. 28, no. 2, pp. 215–229, Feb. 2009.

[3] N. Theera-Umpon and P. D. Gader, “System level training of neural networksfor counting white blood cells,” IEEE Trans. Syst., Man, Cybern.C, App. Rev., vol. 32, no. 1, pp. 48–53, Feb. 2002.

[4] N. Theera-Umpon, “White blood cell segmentation and classification inmicroscopic bone marrowimages,” Lecture Notes Comput. Sci., vol. 3614,pp. 787–796, 2005.

[5] N. Theera-Umpon and S. Dhompongsa, “Morphological granulometricfeatures of nucleus in automatic bone marrow white blood cell classification,”IEEE Trans. Inf. Technol. Biomed., vol. 11, no. 3, pp. 353–359,May 2007.

[6] J. Carballido-Gamio, S. J. Belongie, and S. Majumdar, “Normalized cutsin 3-D for spinal MRI segmentation,” IEEE Trans. Med. Imag., vol. 23,no. 1, pp. 36–44, Jan. 2004.

[7] H. Greenspan, A. Ruf, and J. Goldberger, “Constrained Gaussian mixturemodel framework for automatic segmentation ofMR brain images,” IEEETrans. Med. Imag., vol. 25, no. 9, pp. 1233–1245, Sep. 2006.

[8] J.-D. Lee, H.-R. Su, P. E. Cheng, M. Liou, J. Aston, A. C. Tsai, and

C.-Y. Chen, “MR image segmentation using a power transformation approach,”IEEE Trans. Med. Imag., vol. 28, no. 6, pp. 894–905, Jun. 2009.

[9] P. Jiantao, J. K. Leader, B. Zheng, F. Knollmann, C. Fuhrman, F. C.

Sciurba, and D. Gur, “A computational geometry approach to automated pulmonary fissure segmentation in CT examinations,” IEEE Trans. Med.

Imag., vol. 28, no. 5, pp. 710–719, May 2009.

[10] I. Isgum, M. Staring, A. Rutten, M. Prokop, M. A. Viergever, and

B. van Ginneken, “Multi-Atlas-based segmentation with local decision fusion—Application to cardiac and aortic segmentation in CT scans,”

IEEE Trans. Med. Imag., vol. 28, no. 7, pp. 1000–1010, Jul. 2009.

[11] J. R. Parker, Algorithms for Image Processing and Computer VisionNew York: Wiley, 1997.

[12] R. C. Gonzalez and R. E. Woods, Digital Image Processing. Reading,MA: Addison-Wesley, 1992.