Edge Detection in Ultrasound Images Using Speckle Reducing Anisotropic Diffusion in Canny Edge Detector Framework

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Abstract: - Conventional Canny edge detector can detect edges in image with additive noise effectively but not ultrasound image that are corrupted by multiplicative speckle noise which alleviates image resolution resulting in inaccurate characterization of object features. In this paper, we proposed to incorporate the modified SRAD into the Canny edge detector to replace the Gaussian blurring in the conventional Canny edge detector in order to suppress the multiplicative noise effectively while preserving the edge of the object in ultrasound image. The result shows that the proposed method can provide better result than conventional method in a much wider range of parameter values. The proposed method through experimental result indicates that it is capable of producing promising edge detection result in ultrasound image.

Key-Words: - edge detection, speckle reducing anisotropic diffusion, ultrasound image enhancement, noise filtering

1 Introduction

Edge detection is defined as a process to identify the sharp discontinuities in an image. The discontinuities are often known as abrupt changes in pixel intensity or the pixels that characterize the boundaries of objects in an image. The edge detected contributes in many applications such as image segmentation[1-2], enhancement,[3], [23-27] compression and etc. The edge detection in digital image processing is always implemented by convolving the image with a 2D filter operator. The 2D filter is designed to be of high sensitivity towards large gradients in the image and return null values on pixels in homogenous region of image. Edge detection is a significant issue in image processing and pattern recognition. It is due to its ability to give the outline of an object, to supply information of the boundary between an object and background, to indicate overlapping objects, to calculate the basic properties of the object like area and shape[4-5] and to classify and identify essential information in image. The desired effect of any edge detection operation is giving no response to non-edge pixels and giving only one response to a single edge.

Multitude algorithms of edge detection have been proposed. Among the common edge detection methods are Sobel method[12], Roberts[13], Prewitt[14]and Laplacian method[15], Rosenfeld and Thurston[16] and Marr- Hildreth[17]. These methods detect edges by utilizing masks to perform the convolution on the digital image according to the sudden change of gray level pixel intensity. Canny[18] make a modification on Sobel method. Canny searches the edge direction by inspecting the vertical and horizontal edge pixel intensity and implement non-maximum suppression to sharpen the edge. Among the earliest method, canny is the edge detector that can provide good edge detection performance in terms of single response to edge and good localization.

The conventional canny edge detector implements Gaussian blurring as the first step to reduce the effect of the noise during edge detection. This blurring effect at the same time leads to loss of important feature in the image especially the edge of the object. This issue has been observed by Perona and Malik[19] and they proposed a method, namely nonlinear anisotropic diffusion. This method is capable of blurring of noises and preserving of edges simultaneously. The smoothing effect is non-linear at different region in the image; Homogeneous region will have higher smoothing effect whereas region near edge will have lower smoothing effect. In other words, the algorithm encourages intra-region smoothing and alleviates inter-region smoothing. Besides protecting the edges of the object, the algorithm can even enhance the edge of the object by manipulating the diffusion direction; the diffusion parallel with edge will be higher compare to the diffusion across the edge.

The method has solved the problem of blurring of edge during smoothing process in image. However, it is not without limitation. Anisotropic diffusion is only suitable in filtering of additive noise but not multicative noise. Ultrasound image adherently contains multicative noise and thus need an enhanced version of anisotropic diffusion to cope with the noise. Hence, Acton et al. [20] proposed speckle reducing anisotropic diffusion (SRAD) that capable of filtering the multicative noise. The strength of SRAD[21] is that it combines the statistical information of speckle noise into the anisotropic diffusion framework to smooth homogenous speckle regions while preserving image features.

The remainder of this paper is organized as follows: In section methodology, a series of proposed edge detection step combined with SRAD is discussed. In section result, experiments using the proposed algorithm on ultrasound phantom image will be set up and an elucidation about the result will be included. Finally, conclusions and future directions for edge detection in ultrasound are discussed.

2 Methodology

The methods that we proposed are the incorporation of SRAD in eight directions in Canny edge detector. The equation[22] in the continuous domain version based on a nonlinear partial differential model as following:

$$\frac{\partial I(x,y;t)}{\partial t} = div[c(q)\nabla I(x,y;t)] \tag{1}$$

Where (x,y) are image coordinates, t is diffusion time, $I(x,y;t)$ is the image intensity function, and $c(q) \in [0,1]$ is the diffusion coefficient. This PDE is typically discretezed by computing finite differences in for four directions at each image pixel. Modification has been done on the standard SRAD algorithm in this paper to increase the neighborhoods during discrete SRAD computations

The SRAD diffusion coefficient incorporates local speckle statistics and is defined as following:

$$c(q) = \frac{1}{1 + \dfrac{q^2(x,y;t) - q_o^2(t)}{q_o^2(t)(1+q_o^2(t))}} \tag{2}$$

$q(x,y)$, the instantaneous coefficient of variation (ICOV) is defined as following:

$$q(x,y;t) = \sqrt{\frac{(1/2)(|\nabla I/I|)^2 - (1/4)(\nabla^2 I/I)^2}{[1+(1/4)(\nabla^2 I/I)]^2}} \tag{3}$$

$q_o(t)$, the speckle scale function is defined as following:

$$q_o(t) = \frac{\sqrt{\mathrm{var}[z(t)]}}{\overline{z(t)}} \tag{4}$$

Where $\mathrm{var}[z(t)]$ represent variance and $\overline{z(t)}$ represents mean in a homogeneous region of fully developed speckle, z(t).

The pixels that contain ICOV that similar to speckle scale function are considered as homogenous region. Therefore the SRAD diffusion coefficient at the homogenous will equals to unity and thus will be smoothed. Similarly, the pixels near the edges will have higher value of ICOV and thus lead to a diffusion coefficient close to zero.

The image is anisotropic diffused with the following algorithm using 2D discrete implementation:

$$\frac{\partial}{\partial t} I(x,y,t) = div[g(x,y,t) * \nabla I(x,y,t)]$$
$$= \frac{\partial}{\partial x}[g(x,y,t) * \frac{\partial}{\partial x} I(x,y,t)] + \frac{\partial}{\partial y}[g(x,y,t) . \frac{\partial}{\partial y} I(x,y,t)]$$

$$=\Phi_{east}+\Phi_{west}+\Phi_{north}+\Phi_{south}+\Phi_{eastnorth}+\Phi_{westsouth}+\Phi_{westnorth}+\Phi_{eastsouth} \quad (5)$$

For the relative distance, $\Delta x=\Delta y=1$, $\Delta d=\sqrt{2}$.

The anisotropic diffusion filtering entails iterative update on each pixel in the image by the flow intensity contributed by its eight neighboring pixels:

$$\frac{\partial}{\partial t} I(x, y, t+\Delta t) \approx I(x, y, t) + \Delta t.[\, \Phi_{east}+\Phi_{west}+\Phi_{north}+\Phi_{south}+\frac{1}{(\Delta d)^2}(\Phi_{eastnorth}+\Phi_{westsouth}+\Phi_{westnorth}+\Phi_{eastsouth})]$$

$$= I(x, y, t) + \Delta t.[\, \Phi_{east}+\Phi_{west}+\Phi_{north}+\Phi_{south}+\frac{1}{2}(\Phi_{eastnorth}+\Phi_{westsouth}+\Phi_{westnorth}+\Phi_{eastsouth})] \quad (6)$$

The purpose to smooth the image in canny detector is to reduce noise within an image. The filter used in Canny detector is a Gaussian low-pass filter. In this paper, we have replaced the Gaussian filtering with SRAD. After smoothing the image while preserving the feature edges, the next step is to compute the gradients. The magnitude of gradients is equals to strength of the edge while direction indicates the direction of the pixel that contains the highest grayscale change of intensity. The gradient is computed by convolution of the sobel kernel on each of the image pixel in x-direction and y-direction as following.

$$Kernel_x = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} \quad Kernel_y = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix}$$

The magnitude, $|G|$ and directions θ are computed as following:

$$|G| = \sqrt{G_x^2 + G_y^2} \quad (7)$$

$$\theta = \tan^{-1}\left(\frac{G_y}{G_x}\right) \quad (8)$$

After obtaining the magnitude and direction of gradient, the next step is to sharpen the edge. To achieve this purpose, a series of steps need to be taken. Firstly, the gradient direction is rounded to nearest 45 degree. Next, make a comparison between the current pixel edge strength with the pixels in the positive and negative direction, only the pixel with maximum edge strength will be preserved, otherwise, it will be suppressed. The process mentioned is non-maximum suppression.

After the sharpening step, next to do is the reduction in edge numbers. Not all edges found in previous step are strong edges or true edges due to noises. Therefore, thresholding step is needed to distinguish strong edges from weak edges. First of all, two thresholds will be set, upper threshold and lower threshold. Pixels that contain gradients that higher than upper threshold will be preserved, whereas pixels that contain gradients lower then lower threshold will be suppressed. For pixels contain gradient between upper threshold and lower threshold, they will be called as weak edges and only some of them will be chosen to stay in the last step. The process to select potential edges by setting two thresholds is called double thresholding.

The last step in the edge detection of canny edge detection involve suppressing all edges that are not connected to strong or true edges. The weak edges found in previous step can only be preserved to the final edge image if they are connected to the true edges. The reason for this step is to remove the weak edges that are caused by noises or other small variations. This process of selecting true edges from weak edges is named as hysteresis. The steps started from SRAD until hysteresis is summarized in the following flow chart.

3 Results

In this section, the ultrasound phantom in figure 1 will undergo conventional canny edge detection and the proposed method edge detection at different thresholds and different standard deviation separately and the result is shown in figure 3.

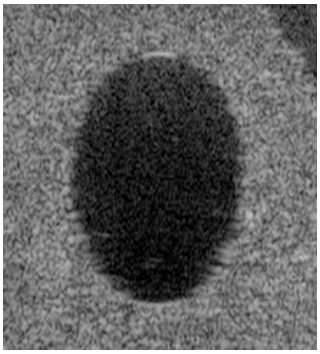


Fig. 1 Original ultrasound phantoms Image

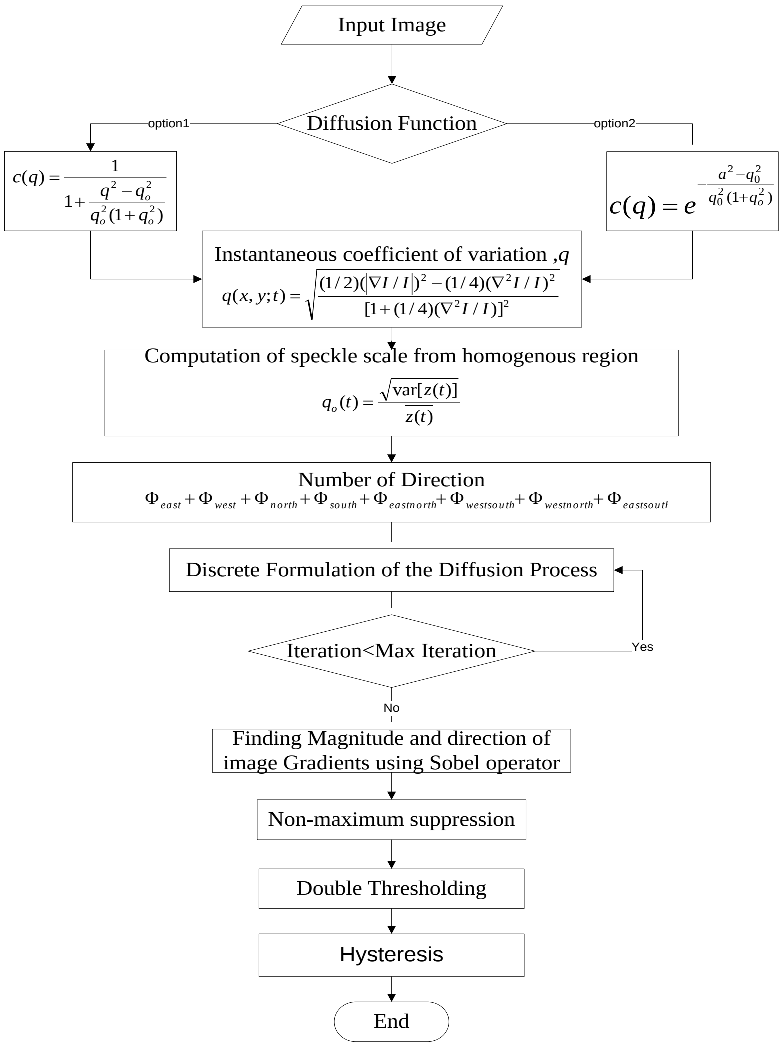
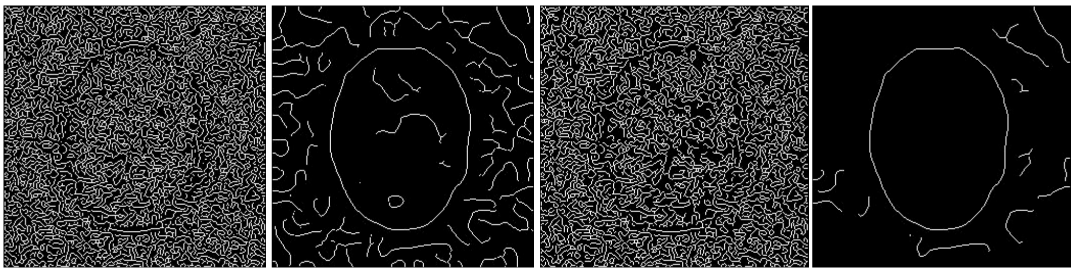
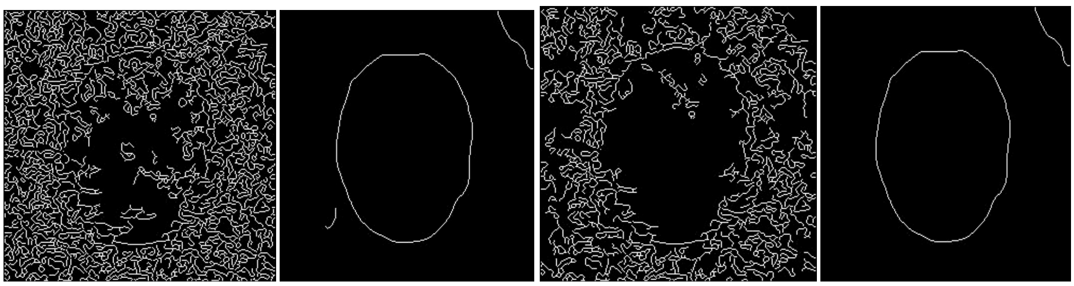


Fig.2 Flow chart of the methodology for the proposed edge detection



(a)Threshold=0.04,0.1 (b) Threshold=0.08,0.2



(c)Threshold=0.12,0.3 (d) Threshold=0.16,0.4

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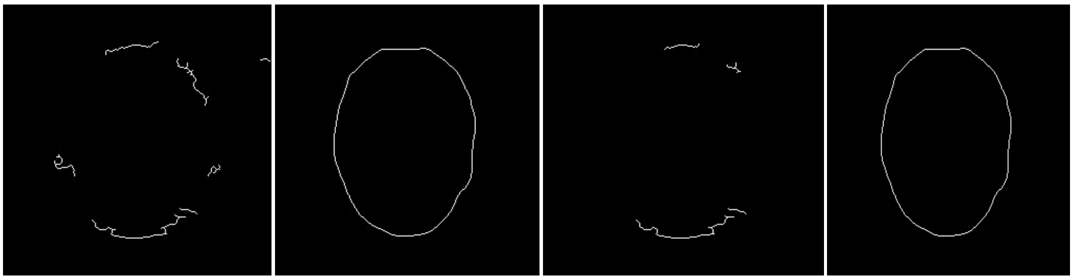
(e) Threshold=0.20,0.5 (f) Threshold=0.24,0.6



(g) Threshold=0.28,0.7 (h)Threshold=0.32,0.8

Fig. 3 Comparison between conventional canny edge detector and SRAD-Canny edge detector on noisy image of ultrasound with standard deviation of 1.0. The first and third columns are the image result by conventional canny detector. The second and fourth columns are the SRAD-Canny edge detector result image.

4 Discussion

From figure 3, it can be observed that at threshold value of 0.1, the image generated from conventionally canny using Gaussian blurring result in a noisy result whereas the image generated using SRAD-Canny Edge detector shows less noisy result with the elliptical shape object observable. At threshold value of 0.2, 0.3 and 0.4, the conventional canny detector result remains a noisy image although the middle of the elliptical shape begin to appear whereas the SRAD-canny edge result in a clear and clean edge of the elliptic shape. At threshold 0.5, 0.6, 0.7, 0.8, the conventional canny detector result in less noisy edge around elliptic shape, however the strong edge of the elliptic shape is reduced as well, and the shape is not observable whereas the SRAD-canny is obviously presenting a complete shape of ellipse and free of noisy edges.

5 Conclusion

This paper presented an improved Canny edge detector by incorporating it with Speckle reducing anisotropic diffusion method in eight directions which can adapt to ultrasonic local speckle statistic. Experimental results on ultrasound phantom shows that the proposed method can preserve edges and small structures while removing speckle noise effectively at a wide range of threshold and standard deviation. Thus, it has the potential to enhance the diagnostic ultrasound imaging and to improve automated segmentation and edge detection technique. Future efforts should be focus on the thresholding step in Canny edge detection in order to make it become more adaptive to the noisy image.

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