# Computerized Anisotropic Diffusion of Two Dimensional Ultrasonic images using multi-direction spreading approaches

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*Abstract:* - Ultrasound medical imaging is widely used nowadays in clinical application due to its intuitive, convenient, safety, non-invasive, and low cost. However, ultrasound image formation always comes with speckle-noise which will greatly reduce the image quality, and makes the identification and analysis of image detail become more challenging. Hence, we present an extended robust diffusion algorithm for optimum diffusion while retain the edge of image features. Total eight spreading diffusion directions are implemented in the proposed algorithm. Finding showed that this method is able to provide consistent and more objective results.

Key-Words: - ultrasound, diffusion, two dimensional, imaging, speckle, noise, filter, spreading, anisotropic

## **1** Introduction

The properties of ultrasound which are portability, simplicity and portability have made it become the indispensable medical diagnosis modality over other modalities [1-4]. It has been frequently implemented in clinical practice such as obstetric ultrasound scanning and emergency medicine, as it is user-friendly, reliable and safe compared to other medical diagnosis tools that entails the emission of ionizing radiation including CT-scan and X-ray [5-8].

Despite the advantages of ultrasound as medical imaging diagnosis tool, it has restrictions on imaging mechanism that will eventually lead to low quality ultrasound images, either polluted by noises or affected by speckle noises. This problem has become the major shortcoming in ultrasound medical imaging modality. This drawback is further intensified during the screening that involves organ and tissue in homogeneity fine structure. The disability to resolve the minor structures by ultrasound formation when coupling with the acoustic signals interference will cause the occurrence of a spot, namely speckle noise [12-18]. It is apparent that the image quality of ultrasound would be greatly degraded. The degradation of the quality will decrease the successful rate of identifying and analysis process for image significant features. Thus, a speckle noise reduction procedure is necessary.

Since it is proposed by Perona and Malik [10], the anisotropic diffusion or P-M model for image denoising processing has emerged as a commonlyused filtering technique for noise disturbance alleviation process of ultrasound medical image processing. This diffusion technique based on nonlinear partial differential equations (PDEs) involves in solving the initial value of input image using nonlinear heat diffusion equation. The major advantage of this filtering technique over others is that this technique able to preserve the edge while smoothing in homogenous image areas. This property enables it to smooth and denoise the noisy image without any distortion on important image features such as edge features. This diffusion model is effective and has aroused the interest of researchers towards the partial differential equation

enhancement in image processing. The main discussion of this technique is about equation and parameter determination with the intent of controlling the spread of the diffusion coefficient, producing the smoothing image without having to sacrifice the image feature information or even have the ability to enhance the image feature [19-22].

Nonetheless, direct implementations of P-M model on medical ultrasonic image are not satisfactory since it is designed for additive noise. For ultrasonic images with additive noise, P-M model [10] presents promising denoising effect. However, the resulting outcome of P-M model on multiplicative noise in ultrasound image having very limited effect, at times, even counterproductive. Over a decade of research and exploration on anisotropic diffusion enhancement, it is currently a powerful speckle noise removal called SRAD for 2D ultrasound images [11]. Many attentions had been focused on 2D diffusion implementation but not 3D ultrasound images.

The technique is sensitive to edge for the proposed method in processing the speckled image. Perona and Malik describe the diffusion method as the combination of image gradient into image diffusion based filtering possesses the ability to retain the edge. Nonetheless, this method is not effective in preserving the edge for the ultrasound image due to its disability to preserve the sharpness of edge during a large number of iteration in the diffusion process. Therefore, a suggested robust diffusion method called SRAD [11] is proposed which consist of a strong edge preserving filter. Mathematically, the edge preserving is accomplished by equation 1 which is known as instantaneous coefficient of variation (ICOV).

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

where I is input image,  $\nabla$  is gradient operator, | denotes the magnitude.

The function shows high value at edge and low value in homogenous region.

The proposed method is a speckle noise reduction approach in ultrasound images. Raw image is diffused by n-iteration to alleviate the speckle noise. Meanwhile, ICOV act as edge detector to retain the sharpness of edge during the diffusion. The process can be illustrated in figure 1.

#### **2** Previous Works

Perona and Malik [10] had incorporated the theory of diffusion in the image processing. They proposed a method of spatial filtering which is non-linear and anisotropic. This filter is able to retain the high-frequency feature in the image (edge) while diminishing the noise in the non-homogenous region of image. Generally, the process can be represented in any dimension as following:

$$\frac{\partial U(\bar{x},t)}{\partial t} = div(g(\bar{x},t)\nabla I(\bar{x},t))$$
(2)

 $g(\bar{x}, t)$ , it denotes the diffusion function that manipulate the strength of diffusion, the  $\bar{x}$  denotes spatial coordinates, t denotes process ordering parameter or iteration step in discrete implementation,  $U(\bar{x}, t)$  is represented by image intensity  $I(\bar{x}, t)$ . The non-linear characteristic is expressed by the diffusion function which enables it to adjust the degree of diffusion in different regions. The diffusion function can be mathematically expressed as following:

$$G_1(x, y, t) = e^{-\left(\frac{\nabla I}{\kappa}\right)^2}$$
(3)

$$G_2(x, y, t) = \frac{1}{1 + (\frac{\nabla I}{\kappa})^{1+\alpha}} \text{ where } \alpha > 1 \tag{4}$$

The diffusion function is manipulated by the gradient of image and it indicates the diffusion strength different region, for example in the region where gradient is high, the diffusion strength will be suppressed and in the region where gradient is low, the diffusion strength will be suppressed. Nonetheless, the effect of the mentioned non-linear characteristic is not sufficient to provide adequate improvement in edge preserving and thus the idea of anisotropic filter is suggested where the intensity of the pixel diffuses in the direction parallel with the edge instead of diffusing in the direction perpendicular to the edge by considering the vector of intensity change of its neighboring pixels. The effect of the diffusion function is determined by the value of parameter  $\kappa$  which is related to the edge gradient and noise level.

## **3** Methodology

The image is anisotropic diffused with the extended algorithm using 2D discrete implementation, as shown in Equation (5).



Fig. 1 Process of the enhanced diffusion method

$$\begin{split} &\frac{\partial}{\partial t}I(x,y,t) = div[g(x,y,t)*\nabla I(x,y,t)] \\ &= \frac{\partial}{\partial x}[g(x,y,t)*\frac{\partial}{\partial x}I(x,y,t)] + \frac{\partial}{\partial y}[g(x,y,t).\frac{\partial}{\partial y}I(x,y,t)] \\ &= \frac{1}{(\Delta x)^2}[g\left(x+\frac{\Delta x}{2},y,t\right).\left(I(x+\Delta x,y,t)-I(x,y,t)\right) + g\left(x-\frac{\Delta x}{2},y,t\right).\left(I(x-\Delta x,y,t)-I(x,y,t)\right) \\ &+ \frac{1}{(\Delta y)^2}[g\left(x,y+\frac{\Delta y}{2},t\right).\left(I(x,y+\Delta y,t)-I(x,y,t)\right) + g\left(x,y-\frac{\Delta y}{2},t\right).\left(I(x,y-\Delta y,t)-I(x,y,t)\right)] \end{split}$$

(5)

$$+ \frac{1}{(\Delta d)^2} \left[ g\left(x + \frac{\Delta x}{2}, y + \frac{\Delta y}{2}, t\right) \cdot \left( I(x + \Delta x, y + \Delta y, t) - I(x, y, t) \right) + g\left(x - \frac{\Delta x}{2}, y - \frac{\Delta y}{2}, t\right) \cdot \left( I(x - \Delta x, y - \Delta y, t) - I(x, y, t) \right) \right]$$

$$+ \frac{1}{(\Delta d)^2} \left[ g\left(x + \frac{\Delta x}{2}, y - \frac{\Delta y}{2}, t\right) \cdot \left( I(x + \Delta x, y - \Delta y, t) - I(x, y, t) \right) + g\left(x - \frac{\Delta x}{2}, y + \frac{\Delta y}{2}, t\right) \cdot \left( I(x - \Delta x, y + \Delta y, t) - I(x, y, t) \right) \right]$$

 $= \Phi_{east} + \Phi_{west} + \Phi_{north} + \Phi_{south} + \Phi_{eastnorth} + \Phi_{westsouth} + \Phi_{westnorth} + \Phi_{eastsouth}$ 

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:

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

The value of parameter used in preprocessing:

Diffusion function = 
$$G_1(x, y, t) = e^{-\left(\frac{\nabla I}{\kappa}\right)^2}$$
 (7)

The flow chart of the overall algorithm for 2D discrete implementation of anisotropic diffusion is illustrated in figure 2.

Gerig [9] carried out a study on the stability analysis of the diffusion filter integration constant,  $\Delta t$ , and conclude that in 2d discrete implementation of 8 neighboring pixels, the constant range should be in between 0 and 1/7 to ensure the stability. The nearer the value of  $\Delta t$  is to zero, the better the integration approximates the continuous case. Nevertheless, more iteration steps are required by the filter to diffuse the image.

The diffusion constant,  $\kappa$  determines the value that triggers the smoothing process. High value of  $\kappa$  will treat only very large gradient as edge depending on how high it is the  $\kappa$  and on the contrary, the low

value of  $\kappa$  will treat even small gradient difference as edge and therefore become a smoothing filter.

#### **4 Results**

In this section, we have shown part of our simulation results at various diffusion iteration and threshold selection. Figure 3 shows the lowest iteration implemented set to value at 5 with diffusion threshold equal to 20, which indicates that any gradient magnitude measured higher than this value will skip the diffusion. It can be observed that the simulation result does not show much effect after algorithm execution.



Fig. 2 Flow chart for 2D Anisotropic Diffusion



(a) (b) Fig. 3 Simulation result with 5 iteration, threshold at 20 (a) after diffusion (b) un-processed raw data



(a)

(b)



(c)

(d)



(e)

(f)

Fig. 4 Simulation result at threshold at 20 (a) after 10 iteration diffusion (b) after 20 iteration diffusion (c) after iteration diffusion 30 (d) after iteration diffusion 40 (e) after iteration diffusion 50 (f) after iteration diffusion 100

Based on the findings, appropriate diffusion iteration and its threshold value must be chosen for prospective image feature in ultrasound images. Fig. 4 (f) shows the counterproductive of executed diffusion at too high number of iteration diffusion. The edge of the image features were diffused and further decreased the image quality. Figure 5 below shows the implementation of proposed algorithm on various organ or subject interest in two dimensional ultrasound images. The proposed algorithms greatly reduced the speckle-noise while retain the image feature edge. The tested ultrasound images included ultrasound fetal phantom, kidney, cross heart and gall bladder.





(c)

(d)





(g)

(h)

Fig. 5 Ultrasound images diffusion at various scanned subject (a), (c), (e) and (g) are the raw ultrasound images for fetal phantom, kidney, cross heart and gall bladder respectively. (b), (d), (f) and (h) are the diffused images

## **5** Conclusion

We have proven that a method for two dimensional ultrasound diffusion using eight spreading directions in ultrasound fetal phantom, kidney, cross heart and gall bladder is better than the conventional four direction diffusion. Existing speckle-noise in 2D ultrasound images were diffused while retain the edge of image features. Findings showed that the system is able to provide consistent and reproducible results. The future works will be focus on designing a fully automated diffusion that will determine the parameter itself according to different ultrasonic image in order to optimize that resulting image.

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