

An Anisotropic Diffusion Filter Based on Multidirectional Separability

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Abstract

Extracting tongue contour from high noised ultrasound image is a key issue of observing speech production procedure. Anisotropic diffusion has been widely used in reducing speckle noise of ultrasound images but it is not very effective in preserving edges and tends to blur them. Hence the blurred edges hamper the succeeding contour-based pattern analysis or modeling. In this study, we modify the standard SRAD (speckle reducing anisotropic diffusion) to improve its edge detection and suppress the intrinsic edge blurring effect of SRAD by exploiting the multidirectional separability. We experimented with both synthetic and real ultrasound images by SRAD and the proposed approach. The extracted contours in denoised images by SRAD and the proposed approach are compared in terms of the corresponding accuracy, both subjectively and objectively. The results show the proposed approach performs better than the conventional SRAD and more accurate contours can be obtained for post processing.

Index Terms: anisotropic diffusion, ultrasound images, tongue contours

1. Introduction

Ultrasound imaging technology has been widely applied in clinic field. B-mode ultrasound imaging technology is also one of the four major speech production observation approaches, as well as X-ray, CT, MRI (magnetic resonance imaging). Comparing with other methods, ultrasound imaging technology illustrated its advantage of convenient, safe, fast and real-time for observing internal articulatory movements, such as tongue movements. However, due to the particularity of the imaging mechanism, ultrasound images have serious speckle noise. This kind of noise can be regarded as the multiplicative noise, and has complex stochastic properties. Speckle noise not only decreases the quality of ultrasound images, but also makes the following image-analyzing become more difficult. Therefore, the speckle noise has to be reduced, before image content analysis of ultrasound images. The target objects such as contours, however, should be retained during the denoising procedure.

During the last two decades, a number of algorithms for denoising ultrasound images have been proposed, including the Lee filter [1], Frost Filter [2] and PM (Perona-Malik) [3]. Yu and Acton proposed SRAD [4] in 2002, a modified AD (Anisotropic Diffusion) filter, which based on PM, Lee Filter and Frost Filter. SRAD intend to preserve edges when reducing speckle noise in homogenous regions. However, these methods based on gradient cannot perform well on both

image denoising and edge preserving. Their performance is sensitive to the parameters such as the threshold for the amount of smoothing. The multidirectional separability is a modification of separability [5]. Separability is based on the statistical analysis of the distribution of image features like image intensity. It is robust to noise compared with gradient-based methods.

In this paper, we modify the standard SRAD and we extract contours from the denoised results by SRAD and the proposed method, respectively. We evaluate the denoised results with MSE (Mean Squared Error) and PSNR (Peak Signal to Noise Ratio) in image denoising. And then we analyze and compare the extracted tongue contours with FOM.

The paper is organized as follows. In section 2, we review SRAD, separability and introduce the multidirectional separability as well as the proposed method. In section 3, we present the experiments and analyze the results with three principles: MSE, PSNR and FOM. The conclusions are given in Section 4.

2. Anisotropic diffusion filter based on the multidirectional separability

2.1. Speckle Reducing Anisotropic Diffusion

SRAD is fit for speckle reducing. SRAD can not only preserve edges but also enhances edges. Given an intensity image $I_0(x, y)$ having finite power and no zero values over the image support Ω , the output image $I(x, y; t)$ is evolved according to the following partial differential equation (PDE) [4]:

$$\begin{cases} \partial I(x, y; t) / \partial t = \text{div} (c(q) \nabla I(x, y; t)) \\ I(x, y; 0) = I_0(x, y), (\partial I(x, y; t) / \partial \vec{n})|_{\partial \Omega} = 0 \end{cases} \quad (1)$$

Where t represents diffusion time, $\partial \Omega$ denotes the borders of Ω , \vec{n} is the outer normal to the $\partial \Omega$, and

$$c(q) = \frac{1}{1 + [q^2(x, y; t) - q_0^2(t)] / [q_0^2(t)(1 + q_0^2(t))]} \quad (2)$$

Here, $q(x, y; t)$ is the instantaneous coefficient of variation and

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

And $q_0(t)$ is the scale factor of speckle and controls the amount of smoothing. For our images in the experiment we can define $q_0(t)$ with

$$q_0(t) \approx q_0 \exp[-\rho t]. \quad (4)$$

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Where ρ is a constant to slow down the decrease of q_0 while the algorithm is iterating.

SRAD can preserve edges even enhance edges; however this character or function highly depends on the precision of edge detecting. If the edge is not detected, the edge will not be enhanced and even smoothed. And if the noise is detected as edges, the noise will not be smoothed and even enhanced. So the performance of SRAD is sensitive to the selection of threshold value. Although SRAD has a dynamic threshold value, its precision of edge detecting is not good. What's more, the diffusion coefficient cannot be zero at any edge; hence some edges in the image will be blurred during smoothing.

2.2. Separability

Separability is based on statistics and it is robust to blurred edges caused by noise and sensitive to detect an edge between different texture regions [6].

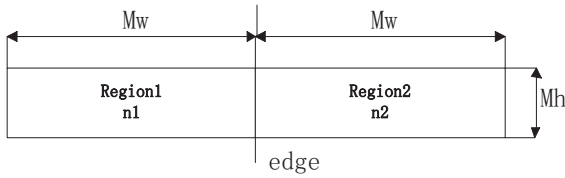


Figure 1: define an edge based on separability.

As Figure 1 shows, a $2Mw \times Mh$ region consists of region 1 and 2. Separability can be calculated by linear discriminant analysis using information from region 1 and region 2. The definition is:

$$\eta = \frac{\sigma_b^2}{\sigma_T^2} \tag{5}$$

Here, σ_b^2 and σ_T^2 are defined as follows:

$$\sigma_b^2 = n_1(\bar{P}_1 - \bar{P})^2 + n_2(\bar{P}_2 - \bar{P})^2. \tag{6}$$

$$\sigma_T^2 = \sum_{i=1}^{n_1+n_2} (\bar{P}_i - \bar{P})^2. \tag{7}$$

Where P_i is the image intensity of an image at a pixel i , and \bar{P}_1 and \bar{P}_2 are the means of the image intensity in region 1 and region 2. \bar{P} is the mean of image intensity for the combined region. n_1 and n_2 are the numbers of pixels in region 1 and region 2 [5].

From the definition, we can conclude that η is $0 \leq \eta \leq 1$. At an ideal step edge, η is 1. When the edge becomes dull, the separability η will decrease. If the change of the image intensity is little, $\eta \approx 0$. And if the intensity changes linearly, η is a constant value $\bar{\eta}$ dependent on Mw . And

$$\bar{\eta} = 0.75 \frac{1}{1 - 1/4Mw^2}. \tag{8}$$

In the experiment, we consider $\bar{\eta}$ is the threshold for judging if current pixel is on the edge. If η is smaller than $\bar{\eta}$, current pixel is not on the edge.

2.3. The Proposed Method

2.3.1. The Multidirectional Separability

Although separability is robust to noise and is powerful to detect edges, it can only detect one direction of the edges. The direction is perpendicular to region 1 and region 2, as Figure 1

shows. Facing this problem, we want to use the multidirectional separability, which is defined with four regions. The multidirectional separability can detect two directions of the edges.

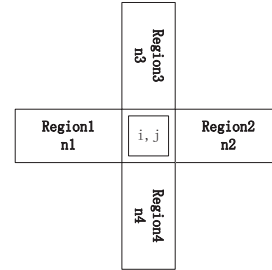


Figure 2: Edge property based on multidirectional separability.

As Figure 2 shows, we define the multidirectional separability as follows:

$$sep = \lambda \eta_h + (1 - \lambda) \eta_v \tag{9}$$

Here, the multidirectional separability sep has the horizontal and vertical component. The horizontal component is η_h and the vertical component is η_v . η_h is calculated with Region 1 and Region 2 by formula (5)-(7). η_v is calculated with Region 3 and Region 4 by formula (5)-(7). And λ is depend on the different direction component of gradients and is calculated by:

$$\begin{aligned} \lambda &= 1 (\nabla I_h \geq \nabla I_v) \\ &= 0 (\nabla I_h < \nabla I_v) \end{aligned} \tag{10}$$

Here, ∇I_h is the horizontal component of the gradient of the current pixel (i, j) and ∇I_v is the vertical component.

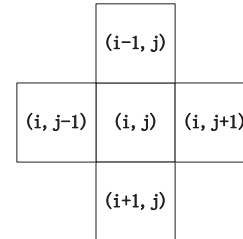


Figure 3: the coordinate of image pixels

According to Figure 3, ∇I_h and ∇I_v are defined as follows:

$$I_h = I(i, j + 1) - I, I_v = I(i + 1, j) - I. \tag{11}$$

We consider each pixel has the edge property which includes: horizontal edge, vertical edge and no edge. The edge property depends on each pixel's gradient and separability: If the horizontal component of the gradient of the current pixel is larger than the vertical and its separability is larger than 0, we will say the edge property of the pixel is horizon edge.

2.3.2. The New Partial Differential Equation

We propose a novel anisotropic diffusion method based on the standard SRAD. In SRAD model, the diffusion coefficient $c(q)$ detects edges and controls the amount of smooth. Hence we modify the diffusion coefficient $c(q)$ of SRAD with the multidirectional separability sep to help SRAD enhance

precision of detecting edges and control the amount of smooth. The PDE of the proposed method is:

$$\begin{cases} \partial I(x, y; t) / \partial t = (1 - sep) \operatorname{div} (c(q) \nabla I(x, y; t)) \\ I(x, y; 0) = I_0(x, y), \quad (\partial I(x, y; t) / \partial \vec{n})|_{\partial \Omega} = 0 \end{cases} \quad (12)$$

In our proposed method, at the edges, the diffusion becomes sluggish because of sep is high. And in the homogeneous regions, the diffusion is encouraged because sep is low. Due to the multidirectional separability, the proposed method is able to detect edges more precisely and less smooth at the edges than SRAD.

3. Experiments and evaluations

In this section, we compare the proposed method with SRAD by using synthetic images and real ultrasound images. We use MSE (Mean Squared Error) and PSNR (Peak Signal to Noise Ratio) to evaluate the two algorithm with denoised results. And FOM (Figure of Merit) [7] is calculated with the contours extracted from the denoised results.

3.1. Experiment with synthetic images

The images we used in this experiment are synthetic images. The size of the images is 400×240 with gray level = 90 in bright regions and gray level = 50 in dark regions [8]. Then we add speckle noise to the original synthetic images with four different intensities by MATLAB. Figure 5 (b) is one of the four noisy images. In this experiment, we set $Mw=5$, $Mh=3$, $\eta=0.75$.

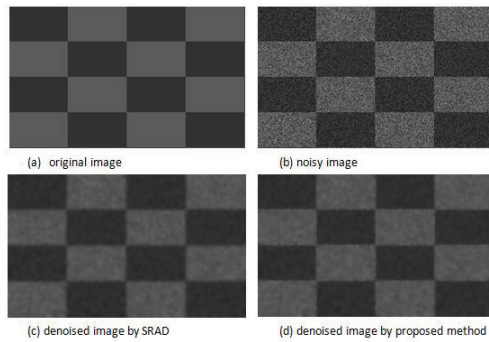


Figure 5: (a) original image (b) one sample noisy image (c)(d) denoised results by SRAD and proposed method

Figure 5 shows original synthetic image, one of the four noisy images, the denoised results by SRAD and proposed method. From Fig.5 (c) and (d), we find edges in the denoised results by proposed method are preserved better than SRAD. And FOM is defined by

$$FOM = \frac{1}{\max(I_I, I_E)} \sum_{i=1}^{I_E} \frac{1}{1 + \frac{1}{9} d^2(i)} \quad (11)$$

Where I_I and I_E are the number of ideal and actual edge pixels. $d(i)$ is the Euclidean distance between the i th detected edge pixel and the nearest ideal edge pixel.

We evaluate the results objectively with MSE, PSNR and FOM. We compare noisy image, the denoised images by SRAD and proposed method with the original synthetic images to calculate MSE and PSNR. We use Sobel filter to extract contours from original synthetic images, noisy images and denoised results by SRAD and the proposed method, respectively. Then in order to calculate FOM, we compare the

contours derived from noisy images and denoised results by SRAD and the proposed method with the ideal contours derived from original synthetic images.

Table 1. The value of MSE, PSNR and FOM

	Noisy	SRAD	Proposed Method
MSE	89.7855	49.9657	42.1538
PSNR	28.6284	31.8488	32.8964
FOM	0.4322	0.8123	0.9144

Table 1 shows the average values of MSE, PSNR and FOM for the four sets of noisy images and the respective denoised results by SRAD and proposed method.

By MSE and PSNR in Table 1, we find the results denoised by the proposed method are closer to the original synthetic image. So the proposed method performs better in image denoising. In Table 1, the denoised results derived by the proposed method can help edge-detector get the highest FOM. So the proposed method improves edge preservation comparing with SRAD method.

From the perspectives of image denoising and edge preservation, the proposed method performs better than SRAD in image denoising.

3.2. Experiment with real ultrasound images

The images we used in this part are real ultrasound images of tongue movements obtained from the ultrasound machine Terason T3000. The size of original ultrasound images is 640×480 . But some parts of the images do not contain any useful information. So we cut off the useless parts and decrease the size to 310×190 . This also can reduce the computation when denoising the images. In the experiment, we set $Mw=30$, $Mh=3$, $\eta=0.75$.

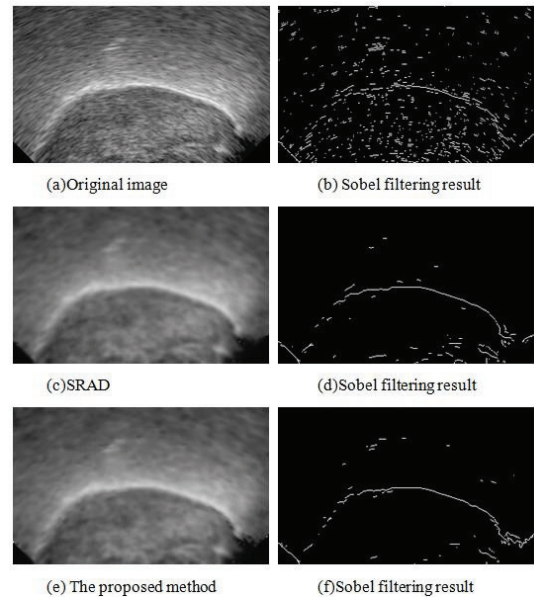


Figure 6: one sample ultrasound image and the contour (a) original ultrasound image to be processed. (c) (e) denoised result by SRAD and proposed method for (a). (b)(d)(f) Sobel contours extracted from (a)(c)(e).

We use Sobel filter to extract contours from original images, denoised results by SRAD and the proposed method, respectively. By Figure 6 (b), (d) and (f) we can find it is necessary to denoise images before detecting the tongue contours with Sobel filter. Moreover, compared (d) and (f), we can find the proposed method can help Sobel filter get more complete tongue contours from real ultrasound images.

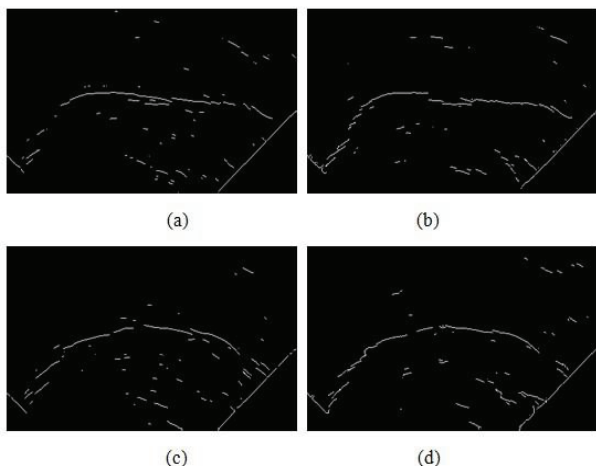


Figure 7: extracted contours of three sample images
 (a)(c) contours for denoised images by SRAD
 (b)(d) contours for denoised images of proposed method.

Figure 7 shows the extracted contours for two more sample ultrasound images. (a) and (c) are the contours extracted from the denoised results by SRAD. (b) and (d) are the contours extracted from the denoised results by the proposed method. We can find the proposed method can help Sobel filter get more complete tongue contours from real ultrasound images. So the proposed method is better than SRAD for Sobel filter to detect tongue contours.

Now we will calculate FOM to compare the two algorithms objectively. In order to calculate FOM, we should get the real and ideal contours. In our experiment we use Mikkel B. Stegmann's aam-api [9] based on AAM [10] to extract real contours. We have 3 different training sets and 3 different test sets. The three sets are: noisy images, denoised results by SRAD and the proposed method. Each training set is 80 images to build a model, which then we use to extract the real contours for the test set automatically. So we get the real contours for each test. Then we annotate the test sets to get the ideal contours. Finally, we can calculate FOM with the real contours and ideal contours. [11]

Table 2. The values of FOM for the three test sets

	Noisy	SRAD	Proposed Method
1	0.3883	0.4129	0.6203
2	0.3072	0.3307	0.4363
3	0.3021	0.3129	0.4633
4	0.3775	0.4511	0.8534
5	0.3534	0.3534	0.5975
6	0.3170	0.3483	0.4431

Table 2 shows the values of FOM for six random images from each of the three test sets. From the data in the Table 2, it is seen that the proposed method perform much better than

SRAD for AAM to extract contours. Moreover, the proposed method can help AAM get more accurate contours. So the proposed method improved edge preservation comparing with standard SRAD method.

4. Conclusions

In this paper, we have proposed a novel denoising method for observing tongue contour from ultrasound image. The present method is an improved version of Yu and Acton's SRAD algorithm. The method can not only suppress speckle noise in ultrasound images, but perform better in edge preservation by exploiting the multidirectional separability of images. The experiment with synthesized images shows that MSE is decreased from 49.96 to 42.15 while FOM improved from 0.81 to 0.91. The experiments with real ultrasound images also demonstrate the proposed method can help Sobel filter and AAM to get more precise and complete edges from the images. The results show that our new method outperforms the standard SRAD method significantly and is very useful for reducing speckle noise and detecting tongue contours in real ultrasound images for follow-up contour based processing.

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