Adaptive speckle reduction of ultrasound images based on maximum likelihood estimation

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A method has been developed in this paper to gain effective speckle reduction in medical ultrasound images. To exploit full knowledge of the speckle distribution, here maximum likelihood was used to estimate speckle parameters corresponding to its statistical mode. Then the results were incorporated into the nonlinear anisotropic diffusion to achieve adaptive speckle reduction. Verified with simulated and ultrasound images, we show that this algorithm is capable of enhancing features of clinical interest and reduces speckle noise more efficiently than just applying classical filters. To avoid edge contribution, changes of contrast-to-noise ratio of different regions are also compared to investigate the performance of this approach.

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Ultrasound has been considered as a powerful modality for medical imaging. However, poor quality is still its main disadvantage, which is characterized by a contamination known as speckle[1]. Speckle significantly degrades image resolution, and may blur the clinical important details such as endocardium border[2]. Since speckle itself being a part of image is the main feature of ultrasound imaging, so when performing denoising, it is crucial to get reliable model describing exact nature of the noise.

The statistics of speckle are significantly non-Gaussian[3], while many processing methods are simply based on the assumption that it is following Gaussian distribution[2]. Filters that exploit the full knowledge of data probability density function (PDF) will work more efficiently. Here we present a parameter estimation method based on maximum likelihood (ML) to investigate the characteristic of speckle in ultrasound image. Then nonlinear anisotropic diffusion was utilized for filtering, with its behavior adapted according to ML estimation outputs.

Image speckle is a phenomenon that occurs when a coherent source and a non-coherent detector are used to interrogate a medium, which is rough to scale of the wavelength. In uniformly spatially distributed speckle regions, the amplitude of fully developed speckle has been determined to follow a Rayleigh distribution[4]

$$f(z) = \frac{z}{\sigma^2} \cdot \exp(\frac{-z^2}{2\sigma^2}), \qquad (1)$$

where z is the observed envelope-detected signal, and σ^2 is the variance of the random backscatter amplitude of the individual scatters, with mean $\sigma\sqrt{(\pi/2)}$ and variance $\sigma^2(2-\pi/2)$. For a more accurate description of displayed ultrasound images, a realistic image formation model[4] is

$$z = x + n \cdot \sqrt{x}, \qquad (2)$$

in which x is the original signal, and n is a noise term statically independent of x.

In classical theory, filtering is often achieved by linear method, which in essence is a kind of isotropic diffusion[5]. It embeds the original image into a family of derived images $I(x,y,t)$, obtained by convolving the original image $I_0(x,y)$ with a Gaussian kernel $G(x,y,t)$ of variance t

$$I(x,y,t) = I_0(x,y) * G(x,y,t). \qquad (3)$$

Larger values of t, the scale-space parameter, corresponds to images at coarser resolution. Isotropic diffusion tends to blur sharp edges with increasing filter iterations[6]. As to nonlinear approaches, median filter is most used for its simplicity and robust to impulsive noise, but similar problems still exist.

The developments of anisotropic diffusion filtering overcome the problems of spatial filtering. Proposed originally by Perona and Malik (PM filter)[7], its basic idea is to obtain a family of filtered versions of $I(x,y)$ as the solution of a suitable diffusion process, with $I_0(x,y)$ as initial condition

$$\begin{cases} I_t = \mathrm{div}[c(|\bigtriangledown I|)\bigtriangledown I] \\ I(x,y,0) = I_0(x,y) \end{cases}, \qquad (4)$$

in which div indicates the divergence operator, $\bigtriangledown$ indicates the gradient operator with respect to the space variables, and $c(\cdot)$ is an "edge stopping" function. So in diffusion process images are modelled as anisotropic conducting mediums, and the thermal diffusion constant is a decreasing function of the local gradient. All these result in that smoothing process are restricted in edge regions and stopped at edges, as shown in Fig. 1. This description is equivalent to image smoothing with Gaussian filters, where the smooth kernel is structure adopted.

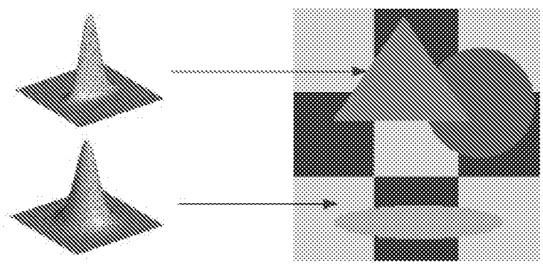

Fig. 1. Property of the nonlinear anisotropic filtering.

The adaption is as that smoothing is mainly parallel to the direction of the structure and minimal perpendicular to it.

To guarantee the effectiveness of the algorithm, choosing of the conductance function is critical and should depend on the nature of the images. As to ultrasound image discussed in this paper, we use the following function, which could avoid the pinhole effects that[7] may produce[8]

$$c(x,t) = \frac{1}{2}[\tanh(\gamma(k - \| \nabla I(x,t)\|)) + 1], \tag{5}$$

in which parameter γ controls the steepness of the min-max transition region, and k controls the extent of the diffusion region in terms of gradient gray level. γ can be fixed to 0.2 for 256 gray level images. In medical image processing, the γ value should be increased proportionally to the range of gray values. So diffusion and flow functions are guided by local gradient and strengths in different directions.

Inspired by the work of Sijbers *et al.*[9], here ML is proposed to incorporate Rayleigh distribution into filter parameters estimation. Kotropoulos *et al.*[1] first derived the ML estimator for the underlying raw ultrasound signal, which could exploit the *a priori* knowledge of data statistics in an optimal way. Estimation is performed by maximizing the conditional PDF

$$p(z|x) = \frac{1}{x}\left[\frac{z}{\sigma^2 x}\exp\left(\frac{-z^2}{2\sigma^2 x^2}\right)\right]. \tag{6}$$

For a series of N observations, $z_i (i \in 1, N)$, the joint conditional PDF can be expressed as a log-likelihood function

$$\ln[p_N(z|x)] = -2N\ln(\sigma) - 2N\ln(x) + \sum_{i=1}^{N}\ln(z_i) + \frac{\sum_{i=1}^{N} z_i^2}{2\sigma^2 x^2}, \tag{7}$$

where the unknown parameter σ is separated, which represents the local intensity gradient. Let $\frac{\partial p_N(z|x)}{\partial x} = 0$, then the maximum likelihood estimator x_{ml} could be obtained with solution[4]

$$x_{ml} = \sqrt{\frac{\sum_{i=1}^{N} z_i^2}{2\sigma^2 N}}. \tag{8}$$

It provides a close approximation to the ML estimator for the displayed ultrasound images. Based on the estimation of σ in different regions, finally a parameter set is fitted to the image, from which anisotropic diffusion gains adaptive weights for filtering.

The performance of anisotropic diffusion incorporating ML estimation was evaluated with simulated and real medical images. In Fig. 2, we give a 191 × 187 grey level image polluted with speckle noise, then process it with PM filter and the proposed algorithm separately. Comparing the detailed line drawn from the same position of column 68 in images, anisotropic diffusion that incorporated with speckle distribution model, could give more efficient and reliable output than PM filter. Taking into account the variance of speckle, their functions was compared in terms of mean squared error (MSE), defined as[9]

$$\mathrm{MSE} = \sqrt{\frac{\sum_{i=1}^{N}(\hat{z}_i - z_i)^2}{\sum_{i=1}^{N} z_i^2}}, \tag{9}$$

where $\hat{z}_i$ denotes the estimated signal at position i. This performance comparison was done as the function of signal-to-noise ratio (SNR), and tested by computing MSE using Eq. (9) for different noise variances. SNR is calculated using the ratio between means μ and standard derivations σ.

Figure 3 gives the results of the MSE from these filters under different SNR. The experiment illustrates that along with the decreasing of SNR, the MSE results of proposed algorithm remain lower than PM filter. To avoid the edge contribution, contrast-to-noise ratio (CNR) is additionally used to evaluate the enhancement

$$\mathrm{CNR} = \frac{\mu_2 - \mu_1}{\sigma_1 + \sigma_2}, \tag{10}$$

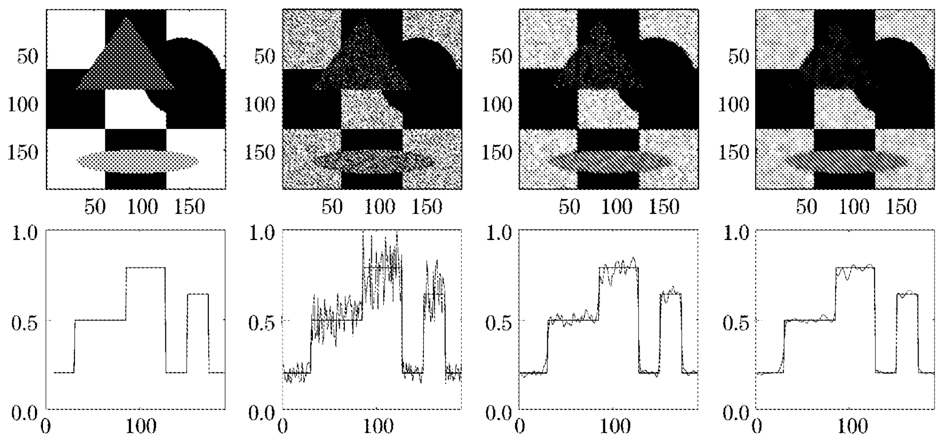

Fig. 2. In upper row they are original, speckled, PM method filtered and proposed method filtered images (left to right), and in lower row they are the comparisons of corresponding lines before and after speckled/filtering.

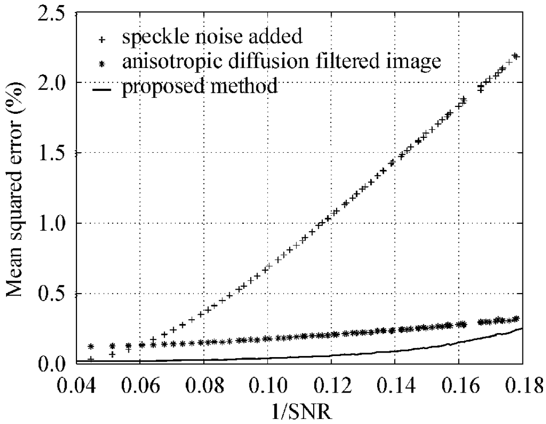

Fig. 3. The MSE of different filters corresponding to SNR.

Table 1. Average SNR and CNR Values in Triangular and Circular Regions

Simulated Image	Unfiltered Image	Filtered Image	Ratio
SNR (Triangle)	4.4651	15.2331	3.4116
SNR (Circle)	3.1983	11.4073	3.5667
CNR	2.3058	4.4437	1.9272

where μ_1 and μ_2 are the mean pixel values in distinct regions, σ_1 and σ_2 are corresponding standard deviations. Table 1 presents some sample data of this test. We can see that in both triangular and circular regions in simulated original images of Fig. 2, SNRs are improved more than 3 times after filtered with proposed method, and CNR is improved nearly 2 times in the test.

Furthermore, these filters were tested on echocardiographic image, which is commonly utilized in diagnosis and therapy monitoring of cardiac diseases. The short axis end-systolic (ES) image of heart used here was obtained during the diagnosis process by transthoracic echocardiography, with the imaging system of Angilent SONOS 5500. Figure 4 shows the original image and filtered results based on different filters. Figure 4(a) is the original noisy image,the result of contrast enhancement is presented in Fig. 4(b), Figure 4(c) displayed the result of median filter with 3×3 mask, Figure 4(d) and (e) display the results from PM filter and proposed algorithm. From the illustration, one can observe that cardiac structure details such as endocardium border were retained more efficiently in Fig. 4(e) than in others.

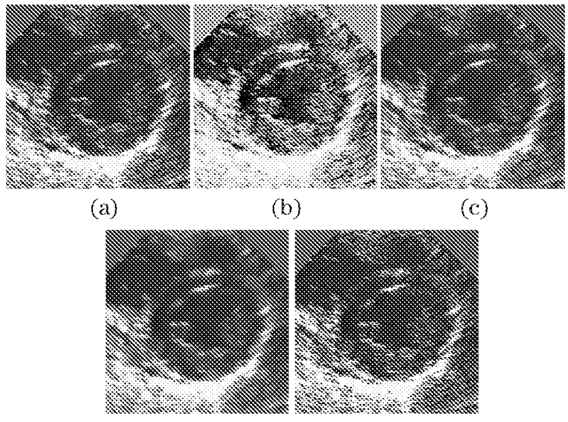

Fig. 4. Results of various denoising methods. (a) Original ES image with speckle noise; (b) contrast enhancement; (c) median filter with 3×3 mask; (d) PM filter; (e) proposed algorithm.

The anisotropic diffusion filter may seem less effective on real ultrasound images than previous simulated test, for the very slow varying regions of ultrasound images. Incorporating knowledge information about cardiac structures into filtering process may improve its performance and robustness, which is the next work we will focus on.

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