A Novel Method for Speckle Reduction and Edge Enhancement in Ultrasonic Images

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ABSTRACT

This paper presents a novel method for speckle reduction in ultrasonic images. Firstly, a particular filtering kernel is defined by decomposing the local rectangular neighborhood into asymmetric sticks pointing outside with variable orientation from the investigated pixel. Then the local mean and variance along each stick are calculated using a template based convolution algorithm. Finally, a pseudo-diffusion model is derived to diffuse the intensity averages of sticks into the central pixel, and a variance sensitive conductance functions is designed to adaptively control the diffusion strength in varying directions. The proposed method is in essence an integration of the linear boundary detection operator, i.e. stick technique, and the nonlinear diffusion model. In homogeneous regions, our method will act as a Gaussian like low pass filter, since the sticks are partially overlapped near the center, which implicitly assigns distance dependent weights to neighboring pixels. In heterogeneous regions, the information is expressed as many structures, which often occur as line boundaries or tube shapes in ultrasonic images, then our approach can encourage smoothing along the sticks falling inside the structures, and penalize blurring along the sticks across edges. The performance of our method is verified in experiments of both synthetic and clinical ultrasonic images. The results show that our method outperforms the existed filtering techniques in term of smoothing homogeneous regions, preserving resolvable features, enhancing weak edges and linear structures.

Keywords: Ultrasonic image, Speckle suppression, Adaptive filter, Nonlinear diffusion

1. INTRODUCTION

The coherent nature of ultrasound leads to a special fluctuation of intensity in ultrasonic images, namely speckle. Speckle is directly caused by the diffuse scattering from unresolvable random structures on the scale of ultrasonic wavelength, and occurs as a granular pattern. Although it is believed that the speckle “texture” conveys information about the region being imaged, the exact method of interpreting that information is still in dispute. Speckle can be considered as an undesirable property and should be eliminated in the sense that it seriously degrades the quality of ultrasonic imaging, and hence reduces the ability of observers or computer to discriminate fine details.

Ultrasonic images hold two obvious features: 1) Speckle is a kind of signal dependent noise, which is correlated in the axial direction of ultrasonic wave propagation, and whose correlation length covers several resolution cells. 2) The edges in ultrasonic images are typically streaks between similar intensity regions, rather than demarcations between regions of differing contrast. The difficulty of denoising in ultrasonic images is to suppress efficiently speckle, while preserve feature details such as organ boundaries. Various speckle suppression methods have been reported in the literature. Among these methods, adaptive speckle suppression filter (ASSF)[1] is one of the most popular techniques. It depends on the signal noise ratio (SNR) and possible the normalized local variance to permit a varying degree of smoothing or to adjust the size and shape of filter kernel. Using SNR as speckle discriminating feature is based on the assumption that the fully formed speckle (FFS) follows a Rayleigh distribution. However, this statistical model is not able to interpret the partially formed speckle (PFS) and structure region. Moreover, in real ultrasonic images, many factors such as the shadow of bones, adjustment of imaging parameters, various post-processing algorithms (including log-compression) in the scanner, will drastically lower the efficiency of the technique. Nonlinear diffusion was introduced into ultrasonic images filtering by different authors [2][3]. It depends on gradient information or neighborhood coherence to control smoothness along the edges rather than across them. This scheme works well in suppressing speckle and enhancing salient edges, but weak edges and feature details will lose with the smoothness. Recently, Czerwinski et al [4][5] presented a stick technique to enhance bright linear boundaries in ultrasonic images. But the stick...
technique is usually used as a pre-process step before denoising and edge detection\cite{6}, since it keeps the dark edges and homogeneous regions unchanged. Another drawback of the stick technique is to produce too many false edges. Guo and Luo\cite{7} reported an adaptive stick technique for edge detection, and their contribution focuses on adaptively estimating the stick length.

To compensate the drawback of the previous techniques, we emerge the stick technique into the framework of nonlinear diffusion, and then propose a new adaptive filtering method, called diffusion stick, for ultrasound speckle reduction. We divide the traditional rectangular filter kernel into a set of asymmetric sticks. These sticks are evenly distributed in orientation, but partially overlapped near the center. The mean values along each stick are diffused into the investigated pixel under the control of a normalized variance-sensitive conductance function. In section 1, we briefly review the traditional ASSR filter for ultrasonic images. The diffusion stick model is described in section 2. In section 3, we present the experiments, and results from other techniques are compared.

2. TRADITIONAL ADAPTIVE SPECKLE SUPPRESSION FILTER (ASSF)

The traditional ASSF applied to ultrasonic images is typically an edge preserving smoothing (unsharp masking) filter, e.g., the adaptive mean filter\cite{1}:

\[ \hat{I} = \bar{I} + c(I - \bar{I}) \]  

(1)

where \( \hat{I} \) is the new (processed) value of a pixel to be computed from the original unprocessed value \( I \), and \( \bar{I} \) represents the local mean inside the rectangular window surrounding the current pixel. The term \( c \) denotes a feature parameter to discriminate speckle and structure in the image. Dutt et al.\cite{8} derived a new statistical parameter to quantify the extent of speckle formation in log-compressed echo images, based on a more general K-distribution statistical model. The parameter is

\[ f_a = \frac{\pi^2 D^2}{24 V} \]  

(2)

where the constant \( D \) is the logarithmic compression ratio, and \( V \) the local variance. Then the feature parameter \( c \) can be written as

\[ c = 1 - f_a \]  

(3)

Substituting (3) into (1), and adding a parameter \( \phi \in (0,1] \) to compensate the reduction of variance due to the low-pass filtering algorithm employed in clinical imaging system, a new ASSR model can be derived, i.e.

\[ \hat{I} = \bar{I} + (1 - \phi \cdot f_a)(I - \bar{I}) \]  

\[ = I + \phi \cdot f_a(\bar{I} - I) \]  

(4)

Here, \( f_a \) is truncated to \([0,1]\). Notice that eq. (4) is actually a variance guided smoothing filter. To put it more explicitly, we rewrite the \( \phi \cdot f_a \) term as a variation function, i.e.

\[ g(V) = \begin{cases} 
1 & \text{if } V \geq k; \\
\frac{1}{V} & \text{if } V < k
\end{cases} \]  

(5)

and \( k = \frac{\pi^2}{24} \phi \cdot D^2 \).

Thus eq. (4) can be transferred to

\[ \hat{I} = I + g(V)(\bar{I} - I) \]  

(6)

The above ASSF is rather limited while applying to real ultrasonic images. Firstly, it is difficult to choose an appropriate window size to keep a balance between stability and localization of feature estimation. Secondly, the uniform smoothing inside the filtering window may cause loss of fine details. Especially, the line structures are blurred out with the inappropriate filtering kernel.
3. DIFFUSION STICK FILTERING

3.1 Asymmetric Stick
To enhance the linear boundaries in ultrasonic images, Czerwinski et al. [4][5] proposed a stick technique, where the sticks are actually a set of line segments passing through the current pixel. The sticks are short enough that they can approximate the edges in images, but long enough that the speckle along the sticks is uncorrelated. Therefore the project along the sticks can smooth out speckle but not damage real edges. In this technique, the gray value of current pixel is replaced by the maximum of all the projects.

The original sticks are symmetric around the central pixel, and it likely leads to interregion smoothness. Here, we define an asymmetric stick. Fig.1 shows a set of 4-pixel long asymmetric stick. Generally, a $N \times N$ ($N$ is odd) rectangle neighborhood can be decomposed into $4N - 4$ possible sticks with length $(N + 1)/2$. The advantage of asymmetric stick is that smoothness can be controlled along but not across the edge for points near the boundaries.

3.2 Proposed model
Under the asymmetric stick filtering kernel, we utilize the sum of weighted averages along each stick to replace the smoothing term in eq. (6). Then a new speckle suppression filter can be developed, i.e.

$$\hat{I} = I + \frac{\lambda}{W} \sum_{j=1}^{4N-4} g(V_i)(T_i - I)$$

and

$$W = \sum_{j=1}^{4N-4} g(V_i)$$

where $\lambda$ is a constant to adjust the smoothing extent. $V_i$ and $T_i$ respectively denote the local variance and mean along the $i$ th stick, the estimation formulations are given as

$$T_i = \frac{2}{N+1} \sum_{j=1}^{(N+1)/2} I_{i,j}$$

and

$$V_i = \frac{2}{N+1} \sum_{j=1}^{(N+1)/2} (I_{i,j} - T_i)^2$$

Here, the subscript $(i, j)$ denotes the $j$ th pixel pointing outside along the $i$ th stick. We actually calculate the local mean and variance by convoluting the image $I$ with the stick templates.

To achieve a monotonic variation of the pixel intensities which is necessary for stability of the following iteration implementation, a normalization factor $W$ is added in eq.(7) to ensure that the weight of the central pixel be larger than or equal to the other neighboring pixels’ weights[9]. From Fig.1 and eq. (7), it follows

![Asymmetric sticks (4 pixels length)](image)

Fig. 1 Asymmetric sticks (4 pixels length)
Obviously, this corresponds to $\lambda \leq 1$. So, we set $\lambda \in (0,1]$ in the model. Due to the normalization of weights, the original restriction of variation function $g(\bullet) \in [0,1]$ can be released. We simply take

$$g_1(x) = k \cdot \frac{1}{x}$$

According to the analysis of Dutt[^10], this results in smoothing extent descending from resolvable structure (coherent signal), fully formed speckle to partially formed speckle. Taking an individual rectangle neighborhood into account, it can be intuitively explained that our model encourages smoothing along sticks with relatively low variance. Other variation functions can also be used to control the smoothing, for example

$$g_2(x) = e^{-x^{2}/\sigma^2}$$

and

$$g_3(x) = \begin{cases} \frac{1}{2} \left[ 1 - \frac{x^{2}}{\sigma^2} \right]^{2} & x \leq \sigma^2 \\ 0 & \text{otherwise} \end{cases}$$

The two functions are similar to the Perona-Malik and Tukey’s bieweight conductance function[^10] used in nonlinear diffusion, and the only discrepancy is that the original square of gradient is replaced by a variance. The stopping levels $k$, $\sigma^2_1$ and $\sigma^2_2$ for these variation functions are set manually or estimated from the speckle and structure regions in ultrasonic images. In our experiments, we did not find obvious difference between the functions $g_1(\bullet)$ and $g_2(\bullet)$, while the $g_3(\bullet)$ preserves sharper boundaries than the former two functions, and improves the automatic stopping of the diffusion.

For further improvement, the proposed filter is implemented in an iteration form. Adding an artificial time $t$ to eq. (7), we obtain

$$I^{t+1}(x,y) = I'(x,y) + \frac{\lambda}{W^2} \sum_{i=1}^{4N-4} g[V_i(x,y)][I(x,y) - I'(x,y)]$$

$$I^0(x,y) = I_0(x,y), \partial I'(x,y)/\partial t = 0$$

where $(x,y)$ represents the index of the investigated pixel, $I_0(x,y)$ is the given intensity image having finite power over the image support $\Omega$, $\partial \Omega$ denotes the border of $\Omega$, and $\vec{n}$ is the outer normal to the $\partial \Omega$. Here, we actually set the time increment $\Delta t = 1$. Observe that this is a pseudo-diffusion equation in the sense that the directional difference $I'_i(x,y) - I'(x,y)$ resembles the concentration gradient, and the diffusivity takes a variance sensitive function. Then our proposed model is called diffusion stick.

**4. EXPERIMENTAL RESULTS**

The performance of diffusion stick is investigated on the synthetic and clinical images. Firstly, we emphasized checking the ability to preserve linear features in synthetic image. Then more comprehensive and detailed evaluation is carried on real ultrasonic images.

**4.1 Synthetic image**

An 8-bit gray level synthetic image containing two diagonal lines is constructed by embedding the objects in Gaussian noise corrupted background with zero mean and variance 3900. Fig.2(a) is the original image, and Fig.2(b) shows the synthetic image. Although the white Gaussian field is not an appropriate statistical model for speckle noise, it is enough to verify the ability of diffusion stick method in preserving fine line structures.

In our method, we adopt the variation function $g_1(\bullet)$ in eq.(13), and set $\sigma^2_1 = 1300$, $\lambda = 1$. The length of stick is 7. Results from two traditional nonlinear diffusion methods including Perona-Malik model and Edge Enhanced Diffusion (EED)[^13] are compared. In both the diffusion methods, the gradient threshold is set to 25.
Fig. 2 Synthesized image (a) Original image (b) Synthetic image (c)-(d) Evolution with the diffusion stick after 4 and 15 iterations (e)-(f) Evolution with PM model after 10 and 30 iterations (g)-(h) Evolution with EED model after 10 and 30 iterations.

Fig. 3 Clinical ultrasonic images of liver (a) Original image with markers (b)-(f) Results from PM model after 8 iterations, EED model after 8 iterations, ASSF, unbiased NCD after 20 iterations and our diffusion stick after 8 iterations.
For the EED, a Gaussian smoothing filter with kernel \( \sigma = 0.7 \) is applied beforehand to improve the stability of estimating diffusion tensor. Fig. 2(c)–(h) show the processed images. It is easy to see that our method can suppress most noise in several iterations, and the diagonal lines are gradually enhanced through the evolution. But the traditional nonlinear diffusion techniques did not preserve well the line objects, which are smoothed out with the noise.

### 4.2 Clinical ultrasonic image

The B-scan liver image of the first author was obtained from an Aloka clinical scanner with a 3.5MHz phased convex probe. We capture the video output and select a 247×289 region of interest (ROI) for demonstration. The original image is shown in Fig.3(a). In the diffusion stick method, we use the variation function \( g_i(\bullet) \) with \( \sigma_i^2 = 80 \) and \( \lambda = 1 \).

The stick length is a critical parameter, which directly affects the performance of the edge detection. A long stick will smooth speckle better than a short one, but possibly at the expense of smoothing out short edge features. In addition, the memory requirement and computation cost will increase drastically with the stick length. Therefore for real ultrasonic images, this parameter is set longer than the correlation length of the speckle, but no longer than the length over which the edges are expected to be roughly straight. In this experiment, we set the stick length to be 9. Fig.3(f) shows the result of our method after 8 iterations.

Fig.4 Results of edge detection using Sobel operator  
(a) Original image  
(b)–(f) the processed image from PM model, EED model, ASSF, unbiased NCD model and diffusion stick, respectively
For comparison, four existed filtering techniques are applied to the same image. The Perona-Malik model is implemented by setting $K^2 = 650$ for the diffusivity function $g(\nabla I) = e^{-|\nabla I|^2/\lambda}$, and the parameter $\lambda = 0.24$. We set the gradient threshold to 13 and smoothing kernel $\sigma = 0.7$ for EED. In the ASSF by Dutt et al. [8], we estimated the log compression ratio $D$ from fully formed speckle region using a recently developed method by Prager [12], and $D = 21$ was obtained. The parameter $\phi$ is adjusted between 0 and 1 to remedy the reduction of variance due to some post-processing algorithms in the scanner. Nonlinear coherent diffusion (NCD) was proposed recently by Abd-Elmoniem et al. [2] and Weickert [13]. Here, we only implement the unbiased diffusion for simplicity, and the same parameters as [2] are utilized. The processed images are shown in Fig.3(b)-(e) corresponding to PM, EED model, ASSF and NCD method respectively.

From the filtered images, it is obvious that all the filters have effectively suppressed speckle. But the weak edges and fine structures are blurred to different extent for the previous three techniques. Our method provides superior performance in smoothing homogeneous regions, preserving edges and feature details, especially for fine structures (see the a–d marked fine structures and 1–3 labeled weak edges in Fig.3a). Further evaluation can be seen from the binary edge map in Fig.4. We used Sobel edge detector with the same sensitivity threshold 0.1 for all the images. Observe that the PM, EED model and ASSF only preserve the strong edges, and the unbiased NCD enhanced many coherent components while damaging the weak edges representing organ features. The diffusion stick technique obtained the best result, where the contour of the main vessels and the boundaries of the marked feature structure can be explicitly seen.

5. CONCLUSION

We have presented a new method for the suppression of speckle noise in ultrasonic B-mode images. Unlike the traditional techniques that depended on the identification of generally shaped image regions with contrasting statistical behavior, our method directly divided the local rectangle neighborhood into an asymmetric stick set, and emphasized selective smoothing along the appropriate directions. This naturally achieved an integration of the ideas of stick and nonlinear diffusion. In synthetic images experiment, we have shown that the new method outperformed the traditional nonlinear diffusion models in preserving linear features. While applying to clinical ultrasonic images, the diffusion stick algorithm provides most desirable result in comparison to the conventional anisotropic diffusion, ASF, and unbiased NCD model, in terms of smoothing uniform regions and preserving feature details. In our filtered image, the edges became very sharp, which will largely benefit the subsequent processing such as edge detection and image segmentation.

REFERENCES


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