A Novel Approach to Speckle Reduction to Ultrasound Image

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Abstract

Speckle noise is inherent in ultrasound images, and it generally tends to reduce the resolution and contrast, thereby, to degrade the diagnostic accuracy of this modality. Speckle reduction is very important and critical for ultrasound imaging. In this paper, we propose a novel approach for speckle reduction using two-dimensional (2D) homogeneity and directional average filters. We have conducted experiments on numerous artificial images, clinic breast ultrasound images and vascular images. The experimental results are compared with that of other methods and the performance is evaluated using several metrics, and they demonstrate that the proposed approach can reduce the speckle noise effectively without blurring the edges and damaging the textual information. It will be useful for computer aided diagnosis (CAD) systems using ultrasound images.

Keywords: Speckle reduction, Homogeneity, 2D homogeneity histogram, Directional average filter, Ultrasound image.

1. Introduction

Ultrasound medical imaging uses low-power, high frequency sound waves to visualize body’s internal structures and create pictures of the tissues and organs [1]. As the sound waves pass through a body, they are reflected back to the ultrasound machine in different ways, depending on the characteristics of the tissues encountered. Among the currently available medical imaging techniques, ultrasound imaging is regarded as a noninvasive, practically harmless, portable, accurate, and cost effective method for diagnosis [2]. These properties make the ultrasound imaging be the most prevalent diagnostic tool in nearly all of the hospitals around the world.

Unfortunately, the quality (resolution and contrast) of ultrasound image is generally limited by the noise called 'speckle' [2-6]. Speckle noise occurs when a coherent source and a non-coherent detector are used to interrogate a medium, whose surface is rough on the scale of a typical ultrasound wavelength. Especially, speckle noise occurs in the images of soft organs such as liver and kidney whose underlying structures are too small to be resolved by the large wavelength ultrasound. Speckle noise can significantly degrade the image quality, and increase the difficulties in diagnosis.

In order to remove the speckles, we propose an algorithm for speckle reduction based on textural homogeneity histogram. A 2D homogeneity histogram is built and the threshold is obtained using the maximal entropy principle. The pixels are divided into two groups according to the threshold: a homogenous set, Hs and a non-homogenous set, NHs. The pixels in the non-homogenous set are handled by the newly proposed directional average filters iteratively, and the speckle

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noise will be removed without blurring the edges.

The paper is organized as follows. In the next section, the proposed speckle reduction method based on 2D homogeneity is presented. Different ultrasound images are used to evaluate the performance of the algorithm and to illustrate the effectiveness and usefulness of the proposed approach. Finally, the conclusions are given.

2. Proposed method

2.1. Texture information extraction

We use texture information to describe speckle noise. The Laws' texture energy measures (TEM) are used to determine the textural properties of an image. Four masks [7] $L5^T \times E5$, $L5^T \times S5$, $E5^T \times L5$ and $S5^T \times L5$ are used:

$$f(i,j)=\sqrt{\begin{array}{l}(f_{L5^T\times E5}(i,j))^2+(f_{L5^T\times S5}(i,j))^2\\+(f_{E5^T\times L5}(i,j))^2+(f_{S5^T\times L5}(i,j))^2\end{array}} \quad (1)$$

where $f_{L5^T \times E5}(i,j)$, $f_{L5^T \times S5}(i,j)$, $f_{E5^T \times L5}(i,j)$ and $f_{S5^T \times L5}(i,j)$ are the convoluted results of the intensity $g(i,j)$ with the four masks ($0 \le i \le H-1$, $0 \le j \le W-1$). H and W are the height and width of the image, respectively.

The value of texture information is normalized.

$$F(i,j)=\frac{f(i,j)-f_{min}}{f_{max}-f_{min}} \quad (2)$$

where $f_{max}=max\{f(i,j)\}$ and $f_{min}=min\{f(i,j)\}$ ($0 \le i \le H-1$, $0 \le j \le W-1$).

2.2. 2D homogeneity histogram

The homogeneity of each pixel and the mean of the homogeneities in a neighborhood of the pixel are calculated. Then, the value of homogeneity threshold $T(Ho_{th}, \overline{Ho_{th}})$ is determined based on the maximal entropy principle. The pixels having the homogeneity values and mean values higher than $T(Ho_{th}, \overline{Ho_{th}})$ are unchanged, and the other pixels are processed by the novel directional average filter. The process will be iterated until it stops.

The value of the homogeneity of each pixel is normalized into the range of [0, K] (K is a constant to normalize the homogeneity values). Here, $K=100$

$$Ho(i,j)=\lfloor K\times(1-F(i,j))\rfloor \quad (3)$$

Then, $\overline{Ho}(i,j)$ is computed.

$$\overline{Ho}(i,j)=\left\lfloor \frac{1}{w\times w}\sum_{m=i-(w-1)/2}^{i+(w-1)/2}\ \sum_{n=j-(w-1)/2}^{j+(w-1)/2} Ho(m,n)\right\rfloor \quad (4)$$

where w is the local widow's size.
Finally, a 2D homogeneity histogram (homogram) $h_{Ho,\overline{Ho}}(m,n)$ is built based on $Ho(i,j)$ and $\overline{Ho}(i,j)$.

$$h_{Ho,\overline{Ho}}(m,n)=\sum_{\substack{Ho_{min}\le m\le Ho_{max}\\ \overline{Ho}_{min}\le n\le \overline{Ho}_{max}\\ 0\le i\le H-1,\,0\le j\le W-1}} \delta\left(Ho(i,j)-m,\overline{Ho}(i,j)-n\right) \quad (5)$$

$$\delta(p,q)=\begin{cases}1 & p=q=0\\ 0 & otherwise\end{cases} \quad (6)$$

where Ho_{min} and Ho_{max} are the minimal and maximal homogeneity values, respectively.

2.3. Determination of the homogeneity threshold

A novel automatic method to determinate the homogeneity threshold is proposed based on the characteristics of the 2D homogram.

Let $Hop(i,j)$ be the probability distribution at the homogeneity i and mean homogeneity j, $i,j=1,2,\cdots\cdots,N$. $N=\lceil max(Ho(m,n),\overline{Ho}(m,n))\rceil$. Two groups, HoF and HoB, are classified according to the threshold, representing the foreground and background in the homogeneity domain, and their entropies are defined as:

$$H_{HoB}(s,t) = -\sum_{i=1}^{s}\sum_{j=1}^{t}\frac{Hop(i,j)}{HoP(s,t)}\ln\frac{Hop(i,j)}{HoP(s,t)} \quad (7)$$

$$H_{HoF}(s,t) = -\sum_{i=s+1}^{N}\sum_{j=t+1}^{N}\frac{Hop(i,j)}{1-HoP(s,t)}\ln\frac{Hop(i,j)}{1-HoP(s,t)} \quad (8)$$

$$Hop(i,j) = \frac{1}{H \times W} h_{ho,\overline{ho}}(i,j) \quad (9)$$

$$HoP(s,t) = \sum_{i=1}^{s}\sum_{j=1}^{t} Hop(i,j) \quad (10)$$

where $H_{HoF}(s,t)$ represents the 2D entropy of the foreground and $H_{HoB}(s,t)$ represents the 2D entropy of the background. $HoP(s,t)$ is the sum of $Hop(i,j)$ whose coordinates are lower than (s,t).

The maximum entropies of the foreground and background are computed and the threshold can be obtained by

$$T(HO_{th},\overline{HO}_{th}) = \mathop{Arg\max}_{1\le s\le N}^{1\le t\le N}\{H_{HoF}(s,t)+H_{HoB}(s,t)\} \quad (11)$$

Once the threshold $T(Ho_{th},\overline{Ho}_{th})$ is obtained, the pixels are divided into two sets: Hs and NHs.

$$Hs = \left\{P(i,j)\left| \begin{array}{l} Ho(i,j) \ge Ho_{th} \\ and\ \overline{Ho}(i,j) \ge \overline{Ho}_{th} \end{array}\right.\right\} \quad (12)$$

$$NHs = \left\{P(i,j)\left| \begin{array}{l} Ho(i,j) < Ho_{th} \\ or\ \overline{Ho}(i,j) < \overline{Ho}_{th} \end{array}\right.\right\} \quad (13)$$

where Hs is the homogenous set and NHs is the non-homogenous set. $P(i,j)$ is the pixel at the coordinates (i,j).

2.4. Handle the non-homogenous set using directional filters

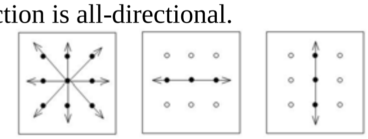
The non-homogenous pixels are handled by the novel directional average filters (DAF) to reduce the speckle noise and the pixels on the edges become more distinct:

$$\tilde{g}(i,j) = \begin{cases} g(i,j) & (i,j) \in Hs \\ DAF(g(i,j)) & (i,j) \in NHs \end{cases} \quad (14)$$

where $DAF(\bullet)$ is the directional average filter function.

Conventional average filter has no directions, and it removes the noise while makes the edge blur. However, the proposed directional average filter can reduce noise and enhance the edge at the same time.

A pixel's direction is determined according to the neighboring information which can be categorized into one of the three types. In Fig. 1(a), the pixel direction is called all-directional. The pixel direction is horizontal in Fig. 1(b), and the pixel direction is vertical in Fig. 1(c). If the value of the horizontal edge is higher than the value of the vertical edge, the pixel direction is horizontal; If the value of the vertical edge is higher than the value of the horizontal edge, the pixel direction is vertical; Otherwise, the pixel direction is all-directional.



(a) (b) (c)

Fig. 1 Pixel's directions

An edge operator, Sobel operator [8] is utilized to compute the edge values which are normalized

$$Eh(i,j) = \frac{e_h(i,j) - e_{min}}{e_{max} - e_{min}} \quad (15)$$

$$Ev(i,j) = \frac{e_v(i,j) - e_{min}}{e_{max} - e_{min}} \quad (16)$$

where $e_h(i,j)$ and $e_v(i,j)$ are the absolute values of the horizontal and vertical edge values obtained by using the Sobel operator, $e_{max} = max(e_h(i,j), e_v(i,j))$, and $e_{min} = min(e_h(i,j), e_v(i,j))$ ($0 \le i \le H-1$, $0 \le j \le W-1$).

The directional average filter has 3 different masks according to the pixel's directions.

$$M_1=\frac{1}{9}\begin{bmatrix}1&1&1\\1&1&1\\1&1&1\end{bmatrix} M_2=\frac{1}{3}\begin{bmatrix}0&0&0\\1&1&1\\0&0&0\end{bmatrix} M_3=\frac{1}{3}\begin{bmatrix}0&1&0\\0&1&0\\0&1&0\end{bmatrix} \quad (17)$$

$$\begin{aligned} R_1 &= \mathrm{cov}(M_1, I) \\ R_2 &= \mathrm{cov}(M_2, I) \quad (18) \\ R_3 &= \mathrm{cov}(M_3, I) \end{aligned}$$

where M_1, M_2 and M_3 are the masks with size 3x3 to process all-directional, horizontal, and vertical pixels, respectively. R_1, R_2 and R_3 are the filtering results when the image is convoluted with M_1, M_2 and M_3, and $\mathrm{cov}(\bullet)$ is the convolution function.

The function of the directional average filter DAF is defined as:

$$DAF(g(i,j)) = \begin{cases} R_1 & Eh(i,j) = Ev(i,j) \\ R_2(1+\delta_l) & Eh(i,j) > Ev(i,j) \\ R_3(1+\delta_l) & Eh(i,j) < Ev(i,j) \end{cases} \quad (19)$$

where δ_l is the variance in the local window.

If $Eh(i,j) = Ev(i,j)$, it means that the region is smooth, and the result after average filtering replaces the current intensity; If $Eh(i,j) \ne Ev(i,j)$, the edges exist in the local region, and the edge values are enhanced and replaced by the weighted directional filtering results.

After the pixels in the non-homogenous set are handled by the iterative process, the speckle noise will be decreased. If the iterative process is conducted, most speckle noises can be eliminated while the edges and details are preserved. A criterion should be used to terminate the iterative process.

We will use the homogenous ratio HR as the criterion to terminate the iterative process. If HR is low, the image is non-homogeneous, and the iterative process should continue. Otherwise, the iterative process should stop.

The homogenous ratio is:

$$HR = \frac{Num(Hs)}{H \times W} \quad (20)$$

where $Num(Hs)$ is the number of elements in Hs. H and W are the height and width of the image, respectively.

The procedure to terminate the iterative process is as following:

Step 1: Calculate $HR[i]$;

Step 2: If $HR[i] > HRTh$, then terminate the process;

Else $i = i+1$ go to Step 1;

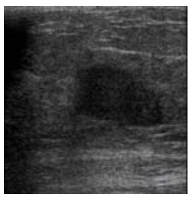
The value of $HRTh$ is determined by experiments, which is equal to 0.9 here.

3. Experimental results and discussions

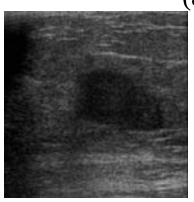
We assess the performance of the proposed method using the clinical breast ultrasound images. To assess the performance of the proposed method, the results by the proposed method were compared with those obtained by a wavelet-based method [9].

Figs. 2(a) and 3(a) are the original images, Figs. 2(b) and 3(b) are the results obtained by using the wavelet-based method [9], and Figs. 2(c) and 3(c) are the results obtained by using the proposed algorithm. The values of the three metrics indicate clearly that the proposed method performs better than the wavelet-based approach.

Fig. 2(a) has a loose mass at the right region, which is an important feature to distinguish malign tumors. The mass is affected by speckle noise and the edges are unclear. The situations were not improved much in Fig. 2(b). However, in Fig. 2(c), the speckles on the mass are removed and the edges become distinct. In addition, some of the speckles appear in the middle line-like area, which relate to the muscle's texture characteristics. In Fig. 2(b), the speckles are not depressed enough; however, they are reduced effectively in Fig. 2(c). Severe speckle noise appears in Figure 3, and many regions become non-homogenous. In Fig. 3(c), the lesion features are significantly improved.

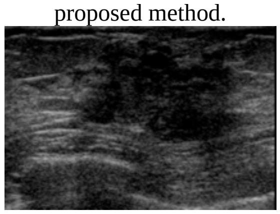


(a)



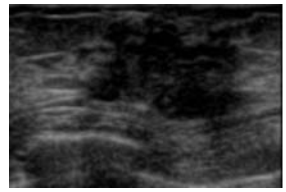
(b) (c)

Fig. 2 (a) The original image. (b) result by the wavelet-based method [9]. (c) result by the proposed method.



(a)

(b)



(c)

Fig. 3. (a) The original image. (b) result by the wavelet-based method [9]. (c) result by the proposed method.

4. Conclusions

In this paper, a novel speckle suppression algorithm using 2D homogram and directional average filter is developed. The local homogeneity defined by using the texture information is used to describe speckle noise, and the pixels are divided into homogenous set and non-homogenous set based on the homogeneity threshold value obtained using the maximum 2D entropy principle. The pixels in the non-homogeneous set will be handled by directional average filters iteratively.

All the parameters for describing speckle and terminating the iterative process are derived automatically based on the characteristics of the given ultrasound images. The experimental results demonstrate that the proposed approach can remove the speckle noise and preserve the edges and details of the ultrasound image at the same time, and the proposed algorithm has better performance. The proposed approach may find wide applications in ultrasound imaging.

5. Acknowledgement

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6. References

[1] K. Classic, "Medical imaging physics, fourth edition," *Health Physics*, vol. 83, no. 6, pp. 921-921, 2002.

[2] A. Fenster and D. B. Downey, "3-D ultrasound imaging: A review," *IEEE Engineering in Medicine and Biology Magazine*, vol. 15, no. 6, pp. 41-51, 1996.

[3] C. B. Burckhardt, "Speckle in Ultrasound B-Mode Scans," *IEEE Transactions on Sonics and Ultrasonics*, vol. 25, no. 1, pp. 1-6, 1978.

[4] J. G. Abbott and F. L. Thurstone, "Acoustic speckle: theory and experimental analysis," *Ultrasonic Imaging*, vol. 1, no. 4, pp. 303-24, 1979.

[5] W. R. Hendee, E. R. Ritenour, and K. R. Hoffmann, "Medical Imaging Physics," *Medical Physics*, vol. 30, pp. 730, 2003.

[6] R. H. Bates and B. S. Robinson, "Ultrasonic transmission speckle imaging," *Ultrasonic Imaging*, vol. 3, no. 4, pp. 378-94, 1981.

[7] Y. H. Guo, H. D. Cheng, J. H. Huang, J. W. Tian, W. Zhao, L. T. Sun, and Y. X. Su, "Breast ultrasound image enhancement using fuzzy logic," *Ultrasound in Medicine and Biology*, vol. 32, no. 2, pp. 237-247, 2006.

[8] R. C. Gonzalez and R. E. Woods, *Digital image processing*, 2 ed: Prentice Hall, 2002.

[9] S. Gupta, R. C. Chauhan, and S. C. Sexana, "Wavelet-based statistical approach for speckle reduction in medical ultrasound images," *Medical & Biological Engineering & Computing*, vol. 42, no. 2, pp. 189-192, 2004.

[10] A. Achim, A. Bezerianos, and P. Tsakalides, "Novel Bayesian multiscale method for speckle removal in medical ultrasound images," *IEEE Transactions on Medical Imaging*, vol. 20, no. 8, pp. 772-783, 2001.

[11] F. Sattar, L. Floreby, G. Salomonsson, and B. Lovstrom, "Image enhancement based on a nonlinear multiscale method," *IEEE Transactions on Image Processing*, vol. 6, no. 6, pp. 888-895, 1997.