Ultrasound Speckle Reduction Based on Image Segmentation and Diffused Region Growing

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Abstract

This paper presents an adaptive speckle reduction method through diffused growing region filtering based on image segmentation. The main idea is to smooth the speckle regions adaptively and preserve the edge and tissue structure. The criterion of speckle region is defined from a similarity value obtained from histogram matching between the histogram in the processing window and a reference one derived from a speckle area. Then the whole image will be classified into five categories according to the similarity values and other tissue characteristics, followed by speckle reduction processing in diffused growing region covering the same structure categories.

Keywords: ultrasound, speckle noise, histogram matching, region growing

1. Introduction

The quality of a medical ultrasonic image is often degraded due to the existence of speckle noise [1]. Speckle is caused by interference effects of echoes from unresolvable random scatterers due to the coherent nature of ultrasound scanners. This occurs especially in imaging organs such as liver and kidney whose underlying structures are too small to be resolved by the transducer. Speckle, shown as granular pattern, degrades the image quality of B-scan, makes the low-contrast objects, small high-contrast targets and small differences in image brightness hard to be detected. Therefore, it is important to improve images quality by reducing speckle noise and also preserving the tissue structure.

Speckle reduction techniques include compounding methods by combining images of differing frequency content [2], of different spatial views [3], or through temporal filtering in the time domain. On the other hand, speckle reduction methods based on local statistics of the B-scan image involve adaptive filtering of the image to smooth out speckle while preserving structure [4]-[6]. Anisotropic diffusion methods [7]-[9] model image filtering as controllable heat flow and is an efficient, nonlinear technique for simultaneously performing contrast enhancement and noise reduction [10].

In this paper, a diffused region growing noise reduction method based on image segmentation using local statistics is presented. The basic idea is to differentiate speckle from structure areas and then apply different region smoothing to them for better quality. Liu [11] proposed a histogram-based scheme for image segmentation and in this paper we apply the same technique to derive a similarity value between the histogram in the processing window and a reference one derived from a speckle area. This similarity value and other related histogram information will be used for classifying the local region into one of five categories: cyst, hypoechoic, mean speckle, hyperechoic, and edge referring to the respective statistics. To get the speckle reduced image without blurring tissue structure, we provide a diffused region growing method to find all the pixels with the same category in a big enough window and then adaptively smooth the noise.

Section 2.1 introduces the speckle artifact filling-in as the pre-processing. Section 2.2 reviews the speckle detection method and presents image segmentation method for obtaining speckle regions which could be irregular in shape, and Section 2.3 discusses the diffused region growing for speckle noise reduction. Section 3 presents computer simulation and results for our algorithm verification, followed by conclusions, Section 4.

2. Methods

2.1. Speckle Artifact Filling-in

Ultrasound images of tissues appear dark spots between the speckle cells, which are equivalently the low amplitude gaps made by the destructive interference in the echo envelope, called “speckle artifact” by Leeman [12]. Therefore, we should firstly fill in, locally, these black holes in order to detect more accurately speckle region. On one hand, these areas look dark compared with the surrounding speckle, which means the speckle artifact has the lower grayscale level than its neighbors. Also, its size is comparatively smaller than the cyst. Thus, we propose the following one dimensional algorithm for pixel $I_{i,j}$ to bring up those dark spots to be more like speckle along the axial and lateral directions:

$$I'_{i,j} = \begin{cases} I_{i,j} & I_{i,j} \geq M \\ M & otherwise \end{cases} \quad (1)$$

$$M = Max\ (P_a, P_l) \quad (2)$$

$$P_a = \frac{1}{2w_1} \sum_{k=1}^{w_1} (I_{i-k,j} + I_{i+k,j} - T_a) \quad (3)$$

$$P_l = \frac{1}{2w_2} \sum_{k=1}^{w_2} (I_{i,j-k} + I_{i,j+k} - T_l) \quad (4)$$

where w_1, w_2 are used to control the artifact size and T_a, T_l are the threshold values to define the grayscale contrast between the speckle and artifact in axial and lateral direction respectively.

2.2. Histogram Matching Based Speckle Detection

Identification of characteristic parameters of speckle statistics is critical for speckle detection. It has been shown that the envelope detected echo signal of fully developed speckle has the Rayleigh distribution [4]. However, it is well known that nonlinear processing (such as logarithmic compression) and any filtering employed on images affects the speckle statistics. Moreover, the estimation of the statistics moments, e.g., the mean and the variance, from a small size of window always showed a bias in computation.

In this paper, we use the local amplitude histogram to extract the information of inherited distribution function of speckle statistics. The histogram for a reference region has a characteristic shape, which defines it as a region dominated by speckle. Other histograms have different shapes and are thus assumed to contain more structure in the block.

According to [11], the optimal number of bins to represent a normal (Gaussian) distribution with a 95% confidence level is

$$\text{Number of bins} = 1.87(n-1)^{2/5} \quad (5)$$

and the number of bins could be 8 for n = 49, i.e., from a 7x7 local window. This window size should be greater than the speckle size on the image, which can be computed from the image system parameters [13]:

$$\frac{S_{lateral}}{D_l} = 1.447 \frac{z_0}{f_c DD_l} \quad (6)$$

$$\frac{S_{axial}}{D_a} = 2.36 \frac{f_s}{BW} \quad (7)$$

where $S_{lateral}$ and S_{axial} are the averaging speckle size in the lateral and axial direction, D_l and D_a are the lateral and axial envelope sampling distances, respectively, and f_s is the axial envelope sampling frequency, f_c the center frequency, D is the aperture size of a linear transducer in the lateral direction, z_0 the distance from the transducer to the focal zone, BW is the bandwidth of the envelope spectrum.

As shown in [11], if the processing window contains some resolved structure, its histogram always shows a bias in shape, for example, narrow for echo-free region and wide for specular reflectivity area or even multimodal for edges. These will result in "less similar" to the reference histogram of fully developed speckle. Also, for low-contrast objects, histograms from different objects will also be different, for example, the width of the histograms is also a function of tissue type. The similarity value of two histogram shapes has been defined by comparing the two histograms bin by bin through a user-controlled error function [11],

$$S = \frac{1}{L}\sum_{i=1}^{L} e^{-\beta x_i^2}, \quad \beta = \frac{q \ln 10}{20\gamma^2 D^2} \quad (8)$$

where x_i denotes the difference of two histograms at bin i and β is a user-controlled parameter through the system user interface. For a fixed β, a large similarity value (i.e., close to 1) means all the x_i are close to zero, i.e., the processing histogram is very similar to the reference histogram. Otherwise, a small similarity S means the processing histogram is very likely a tissue structure.

We then classify the local region by different characteristics. In [11] Liu et.al., proposed an image segmentation method based on the speckle characteristics (i.e., the similarity value) and the gray level of echograms, called fuzzy associative memory (FAM). Here, we extend this approach by adding one more parameter of histogram range defined as the difference of *hr* and *hl*, see the right-bottom panel of Fig. 1. This parameter will enhance the cases of echo-free and edge regions. The fuzzy classification rule is now based on the speckle similarity value, the histogram range and the local mean of the processed window, Table 1. The linguistic criterion (e.g., low, high) used for similarity and range in Table 1 is referred to the reference speckle but the local mean is compared with the global mean of the image. Also, the user can adjust those values to fine-tune the classified features according to different applications.

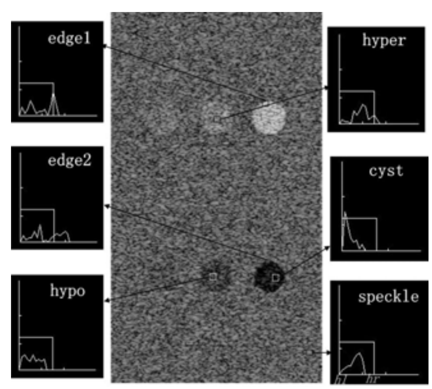

Fig.1: Histograms of different structures from a computer simulated phantom image

Table 1: the fuzzy classification rule

Feature	Similarity	Range	Mean
cyst	very low	very low	very low
hypo	low	medium	low
hyper	low	high	high
edge	very low	very high	medium
speckle	high	medium	high

2.3. Processing of Diffused Region Growing

The idea of our speckle reduction method is to get pixel averaging from the same feature pattern, for example, pixels belong to the speckle feature (from Table 1) have the same value as the averaging from a group of speckle pixels in a big enough window. This approach is different from traditional region growing methods [13][14] where the region grows with increasing window size under certain conditions. This derived region is always regular (e.g., a rectangular) and can be seen as a "speckle-dominated" region for further smoothing. It's clear that, the traditional approach always includes both speckle and non-speckle pixels even the later ones are not significant. Averaging with non-speckle pixels, however, will degrade the quality of speckle reduced imaging. Similarly, averaging with speckle pixels for structure pixels will get the structure or edge blurring.

In this paper, our region to be smoothed is growing diffusely according to the feature patterns defined in Table 1. The growing region could be seen as the connected pixels with the same feature pattern in a big enough area (i.e., at least bigger than the speckle size).

To implement the diffused method, we start from one pixel (seed), and include the 8 neighbors with the same feature pattern as [15]:

- Choose the seed pixel;
- Check the neighboring pixels and add them to the region if they have the same feature pattern as the seed and the current region is simply connective;
- Repeat the last step for each of the newly added pixels; stop if no more pixels can be added.

For example, to find the connected region in a two-patterns case of Figure 2a, the algorithm returns the region of 2b, which covers as many connected pixels with the same feature of the value 1,

$$\begin{matrix} 1&0&0&1&0&0&1&1&0\\ 0&0&1&0&0&1&1&1&1\\ 1&1&1&1&0&1&1&1&1\\ 0&0&1&1&1&1&1&0&0\\ 0&1&0&1&1&1&0&1&0\\ 1&0&1&1&0&0&0&0&1\\ 0&1&0&1&0&1&1&1&1\\ 0&1&1&0&1&1&1&0&1\\ 0&0&1&1&1&0&1&1&1 \end{matrix} \qquad \begin{matrix} 0&0&0&0&0&0&1&1&0\\ 0&0&1&0&0&1&1&1&1\\ 1&1&1&1&0&1&1&1&1\\ 0&0&1&1&1&1&1&0&0\\ 0&0&0&1&1&1&0&0&0\\ 0&0&1&1&0&0&0&0&0\\ 0&0&0&1&0&0&0&0&0\\ 0&0&0&0&0&0&0&0&0\\ 0&0&0&0&0&0&0&0&0 \end{matrix}$$

Fig. 2a: A search region with two feature patterns; 2b: Searched result from the diffused method

To analyze the performance of the proposed speckle reduction algorithm in terms of the contrast improvement, we will calculate the contrast-to-speckle ratio CSR [16] as

$$CSR = \frac{\mu_c - \mu_s}{\sqrt{\sigma_c^2 + \sigma_s^2}} \qquad (9)$$

where μ_c denotes the mean of the "object", μ_s is the mean of the background speckle which encloses the object and σ^2_c, σ^2_s are the variances of the corresponding areas. In general, if the absolute of CSR is larger, the contrast resolution of the local object is better.

3. Computer Simulations and Results

We have verified our proposed algorithms using both computer simulated speckle image and *in vivo* image obtained from a digital ultrasound scanner built in our lab. Algorithm flowchart is shown in Figure 3 where the input image is a set of beam vectors and processed by a 1-D speckle artifact filling-in and then a 2-D image segmentation for speckle detection. The classified result will be used in diffused region growing so that the adaptive smoothing for speckle reduction can be achieved.

Figure 4a is a computer simulated image with ±3db, ±6db and ±15db lesion (the bright one) and cyst (the dark one); followed by 4b, the result of our method

From Figure 4, the CSR of the speckle reduced image has been increased by three times. Figure 5a shows the *in vivo* liver image and 5b is the speckle reduced image. Obviously, 5b has much better contrast resolution than 5a and also preserve useful clinical information. Figure 6a is the human neck image from a 7.5MHz probe at a scanning of 3.9 cm, which presents quite big speckle noise. Figure 6b is the speckle reduced result from our algorithm with clear structure profile.

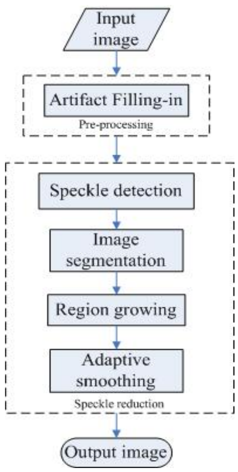

Fig. 3: Functional blocks of proposed speckle reduction method

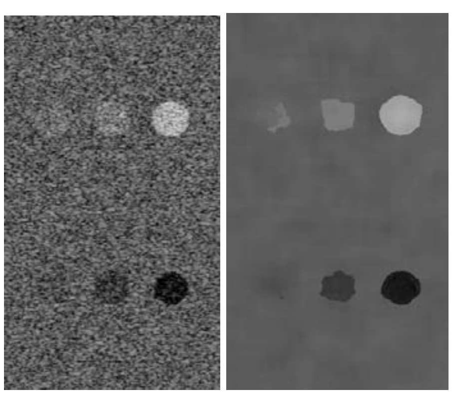

Fig. 4a: Computer simulated speckle image; 4b: Speckle reduced image

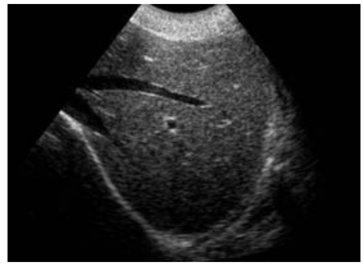

Fig. 5a: Liver image

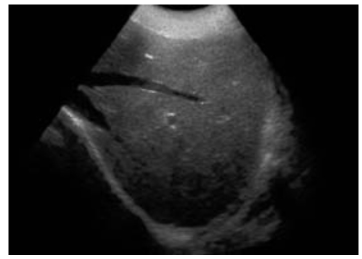

Fig. 5b: Result of our method

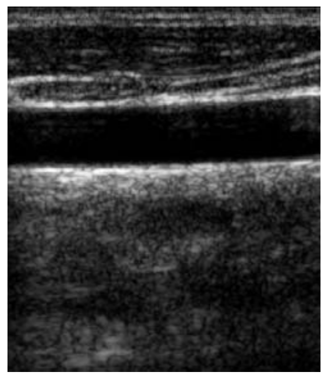

Fig. 6a: Human neck image

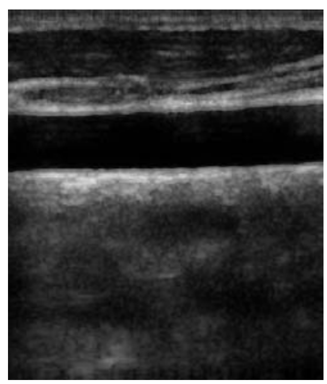

Fig. 6b: Result of our method

Although the results from our presented algorithm is promising, it takes seconds to get the speckle reduced image due to searching for every pixel in the diffused region growing method, which means our current algorithm works offline. However, we do believe parallel programming will resolve this problem and we are on this way to make our algorithm run in the real-time system.

4. Conclusions

We have proposed an ultrasound speckle reduction method based on image segmentation, diffused growing region and adaptive smoothing. Our aim is to reduce the speckle noise and leave the structure region unchanged. We have applied a histogram matching technique to differentiate speckle from tissue structure and classify the whole image into different feature patterns. This scheme also gives us a similarity value which can be used to adaptively classify the local region and then smooth the speckle area with diffused growing region based on the same feature pattern searching from the seed pixel.

In this paper, we have done tests from simulated speckle images and *in vivo* images. Results are promising with better contrast resolution than the original, and also preserve the structure without losing useful clinical information.

Currently, we are investigating the way to speed up the processing both in DSP and GPU platforms. More *in vivo* images will be required for algorithms fine-tune and parameters optimized specifically to the setting of feature patterns.

5. References

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Acknowledgements

The authors sincerely thank Paul S. Liu for providing the computer simulated speckle images and Mengqin Huang for his help to acquire *in vivo* images from iMago c21 color ultrasound system which is designed and made in our lab.