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Speckle Reduction of Ultrasound B-mode Image using Patch Recurrence

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Abstract **-** In this paper, a novel speckle reduction method using the patch recurrence (SRPR) of the medical ultrasound B-mode image with the self-similarity is proposed. The SRPR utilizes the additive white Gaussian noise to model the speckle and provides the despeckled ultrasound B-mode image from the similar patches based on minimum mean square error estimation (MMSE). It also improves the performance of the edge preservation and speckle reduction using the local variance of the patch which adjusts the threshold of the Euclidean distance that determines the similarity between the patches. In the MMSE process, the proposed SRPR has a low computational complexity since it uses pre-calculated local information on the 2D input image when extracting statistical information from 3D data set composed of similar patches, thus it offers advantages for hardware logic implementation and real-time processing. From the simulation study, the proposed SRPR shows improved results of signal-to-noise ratio (SNR) and similarity quality measurement (SSIM) compared with conventional methods. The visual assessment and contrast-to-noise ratio (CNR) of real ultrasound B-mode images (e.g. thyroid images) also show that the proposed method is superior to the previous methods.

Keywords**:** speckle reduction, patch recurrence, minimum mean square error estimation

1. Introduction

Medical ultrasound imaging provides important clinical information and is not harmful to the patient. So, it is used in a variety of clinical applications. Ultrasound imaging is influenced by the speckle, which arise from interference caused by scattered ultrasonic waves in the medium. Many researchers have confirmed the negative effect of speckle that interfere with diagnostic analysis [1]. For example, the speckle noise hides the boundary of the anatomical structure and reduce the contrast between the organ and tissue. Thus, the ultrasound imaging has a difficulty in practical diagnosis despite the high resolution.

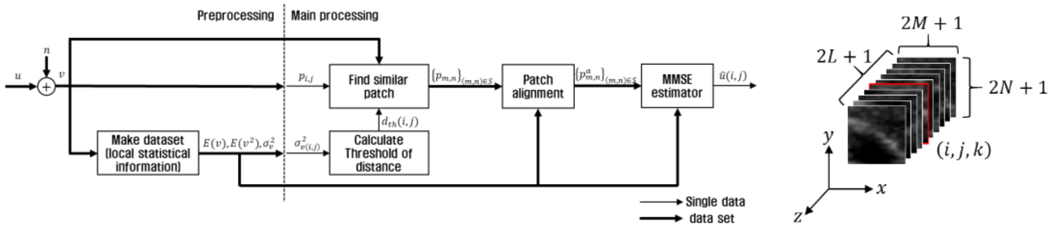
Various methods have been proposed to remove speckle noise. Lee [2] and Frost *et al.* [3] proposed an adaptive filtering method for removing by using the local statistical properties of the speckle. Yu and Acton extended the anisotropic diffusion approach to speckled application, known as speckle reducing anisotropic diffusion (SRAD) [4]. The nonlinear coherent diffusion (NCD) method of Abd-Elmoniem *et al.* [5] is the tensor valued anisotropic diffusion using the local image geometry. These previous methods can't be satisfied the speckle reduction and the edge preserving performance at the same time. To overcome this limit, multiscale method [6] decomposes the noisy image into the subband images in the scale space and apply the suitable method of each subband image such as noise reduction, edge enhancement, etc. then, it synthesizes all processed subband images. This method is difficult to apply the suitable method for each decomposed image automatically. Recently, the optimized block-wised non-local mean (OBNLM) method [7] has been proposed to remove the speckle by using a self-similarity. This method utilizes the weighted mean of all patches in the searching area. It spends huge amount of the computing time.

In this paper, we propose a novel speckle reduction method using patch recurrence of the ultrasound image. At first, this method searches a small number of similar patches. Then, it removes the speckle noise, while preserving the edges using the MMSE of these patches.

2. Speckle Reduction Using Patch Recurrence

The display device of the ultrasound imaging system has a limited dynamic range. So, the echo signals are compressed to fit the dynamic range of the image intensity. Since the system compress the signal to log scale, the speckle noise which is represented by the multiplicative noise is converted to the additive Gaussian noise. The ultrasound image is modeled by where $v(i,j)$ and $u(i,j)$ are the acquisition image and latent image and $n(i,j)$ is the speckle noise which is approximated by additive Gaussian noise.

$$v(i,j) = u(i,j) + n(i,j) \tag{1}$$



(a) Block diagram of the proposed (b) patch alignment

Fig. 1: Block diagram of the proposed method and the aligned similar patches in the main processing block.

Fig. 1(a) shows the block diagram of the proposed method, where $p_{i,j}$ is the patch centered on the position (i,j) and $(m,n) \in S$ are the position of the similar patches. $\{p^a_{m,n}\}$ is the set of the aligned similar patches and $\hat{u}(i,j)$ is the pixel value restored by the speckle reduction method. The proposed method consists of the pre-processing block and main processing block. The pre-processing block calculates and saves the local statistical information about the entire input image. These local data are used to restore the despeckled image. The main processing block searches the similar patches with the patch recurrence characteristics for each position of the image and remove the speckle noise using MMSE method. Condition for determining the similar patches is

$$\left\| v(p_{i,j}) - v(p_{x,y}) \right\| \le d_{th} \tag{2}$$

where $p_{i,j}$ is the patch containing the pixel to be restored, $p_{x,y}$ is the patch included in the searching area, and d_{th} is the threshold value.

The fig. 1(b) shows the aligned similar patches and the patch (red box) to be restored in three-dimensional space. In the fig. 1(b), the image coordinates are the positions on the x-y plane and z-axis is the new axis created by the aligned similar patches. For convenience, it is assumed that the patch size is $(2M+1) \times (2N+1)$ and the number of similar patches is $2L+1$. From the set of the similar patches displayed in three dimensional space, the pixel value to be restored by using the MMSE is

$$\hat{u}(i,j,k) = \bar{u}(i,j,k) + \frac{\sigma^2_{u(i,j,k)}}{\sigma^2_{v(i,j,k)}}\left(v(i,j,k) - \bar{v}(i,j,k)\right) \tag{3}$$

where $\bar{u}$ and $\bar{v}$ are the local mean values of the ideal image and input noisy patch and σ^2 is the variance of the patch. In eq. (3), the ideal pixel value $\bar{u}(i,j,k)$ is an unknown. Therefore, the local mean value $\bar{v}(i,j,k)$ is employed instead of the ideal pixel value. The local variance of the input image is

$$\sigma^2_{v(i,j,k)} = \frac{1}{2(N+1)} \sum_{z=k-N}^{k+N} \left\{ \bar{v}^2_{i,j}(z) - \left(\bar{v}_{i,j}(z)\right)^2 \right\} \tag{4}$$

where $v_{i,j}(z)$ is the intensity of the z^{th} patch in the aligned patches. From eq. (1), the local variance is given by

$$\sigma^2_{v(i,j,k)} = \sigma^2_{u(i,j,k)} + \sigma^2_{n(i,j,k)} \tag{5}$$

where $\sigma^2_{n(i,j,k)}$ is the local variance of the speckle noise. Since $\sigma^2_{u(i,j,k)}$ is positive, it is written as

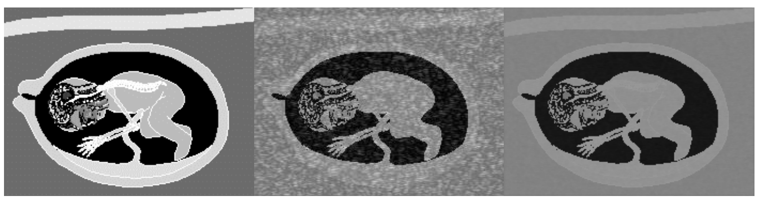
$$\sigma^2_{u(i,j,k)} = \begin{cases} \sigma^2_{v(i,j,k)} - \sigma^2_{n(i,j,k)}, & \sigma^2_{v(i,j,k)} > \sigma^2_{n(i,j,k)} \\ 0 & , \text{ otherwise} \end{cases} \tag{6}$$

In eq. (3), the difference between $v(i,j,k)$ and $\bar{v}(i,j,k)$ contains the intensity of the latent image and the speckle noise.

If the speckle noise of the pixel to be restored is small, then the gain $(\sigma^2_{u(i,j,k)}/\sigma^2_{v(i,j,k)})$ become high and $\hat{u}(i,j,k) \cong v(i,j,k)$. Conversely, if the speckle noise level is high, then $\hat{u}(i,j,k) \cong \bar{v}(i,j,k)$. Additionally, the results of eq. (4), (5) and (6) can be calculated using the local statistical information obtained in the pre-processing block. Thus, the proposed method has the advantage of having a fast operation speed.

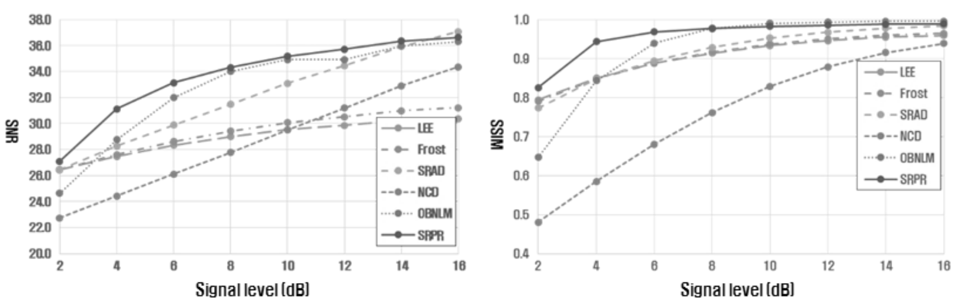
3. Experimental results

To evaluate the performance of the proposed method, simulation and *in vivo* experiments were conducted. The performance of the proposed SRPR method was compared with that of other speckle reduction methods, i.e., Lee filter [2], Frost filter [3], SRAD [4], NCD [5], and OBNLM [7]. All of the methods were implemented in the MATLAB environment.



(a) Echogenicity map (b) Simulated image with speckle (c) reference image
Fig. 2: Simulated image.

To generate the B-mode ultrasound image, pseudo B-mode pulse-echo image generation[8] was conducted. Fig. 2 shows the simulated image with speckle. Fig. 2(c) is the reference image made by compounding one hundred of speckled images(fig. 2(b)) . We varied the signal level compared to noise from 2 dBs to 16 dBs by 2 dBs and generated each hundred of ultrasound images. Signal-to-noise ratio (SNR) and similarity quality measurement (SSIM) were used to quantify the performance.



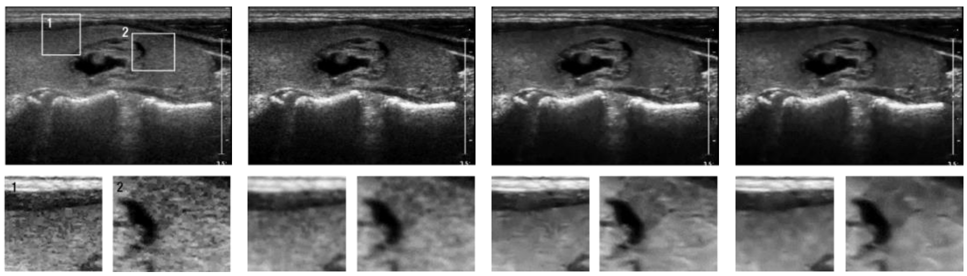
(a) SNR (b) SSIM
Fig. 3: Result comparison under different signal levels.

Fig. 3 compared the results of the proposed SRPR and five conventional methods. In fig. 3(a), SRPR, OBNLM, SRAD are superior to the other methods with respect to SNR. In particular, SRPR and OBNLM based on self-similarity showed excellent performance in the case of the high signal level. However, if the signal level is low, the proposed SRPR showed better results than the OBNLM. In fig. 3(b), SSIM graph also gave the results similar to the CNR graph.

Based on the simulation results, a visual assessment was conducted for SRAD, OBNLM, and SRPR. For quantitative comparison, the CNR values was measured for 20 sets of the diagnostic thyroid video which included the normal, cyst and nodule tissues. In table 1, CNRs of SRPR are larger than those of the other methods. Fig. 5 shows the results of the speckle reduction of the thyroid image with cyst. As you can see from the enlarged image of the region 1 and 2, the SRPR depicted boundaries of the cyst while reducing speckle in the homogeneous regions. Through the overall results, it was confirmed that the proposed SRPR method has the best performance.

Table 1: CNR comparison of the despeckled images.

position	type	method			
		input	SRAD	OBNLM	SRPR
thyroid	normal	8.02	11.92	14.14	13.99
	cyst	0.82	1.06	1.02	1.11
	nodule	3.10	5.52	6.17	6.24


(a) input image (b) SRAD (c) OBNLM (d) SRPR
Fig. 4: results obtained with different methods applied to the thyroid image.

4. Conclusion

In this paper, a novel speckle reduction method based on the patch recurrence of the B-mode ultrasound image. The proposed method searches for a small number of similar patches and removes speckle using the local statistical information and MMSE estimator. It has the good edge preserving performance when removing the speckle and the short processing time compared to the OBNLM using self-similarity. From the simulation and *in vivo* experiments, we proved that the proposed method had the above mentioned advantages. It can improve the interpreting accuracy of the lesion image and assist the computer aided diagnosis.

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