Neurocomputing 195 (2016) 88–95

Contents lists available at ScienceDirect

Neurocomputing

journal homepage: www.elsevier.com/locate/neucom

Local statistics and non-local mean filter for speckle noise reduction in medical ultrasound image

Jian Yang [a], Jingfan Fan [a], Danni Ai [a], Xuehu Wang [a], Yongchang Zheng [b], Songyuan Tang [a,*], Yongtian Wang [a]

[a] Beijing Engineering Research Center of Mixed Reality and Advanced Display, School of Optics and Electronics, Beijing Institute of Technology, Beijing 100081, China

[b] Department of Liver Surgery, Peking Union Medical College Hospital, Chinese Academy of Medical Sciences and Peking Union Medical College, Beijing 100730, China

ARTICLE INFO

Article history:
Received 26 March 2015
Received in revised form
18 May 2015
Accepted 20 May 2015
Available online 5 February 2016

Keywords:
Ultrasound image
Denoising
Speckle noise
Non-local means

ABSTRACT

Medical ultrasound images are corrupted by speckle noise, which is multiplicative. This noise limits the contrast resolution in these images and complicates image-based quantitative measurement and diagnosis. In this study, the speckle noise in the ultrasound image is modeled by local statistics of the intensity distribution. And the non-local mean (NLM) filter is utilized to filter additional noise by applying the redundancy information in noisy images. A hybrid denoising method is proposed in consideration of the characteristics of both the local statistics of speckle noise and the NLM filter. The study combines local statistics with the NLM filter to reduce speckle in ultrasound images. The local statistics of speckle noise is estimated by local patches, while the intensity of the denoising pixel is computed by the weighted average of all the pixels by using the NLM. The weight is determined according to the similarity measures between the intensities of the local patches. The performance of the proposed method is evaluated on synthetic data, simulated images, and real images. Results of quantitative analysis and visual inspection of the synthetic data and of the real images demonstrate that the proposed method outperforms the original NLM, as well as many previously developed methods.

1. Introduction

Ultrasound has been used to image the human body for over 60 years and is among the most widely used imaging technologies in medicine. Ultrasound is advantageous over existent non-invasive imaging techniques, such as CT, MRI, and PET, in that it is portable, inexpensive, free of radiation risk, and acquires images in real time. This imaging technology is widely used to visualize internal body structures, including tendons, muscles, joints, vessels, and internal organs for potential pathology or lesions. Ultrasound is also widely used to examine pregnant women.

An inherent characteristic of ultrasound imaging is the presence of speckle noise. Speckle is a random deterministic interference pattern that degrades the edges and fine details in an image. This phenomenon complicates the detection of small and low-contrast lesions. It also reduces the accuracy of ultrasound image processing tasks such as feature extraction, segmentation, registration, and classification. To obtain reliable analysis and diagonal results, speckle reduction is a necessary preprocessing step in ultrasound image processing. Moreover, as the denoising technique can remove the speckle noise that may interfere the similarity measurement determination, it is also benefited for the 3D reconstruction procedures for accurately recovering the ultrasound volume data [1–3]. Therefore, the main objective of the current study is to remove speckle noise on ultrasound images.

Speckle noise can be removed by compounding [4], post-processing, or both [5]. The compounding method minimizes noises when images are acquired using many transducers. Similar regions of images acquired by each transducer are combined to form a final image with improved quality. The post-processing method mainly includes the following two classes: (i) a spatial domain that is applied directly to the original image and (ii) a transform domain that is initially transformed into the frequency domain by fast Fourier transformation and is followed by denoising in the frequency domain. Many methods have recently been developed to eliminate speckle noise from medical ultrasound images in the spatial domain. These methods usually assume that this noise is modeled as multiplicative. Therefore, specific filters must be designed to reduce it. The most commonly used filters include the median [5,6], Lee [7], Frost [8], and Kuan filters [9]. These filters

* Corresponding author.
E-mail address: sytang@bit.edu.cn (S. Tang).

http://dx.doi.org/10.1016/j.neucom.2015.05.140
0925-2312/© 2016 Published by Elsevier B.V.

are based on the multiplicative speckle model and on local statistics [10].

The median filter is a nonlinear filter that effectively removes impulsive noise. It also reduces speckle. This filter applies median intensity in a selected region as the output pixel value of the center position of the region. Lee filters are based on minimum mean-square error (MMSE) [11]. The smoothing degree of Lee filter is inversely proportional to the variance over a local region. If the variance is high, usually near the edge, then the smoothing process is not performed. Otherwise, smoothing is conducted. Frost filter is an adaptive and exponentially weighted averaging filter [12]. The weights are computed based on the ratio of the local standard deviation to the local mean of the degraded image. The pixel of interest is replaced by a weighted averaging value within the moving window. The weighting factors decrease with distance from the pixel of interest and increase when the variance within the window increases. Once the transformation of the multiplicative noise model into a signal-dependent additive noise model is combined with the minimum square error criterion, Kuan filter can generate the linear MMSE for an image that is corrupted with uncorrelated, image-dependent noise [13]. The form of Kuan filter is similar to that of Lee filter, but it uses a different weighting value. Based on the Lee and Frost filters, an adaptive speckle reduction filter is designed by classifying the pixels [14]. Although these methods reduce speckle noise effectively, they also erase weak and diffused edges.

To preserve edges in images, the anisotropic diffusion (AD) filter [15] is applied to suppress speckle noise. This filter is effective for images corrupted by additive noise. The nonlinear coherent diffusion filter [16] log-transforms multiplicative speckle noises in ultrasonic images into additive Gaussian noises. The speckle reducing AD (SRAD) filter [17] processes images directly to preserve useful information. This filter is based on a partial differential equation and on the MMSE, which can be related directly to Lee and Frost filters [17,18]. The oriented SRAD filter [19] improves on the denoising results of the SRAD filter using the local directional variance of image intensity. These methods are iterative and can preserve the edges in images while reducing noise. However, many fine structures are removed during iterations. The squeeze box filter (SBF) was developed to enhance the contrast in B-mode ultrasound images with respect to decreasing pixel variations in homogeneous regions while maintaining or improving the differences in the mean values of distinct regions [20]. The smoothing parameter determines the amount of smoothing and is derived from a few functions of the local statistics. This filter not only generates high signal-to-noise ratio (SNR) value but also effectively preserves edges. Wavelet denoising methods are also used to reduce speckle. Moreover, fixed [21] and soft thresholds [22] are used to limit speckle noise. Artifacts are produced by these methods.

The aforementioned methods for speckle noise reduction are based on local information. A method based on non-local mean (NLM) filter has been proposed recently [23]. No assumptions are made about the location of the pixels used to denoise the pixel of interest. Each pixel of the image denoised with the NLM algorithm can represent the weighted average of all pixels in the noisy image when a Gaussian function is employed as the smoothing function. The NLM filter is an effective denoising method and has also been adapted to reduce speckle noise. Optimized Bayesian NLM (OBNLM) applies a Bayesian framework to derive an NLM filter, which is adopted for the speckle noise model [24]. A Pearson distance is introduced to compute the similarity between two patches. The method can improve speckle denoising. In the current paper, we introduce a hybrid method that combines the local property of the local statistics with that of the non-local property of the NLM method. The patches used in the NLM are pre-processed based on the local statistics. Then, the processed patches are used to compute the weights for the NLM. The performance of the proposed method is also compared with that of other methods (median, Lee, Frost, Kuan, SRAD, SBF, NLM, and OBNLM). Synthetic data, simulated images, and real images are used to evaluate this performance.

2. Methodology

2.1. Speckle noise model

In many methods, the speckle noise in ultrasound images is approximately modeled to a multiplicative noise as follows [7–10,14,16,17,19,21,22]:

$$g(\boldsymbol{x}) \approx f(\boldsymbol{x}) u(\boldsymbol{x}) \tag{1}$$

where $\boldsymbol{x}$ is the pixel position; $g(\boldsymbol{x})$ is the observed image; $f(\boldsymbol{x})$ is the original image; and $u(\boldsymbol{x})$ is a Gaussian noise.

This model is simple and is easily log-transformed into an additive noise. Hence, we obtain the following equation:

$$\log(g(\boldsymbol{x})) \approx \log(f(\boldsymbol{x})) + \log(u(\boldsymbol{x})) \tag{2}$$

Recently studies indicate that the general speckle noise model accurately represents the speckle noise in the ultrasound images. This model has been successfully applied in many studies [24,25].

The general speckle noise model can be defined as follows:

$$g(\boldsymbol{x}) = f(\boldsymbol{x}) + f(\boldsymbol{x})^r u(\boldsymbol{x}) \tag{3}$$

where factor r is related to the hardware of the ultrasound devices and $u(\boldsymbol{x})$ is a zero mean Gaussian distribution. In B-mode ultrasound image study, r is set to 0.5 because it represents ultrasound data well [24,26]. When r is equal to 1, the model is the multiplicative noise.

2.2. Noise estimation using local statistics

The noise-free image $f(\boldsymbol{x})$ can be estimated by the local linear MMSE as follows [9]:

$$\hat{f}_{LLMMSE}(\boldsymbol{x}) = E[f(\boldsymbol{x})] + \frac{\sigma_f^2(\boldsymbol{x})}{\sigma_g^2(\boldsymbol{x})}[g(\boldsymbol{x}) - E(g(\boldsymbol{x}))] \tag{4}$$

where $\hat{f}_{LLMMSE}(\boldsymbol{x})$ is the estimation of $f(\boldsymbol{x})$; $\sigma_f^2(\boldsymbol{x})$ and $\sigma_g^2(\boldsymbol{x})$ are the variances of $f(\boldsymbol{x})$ and $g(\boldsymbol{x})$, respectively; and $E[f(\boldsymbol{x})]$ and $E(g(\boldsymbol{x}))$ are the expectations of the $f(\boldsymbol{x})$ and $g(\boldsymbol{x})$, respectively.

Given that $u(\mathbf{x})$ is a zero mean Gaussian noise as per the model in Eq. (3), we obtain

$$E(g(\boldsymbol{x})) = E[f(\boldsymbol{x})] \tag{5}$$

Hence, the variance $\sigma_g^2(\boldsymbol{x})$ can be defined as follows:

$$\begin{aligned}\sigma_g^2(\boldsymbol{x}) &= E(g^2(\boldsymbol{x})) - E(g(\boldsymbol{x}))^2 = E\left(f(\boldsymbol{x}) + f(\boldsymbol{x})^r u(\boldsymbol{x})\right)^2 - E(f(\boldsymbol{x}))^2 \\ &= \sigma_f^2 = (\boldsymbol{x}) + \sigma_u^2(\boldsymbol{x}) E\left(f(\boldsymbol{x})^{2r}\right)\end{aligned} \tag{6}$$

where $\sigma_u^2(\boldsymbol{x})$ is the variances of $u(\boldsymbol{x})$.

In addition, $\hat{f}_{LLMMSE}(\boldsymbol{x})$ is revised as follows:

$$\hat{f}_{LLMMSE}(\boldsymbol{x}) = E(g(\boldsymbol{x})) + \frac{\sigma_g^2(\boldsymbol{x}) - \sigma_u^2(\boldsymbol{x}) E(g(\boldsymbol{x}))}{\sigma_g^2(\boldsymbol{x})}[g(\boldsymbol{x}) - E(g(\boldsymbol{x}))], \quad \text{when } r = 0.5 \tag{7}$$

$$\hat{f}_{LLMMSE}(\boldsymbol{x}) = E(g(\boldsymbol{x})) + \frac{\sigma_g^2(\boldsymbol{x}) - \sigma_u^2(\boldsymbol{x}) E(g(\boldsymbol{x}))^2}{(1 + \sigma_u^2(\boldsymbol{x}))\sigma_g^2(\boldsymbol{x})}[g(\boldsymbol{x}) - E(g(\boldsymbol{x}))], \quad \text{when } r = 1 \tag{8}$$

where $E(g(\boldsymbol{x}))$ and $\sigma_g^2(\boldsymbol{x})$ are approximated by the local mean. Meanwhile, the variance can be defined as follows: