Biomedical Signal Processing and Control 28 (2016) 1–8

Contents lists available at ScienceDirect

Biomedical Signal Processing and Control

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

Speckle reduction in medical ultrasound images using an unbiased non-local means method

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ARTICLE INFO

Article history:
Received 6 July 2015
Received in revised form 14 March 2016
Accepted 15 March 2016
Available online 2 April 2016

Keywords:
Denoising
Maximum likelihood estimation
Non-local means
Speckle noise reduction
Ultrasound image

ABSTRACT

Enhancement of ultrasound (US) images is required for proper visual inspection and further pre-processing since US images are generally corrupted with speckle. In this paper, a new approach based on non-local means (NLM) method is proposed to remove the speckle noise in the US images. Since the interpolated final Cartesian image produced from uncompressed ultrasound data contaminated with fully developed speckle can be represented by a Gamma distribution, a Gamma model is incorporated in the proposed denoising procedure. In addition, the scale and shape parameters of the Gamma distribution are estimated using the maximum likelihood (ML) method. Bias due to speckle noise is expressed using these parameters and is removed from the NLM filtered output. The experiments on phantom images and real 2D ultrasound datasets show that the proposed method outperforms other related well-accepted methods, both in terms of objective and subjective evaluations. The results demonstrate that the proposed method has a better performance in both speckle reduction and preservation of structural features.

1. Introduction

Ultrasound (US) imaging is a prominent diagnostic imaging technique since it offers several benefits such as more economic, safe, real-time and ergonomically adaptable in practice. The clinical utility of ultrasound is useful in the visual inspection of internal organs, muscles and tissues or in quantitative analysis in order to obtain measures that can be used as biomarkers for diagnosis [1–3]. The impact of ultrasound is felt in several fields of medicine [4,5], both in invasive and non-invasive applications. Non-invasive applications include the usage of US in outpatient clinics, while invasive applications include the assessment of many coronary arterial diseases [6–8]. B-mode US images suffer from quality degradation due to speckle noise [9]. Many post-processing algorithms such as image segmentation, registration or classification of tissue parenchyma are based on raw US images and hence can get affected by the presence of the speckle noise [10] if not removed. Hence, effective speckle reduction is vital for proper clinical interpretation and quantitative measurements.

A plethora of despeckling methods have been developed for improving the quality of US images that can be performed either in the transform domain or in the spatial domain [11]. Loizou et al. in [3] conducted a comparative study of different US despeckling methods for carotid artery, and provided a Matlab toolbox for US image despeckling. The details are available in [12]. The Lee's filter [13], Frost's filter [14], and Kuan's filter [15] are the most widely discussed spatial adaptive filters to attenuate the speckle noise. These classical filters consider the speckle as multiplicative noise and described them mathematically using a Gaussian distributed noise model. Lopes et al. [16] proposed improved versions of the Lee's and Frost's filters by organizing the pixels in different classes in which precise processing is defined. Squeeze box filter (SBF) designed in [17,18] removes outliers at each iteration and smooths the random distributed pixel values to some confining value through adaptively computed mean. Recently, the Rayleigh-Maximum-Likelihood (R-ML) filter in [19] was employed with the Rayleigh density model

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http://dx.doi.org/10.1016/j.bspc.2016.03.001
1746-8094/

and the ML method was adapted for solving the estimation problem.

Diffusion filters such as speckle reducing anisotropic diffusion filter (SRAD) [20] and its sophisticated variants such as the detail preserving anisotropic diffusion filter (DPAD) [21] and the oriented speckle reducing anisotropic diffusion filter (OSRAD) [22] eliminate the unwanted components from an image by finding solutions to a partial differential equation (PDE)[23]. However, these filters suffer from a significant loss of sharp-transition detail. The probability-driven OSRAD (POSRAD) [24] computes the statistical models of tissues and provides superior results compared to above mentioned diffusion filters.

The multi-scale techniques based on Wavelets are another class of filters introduced for speckle reduction in US imaging. These filters can be mainly classified into three categories-namely thresholding methods [25,26], coefficients correlation methods [27] and Bayesian estimation methods. In [28–30], the Bayesian framework was investigated to perform wavelet thresholding adapted to the non-Gaussian statistics of the signal. Pizurica et al. [31] proposed a non-decimated wavelet-based denoising method, called *GenLik*, which uses a generalized likelihood ratio formulation and imposes no prior statistics for noise and data. Similar to wavelet based approaches, principle component analysis (PCA)-based method in [32] is an example of a transform domain despeckling filter used for denoising medical US images.

In the past, different hybrid filters have been proposed to integrate the benefits of the above mentioned paradigms. In [33], the image is decomposed into two components by an adaptive filter and each component, after performing Donoho's soft thresholding, is merged to suppress speckle. The hybrid filter in [34] combines PDE-based approaches and a wavelet transform. More recently, a patch-based non-local recovery paradigm such as optimized Bayesian NL-means with block selection (OBNLM) [35] has been applied to reduce speckle noise.

Since the speckle intensity has a signal dependent nature, filters based on the standard additive Gaussian noise model are inadequate. Therefore, specific filters are required to suppress speckle without compromising important image features. Many statistical models have been attempted in the literature; specifically, Rayleigh, K, homodyned K, Nakagami, generalized Nakagami and Rician inverse Gaussian (RiIG) distributions have been shown to achieve a perfect statistical characterisation of ultrasound signals and to address the restoration of speckled images [19]. When compressionless data with fully developed speckle is considered, it is well known that the interpolated output B-mode US images follow a Gamma distribution, which is a good approximation for the weighted sum of Rayleigh variables [36,37].

In this article, an unbiased NLM speckle filter based on Gamma statistics has been presented. We used a three parameter Gamma distribution function to fit the real US image and the ML estimation was adapted to find the two key parameters that control the filter performance. The proposed filter was scientifically validated by taking into consideration both real US and synthetic standardized images.

The remainder of this paper is organized as follows: Section 2 gives an overview of noise characteristics in B-mode US images. Section 3 elaborates the ML approach to estimate the bias in terms of the parameters of the Gamma distribution. The proposed NLM filtering procedure is discussed in Section 4. Section 5 reports the quantitative and qualitative results, followed by the conclusions in Section 6.

2. Noise characteristics in B-mode ultrasound images

In [38], Goodman described the fundamentals and statistical properties of speckle noise and mathematically modelled it as a *complex random walk*, represented as a sum of a huge number of complex phasors. Even though these phasors can have either constructive or destructive relationship with each other, the destructive interferences cause the speckle formation. The severity of destructive interference depends on the relative phase between two overlapping reflected echoes produced by the interaction of transmitted US waves with a number of obstacles of the tissue, *scatters*, present in a given volume of medium, known as *resolution cell*. The complex observation in a given resolution cell is determined by the in-phase and quadrature components acquired by two demodulators of the coherent system [39].

On the basis of the scatter number density per cell (SND), four types of speckle can be defined: (i) fully-developed, (ii) fully-resolved, (iii) partially-developed and (iv) partially-resolved [40]. However, most commonly adapted in practice are fully-developed and fully-removed speckled. When number of scatters is high, the model is known as *fully-developed* and the envelope has Rayleigh distribution. This model usually holds in blood regions. For the positive envelope amplitude M and the variance of the Gaussian distributed in-phase and quadrature components of the complex echo envelope σ_n^2, the Rayleigh probability density function (PDF) is given as [41]:

$$p_M\left(M, \sigma_n^2\right) = \frac{M}{\sigma_n^2} e^{-\frac{M^2}{2\sigma_n^2}} \tag{1}$$

In the random walk, *fully-resolved* speckle arises as a result of a deterministic component. Also, the Rayleigh distribution is replaced by a Rician distribution and holds in regions with high echolucent response such as myocardium. The Rician PDF is given as [42]:

$$p_M(M|A, \sigma_n) = \frac{M}{\sigma_n^2} e^{-\frac{(M^2+A^2)}{2\sigma_n^2}} I_0\left(\frac{AM}{\sigma_n^2}\right) \tag{2}$$

where I_0 is the zeroth order modified Bessel function of the first kind. Here, M denotes the Rician random variable and A is the noise-free envelope amplitude value.

Although in practice fully-developed and fully-resolved speckle are the most common, the empirical distributions obtained from the US images deviate due to signal post-processing steps [24]. Consequently, some attempts have been made in literature to model the empirical distributions with useful probabilistic models, e.g., Nakagami, Gamma or Weibull [37].

As previously stated, the acquired signal with fully-developed speckle regions follow a Rayleigh distribution. Although the interpolation to form the final Cartesian image alters the data distribution, therefore the resulting image will no longer follow a Rayleigh distribution. On the other hand, a Gamma distribution accurately fits such an image [36]. Fig. 1(c) and (d) display the distribution of two local regions of a real B-mode carotid US image (shown in Fig. 1(a) and (b) respectively). Comparison with the true Gamma distribution with parameters estimated from the selected local region shows that the data distribution can be modelled with a Gamma PDF.

3. Maximum likelihood based parameter estimation

In this section, we first introduce our speckle model. Based on the assumption that the interpolated Cartesian image of the corrupted back-scattered signal fits Gamma distribution, a Gamma distributed synthetic image G can be produced as:

$$G = F + N_g \tag{3}$$

where F and N_g denote the noiseless image and fading variable, respectively.