Ultrasound in Med. & Biol., Vol. 36, No. 8, pp. 1353–1363, 2010

0301-5629/$ - see front matter

doi:10.1016/j.ultrasmedbio.2010.05.007

● *Original Contribution*

SRBF: SPECKLE REDUCING BILATERAL FILTERING

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(*Received* 8 *October* 2009; *revised* 5 *May* 2010; *in final form* 8 *May* 2010)

Abstract—Speckle noise negatively affects medical ultrasound image shape interpretation and boundary detection. Speckle removal filters are widely used to selectively remove speckle noise without destroying important image features to enhance object boundaries. In this article, a fully automatic bilateral filter tailored to ultrasound images is proposed. The edge preservation property is obtained by embedding noise statistics in the filter framework. Consequently, the filter is able to tackle the multiplicative behavior modulating the smoothing strength with respect to local statistics. The *in silico* experiments clearly showed that the speckle reducing bilateral filter (SRBF) has superior performances to most of the state of the art filtering methods. The filter is tested on 50 *in vivo* US images and its influence on a segmentation task is quantified. The results using SRBF filtered data sets show a superior performance to using oriented anisotropic diffusion filtered images. This improvement is due to the adaptive support of SRBF and the embedded noise statistics, yielding a more homogeneous smoothing. SRBF results in a fully automatic, fast and flexible algorithm potentially suitable in wide ranges of speckle noise sizes, for different medical applications (IVUS, B-mode, 3-D matrix array US). (E-mail: balocco.simone@gmail.com) © 2010 World Federation for Ultrasound in Medicine & Biology.

Key Words: **Bilateral filter, Ultrasound speckle reduction.**

INTRODUCTION

Speckle, a form of multiplicative noise, affects imaging applications such as medical ultrasound (US). Speckle is the primary factor that limits the contrast in diagnostic ultrasound imaging, thereby reducing the effective application of image processing and analysis algorithms (*i.e.*, edge detection, segmentation) and two-dimensional (2-D) and three-dimensional (3-D) volume rendering (Aysal and Barner 2007). The effectiveness of a segmentation can be improved when the noise is removed without affecting important image features. Speckle removal filters are often used as a preprocessing step for region-based detection, segmentation and classification algorithms (Munteanu et al. 2008; Li and Acton 2007; Tsai and Watanabe 1998). Their goal is to selectively remove the noise without destroying important image features and enhance object boundaries. Additionally, due to the recent diffusion of 3-D devices and real-time US applications in medical environments, computationally efficient speckle removal filters become an unavoidable need. In literature, de-speckling has been tackled by means of different techniques. Speckle reducing filters based on anisotropic diffusion algorithms were introduced by Perona and Malik (Perona and Malik 1990) and later improved by several authors (Yu and Acton 2002; Black et al. 1998). This filter removes the noise by computing a local weighted average of the central pixel intensity with the ones of its neighbors. The iterative process achieves a balance between averaging (in homogeneous regions) and the identity filter (where edges exist) according to a coefficient proportional to the directional gradient. Yu (Yu and Acton 2002) successively improved Perona's method by proposing a partial differential equation approach called speckle reducing anisotropic diffusion (SRAD) with the main purpose to enhance edges. Successively, Krissian (Krissian et al. 2007) proposed an extension called oriented speckle reduction anisotropic diffusion (OSRAD) that allows different levels of filtering along the image contours and their principal curvature directions. In 1998, Tomasi (Tomasi and Manduchi 1998) introduced the bilateral filter (BF) framework in which each output pixel value in the image is a Gaussian weighted average of its

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neighbors in both space and intensity range. Comaniciu (Comaniciu and Meer 2002) proposed the mean shift approach based on a statistical local modes analysis of the image distribution in the joint spatial-range domain. The relationship between anisotropic diffusion, adaptive smoothing, bilateral filtering and mean shift procedure was then established by Barash and Comaniciu (Barash and Comaniciu 2004) in 2004. More recently, adaptive filters based on local noise statistics were proposed by Guo and Thakur (Guo et al. 2009; Thakur and Anand 2007). Dantas (Dantas and Costa 2007) introduced a filter based on a set of modified Gabor filters. However, most filters are developed independently of the image nature and its noise statistical model. In contrast, Rayleigh noise statistics were embedded in a basic filter framework by Aysal (Aysal and Barner 2007). In this article, a fully automatic speckle reducing bilateral filter (SRBF) tailored to US Images is proposed. The edge preserving feature for US images is obtained by embedding noise statistics in the filter framework. Consequently, the filter is able to tackle the noise multiplicative behavior modulating selectively the smoothing strength with respect to local statistics. Additionally, the filter support is automatically adapted to the speckle size. To obtain a strong reduction of speckle noise, the SRBF is iterated as suggested by (Tomasi and Manduchi 1998). In the Materials and Methods section, the bilateral filter framework tailored to US speckle statistics is introduced. The accuracy and robustness of our approach is compared with other speckle reducing filters. In the Results section, the filter is then tested on *in vivo* US images and its influence on a segmentation task is quantified. The final section is devoted to the discussion and conclusion.

MATERIALS AND METHODS

In this section, a brief description of the classical BF is given, followed by the characterization of the speckle noise. Then the BF framework is adapted to the *a priori* knowledge on speckle noise statistics and estimated speckle size.

Bilateral filter framework

The BF has been introduced as a technique for edge-preserving image smoothing (Tomasi and Manduchi 1998). It has been successfully used in different image processing and computer graphics applications (Durand et al. 2002; Choudhury and Tumblin 2005). The general BF functional can be expressed as:

$$h(p)=\Gamma^{-1}(p)\int_{\Omega(p)}f(\xi)c(\xi,p)s(f(\xi),f(p))d\xi \qquad (1)$$

with the normalization factor:

$$\Gamma(p)=\int_{\Omega(p)}c(\xi,p)s(f(\xi),f(p))d\xi \qquad (2)$$

where f is the input image, h is the output image, $\Omega(p)$ is the spatial neighborhood of the coordinate of a generic pixel p in the image and ξ is the integration variable representing pixels coordinates in Ω. The classical BF framework (Tomasi and Manduchi 1998) defines both c and s functions as unbiased isotropic Gaussian functions.

$$c(\xi,p)=\exp\left(-\frac{\| p-\xi \|^2}{2\sigma_c^2}\right) \qquad (3)$$

$$s(f(\xi),f(p))=\exp\left(-\frac{(f(p)-f(\xi))^2}{2\sigma_s^2}\right) \qquad (4)$$

where σ_c represents the standard deviation of the Gaussian on the spatial support and σ_s is the standard deviation in the range domain. Function c [eqn (3)] spatially weights the Euclidean distance between c and ξ while s [eqn (4)] operates on the intensity domain.

Speckle noise statistics

Speckle appears in medical images when the characteristic size of the scatterers is small compared with the wavelength. Under the hypothesis of fully developed speckle, (Jensen 1996), biologic tissue can be modelled by a network of identical discrete scatterers, randomly distributed in a homogeneous media (Chivers 1977), thus the radio-frequency echo signal can be described as a complex Gaussian probability function with zero mean (Wagner et al. 1983). Envelope detection removes the phase component, generating a speckle distribution with statistics described by a Rayleigh probability function (P_{RL}):

$$P_{RL}(f(p),\alpha)=\frac{f(p)}{\alpha^2}\exp\left(\frac{-f(p)^2}{2\alpha^2}\right) \qquad (5)$$

where $f(p)$ is the image pixel intensity at position p and α is the shape parameter of P_{RL} related to the mean of the distribution by $\mu=\alpha\sqrt{\frac{\pi}{2}}$.

It is worth noting that some commercial ultrasound scanners only provide log-compressed data whose noise statistic is not Rayleigh distributed. Ultrasound raw signal can be recovered from DICOM images using nonlinear compression parametric functions (Seabra and Sanches 2008).

Given a spatial neighborhood of pixels with uniform intensity of $f(p)$, α can be computed using the maximum likelihood estimator (MLE) (Steven 1993) defined for Rayleigh functions as:

$$\widehat{\alpha}=\sqrt{\frac{1}{2N}\sum_{q\in\Omega}f(q)^2} \qquad (6)$$