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● *Original Contribution*

BREAST ULTRASOUND DESPECKLING USING ANISOTROPIC DIFFUSION GUIDED BY TEXTURE DESCRIPTORS

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Abstract—Breast ultrasound (BUS) is considered the most important adjunct method to mammography for diagnosing cancer. However, this image modality suffers from an intrinsic artifact called speckle noise, which degrades spatial and contrast resolution and obscures the screened anatomy. Hence, it is necessary to reduce speckle artifacts before performing image analysis by means of computer-aided diagnosis systems, for example. In addition, the trade-off between smoothing level and preservation of lesion contour details should be addressed by speckle reduction schemes. In this scenario, we propose a BUS despeckling method based on anisotropic diffusion guided by Log–Gabor filters (ADLG). Because we assume that different breast tissues have distinct textures, in our approach we perform a multichannel decomposition of the BUS image using Log–Gabor filters. Next, the conduction coefficient of anisotropic diffusion filtering is computed using texture responses instead of intensity values as stated originally. The proposed algorithm is validated using both synthetic and real breast data sets, with 900 and 50 images, respectively. The performance measures are compared with four existing speckle reduction schemes based on anisotropic diffusion: conventional anisotropic diffusion filtering (CADF), speckle-reducing anisotropic diffusion (SRAD), texture-oriented anisotropic diffusion (TOAD), and interference-based speckle filtering followed by anisotropic diffusion (ISFAD). The validity metrics are the Pratt's figure of merit, for synthetic images, and the mean radial distance (in pixels), for real sonographies. Figure of merit and mean radial distance indices should tend toward '1' and '0', respectively, to indicate adequate edge preservation. The results suggest that ADLG outperforms the four speckle removal filters compared with respect to simulated and real BUS images. For each method—ADLG, CADF, SRAD, TOAD and ISFAD—the figure of merit median values are 0.83, 0.40, 0.39, 0.51 and 0.59, and the mean radial distance median results are 4.19, 6.29, 6.39, 6.43 and 5.88. (E-mail: wgomez@tamps.cinvestav.mx)

Key Words: **Breast ultrasound, Speckle filtering, Anisotropic diffusion, Log–Gabor filters, Texture features.**

INTRODUCTION

Currently, breast ultrasound (BUS) is the most important adjunct to mammography for patients with palpable masses and normal or inconclusive mammograms. Additionally, BUS has the ability to visualize hidden lesions in women with dense breast tissue (Corsetti et al. 2011) and is particularly useful in distinguishing cystic from solid lesions, with an accuracy of nearly 100% (Jackson 1990). BUS is also used to differentiate between benign and malignant tumors, which can be characterized by their shapes, borders, internal echo features and posterior acoustic behavior (Rahbar et al. 1999).

Ultrasound image quality is affected mainly by an inherent imaging artifact called speckle, which results from interference effects between returning echoes produced by discontinuities of tissue below ultrasonic beam resolution (unresolved scatterers) (Thijssen 2003). Speckle can be interpreted as a locally correlated noise (or random granular texture) that degrades the US image by concealing fine structures and reducing the signal-to-noise ratio (SNR). Further, speckle tends to reduce the image contrast and to obscure and blur image details (Michailovich and Tannenbaum 2006).

With respect to BUS images, the speckle could make human interpretation difficult and, consequently, influence inter-/intra-observer variations. Moreover, computer-aided diagnosis (CAD) systems commonly extract shape or contour features from segmented breast lesions to classify them as benign or malignant (Cheng

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et al. 2010). However, the performance of the segmentation stage depends not only on its technical strategy, but also on adequate image preprocessing schemes for reducing the speckle.

Several filtering approaches aimed at reducing speckle in US images while preserving edge details have been proposed in the literature. Popular despeckling techniques based on local statistics include median filter (Horsch et al. 2001), truncated median filter (Evans and Nixon 1993), adaptive weighted median filter (Loupas et al. 1989) and the well-known Frost, Lee and Kuan filters (Lopes et al. 1990). In addition, the use of directive filtering, such as modified Gabor filters (Dantas and Costa 2007) or the "stick" method (Czerwinski et al. 1999), to reduce ultrasonic speckle has been investigated. Morphologic filters have also been used in BUS images to preserve lesion contour anfractuosities (Alvarenga et al. 2009; Infantosi et al. 2008).

Furthermore, non-linear anisotropic diffusion filtering (ADF), proposed by Perona and Malik (1990), has attracted much attention because it is capable of reducing noise in images without blurring the boundaries between homogeneous regions. Several variants of ADF have been developed for US images, including speckle-reducing anisotropic diffusion (SRAD) (Yu and Acton 2002), median-guided anisotropic diffusion (MADF) (Yang and Fox 2004), texture-oriented anisotropic diffusion (TOAD) (Alemán-Flores et al. 2007) and interference-based speckle filtering followed by anisotropic diffusion (ISFAD) (Cardoso et al. 2012).

The main advantage of ADF is the computation of the gradient-based conduction coefficient to stop the diffusion process through "strong" or significant edges. Thus, the speckle is reduced efficiently within homogeneous regions while important edges details are preserved (Yu and Acton 2002). This characteristic is desired when filtering BUS images to avoid overblurring lesion contours for further lesion segmentation and extraction of useful shape and contour features by means of CAD systems. However, the reduction of speckle in BUS images is a difficult task because of the large variance in lesions shapes and low contrasts produced by shadows, echo features and blurry or ill-defined boundaries. Therefore, if the local contrast between breast lesion and adjacent tissues is poor, the diffusion process will pass through the edges.

To overcome this drawback, texture descriptors have been employed to guide the diffusion process in the ADF approach by using the responses of Gabor filters (Alemán-Flores et al. 2007). In this context, texture can be defined as the spatial variation of pixel intensities at scales smaller than the scales of interest (Petrou and García-Sevilla 2006). The main idea is to perform a multichannel decomposition of the BUS image to find strong edges between tissues with different textures. Therefore, the conduction coefficient is computed by using texture responses instead of pure intensity values.

Despite finding strong edges between distinct textured regions could increase the filter performance, in terms of boundary preservation, it is important to consider a suitable value of the edge magnitude parameter in the conduction coefficient, denoted as κ, to control the diffusion extension of the ADF process. Such a parameter is commonly fixed either heuristically by the user or by computing a "noise estimator" (Perona and Malik 1990). Hence, depending on its value the filter should perform as an all-pass filter, on strong edges, or as Gaussian smoothing, on homogeneous regions. Also, the κ value is considered global; that is, all pixels in the image are treated equally. Thus, the κ parameter should be adequately chosen to cope with some characteristics of the image such as noise power and local contrast. However, these characteristics could vary among BUS images, depending on the ultrasound equipment, operator skills, scanned tissues or inherent artifacts (Feldman et al. 2009).

The goal of the work described in this article was to reduce the speckle within regions with similar textures while avoiding overblurring of tissue-structure edges. In this sense, we were interested in preserving breast lesion shape for CAD purposes to enhance further tasks such as lesion segmentation. We proposed to adapt the conduction coefficient parameter, κ, for each pixel in the BUS image by using 2-D Log–Gabor filters to depict textures in specific directions. Also, we compared the performance of the proposed technique with that of four ADF-based techniques used in US images.

METHODS

Anisotropic diffusion filtering

The 4- or 8-nearest neighbor ($\mathcal{N}_4$ or $\mathcal{N}_8$) discretization of the non-linear partial differential equation for the ADF approach is expressed as (Perona and Malik 1990)

$$I_{i,j}^{t+1} = I_{i,j}^{t} + \tau \sum_{d \in \mathcal{N}_d} [g(|\nabla_d I|)\nabla_d I]_{i,j}^{t} \tag{1}$$

where t is the iteration step; $I_{i,j}^t$ is the noisy pixel at iteration t; the pair i, j is the pixel location; $0 < \tau \le ¼$ for the numerical approximation to be stable; $|x|$ denotes the magnitude; $\mathcal{N}_d$ indicates the set of d-directions for the nearest-neighbor difference, $\mathcal{N}_4 = \{\mathrm{N, S, W, E}\}$ or $\mathcal{N}_8 = \{\mathcal{N}_4, \mathrm{NW, SW, NE, SE}\}$, denoted by the symbol ∇:

$$\begin{array}{ll} \nabla_{\mathrm{N}} I = I_{i,j-1} - I_{i,j}, & \nabla_{\mathrm{NW}} I = I_{i-1,j-1} - I_{i,j} \\ \nabla_{\mathrm{S}} I = I_{i,j+1} - I_{i,j}, & \nabla_{\mathrm{SW}} I = I_{i-1,j+1} - I_{i,j} \\ \nabla_{\mathrm{W}} I = I_{i-1,j} - I_{i,j}, & \nabla_{\mathrm{NE}} I = I_{i+1,j-1} - I_{i,j} \\ \nabla_{\mathrm{E}} I = I_{i+1,j} - I_{i,j}, & \nabla_{\mathrm{SE}} I = I_{i+1,j+1} - I_{i,j} \end{array} \tag{2}$$