Segmentation of Ultrasound Imagery Using Anisotropic Diffusion

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Abstract

We present an anisotropic diffusion technique that is tailored to ultrasound images. Taking into account the speckle characteristics of ultrasound imaging, we introduce a specialized set of partial differential equations to adaptively enhance the raw ultrasound data. The diffusion method mimics traditional anisotropic diffusion in the sense of directional sensitivity. As a result, homogeneous regions are smoothed in an intra-region manner and edges can be enhanced and extracted in the presence of speckle. We provide a series of experiments using synthetically developed models of the carotid artery. The experiments investigate the effect of varying edge orientation, level of noise, and amount of image contrast. Results from the novel diffusion technique are compared with the conventional approaches, revealing the efficacy of the proposed method.

1. Introduction

Ultrasound imaging has become an important medical imaging modality with numerous diagnostic applications such as analyzing blood flow through a vessel, estimating the extent of prostatic cancer, assessing the health of a fetus, *etc.* The remarkable advantages of the use of ultrasound imaging include the low cost, the real-time imaging ability and the absence of dangerous ionizing radiation.

The aim of *segmentation* is to automatically partition the imagery scene into disjoint, spatially connected, homogeneous regions representing meaningful objects and background. Segmentation may be used to assist the user in selecting the region of interest (ROI) in an image by finding the boundary of the region. With a segmented image, both the geometric and irradiance characteristics about the ROI can be computed and analyzed, greatly facilitating the possibilities of automatic object recognition and classification.

Due to the wave interference phenomenon inherent in any coherent imaging process, ultrasound imagery suffers from speckle noise that renders the segmentation of ultrasound imagery difficult even by humans, not to mention by computer vision techniques.

An important strategy for segmentation of ultrasonic imagery relies on edge-sensitive speckle filtering as a building block. The traditional speckle reducing filters used have originated mainly in the synthetic aperture radar (SAR) community. The most widely cited and applied filters in this category include the Lee [6, 7, 8], Frost [4], Kuan [5], and Gamma MAP filters [9].

Although the signal model assumptions and the derivations are different, the Lee and Kuan filters have essentially the same formation. Both the Lee and Kuan filters form an output image by computing a linear combination of the center pixel intensity in a filter window with the average intensity of the window. So, the filter achieves a balance between straightforward averaging (in homogeneous regions) and the identity filter (where edges and point features exist). This balance depends on the coefficient of variation inside the moving window.

The Frost filter [4] is similar. In this case, the balance between the all-pass filter and the average filter is achieved by a forming an exponentially shaped filter kernel that can vary on a pointwise, adaptive basis. The Frost filter response is also dependent on the local coefficient of variation. In the presence of a low coefficient of variation, the filter is more average-like. In the case of a high coefficient of variation, the filter does not alter the signal.

In more recent research, the extended versions of the Lee filter and the Frost filter have been introduced to alter performance locally according to three conditions [9,10]. Pure averaging is enacted when the local coefficient of variation is below a lower threshold. Above a higher threshold, the filter performs as an identity filter. When the coefficient of variation is between the two thresholds, a balance between averaging and the identity is computed as with the standard Lee and Frost filters.

Even though these existing despeckle filters are described as "feature preserving," four major limitations preclude successful filtering for segmentation. First, the filters are sensitive to the size and shape of the filter window. Given a filter window that is too large, over-smoothing will occur and edges will be blurred. A small window will decrease the smoothing capability of the filter and will leave speckle. In terms of window shape, a square window (as is typically applied) will lead to corner rounding of rectangular features that are not oriented at perfect 90-degree rotations, for example. Second, the existing filters do not enhance edges — they only inhibit smoothing near edges. When any portion of the filter window contains an edge, the coefficient of variation will be high and smoothing will be inhibited. Therefore, noise/speckle in the neighborhood of an edge (or in the neighborhood of a point feature with high contrast) will remain after filtering. Third, the despeckle filters are not directional. In the vicinity of an edge, all smoothing is precluded, instead of inhibiting smoothing in directions perpendicular to the edge and encouraging smoothing in directions parallel to the edge. Last, the thresholds used in the enhanced filters, although motivated by statistical arguments, are *ad hoc* improvements that only demonstrate the insufficiency of the window-based approaches. The hard thresholds that enact neighborhood averaging and identity filtering in the extreme cases lead to blotching artifacts from averaging filtering and noisy boundaries from leaving the sharp features unfiltered.

Here, we first discuss a partial differential equation (PDE) approach to speckle removal for ultrasonic image enhancement. Then, we show that this method, speckle reducing anisotropic diffusion (SRAD), can be used for segmentation. SRAD preserves and enhances edges by inhibiting diffusion across edges and allowing diffusion on an intra-region basis. SRAD does not utilize *ad hoc* thresholds as do the enhanced versions of the Lee and Frost filters.

The SRAD diffusion PDE is based on the minimum mean square error (MMSE) derivation used in designing the Lee and Frost filters. Thus, SRAD is the edge sensitive extension of conventional adaptive speckle filters, just as anisotropic diffusion [11] is the edge sensitive extension of the Gaussian filter. For images containing signal-dependent, spatially correlated multiplicative noise, SRAD excels over the diffusion techniques designed with additive noise models in mind.

2. Speckle Reducing Anisotropic Diffusion

It can be shown that both the Lee and Frost filters resemble isotropic diffusion processes and can be modified to enact anisotropic diffusion. These observations lead to the construction of speckle reducing anisotropic diffusion. Developing a PDE interpretation of the Lee and Frost filters bridges the PDE approach and the adaptive filtering approach for speckled imagery. The PDE framework allows the development of a new model for speckle reduction, which may open new approaches to interpreting ultrasound and radar images. In this section, we present the speckle reducing anisotropic diffusion (SRAD) method.

2.1. The Instantaneous Coefficient of Variation

In the Lee and Frost filters, we have noted the importance of the local statistic $C_{i,j}$, the coefficient of variation at position (i, j), in speckle filtering. To implement a PDE version of the speckle reducing filters, we compute a discretized version of the coefficient of variation. We have derived the following approximation for $C_{i,j}$:

$$C_{i,j}^2 = \frac{(1/2)\left|\nabla I_{i,j}\right|^2 - (1/16)\left(\nabla^2 I_{i,j}\right)^2}{\left[I_{i,j} + (1/4)\nabla^2 I_{i,j}\right]^2}. \quad (1)$$

We denote a special case of $C_{i,j}$ by $q_{i,j}$ for convenience and assume that the image intensity function has non-zero support over the domain. So, $q_{i,j}$ can be viewed as a discretization of

$$q(x, y; t) = \sqrt{\frac{(1/2)\left(|\nabla I|/I\right)^2 - (1/16)\left(\nabla^2 I/I\right)^2}{\left[1 + (1/4)\left(\nabla^2 I/I\right)\right]^2}}. \quad (2)$$

While $C_{i,j}$ is coefficient of variation, we call the function q the *instantaneous coefficient of variation*. This term combines a normalized gradient magnitude operator and a normalized Laplacian operator to act as an edge detector for speckled imagery. High relative gradient magnitude and low relative Laplacian tend to indicate an edge. At the center of an edge, the Laplacian term undergoes a zero crossing and the gradient term dominates, resulting in the limiting behavior of $q_{i,j} \to \left|\nabla I_{i,j}\right| / I_{i,j}$.

2.2. Speckle Removing Anisotropic Diffusion

Given an intensity image $I_0(x, y)$ with non-zero support over the image domain Ω, the output image $I(x, y; t)$ is evolved according to the SRAD PDE:

$$\begin{cases} \partial I(x, y; t)/\partial t = div\left[c(q)\nabla I(x, y; t)\right] \\ I(x, y; 0) = I_0(x, y), \left(\partial I(x, y; t)/\partial \vec{n}\right)|_{\partial\Omega} = 0 \end{cases} \quad (3)$$

where $\partial\Omega$ denotes the border of Ω, $\vec{n}$ is the normal to the $\partial\Omega$, and

$$c(q) = \left\{1 + \left[q^2(x, y; t) - q_0^2(t)\right] / \left[q_0^2(t)\left(1 + q_0^2(t)\right)\right]\right\}^{-1}. \quad (4)$$

In (4), $q(x, y; t)$ is the instantaneous coefficient of variation (2) and $q_0(t)$ is a scaling function that can be determined using

$$q_0(t) = \sqrt{\mathrm{var}[z(t)]} / \overline{z(t)} \quad (5)$$

where $\text{var}[z(t)]$ and $\overline{z(t)}$ are the variance and mean over any homogeneous region at instance t, respectively. In SRAD, $q(x, y; t)$ serves as the edge detector in speckled imagery. The function will exhibit high values at edges and yields values near $q_0(t)$ in homogeneous regions.

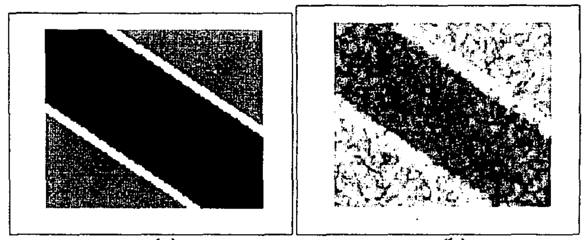
So, the original anisotropic diffusion algorithm [11] may be viewed as the edge-sensitive PDE extension of the Gaussian-weighted (constant coefficient) filter. In the same way, SRAD may be viewed as the edge sensitive PDE version of the conventional adaptive speckle reducing filters such as Lee and Frost.

3. Experiments and Results

The SRAD PDE is validated using both simulated and real ultrasound data. We conduct three experiments using simulated data in order to verify the performance of SRAD. In each simulation experiment, we compare the results of the SRAD with those of three existing enhancement schemes: the enhanced Lee filter [9], the enhanced Frost filter [9], and anisotropic diffusion [11] applied as a homomorphic filter. To examine the ability of SRAD to preserve the mean intensity and to minimize variation within homogeneous regions, we examine the mean preservation error and the standard deviation reduction. To compare the edge preservation performance of SRAD with that of the existing methods, we use the widely adopted Pratt figure of merit [12]. Finally, we present the results of applying SRAD and the other methods to real ultrasonic imagery of the carotid artery. Whereas the synthetic experiments allow the computation of ground truth information and thus the quantification of algorithm performance, the real image examples show the usefulness of SRAD for actual processing and interpretation in a clinical setting.

3.1. Simulation of ultrasound imaging

Fig. 1(a) shows the backscatter cross-section distribution of a section of artery model. The biomedical model [2] also includes local variations in tissue impedance from average value. Before applying the point spread function via convolution, we pointwise multiply the backscatter image with an image containing Gaussian noise (of zero mean). The bandpass signal is computed by convolving the model signal with the point spread function of a typical ultrasound imaging system. The simulated ultrasound image is taken as the envelope-detected amplitude of the bandpass signal. Fig. 1(b) is the simulated image corresponding to Fig. 1(a). The image is log-compressed for display.



(a) (b)

Fig. 1. Simulated data (a) backscatter cross section distribution (b) simulated image

3.2. Criteria for quantifying algorithm performance

In the synthetic experiments, we quantify the algorithm performance in terms of edge preservation, mean preservation in a homogenous region and variance reduction in a homogeneous region.

3.2.1. Edge preservation

To compare edge preservation performances of different speckle reduction schemes, we utilize the Pratt figure of merit (FOM) [12]. So, filtering by one of the stated methods is followed by edge detection, which can be evaluated using the FOM. To maintain consistency, we apply the same detector, the Canny edge detector [3] to each filtered image. To avoid oversmoothing due to the detector itself, we set the standard deviation of the Gaussian kernel in the Canny detector at $\sigma = 0.1$. Note that edge detection is performed on the processed raw data, not the log-compressed imagery used in display.

3.2.2. Mean preservation and variance reduction

The mean preservation and variance reduction in homogeneous region are measures of success in terms of radiometric estimation. To achieve segmentation, we want to delineate the homogeneous regions, while, at the same time, preserving the radiometric characteristics of those regions. A successful speckle reducing filter will not significantly alter the mean intensity within a homogeneous region. Likewise, the effective speckle-reducing filter will reduce the variation within each homogeneous region. The statistics are computed here within three different regions in our simulated carotid artery. The three regions correspond to the region within the artery, within the vessel wall and within fat / muscle regions.

3.3. Results

3.3.1. Simulation results

We provide the results from three synthetically generated artery models. The three experiments address variation of the mean values in the artery model and the variance of the noise Fig. 1(b) shows the simulated noisy image used in experiment I. Fig. 2 shows the smoothed images in experiment I, processed by using four speckle reduction schemes: the enhanced Lee filter [9], the enhanced Frost filter [9], anisotropic diffusion-based homomorphic filtering (denoted by "AD-homomorph." in the results), and SRAD. When applying the enhanced Lee filter (En-Lee) and enhanced Frost filter (En-Frost), the input data are raw intensities, and the window sizes are set as 7x7 pixels. To compare SRAD to the existing anisotropic diffusion technique [11], we implemented diffusion in a homomorphic manner. Hence, the filtering is performed by first computing the logarithmic point operation, then applying anisotropic diffusion (with scaling factor k=3), and then re-scaling with an exponential point operation. The SRAD algorithm, in contrast, is applied directly to the raw data.

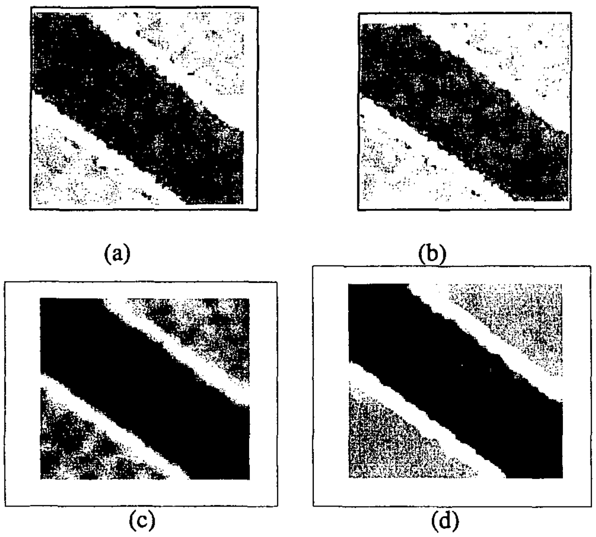


Fig. 2. (a) -(d) Filtered images using En-Lee, En-Frost., AD-Homomorphic, and SRAD. In each case, the image displayed in Fig. 1(b) is the input image.

The mean preservation and variance reduction measures of the four filtering schemes in the three experiments are given in Table I. Table II provides the edge preservation FOM's of the four filtering techniques in the three experiments. These quantitative results show that the SRAD can eliminate speckle without distorting the image statistics and without destroying the important image edges. In each experiment, SRAD outperformed the conventional speckle reducing filters and the conventional anisotropic diffusion algorithm in terms of edge preservation measured by the Pratt FOM. In nearly every case, SRAD also produced the lowest standard deviation and was able to preserve the mean value of the region. The numerical results are further supported by qualitative examination (see Fig. 2, for example).

3.3.2. Real image results

Fig. 3(a) depicts a human carotid artery imaged via ultrasound. The image data set was acquired using a LOGIQ 700 MR ultrasonic scanner manufactured by GE Medical Systems. During the data acquisition, baseband complex, or the I and Q channels, were recorded. The real ultrasound image is taken as the amplitude of the baseband complex data set. Figs. 3(b)-(e) show the smoothed images given by the four filters tested on the synthetic data. The SRAD result in Fig. 3(e) is the most amenable to segmentation with strong edges and uniform regions.

Table I. MEAN AND STANDARD DEVIATION FOR HOMOGENEOUS REGIONS.

Expt. I	**Area I**		**Area II**		**Area III**	
	Mean	**Std.**	**Mean**	**Std.**	**Mean**	**Std.**
Noisy image	1.02	0.56	5.30	2.69	22.80	0.61
En-Lee	1.11	0.32	5.72	1.42	21.75	5.37
En-Frost	1.12	0.32	5.74	1.41	21.83	5.30
AD-Homom.	0.90	0.20	4.64	1.09	14.65	3.51
SRAD	1.19	0.15	6.17	0.69	18.89	2.85
Expt. II	**Area I**		**Area II**		**Area III**	
	Mean	**Std.**	**Mean**	**Std.**	**Mean**	**Std.**
Noisy image	1.02	0.56	5.25	2.72	14.32	7.44
En-Lee	1.10	0.33	5.70	1.35	13.95	3.58
En-Frost	1.11	0.33	5.72	1.34	14.03	3.54
AD-Homom.	0.89	0.23	4.60	0.89	9.52	1.91
SRAD	1.16	0.16	6.08	0.42	12.90	2.40
Expt. III	**Area I**		**Area II**		**Area III**	
	Mean	**Std.**	**Mean**	**Std.**	**Mean**	**Std.**
Noisy image	1.23	0.67	5.56	2.94	20.28	10.77
En-Lee	1.33	0.37	6.08	1.49	19.68	4.95
En-Frost	1.34	0.37	6.10	1.48	19.74	4.89
AD-Homom.	1.07	0.23	4.88	1.08	13.23	2.88
SRAD	1.41	0.15	6.49	0.69	17.64	2.99

Table II. PRATT'S FIGURE OF MERIT (FOM)

	Expt. I	**Expt. II**	**Expt. III**
Image	***FOM***	***FOM***	***FOM***
Noisy	0.53	0.52	0.53
En-Lee	0.63	0.59	0.64
En-Frost	0.63	0.61	0.64
AD-Homom.	0.66	0.66	0.69
SRAD	0.88	0.85	0.86

From Fig. 3, it may be observed qualitatively that the conventional anisotropic diffusion cannot preserve feature in the presence of speckle. The En-Lee filter does not significantly reduce the speckle, while the En-Frost does reduce speckle but blurs details. The proposed technique, SRAD, gives the best performance in terms of smoothing noise and preserving features at various scales.

Finally, Fig. 4 demonstrates the effectiveness of applying SRAD to image segmentation of ultrasound imagery of a prostate phantom. The bright spots in Fig. 4 are radioactive seeds implanted for treating prostatic carcinoma. A goal in this experiment is to localize these seeds using image segmentation. As seen, the seeds are clearly segmented from surrounding tissues with the SRAD technique.

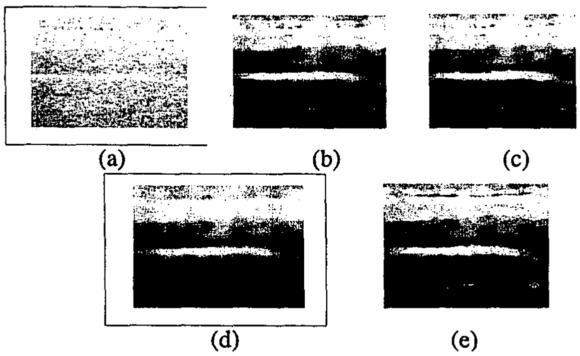


Fig. 3. (a) Original noisy image, (b) -(e) filtered images from En-Lee, En-Frost, AD-Homomorphic, and SRAD.

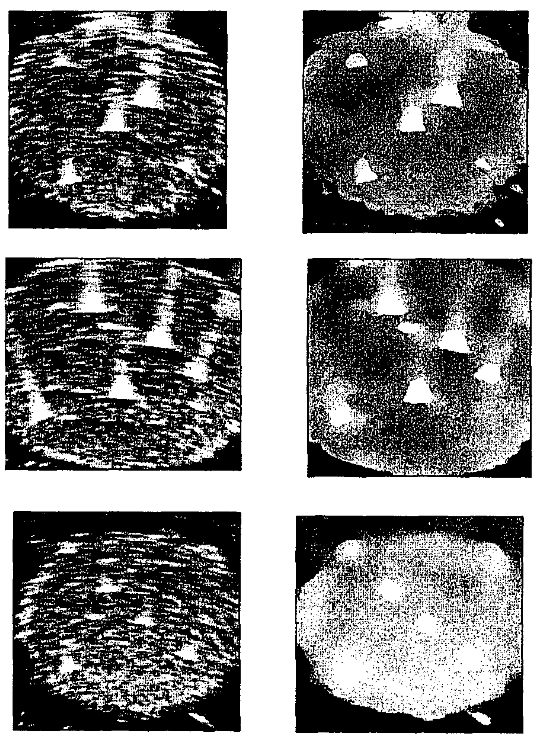


Fig. 4. Noisy (left column) and SRAD-diffused (right column) ultrasound images of prostate phantom implanted with radioactive seeds for the treatment of prostatic carcinoma.

4. Conclusions

Speckle reducing anisotropic diffusion has been introduced here for the purpose of enhancing and segmenting medical ultrasound imagery. SRAD is the first PDE method directed toward reducing speckle within images corrupted by signal-dependent multiplicative noise sources. SRAD avoids diffusing the image in a homomorphic framework [1] by utilizing a novel instantaneous measure of the coefficient of variation. The performance figures obtained by means of computer simulation reveal that the SRAD algorithm provides superior performance in comparison to the conventional anisotropic diffusion, the enhanced Lee filter and the enhanced Frost filter, in terms of smoothing uniform regions and preserving edges and features. In future work, we wish to provide a full derivation of the SRAD method and a complete analysis of the SRAD properties. In terms of application, we are considering the use of SRAD in both medical ultrasound and radar imaging problems.

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