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A Comparison of Speckle Reduction Techniques in Medical Ultrasound Imaging

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Abstract
Speckle noise is a multiplicative noise that degrades the visual evaluation in ultrasound imaging. In addition, it limits the efficient application of intelligent image processing algorithms, such as segmentation techniques. Thus, speckle noise reduction is considered an essential pre-processing step. The objective of this paper is to carry out a comparative evaluation of speckle filtering techniques, based on two image quality evaluation metrics, the Peak Signal to Noise Ratio (PSNR), and the Structural SIMilarity (SSIM) index, and visual evaluation.

Keywords: Filtering; Medical imaging; Noise; Ultrasonography

Introduction

Ultrasound imaging is a powerful non-invasive diagnostic tool in medicine. However, medical ultrasound images are inevitably affected by the presence of speckle noise, a multiplicative noise that significantly influences the visual interpretation of the image and complicates diagnostic decisions. The presence of speckle noise requires the use of despeckling/denoising algorithms. The purpose of a denoising algorithm is to reduce the noise level, while preserving the images features. Over the years, various images denoising techniques have been proposed in literature, each of them being based on particular assumptions and having advantages and limitations. Speckle-reducing filters have been originally used by the Synthetic Aperture Radar (SAR) community. They have been applied to ultrasound imaging since the early 1980s [1]. Filters that are widely used for both SAR and ultrasound images were originally proposed by Lee [2], Kuan et al. [3], and Frost et al. [4]. However, during the years, various other techniques have been developed for despeckling in medical ultrasound images [1, 5-8].

The aim of the paper was to compare several standard filters used for medical ultrasound images despeckling.

Speckle filtering techniques for ultrasound imaging can be grouped in two categories [8]: spatial filtering methods that include linear and space invariant filtering, nonlinear and space invariant filtering, and linear and space variant filtering (diffusion filtering) and filtering in a transform domain, for example multi-scale methods (wavelet filtering).

Linear and Space Invariant Filtering

The most popular local linear filters are Lee [2], Frost [4], and Kuan [3]. Lee and Kuan filters have the same structure, Kuan being a generalization of the Lee filter.

Lee and Kuan are based on the equation:

$$f_{i,j} = \overline{g} + w_{i,j}(g_{i,j} - \overline{g}) \tag{1}$$

where $f_{i,j}$ is the estimated pixel value after filtering, $w_{i,j}$ is the moving window and $\overline{g}$ is the local mean value of a moving window $w_{i,j}$ that includes the noisy pixel $g_{i,j}$.

The weighting factor, $w_{i,j}$, in the case of Lee filter is defined as:

$$w_{i,j} = 1 - C_n^2 / C_g^2(i,j) \tag{2}$$

where C_g is the coefficient of variations of the acquired image and C_n is the coefficient of variations of the noise.

For Kuan filter, $w_{i,j}$ has the following expression:

$$w_{i,j\,Kuan} = w_{i,j\,Lee} / 1 + C_n^2 \tag{3}$$

Frost filtering algorithm is based on the equation:

$$f_{i,j} = \sum_{(l,k)\in W(i,j)} w_{l,k} g_{l,k} \tag{4}$$

with the weight defined as:

$$w_{l,k} = K_0 \exp(-KC_g^2 d_{l,k}) \tag{5}$$

where K_0 is a normalizing constant, $d_{l,k}$ represents the Euclidean distance between the current pixel localized in (l, k) and the central pixel of the moving window localized in (i, j), and K is a factor selected such that in homogeneous regions $KC_g^2 \to 0$ and $w_{i,j} \to 0$.

Nonlinear and Space Invariant Filtering

Nonlinear digital filter category includes the ***median filter*** [5, 6], a simple but robust filter used to remove impulsive noises. The median filter is widely used in digital image processing due to its capability of preserving edges, while removing noises. It is not especially conceived for despeckling purpose, but can be used to reduce the speckle as well. The main idea of the median filter is to replace the middle pixel in the window with the median-value of its neighbors. Generally, an odd number is chosen as the size of the window, so that a well defined center value exists. An example of computation is given in Figure 1.

124	126	127
120	150	125
115	119	123

Figure 1. The computation of the median value of a pixel neighborhood

The median is computed by sorting all the pixel values from the neighborhood into numerical order and then replacing the pixel being considered with the median pixel value. In the example shown in Fig. 1, the central pixel value, 150, of the 3×3 window is rather unrepresentative for the pixels in the neighborhood. So, it is replaced with the median value, 124. An important advantage of the median filter over linear filters is that the median filter can eliminate the effect of isolated input noise values with extremely large magnitudes (impulsive noise). It has a reduced computation complexity, the most complex computation being the sorting operation.

Geometric filtering is a non-linear iterative algorithm that compares the intensity of a central pixel in a neighborhood with the intensities corresponding to its eight neighbors and it increments/decrements the intensity of the central pixel based on the intensities neighborhood pixels. Thus, the intensity of the central pixel will become representative for its surroundings.

The algorithm has three steps [6]:

1. Selecting the direction (north-south) and assigning the pixels values as shown in Figure 2;
2. Performing pixels intensity adjustments; the intensity of central pixel b is adjusted based on the values of intensities of pixels a, b, and c;
3. Repeat the previous steps for the other directions.

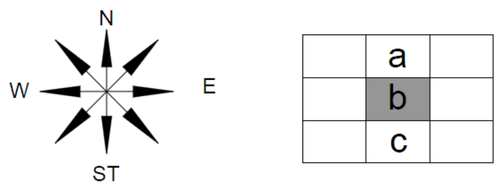


Figure 2. The geometric filtering algorithm

Homomorphic filtering [6] involves the computation of the Fast Fourier Transform (FFT) of the logarithmic compressed image, the use of a denoising homomorphic filter function, and, in the end the computation of the inverse FFT of the image. The homomorphic filter function is constructed using a high-boost Butterworth filter:

$$H_{u,v} = \gamma L + \frac{\gamma H}{1 + (D_0 / D_{u,v})^2}, \tag{6}$$

where D_0 is the cut of frequency of the filter, γL and γH are the gains for the low and high frequencies, and:

$$D_{u,v} = \sqrt{u - N/2)^2 + (v - N/2)^2}, \tag{7}$$

u and v being the spatial coordinates of the frequency transformed image, and N is the dimension of the image in the *u* and *v* space [6].

Linear and Space Variant Filtering

Linear and space variant filtering include **diffusion filters** which are based on partial differential equations (PDE).

Anisotropic diffusion is a nonlinear technique that smoothes homogenous image regions, retaining image edges without requiring any information from the image power spectrum [6]. The classical isotropic diffusion equation is given by:

$$\frac{dg_{i,j,t}}{dt} = \mathrm{div}(cd\nabla g), \tag{8}$$

where ∇ is the gradient operator, div is the divergence operator, $g_{i,j,t=0}$.

Perona and Malik [7] proposed the following PDE for smoothing an image:

$$\frac{dg_{i,j,t}}{dt} = \mathrm{div}[d_{i,j,t} \nabla g_{i,j,t}] \tag{9}$$

In the end the following equation is obtained:

$$\frac{dg_{i,j,t}}{dt} = \left[\frac{d}{di} d_{i,j,t} \frac{d}{di} g_{i,j,t}\right] + \left[\frac{d}{dj} d_{i,j,t} \frac{d}{dj} g_{i,j,t}\right], \tag{10}$$

where $d_{i,j,t} = f(|\nabla g|)$, with $|\nabla g|$ being the gradient magnitude. The function $d(|\nabla g|)$ is an edge stopping function (also called diffusion coefficient) that stops the diffusion at the image edges. Various choices can be made for the diffusion coefficient, which can greatly affect the extent to which discontinuities are preserved. In this paper we used the diffusion coefficient proposed in [7]:

$$d(|\nabla g|) = \frac{1}{1 + (|\nabla g_{i,j}|/K)^2} \quad (11)$$

where K is a positive gradient threshold parameter, called diffusion constant or flow constant. In the experimental part, the method based on anisotropic diffusion using this first variant of diffusion coefficient will be called anisotropic diffusion 1.

A second choice of diffusion coefficient has been proposed in [9] and has the following form:

$$d(|\nabla g|) = \frac{2|\nabla g_{i,j}|}{2 + (|\nabla g_{i,j}|/K_1)^2} \quad (12)$$

where $K_1 = K/2$.

In the experimental part, the method based on anisotropic diffusion using this variant of diffusion coefficient will be called anisotropic diffusion 2.

Methods

To investigate the performance of the considered despeckling methods, we used real noise-free ultrasound images of the liver (as reference images) and we added artificial speckle noise obtaining the test images. The following denoising methods were compared: the filters proposed by Lee, Kuan and Frost, the median filter, the geometric filter, the homomorphic filter and two anisotropic diffusion filters.

We compared the performance of the considered denoising techniques in terms of the Peak Signal to Noise Ratio (PSNR) measured in decibels (dB) and defined as:

$$\mathrm{PSNR} = 10\log_{10}\left(255^2 / \mathrm{MSE}\right) \quad (13)$$

where *MSE* represents the Mean Square Error computed as:

$$\mathrm{MSE} = \frac{1}{m \times n}\sum_{i=1}^{m-1}\sum_{j=1}^{n-1}\left[f_{i,j} - \hat{S}_{i,j}\right]^2, \quad (14)$$

with $\hat{S}_{i,j}$ representing the estimation of the noiseless component of the acquired image, and m and n being the dimensions of both images $f_{i,j}$ and $\hat{S}_{i,j}$ (in pixels).

A high value of the PSNR shows a great similarity between the noiseless component of the acquired image and the image obtained after denoising. The PSNR is one of simplest and most widely used full-reference quality metric. However, the PSNR is not very well matched to perceived visual quality, meaning that two distorted images with the same PSNR may have very different types of errors, some of them more visible than others.

An alternative evaluation metric is the Structural SIMimilarity (index) (SSIM) index gives a better indication of image quality [10]. A value SSIM = 1 indicates that the two images are identical. The SSIM of two images denoted by x and y can be computed with the following formula:

$$\mathrm{SSIM}(x,y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)}, \quad (15)$$

where μ_x and μ_y are the means of x and y respectively, σ_x and σ_y are the standard deviations of x and y, σ_{xy} is the covariance of x and y and C_1 and C_2 are constants used to avoid instability, in certain conditions.

All the compared denoising methods and the quality measures have been implemented in MATLAB R2008a.

Results and Discussion

The PSNR and SSIM values obtained using the eight denoising methods are shown in Table 1.

The best values are highlighted with bold fonts.

Table 1. PSNR and SSIM values comparison

Parameter	PSNR	SSIM
Lee	29.33	0.8516
Kuan	29.80	0.8763
Frost	29.49	0.8551
Median	30.98	0.8864
Geometric	21.73	0.6543
Homomorphic	30.33	0.8640
Anisotropic diffusion 1	**33.73**	**0.9411**
Anisotropic diffusion 2	32.48	0.9247

It can be observed that the highest values for the two evaluation metrics are obtained by using the method Anisotropic diffusion 1, followed by the results obtained using Anisotropic diffusion 2 and median filtering.

The performance comparison of the considered denoising methods by visual inspection is presented in Figure 3. The reference ultrasound image is presented in Figure 3a), the original image corrupted by speckle noise is shown in Figure 3b), while the results obtained by applying eight despeckling techniques are presented in Figure 3c) - j).

By visual inspection of these resulting images it seems that the best results are obtained for the method Anisotropic diffusion methods followed by the median filtering based method.

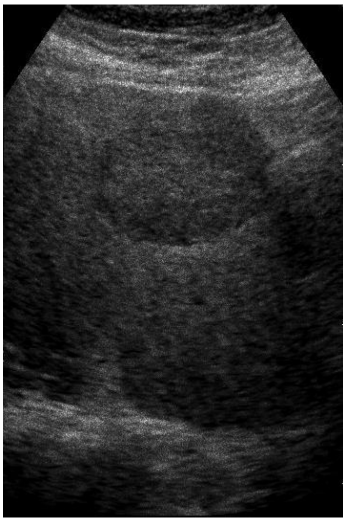
Noise reduction in medical ultrasonography is important for improving the visual observation quality or as a pre-processing step for further automated analysis, for example image segmentation. A software application implementing different denoising techniques along with quality evaluations of the results would help physicians in their decision regarding disease diagnosis, treatment or surgery planning.

The evaluated despeckling methods in this paper were: Lee, Kuan and Frost filters, the median filter, the geometric filter, the homomorphic filter and two anisotropic diffusion filters. These methods belong to the spatial filtering category. The advantage of spatial filters is that they are fast.

However, most of classical denoising techniques have certain limitations: they are sensitive to the size and the shape of the window, some methods require thresholds in the filtering process and the choice of the threshold may lead to average filtering and noisy boundaries, others inhibit filtering in the neighborhood of an edge. The main disadvantage of Lee filter is that it tends to ignore the speckle noise in areas close to edges. A disadvantage of the Kuan filter is that the ENL parameter needs to be computed. Frost filter has an increased computational complexity and requires the selection of a supplementary parameter (the damping factor K). The geometric filter does not require the statistics of the noise and, thus it is applicable to a wide range of images. However, in this case it gives the worst results. The homomorphic filter is usually more effective, especially on images with relatively low contrast and has an easy and effective implementation. In our case it gives a good result, comparable with the results obtained using median filtering. Anisotropic diffusion filtering is an efficient technique, performing contrast enhancement and noise reduction. The advantages of anisotropic diffusion filtering include intra-region smoothing and edge preservation. In this paper, the best results were obtained when anisotropic diffusion filters were used. However, we observed that all the considered denoising techniques more or less reduce the speckle noise.

In this paper we focused on the removal of speckle noise in medical ultrasound images of the liver and we proposed a comparison of various popular despeckling techniques.

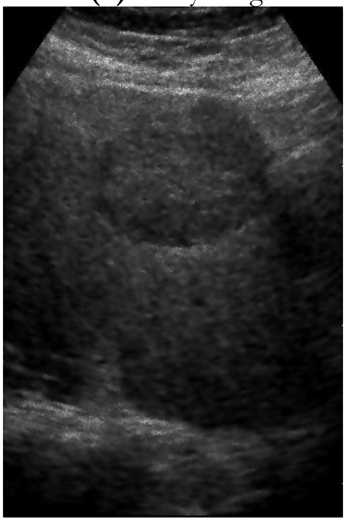
(a) Original image



(b) Noisy image

(c) Lee filter

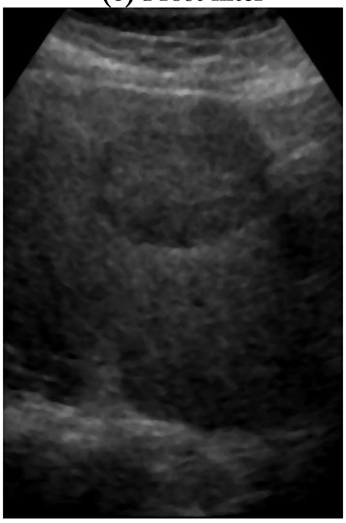
(d) Kuan filter



(e) Frost filter

(f) Median filter

(g) Geometric filter



(h) Homomorphic filter

(i) Anisotropic diffusion filter 1

Figure 3. Performance comparison of various denoising methods by visual inspection

(j) Anisotropic diffusion filter 2

Figure 3. (continuation)

In future papers/experiments we aim to increase the diversity of the denoising methods by including representatives of the class of multi-scale denoising methods, for example wavelets based methods. Our final goal is to create a software product which will include denoising, segmentation and evaluation of medical ultrasound images, and will improve the final diagnosis made by physicians.

List of abbreviations

FFT - Fast Fourier Transform
MSE - Mean Square Error
PDE – Partial Differential Equations
PSNR - Peak Signal to Noise Ratio
SAR - Synthetic Aperture Radar
SSIM - Structural Similarity index.

Conflict of Interest

The author declares that she has no conflict of interest.

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