2011 8th International Multi-Conference on Systems, Signals & Devices

# SPECKLE NOISE REDUCTION IN BREAST ULTRASOUND IMAGES: SMU (SRAD MEDIAN UNSHARP) APPROCH

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**ABSTRACT**

In medical image processing, image denoising has become a very essential for better information extraction from the image and mainly from so noised ones, such as ultrasound (US) images. On the other hand, processed image must preserve the pertinent details of the primary image. So, arbitration between the perpetuation of useful diagnostic information and noise suppression must be treasured in medical images. In general we rely on the intervention of a proficient to control the quality of processed images. In certain cases, for instance in ultrasound images, the noise can restrain information which is valuable for the general practitioner. Consequently medical images are very inconsistent, and it is crucial to operate case to case. This paper presents a novel algorithm SMU (Srad Median Unsharp) for noise suppression in ultrasound breast images in order to realize a computer aided diagnosis (CAD) for breast cancer. A comparative study of the results obtained by the proposed method with the results achieved from the other speckle noise reduction techniques demonstrates its higher performance for speckle reduction

***Index Terms*—** Biomedical image processing, Medical diagnostic imaging Image processing, Image sequence analysis, Image denoising , Active noise reduction

## 1. INTRODUCTION

Ultrasound imaging becomes one of the most useful techniques for breast cancer diagnosis. In fact, comparing to mammography, it provide a real-time imaging. Moreover, it is noninvasive and doesn't use X ray, low cost and no painful. Nevertheless, one of its main shortcomings is the poor quality of image, which is corrupted by noise during its acquisition. The existence of speckle is unattractive since it destroys image quality and it affects the accuracy of human interpretation and diagnosis. The main objective of image denoising is to remove noise while retaining as much as possible the important signal features. Accordingly, speckle filtering is a crucial pre-processing step, for feature and for better image visualization. In the case of breast ultrasound images, Computer Aided Diagnosis (CAD) [1] algorithms are added to echograph machines to get more precise information about some pathology and mainly cancer. So speckle filtering is an essential pre-processing step for CAD and can give better differentiation between benign and malignant nodules. Many techniques are proposed in literature to reduce speckle noise such as Kuan filter [2], Frost filter [3], Speckle Reduction Anisotropic Diffusion SRAD [4], Wiener filter [5], and Wavelet thresholding [6].

In our work, we recommend a novel algorithm (Srad Median Unsharp) SMU for denoising speckle in breast ultrasound images and we give a comparative study between filters used to reduce speckle noise. This paper is organized as follows: Section 2 depicts about the approach used for speckle noise reduction and metrics applied to quantify the performance improvements of the various speckle denoising methods. Experimental results and a comparison study are given in section 3, and section 4 is reserved for the discussions. Finally, Section 5 concludes the paper.

## 2. SPECKLE NOISE REDUCTION

### 2.1. Speckle noise

Speckle noise [6] affects all coherent imaging systems including medical ultrasound. Within each resolution cell a number of elementary scatterers reflect the incident wave towards the sensor. The backscattered coherent waves with different phases undergo a constructive or a destructive interference in a random manner. The acquired image is thus corrupted by a random granular pattern, called speckle that delays the interpretation of the image content.

We can summarize the idea of speckle as an undesirable consequence of the combination of incident waves reflected (presented by red in figure 1) by different points on the surface of the ground (called reflecting objects and presented by green in figure1).

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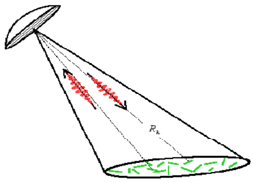


**Figure1.** *Multiples reflexions of a coherent wave*

### 2.2. SMU: A Novel Algorithm for Speckle Reduction

In signal processing, it is often desirable to be able to perform some kind of noise reduction on an image or signal in order to improve the results of later treatment. Our new preprocessing approach SMU is composed of many steps. In fact, it combines three types of filters as it is shown in the diagram below figure 2.

Initial image
↓
Speckle Reduction Anisotropic Diffusion
↓
Median filter
↓
Unsharp mask
↓
Median filter
↓
Filtered image

**Figure2.** SMU flowchar

2.1.1. Speckle Reduction Anisotropic Diffusion

Anisotropic diffusion works well for images corrupted by additive noise. Several supplements and methods of edge detection have been described in the literature [6] for images with additive noise. The advantage of the anisotropic diffusion includes the smoothing of intra-region and the preservation of contours. In the case of images with speckle noise as ultrasound images, the speckle reducing anisotropic diffusion is approved. We have adopted the approach proposed by Yongjian Yu et al [4] which provides an improvement to the approach proposed by Perona and Malik [7].

The equation of partial derivatives is defined as follows:

$$\begin{cases} \partial I(x,y,t)/\partial t = \mathrm{div}\,[c(q)\nabla I(x,y,t)] \\ I(x,y,0) = I_0(x,y) \quad \left.\dfrac{\partial I(x,y,t)}{\partial \vec{n}}\right|_{\partial\Omega} = 0 \end{cases} \qquad (1)$$

Where $I_0(x,y)$ is the intensity of the image that has a finite energy and nonzero values in support image $\Omega$, $I(x,y,t)$ is the output image, $\partial\Omega$ denotes the border of $\Omega$, $\vec{n}$ is the outer normal to the $\partial\Omega$.

The variation coefficient $c(q)$ is defined as:

$$c(q) = \frac{1}{1 + \dfrac{[q^2(x,y,t) - q_0^2(t)]}{[q_0^2(t)(1 + q_0^2(t))]}} \qquad (2)$$

Where $q(x,y,t)$ is the instantaneous variation coefficient and it is defined as:

$$q = \sqrt{\frac{\left(\frac{1}{2}\right)(|\nabla I/I|)^2 - \left(\frac{1}{4}\right)^2 \left(\frac{\nabla^2 I}{I}\right)^2}{\left[1 + \left(\frac{1}{4}\right)\left(\frac{\nabla^2 I}{I}\right)\right]^2}} \qquad (3)$$

Where $\nabla I$ represent the image Laplacien I.

2.1.2. Median filter

The median filter [8] is a nonlinear digital filtering technique, often used to remove noise. It is very widely used in digital image processing because under certain conditions, it preserves edges while removing noise.

For a given I image, the median filter turns I into an image J, in the case of such filter, for any pixel p, the gray level J (p) is the median of shades of gray pixels I (q) for any pixel q of original image in the window W (p):

$$J(p) = \mathrm{med}(I(q) | q \text{ in } W(p)) \qquad (4)$$

2.1.3. Unsharp masking

Unsharp masking [9] is a technique that produces an edge image $g(x,y)$ from an input image $f(x,y)$ via equation (5).

$$g(x,y) = f(x,y) - f_{smooth}(x,y) \qquad (5)$$

Where $f_{smooth}(x,y)$ is a smoothed version of $f(x,y)$.

The final image can be determined by the equation (6)

$$f_{sharp}(x,y) = f(x,y) + k * g(x,y) \qquad (6)$$

Where *k* is a scaling constant. Reasonable values for *k* vary between 0.2 and 0.7 [9].

### 2.3. Performance Metrics

To quantify the performance of the speckle reduction techniques, various methods are used [10]. The commonly preferred metrics are the Mean, the Mean Squared Error (MSE) [10], the Peak Signal to Noise Ratio (PSNR) [11], the Edge Preservation Index (EPI)

[12], and the Structural Similarity Index (SSIM) [13]. The definition and parameters of this metrics are listed in Tabel1.

**Tabel1**. *Performance metrics*

| | |
|---|---|
| Mean | $$Mean = \frac{1}{MXN} \sum_{MXN} \hat{I}(i,j)$$ $\hat{I}(i,j)$: filtered image |
| MSE | $$MSE = \frac{1}{MXN} \sum_{(t,f)=1}^{MXN} \left(\hat{I}(i,j) - I(i,j)\right)^2$$ $I(i,j)$: reference image<br>$\hat{I}(i,j)$: filtered image |
| PSNR | $PSNR = 10 \log \left(\frac{\sigma_s^2}{\sigma_{\hat{s}}}\right)$<br>$\sigma_s^2$:variance of noise free image<br>$\sigma_{\hat{s}}$: variance of filtered image |
| EPI | $EPI = \frac{\sum(\Delta S - \Delta\bar{S})(\Delta\hat{S} - \Delta\bar{S})}{\sqrt{\sqrt{\sum(\Delta S - \Delta\bar{S})^2} \sum(\Delta\hat{S} - \Delta\bar{S})^2}}$<br>$\Delta S$: laplace operator of reference image<br>$\Delta\bar{S}$: laplace operator of mean image<br>$\Delta\hat{S}$: laplace operator of filtered image |
| SSIM | $SSIM(x,y) = \frac{(2\mu_I\mu_{\hat{I}} + c1)(2cov_{I\hat{I}} + c2)}{(\mu_I^2 + \mu_{\hat{I}}^2 + c1)(\sigma_I^2 + \sigma_{\hat{I}}^2 + c2)}$<br>$\mu_I$: mean of reference image<br>$\mu_{\hat{I}}$ : mean of filtered image<br>$\sigma_I^2$ :variance of reference image<br>$\sigma_{\hat{I}}^2$ :variance of filtered image<br>$cov_{I\hat{I}}$ : covariance of filtered image<br>$c1$ et $c2$ : constants to avoid instability |

The best filter preserves mean's initial image, has the low value of mean square error (MSE), offers the best value of peak signal to noise ratio (PSNR), presents the higher value of edge preservation index (EPI), and gives a structural similarity index nearest to 1.

## 3. EXPERIMENTAL RESULTS

### 3.1. Filtering Speckle by SMU Approach

We have applied the different preprocessing steps of SMU approach on synthetic images by adding speckle noise with square standard deviation 0.5 using MATLAB simulation software. After several simulations, we opted for the dimension 14 X 14 for the first median filter and the dimension 4X4 for the second. Figure 3 shows the results obtained due to application of the different stages of our new pre-processing approach.

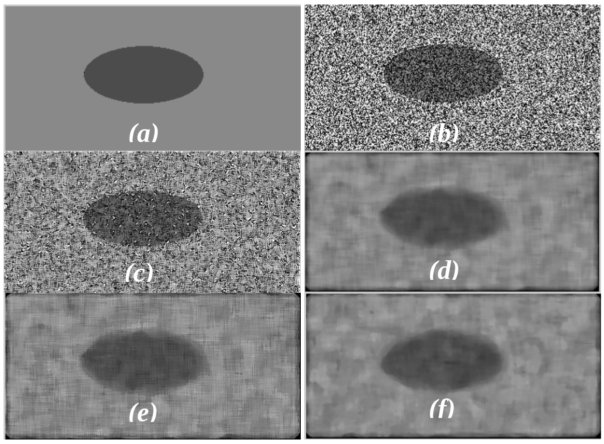



**Figure3.** SMU preprocessing approach steps **(a)** Initial image. **(b)** Noisy image ($\sigma^2$=0.5). **(c)** Image after SRAD. **(d)** Image after 14X14 median filter. **(e)** Image after unsharp mask. **(f)** Image after 4X4 median filter (filtered image)

### 3.2. Comparative study

A comparative study between our new SMU pre-processing approach and different methods proposed in the literature to reduce speckle noise is explained in this part. Figure 4 shows the initial image, the noisy image which have a square standard deviation equal to 0.5 and the results obtained due to the application of different filters such as SMU filter, Frost filter, Kuan filter, Wiener filter, SRAD filter, and Wavelet thresholding.

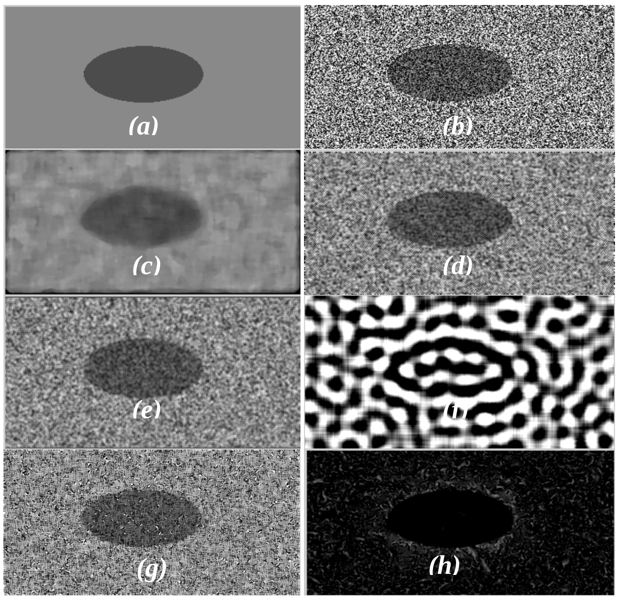
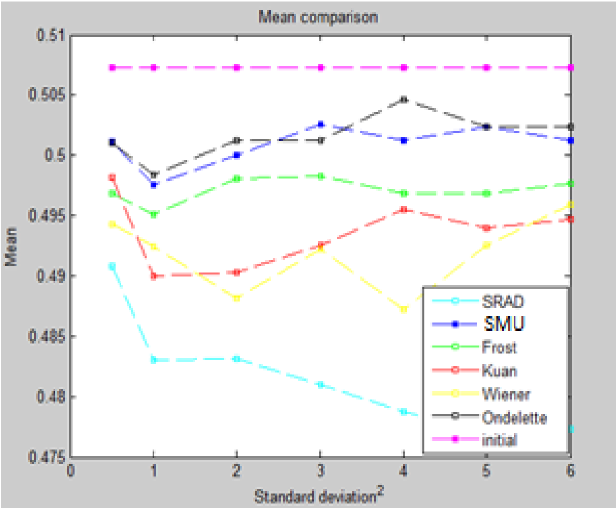


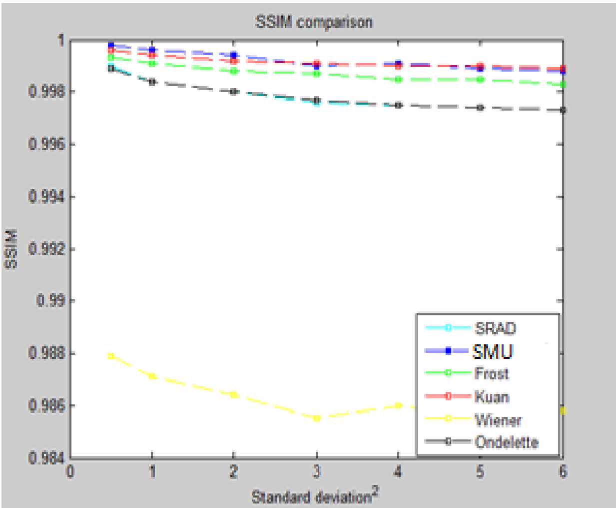

**Figure4.** Speckle reduction by different filter (a) Initial image. (b) Noisy image ($\sigma^2$=0.5). (c) SMU Filter (d) Frost Filter (e) Kuan Filter . (f) Wiener Filter. (g) SRAD Filter .(h)Wavelet threshold Filter.

The performance of SMU approach that has been proposed in this paper is investigated with simulations. We have represented different metrics against the noise variance.

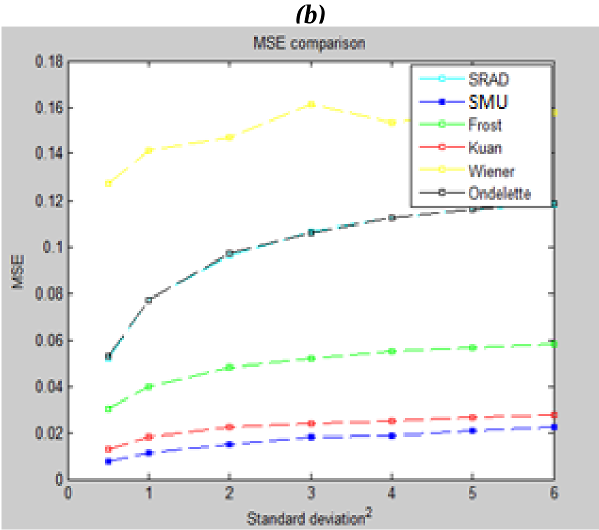
Figure5 presents the results obtained from the application of different metrics on the follow synthetic image.



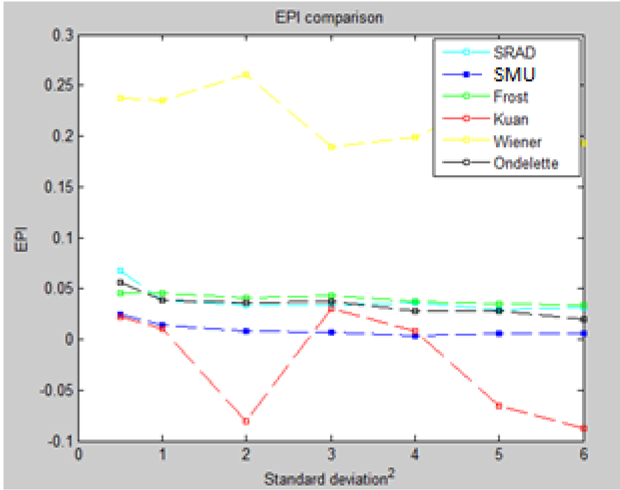

*(a)*



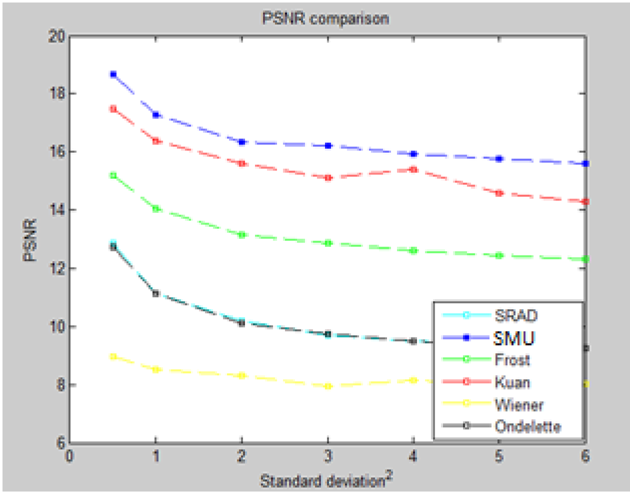

*(b)*




*(c)*




*(d)*




*(e)*

**Figure5.**Comparative study
**(a)** Mean comparison. **(b)** SSIM comparison. **(c)** MSE comparison. **(d)** EPI comparison.
**(e)** PSNR comparison

## 4. DISCUSSIONS

Through the comparative study, we can note that the proposed technique outperforms all the standard speckle filters. In fact, compared with Frost filter, Kuan filter, Wiener filter, SRAD filter, and wavelet thresholding, we remark that SMU conserves the mean's initial image, presents the highest value of structural similarity index (SSIM), fig.5.b, and reduces the mean squared error (MSE) fig.5.c. On the other hand, the SMU offers the highest value of peak signal to noise ratio (PSNR), fig.5.e. and it contributes to the contour conservation by presenting an acceptable edge preservation index (EPI), fig. 5.d. We found that results obtained on synthetic images are good enough and prove the performance of SMU Approach for Filtering Speckle. Thus, we have used this later new preprocessing approach for ultrasound breast images (figures 6-7). We note that we have used the histogram equalization after the SMU preprocessing, and this, to improve the quality of ultrasound image. Indeed, this operation is important to adjust the contrast of ultrasound images.

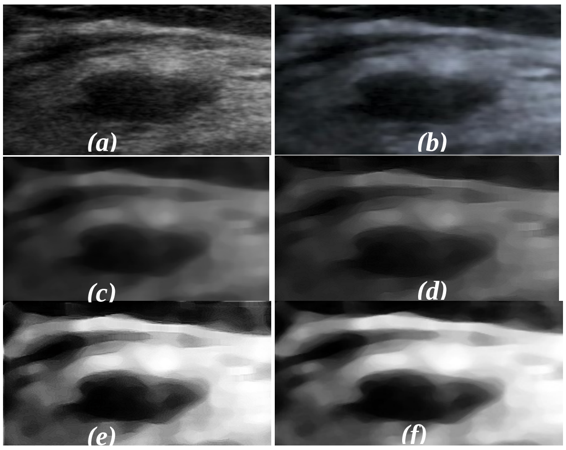



**Figure6**. Ultarsound image1 filtering
(a) Initial image. (b) SRAD filter. (c)14X14 median filter. (d) Unsharp masking application. (e) Histogram equalization. (f) 4X4 median filter

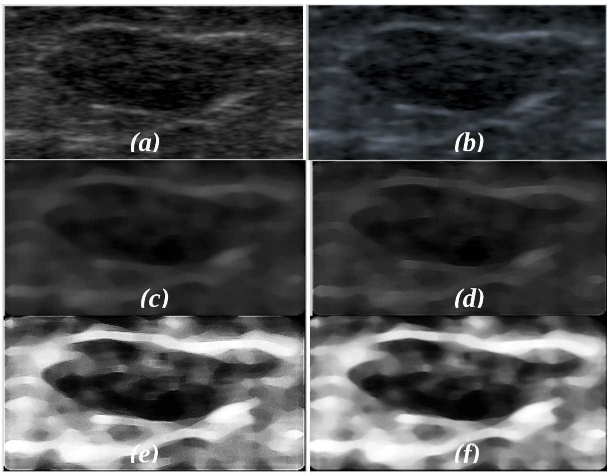



**Figure7.** Ultarsound image2 filtering
(a) Initial image. (b) SRAD filter. (c) 14X14 median filter.
(d) Unsharp masking application. (e) Histogram equalization. (f) 4X4 median filter

Experimental results show that speckle noise reduction in breast ultrasound images by SMU approach presents good performances. Indeed, by visual inspection it is evident that the denoised image, while removing a substantial amount of noise, doesn't suffer from degradation in sharpness and details.

## 5. CONCLUSION

Speckle noise in ultrasound images has very complex statistical properties which depend on several factors. In this work, we presented a new approach for speckle reduction. We have simulated this method on synthetic images and breast ultrasound images, and carry a comparative study. Experimental results show that our proposed approach presents the best performance compared to the other denoising techniques in the literature. The proposed method reduces significantly the speckle while preserving the resolution and the structure of the original ultrasound images and this is suitable to get a precise extraction of the region of interest.

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