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Research paper

Optimized Bayesian NL-means Blockwise approach for Ultra Sound Images

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Abstract

Ultrasound imaging is a portable medical diagnostic tool provides real time clear images of soft tissues compared to x-ray imaging in which tissues are not visible up to the mark. Other diagnostic tools like Magnetic Resonance Imaging and Computer Tomography can well visualize the tissues but are cost effective. Due to the presence of speckle noise Ultrasound images gets degraded leads to low quality imaging. This noise down the spatial, contrast resolutions and Peak Signal to Noise Ratio (PSNR) in US images. Consequently, filtering techniques for speckle noise reduction are of unique interest for clinical ultrasound imaging.
To reduce the speckle noise in US images, Blockwise scheme is adapted to the Non Local (NL) means filter based on Bayesian formula here in this paper. We proposed this Blockwise scheme to a NL-means filter to develop Optimized Bayesian NL-Means (OBNLM) filter which is suitable for removing speckle noise in US images. The experimental qualitative and quantitative result proves the proposed method is better than the NLM filter method. Also OBNLM filter keeps shape of original images with edges.

Keywords: *Ultrasound Image; Speckle Noise; NLM Filter; OBNLM filter; $\tilde{Q}$ index; PSNR.*

1. Introduction

Image restoration is an objective technique of getting original image from corrupted image by some knowledge of degradation phenomenon H and noise term. Finally modelling and inverse process of degradation is used to recover the original image.

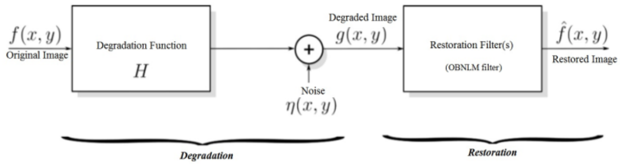

Fig 1: Block diagram of Image Degradation and Restoration

The goal of image restoration is to models the degradation to recover the original image f(x,y). Here, by some knowledge of ***H*** and η(x,y) , we find the appropriate restoration filters, so that output image is as close as original image as possible since it is practically not possible (or very difficult) to completely (or exactly) restore the original image. In Spatial domain restored image is

$$g(x,y) = h(x,y) \circledast f(x,y) + \eta(x,y) \tag{1}$$

After Fourier Transform

$$G(u,v) = H(u,v)F(u,v) + N(u,v) \tag{2}$$

If the restoration filter applied is R(x,y) which reverses the degradation H(x,y) then

$$\widehat{F}(u,v) = R(u,v)[G(u,v)] \tag{3}$$

$$\widehat{F}(u,v) = R(u,v)H(u,v)F(u,v) + R(u,v)N(u,v) \tag{4}$$

Here H(x,y) is linear and position invariant, if noise term is neglected restored image is approximately equal to original image as

$$\widehat{F}(u,v) \approx F(u,v) \tag{5}$$

1.1 Mathematical model of Speckle Noise

The main artifact in ultrasound imaging is speckle, which results due to scattered ultrasound from structures of a tissue which are small in size. Speckle noise is random and deterministic in nature. Mathematically, speckle noise is given by equation (6).

$$y_d(i,j)= x_o(i,j)*n_m(i,j)+a_a(i,j) \tag{6}$$

Where $y_d(i,j)$ is a noise pixel in degraded ultrasound image with Speckle noise, $x_o(i,j)$ is original image pixel without noise, $n_m(i,j)$ and $a_a(i,j)$ are multiplicative and additive noise respectively and i,j indicates spatial coordinates. The impact of additive noise is extremely very less than multiplicative noise, neglecting $a_a(i,j)$ equation (6) becomes (7).

$$y_d(i,j)= x_o(i,j)*n_m(i,j) \tag{7}$$

Apply logarithmic transformation to equation (7) converts multiplicative noise into additive noise.

$$\log[y_d(i,j)] = \log[x_o(i,j)] + \log[n_m(i,j)] \quad (8)$$

Speckle Noise reduction is based on estimating of true pixel $x_o(x,y)$ from $y_d(x,y)$.
The entire Steps involved in Ultrasound scanner for converting RF signal from transducer into Ultrasound image is shown in Fig2

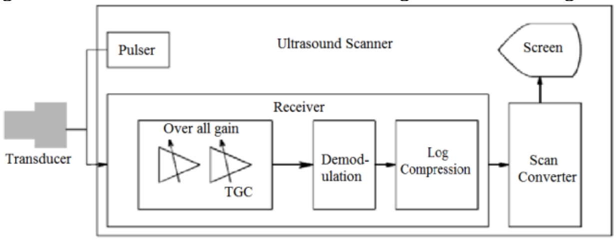

Fig 2: Steps involved in Ultrasound scanner for converting RF signal from transducer into Ultrasound image

The statistics of the RF signal is affected since it is subjected to several transformations. Log compression of the signal plays a major role in reduce the dynamic range of the input signal suitable for display device. Normally display devices have dynamic range about 20-30 dB.

2. Speckle Filters

For Denoising of Speckle noised ultrasound images, Speckle filter used in spatial domain are: Median Filter, Mean Filter, Wiener, Lee Filter, Kaun Filter, Frost Filter, anisotropic diffusion filter, Geometric filter, NL-Means filter and Optimized Bayesian NL-means (OBNLM).

2.1 Non-Local Means (NLM) Filter

Fig4 shows four pixels, p, p_1, p_2, and p_3. Here p_1, p_2, and p_3 are neighborhood of p. The weights $w(p, p_1)$, $w(p, p_2)$ and $w(p, p_3)$ are the weights between pixel p and its neighboring pixels. Similar pixels give more weight while other gives lower weight. Self similarity is measured based on these weights.

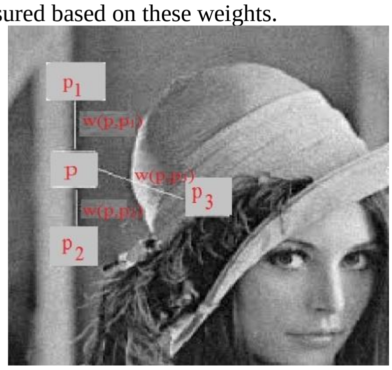

Fig 3: Non-Local Means Scheme

Non-Local means denoising image each pixel 'i' can be obtained from equation (4).

$$\mathrm{NL}[y](i) = \sum_{j\in I} w(i,j)y(j) \quad (9)$$

Here noisy image $y=\{y(i)|i\in I\}$, and $w(i,j)$ are weights depends on the similarity between pixel i and j , satisfies the conditions $\sum_{j\in I} w(i,j)$ equal to unity and $0\leq w(i,j)\leq 1$. Using equation (10) Euclidean distance is measured to know the self similarity.

$$\|y(N_i) - y(N_j)\|_{2,F}^2 = \|u(N_i) - u(N_j)\|_{2,F}^2 + 2\sigma^2 \quad (10)$$

Where u is search area and F is standard deviation of neighborhood filter, N_i and N_j neighborhood of i and j pixels respectively. The weighting function can be calculated using equation (11) in which 'h' indicate smoothing parameter with normalized constant z(i).

$$w(i,j) = \frac{1}{z(i)} e^{-\frac{\|y(N_i)-y(N_j)\|_{2,F}^2}{h^2}} \quad (11)$$

Low PSNR and $\tilde{Q}$ value is the major problem with Non-Local Means filter

2.2 Optimized Bayesian NL-means (OBNLM) Filter

In proposed OBNLM filter Blockwise approach is performed in which weighted average of blocks is presented instead of individual pixel as shown below Fig (4).

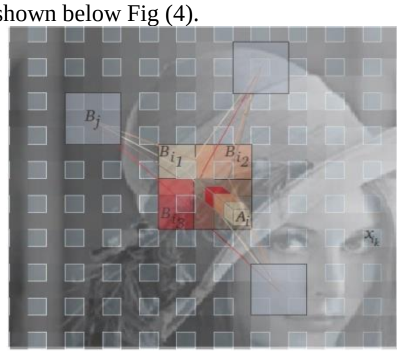

Fig 4: Optimized Bayesian NL-means Scheme

The blockwise approach can be performed in three steps:
Step-1: The image 'f' is partitioned into B_{it} blocks of size $s = (2\alpha+1)^2$ for 2D-image and $s = (2\alpha+1)^3$ for 3D-image which are overlapped such that f=intersection(B_{it}) for all values of 't' with $2\alpha\geq n$, where n is distance between overlapping blocks. The overlapping blocks x_{it} are equally distributed at locations $i_t= (t_1 n, t_2 n, t_3 n)$, $(t_1, t_2, t_3) \in N^d$.
Step-2: NL means based restoration of B_{it} block is performed based on the following equation (12)

$$\mathrm{NL}(y)(B_{it}) = \sum_{B_j\in v_{it}} w(i_t, j) y(B_j) \quad (12)$$

With

$$w(i_t, j) = \frac{1}{z(i_t)} e^{-\frac{\|y(B_{it})-y(B_j)\|_{2,F}^2}{h^2}} \quad (13)$$

Where $y(B_i)=(y^{(1)}(B_i),\ldots\, y^{(s)}(B_i))^T$ and $z(i_t)$ is normalization constant value.
Step-3: Compute several estimations of the same pixel 'i' from different NL means based restoration of B_{it} block and keep in D_i which is a vector. Finally the restored pixel 'i' is defined in the equation (14).

$$\mathrm{NL}(y)(i) = \frac{1}{|D_i|} \sum_{r\in D_i} D_i(r) \quad (14)$$

This blockwise approach reduces the complexity by 4 times in 2D image with n=2 and reduced by 8 times in 3D image. The Optimized Bayesian NL-means is based on the Bayesian formulation of this blockwise approach given by the equation (15).

$$\mathrm{NL}(y)(B_{it}) = \frac{\frac{1}{|V_{it}|}\sum_{j=1}^{|V_{it}|} s(y(B_{it})|y(B_j))\, s(y(B_j)) y(B_j)}{\frac{1}{V_{it}}\sum_{j=1}^{|V_{it}|} s(y(B_{it})|y(B_j))\, s(y(B_j))} \quad (15)$$

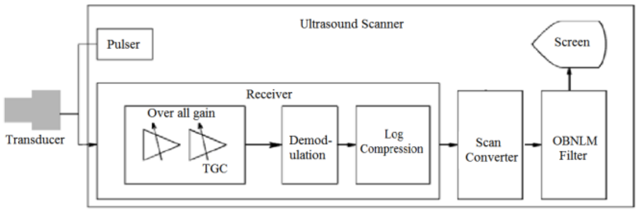

Fig 5: Ultrasound Scanner with OBNLM filter

3. Implementation Results

To evaluate the outcomes of proposed filter, the following quantitative analysis with equation (16) and (17) are carried out for quantifying the quality of denoising in breast cyst ultrasound image.

$$\mathrm{PSNR} = 10\log_{10}\frac{\sum_{i\epsilon f}\left(p(i)^2+\tilde{p}(i)^2\right)}{\sum_{i\epsilon f}\left(p(i)^2-\tilde{p}(i)^2\right)} \tag{16}$$

Where the original value of the pixel is $p(i)$ and the restored one is $\tilde{p}(i)$.The despeckling quality assessment index ($\tilde{Q}$) is computed with (17)

$$\tilde{Q} = \sum_{s=1}^{S}\frac{\left(y^{(s)}B(i)-y^{(s)}B(j)\right)^2}{y^{(s)}B(j)} \tag{17}$$

The two quantitative parameters analyzed in this manuscript are PSNR and ($\tilde{Q}$) index. These quantitative results are shown in the table-1 below.

Table1: Quantitative Results

Filter Approach	PSNR Value	$\tilde{Q}$ index value
NLM	62.2	1.97
OBNLM	64.2	2.72

The used Matlab simulation model in this paper for despeckling with σ=0.2

f(i)=p(i)+p(i)P(i) with $P(i)\sim N(0,\sigma^2)$ shows the qualitative results as shown in Fig(6)

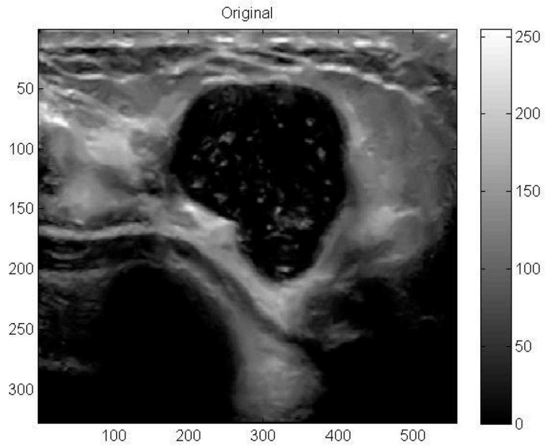

Fig 6: Breast Cyst ultrasound image with Speckle Noise

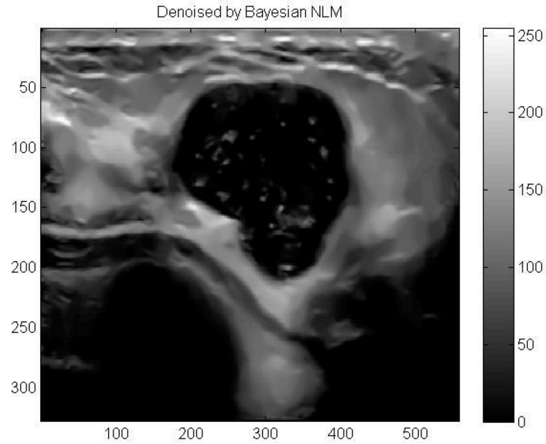

Fig 7: Breast Cyst ultrasound image denoised by OBNLM filter

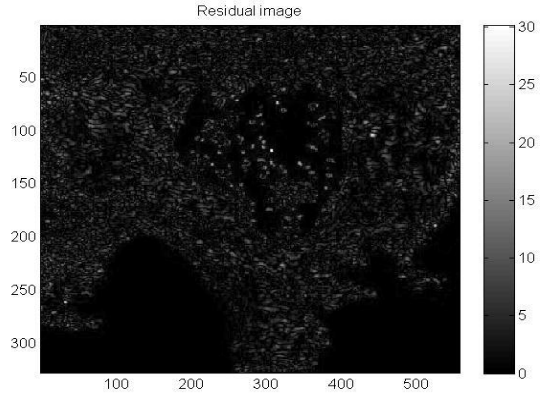

Fig 8: Residual Image showing amount of Despeckling

4. Conclusion

The proposed Blockwise scheme to a NL-means filter to develop Optimized Bayesian NL-Means (OBNLM) filter which is suitable for removing speckle noise in US images. Qualitative and Quantitative estimations on ultra sound image are evidences of the OB-NLM method compared to NLM filter. In OBNLM proposed filter, Despeckling quality assessment index ($\tilde{Q}$) is increased by 40% approximately when compared with NLM filter. Also Results shows OBNLM filter keeps shape of original images with edges.

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