Denoising Ultrasound Images and Error Estimate by Non Local Means

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Abstract*—Image denoising is one of the main techniques in the field of computer graphic and computer vision. Non-local means method is one of the great useful methods which arouse tremendous research [1]. In this paper, we will study the utility of the Non Local Means method in denoising ultrasound images by error estimate. This method based on replacing a pixel by the average of similar pixels. But the most similar pixels to a given pixel can be also non adjacents. We can scan a big portion in search of all the pixels of the image that really resemble the pixel we want to denoise. [2]

***Keywords*—Denoising, Ultrasound Images, Non Local Means Method**

I. INTRODUCTION

In the image processing literature, several methods have been proposed and used in image denoising methods have been proposed. We find as example methods using the spatial filtering, approaches based on PDEs variational [3, 4], other approaches using Markov random fields and methods based on multiscale transforms, like wavelet transform [5, 6, 7]. Each approach has its own assumptions, benefits, and limitations. However, many of these methods remove more and more noise from the details of the image. As a result, denoising algorithms continue to be developed to solve this problem. Among these methods, Non Local Means and the one we applied on ultrasound images [8]

II. NON-LOCAL MEANS THEORY

The algorithm of Non Local Means is used for image denoising, and it's different from « local means »filters where we calculate the mean value of all pixels surrounding the target pixel in aim to smooth the image. While, Non Local Means filters searches all the pixels that have similarities with the target one and take the mean value of these pixels. In this case, we have cleared image and less loss of detail compared with local means algorithm [9].

This approach is based on the self-similarity existing in the image it self; it is a question of finding similar pixels (patches) in the image, and then calculating their weighted average according to their similarity with the pixel denoised [10]. Fig 1 below presents an example of self-similarity.

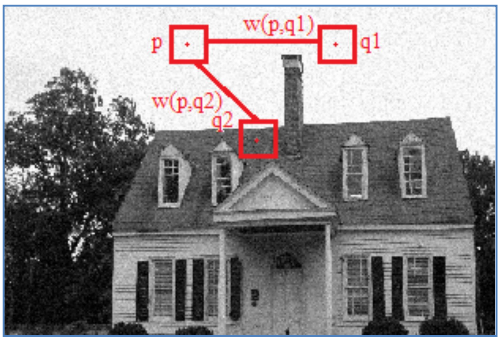


Fig. 1. Sel-fsimilarity in an image.

Neighborhoods Pixels of p and q1 are similar, but those for pixels p and q2 are not similar. For this reason, pixel q1 will have a big affect on the denoised value of p than q2 [10]

III. PRINCIPLE AND ALGORITHM OF THE METHOD

As shown by Buades et al, the principle of non-local averages (NL Means), is to take advantage of the remote information that can be found in images. This approach is based on the self-similarity existing in the image itself, so it is a question of finding the pixels (patches) similar in the image, then calculating their weighted average with their similarity with the pixel to denoise [11]

Let x ($x\varepsilon\Omega$):

s(x) the set of pixels similar to $x(x\varepsilon\Omega)$. Thus :

$$u(x) = \sum_{y \wedge x} w(x,y)v(y) \tag{1}$$

And

$$\sum_{y \wedge x} w(x,y) = 1 \tag{2}$$

$$k(x,y) = e^{-\frac{\|v(x)-v(y)\|^2}{h^2}} \tag{3}$$

$$Z(x) = \sum_{y \wedge x} k(x,y) \tag{4}$$

And

$$w(x,y) = \frac{k(x,y)}{\sum_{y \wedge x} k(x,y)} = \frac{1}{Z(x)} k(x,y) \tag{5}$$

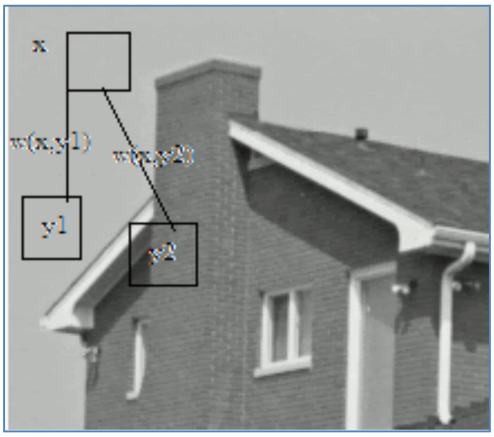


Fig. 2. Principle of the NL-Means algorithm

$$w(x,y) = \sum_{y\in\Omega_x} \frac{1}{Z(x)} e^{-\frac{\|v(x)-v(y)\|^2{}_{2,a}}{2h^2}} \quad (6)$$

Where $u(x)$ is the denoise value of a pixel x.
$v(y)$ The value to denoise at the point $y(y\epsilon\Omega_x)$
$k(x,y)$ The similarity between pixels x and y
$w(x,y)$ Weights

let $v:\Omega \to R$ tq $v = u + b$ noised image

u: Original image.

$\{b(x)\}_{x\epsilon\Omega}$ is the gaussien white noise with variance σ^2.

Spatial Denoising by the Non-Local means algorithm (NL-means) is classically written

$\forall x \in \Omega$, where the NL-means weights are written

$$NLM[v](x) = \sum_{y\in\Omega_x} \frac{1}{Z(x)} e^{-\frac{\|v(x)-v(y)\|^2{}_{2,a}}{2h^2}} v(y) \quad (7)$$

where $v(x)$ is the 7×7 patch centered in x in the image v that is, the grayscale.

$\{v(y) | y \in \Omega, \|x-y\|_\infty \leq 3\}$,

h a filtering parameter,

Z(x) a standardization coefficient

$\|.\|_{2,a}$ Euclidean norm weighted by a Gaussian of standard deviation “a” which defines the similarity between the patches

$\Omega_x = \{y \in \Omega \,|\, \|x-y\|_2 \leq d\}$ is the area of search for similarities and radius d [12]

IV. Results

In this study, we have used ultrasound image pixels. We load our image and transform it to gray level, where (N=256) is the number of pixels of two different grey level values, then we add White Gaussian Noise to obtain the denoised one.

For the Non Local Means method, we obtain the denoised image by changing the values of sigma of White Gaussian Noise when we add it to the original image (Fig 3). Than we applied NLM filter as shows the tables (I,II,III,IV).

We try to compare the results with those obtained by Gaussian, median and average filters as shown in the tables (V, VI).

The quality between the original image and the filtered is measured by the first parameter PSNR. Big value of PSNR means the quality of the image treated is good. It calculates the peak signal- to- noise ratio between two images by the following equation [13]:

$$PSNR = 10\log_{10}\left[\frac{255^2}{MSE}\right] \text{ dB} \quad (8)$$

MSE is the Mean Square Error, which is the square of the accumulated error between the original and filtered image. The lower value of MSE means quality is good. MSE is calculated by the equation:

$$MSE = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}(X(i,j) - Y(i,j))^2 \quad (9)$$

(6)

M and N are rows and columns of the input images, respectively

The mean square error (MSE) and peak ratio of signal to noise (PSNR) are the two error parameters used to compare the quality of image compression [14]

The second parameter is Structural Similarity (SSIM) is measure of similarity between two digital images.

The idea of SSIM is to measure the similarity of structure between the two images, rather than a pixel to pixel difference as for example the PSNR. The underlying assumption is that the human eye is more sensitive to changes in the structure of the image.

The SSIM metric is calculated on multiple windows of an image. The measurement between two windows x and (7) y of size NxN is

$$SSIM(x,y) = l(x,y).c(x,y).s(x,y) = \frac{(2\mu_x\mu_y+c_1)(2\sigma_x\sigma_y+c_2)(cov_{xy}+c_3)}{(\mu_x^2+\mu_y^2+c_1)(\sigma_x^2+\sigma_y^2+c_2)(\sigma_x\sigma_y+c_3)} \quad (10)$$

μ_x the average of x

μ_y the average of y

σ_x^2 the variance of x

σ_y^2 the variance of y

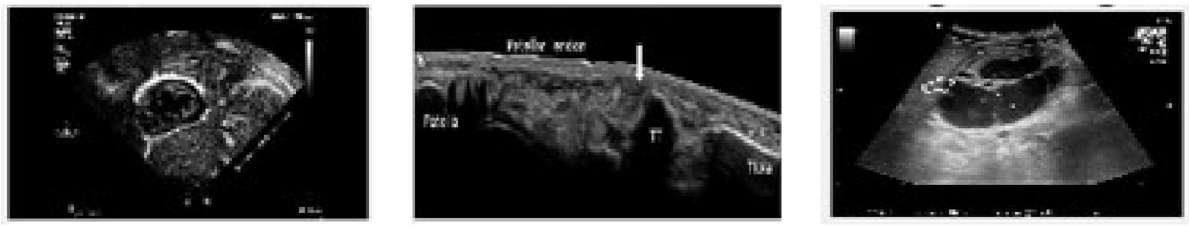
cov_{xy} is covariance of x et and y

$c_1 = (K_1L)^2, c_2 = (K_2L)^2$ et $c_3 = \frac{c_2}{2}$: Parameters to stabilize the equation, when the denominator is very low.

L is the dynamic of pixel values, ie 255 for 8-bit coded images

$k_1 = 0.01$ et $k_2 = 0.03$ by default

The value of SSIM is between 0 and 1, which indicates the correlation with respect to the source, 1 indicating a perfect correlation [15].



a b c

Fig. 3. Original Images a(stomach), b(the patellar tendon), c(Endoscopic Heterogeneous mass in the the gastric wall)

There is also the visual aspect as a third parameter: sometimes we get a high PSNR and SSIM near to 1 but the image is blurry which means there is a loss of detail.

In the following tables, the results obtained for different values of f (neighborhood window of the pixel), t (similarity window) and sigma, for the ultrasound image (a) of a stomach

TABLE I. PSNR AND SSIM FOR AN IMAGE DENOISED BY NLM METHOD FOR DIFFERENT SIGMA VALUES (F=2 T=5)

σ	PSNR (dB)	SSIM
0.001	38.7070	0.5996
0.0015	38.1607	0.5447
0.002	37.6332	0.5117
0.01	34.7745	0.2921
0.06	33.3832	0.1145
0.5	32.9653	0.0315

TABLE II. PSNR AND SSIM FOR AN IMAGE DENOISED BY NLM METHOD FOR DIFFERENT SIGMA VALUES (F=6 T=8)

σ	PSNR (dB)	SSIM
0.001	35.7043	0.5590
0.0015	35.6911	0.4985
0.002	35.6515	0.4662
0.01	35.2490	0.3265.
0.06	33.9151	0.1269
0.5	32.9830	0.0316

TABLE III. PSNR AND SSIM FOR AN IMAGE DENOISED BY NLM METHOD FOR DIFFERENT SIGMA VALUES (F=3 T=8)

σ	PSNR (dB)	SSIM
0.001	37.488	0.5861
0.0015	37.2072	0.5821
0.002	36.9725	0.4943
0.01	35.0997	0.3167
0.06	33.5062	0.1149
0.5	32.9498	0.0329

TABLE IV. PSNR AND SSIM FOR AN IMAGE DENOISED BY NLM METHOD FOR DIFFERENT SIGMA VALUES (F=3 T=12)

σ	PSNR (dB)	SSIM
0.001	36.9444	0.5859
0.0015	36.8426	0.5223
0.002	36.6679	0.4931
0.01	35.1133	0.3210
0.06	33.5524	0.1170
0.5	32.9262	0.0316

Interpretation

According to the results obtained when different sigma values were used in different windows, it is clear that the values of PSNR and SSIM are better in the case of sigma ≤0.002, F=2 and T=5 but in the case. From sigma = 0.06.the image remains noise whatever the size of the window, which is an inconvenient. As shown fig (4) in case of sigma=0.002and 0.01.

In the following tables (V, VI), a comparison has been presented between the PSNR and SSIM for the different types of filters (Gaussian, median and average) and the NLM method. An example is shown in fig (5) for sigma=0.06.

TABLE V. COMPARAISON BETWEEN THE VALUES OF PSNR FOR THREE FILTERS AND NLM METHOD

σ	0.001	0.0015	0.002	0.01	0.06	0.5
Gaussian Filter	38.4190	37.9282	37.4144	35.5195	34.699	35.0907
Median Filter	34.3692	34.3376	34.2861	34.1691	33.7409	33.2924
Avergae Filter	34.5473	34.5678	34.562	34.7678	35.6277	37.4081
NLM method	38.7070	38.1607	37.6332	34.7745	33.3832	32.9653

TABLE VI. COMPARAISON BETWEEN THE VALUES OF SSIM FOR THREE FILTERS AND NLM METHOD

σ.	0.001	0.0015	0.002	0.01	0.06	0.5
Gaussian Filter	0.5972	0.5150	0.4687	0.2896	0.1553	0.0488
Median Filter	0.7473	0.7236	0.6947	0.5326	0.3288	0.1438
Avergae Filter	0.4436	0.3876	0.3479	0.2121	0.1373	0.0643
NLM method	0.5996	0.5447	0.5117	0.2921	0.1145	0.0315

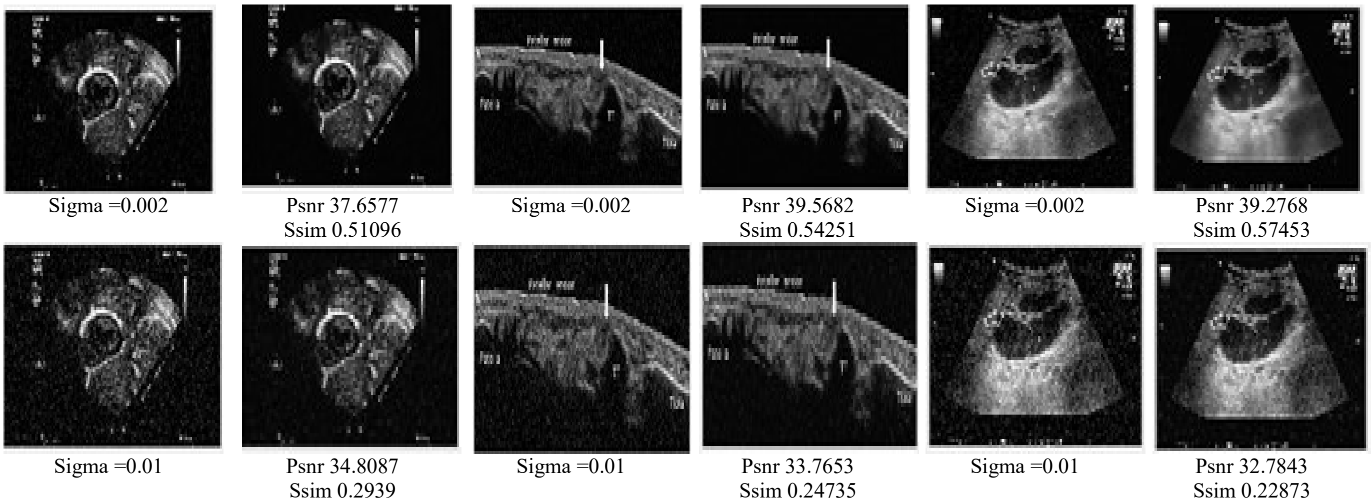


Fig. 4. Noised Image (0.002and 0.01) and filtered imaged by NL Means filter

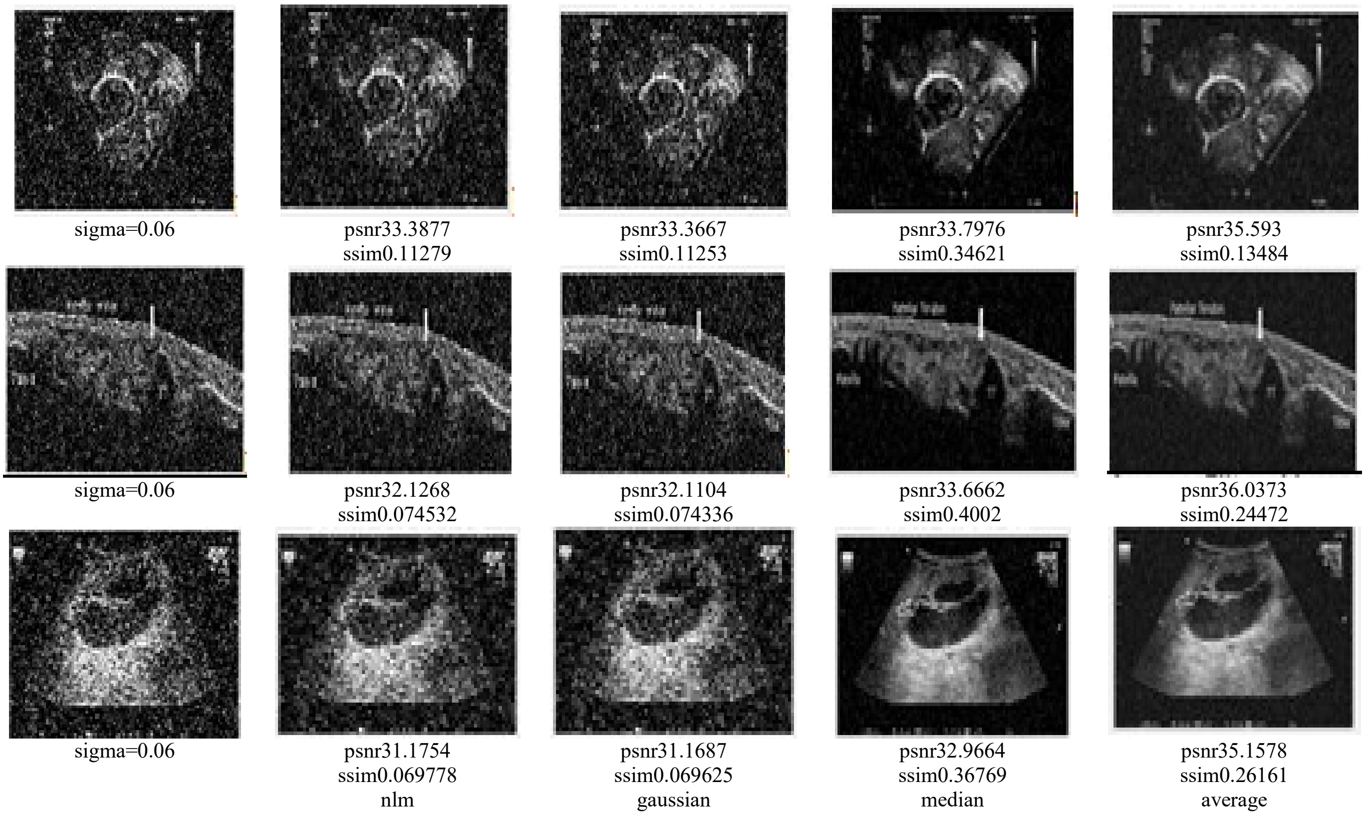


Fig. 5. PSNR and SSIM values obtanied by different filters

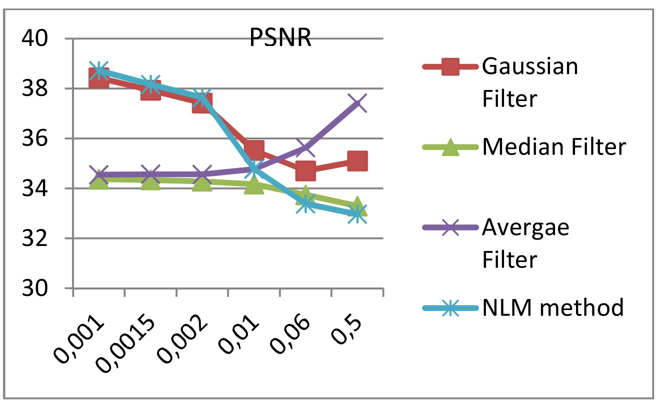


Fig. 6. PSNR values obtanied by different filters

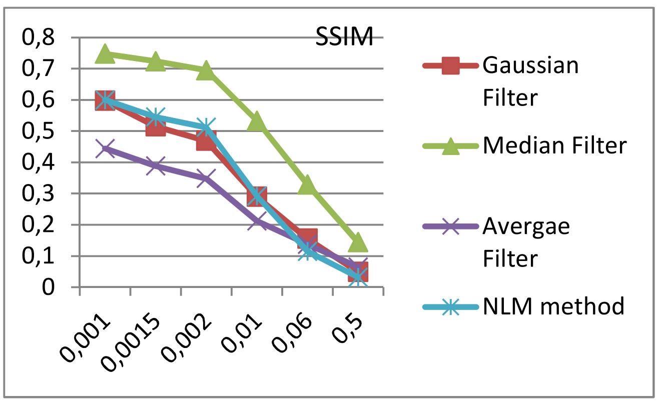


Fig. 7. SSIM values obtanied by different filters

Interpretation

In Fig. 5 and Fig. 6, The comparison shows that the PSNR and SSIM in the case of sigma <= 0.002 is best in the case of NLM Method than the other filters. For sigma>0.002 we get blurred image. We distinguished that the NLM method is very sensitive to noise and to the type of organ tissue (in case of ultrasound images).

V. Conclusion

We have seen in this paper the use of Non Local Means in reducing noise, which has a bad effect on medical imaging. This paper is organized in five sections. The first section, presents an introduction about different methods used in denoising images. Section 2 talks about Non Local Means Theory. Principle and Algorithm of this method are described in the Section3. In Section 4 we applied NLM on an ultrasound image denoised by White Gaussian Noise, and then we compared it with classic filters (Gaussian, Median and Average). Section 6 shows the conclusion of this study.

In this paper we have studied the use of NLM Method in denoising Ultrasound Images and we have demonstrated that NLM method is could offer better results

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