Report for NONLOCALMEANS –BASED ON SPECKLE FILTERING FOR ULTRASOUND IMAGES (December 2019, Project of ELEC 6661)

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***Abstract*— In the field of image processing, the nonlocal-means filter is a traditional and effective method widely applied to denoise the images. Comparing with some other traditional de-noising methods, like Gaussian Kernel, the nonlocal-means (NLM) filtering provides better quality of the result image with more details. But the Elapsed time of the traditional NLM has a heavy computational load with a long elapsed time.**

For this reason, the evolution of traditional NLM is required for improving the running time. The Optimized Bayesian Non-Local Mean (OBNLM) is a pretty successful method with a high denoising quality and shorter elapsed time comparing with the traditional NLM introduced from this project. We are going to comparing the different algorithms of denoising kernel, especially comparing between the NLM and OBNLM in some criteria, like SNR, MSE and operating time.

I. INTRODUCTION

In our real life, there are a lot of types of images, like MRI and Ultrasound images. And those images are consisted with noises naturally. In our project, the kernel is focused on the ultrasound images' de-noising. Generally speaking, if we create an image, speckle will be presented on the image as noise, for example like Gaussian noise speckle. Ultrasound images are usually depends on the level of speckle noise which is the noise that is due to the environmental conditions on the imaging sensor during image creating, and this kind of noise covers up a lot of useful details and reducing the quality of the image. That's why we need denoising the image for more accurate diagnosis . Moreover, speckle removing becomes is also a very popular research topic of image processing field in recent years.

Gaussian filtering, Lee's filter Kuan's filter and Frost's filter, are some major de-nosing methods that wildly applied in the field of image processing. Each of those methods has their own advantages and disadvantages in the aspects of implementation complexity, de-nosing quality, elapsed time etc. But those filters are not very appropriate in denoising the speckle noise for ultrasound images. But the NLM can deal with such problem and provide a high quality restored image. The general idea of NL-means de-noising method is that take mean values of all pixels' intensity of the whole image. Thus, all pixels of the whole image are related, and that's the reason why NL-means filtering provides a good image quality.

However classical then elapsed time of NLM is too long due to that it requires the calculation for each pixel. It means if the size of the image is too large, a longer operating time is taken due to the calculation of Gaussian average value of every pixels in the search window, and sometimes it needs more than ten minutes to restore an medical image. Therefore, the Optimized Bayesian Nonlocal-means method is introduced to deal with the problem of long elapsed time with a not bad image quality. The OBNLM filter divides total volume of the noise image into several blocks, then calculate the Gaussian average value for the blocks, restore the blocks then restore the pixels. OBNLM reduces the dimension, local search, adjacent block transfer and so on. So it significantly reduces the computational complexity and reduce the operating time.

In our paper, we completed the implementation for NLM OBNLM and some other methods, like Lee' and Kuan' methods. But we mainly compare the performance of NLM and OBNLM by the numeral data of signal noise ratio (SNR), mean square error (MSE) and Elapsed time. In or der to prove that OBNLM has a better quality of denoising and shorter elapsed time than traditional NLM, we applied different level of noise in different image, and then denoises those images separately under NLM filter and OBNLM filter.

II. METHOD

The table below is the notations given for NLM and OBNLM algorithms:

symbol	explanation
$NL(u)(x_i)$	The intensity value of x_i after restored
$\omega(x_i, x_j)$	Weights of each pixel
$u(x_j)$	The true intensity of pixel x_j
Z_i	The normalization constant
$\left\Vert u(N_i) - u(N_j) \right\Vert_2^2$	The Gaussian Euclidean distance between two neighbor blocks

Nj	Square Block of xj and its neighborhood
u(Ni)	Vectors gathering the intensity values of Ni
h	smoothing parameter
a	Standard deviation of the Gaussian kernel
B(i)	Square Block centered in xi
B(j)	Square Block centered in xj

A. Traditional Nonlocal-means filter

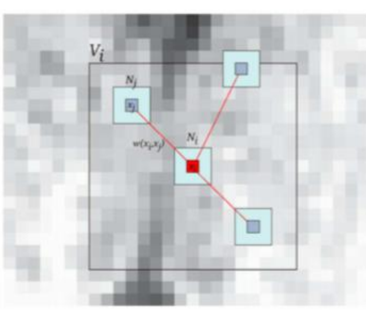
For obtaining filtered intensity of x_i, we use the equation below:

$$NL(u)(x_i) = \sum_{x_j \in \Omega^{\dim}} w(x_i, x_j) u(x_j) \qquad (1)$$

The NL(u)(x_i) represents the intensity value of the pixel x_i. And ω(x_i, x_j) is the weights of each pixel, and every pixel is weighted average in all pixels that in the search window. The weight is based on the similarity between the neighbor pixels. As we can see, the procedure to calculate the NL-means filtered intensity is calculating the product of the pixel's true intensity and the related Euclidean distance firstly. Then do a summation for all pixel's product in the search window which is the restored intensity for the central pixel of the search window. The weight equation is shown below:

$$w(x_i, x_j) = \frac{1}{Z_i} \exp - \frac{\|\mathbf{u}(\mathcal{N}_i) - \mathbf{u}(\mathcal{N}_j)\|_{2,a}^2}{h^2} \qquad (2)$$

Generally speaking, NL-means method is denoising by comparing the similarity between neighborhood by using Gaussian-weighted Euclidian distance, then doing calculate the weight in a search window. And repeat the procedure to restore all of the pixels in the whole image. The figure below shows how the traditional NL-means filter works.



From: Coupé, Pierrick, et al. "An optimized blockwise nonlocal means denoising filter for 3-D magnetic resonance images." Medical Imaging, IEEE Transactions on 27.4 (2008): 425-441.

Fig.1 Principle of Non-Local Mean denoising

B. Optimized Bayesian Non-local mean filter

Optimized Bayesian nonlocal-means is a great optimization denoising method based on nonlocal-mean.

For traditional NLM, we have to calculate the weight for all the pixels in the search window. Basically, it costs more than several minutes to restore a normal medical ultrasound image. It's not practical in real life.

But for OBNLM, we divide the pixels into blocks with each other, then performing an NL-means-like restoration of these blocks. The following are the equations for OBNLM:

Dividing the volume into blocks with overlapping supports,

$$\Omega^{\dim} = \bigcup_k B_{i_k} \qquad (3)$$

For each block B_{ik}, the restoration formula are:

$$\mathrm{NL(u)(B_{ik})} = \sum w(\mathrm{B_{ik}}, \mathrm{B_j})\mathrm{u(B_j)} \qquad (4)$$

and

$$\mathrm{w(B_{ik}, B_j)} = \frac{1}{\mathrm{Z_i}} \mathrm{e}^{\frac{\|\mathrm{u(B_{ik})} - \mathrm{u(B_j)}\|_2^2}{2\beta\sigma^2|\mathrm{N_i}|}} \qquad (5)$$

Then, restoring the pixel intensities form those restored blocks. And in this case, some pixels are might be the result of several overlapping blocks. It means we can get the several pixels intensity NL(u)(xi) in different NL(u)(Bik).

In addition, instead of using Gaussian Euclidean distance, OBNLM using the Pearson distance to compare the image patches. For each pixel, we assume:

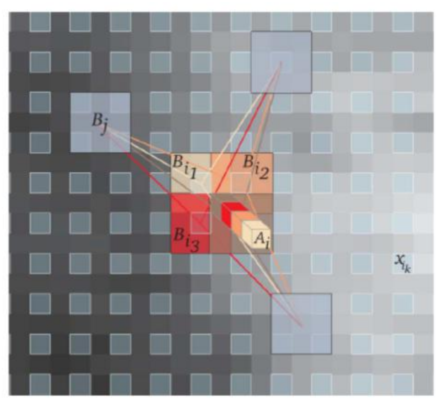
$$u(x)|v(x) \backsim \mathcal{N}(v(x), v(x)^{2\gamma}\sigma^2) \qquad (6)$$

Which yields

$$p(u(x)|v(x)) \propto \exp - \frac{(u(x) - v(x))^2}{2v(x)^{2\gamma}\sigma^2}. \qquad (7)$$

The do-called Pearson distance defined as:

$$d_P(\mathbf{u}(B_i), \mathbf{u}(B_j)) = \sum_{p=1}^{P} \frac{(u^{(p)}(B_i) - u^{(p)}(B_j))^2}{(u^{(p)})^{2\gamma}(B_j)} \qquad (8)$$



From Coupe et al, IEEE TMI, 2008

Fig.2 Principle of Optimized Bayesian Non-Local Mean denoising

C. Lee filter

The Lee filter is one of the well-known filters for despeckling and enhancing SAR images. It uses the minimum mean square error (MMSE) filtering criterion to carry out the despeckling. Lee filter is based on the following equation

$$\hat{Y}(t) = \hat{I}(t) + W(t)[I(t) - \bar{I}(t)] \quad (9)$$

$\hat{Y}(t)$ is the value of the image after it had been filtered. It is also the approximated version of Y(t), I(T) is the noise free image, while $\hat{I}(t)$ is the mean of I(t), $Cv=\sigma_v/\bar{V}$ is coefficient of variance of speckled image and $CI=\sigma_I/\bar{I}$ is the coefficient of variance of noise-free image.

And the weighting function W(t) is given by

$$W(t) = 1 - \frac{C_V}{C_I} \quad (10)$$

The Lee filter assumes that speckle noise is the same in all regions of a SAR image. This assumption is not suited to rapidly varied regions, such as edges, details of intensity image. It results in blurring the edges of SAR image when smoothing the speckle, then it does not hold the details effectively.

D. Result evaluation criteria

For this experiment, we chose three different evaluation methods to analyze the results of the experiment. The parameters we selected were Elapsed Time, SNR, and MSE, which were not filtered.

Elapsed Time This parameter can be used to measure the running time of the filter for noise processing. It represents the complexity and running cost of the related algorithm, and the lower the time, the lower the complexity of the algorithm and the better the running cost.

Signal-to-Noise Ratio (SNR)This parameter represents the ratio of signal strength to noise power. This data is often used to compare the level of the desired signal to the background noise:

$$SNR = \frac{P_{\text{Signal}}}{P_{Noise}} \quad (11)$$

This parameter can also be expressed in decibels (dB) using the following formula::

$$SNR_{\text{dB}} = 10\log_{10}\left(\frac{P_{Signal}}{P_{Noise}}\right) \quad (12)$$

Mean Square Error (MSE) This parameter can be used to represent the mean square value of the original image and the pixel difference of the restored image, and further determine the distortion of the restored image by the mean square value.Suppose that $\hat{Y}$ is a predicted vector and Y is a vector of observations corresponding to the function input. The MSE of the predictor can be estimated by the following formula:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(\hat{Y} - Y)^2 \quad (13)$$

III. RESULTS AND ANALYSIS

In order to prove that OBNLM is more useful than NLM filters, and to verify the performance of Lee filters, we chose to use MATLAB for simulation. In the program, we use different filters for filtering after adding noise to the same image, so as to obtain parameters generated by the different filters in the filtering process to verify the filtering efficiency and image quality, and analyze whether the generated image is obtained Better noise reduction and recovery.

A. Simulation

In order to be able to make a preliminary judgment on two different filters, OBNLM and NLM, we select the image "peppers.png" inside MATLAB as the original image and add random noise to it, then, use two filters to denoise the image . The output is shown in Figure 3. The time consumed by OBNLM is 15.696152 seconds and the time of NLM is 274.105370 seconds.

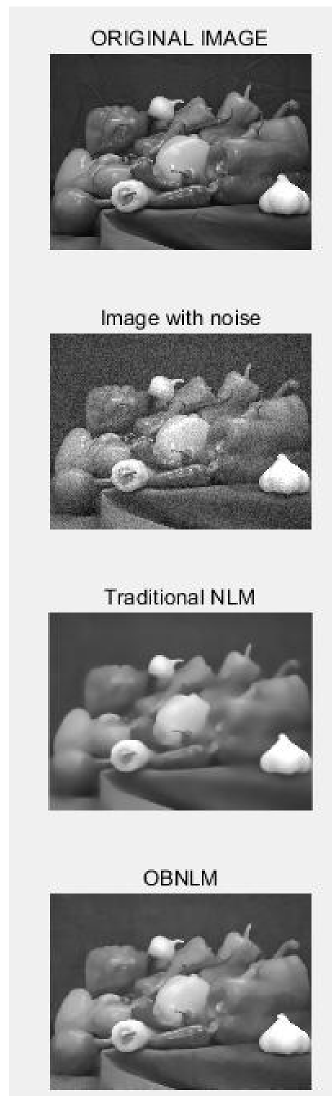


Fig. 3. The result of adding noise to the image "peppers.png" and processing it with NLM and OBNLM

In terms of visual effects, both processing methods can significantly reduce the effect of noise and image smoothing. Therefore, both conversion methods can be considered effective.

B. Practical Usage

In order to test the performance of two different filters in the actual ultrasound image processing process, we chose a liver ultrasound image for further comparison experiments.FIG. 4 is a simulation result diagram of processing an ultrasound image of the liver.

Fig. 4. The result of adding noise to an ultrasound image and processing it with NLM and OBNLM

The test results still show that both NLM and OBNLM filters can effectively denoise the ultrasound image. At the same time, for the two denoising methods, we can hardly distinguish which is better with the naked eye.

In the image in Figure 4, we chose to keep the value of the filter constant h fixed at 10 to keep the image clear. After several comparison experiments, we found that when the filter constant increases, the image will become smoother at the same time, but some original details of the image will be lost accordingly. therefore. We fixed h at 10, a constant that maintains both smoothness and detail.

C. Parameters for outcome evaluation

a). **Elapsed Time**

In order to be able to accurately analyze Elapsed Time, our group performed comparative experiments on a variety of different images. The results of the experiment are summarized as following Table 1:

Image number	NLM-ET	OBNLM-ET
1	84.181887s	4.230058s
2	318.076598s	23.189426s
3	77.615419s	13.109376s

Tab. 1. Elapsed Time when applied NLM & OBNLM

From Table 1, we can conclude that compared with NLM, OBNLM can significantly save image processing time. At the same time, the longer the NLM processing process consumes, the lower the proportion of OBNLM processing time used.

Tab. 1. Elapsed Time when applied NLM & OBNLM

b). **SNR** & **MSE**

We randomly selected a picture "cat.jpg" to analyze and compare the results of the other two parameters (SNR and MSE), the elapsed time and the denoising performance will be demonstrated in Table 2, the result is as Figure 5.

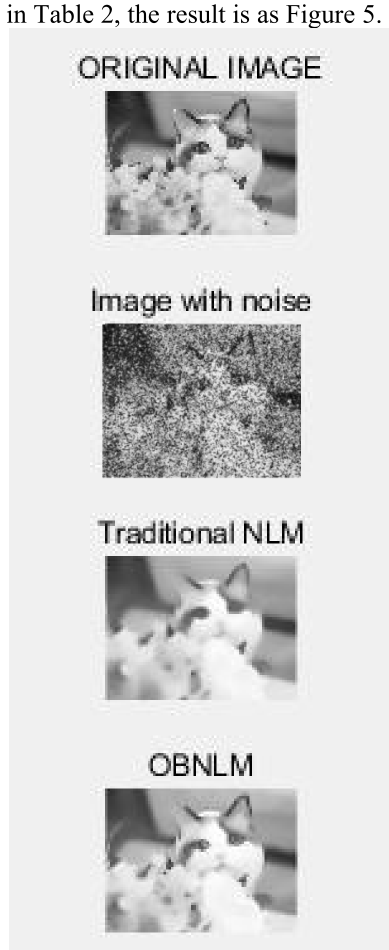


Fig. 5. The result of adding noise to an ultrasound image and processing it with NLM and OBNLM

	With noise	NLM	OBNLM
Elapsed Time(s)	Na	92.884480	23.036409
SNR(dB)	0.13084	21.6371	24.3786
MSE	2303.9085	2037.1477	2002.348

Tab. 2. Elapsed Time, SNR, MSE when applied NLM & OBNLM

From this result, we can see that both methods can effectively improve the SNR of the image, and the signal-to-noise ratio of OBNLM is higher than the signal-to-noise ratio of NLM, which shows that OBNLM has a better performance. Noise effect, the resulting image is also smoother.

We also analyzed the effect of σ on SNR, and compared NLM and OBNLM by changing the noise level (σ). We tested the SNR changes at three different noise levels of 0.2, 0.3, and 0.5 as shown in Table 3. As the noise level increases, the SNR of both NLM and OBNLM decreases.

	σ =0.2	σ =0.4	σ =0.6
NLM	23.3112	21.6371	17.5056
OBNLM	27.0021	24.3786	20.4172

Tab. 3. Elapsed Time, SNR, MSE when applied Lee

For the MSE aspect, both methods can significantly reduce the MSE, and the MSE reduction effect of OBNLM is more obvious, indicating that the image recovery is better.

c). Lee filter

The elapsed time and the denoising performance of Lee filter will be demonstrated in Table 3, the result is as Figure 6.

	With noise	Lee
Elapsed Time(s)	Na	0.0319965
SNR(dB)	0.13084	0.14238
MSE	2303.9085	2031.5166

Tab. 4. Elapsed Time, SNR, MSE when applied Lee

We also denoise the same image for the Lee filter. We can clearly see from the results that compared with the two methods of OBNLM and NLM, the Lee filter can complete the image processing at the fastest speed, but his MSE is much higher than the other two filters and the SNR is improved The amplitude is small. In other words, the Lee filter is more suitable for the period when the result needs to be obtained quickly.

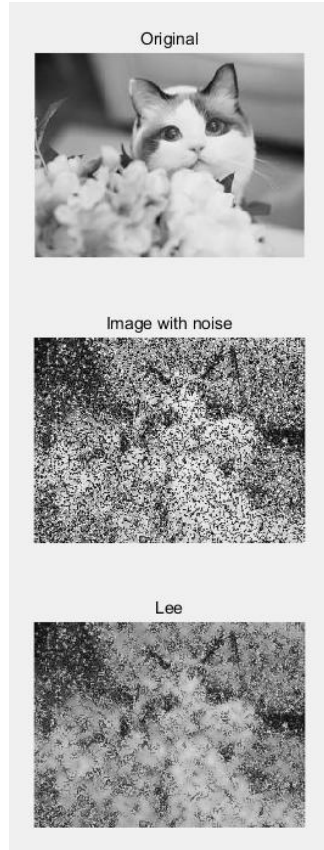


Fig. 6. The result of adding noise to an ultrasound image and processing it with Lee

IV. CONCLUSION

In summary, we can grind the running time, higher SNR and reflected MSE that OBNLM has during the denoising process. The Lee filter has the worst image denoising ability and the shortest processing time, which is suitable for the denoising process that requires fast image generation.

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