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Noise Estimation and Removal from Gray-scale Image using Non-Local Means Algorithm

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Abstract— ***Estimation of the level of noise from an image then deviate its variance from each pixel is a challenging task in image processing. In practice, an effective noise reduction algorithm should give information about type and level of noise present in the image then remove it without harming the fine details of the image. In this paper a noise estimation method is applied to know noise standard deviation and then noise variance is calculated. In this paper we first estimate level of noise present in noisy images by selecting low rank patches in image on the basis of gradient matrix and its statistical properties. Then remove that noise using non local means denoising technique that will use estimated noise level as filtering parameter for removing noise from image. This technique is based on weighted average of similar pixels in an image. Non local means techniques removes noise from images and preserve fine edges and fine details present in image.***

Keywords: NLM, FNLM, PSNR

I. INTRODUCTION

Image denoising is one of the most important and widely used concepts in various image related applications such as medical image analysis, object detection, satellite imagery etc. It is very difficult to get useful information from noisy images.That is why it is necessary to denoise images for accessing useful information from them. But performance of denoising techniques or degree of removal of noise from noisy images widely depends on the level of noise present in images. So it is also an important task to know about the true level of noise present in images and then basis on that standard deviation of noise, noise can be removed from images by using specific image denoising techniques.

Many algorithms [1]–[6] have been proposed for this topic.These approaches are filter-based and patch-based. In filter-based approaches [1 [3] [4] the noisy image is firstly filtered using a high-pass filter to suppress the image structures. Then the noise variance is computed from the difference between the noisy image and the filtered image. The main difficulty of filter-based approaches is that the difference of the two images is assumed to be the noise, but this assumption is not always true, especially for images with complex structures or fine details. In patch-based approaches [2] [5] [6], images are decomposed into a number of patches. The patches whose standard deviations of intensity close to the minimum standard deviation among decomposed patches are selected. Then the noise level is computed from the selected patches. This algorithm is simple and effective, but it tends to overestimate the noise level for small noise level cases and is underestimated in large noise level cases.

In this paper we use single image noise level estimation for blind denoising [7]. This approach includes the process of selecting low-rank patches without high frequency components from a single noisy image. The selection is based on the gradients of the patches and their statistics. Then, the noise level is estimated from the selected patches. After that we apply Non Local Means Algorithm [8] for the removal of noise from images.Non Local Means Algorithm use standard deviation of noise as filtering parameter to denoise noise.

Rest of the paper is organized as follow: Noise level estimation is discussed in section II, Removal of noise using NLM discussed in section III, experimental results are discussed in section IV and finally conclusion is drawn in section V.

II. NOISE LEVEL ESTIMATION

We use single image noise level estimation for blind denoising [7] for estimation of noise level in noisy image. In this approach image is divided in number of patches in a raster scan.

$$y_i = z_i + n_i \qquad (1)$$

Where $i = 1, 2, 3.....M$

Where M is the number of patches, z_i is the i-th noise free image patch with size $N \times N$ written in a vectorized format and each patch is defined by its center pixel, y_i is observed vectorized patch corrupted by Gaussian noise vector n_i with zero mean and variance σ_n^2. In this approach *xinhao liu* et.al propose a texture strength metric which is based on the local image gradient matrix and its statistical properties to select low rank patches.

xinhao liu et.al reported that image structure can be measured effectively by the gradient covariance matrix. Assuming an image patch y_i , its $N^2 \times N^2$ gradient matrix G_{y_i} can be expressed as

$$G_{y_i} = \left[D_h y_i \; D_v y_i \right] \tag{2}$$

Where D_h and D_v represent the matrices of horizontal and vertical derivative operators. The gradient covariance matrix C_{y_i} for the image patch y_i is defined[7] as:

$$\begin{aligned} c_{y_i} &= G_{y_i}^T G_{y_i} \\ &= \begin{pmatrix} y_i^T D_h^T D_h y_i & y_i^T D_h^T D_v y_i \\ y_i^T D_v^T D_v y & y_i^T D_v^T D_v y \end{pmatrix} \end{aligned} \tag{3}$$

where T denotes the transpose operator. The dominant direction and its energy can be measured using the eigenvectors and eigenvalues of C_{y_i} [7]

$$c_{y_i} = v \begin{pmatrix} s_1^2 & 0 \\ 0 & s_2^2 \end{pmatrix} v^T \tag{4}$$

Sum of all Eigen values of the covariance matrix reflects the texture strength of that patch. A larger trace reflects a richer texture. We define the texture
Strength ξ_i as

$$\xi_i = tr(C_{y_i}) \tag{5}$$

To analyze the statistical properties of texture strength, *xinhao liu* et.al approximate the distribution of ξ_i by the gamma distribution to simplify the problem. The p.d.f. of $\xi(i)$ can be derived as shown below:

$$\xi(i) = Gamma\left(\frac{N^2}{2}, \frac{2}{N^2}, \sigma_i^2 tr(D_h^T D_h + D_v^T D) \right) \tag{6}$$

To select the weak textured patches, we define the null hypothesis: “the given patch is a flat patch with the white Gaussian noise”. We select the patches for which the null hypothesis is accepted. The confidence interval that covers the value of $\xi(i)$ is defined

$$p(0 < \xi(i) < \tau) = \delta \tag{7}$$

If the texture strength of that patch is less than the threshold τ , then the null hypothesis is accepted and that patch can be regarded as the weak textured patch. The threshold τ can be expressed as a function of the given significant level δ and noise level σ_n , as shown

$$\tau = \sigma_i^2 F^{-1}\left(\partial, \frac{N^2}{2}, \frac{2}{N^2}, tr(D_h^T D_h + D_v^T D) \right) \tag{8}$$

Therein, $F^{-1}(\delta, \alpha, \beta)$ is the inverse Gamma cumulative distribution function with the shape parameter α and scale parameter β. Also, δ is the confidence level σ_i is the standard deviation of the Gaussian noise, N^2 represents the number of pixels in the patch, and D_h , D_v are matrices derived from the gradient filter.In this approach noise is estimated in an iterative process until the estimated noise level remains unchanged.
Thus using this approach first we estimate level of noise present in image then after that that we denoise the image by using Non Local means denoising algorithm that will use this estimated noise level as filtering parameter to remove noise from image.

III. REMOVAL OF NOISE USING NLM

After estimating noise level we remove noise from images using non local means algorithm [8].This algorithm uses noise level calculated by Noise level estimation techniques [7] techinique as filter parameter to denoise images. This technique is based on weighted average of similar pixels in an image. In non local means algorithm [8] two windows are placed on image: one is similarity window and other is search window. In this techniques first of all using similarity window, the similarity between central pixel and all its neighbors in the region of search window, is calculated. Then calculate the average weight of similar pixels. After that weight of central pixel is replaced with that average weight. This process is repeated for every pixel of image.
NL means algorithm given by *Buades et al* is described as:
Buades et al defined NL means algorithm by a simple formula

$$NL[u](x) = \frac{1}{c(x)} \int_{\Omega} \ell^{-\frac{G_a * |u(x+.)-u(y+.)|^2(0)}{h^2}} u(y)\,dy \tag{9}$$

where $x \in \Omega$

and
$$c(x) = \int_{\Omega} \ell^{-\frac{G_a * |u(x+.)-u(y+.)|^2(0)}{h^2}} dz \tag{10}$$

is a normalizing constant, G_a is a Gaussian kernel and h act as filtering parameter.

h = *estimated noise level* (σ)

This formula amounts to say that denoised value at x is a mean of the values of all points whose Gaussian neighborhood looks like the neighborhood of x.

Given a discrete noisy image $v = \{v(i) \mid i \in I)$, the Estimated value $NL[v](i)$, for a pixel i, is computed as a weighted average of all the pixels in the image,

$$NL[v](i) = \sum_{j \in i} w(i, j) v(j) \tag{11}$$

where weights $\{w(i, j)\}_j$ depend on the similarity between the pixels i and j satisfy the following condition

$$0 \le w(i, j) \le 1 and \sum_{j} w(i, j) = 1 \tag{12}$$

This similarity is measured using Euclidean distance, The Euclidean distance between two points i and j is measured as:

$$d(i, j) = \sum_{k=1}^{n} \sqrt{(i_k - j_k)^2} \tag{13}$$

The similarity between two pixels i and j depends on the similarity of the intensity gray level vectors $v(N_i)$ and $v(N_j)$, where N_k denotes a square neighborhood of fixed size and centered at a pixel k. Euclidean distance of these vectors N_i and N_j is measured as:

$$\left\| v(N_i) - v(N_j) \right\|_2^2 \tag{14}$$

The application of the Euclidean distance to the noisy neighborhoods raises the following equality:

$$E\left\| v(N_i) - v(N_j) \right\|_{2,a}^2 = \left\| u(N_i) - u(N_j) \right\|_{2,a}^2 + 2\sigma^2 \tag{15}$$

This equality shows the robustness of the algorithm.

The pixels with a similar grey level neighborhood to $v(N_i)$ have larger weights in the average. These weights are defined as:

$$w(i, j) = \frac{1}{Z(i)} e^{-\frac{\left\| v(N_i) - v(N_j) \right\|_{2,a}^2}{h^2}} \tag{16}$$

Where $z(i)$ is the normalize constant

$$Z(i) = \sum_{j} e^{-\frac{\left\| v(N_i) - v(N_j) \right\|_{2,a}^2}{h^2}} \tag{17}$$

the parameter h acts as a degree of filtering which is equal to standard deviation of noise which is calculated by Noise estimation technique[7]. Thus using estimated noise level and applying NL means algorithm we remove noise from image while preserving structure of image. Results of denoising discussed in next section.

IV. EXPERIMENTAL RESULTS

First of all we take some Lena images of size 512 ×512 that are corrupted with gaussian noise. In these type of images we don't have any idea about the noise level (σ).So first we use noise level estimation technique [7] and calculate the noise level (σ) present in images. Then we apply Non local means algorithm for removal of noise from images that uses noise level as a filter parameter for noise removal. Then we calculate mean square error and peak signal to noise ratio of denoised image. It shows that Non local means provide better results in image denoising.

We compare results of Non local means technique with Fast non local means technique [9] and another fast non local means technique given by *Zhengguo*[10] in terms of MSE and PSNR. Results of NLM[8] and Fast non local means algorithm by Zhengguo[10] are comparable and also are much better than FNLM[9] . These results are shown by following tables. Table1. Show results of mean square error of these techniques and table2. Show results of PSNR values of these techniques.

Table 1. MSE Results in case of Lena images

Estimated noise level(σ)	MSE of NLM	MSE of FNLM	MSE of NLM_zhengguo
10.13	20.66	53.31	20.00
15.08	32.59	107.86	30.39
19.79	46.14	182.49	41.92
24.78	59.86	272.47	54.16
29.35	77.19	382.39	68.23

Table 2. PSNR Results in case of Lena images

Estimated noise level(σ)	PSNR of NLM	PSNR of FNLM	PSNR of NLM_zhengguo
10.13	35.012	30.896	35.155
15.08	33.033	27.836	33.338
19.79	31.523	25.552	31.940
24.78	30.393	23.811	30.827
29.35	29.289	22.339	29.825

Figure 1 & 2 visualize the comparison of MSE and PSNR values of techniques.

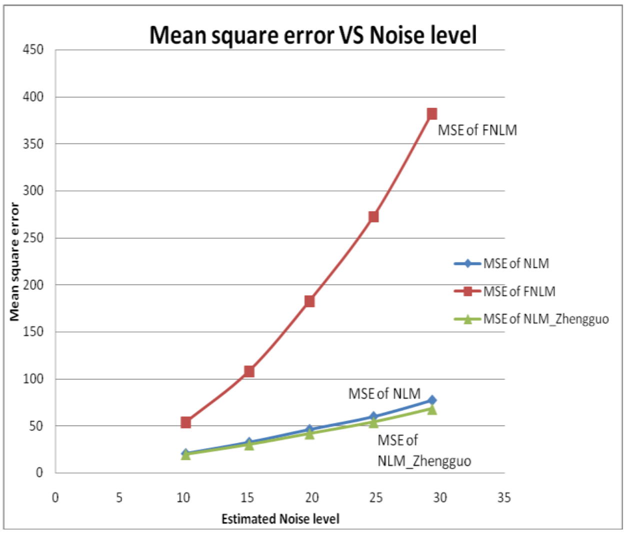

Figure.1 Estimated noise level (σ) and mean square error of denoised Lena image.

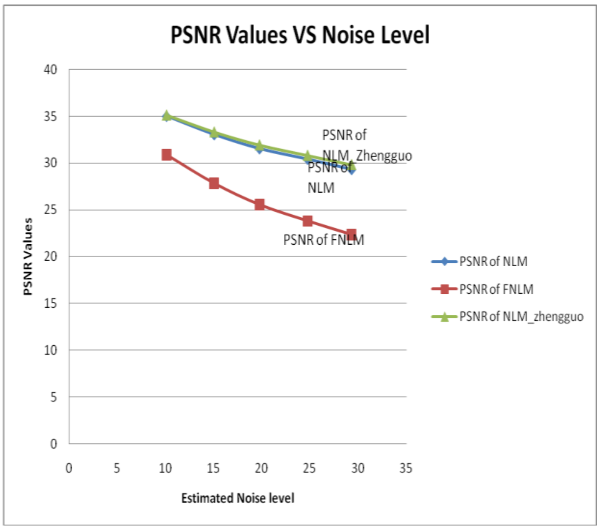

Figure2 Estimated noise level (σ) and PSNR of denoised lena image

Figure.3 (a) Noisy lena image (b) image denoised with NLM (c) Image denoised with FNLM (d)Image denoised with NLMF_Zhengguo

We also apply same techniques on other images like Barbara images512×512) and Goldhill images(512×512) that contains different level of gaussian noise. We first calculate level of noise by using noise estimation technique then apply Non Local Means technique to denoise them .After that we also apply fast non local means[9] and NLM_Zhengguo[10] to denoise image and compare their results with the results of Non local Means techniques. This shows that In case of Barbara image results of Non Local means techniques and NLMF_Zhengguo are comparable and much better than FNLM . But in case of Goldhill images that are rich texture images results of NLM are better than both FNLM and NLMF_Zhengguo.

Table 3 and table 4 shows MSE and PSNR results of these techniques in case of barbara image. Fig 4 &5 visualize the comparison of results of these techniques in case of barbara images.

Table 3. MSE results in case barbara images

Estimated noise level(σ)	MSE of NLM	MSE of FNLM	MSE of NLM_zhengguo
19.72	063.34	0200.01	058.24
24.43	086.56	0297.42	078.94
28.96	113.58	0413.10	103.57
37.84	172.45	0681.46	157.23
46.20	240.33	1001.93	219.90

Table 4. PSNR results in case barbara images

Estimated noise level(σ)	PSNR of NLM	PSNR of FNLM	PSNR of NLM_zhengguo
19.72	30.148	25.152	30.512
24.43	28.791	23.431	29.191
28.96	27.611	22.001	28.012
37.84	25.798	19.830	26.199
46.20	24.356	18.156	24.742

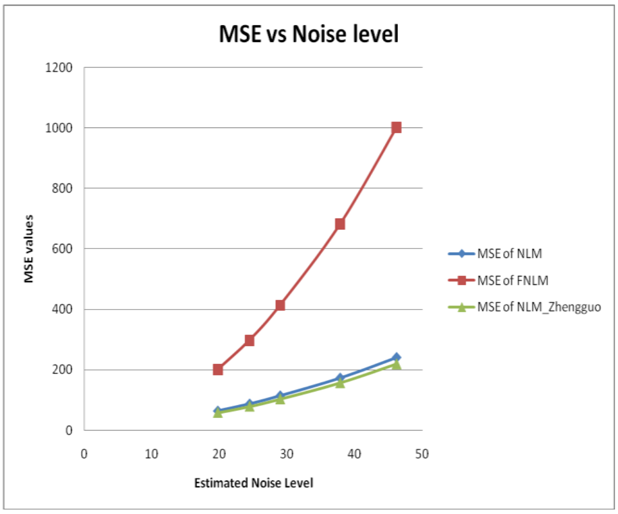

Figure 4 Estimated noise level (σ) and mean square error of denoised Barbara image.(512×512)

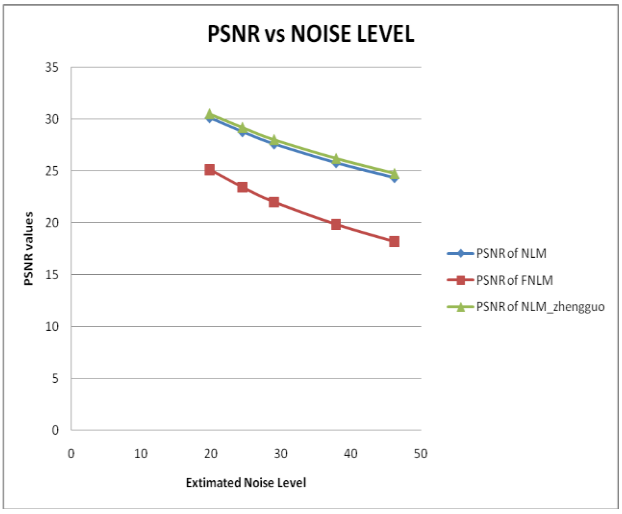

Figure.5 Estimated noise level (σ) and PSNR of denoised barbara image(512×512)

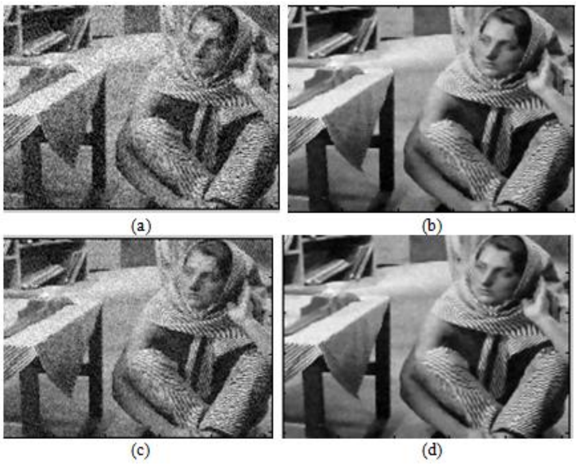

Figure.6 (a) Noisy Barbara image (b) image denoised with NLM (c) Image denoised with FNLM (d)Image denoised with NLMF_Zhengguo

Table 5 and table 6 shows MSE and PSNR results of these techniques in case of goldhill image. Fig 7 &8 visualize the comparison of results of these techniques in case of Goldhill images

Table 5. MSE results in case of Goldhill images(rich texture)

Estimated noise level(σ)	MSE of NLM	MSE of FNLM	MSE of NLM_zhengguo
10.27	34.50	60.59	37.87
14.96	51.77	119.51	55.16
19.98	70.05	193.06	73.29
24.72	90.01	284.43	91.43

Table6. PSNR results in case Goldhill images

Estimated noise level(σ)	PSNR of NLM	PSNR of FNLM	PSNR of NLM_zhengguo
10.27	32.787	30.340	32.381
14.96	31.023	27.390	30.748
19.98	29.711	25.307	29.514
24.72	28.621	23.625	28.553

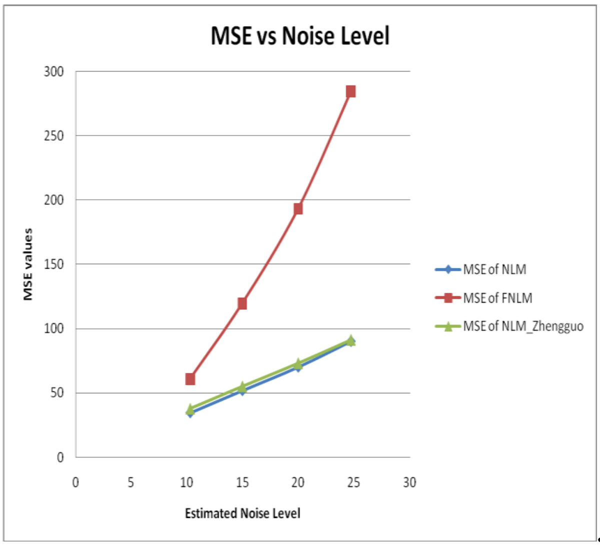

Figure.7 Estimated noise level (σ) and mean square error of denoised Goldhill image.(512×512)

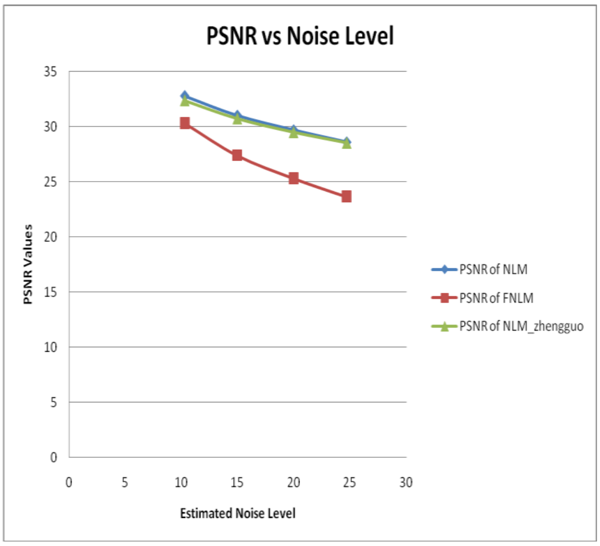

Figure.8 Estimated noise level (σ) and PSNR values of denoised goldhill image.(512×512)

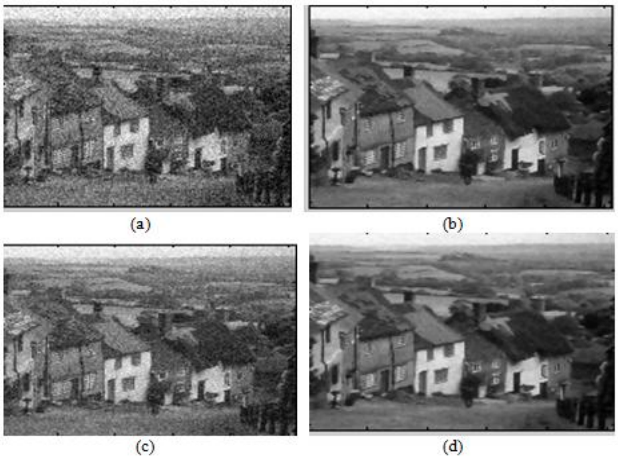

Figure.9 (a) Noisy Goldhill image (b) image denoised with NLM (c) Image denoised with FNLM (d)Image denoised with NLMF_Zhengguo

V. CONCLUSION

In the end this work meets its goal. Noise level estimation technique estimates noise present in image and Non Local Means Agorithm removes noise from image using that estimated noise level. Non Local Means algorithm provides outstanding results in denoising images and also preserves edges, lines and fine details present in image But this techniques is very time consuming.It takes lot of time for denoising images those have a high level of noise.

REFERENCES

[1] K. Rank, M. Lendl, and R. Unbehauen, "Estimation of image noise variance," *IEEE Proc. Vis., Image, Signal Process.*, vol. 146, no. 2, pp. 80–84, Aug. 1999.

[2] A. Amer, A. Mitiche, and E. Dubois, "Reliable and fast structure oriented video noise estimation," in *Proc. Int. Conf. Image Process.*,vol. 51. 2002, pp. I–840–I–843.

[3] B. R. Cornera, R. M. Narayanana, and S. E. Reichenbach, "Noise estimation in remote sensing imagery using data masking," *Int. J. Remote Sens.*, vol. 24, no. 4, pp. 689–702, 2003.

[4] S.-C. Tai and S.-M. Yang, "A fast method for image noise estimation using Laplacian operator and adaptive edge detection," in *Proc. 3rd Int. Symp. Commun., Control Signal Process.*, Mar. 2008, pp. 1077–1081.

[5] D.-H. Shin, R.-H. Park, S. Yang, and J.-H. Jung, "Block-based noise estimation using adaptive Gaussian filtering,"*IEEE Trans. Consumer Electron.*, vol. 51, no. 1, pp. 218–226, Feb. 2005.

[6] C. Liu, R. Szeliski, S. B. Kang, C. L. Zitnick, and W. T. Freeman, "Automatic estimation and removal of noise from a single image," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 30, no. 2, pp. 299–314,Feb. 2008.

[7] Xinhao Liu,Masayuki Tanaka, Masatoshi okutomi, "Single image noise level estimation for Blind denoising", *IEEE trans. On image processing, vol. 22 No.12 dec2013.*

[8] A. Buades, B. Coll, and J. M. Morel, "A non-local algorithm for image denoising," *In: Proc. IEEE CVPR*, vol.2, 2005.

[9] Jerome Darbon,Alexandre Cunha, Tony F. Chan, Stanely Osher, Grant J Jensen, "Fast non local filtering applied to electronic cryomicroscopy", *IEEE transacyion on image processing dec 2012*

[10] Pierrick Coupé, Jose V. Manjón, Montserrat Robles, D. Louis Collins, "Adaptive Multiresolution Non-Local Means Filter for 3D MR Image Denoising", IET Image processing, 6(5): 558-568, 2012.

