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A Study on Image Noise Removal Techniques for Magnetic Resonance Imaging

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Abstract
Medical image denoising is very important and challenging area in the field of image processing. MRI (Magnetic resonance imaging) is very popular and most effective imaging technique. During the acquisition, MR images affected by random noise can be modeled as Gaussian or Rician distribution. In last few decades, so many denoising techniques were proposed but there are some limitations with the algorithms, because image edges and fine details are need to preserve. So there is need of compromise between de-noising quality and edge preservation to use images for real time application. Computation time is also very important parameter to implement the algorithms. In this paper, we have done an overview of different denoising algorithm. It observes that NLM (Non-Local Means) filter is much better than other existing state of art methods. Here study is done for enhancement of NLM to improve the performance. Results of different algorithms show that PCA (Principal Component Analysis) based algorithm with NLM performs much better in both quantitative and qualitative manner.

Keywords: MRI, Rician Noise, Gaussian Noise, Non Local means, PCA, PSNR, BC.

1. Introduction:

Digital Image Processing is most important and widely used domain of research work. It has applications in many areas like computer vision, remote sensing, communication, defence and medical field. Computers are very good at storing and manipulating data, so that digitized image can used to archive, examine, alter, display, transmit, or print in an incredible variety of ways. Image processing in the field of medical science is also known as Biomedical Image Processing. Medical image processing include the study of internal body structure like organs, tissues, etc., which produce better information and help to detect disease using the digitalized data of human organs. It makes the diagnose process much easier, faster and cost effective [1].

With the software development in image processing, new techniques and algorithms have been introduced in last decades, which are used before, during and after the treatment. Some processes like segmentation, registration, visualization and simulation are main key components of medical image processing. X-ray, computed tomography (CT), Ultrasound and Magnetic Resonance Imaging (MRI) are most useful terms of image processing. These different types of imaging techniques are generally known as modalities [2].

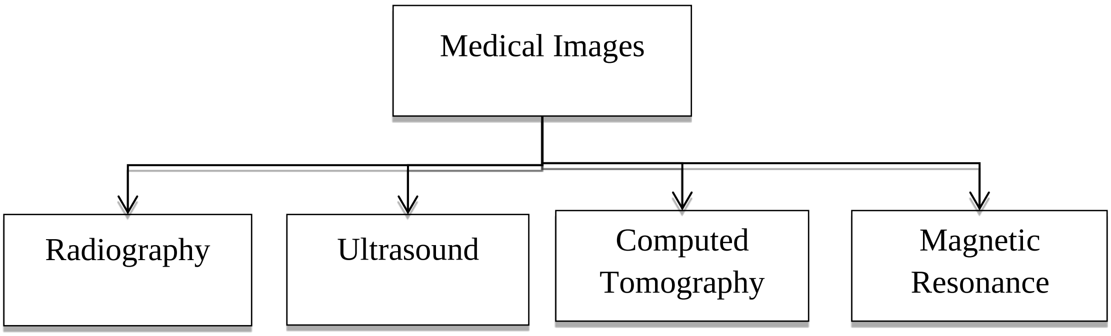

Figure 1. Typed of Medical Images

Roentgen discovered [3] X-rays and pioneered medical imaging in 1985, which can allows to visualize the interior of the human body without going through surgery. X-ray diagnoses bone degeneration, fractures and dislocation [3]. On the other side Ultrasound imaging does not uses ionizing radiation which damage body tissues. Ultrasound use high frequency sound waves for imaging human body structure and observe distinctive patterns of echoes. The only drawback with ultrasound is that it produce high noisy image, which made difficult to analyze small features of body. The computer tomography (CT) is a 3D view of X-ray radiography. A contrast agent can be used to artificially increase the contrast in the tissues of human body to get better image quality [3].

CT images show the inner auditory canals and produce superior visualization of cells.Cancer, abnormal chest x-rays and bleeding in the brain because of injury is better shown in CT scan, but tendons and ligaments cannot be shown very well. These all are best seen by MRI like Spinal cord of knees and shoulders. MRI images produce clearer differences between normal and abnormal tissue than CT images [4].In MRI, Body is placed into magnetic field. Hydrogen molecules of water in body start to spin in the same direction of the magnetic field. These hydrogen molecules starts wobble at certain frequency. At this frequency, when a radio frequency is introduced into the magnetic field, both the hydrogen molecules frequency and radio frequency resonate. It is further used by the MRI computer to produce the images. The MRI technique does not use High radiation like X-ray images, therefore it is “safe method” [4].

2. Noise Model for Medical Images:

During acquisition or transmission, MRI images are mostly corrupted by noise. Noise is not only generated by receiving coil resistance, but inductive losses also include with it. It may be due to imperfect instrument, susceptibilities between neighboring tissues, interference, rigid body motion and compression. The magnitude MRI images are best explained by a Gaussian distribution [5].

Henkelman [6] studied about the characteristics of noise in magnitude images, and developed an analytical expression of noise. The quadrature detector [7] measure the signals in real and imaginary form. The Fourier transform uses acquired data to reconstruct real and imaginary images. Due to linear and orthogonality of complex Fourier transform, Gaussian characteristic of noise will be preserved and variance of the noise will be uniform.

2.1 Magnitude Images:

Magnitude images calculated using magnitudes of each pixel one by one from real and imaginary images. Because of non-linearity of calculations, noise cannot be represented as Gaussian distribution. Now probability distribution for measured pixel intensity can be shown as

$$p_M(M) = \frac{M}{\sigma^2} e^{-\frac{A^2+M^2}{2\sigma^2}} I_0\left(\frac{A.M}{\sigma^2}\right) \tag{1}$$

Where A is represent original pixel intensity and M as measured pixel intensity.

I_0 = Modified zeroth order Bessel function of the first kind and

σ= standard deviation of the Gaussian noise in the real and the imaginary images.

It is observed that the distribution of noise is considered as rician for the range of $1 \leq \frac{A}{\sigma} \leq 3$. For$\frac{A}{\sigma} \geq 3$, this cannot be rician but approximated towardsGaussian distribution. For $\frac{A}{\sigma} = 0 \text{or} A = 0$, Rician distribution is known as Rayleigh distribution, where no image signal and only noise present in MRI image.

$$\frac{A}{\sigma} = \begin{cases} \frac{A}{\sigma} = 0 \quad \text{Rayleigh distribution} \\ 1 \leq \frac{A}{\sigma} \leq 3 \quad \text{Rician distribution} \\ \frac{A}{\sigma} \geq 3 \quad \text{Gaussian distribution} \end{cases}$$

3. MRI Denoising Methods:

This section includes a long term study of different noise removal algorithms for magnetic resonance images. The evaluations of modern de-noising techniques in medical imaging are become very advance, analytic and complex.

There is always a compromise between the SNR (Signal to Noise Ratio) and resolution. If SNR is very low it is difficult to analyze the image. Noise removal process can be categorized in two ways, noise removal during image acquisition and noise removal after acquisition. While removal of noise during acquisition, either acquisition time increases or visual quality decreases. But for higher level medical imaging like CT images and MRI images, it will take very large acquisition time which makes patient uncomfortable because they have to be steady for long time. So noise removal after image acquisition is preferred.

During the noise removal of MRI image after the acquisition, fine details of image and other parameter should not effected by noise removal process. Here, different algorithms of noise removal in post-acquisition are discussed. The noise removal techniques can be divided in three main categories, i.e. filtering domain, transform domain and statistical domain [8].These domains can be further classified in sub-categories such as filtering process can be linear or non-linear. Transform domain can be classified as wavelet transform, curvelet transform or counterlet transform. Statistical domain can be based on maximum likelihood, LMMSE (Linear Minimum Mean Square Error) or error based estimation.

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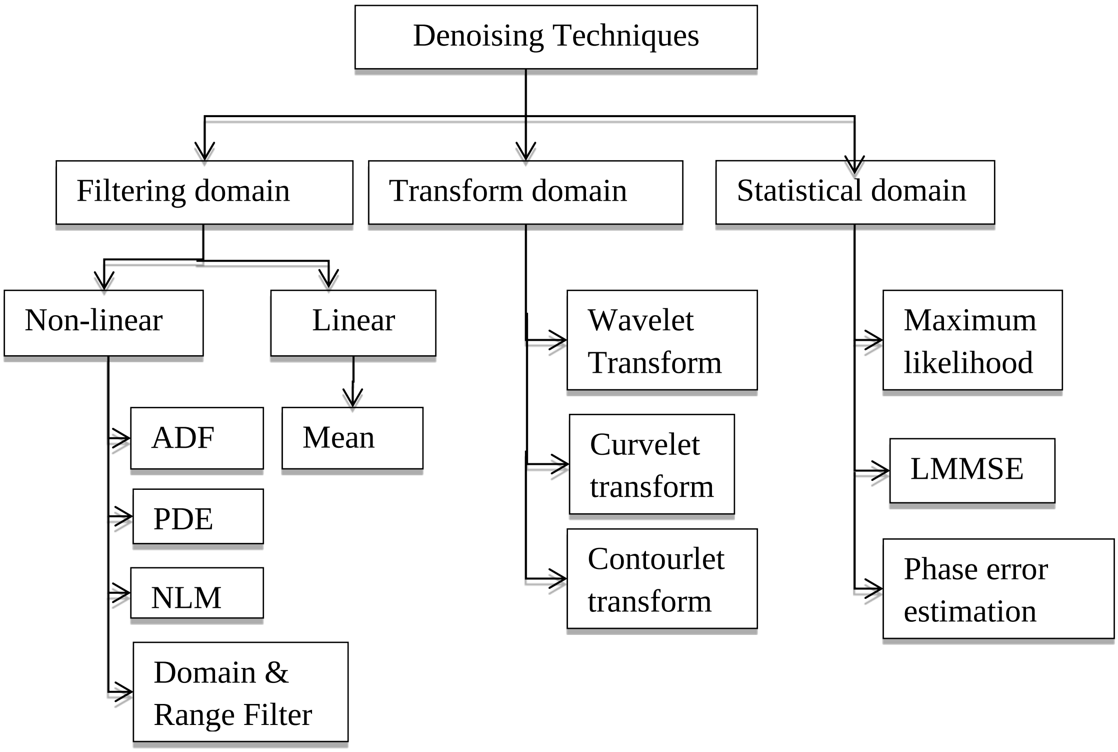

Figure 2. Classification of Denoising Methods

3.1 Transform Domain:

Wavelet-domain filtering is very important and effective for spatial variations in the signal behavior. It also preserves important edges and other fine details while removing noise [10].Wavelet divides the signal into different frequency components according to their scale of hierarchy. It is a multi-resolution representation of signal. First it transforms the image into wavelet domain signals and calculates the wavelet co-efficient. There after it reduce the effect of noise by thresholding wavelet co-efficient. Finally it takes inverse wavelet transform of these coefficients and recovers the de-noised image.
To deal with high dimensional data and sharp edges, which cannot be described well by wavelet, curvelet transform based method [11] is better option. First it compute all thresholds and norms of curvelet, then apply curvelet transform by hard thresholding on curvelet coefficient and finally inverse curvelet transform to reconstruct de-noised image.

3.2 Statistical approach:

Maximum likelihood (ML) based approaches are suggested to remove Rician noise. L. He and I.R. Greenshields combine non local and ML concept to estimate Rician noise and Rajan et al. [12] uses local variance for ML based estimator. Some statistical methods [13] uses Linear minimum mean square error estimator for rician noise, which use local variance, the local mean and the local mean square value. Many de-noising methods are reviewed by Aja-Fernandez et al. [14] for non-central Chi and central Chi distribution used for multiple coil imaging.

3.3 Filtering domain:

Filters are of two type i.e. linear filters and non-linear filters. Linear filters are spatial filters and temporal filters. These filters are very effective to remove the gauss ion noise from MRI images therefore also known as Gaussian filter. But these filters introduce blurring into edges because it average pixels of non-similar patterns. Spatial filter is based on convolution of image with filters function in spatial domain. Also temporal filter remove the aliasing effect by proper selection of sampling interval because large frequency band introduce aliasing and narrow frequency band affect the sharp edges of image. To overcome this problem of blurring edges, Non-linear filters were introduced like Perona and Malik [15] developed a multiscale smoothing algorithm with edge preservation called as anisotropic diffusion algorithm. It is based on second order partial differential equation (PDE). Adaptive anisotropic diffusion filter is used for edge sharpening and contour orientation and curvature control.

All these methods are basically based on the assumption that noise is spatially uniform noise distribution. Another nonlinear filter is Non local means (NLM) filter which is based on providing different weights to neighbours and taking average of those pixels.

Jose V. Manjon et al [16] proposed Non local means filter based on pixels comparison, but NLM works on the concept of region comparison based on their distance of intensity and then average the same image pixels. The weighted average of NLM filter is based on the formula

$$NLM\left(Y(p)\right) = \sum_{\forall_q \in Y} W(p,q)\, Y(q) \qquad (2)$$

Where

$$0 \le W(p,q) \le 1$$
$$\sum_{\forall_q \in Y} W(p,q) = 1$$

p = point being filtered and

q = each one of the pixels in the image

N_i= square neighbourhood window centered around pixel i

R_{sim} = user-defined radius

w(p,q) = based on the similarity between the neighborhoods Np and Nq of pixels p and q.

$$W(p,q) = \frac{1}{Z(p)} e^{-\frac{d(p,q)}{h^2}}$$
$$Z(p) = \sum_{\forall_q} e^{-\frac{d(p,q)}{h^2}}$$

Z(p) = normalizing constant,

h = exponential decay control parameter

d = Gaussian weighted Euclidian distance which shows the order of similarity.

And finally, the unbiased NLM (UNLM) will be calculated as

$$NLM\,(Y) = \sqrt{NLM\,(Y)^2 - 2\sigma^2} \qquad (3)$$

3.3.1 Fast Non Local Means:

[17] One of the drawbacks of unbiased non-local means algorithm is complexity. The computational burden of NLM is quite high which can be resolve by proper selection of voxels in search volume. Pierrick Coupe1et al suggested a way is to reduce the number of voxels used to calculate the weighted average. In this fast algorithm, the pre-selection of the voxels is depends on the first and second order moments of two regions.

3.3.2 Optimized Blockwise Nonlocal Means Denoising Filter:

To overcome the above drawback, the method proposed by Pierrick Coupe et al [18] is Blockwise non-local means filtering and concept of parallel computing, which reduce computation time. This filter provides Automatic Tuning of the Smoothing Parameter h, which depends on the standard deviation of the noise σ. To deal with computational burden, it improves process of Selection of Voxel in the Search Volume. According to Mahmoudi and Sapiro method, subset pre-selection based on most relevant voxels reduce the unnecessary computations weight. The selection depends on the similarity of intensity average value and gradient orientation of neighbourhood voxels and voxel under study. The block-wise implementation consists of three approaches. First it divides the search volume into no of blocks, and then uses non-local means filtering to restore the value of each block and these restored values from the blocks uses to restore the final voxel values. The advantage of this method is to reduce the computational burden of the algorithm. Another option for computational reduction is parallel computation. This requires dividing the complete operation into different processes using cluster or grid.

3.3.3 Adaptive NLM Method:

Most previous denoising techniques consider uniform distribution of noise but noise is not uniform always. For varying noise level, adaptive methods [19] need to be used in which optimal parameters are automatically adopted for different noise regions. It set the filtering parameter h to minimum distance, which reduce the overestimation of noise variance and compensate in homogeneity by finding more similar patches. It has main advantage that it does not require any parameter to represent noise level instead it adapted automatically the noise density present in image.

Previous NL-means filter developed to remove Rician noise with the help of conventional approaches and maximum likelihood estimator (MLE). This filter removes the noise very efficiently while preserving the fine details of images especially for high density noisy images.

4. Results Analysis:

The analysis of different de-noising algorithm is based on quality measure like Peak Signal to Noise Ratio (PSNR) [19], Mean Squared Error (MSE) [19] and structural similarity index (SSIM) [19] measure of blurring of image edges.

PSNR defines the performance of algorithm and it represents mathematically as

$$PSNR = 10 \; \log\left[\frac{255^2}{\frac{1}{MN}\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}\left(I(i,j) - \hat{I}(i,j)\right)^2}\right] \qquad (5)$$

And Mean Square error (MSE) define as

$$MSE = \frac{1}{MN}\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}\left(I(i,j) - \hat{I}(i,j)\right)^2 \quad (6)$$

Where M xN is size of the image $I(i,j)$ represents original image and $\hat{I}(i,j)$ represents restored image. Another quality measures is Structural similarity index matrix (SSIM), which specify the human visual system.

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)} \quad (7)$$

The parameters $\mu_x$and μ_y represrnt mean value of images x and y. σ_x and σ_y are standared deviation of images x and y. σ_{xy} represents covariance of x and y. Constant C_1 and C_2 are $C_1 = (K_1L)^2$ and $C_2 = (K_2L)^2$, where L is dynamic range and $K_1 = 0.01$, $K_2 = 0.03$. For 8 bit images, the value of L is 255 for 8 bit gray images.

Figure 4 showing the Simulated T1, PD and T2 phantom images and figure 5 shows theT1 image effected by Rician noise and then de-noised using NLM and ANLM filter.

The results are compared for different denoising algorithms for different noise densities experimented on brainweb T1 weighted phantom image. The Table 2 showing the quantitative analysisbased on PSNR of different denoising techniqueslike PRI-NLM, ODCT, BM4D, OBNLM, NL-PCAand PRI-NL-PCA. The results shows that Principal component analysis method combined with Non-Local means (PRI-NL-PCA) produces much better results the other state of art methods. Table 3 showing the comparison of SSIM which shows that NL-PCA andPRI-NL-PCA produces best results among all other methods. Computational time is also very important parameter of any algorithm to implement it in real time application. Here Table 5 shows the computational time require for the execution of different algorithm like NLML (Maximum Likelihood NL), RNLM (Rician Non-Local means)and ORNLM (Optimized RNLM). NLM with wavelet is very fast method for Gaussian Noise and RLML is faster for Rician noise.

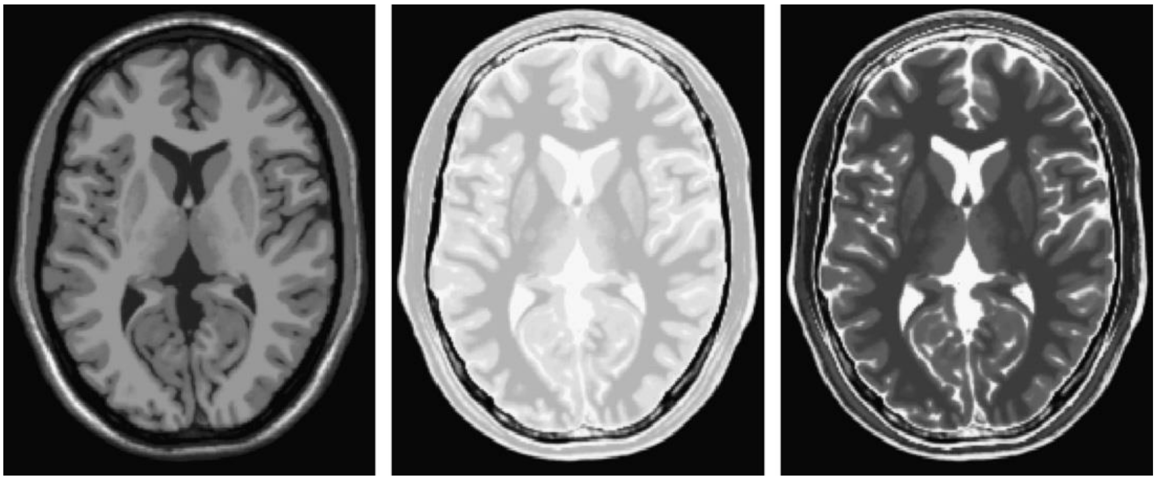

Figure 4. Simulated MR images (T1, PD and T2) from the Brainweb phantom

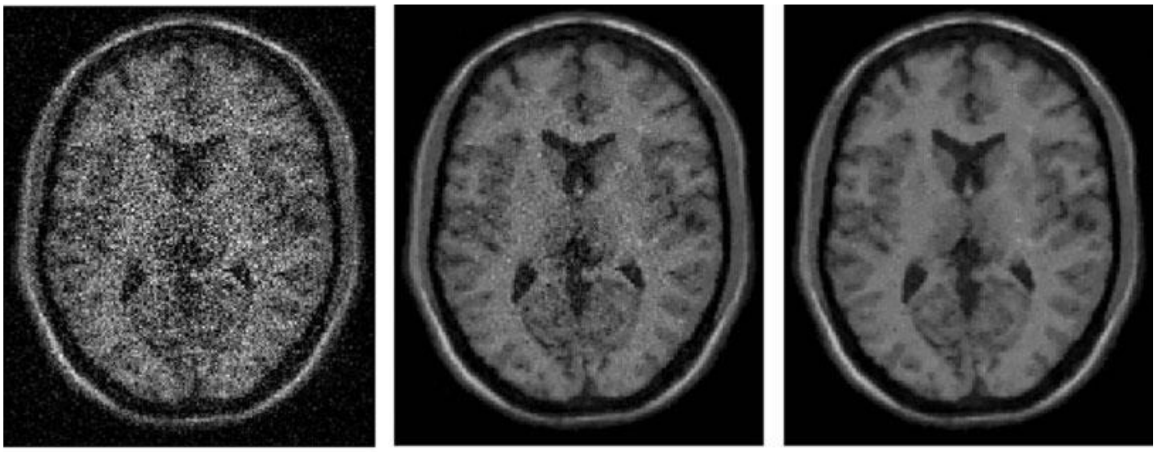

Figure 5. (a) Noisy Image, (b) Filtered by NLM, (c) Filtered by ANLM [71]

Table 2. Peak Signal to Noise Ratio (PSNR) in dB

Sr. no.	Technique	Noise Density (%)				
		1%	3%	5%	7%	9%
1.	Noisy [20]	40.00	30.49	26.09	23.20	21.04
2.	PRI-NLM [20]	43.97	38.19	35.34	33.37	31.94
3.	ODCT [20]	42.96	37.38	34.70	32.90	31.53
4.	BM4D [20]	44.09	38.34	35.82	34.17	32.89
5.	OBNLM [20]	42.41	37.45	34.54	32.51	30.97
6.	NL-PCA[21]	44.79	38.90	36.23	34.37	32.88
7.	PRI-NL-PCA[21]	**45.31**	**39.34**	**36.58**	**34.74**	**33.28**

Table 3. Structural similarity index matrix (SSIM)

Sr. no.	Technique	Noise Density (%)				
		1%	3%	5%	7%	9%
1.	Noisy [21]	0.97	0.815	0.656	0.529	0.43
2.	PRINLM [21]	0.993	0.976	0.957	0.935	0.913
3.	ODCT [21]	0.991	0.970	0.949	0.927	0.905
4.	BM4D[21]	0.992	0.975	0.959	0.942	0.924
5.	OBNLM [20]	0.99	0.97	0.94	0.91	0.88
6.	NL-PCA [21]	0.994	0.978	0.962	0.943	0.923
7.	PRI-NL-PCA[21]	**0.994**	**0.981**	**0.967**	**0.952**	**0.935**

Table 4. Computational time

Gaussian Noise(Dual Core 3.4 GhZ processor)					
Methods	NLM [22]	Blockwise NLM [22]	Optimized NLM [22]	Optimized block-wise NLM [22]	Optimized block-wise NLM with WM (Wavelet mixing) [22]
Time (Sec.)	4208	734	778	135	**181**

Racian Noise (Quad Core 2.4 GHz)			
Method	NLML[23]	RNLM[23]	ORNLM [23]
Time (Sec.)	4208	**734**	778

The figure 6 shows graphical representation of Computation time of different denoising algorithms for different noise densities. Optimized block-wise NLM with WM takes least computation time for Gaussian noise and RNLM for Rician noise.

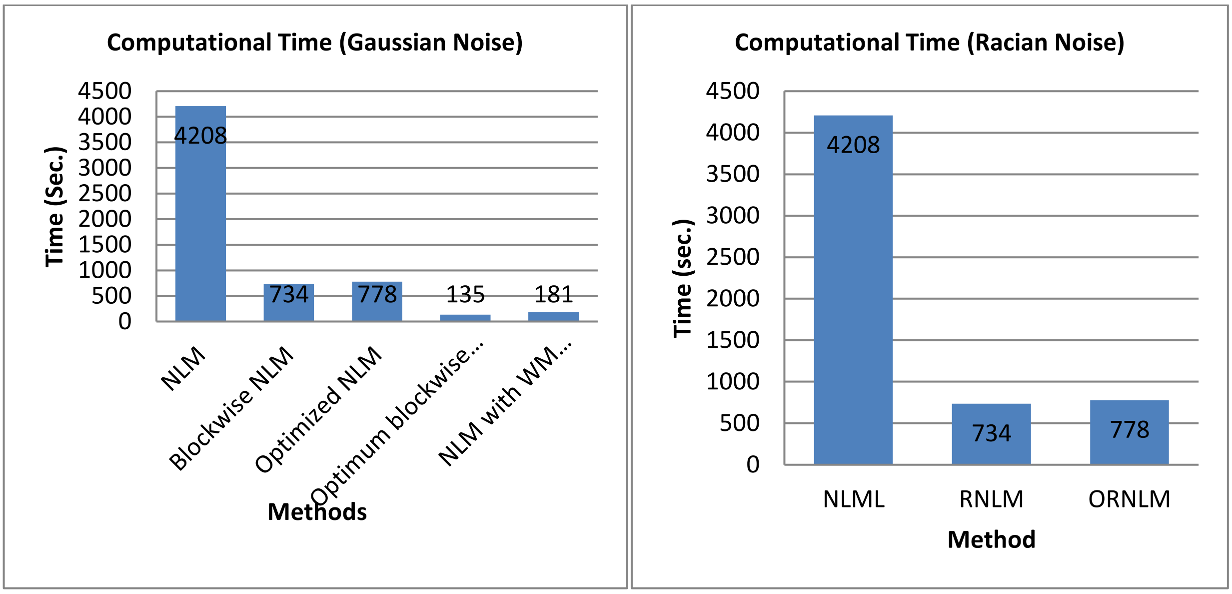

Figure 6. Computation time of denoising methods for different noise density

7. Conclusion:

An efficient filter should be capable of remove the maximum noise and restore the image while keeping the image structure and fine details unaltered. It should not only fulfill the quantitative criteria but also preserve the visual quality of images.

Wavelet domain filters uses threshold to detect noise but add some artifacts into the image because of which detection process get effected. Curvelet transform does not work well in smooth region. Contourlet transform has high complexity. Non local mean filter remove these drawbacks but introduce heavy computational load. Fast NLM reduce the computational time and optimized block-wise NLM can tune the smoothing parameter automatically. Adaptive NLM also improve the denoising efficiency but increase the computational time.

Maximum likely hood NLM filters better preserve the edges but causes over-smoothing or under-smoothing which reduced using the Kolmogorov–Smirnov test.ABM4D method id very good for Gaussian noise but not very effective for Rician noise because it over-smooth the image details and increase the processing time.PCA based filter having the property of sparseness which reduce the noise up to minimum level without effective visual quality of image. PRI-NL-PCA remove the Rician noise very well and also preserve the fine details of image.

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