AN ADAPTIVE APPROACH FOR DENOISING CT IMAGE USING NONLOCAL-MEANS FILTER

[1]Darbara Singh, [2]Sukhjeet Kaur
[1]Research Scholar
[2]Associate Professor
[1]Department of Computer Science
[1]Punjabi University, Patiala, Punjab, India

Abstract- In today's world, CT imaging is one of the mostly used technique for medical imaging. It helps to diagnose human diseases and anatomical distorts by providing high resolution images of internal organs of body. A basic problem in low-dose CT image is its quality degradation caused by photon starvation. There are a lot of techniques for different domains (sinogram or image domain) to denoise the CT image. In view of strong self-similarity contained in the special sinusoid-like strip data in the sinogram space, we propose an adaptive non-local filtering, in which the average weights are calculated on the basis of image directly reconstructed from noisy sinogram data by FBP, and image reconstructed from NLM restored sinogram data by FBP (filtered backprojection). In the process of sinogram restoration, we applied a non-local method with smoothness parameters adjusted adaptively to the variance of noisy sinogram data. This makes the approach much effective for noise reduction in sinogram domain. Simulation and experiments shows that the proposed method has a better performance in noise suppression and details preservation in reconstructed images.

***Index Terms* –Introduction, Noise in CT image, Proposed Approach, Experimental Results, Conclusion.**

I. INTRODUCTION

In medical imaging CT is one of the mostly used imaging technique. It uses the X-Ray to acquire the image. It uses different radiation (mAs) levels depending on the organ, patient health and type of diagnosis. Higher dose of radiation dose cause risk of cancer during the whole lifetime of patients and operators [1]. But the lower dose leads to more degraded image due to photon starvation [2]. To reduce the risk of cancer, the radiation exposure is reduced to a certain level and image is restored using some denoising approach for better results.

II. NOISE IN CT IMAGE

On the basis of previous analysis of repeated measurements from the same phantom indicates that the calibrated log- transformed projection data of low-done CT image follows approximately a Gaussian distribution as Eq: (1) The associated relationship between the data sample mean and variance can be described by the following analytical Eq: (2) [1].

$$\hat{P}_G(z) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(z-\mu)^2}{2\sigma^2}} \qquad (1)$$

$$\sigma_i^2(\mu_i) = f_i \exp(\frac{\mu_i}{\eta}) \qquad (2)$$

Eq: (1) shows the $\hat{P}_G(z)$ probability density function of Gaussian Noise with variance σ and mean μ. In Eq: (2), the μ_i is the mean and σ_i^2 is the variance at detector bin i.

The non-linear relationship of mean and variance as Eq: (2), makes this noise Non-Stationary in nature. The CT image noise doesn't follow pure Gaussian distribution. It is a combination of Gaussian as well as poisson distribution.

In Eq: (2), the parameters f_i and η are scaling parameter known as "*Anisotropic Adjustable Factors*" determined by the property of detectors [2], which enables the measured photon energies to be stored as integers while retaining the dynamic range of the line integrals of the attenuation coefficients. These are system specific parameters, and different CT manufacturers may choose different value of η. The notation f_i in equation represents an adjustable factor adaptive to each detector bin i.

III. NLM FILTERING APPROACH

NLM filter is one of the latest and mostly used image denoising algorithm used in these days. The non-local means (NLM) algorithm was first proposed by Buades et al [11] for image denoising. Instead of using neighborhood (Spatial Filtering) or Frequency (Frequency domain filtering), NLM assumes that the image contains the huge amount of self-similarity within the image itself. In case of CT image denoising, it is used in both image and sinogram domain. This approach fully utilizes the self-similarity of natural images and has been successfully applied to low-dose CT imaging. To find out denoised intensity value $NLM(x_i)$ at pixel i can be expressed as:

$$NLM(x_i) = \frac{\sum_{j \in \Omega} w(i,j) x_j}{\sum_{j \in \Omega} w(i,j)} \qquad (3)$$

Where Ω is a discrete grid of image pixels of noisy image $x = \{x | i \in \Omega\}$ and $w(i,j)$ is the average weight determined by similarity between pixel i and j, is calculated as:

$$w(i,j) = \exp\left\{ -\frac{\left\| x(N_i) - x(N_j) \right\|_{2,a}^2}{h^2} \right\}, \qquad (4)$$

Where N_i and N_j are two similarity windows, centered at pixel i and j respectively; h denotes a smoothing parameter that controls the decay of the exponential function and $\|.\|_{2,a}$ denotes the gaussian distance between two similarity windows N_i and N_j, with a standard deviation a. To improve the efficiency and reduce the computational burden, the search window is always restricted to a proper local neighborhood S_i in Ω.

In Eq. (4), there is a special case when $i = j$; here the self-similarity is very high and can produce an over-weighting effect. To solve this issue $w(i,i)$ is calculated as:

$$w(i,i) = \max(w(i,j)\forall i \neq j) \quad (5)$$

In case of CT image denoising, NLM is very efficient because it works in both sinogram and spatial space. Different studies show that this filter can be used with other filters to get better result.

IV. PROPOSED METHOD.

The output of CT imaging system is in the form if sinogram that contains noise in it. There are many different approaches which are directly implemented on sinogram for denoising purpose. Modified ROF modelling [4], Edge Preservation Total Variation (EPTV) [5], Adaptive Trimmed Mean Filter (ATM) [6], NLMIC-POCS [7], Iterative Image Reconstruction based on MAP and Normal Dose induced NLM [8] are directly implemented on sinogram data where Previous Normal dose induced NLM (ndiNLM) [9] and Localized Patch based CT Restoration [10] approaches are implemented on image (spatial) domain.

The denoising approach proposed in this study purely based SINLM [11], in existing studies, while denoising the CT images, the NLM is applied on either in projection domain or spatial domain. In this approach, filtration process is performed on both domains.

The projection (sinogram) is formed with a set of overlapped sine curves in the sinogram space because any object can be approximated by a collection of points located in space. As Buades et al. pointed that natural images have properties of sparsity and self-similarity. The sinogram data in low-dose CT is composed of special sinusoid-like strip with same stronger self-similarity among these strip data. FBP reconstructed images also have the same properties but noise does not have these special properties. So this property of image similarity and noise can be used to restore image data contaminated seriously by noise. At the same time, we can use the reconstructed image data after sinogram restoration by alfa trimmed mean filter to match the similar points more exactly to remove noise and preserve the important structural details in image.

Existing SINLM [11], approach uses median filter to remove isolated noise in sinogram and then SNLM was used to smooth the sinogram data. In proposed approach, the median filter is replaced with alfa trimmed mean filter, explained later in this study. As we know the alfa trim mean filter better performs both short and long tailed types of noise (e.g. both Gaussian and salt and pepper noise), the use of alfa trimmed mean filter provides smoothness to sinogram data along with removal of isolated noise.

In the NLM algorithm, there are three parameters, i.e. search window, similarity window and smoothness parameter h, play an important role. The parameter h is especially critical; a larger h could cause too more smoothness in the data, while a smaller would leave the restored data with excessive noise.

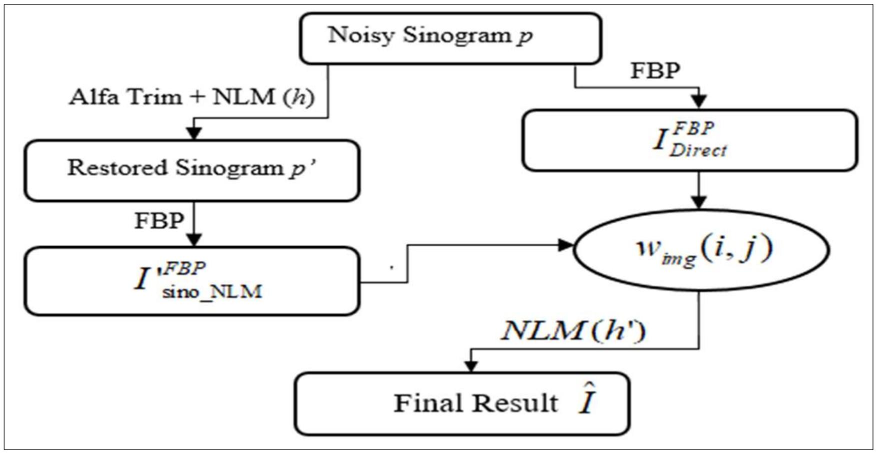

Fig 1. Flow Diagram of Proposed Approach.

In this study, in order to get better weights in the NLM filter, the opposed algorithm works along two directions; including modifying the smoothness parameter h and the image intensity difference in similar neighborhoods. In order to find an appropriate h to ensuring the removal of large amount of noise and the structural details preserved at the same time; this study works to adjust h in both the sinogram domain and in the image.

The whole process of denoising splits into two parts in the beginning, and at the end again combined. As shown in Fig: (1) , p is the low dose sinogram data contaminated with noise as per Eq: (2). $I^{FBP}_{Direct} = \{I^{FBP}_{Direct,k}, k \in \Omega\}$ is the image reconstructed from the noisy sinogram p and $I'^{FBP}_{\text{sino\_NLM}} = \{I'^{FBP}_{\text{sino\_NLM},k}, k \in \Omega\}$ is the image reconstructed from the NLM filtered sinogram data p', which is already filtered by Alfa Trimmed Mean Filter as Eq: (10) with $d=3$ and window size 3×3. In whole filtration process NLM filter works two times; once with parameter h and second time with parameter h'. In the sinogram space, the standard deviation of local window of sinogram data controls the smoothness of NLM filtering parameter h adjusted as $h = \{h_i, i \in \Omega\}$.

$$h_i = k_0 * \sigma_i \tag{6}$$

Where k_0 is a constant and σ_i is the standard deviation of the search window in sinogram. The weights $w_{\text{sino}}(i,j)$ are calculated as:

$$w_{\text{sino}}(i,j) = \exp\left\{ -\frac{\left\| p(N_i) - p(N_j) \right\|^2_{2,a}}{h_i^2} \right\} \tag{7}$$

Where N_i and N_j are the similarity windows centered at pixel i and j respectively in sinogram p, and term $p(N_i) = \{p_k, k \in N_i\}$ denotes the image intensity restricted in the similarity window N_i. By using above Eq: (7), the restored sinogram p' can be expressed by:

$$p' = \frac{\sum_{j \in \Omega} w_{\text{sino}}(i,j) p_j}{\sum_{j \in \Omega} w_{\text{sino}}(i,j)} \quad (8)$$

To reduce the over-weight affect where $i = j$ in Eq: (7); high self-similarity is reduced by using Eq: 5.

On the other hand, in image domain; the smoothness parameter h' is calculated imperially on the basis of experiments and the weight $w_{img}(i,j)$ is determined by images $I'^{FBP}_{\text{sino\_NLM}}$ and I^{FBP}_{Direct}. Finally, NLM filter weights are calculated using:

$$w_{img}(i,j) = \exp\left\{ - \frac{\left\| I^{FBP}_{Direct}(\overline{N}_i) - I'^{FBP}_{\text{sino\_NLM}}(\overline{N}_j) \right\|^2_{2,a}}{h_i^2} \right\} \quad (9)$$

Where $\overline{N}_i$ and $\overline{N}_j$ are the similarity windows centered at pixel i and j in images I^{FBP}_{Direct} and $I'^{FBP}_{\text{sino\_NLM}}$ respectively. While calculating the weights as Eq: (9), the overweight controlling Eq: (5) is eliminated because the search window and local window belongs to different images. Because the similarity windows are taken from two different images, it is more effective for better suppression of noise and structural detail preservation.

As per the nature of NLM filter, closer to exact image leads to higher average weights. In this approach, both the $I'^{FBP}_{\text{sino\_NLM}}$ and I^{FBP}_{Direct} are filtered and closer to each other makes this approach more effective in its objective. At the end, the restored image $\hat{I}$ is obtained by:

$$\hat{I} = \frac{\sum_{j \in N'_i} w_{img}(i,j) I^{FBP}_{Direct,j}}{\sum_{j \in N'_i} w_{img}(i,j)} \quad (10)$$

Where N'_i denotes the window centered at pixel i in the image I^{FBP}_{Direct}.

The proposed approach require Alfa trimmed mean filter. It is a type of spatial filter. It is a mean filter in which doesn’t include the $d/2$ highest and $d/2$ lowest points from the sub-image while calculating the mean value for output image. The output intensity value is calculated by averaging only $mn - d$ points of sub image where mn is the size of sub-image and trims the both high and low endpoints by $d/2$.

$$f(x,y) = \frac{1}{mn-d} \sum_{(s,t) \in S_{xy}} \{g(s,t)\} \quad (11)$$

In above equation if the value of $d = mn - 1$, this filter works as a median filter and if $d = 0$, this filter works as an average filter.

V. EXPERIMENTAL RESULTS

For experimental analysis CT image stimulation is performed on Sheep-Logan Head phantom fig: (2-A). The noisy free sinogram created by taking 600 projections at 360° view of Shepp-Logan Head phantom Fig: 2-A. The noisy sinogram data for low-dose CT are simulated by adding isolated data and non-stationary Gaussian noise to the noise-free sinogram, where the variance of the non-stationary Gaussian noise is determined by the exponential relationship following Eq:(2), where value of $f_i = 100$, $\eta = 22{,}000$ and the mean μ_i of each bin is estimated locally by an average with a window size of 3×3 pixels. Fig (2-B) and Fig (2-C) shows the noise free and noisy sinogram of Shepp-Logan Head Phantom. Firstly, the direct FBP reconstructed image from the noisy sinogram by applying Hanning filter in filtered backprojection. For removal isolated points in the noisy sinogram p, we use Alfa Trimmed filtering before applying NLM follows in Fig: (1). The $I'^{FBP}_{\text{sino\_NLM}}$ is reconstructed image by the FBP algorithm from the adaptive NLM filtered sinogram (sino_NLM) where parameter h is calculated adaptively on the basis of sinogram data as Eq: (6). Finally, the weights for NLM filter are calculated on the basis of Direct-FBP and sino_NLM by using Eq: (9) and output image is generated using Eq: (10).

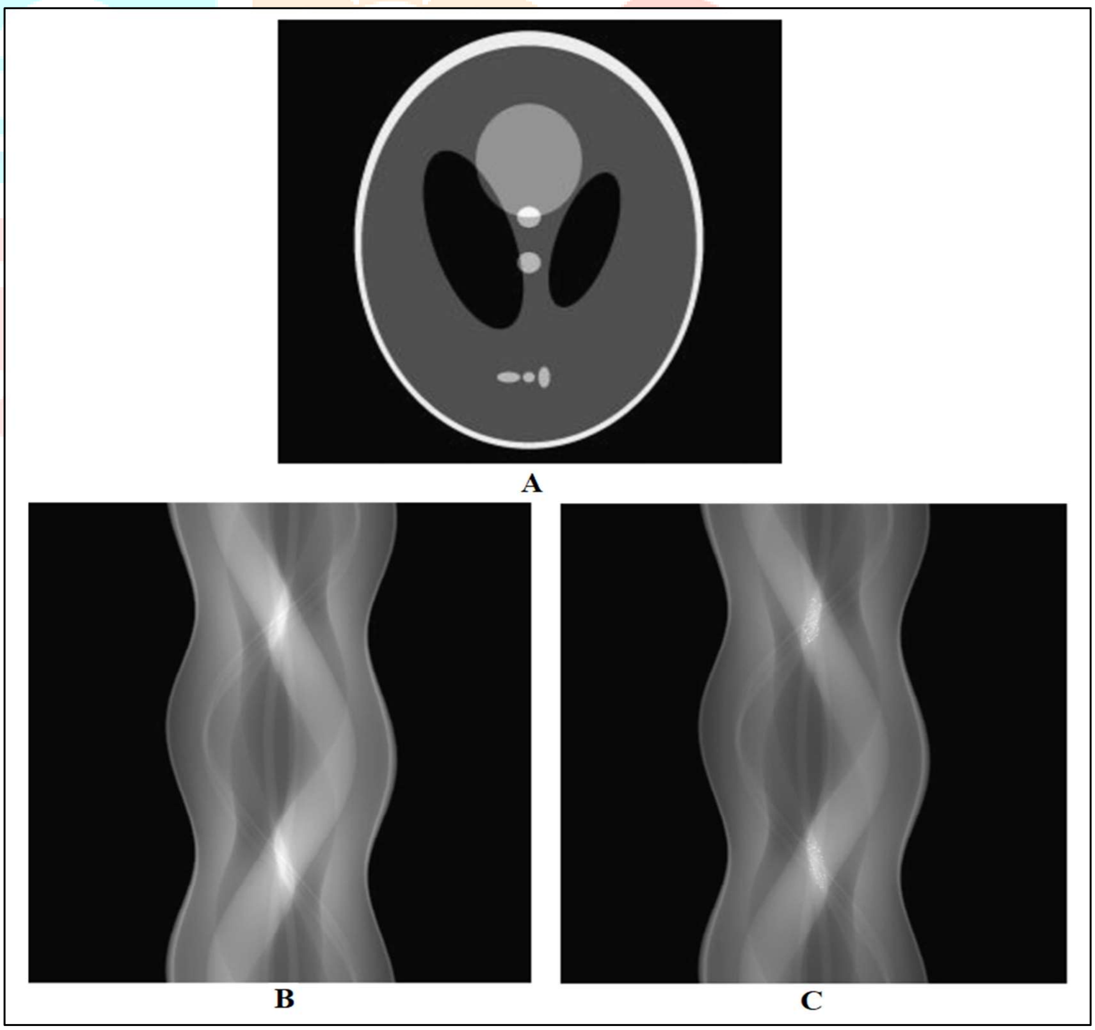

Fig (2)

For visual analysis, final output of Direct FBP, SNLM based on Alfa Trimmed Mean and proposed approach can be seen in Fig: 3-A, 3-B and 3-C respectively. We can see some streak artifacts in the output of Direct FBP where the SNLM based on Alfa Trimmed Mean filter performs better in terms of reducing the streak artifacts but the proposed approach performs better in terms of reducing streak artifacts and edge preservation.

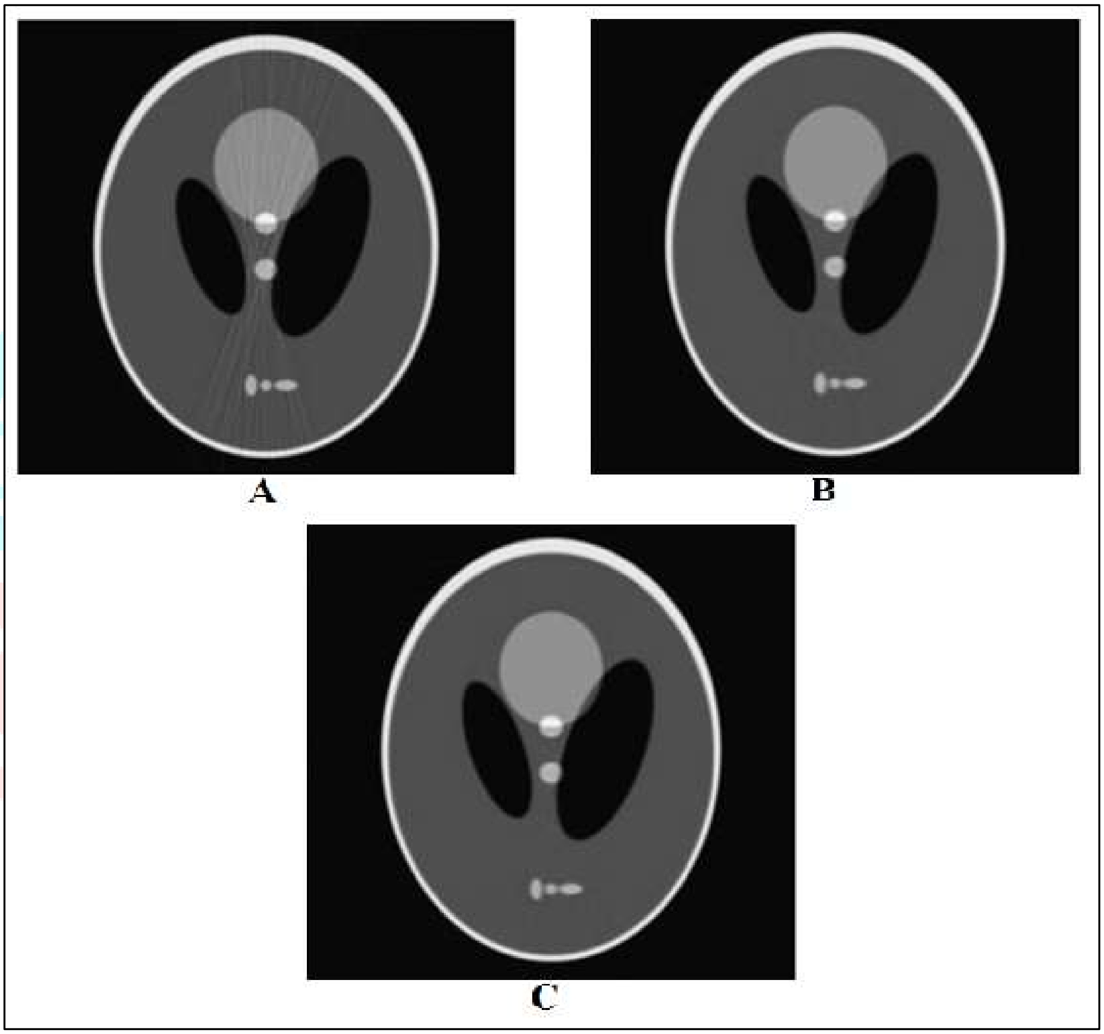

Fig: 3

For result analysis, DFBP and SNLM approaches are compared with the proposed method on the basis of MSE Eq: (12), PSNR Eq: (13) and MSSIM Eq: (14).

$$MSE = \frac{1}{MN}\sum_{x=1}^{M}\sum_{y=1}^{N}\left[I(x,y) - I'(x,y)\right]^2 \qquad (12)$$

Where $I(x,y)$ is the original image and $I^{'}(x,y)$ is denoised image and M and N is the horizontal and vertical resolution of image.

The PSNR index is defined as the power of corrupting noise that affects the accuracy of its representation and the ratio between the maximum possible power of signals. It is most easily defined via the mean squared error (MSE). The PSNR (in dB) is defined as:

$$PSNR = 20 * \log 10\left(MAX_I / \sqrt{MSE}\right) \tag{13}$$

MSSIM (mean SSIM index) values shows much better consistency with the qualitative appearance of the image. MSSIM is given by:

$$MSSIM = \frac{1}{M}\sum_{j=1}^{M} SSIM(I, I^{'}) \tag{14}$$

$$SSIM = \frac{(2\mu_I \mu_{I'} + C_1)(2\sigma_{I\,I'} + C_2)}{(\mu_I^2 + \mu_{I'}^2 + C_1)(\sigma_I^2 + \sigma_{I'}^2 + C_2)} \tag{15}$$

where μ_I and $\mu_{I'}$ represents the mean, and the σ_I^2 and $\sigma_{I'}^2$ represents the variance of the reference I image and its estimation I' respectively. The term $\sigma_{I\,I'}$ represents the covariance of image I and image I' . C_1 and C_2 are selected as positive values. The output MSSIM index is value lies between 0 and 1. The output value of MSSIM is 1 when both the images are identical. The higher value of MSSIM indicates the higher quality of image and vice versa.

The comparative analysis is performed between Direct FBP, SNLM and Proposed approach on the basis of MSE, PSNR and MSSIM. Table (1) shows the MSE, PSNR and MSSIM values and Fig: 4, 5, 6 shows the graphical view of performance of proposed approach.

In both numerical and graphical view shows that the proposed method performs better in terms of different image quality measures.

FILTERS ⟶	FBP	sino_NLM	PROPOSED
MSE	30.5721	32.0625	33.0262
PSNR	33.456	34.2426	35.4251
SSIM	0.6281	0.6372	0.6632

Table: (1).

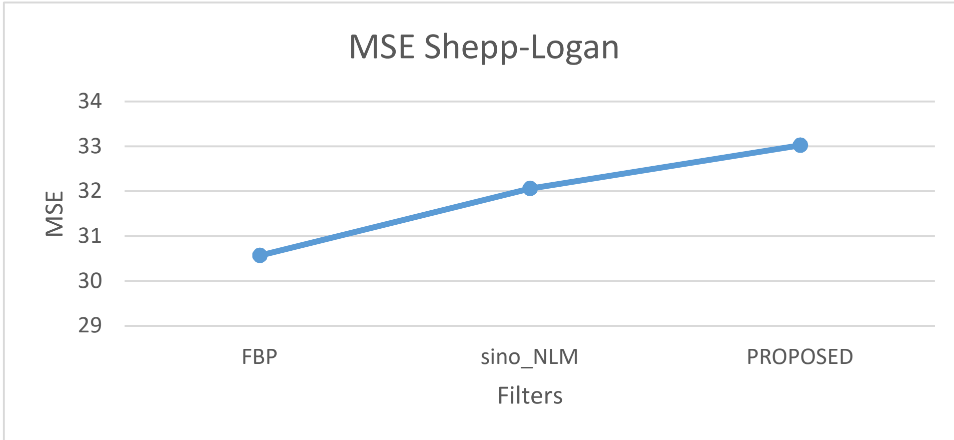

Fig: 4

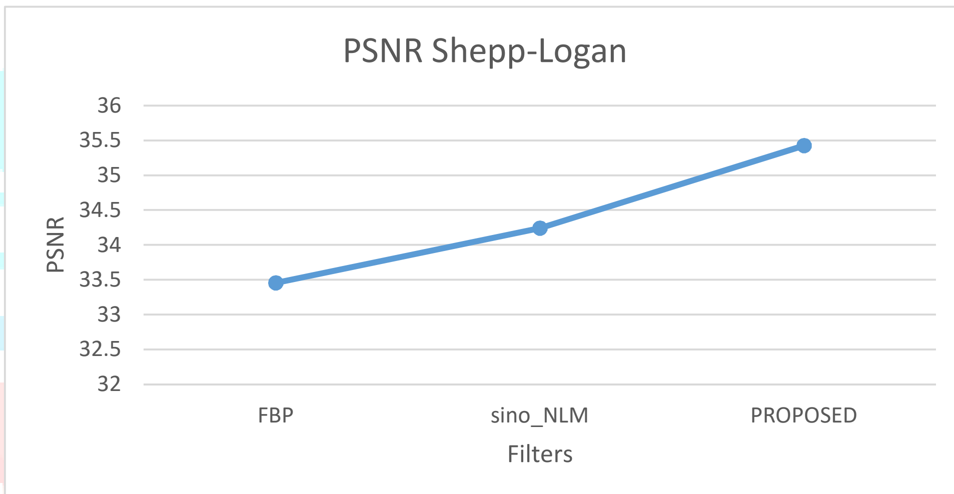

Fig: 5

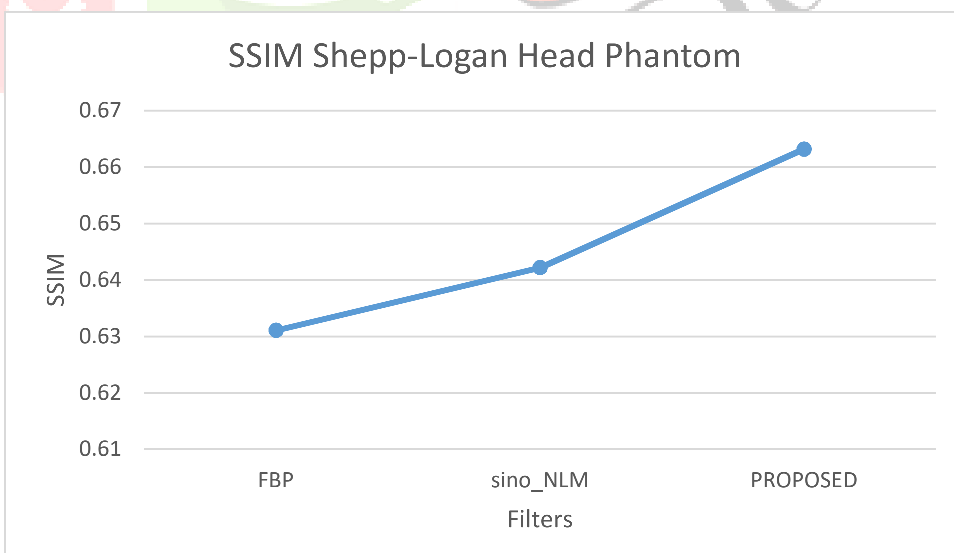

Fig: 6

VI. Conclusion: As per study and experiments in terms our proposed algorithm performs much better than other methods in experiments on the basis of numerical and visual observations. The proposed algorithm takes the advantage of self- similarity in both sinogram and image domains. It better suppress noise while preserving main details of important data. Future research can be carried out to optimize smoothness parameters in the process of nonlocal filtering according to the statistical properties of CT image noise.

References

[1] Hall EJ, Brenner DJ. "Cancer risks from diagnostic radiology." (2008) Vol 81, pp.362–78.

[2] Jiang Wang, Hongbing Lu, Zhengrong Liang, Daria Eremina, Guangxiang Zhang, Su Wang, John Chen, and James Manzione "An experimental study on the noise properties of x-ray CT sinogram data in Radon space." (2008), vol.53, issue.12, pp.3327-3341.

[3] Buades, A., Coll, B. and Morel, J. "A Review of Image Denoising Algorithms, with a New One" (2005), Vol 4 Issue 2, pp.490-530.

[4] Yining Zhu, Mengliu Zhao, Yunsong Zhao, Hongwei Li and Peng Zhang "Noise reduction with low dose CT data based on a modified ROF model." (2012), vol.20, issue.16, pp.17987-18004.

[5] Zhen Tian, Xun Jia, Kehong Yuan, Tinsu Pan and Steve B. Jiang," CT Reconstruction from Undersampled Projection Data Via Edge-Preserving Total Variation Regularization." (2010), Vol 37 Issue 6, pp.3378-3378.

[6] Jiang Hsieh, "Adaptive streak artifact reduction in computed tomography resulting from excessive x-ray photon noise." (1998), Vol.25 issue 11, pp.2139-2147.

[7] Jing Huang, Jianhua Ma, Nanliu Liu, Huazhang Zhang, Zhaoying Bian, Yanqiu Feng, Qianjin Feng, and Wufan Chen," Sparse angular CT reconstruction using non-local means based iterative-correction POCS." (2011), Vol 41 Issue 4, pp.195-205.

[8] Ma, J., Zhang, H., Gao, Y., Huang, J., Liang, Z., Feng, Q. and Chen, W. "Iterative image reconstruction for cerebral perfusion CT using a pre-contrast scan induced edge-preserving prior." (2012), Vol 57 Issue22, pp.7519-7542.

[9] Jianhua Ma, Jing Huang, Qianjian Feng, Hua Zhang, Hongbing Lu, Zhengrong Liang and Wufan Chen." Low-dose computed tomography image restoration using previous normal-dose scan." (2011). Vol 38 Issue 10, pp.5713-5731.

[10] Sungsoo Ha and Klaus Mueller."Low dose CT image restoration using a localized patch database." (2013).

[11] Yingmei Wang, ShujunFu, Wanlong Li, Caiming Zhang 'An adaptive nonlocal filtering for low-dose CT in both image and projection domains." (2015), Vol 2 Issue 2, pp.113-118.