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An efficient non-local approach for noise reduction in natural images

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Abstract: The ambition of Noise reduction in image is to retrieve the genuine image from a noisy image and also a demanding problem for researchers. Non-local means uses the averages weight of neighborhoods pixels, where weight depends on self-similarity concept of these pixels. Basically, most of the algorithms for Noise reduction in image assuming Gaussian noise but in some example, others noise existing like X-Ray contains Poisson noise. In this paper, we proposed a Noise reduction method using non-local means for Noise reduction in image .In the first term; proposed a new technique noise removal set of rules based totally on a non-nearby averaging of entire pixels in the image. In the second term; to put effect and compare the proposed scheme the use of numerous metrics including MSE, SSIM, PSNR etc. with improving performance than a traditional algorithm with reducing complexity.

Keywords: Noise reduction, Non-local means algorithm, MSE, PSNR, Poisson Noise, Gaussian Noise, Impulse noise

1. INTRODUCTION

Image processing concedes the utility of many more confused algorithms. It can offer dissolve performance at simple problems and implementation of methods. Digital image processing uses everywhere fields like Medical industry (X-Ray, MRI etc), Satellite television. Noise reduction is the procedure of removing noise from an image which captured by a different medium device like CCTV camera, MRI pictures, camera, digitally or analogue, some noise occurred in the image. The main purpose of noise reduction are to retrieve original image from noisy image:

$$r(i) = p(i) + n(i)$$

Where,

$$r(i) = \text{observed value}, p(i) = \text{true value and } n(i) = \text{noise in image}$$

Noise reduction in image corrupted by some noise like Gaussian noise, impulse noise, Poisson noise and another noises are demanding problem in image processing.The noise in a image presented during image acquisition, restoration processing. Due to electric transmission of the image, capturing image from devices or coding.The main challenging problem for researchers, recover the original image from the noisy image.So many algorithms are used for retrieving original image from the noisy image but Non-local means method performance better than other algorithms. The Non-Local means method useing a “self-similarity concept” between pixels.

Improving non-local noise reduction algorithm for image proposed by B. Goossens, H. Luong , A. pizurica and W. Philips for remove noise with add extension of color noise [1]. Julien Mairal, M. Elad, Guillermo Sapiro propsed method For color image,Designing of well adapted dictionaries has been big demanding problem . K-SVD algorithm has been proposed with some extend and showing performance for different different gray scale image processing task[2].Principal neighborhood dictionaries non-local mean noise reduction for image proposed by T. Tasdizen .Presented in-depth analysis of non-local means noise reduction algorithm[3] . Speed Fast non-local means with PET(probabilistic early termination) proposed by R. Vignesh ,B. Tae oh and C.C JAY Kuo. In this algorithm computation in non-local means the scheme depends on contortion calculation between pixels nearby neighborhoods. PET algorithms accept probability model for ambition early termination algorithm. Comparison with others fasts non-local means for providing exhibit the effectiveness of the algorithm.[4]. Li YL, Wang J, Chen X Integrates non local means algorithm and Laplacian Pyramid. Firstly, splitting it into Laplacian pyramid and Exploiting the repition property of Laplacian pyramid, perform non-local means on every level image of Laplacian pyramid. speedup, This algorithm is fifty times faster than original non-local means algorithm.[5]. B. Yang, M. Guo, Xinhua Dou In traditional method of Non-local mean algorithm , measurement and filter parameter of search neighborhood windows in image are globally constant ,not showing diverse structural features of different different area in images which showing weight of similarity of image blocks distributed without any reason and not effecting noisy image.Improving in PSNR snd other type of information at same time.[6]. J. Mairal, F. Bach, J. Ponce, G. Sapiro, and A. Zisserman In this algorithm, developing a self-similarity and and find out sparse representation in image. And also provide fast online algorithm for learning dictionaries with various formulation for image and video processing[7]. Florian Luisier, CedricVonesch, T. Blu, M. Unser Proposed new approach, firstly discuss the minimization of an unbiased estimate of the MSE for Poisson noise, second show a linear parameterization of the denoising process and third process the preservation of Poisson statistics across scales within the Haar DWT . Sawatzky, C. Brune, J. Mller, M. Burger Proposed with some total variation (TV) based regularization methods adapted for Poisson data, it derived from approximations of ogarithmic a-posteriori probabilities This approach provide guarantee sharp edges and avoid smoothing of the total variation[9]. Stamatios Lefkimmiatis, P. Maragos, G. Papandreou Proposed work where accept a multiscale representation of the Poisson process .In this algorithm basically 3 approaches proposed 1st a rigorous and robust regularized expectation- maximization (EM) algorithm for maximum-likelihood estimation 2nd use method multiscale hidden Markov tree model 3rd exploration of a 2-D recursive quad-tree image representation4th a novel multiscale image representation, thus yielding improved performance[10]. K. Hirakawa, P. Wolfe, showing Skellam mean estimator provided a Poisson intensity estimation method based on shrinkage of filterbank coefficients, and a means of reckoning the risk of any Skellam mean estimator is copied in closed form under a affect model[11]. B. Zhang, J. M. Fadili, J.-L. Starck show the power of this MS-VST method for retreiving important structures of different morphologies in (very) low-count images. These results also prove that the MS-VST method is competitive relative to many existing noise reduction methods[12]. Nonlocal means algorithm for noise reduction in image proposed by A. Buades, B. Coll & J. Michel morel for recovering original image , also provide better performance than others technique. In this algorithm, propose a new concept for removing noise, evaluate and compare the performance of noise reduction of the image.[13]. New technique Fast non-local algorithm for noise reduction in image proposed by J. Wang,Y. Guo ,Y. Ying , Yanli Liv, Q. Peng presented a new algorithm for reducing the computational cost. Calculate similarity of neighborhood windows is proposed.This algorithm result provides 50 times faster than the traditional non-local algorithm, both based on theoretically & experimentally in terms of mean squared error and percentage image quality[14]. K. Imamura,N. Kimura, F. Satou, S. Sanada and Y. Matsuda propose an noise reduction using non-local means for Poisson noise. proposed method adjusts the weight parameter based on the supposing noise strength from the pixels in a local area. The proposed method provides good noise reduction performance for Poisson noise with improvement of 0.1-0.9 dB compared to the standard non-local means[15]. Luisier, Florian, Thierry Blu, and Michael Unser propose a general methodology (PURE-LET) to design and optimize a wide class of transform-domain thresholding algorithms for denoising images corrupted by mixed Poisson–Gaussian noise. We express the denoising process as a linear expansion of thresholds (LET) that Showing the implied of the proposed method through extensive comparisons with state-of-the-art method i.e. specifically tailored to the estimation of Poisson intensities.We also present noise reduction results obtained on natural images of low-count fluorescence microscopy[16]. J. Boulanger, C. Kervrann, J. Salamero, J.-B. Sibarita, P. Elbau, P. Bouthemy started a non-parametric regression approach for noise reduction 3D image sequences gatherd via fluorescence microscopy. The proposed technique exploits the excess of the 3D+time information to upgrade the signal-to-noise ratio of images exploiting by Poisson- Gaussian noise.. The idea is to minimize an objective non-local energy functional involving spatiotemporal image patches. The minimizer defined as the weighted average of input data taken in spatially-varying neighborhoods. The size of each neighborhood is optimized to improve the performance of the pointwise estimator[17]. Liu, Xiaoming, proposed method for noise reduction the optical coherence tomography image. When choosing the similar patches for the noisy patch in image , This method merged internal and external denoising, using the other images suitable to the noisy image, Next, we take advantages the low-rank method to reduction the group matrix consisting of the noisy patch and the respectively similar patches, for a clean image can be seen as a low-rank matrix and rank of the noisy image is much more larger than the clean image Experimental results determine that our method compares favorably with the existing state-art methods. [18]

1.1PROPOSED METHOD:

In proposed algorithm, to evaluate and investigate the performance of virtual noise reduction methods. We first compute and examine this approach noise for a huge elegance of denoising algorithms, specifically the nearby smoothing filters. Second, we propose a brand new set of rules, the non local manner (NL-manner), primarily based on a non-nearby averaging of all pixels within the picture. Finally, we gift a few experiments evaluating the NL-method algorithm and the local smoothing filters. In this paper Compare nearby neighborhoods smoothing filters and NL-mean algorithm with method noise, restoring image quality and mean square error, PSNR(Peak signal-to-noise ratio), SSIM(structural similarity index) for improving performance by proposed method than the traditional method . The objectives of proposed approach to reducing the computational complexity and improves PSNR overall performance

2. METHOLOGY

The NLM method computed by pixel with nearby neighborhoods. In the Figure(1), Three pixels r, s_1 and s_2 respectively neighborhoods. In figure shows that r and s_1 neighborhood pixels are much more nearby than pixel r & s_2 . and nearby neighborhood r and s_2 do not similar. In non-local means algorithm use similarity concept. So according to image non-nearby pixels are also nearby neighborhoods.

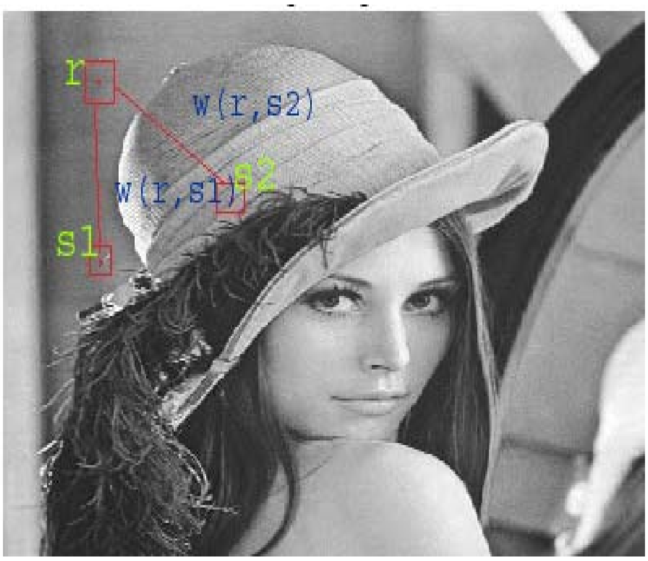

Figure1.1: Pixel r and s1 are nearby neighborhoods and respectively r and s2 not nearby neighborhoods. So similar weights of pixels respectively w(r,s1) w(r,s2)

For computational purpose ,in image search window of size A*A pixels. For experiment, purpose fixed with 21*21 pixel and similarly 7*7 or 3*3 pixel size windows for image. If N^2 number of pixel so complexity of algorithm is

$49*441*N^2$.The 7*7 pixel size window is enough for robust to noise and to take detail of image structure.
For pixel t of NL-means algorithm is calculated by following formula:

$$\mathrm{NLM}(V)(t) = \sum_{s=V} w(r,s)V(s)$$

Where, V : Noisy image and weight $w(r,s)$ totally depend on similarity between r & s pixels and satisfy condition $0 \leq w(r,s) \leq 1$ and $\sum_s w(r,s) = 1$
In the image, take the weighted average of all pixels for each pixel ,taken the weight of pixel depends on the similarity between a nearby neighborhood of pixels r, s. In the example, Figure1 above weight $w(r,s_1)$ is greater than $w(r,s_2)$ because r and s_1 pixels have nearby neighborhoods and also r and s_2 pixels do not have nearby neighborhoods.

Measuring similarity between neighborhoods : take the difference of weighted squares sum , so calculate as:

$$d(r,s) = \| V(N^r) - V(N^s) \|_{2,c}^2$$

Where c>0 is a standard deviation of neighborhoods. The weights for all pixels is computed as:

$$w(r,s) = \frac{1}{z(r)} e^{-\frac{d(r,s)}{h}}$$

Where, $d(r,s) = \| V(N^r) - V(N^s) \|_{2,c}^2$ and z(r) normalizing constant is defined as:

$$z(r) = \sum_s e^{-\frac{d(r,s)}{h}},$$

And h=control decay of weights. The algorithm does not compare only gray level in a single point but the geometrical configuration in a whole nearby neighborhood filters. In the figure, pixel s2 has similar gray level value but the neighborhood is different. So, weight $w(r,s_2) = 0$

3. DISCUSSION AND EXPERIMENTATION

The main objective of proposed approach to reduce the computational complexity and improves PSNR overall performance. For Simulation take 512*512 bit gray level image for recover original image. In the first term, shows retrieve original image from the noisy image and the Second term shows performance Comparison between proposed method with other conventional method.
In this section, Apply Noise reduction technique which image is corrupted by Poisson noise for recover original image and the result shows that denoised image.

Fig 3.1 Original Lena Image 512x512

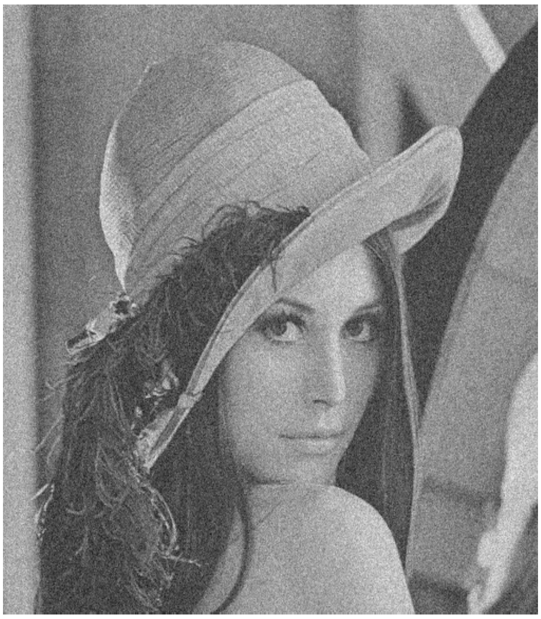

Fig 3.2 Noisy image at Poisson Noise (σ=15)

Fig 3.3 Noisy Image and NL Filtered Image at Poisson Noise (σ=15)

In this section, compare the performance of proposed method with other methods with variety form of images(.jpg,.bmp, etc)

Table 3.1 Comparison of various image at Poisson Noise (σ=25)

Image	Noise Image	Normal Method	base paper	NL Proposed
Bridge	22.2	26.05	26.7	31.34
Lenna	22.17	29.9	30.7	39.61
Mandrill	22.13	25.95	26	39.64
Peppers	22.07	29.85	30.8	37.09

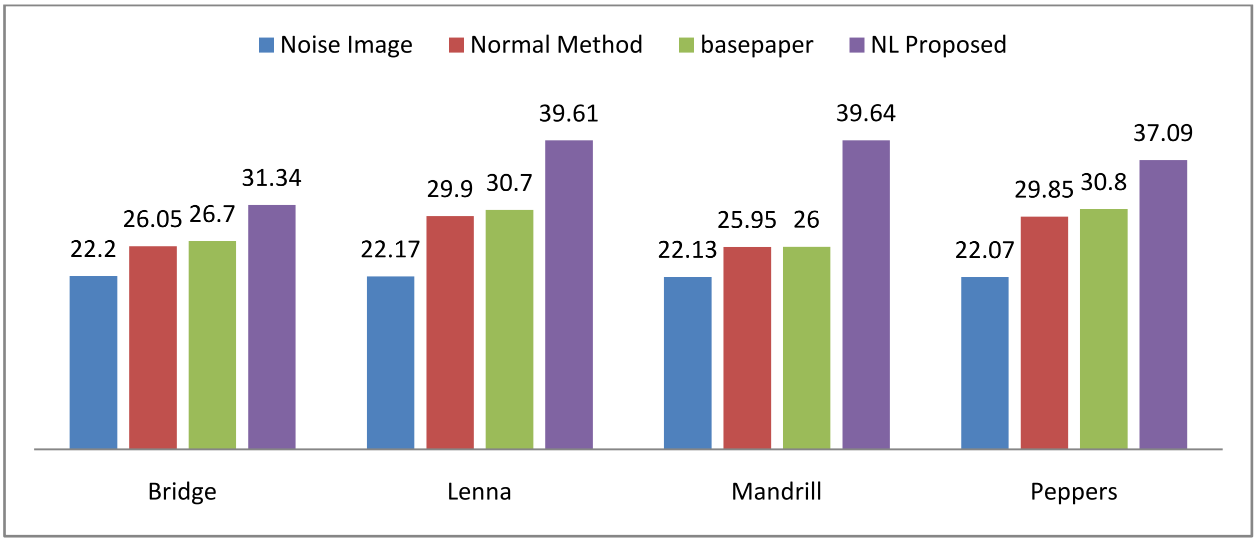

Fig 3.4 Comparison of various image at Poisson Noise (σ=25)

Table 3.2 Comparison of various image at Poisson Noise (σ=15)

Image	Noise Image	Normal Method	Base Paper	NL-Proposed
Bridge	24.8	27.8	28.2	30.30
Lenna	24.6	31.5	32.1	34.56
Mandrill	24.6	27.5	27.7	30.57
Peppers	24.6	31.4	32.2	35.33

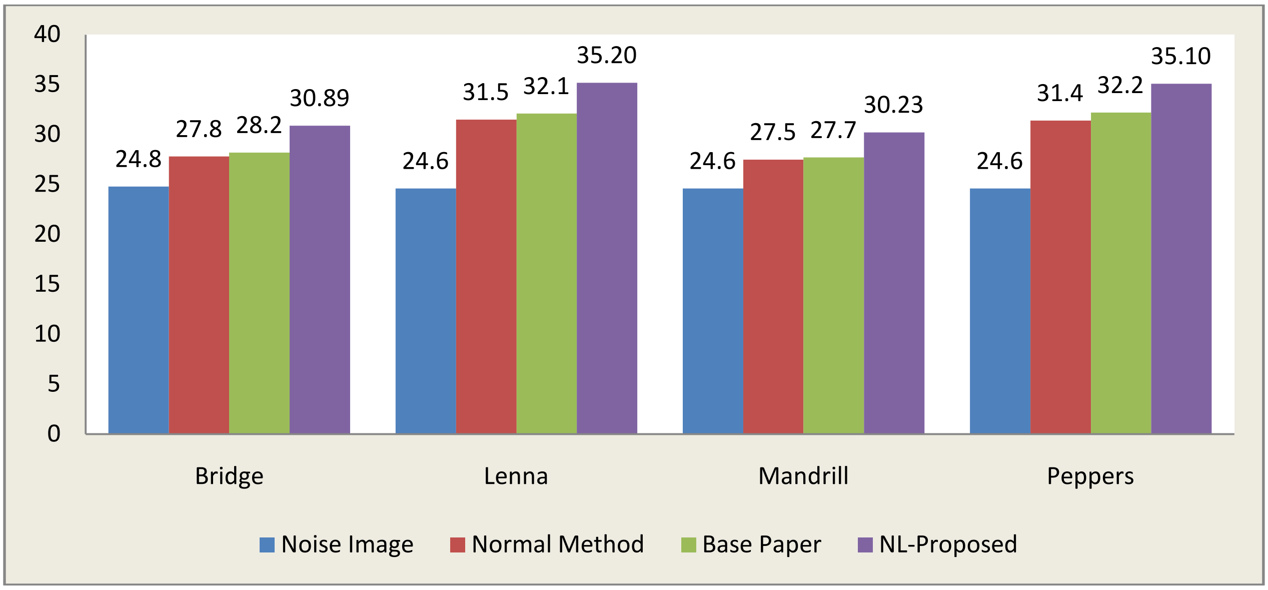

Fig 3.5 Comparison of various image at Poisson Noise (σ=15)

Table5.3 Comparison of various image at Poisson Noise (σ=10)

image	Noise Image	Normal Method	Base Paper	NL Proposed
Bridge	28.2	30.2	30.6	32.48
Lenna	28.15	33.9	34.3	36.11
Mandrill	28.1	29.95	30.05	31.93
Peppers	28.05	33.8	34.2	35.84

In the tables show different values of variety form of images in 512*512 bit gray level for performance comparison with proposed method:

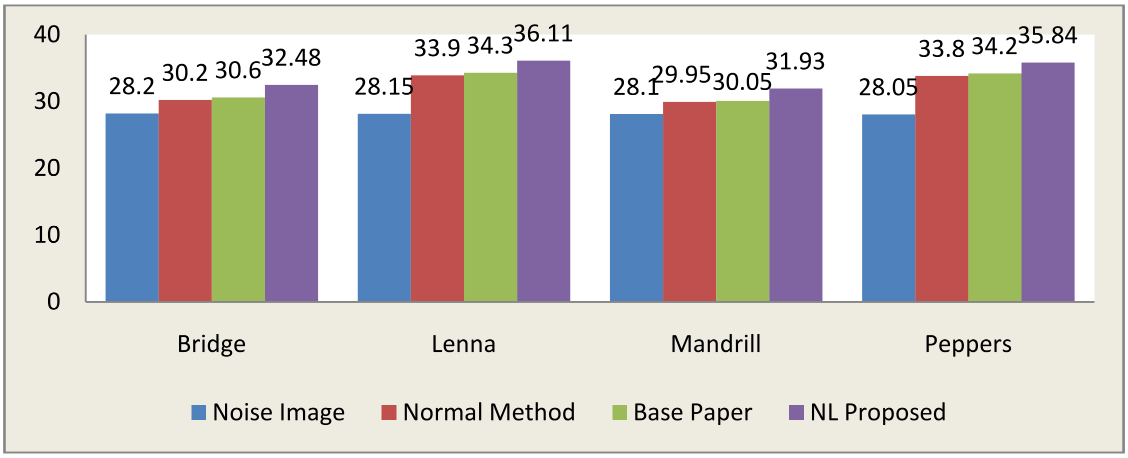

Fig 3.6 Comparison of various image at Poisson Noise (σ=10)

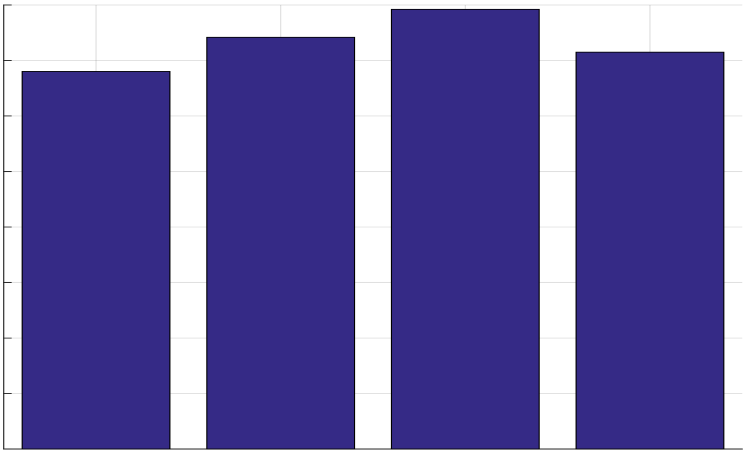

Fig 3.7

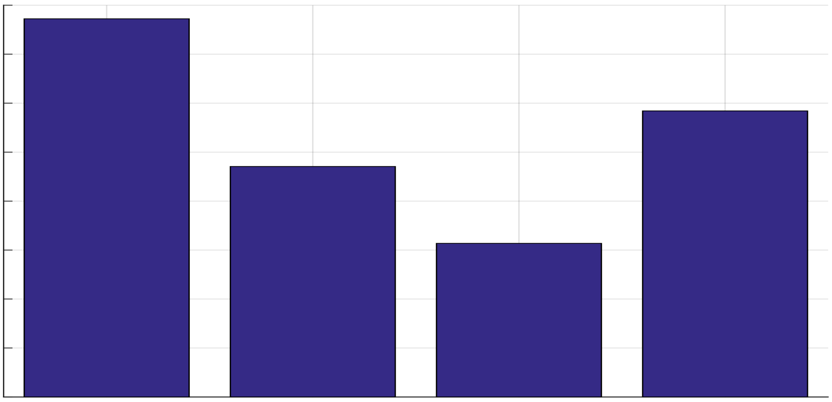

Fig 3.8

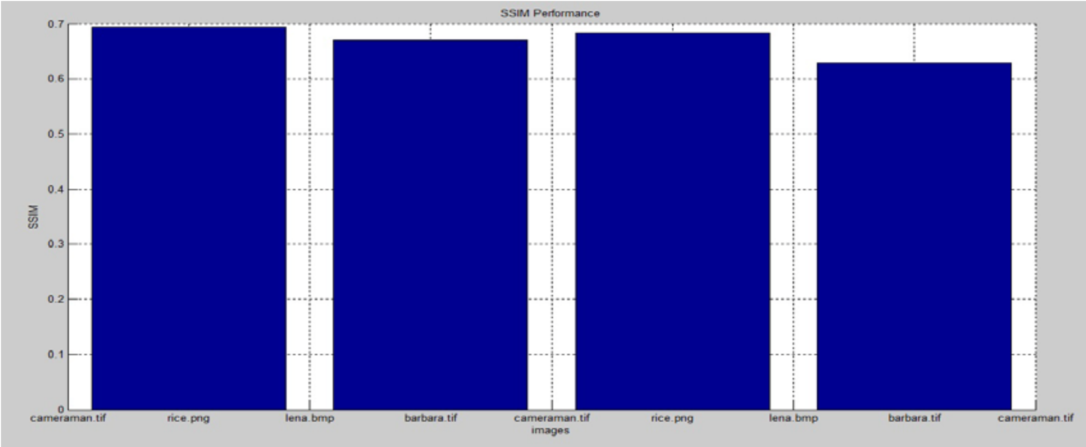

Fig 3.9

The results show that proposed algorithm retrieves the original image from the noisy image and reduces the computational complexity and also improves PSNR overall performance. Comparative evaluation of the proposed method with Traditional NLML is based at execution time in phrases of PSNR, SSIM, and MSE.

4. CONCLUSION

In this paper, we recover the original image from noisy image, image captured from different devices like camera, satellite image etc and reduce computational complexity and improve PSNR overall performance in terms of MSE,PSNR,SSIM with showing comparative evaluation of proposed method with conventional NLML method based on the execution time and quantitative time evaluation in terms of PSNR,MSE,SSIM and suggests that proposed method has an aspect over the traditional method.

5. FUTURE SCOPE

In Future, a method to improve the overall performance of the proposed NLML approach might be brought. We may even work a non-local means approach for the reduction of noise with the goal of lowering the quantity of radiation required in X-ray imaging prognosis. In the future, we additionally intend to improve the technique by way of thinking about attenuation of each frame tissue and behavior an assessment of the technique the usage of an actual diagnostic photo.

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