PNLM and GLCM based Hybrid technique for MRI Image Denoising

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Abstract-The Image processing is the technique which can store the information stored in the form of pixels. The noise is the extra pixels on the image which reduce image quality. The MRI images are medical images on which rician noise is present. The PNLM is the algorithm which can denoise the MRI image. In this research, GLCM is the used which will analyze the textural features of the image and define window size for image denoising. The proposed algorithm is implemented in MATLAB and results are analyzed in terms of certain parameters. It has been analyzed that proposed technique performs well as compared to other techniques in terms of PSNR, RMSE and MSSIM.

***IndexTerms*—PNLM, NLM, GLCM, PSNR, MSSIM, RMSE.**

I. INTRODUCTION

1.1 Image Denoising

A major part of studies in digital image processing is devoted to image denoising. Image denoising is a classical research topic in image processing [1]. The transformation of images has become a major method of communication in the modern era, but the image obtained after transmission is often corrupted with noise. The corrupt image needs to be processed or denoised before it can be used, because it decreases the image quality and brings lots of inconvenience for the diagnosis purpose [2].

1.2 MRI Images

MRI (magnetic resonance imaging) plays an important role in medical and research procedures. It is one of the most effective medical equipment that has been proved to be less harmful for patients as compared to the other medical modalities [3]. MRI is more accurate for imaging soft tissues such as brain and muscles. It can diagnose a broad range of abnormality conditions like cancer, tumor, blockages, internal injuries etc. It does not depend on the ionizing radiation, hence is a non–invasive technique. The MRI technique provides excellent contrast between the normal tissues and the diseased tissues [3]. In the pre-processing technique of enhancement, the unwanted atmospheric noise removed and it can correcting the data from irregularities in the image and enhance the original image while segmentation, image divides into several parts but the main difficulties in segmenting the images are noise, blur, low contrast and a pixel contributing to multiple tissue types. Noise is introduced into the MRI image due to some technical limitation, which includes non-uniform radio frequency (RF) fields. This noise includes intensity variations, partial volume effects and some random image noise [4]. Two stages are very important in medical image processing, image filtering and enhancement. The pre-processing stage is utilized for lessening noise in the image, highlighting the desired regions, enhancing the contrasts and modifying various shapes. The enhancement stage may include resolution and contrast enhancement [4]. This is used to suppress the noise in MRI image and after removing noise from MRI image it can be converted into standard image.

1.3 Rician noise

Rician noise is used to refer the error between the image intensities and the observed data. Like Gaussian distribution, Rician distribution is not corrupted with zero-mean. For removing Rician noise various filters can be used. Rician probability density function of the measured pixel intensity *x* is given as [2],

$$p\left({}^{x}/_{A}\right)=\frac{x}{\sigma^2}\exp\left(-\frac{x^2+y^2}{2\sigma^2}\right)I_0\left(\frac{A.x}{\sigma^2}\right) \quad (1)$$

Where I_0 is the modified zeroth-order based function, A represents noise-free signal amplitude and σ is standard deviation of Gaussian noise is the real and imaginary images.

When $A/_{\sigma}$ is high, the Rician distribution becomes Gaussian distribution and when $A/_{\sigma}$ is 0, rician distribution becomes Rayleigh distribution, equation can be written as [2],

$$p(x/_{A}) = \frac{x}{\sigma^2} \exp\left(-\frac{x^2}{2\sigma^2}\right) \qquad (2)$$

Rician noise is signal-dependent mean that by both the wavelet and scaling coefficients of noisy images are biased.

1.4 Non-Local means (NLM) filter

Almost every denoising method mainly relies on the local pixels within a small neighbour to remove noise. While this process, large scale structures are preserved while small structures are considered as noise and are removed. The NLM filter exploits the redundancy of information contained within the images to get rid of the noise [5]. The improved intensity value of the voxel is calculated because the weighted average of all the voxel intensities within the images.

Equation of NLM is expressed as,

$$NL[u](i) = \sum_{j \in I} w(i,j)u(j) \qquad (3)$$

Here $NL[u](i)$ is represents the estimated value, i represents pixel value and the family of weights {w(i,j)} j depends on the similarity between the pixels i and j and satisfy the usual conditions 0<w(i,j)<=1 and $\sum_j w(i,j) = 1$.

II. LITERATURE REVIEW

Buades A. et al. (2005) [6] proposed a method non local means algorithm (NLM) and a method to measure the method noise. Method noise is used to compute and analyze the noise in medical images. The NLM algorithm is based on a non local averaging of all pixels in the image. Several methods have been proposed to remove the noise from medical images but these methods also remove the important features, textures and edges of image while denoising. This method is better than other methods because it saves the important information of image and recover the true image after denoising. The best simple way to model the effect of noise on a medical image is to add Gaussian white noise. Method noise and mean square error (MSE) are two performance parameters which are used in this paper. In NLM algorithm, search the similar windows in a larger "search window" of size S*S pixels. When a noise of standard deviation σ is added, fixed the filtering parameter h to 10*σ. The NLM takes less time and give better result as compared to other methods. To remove the rician noise from MRI images, NLM algorithm is used.

J. Mohan et al. (2014) [7] – presented a survey on the MRI images denoising methods. In the course of recent years, despite the fact that the resolution, signal-to-noise ratio and acquisition speed of magnetic resonance imaging (MRI) innovation have been increased, MR images are as yet influenced by artifacts and noise. A tradeoffs between noise reduction and the preservation of real detail features must be made in the way that enhances the diagnostically relevant image content. In this manner, noise reduction is as yet a troublesome task. An assortment of techniques has been presented in the literature on denoising MR images and every strategy has its own particular assumptions, advantages and limitations. The reason for this paper is to presents a survey of the distributed literature in dealing with denoising methods in MR images. After a brief introduction about magnetic resonance imaging and the characteristics of noise in MRI, the popular approaches are classified into different groups and a review of different methods is given. The denoising method's advantages and limitations are likewise discussed. The point of this survey is to give a general perspective of the accessible MRI denoising techniques.

R. Balamurugan et al. (2014) [8] - explored a novel filter based on the nonlocal mean (NLM) filter which improves the denoising impact using bilateral filtering for MR images. Its formulation and implementation are simple however the performance of bilateral filter depends upon its parameter. In this paper, bilateral filtering is connected with Brain web MR images which are corrupted by rician noise. It is nonlinear filter to preserve edges. The performance of this filter is evaluated via doing a qualitative and quantitative comparison of this method with two different filters, to be specific, the NLM filter, the Bilateral filter. The contribution of the proposed filter essentially incorporate (a) figuring similarity based on bilateral filtered image to reduce the disturbance of the noise ,and (b) another neighbor for more accurate computation of the similarity. Comparative experiments were performed On T1 and T2 – weighted images from the Brain web Database to compare and break down the proposed filter with the original NLM filter, Bilateral filter. Experimental results demonstrated that, the noise bias can be removed and the original information can be successfully restored, the proposed filter can turn into a high-quality and real time filter. Compare the qualitative and quantitative analysis of Existing filter to proposed filter has been indicate great performance to recognizing the rician noise models.

Danni Ai et al. (2015) [9] – proposed eleven denoising filters, which are introduced and compared for magnetic resonance images. Among them, the state-of-art denoising algorithms, NLM and BM3D, have pulled in much consideration. Several expansions are proposed to improve the noise reduction based on these two algorithms. The optimal dictionaries, sparse representations and appropriate shapes of the transform's help are likewise considered for the image denoising. Based on the estimated noise variance, the comparison of different filters is implemented by measuring the signal-noise-ratio (SNR), resolution and consistency of a phantom image. The subjective judgment of denoising effectiveness is executed for a clinical image and the computational time is finally evaluated. Based on this conclusion, the automatic method is straightforwardly used for the clinical image. The comparative study of different denoising filters for MRI demonstrates that the UNLM is the best with objective judgment for the phantom image, while BM3D SAPCA is superior to different filters with subjective judgment for the clinical image.

Jose V Manjon et al. (2015) [10] - proposed a novel method for MRI denoising that exploits both the sparseness and self-similarity properties of the MR images. This method having a two-stage approach that first filters the noisy image utilizing a non local PCA thresholding strategy via automatically assessing the local noise level present in the image and second uses this filtered image as a guide image inside a rotationally invariant non-local means filter. Magnetic resonance (MR) imaging has vital part on current medical and research procedures. These images are inherently noisy and in this manner filtering methods are required to improve the data quality. This denoising process is normally performed as a pre-processing step in many image processing and analysis tasks, for example, registration or segmentation. There is a lot of bibliography related to the denoising topic that highlights the relevance of this issue for the scientific community. This method internally estimates the measure of local noise shows in the images that enable applying it automatically to images with spatially varying noise levels and furthermore corrects the Rician noise prompted bias locally. This approach has been compared with related state-of-the-art methods indicating competitive results in all the studied cases.

Xu Mingliang et al. (2016) [11] improved in this paper, the classical NLM algorithm to denoise medical images by including a novel noise weighting function and parallelizing. In the experiment, plenty of medical images have been tested and experiment results demonstrate that the algorithm can accomplish better results and higher efficiency compared with the original NLM method. This paper improves the weighted kernel function in NL-means algorithm to denoise the medical image, and furthermore propose a GPU-based parallel non-local means denoising algorithm. Results demonstrate that compared with the traditional sequential algorithm, this new method can have great performance on different levels of noise. The algorithm has been improved two orders of magnitude, in the aspect of processing speed.

III. PNLM ALGORITHM

In order to provide an enhanced noise weighted kernel function for medical image there are various improvements proposed in NL-means algorithm. The ensuring of scenario that greater weight is held by high similarity areas can also be a reason to propose such enhancements. There are smaller weights of low similarity fields. Thus, it is to be made sure that larger weighting coefficients or weights can be provided as output by neighborhood pixels. On the basis of reduction of distance, the output increases. Within the quality of medical image denoising, the matching kernel weighting is to be chosen very carefully. A programming model is presented in this algorithm. On the execution thread, the operation of each pixel on an image is placed. The entire image can be denoised parallelly at same time when the parallel algorithms operate on those pixels[11]. The initial step here is to copy the image from host computer memory to the GPU device memory. Further, within the GPU kernel, single pixel processing is performed. Towards the end, to the host memory, the denoising results are transmitted.

The step-wise procedure of this algorithm is explained below:

Step 1: From the computer, the image and associated parameters are copied to the host memory device GPU memory area.

Step 2: The weight is calculated using:

$$w(i,j) = \frac{1}{Z(i)} e^{\frac{\left\| v(N_i - v(N_j)) \right\|_{2,a}^2}{h^2}} \qquad (4)$$

Using the further following steps, the weights are calculated.

Step 3: Till the weights between the pixels and center pixel of each window are calculated, the Step 2 is repeated.

Step 4: The estimated value of gray pixels are calculated by:

$$NL(v)(i) = \sum_{j \in I} w(i,j) v(j) \qquad (5)$$

This helps in providing the denoising result.

Step 5: From the GPU device memory area, the denoising result is copied to the host computer memory.

IV. PROPOSED WORK

In this work, the NLM technique is studied which is the filtering technique to denoise the MRI Images. The MRI Images has the rician noise which reduces quality of the image. The PNLM is the improved method of NLM in which the pixels of the image processed parallel for the image de-noising. The GLCM algorithm is applied with the PNLM which improve performance of PNLM by selected window size efficiently. The parameters which are used for the analysis are Peak signal-to-Noise Ratio (PSNR), Root Mean Square Error (RMSE), Mean Structural Similarity index (MSSIM). GLCM stands for the Grey level Co-occurrence Matrix, it is also known as the Grey Tone Spatial Dependency Matrix. A GLCM is defined as the matrix where the number of rows and column is equal to the number of grey levels in an image. It is in tabulation format and tells how often different combinations of pixel brightness values occur in an image. GLCM method is used to extract statistical surface parameters such as Inverse Difference Moment, Entropy, Angular Second Moment and Correlation. It is proved to be best statistical method for extracting textual feature from an image. It is also contains the second order statistical information of the adjoining pixels of an image. This second order statistical method feature used for the implementation in VERILOG language. GLCM is calculated using grey co-matrix in a scaled version of the image. Suppose 'I' is a binary image, grey co-matrix scales the image into two gray-levels. If 'I' is an intensity image, it scales the image into eight grey-levels. 'Numlevels' parameter is used to specify the number of grey-levels and gray co-matrix scales the values using 'GrayLimits' parameter.

Pseudo Code of GLCM Algorithm

1. Count all the number of pixels in the matrix in which the data is saved.

2. Store the counted pixels in matrix P[I,j].

3. Check similarity between pixels in the matrix by applying histogram technique.

4. Calculate contrast factor from the matrix:

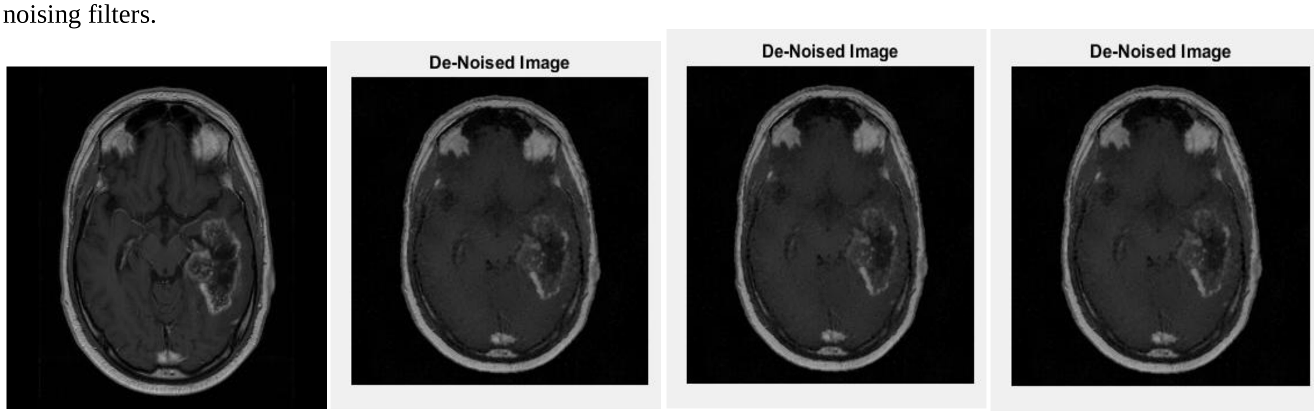
$$g = \exp\left[\frac{mean\ (I) - minimum\ \ (I)}{maximum\ \ (I) - mean\ (I)}\right] \qquad (6)$$

5. The elements of g need to be normalized by dividing the pixels.

$$g = \begin{bmatrix} 0.8\ if\ g < 0.8 \\ 1.2\ if\ g > 1.2 \\ g\ otherwise \end{bmatrix} \qquad (7)$$

V. RESULTS AND DISCUSSION

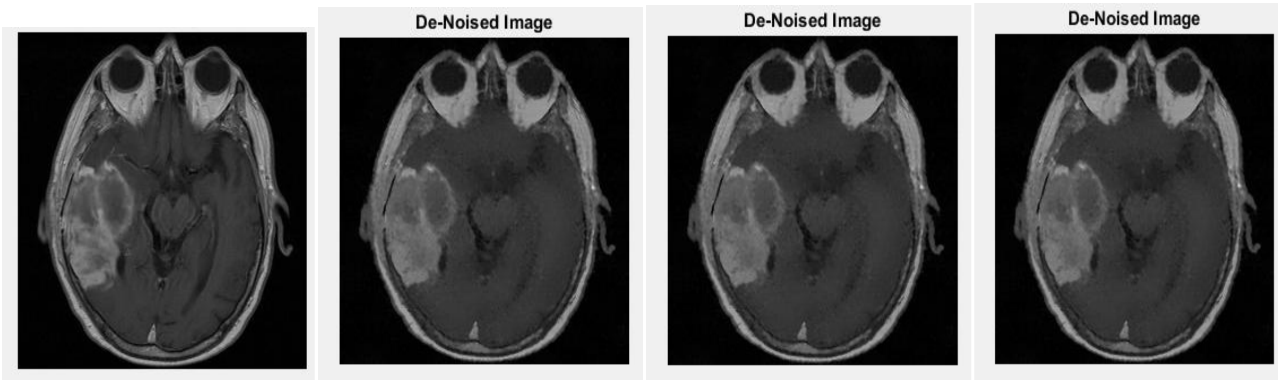
The MRI images are used for the purpose of experimentation. Images are taken from the http://nist.mni.mcgill.ca/?page_id=672. The given site contains are the large set of MRI images which are acquired from Neuroimages and Surgical Technologies Lab. The imaged are the MRI images which have the B-mode image pre and post –reactions. The performance of PNLM and improved PNLM algorithm is tested on the mentioned dataset. The images which dataset contains have the MRI images of Brain from different angles. All the experiments are performed in MATLAB 7.10.0 (R2016a). The following figure shows the images used for testing different de-noising filters.



1a) Image 1 1b) NLM 1c) PNLM 1d) Proposed

Fig 1: Denoising of Image 1.

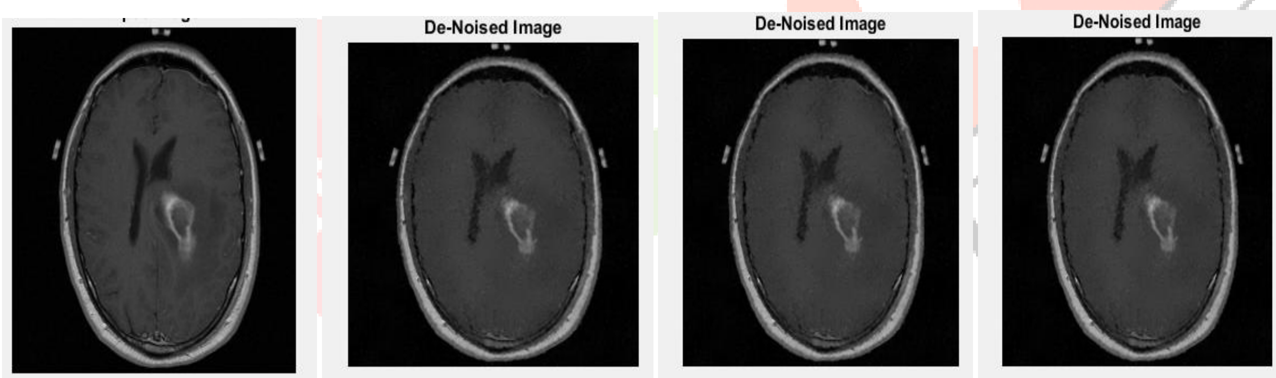
As shown in figure 1b, the NLM filtering technique is applied which can define the window size statically to denoise the input image. In figure 1c, the PNLM is the improved version of NLM algorithm. The PNLM algorithm will process the image parallel and remove noisy pixels from the image . In figure 1d., the proposed method is applied in which the window size is defined by the GLCM algorithm. The proposed method shows improved results as compared to other methods



2a) Image 2 2b) NLM 2c) PNLM 2d) Proposed

Fig 2: Denoising of Image 2

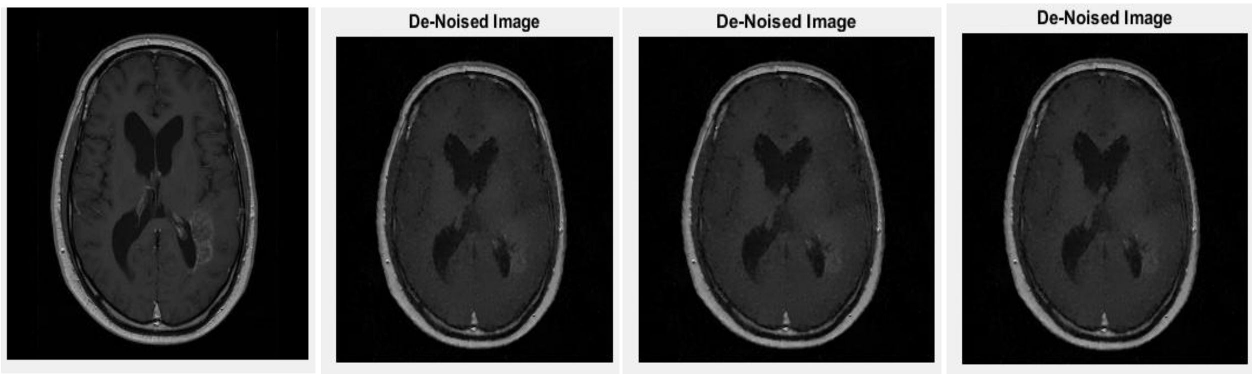
As shown in figure 2b, the NLM filtering technique is applied which can define the window size statically to denoise the input image. In figure 2c, the PNLM is the improved version of NLM algorithm. The PNLM algorithm will process the image parallel and remove noisy pixels from the image . In figure 2d., the proposed method is applied in which the window size is defined by the GLCM algorithm. The proposed method shows improved results as compared to other methods



3a) Image 3 3b) NLM 3c)PNLM 3d) Proposed

Fig 3: Denoising of Image 3

As shown in figure 3b, the NLM filtering technique is applied which can define the window size statically to denoise the input image. In figure 3c, the PNLM is the improved version of NLM algorithm. The PNLM algorithm will process the image parallel and remove noisy pixels from the image . In figure 3d., the proposed method is applied in which the window size is defined by the GLCM algorithm. The proposed method shows improved results as compared to other methods.



4a)Image 1 4b) NLM 4c)PNLM 4d) Proposed

Fig4: Denoising of Image 4

As shown in figure 4b, the NLM filtering technique is applied which can define the window size statically to denoise the input image. In figure 4c, the PNLM is the improved version of NLM algorithm. The PNLM algorithm will process the image parallel and remove noisy pixels from the image . In figure 4d., the proposed method is applied in which the window size is defined by the GLCM algorithm. The proposed method shows improved results as compared to other methods.

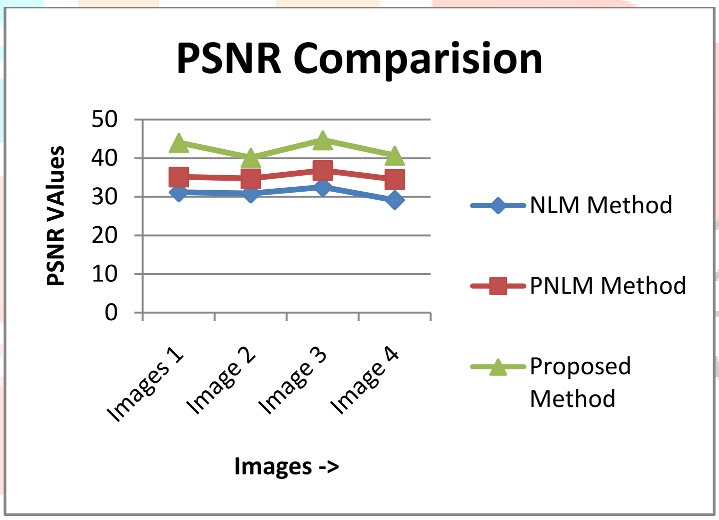


Fig 5: PSNR Comparison

As shown in figure 2, the PSNR values of NLM, PNLM and proposed algorithms are compared graphically. It has been analyzed that PSNR value of proposed algorithm is maximum due to implementation of GLCM Algorithm.

Method Name	Images 1	Image 2	Image 3	Image 4
NLM Method	31.12	30.82	32.45	29.10
PNLM Method	35.06	34.67	36.78	34.43
Proposed Method	43.98	40.12	44.67	40.67

Table 1: Comparison of PSNR Values

As illustrated in table 1, the NLM, PNLM and Proposed Methods are compared in terms of PSNR and it has been analyzed that proposed method has maximum PSNR as compared to other methods

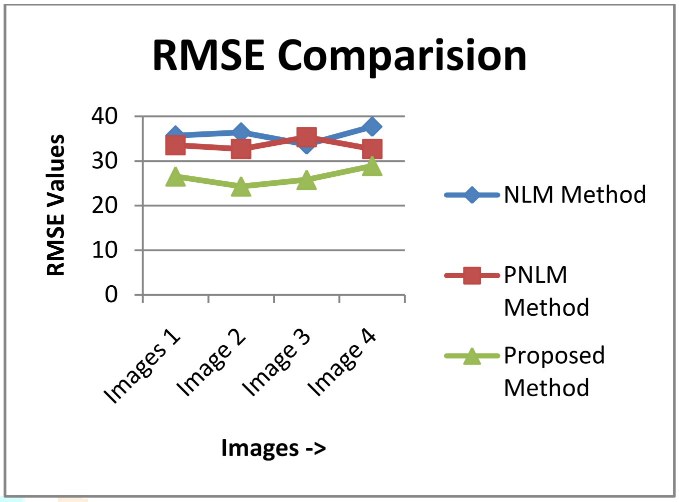


Fig 6: RMSE Comparison

As shown in figure 3, the RMSE values of NLM, PNLM and proposed algorithms are compared graphically. It has been analyzed that RMSE value of proposed algorithm is minimum due to implementation of GLCM Algorithm

Method Name	Images 1	Images 2	Images 3	Images 4
NLM Method	35.67	36.36	33.67	37.67
PNLM Method	33.53	32.67	35.31	32.67
Proposed Method	26.54	24.31	25.78	28.89

Table 2: Comparison of RMSE Values

As illustrated in table 2, the NLM, PNLM and Proposed Methods are compared in terms of RMSE and it has been analyzed that proposed method has minimum RMSE as compared to other methods

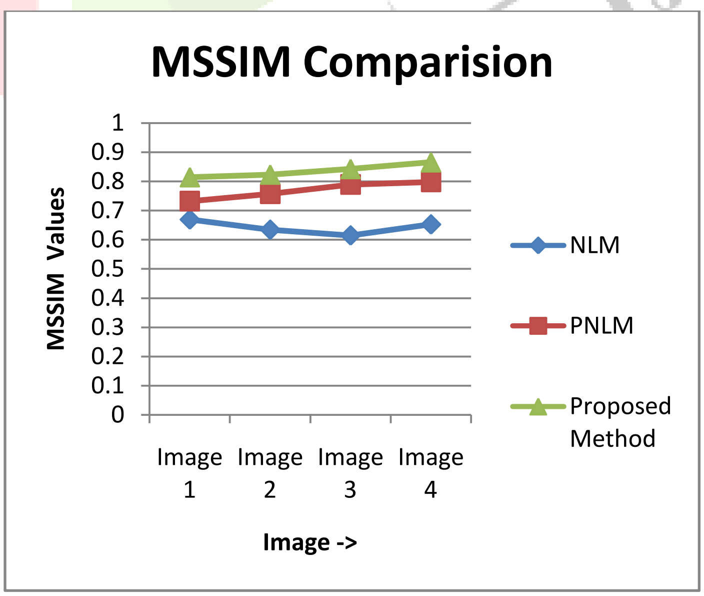


Fig 7: MSSIM Comparison

As shown in figure 3, the MSSIM values of NLM, PNLM and proposed algorithms are compared graphically. It has been analyzed that MSSIM value of proposed algorithm is minimum due to implementation of GLCM Algorithm

Method Name	Images 1	Images 2	Images 3	Images 4
NLM	0.669	0.6342	0.6145	0.6523
PNLM	0.7324	0.7578	0.7891	0.7981
Proposed Method	0.8145	0.8234	0.8425	0.8654

Table 3. Comparison of MSSIM Values

As illustrated in table 3, the NLM, PNLM and Proposed Methods are compared in terms of MSSIM and it has been analyzed that proposed method has minimum MSSIM as compared to other methods

VI. CONCLUSION

In this work, it has been concluded that PNLM is the image de-noising technique which performs operation in the parallel manner. The algorithm take window size, noisy image as input and remove the noisy pixels from the image. In this research paper, GLCM algorithm is applied which will calculate textual features and define the window size according to the image. The proposed improvement increase the algorithm efficiency in terms of PSNR , MSSIM and RMSE.

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