www.ijecs.in
*International Journal Of Engineering And Computer Science ISSN:2319-7242*
*Volume 4 Issue 7 July 2015, Page No. 13035-13041*

# Wavelet based denoising of brain MRI images

***Sujata Desai[1], Lubna.M.Kazi[2]***

[1]Assistant Professor Department of Computer Science and Engineering B.L.D.E.A's Dr. P. G. H Engineering college Bijapur, Karnataka, India
*shreeja.clg@gmail.com*

[2]Mtech Computer Science and Engineering B.L.D.E.A's Dr. P. G. H Engineering college Bijapur, Karnataka, India
*lubnakazi64@gmail.com*

Abstract: ***Image denoising has been evolving as an essential exercise in medical imaging especially the Magnetic Resonance Imaging (MRI). The presence of noise in the biomedical images is one of the major challenge in image analysis and image processing. Denoising techniques are aimed at removing distortion or noise from the image while retaining the original quality of the image. Medical image obtained are often corrupted with noise. The MR images are processed to improve visual appearance to the viewers. Here we will discuss the multiresolution techniques such as scalar wavelet, multiwavelet and laplacian pyramid, Non local means (NLM) and compare their statistical parameters.***

**Keywords:** Magnetic Resonance Imaging (MRI), denoising, PSNR, MSE, Multiresolution image decomposition.

## 1. Introduction

In present growing digital world, the digital images play an important role in applications such as Magnetic Resonance Imaging (MRI), satellite, television and also in areas such as research and technology including Geographical Information System. Noise is unwanted signal that interferes with that of the original image and degrades the visual quality of original image. The primary sources of noise in digital images are problem with data acquisition process, imperfect instruments, interference natural phenomena, transmission and compression [1].

Digital images are extensively used by medical practitioners during the different stages of disease, diagnosis and treatment process. In the medical field, noise can possibly occur in an image during two phases: acquisition and transmission. During the acquisition phase, noise is introduced into an image, because of the manufacturing defects, improper functioning of some internal components, minute component failures and can be due to the manual handling errors of the electronic scanning devices such as PECT/SPECT, MRI/CT scanners.

Medical imaging is the process of collecting information about a particular physiological structure such as tissue or an organ. It uses the predefined characteristic property which is displayed in the image form. The powerful technique used in medical imaging is the Magnetic resonance imaging (MRI). Physicians use this technique to detect the structural abnormalities. The image visualization deficiency is caused because there are small differences in the soft tissues. Few years ago, physicians had the medical images or pictures on a light board and they make diagnosis using their knowledge [1]. During last twenty years, the progress in the medical MRI technology has created a very wide collection of medical imaging techniques which are available to researchers and physician.

The images usually contain noise which is not easily eliminated in image processing. People have developed many methods of eliminating noises. The advent of digital imaging technologies such as MRI has revolutionized modern medicine.

The Non Local Means (NLM) is the denoising technique used for removing unwanted noise from the image pixels. It compares the weighted average of the neighborhood pixels in an image. Ideally the resulting denoised image will not contain any noise or added artifacts. The NLM denoising method performance is exceptionally well as compared to the other denoising methods. The need of NLM algorithm is to accomplish its goals of removing noise and preserving detail. Here a new algorithm is introduced to reduce noise from medical images and to determine a more correct value of pixels of noisy image. The experimental results will show the efficiency of proposed NLM method and discuss the multiresolution technique and compare their statistical parameters.

The Peak-Signal-to-Noise-Ratio (PSNR), Mean Square Error (MSE) and Energy are used to evaluate the enhancement performance of various multiresolution techniques.

The medical image denoising still remains a challenge for researchers because the noise removal process introduces artifacts and causes blurring of image. A universal property of images is the presence of granular pattern of some noise, often called as rice or the rician noise. The computerized MR images are corrupted by noise which is rician distributed. The rician noise is the error between underlying image intensities and the observed data in the given image. The mean of rician noise depends on the local intensity of the image. Because of the image suppression, it is challenging situation to recover an original image from noisy atmosphere.

Wavelet transform is best suited for denoising, because of its properties like sparsity, multiresolution and multiscale nature.

## 2. IMAGE DENOISING

Image denoising is the fundamental problem in Image processing. Wavelet gives the excellent performance in field of image denoising because of its characteristics like sparsity and multiresolution structure. With the popularity of Wavelet Transform for the last two decades, several algorithms have been developed in wavelet domain.

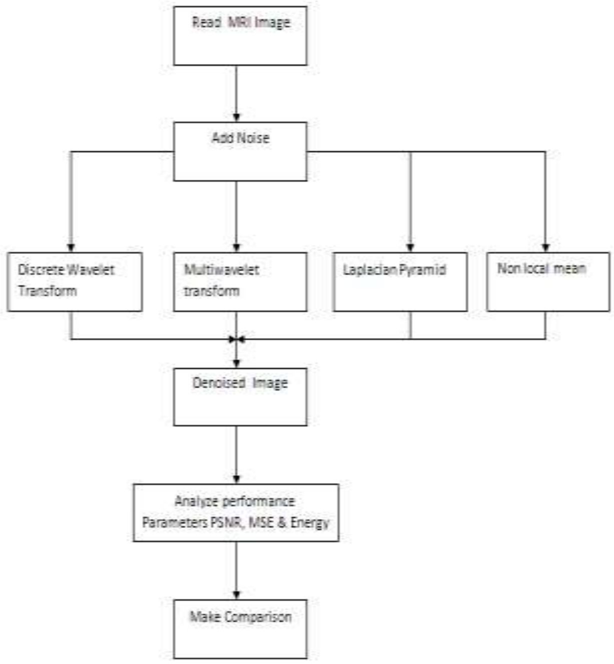



Fig 1.Block diagram

### 2.1 Noise

The brain MRI image generally consists of the various types of noise. Some of the typical noise is a Gaussian noise, which is additive in nature & also speckle noise, which is multiplicative in nature. Some are corrupted with salt & pepper noise or uniform distribution noise.

**Gaussian Noise**

Gaussian noise is evenly distributed over the signal. Each pixel in noisy image is the sum of true pixel value and a random gaussian distributed noise value. Gaussian noise which is independent at each pixel and independent of the signal intensity. In color cameras, blue colour channels are more amplified than red or green channel, therefore, blue channel generates more noise.

**Salt and Pepper Noise**

The salt-and-pepper noise are also called shot noise, impulse noise or spike noise that is usually caused by faulty memory locations ,malfunctioning pixel elements in the camera sensors, or there can be timing errors in the process of This kind of noise is usually seen on images. It consists of white and black pixels. An image containing salt and pepper noise consists of two regions i.e. bright and dark regions. Bright regions consist of dark pixels whereas dark regions consist of bright pixels. Transmitted bit errors, analog-to-digital converter errors and dead pixels contain this type of noise [5].

Reasons for Salt and Pepper Noise:

a. By memory cell failure.
b. By malfunctioning of camera's sensor cells.
c. By synchronization errors in image digitizing or transmission.

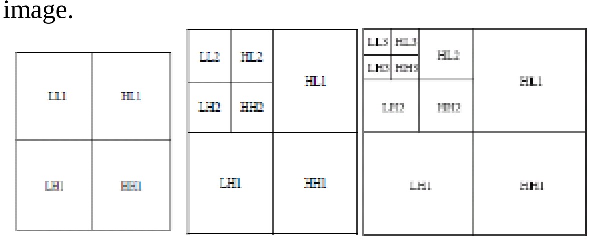
**Speckle Noise**

Speckle noise is a multiplicative noise. It is a granular noise that commonly exists in and the active radar and synthetic aperture radar (SAR) images. Speckle noise increases the mean grey level of a local area. It is causing difficulties for image analysis in SAR images .It is mainly due to coherent processing of backscattered signals from multiple distributed targets [4].

**(a) Discrete Wavelet Transform**

In signal processing and image compression the wavelet transform has gained wide spread acceptance. JPEG committee has released a new image coding standard, JPEG-2000, which is based upon DWT. Wavelet transform will decompose a signal into a set of basis functions. These basis functions are called wavelets. Wavelets are obtained from a single prototype wavelet called mother wavelet by dilations and shifting [8]. The DWT has been introduced as a highly flexible and efficient method for sub band decomposition of signals. The 2D DWT is now a day's performed as a key operation in image processing. DWT is multi-resolution analysis and it decomposes images into wavelet coefficients and scaling function. In Discrete Wavelet Transform, signal energy concentrates to specific wavelet coefficients. This characteristic is useful for compressing images [9]. Wavelets have rough edges, and these wavelets are able to render pictures in a better way by eliminating the blockiness. Wavelets convert the image into a series of wavelets that can be stored more efficiently than pixel blocks. In DWT, a timescale representation of a digital signal is obtained using digital filtering techniques.

It is easy to implement and also reduces computation time and resources required. The signal which is to be analyzed is passed through filters with different cut-off frequencies at different scales [8]. A 2-D DWT can be seen as a 1-D wavelet scheme which transforms along the rows and then a 1-D wavelet transform along the columns. The 2-D DWT operates by inserting array transposition between the two 1-D DWT. The rows of array are processed first with only one level of decomposition. This essentially will divide the array into two vertical halves, first half stores the average coefficients, while second vertical half stores the detail coefficients.
This process is repeated again with the columns, resulting in four sub-bands within the array defined by filter output. Figure below shows a three level 2- D DWT decomposition of the image.



(a)1-level (b)2-level (c)3-level

Fig 2. Image decomposition

Image consists of pixels that are arranged in two dimensional matrix, each pixel represents the digital equivalent of image intensity. In spatial domain adjacent pixel values are highly correlated and hence redundant. In order to compress the digital images, the redundancies existing among pixels needs to be eliminated. DWT processor transforms the spatial domain pixels into frequency domain information that are represented in multiple sub-bands, representing different time scale and frequency points. One of the most important features of JPEG2000 standard, providing it the resolution scalability, is the use of the 2D-DWT to convert the image into more compressible form. The JPEG 2000 standard propose a wavelet transform stage since it offers better rate/distortion (R/D) performance than the traditional DCT.

**(b) Multi wavelet**

Multi-wavelet transformation is a new concept of wavelet transformation architecture. In multiwavelet transform, we use multiwavelet as transform basis. Multiwavelets have two or more scaling functions and mother wavelet for signal representation. The properties of GHM (Geronimo–Hardin–Massopust) multiwavelet filter are orthogonality, symmetry and compact support. To implement the multiwavelet transform, we require a new filter bank structure where the low pass and high pass filter banks are matrices rather than scalars. Multiwavelet transform domain that there are first and second low pass coefficient followed by first and second high pass coefficient rather than one low pass coefficient followed by one high pass coefficient shown in fig 3.

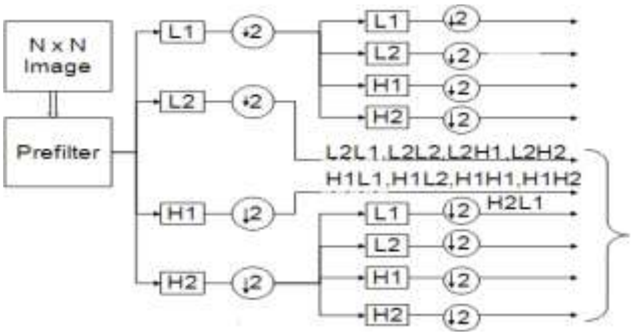



Fig 3. Multiwavelet decomposition flowchart

**(c)Laplacian Pyramid**

A pyramid structure has different levels of an original image. The Laplacian pyramid [7] is a versatile data structure with many of the attractive features for the processing of digital images. The levels are obtained recursively by filtering the lower level image with a low pass filter. The Laplacian pyramid is a technique for decomposing images into multiple scales and is widely used for image analysis. Decomposition is performed where, the image is recursively decomposed into lowpass and highpass bands [7]. Laplacian pyramids are widely used to analyze images at multiple scales for a broad range of applications such as harmonization and compression. The benefit of computing the Laplacian pyramid is that, one has automatic access to quasi-bandpass copies of the image. In this denoising technique, image features of various sizes are enhanced and are directly available for various image processing and pattern recognition tasks.

First step in Laplacian pyramid coding is to low-pass filter the original image $g0$ to obtain image $g1$. Therefore we say that $g1$ is "reduced" version of $g0$ in that both sample density and resolution are decreased. In a similar way we form $g2$ as a reduced version of $g1$, and so on. For constructing the reduced image $g1$ is that it may serve as a prediction for pixel values in the original image $g0$. To obtain a compressed representation, we encode the error image which remains when an expanded $g1$ is subtracted from $g0$. This image becomes the bottom level of the Laplacian pyramid. The next level is generated by encoding $g1$ in the same way.

We subtract a low pass filtered copy of the image from the image itself, in this way Pixels to pixel correlation are first removed. Iteration of the process at appropriately expanded scales generates a pyramid data structure. The difference or error image has low variance and entropy [1]. Let I be the original image and J be the result of applying an appropriate low pass filter. The prediction error E is given by E1=I1-J1. The reduced image I1 is itself low pass filtered to yield I2 and a second error image is obtained E2=I2-J2. By the above mentioned steps we obtain a two dimensional arrays EI, E2,.....En. If we now imagine these arrays stacked one above another, the result is a tapering pyramid data structure shown in fig below.

The value at each node at the pyramid represents the difference between two Gaussian like or related functions convolved with the original image. The difference between these two functions is similar to the Laplacian operators. The value at each node in the Laplacian pyramid is the difference between the convolution of two equivalent weighting functions with the original image. Again this is similar to convolving an appropriately scaled Laplacian weighting function with the image .The node value can be obtained directly by applying this operator .The pyramid decompositions are performed on each source image, all these decomposition are integrated to form a composite representation.

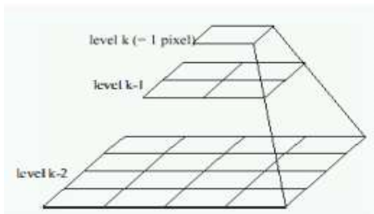



Fig 4. Image Pyramid Decomposition

**(d)Non Local Means Filter**

Over the years, many denoisng methods have been proposed. Some of the major denosing methods include Wiener filtering and Gaussian filtering. However, most of these methods tend to lose fine detail of the image which leads to blurring of the images. A non-local means approach is presented, which performs image denoising while preserving most of the fine detail of the noisy image.

The Previous methods attempt to separate the image into the smooth part which is the true image and the oscillatory part that is noise, by removing the higher frequencies from the lower frequencies. However, all images are not smooth. Images contains fine details and structures which have high frequencies. When the high frequencies are removed from the given image, the high frequency content of the true image will be removed along with the high frequency noise because, the methods cannot tell the difference between the noise and true image. This results in loss of fine detail in the denoised image. Also, nothing is done to remove the low frequency noise from the image. Therefore even after denoising, low frequency noise will remain in the image.

Numerous and diverse denoising methods have already been proposed in the past few years, such as total variation [15] and wavelet-based technique. All these methods estimate the denoised pixel value based on the information provided in a surrounding local limited window. Unlike the local denoising methods, non-local methods estimate the noisy pixel is replaced based on the information of the whole image. Because of this loss of detail non-local means algorithm was proposed.

The non local means algorithm does not make the same assumptions about the image as other methods. The non local means algorithm assumes the image contains an extensive amount of self-similarity. Efros and Leung originally developed the concept of self-similarity. An example of self-similarity is displayed in Figure below. The figure shows three pixels *p*, *q1*, and *q2* and their respective neighborhoods. The neighborhoods of the pixels *p* and *q1* are similar, but the neighborhoods of pixels *p* and *q2* are not similar. The Adjacent pixels tend to have similar neighborhoods, but non-adjacent pixels will also have similar neighborhoods when there is structure in the image. For example, in Figure below most of the pixels in the same column as *p* will have similar neighborhoods to *p*'s neighborhood. The self-similarity assumption can be exploited to denoise an image. Pixels with similar neighborhoods can be used to determine the denoised value of a pixel.

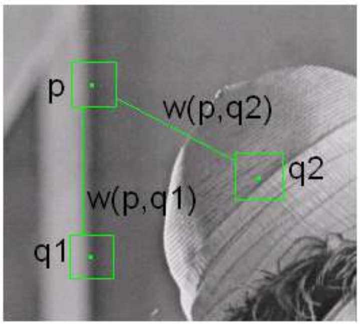



Fig 5. Example of self-similarity in an image. Pixels *p* and *q1* have similar neighborhoods, but pixels *p* and *q2* do not have similar neighborhoods. Because of this, pixel *q1* will have a stronger influence on the denoised value of *p* than *q2*.

The NL-means algorithm replaces the noisy value by a weighted average of all the pixels of the image. The weight of a pixel is significant only if a Gaussian window around it looks like the corresponding Gaussian window around the reference pixel. Thus the nonlocal means algorithm uses image self-similarity to reduce the noise by averaging similar pixels. This average preserves the integrity of the image but reduces its small fluctuations, which are essentially due to noise.

Each pixel p of the non local means denoised image is computed as

$$\boldsymbol{NL(V)(p)} = \sum\nolimits_{q \epsilon v} \boldsymbol{w(p,q)\, V\,(q)} \qquad (1)$$

Where, V is the noisy image, and weights w(p,q) meet the following conditions $0 \leq w(p,q) \leq 1$ and $\sum_q w(p,q) = 1$. Each pixel is a weighted average of all the pixels in the image. The weights are based on the similarity between the neighborhoods of pixels.

The weights can then be computed using

$$w(p,q) = \frac{1}{z(p)}\, e^{\frac{d(p,q)}{h}} \qquad (2)$$

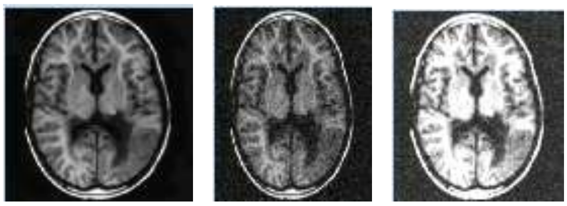
Z(P) is the normalizing constant and h is the weight-decay control parameter**.** Given h is the first parameter, the weight-decay control parameter which controls where the weights lay on the decaying exponential curve. If h is set too low, not enough noise will be removed. If h is set too high, the image will become blurry. If an image contains white noise with a standard deviation of σ, h should be set between the range 10σ and 15σ.

The second parameter, Rsim, is the radius of the neighborhoods used to find the similarity between two pixels. If Rsim is too large, no similar neighborhoods will be found, but if it is too small, too many similar neighborhoods will be found. Common values for Rsim are 3 and 4 to give neighborhoods of size 7x7 and 9x9, respectively.

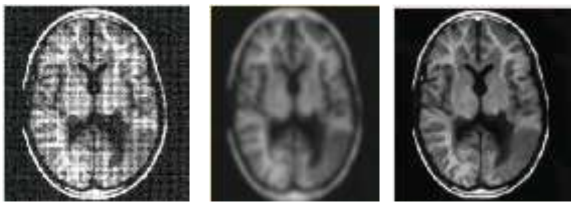
The third parameter, Rwin, is the radius of a search window. Because of the inefficiency of taking the weighted average of every pixel, it will be reduced to a weighted average of all pixels in a window. The window is centered at the current pixel being computed. Common values for Rwin are 7 and 9 to give windows of size 15x15 and 19x19, respectively. With this change the algorithm will take a weighted average of $15^2$ pixels rather than a weighted average of $N^2$ pixels for an NxN image.

## 3. Experiments and results

Magnetic resonance imaging of human brain is used to test the proposed algorithm. Experimental results show that our proposed method performs much better than the other denoising methods. The proposed method has been compared with scalar wavelet, multiwavelet, and laplacian pyramid using quantitative parameters like PSNR, MSE and energy. It has been found that the Non Local Means performs better than all other methods by removing the noise, while still retaining the structural details of the brain MRI image.



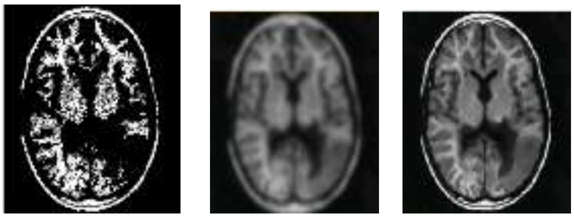
(a) (b) (c)



(d) (e) (f)

Fig 6.(a)Original image (b)Rician distributed (c)denoised image with scalar wavelet (d)Denoised image with multi wavelet (e) Denoised image with Laplacian pyramid (f) Denoised image with NLM

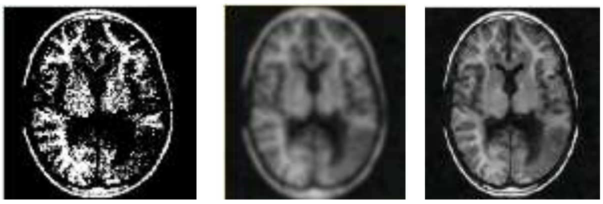
(a) (b) (c)



(d) (e) (f)

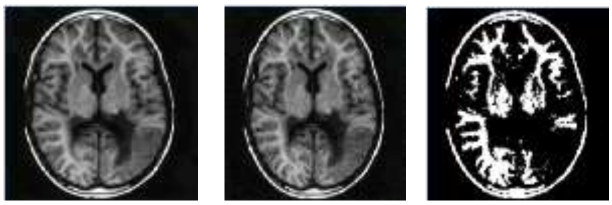
Fig 7.(a)Original image (b)Speckle noise MR image (c)denoised image with scalar wavelet (d)Denoised image with multi wavelet (e) Denoised image with Laplacian pyramid (f) Denoised image with NLM

(a) (b) (c)

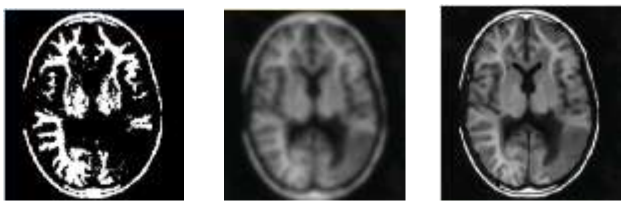


(d) (e) (f)

Fig 8. (a)Original image (b)Gaussian noise MR image (c)denoised image with scalar wavelet (d)Denoised image with multi wavelet (e) Denoised image with Laplacian pyramid (f) Denoised image with NLM.



(a) (b) (c)



(d) (e) (f)

Fig 9.(a)Original image (b)poisson noise MR image (c)denoised image with scalar wavelet (d)Denoised image with multi wavelet (e) Denoised image with Laplacian pyramid (f) Denoised image with NLM.

We can also detect the type of noise present in brain MR image.

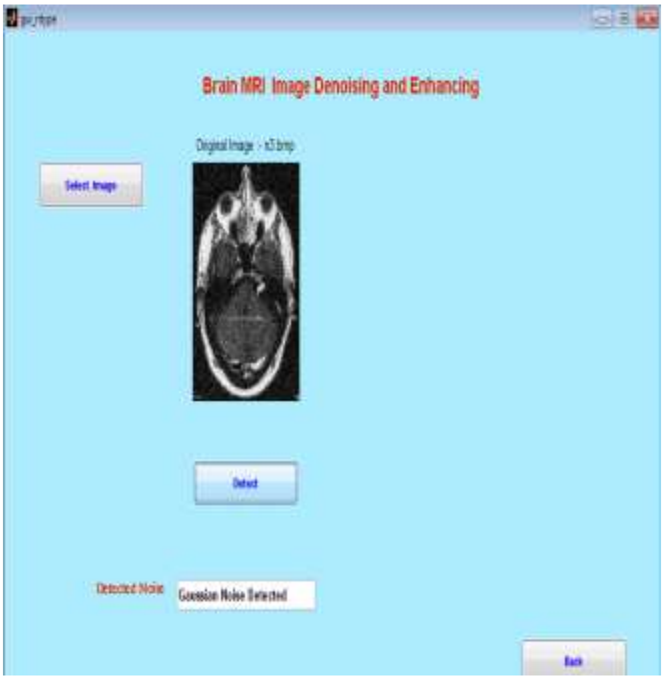




**Table 1:** Comparision of PSNR, MSE, Entropy for MR image corrupted with Rician noise.

| *Type of noise* | *Type of denoising method* | *MSE* | *PSNR* | *Entropy* |
|---|---|---|---|---|
| Rician noise | Scalar wavelet | 0.12401 | 9.0654 | 7.9631 |
| | Multi wavelet | 0.031766 | 14.9804 | 9.724 |
| | Laplacian pyramid | 0.013177 | 18.8019 | 6.7426 |
| | NLM | 0.00054114 | 32.6669 | 8.2316 |

**Table 2:** Comparision of PSNR, MSE, Entropy for MR image corrupted with Speckle noise

| *Type of noise* | *Type of denoising method* | *MSE* | *PSNR* | *Entropy* |
|---|---|---|---|---|
| Speckle noise | Scalar wavelet | 0.14172 | 8.4858 | 3.2348 |
| | Multi wavelet | 0.091793 | 10.3719 | 2.082 |
| | Laplacian pyramid | 0.011431 | 19.4193 | 6.8595 |
| | NLM | 0.00064401 | 31.9111 | 7.1373 |

**Table 3:** Comparision of PSNR, MSE, Entropy for MR image corrupted with Gaussian noise

| *Type of noise* | *Type of denoising method* | *MSE* | *PSNR* | *Entropy* |
|---|---|---|---|---|
| Gaussian noise | Scalar wavelet | 0.15687 | 8.0446 | 3.7637 |
| | Multi wavelet | 0.10049 | 9.9789 | 2.3015 |
| | Laplacian pyramid | 0.011735 | 19.3053 | 7.0061 |
| | NLM | 0.00081961 | 30.8639 | 8.155 |

**Table 4:** Comparision of PSNR, MSE, Entropy for MR image corrupted with poisson noise

| *Type of noise* | *Type of denoising method* | *MSE* | *PSNR* | *Entropy* |
|---|---|---|---|---|
| Poisson noise | Scalar wavelet | 0.19171 | 7.1736 | 2.5568 |
| | Multi wavelet | 0.1289 | 8.8975 | 1.5621 |
| | Laplacian pyramid | 0.011327 | 19.459 | 6.8927 |
| | NLM | 0.00033952 | 34.6914 | 7.0118 |

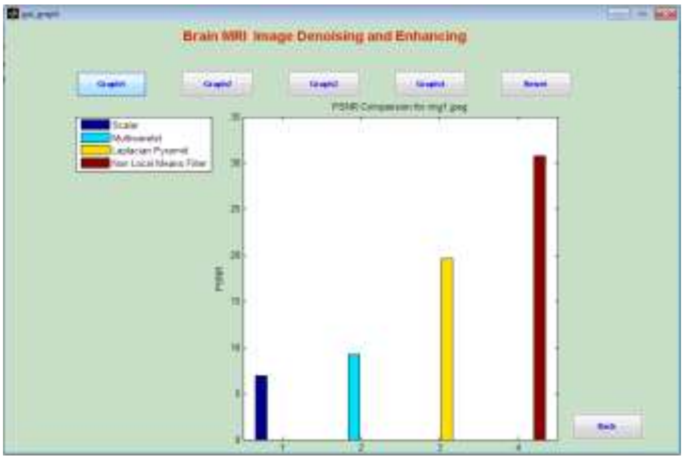



Fig 10. PSNR comparision for scalar, multiwavelet, laplacian pyramid, NLM

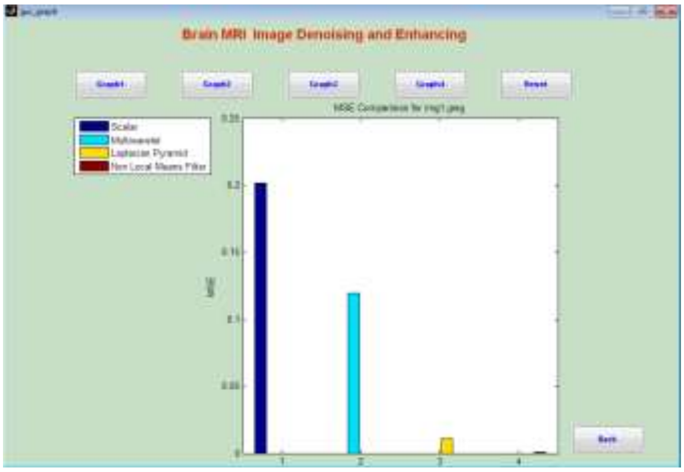



Fig 11. MSE comparision for scalar, multiwavelet, laplacian pyramid, NLM

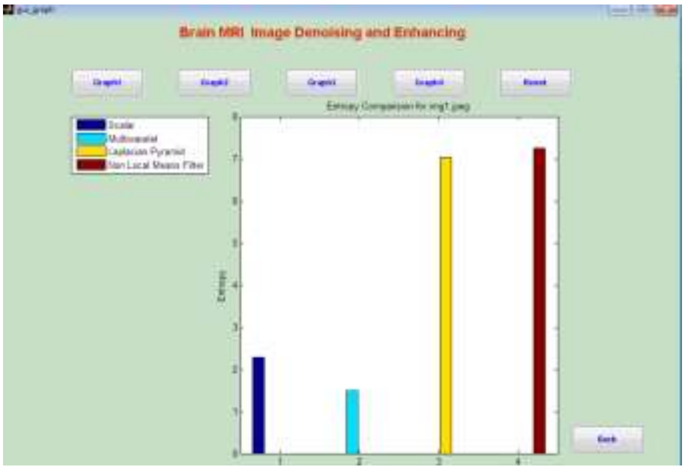



Fig 12. Entropy comparision for scalar, multiwavelet, laplacian pyramid, NLM

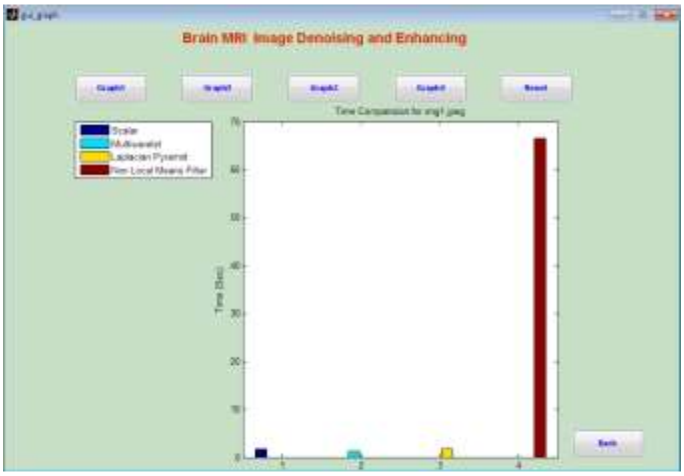



Fig 13. Time comparision for scalar, multiwavelet, laplacian pyramid, NLM

## Conclusion

In this paper, an analysis of denoising techniques like scalar wavelets, multi wavelets, laplacian pyramid, non local means filter (NLM) has been carried out. The experimental results using MATLAB shows that the performance parameters for NLM are better than the other denoising techniques. That is the non local means (NLM) denoising method has high PSNR and low MSE in presense of different noises such as rician noise, speckle noise, Gaussian noise, poisson noise.

## References


[1] V. Vanathe, S .Boopathy, M.A .Manikandan "MR Image Denoising and Enhancing using Multiresolution Image Decomposition technique."

[2] V.Vanathe, S.Boopathy "A Modem Criterion for Denoising and Enhancing the Magnetic Resonance Images " International Journal of Emerging Technology and Advanced Engineering Website: www.ijetae.com (ISSN 2250-2459, volume 2, Issue 8, August 2012).

[3] A. Macovski, "Noise in MRI," Magn. Reson. Med., vol, 36, pp.494 – 497, 1996.

[4] Xu Yan, Min-Xiong Zhou, Ling Xu, Wei Liu, Guang Yang, "Noise removal of MRI data with Edge Enhanceing "978-1-4244-5089-32011 IEEE.

[5] K. Deb, S. Agrawal, A. Pratab, T. Meyarivan, "A Fast Elitist Non-dominated Sorting Genetic Algorithms for Multiobjective Optimization: NSGA II," KanGAL report 200001, Indian Institute of Technology, Kanpur, India, 2000. (technical report style)

[6] J. Geralds, "Sega Ends Production of Dreamcast," vnunet.com, para. 2, Jan. 31, 2001. [Online]. Available: http://nl1.vnunet.com/news/1116995. [Accessed: Sept. 12, 2004]. (General Internet site)

[7] P. J. Burt, E. Adelson, The Laplacian pyramid as a compact image code, IEEE Trans. Commun. Com-31(4), 532-540 (1983).

[8] Dipalee Gupta, Siddhartha Choubey, Discrete Wavelet Transform for Image Processing, March 2015.

[9] Rafael C. Gonzalez University of Tennessee, Richard E. Woods. Digital image processing Third Edition 2008.

[10] Pearson Education. H.Gudbjartsson and S.Patz, "The Rician Distribution of noisy MRI data," Magn. Reson. Med., vol, 34, pp.91 0 - 914, 1995. C.

[11] Tomasi and R. Manduchi, "Bilateral filtering for gray and color images," in Book Bilateral filtering for gray and color images, Series Bilateral filtering for gray and color images, Editor ed."eds., City, 1998, pp. 839-846.

[12] Wong, A Chung, and S. Yu, "Tri lateral filtering for biomedical images" in Book Trilateral filtering for biomedical images, Series Trilateral filtering for biomedical images, Editor ed."eds., City, 2004, pp. 820-823.

[13] ABuades, B. Coll, and lM. Morel, "A Review of Image Denoising Algorithms, with a New One," Multiscale Model. Simul., vol. 4, (no.2), pp. 490-530, 2005.


## Author Profile

**Sujata desai**

She is currently Associate Professor at Department of Computer Science and Engineering B.L.D.E.A's Dr. P. G. H Engineering college Bijapur, Karnataka, India. She has completed her B.E from PDA ,Gulbarga from Gulbarga university in 1996 and M.tech in CSE from KBN, Gulbarga, VTU University.

**Lubna .M. Kazi**

She is currently pursuing M.tech from B.L.D.E.A's Dr. P. G. H Engineering college Bijapur, Karnataka, India. She has completed B.E from S.I.E.T, Bijapur in Computer science and Engineering in 2013. Her areas of interest includes Medical image processing.