Denoising of Magnetic Resonance Images using Wavelet Domain Transform based methods

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ABSTRACT
The field of image processing developed from electrical engineering as an extension to the signal processing branch. When the images are created, transmitted and decoded they are distorted by different type of noises. Thus further processing these images does not lead to good results. Hence it is necessary that data should be kept close to originality. In this paper the undecimated discrete wavelet transform (UDWT) is used for denoising of Magnetic Resonance Images (MRI). The Undecimated discrete wavelet transform is based on the idea of no decimation. It omits the down sampling at the decomposition step and up sampling at the synthesis step, thus it produces more precise information. A quantitative measure of comparison is provided by the Peak signal to noise ratio (PSNR) of the image and by the Mean structural similarity index metrics (MSSIM) of the image.

Keywords- *Magnetic Resonance Images (MRI), Mean structural similarity index metrics (MSSIM), Peak signal to noise ratio (PSNR), Undecimated discrete wavelet transform (UDWT)*

I. INTRODUCTION
The ever-increasing number and variety of digital images generated everyday are becoming a major information source in daily life. Examples include natural images, digital commercial television, magnetic resonance images, as well as geographical information systems and astronomy. However, when these images are created, transmitted and decoded, they are always distorted by different types of noise. Noise reduction has become a required step for any sophisticated algorithms in computer vision and image processing. A tradeoff between removing noise and blurring the image always exists. This challenging issue has existed for a long time, yet there is no completely satisfactory solution. This paper is more focused on noise removal techniques in MRI's, but in fact the methods described here can be applied for reducing noise in any kind of images. The next section describes how MRI images are created, third section briefly describes different types of noises in MRI's, Fourth section describes various methods for noise reduction, Fifth section describes wavelet transform, Sixth section describes different wavelet families, seventh section describes DWT and UDWT methods, Eighth section describes methodology, in the ninth section experimental results are shown and the tenth section concludes the paper followed by references.

II. BIOMEDICAL IMAGES
Biomedical images are of great interest because they can be a useful tool when diagnosing and analyzing diseases, so how is it that the body can be analyzed by magnetic resonance? Well, the biological tissue contains a lot of hydrogen atoms which are possible to detect. Nuclear magnetic resonance is a technique in which the electromagnetic field is applied to the sample, in this case the brain. The nuclei of the hydrogen atoms in the biological tissue align themselves to the magnetic field, after this a radio magnetic pulse will raise their energy level further, when the pulse ends they will relax and during the relaxation this energy will be transmitted from the atoms. The transmitted signal will be detected by the equipment and processed further into the pixels that make up the biomedical image.

III. NOISE IN MRI
MRI, Cancer and Brain images often consist of random noise that does not come from tissues but from other sources in the Electronics instrumentation during

acquisition. The noise of an image gives it a gray appearances and mainly the noise is evenly spread and more uniform. In such situation it is very difficult to diagnosis the particular disease. Therefore it is necessary to remove the noise from the image. MRI, Cancer and X-ray, MRI Brain images are prone to a variety of types of noise [1].

A. *Gaussian Noise*

Gaussian noise is evenly distributed over the signal. This means that each pixel in the noisy image is the sum of the true pixel value and a random Gaussian distributed noise value. As the name indicates, this type of noise has a Gaussian distribution, which has a bell shaped probability distribution function [1].

B. *Salt & Pepper Noise*

Salt and pepper noise is an impulse type of noise, which is also referred to as intensity spikes. This is caused generally due to errors in data transmission. It has only two possible values, 'a' and 'b'. The probability of each is typically less than 0.1. The corrupted pixels are set alternatively to the minimum or to the maximum value, giving the image a "salt and pepper" like appearance. Unaffected pixels remain unchanged. For an 8-bit image, the typical value for pepper noise is 0 and for salt noise 255. The salt and pepper noise is generally caused by malfunctioning of pixel elements in the camera sensors, faulty memory locations, or timing errors in the digitization process [1] [2].

C. *Speckle Noise*

Speckle noise is a multiplicative noise. This type of noise occurs in almost all coherent imaging systems such as laser, acoustics and SAR imagery. The source of this noise is attributed to random interference between the coherent returns. Speckle noise follows a gamma distribution [1].

IV. CLASSIFICATION OF NOISE REDUCTION METHODS

There are two basic approaches for reduction of noise, spatial domain filtering methods and transform domain filtering methods [3].

A. *Spatial Domain Denoising Methods*

For removal of noise from image data by using spatial filters there are two typical methods:

- Linear Filtering
- Non-linear Filtering

Linear filtering does not take into account any structures in the image so the smoothing is same over all parts of the image and may cause loss of some details [4]. The Nonlinear filters modify the value of each pixel in an image based on the value returned by a nonlinear function that depends on the neighboring pixels. Nonlinear filters are mostly used for noise removal and edge detection. For example, the traditional nonlinear filter is the median filter. It can efficiently decrease additive noise, especially impulsive noise. There are also many improved median filters, such as the weighted median filter [5], center weighted median filters [6], detail preserving median based filters [7], the multilevel hybrid median filter [8], etc.

B. *Transform Domain Filtering*

According to the choice of the "analysis function" [9], the transform domain filtering methods can be classified into the following two categories:

- Spatial-Frequency Filtering

In the Spatial-Frequency Filtering the low pass filters using Fast Fourier Transform (FFT) are employed. For denoising an image a frequency domain filter is designed and then it is allowed to adapt to a cut-off frequency so as to distinguish the noise components from the useful signal in the frequency domain. These methods are time consuming and depend on the cut-off frequency and the filter function behavior. Furthermore, they may produce frequency artifacts in the processed image.

- Wavelet domain

Usually noise is concentrated in the high frequency components of the signal, which correspond to small detail size when performing a wavelet analysis. Therefore, removing of some high frequency (small detail components), which may be distorted by noise, is a denoising process in the wavelet domain. The filtering operations in the wavelet domain can be categorized into wavelet thresholding, statistical wavelet coefficient model and Undecimated wavelet domain transform based methods.

V. WAVELET TRANSFORM

A. *Introduction to Wavelet Transform*

Wavelet means a "small wave". A wave is an oscillating function of time or space and is periodic, whereas wavelets are localized waves. Wavelets have their energy concentrated in time. In wavelet analysis the signal to be analyzed is multiplied with a wavelet function and then transform is computed for each segment generated .Wavelets are functions that are generated from the single function called the prototype or mother wavelet. These functions are generated by dilations (scaling) and translations (shifts) in time frequency domain [10]. In wavelet analysis, we often speak of approximations and details. The approximations are the high-scale, low-frequency components of the signal. The details are the low-scale, high-frequency components.

B. *Background*

During the past years, considerable research has been done on noise reduction. Depending on the noise model different algorithms are used. The most common type of noise which corrupts an Image is additive random Gaussian noise. There are many approaches to remove additive noise, such as average filters and mean filters. But the drawback with the linear filters is that they tend to blur sharp edges, destroy lines and other fine image details, and perform poorly in the presence of noise. Non-linear spatial filters employ a low pass filtering on groups of pixels with the assumption that the noise occupies the higher region of frequency spectrum. Low-pass filters will not only smooth away noise but also blur edges in images while the high-pass filters can make edges even sharper and improve the spatial resolution but will also amplify the noisy background. Using Wavelets for noise reduction have captured researcher's attention in image denoising due to their properties. Wavelets have capability of extracting detailed spatial-frequency information. This property gives a better discrimination between the noise and the real data.

C. *Mathematical Representation*

Let the mother wavelet be denoted by ψ (t), the other wavelets $\psi_{a,b}$ (t) can be represented as

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right) \tag{5.1}$$

Where 'a' and 'b' are two arbitrary real numbers which represents the parameters for dilation and translation respectively in the time axis. The Mother wavelet is represented as :

$$\psi(t) = \psi_{1,0}(t) \tag{5.2}$$

For any value of $a \neq 1$ and $b = 0$ we get

$$\psi_{a,0}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t}{a}\right) \tag{5.3}$$

From the equation we see that ψa,0(t) is time scaled (by a)and amplitude scaled (by (1/√a)) version of mother wavelet function ψ(t). The parameter 'a' causes contraction of ψ (t) in the time axis when 'a' < 1 and expansion or stretching when 'a' > 1. That's why 'a' is called the dilation (scaling) parameter [10]. Figure 1, 2, 3 shows the effect of dilation parameter 'a'on Mother Wavelet.

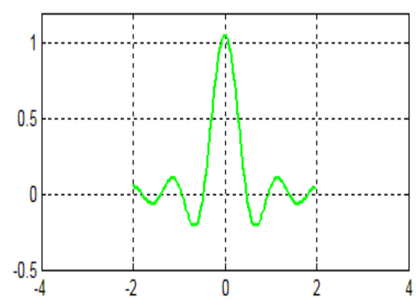

Fig1. Mother Wavelet

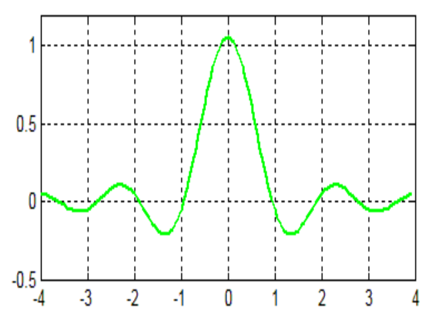

Fig2. ψ (t/a): 0<a<1

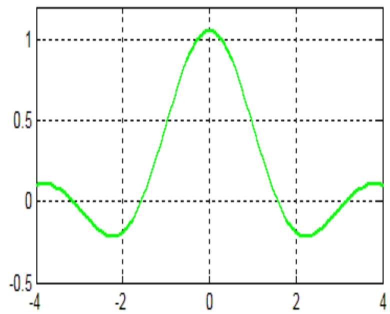

Fig3. ψ (t/a): a>1

VI. INTRODUCTION TO WAVELET FAMILIES

The introduction of different families of wavelets that have proven to be especially useful is given below:

- Haar
- Daubechies
- Biorthogonal
- Coiflets
- Symlets
- Meyer

A. *Haar*

Any discussion of wavelets begins with Haar wavelet, the first and simplest. Haar wavelet is discontinuous, and resembles a step function. It represents the same wavelet as Daubechies db1. Fig. 4 shows the Haar wavelet [11].

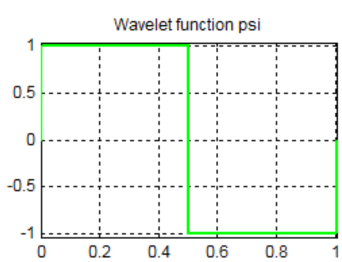

Fig4. Haar wavelet

B. *Daubechies*

The names of the Daubechies family wavelets are written 'dbN', where 'N' is the order, and 'db' the "surname" of the wavelet. The 'db1' wavelet, as mentioned above, is the same as Haar wavelet. Fig. 5 shows the scaling function phi and wavelet functions psi of the db2 members of the family [11].

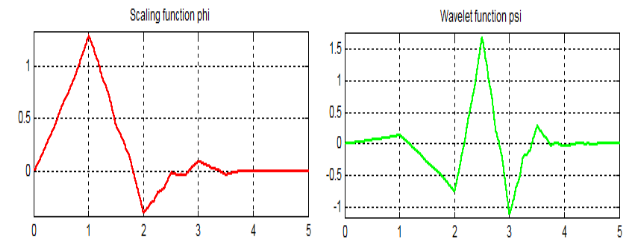

Fig5. Daubecheis wavelet

C. *Biorthogonal*

This family of wavelets exhibits the property of linear phase, which is needed for signal and image reconstruction. Fig. 6 shows the scaling function phi and wavelet function psi of bior 2.2 wavelet [11].

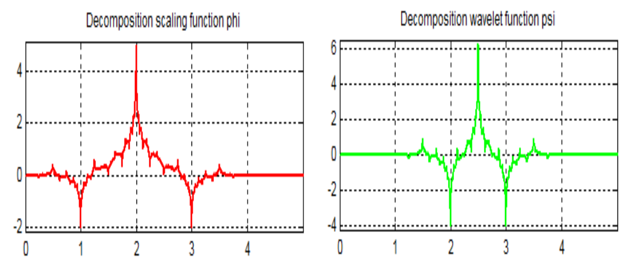

Fig6. Biorthogonal wavelet

D. *Cioflet*

The wavelet function has 2N moments equal to 0 and the scaling function has 2N-1 moments equal to 0. The two functions have a support of length 6N-1. Fig. 7 shows the scaling function phi and wavelet function psi of coif 5 wavelet [11].

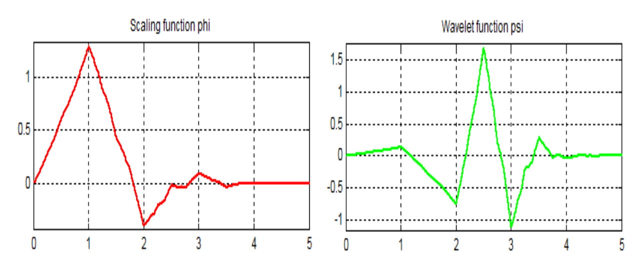

Fig7. Coiflet wavelet

International Journal of Scientific Research Engineering &Technology (IJSRET)
Volume 1 Issue4 pp 031-038 July 2012 www.ijsret.org ISSN 2278 - 0882

E. ***Symlets***

The symlets are nearly symmetrical wavelets proposed by Daubechies as modifications to the 'db' family. The properties of the two wavelet families are similar. Fig. 8 shows the scaling function phi and wavelet function psi of sym2 wavelet [11].

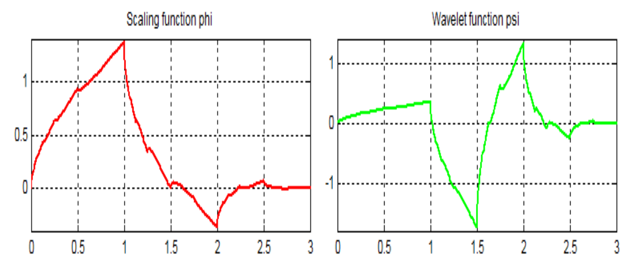

Fig8. Symlet wavelet

F. ***Meyer***

The Meyer wavelet and scaling function are defined in the frequency domain. Fig. 9 shows the scaling function phi and wavelet function psi of Meyer wavelet [11].

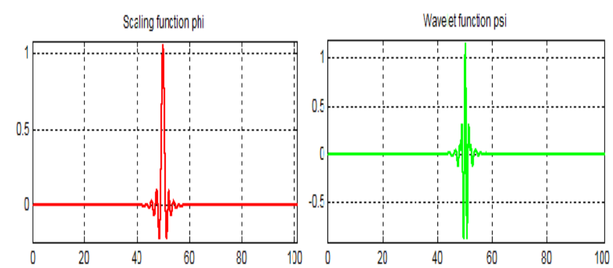

Fig9. Meyer wavelet

VII. DISCRETE WAVELET TRANSFORM (DWT) & UNDECIMATED DISCRETE WAVELET TRANSFORM (UDWT)

A. Discrete wavelet transform

The Discrete Wavelet Transform can be viewed as a filter bank which is composed of two types of filters i.e. low pass and high pass filters. First the image is high and low pass filtered along the rows and the result is down sampled by two. Then each of these sub signals are again high and low pass filtered along column data. The result is again down sampled by two.

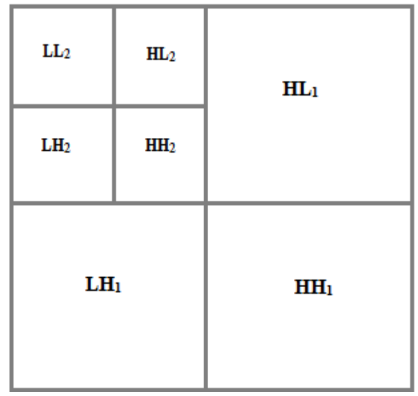

Fig10. Pyramidal decomposition by DWT

Fig. 10 shows the pyramidal decomposition that result from this decomposition. Fig. 11 shows compete decomposition and reconstruction process [12].

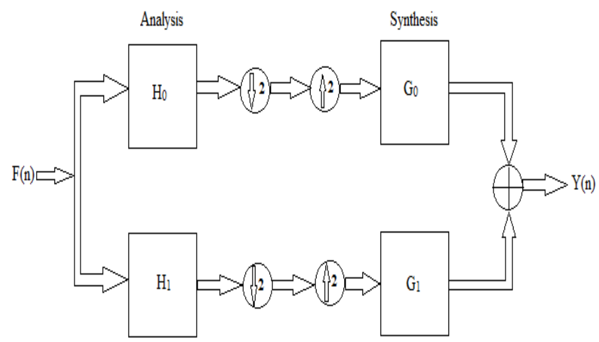

Fig11. DWT

B. Undecimated Discrete wavelet transform

The discrete wavelet transform is very efficient but its only drawback is that it is not translation invariant. Translations of the original signal lead to different wavelet coefficients; this may cause visual artifacts such as pseudo-Gibbs phenomenon [13]. To overcome these artifacts and get complete information of the analyzed signal the undecimated discrete wavelet transform (UDWT) is used. Since it does not decimate the signal, it produces more precise information for frequency localization. From the computational point of view the undecimated wavelet transform has larger storage space requirements and involves more computations. With the increase of the speed and storage of computers, this issue does not affect computational cost too much. Mignotte proposes an image denoising algorithm using shrinkage of undecimated wavelet coefficients. It is reported that the algorithm yields improvements in terms of image quality and lower mean square error, especially when the image is corrupted by strong additive white Gaussian noise [13].

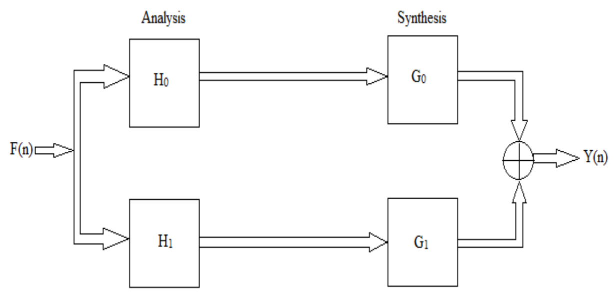

Fig12. UDWT

VIII. METHODOLOGY

Usually noise is concentrated in the high frequency components of the signal, which correspond to small detail size when performing a wavelet analysis. Therefore, removing of some high frequency (small detail components), which may be distorted by noise, is a denoising process in the wavelet domain. The MRI data is first decomposed using the discrete wavelet transform (DWT). The data is corrupted by adding Gaussian noise at 5 different variance values i.e. 0.01, 0.03, 0.05, 0.07, 0.09. The decomposition is done up to levels j (j = 1 … 10), by the six wavelet families described. From the decompositions obtained a threshold value is calculated and the decompositions are denoised using soft thresholding technique. The denoised image is then reconstructed using these thresholded coefficients. The wavelet which gives the best result is then found. The same procedure is then performed for the undecimated discrete wavelet transform (UDWT). The undecimated discrete wavelet transform does not down sample the data at the decomposition step and also it does not perform up sampling while reconstruction. Due to this it gives more precise information and therefore it gives better results as compared to discrete wavelet transform. To compare the performance of the above two type of wavelet transforms we used two different performance measures i.e. PSNR value and MSSIM value. The denoising algorithm is presented below:

1) Load an MRI image from the database.
2) Corrupt the image by adding Gaussian noise to the Image at five noise variance Levels (0.01, … , 0.09).
3) Decompose the image using DWT and UDWT.
4) Estimate a threshold value from the decompositions.
5) Remove the coefficients that are smaller than the Threshold value by using soft thresholding technique.
6) Reconstruct the image from the thresholded wavelet coefficients.
7) Calculate the PSNR value and MSSIM value of the original and of the denoised images.

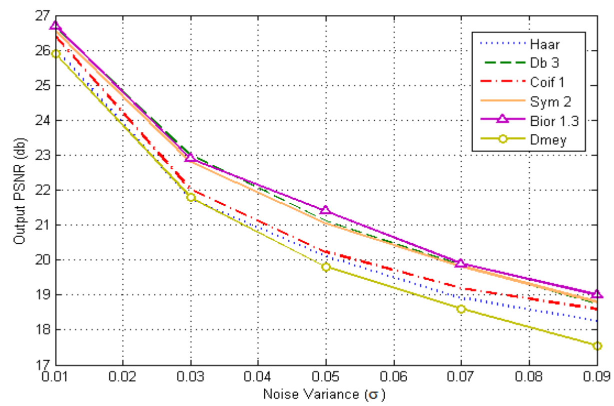

Fig13. Comparison between different wavelet families

IX. EXPERIMENTAL RESULTS

To begin the experiment first an MRI image is chosen from the database, and Gaussian noise is added to the image. The noise variance ranges from 0.01 to 0.09. The images were denoised using discrete wavelet transform and by undecimated discrete wavelet transform. To evaluate the performance of the two methods PSNR and MSSIM value is used as a quality metric. The experimental result shown in Fig. 13 gives the comparison between different wavelet families used for denoising. The wavelet families are compared on the basis of output PSNR value obtained by Undecimated discrete wavelet transform at five different noise levels ranging from 0.01 to 0.09. From the figure it can be seen that Biorthogonal wavelet performs the best amongst the other wavelets. Fig. 14 shows comparison between the two wavelet transforms i.e. DWT and UDWT. From the result it can be seen that the output obtained from the UDWT has a higher PSNR value than DWT. The denoised images obtained by DWT and UDWT are shown in fig. 18, 19 respectively. For a noisy image with PSNR of 21.34 db the UDWT method improves the PSNR to 25.47 db whereas the PSNR obtained by the DWT is 22.32 db . Table I shows the result of denoising by discrete wavelet transform the PSNR value of the original and denoised image at different noise level is shown also the MSSIM value is shown of the noisy and denoised image. Similarly Table II shows the result of denoising by Undecimated discrete wavelet transform.

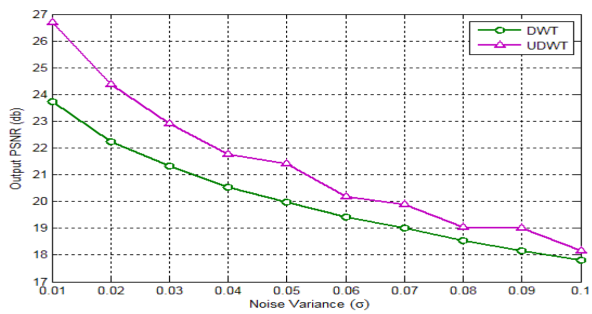

Fig14. Comparison of PSNR after denoising images by the two methods

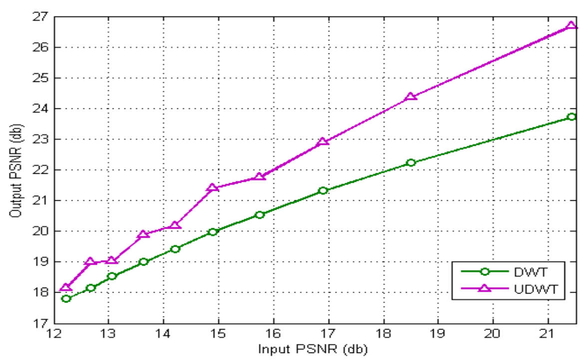

Fig15. Comparison between input and output PSNR obtained by the two methods

TABLE I. DENOISING BY DWT

Noise Level	P.S.N.R (Original)	P.S.N.R (Denoised)	M.S.S.I.M (Original)	M.S.S.I.M (Denoised)
0.01	21.43	23.72	0.9997	0.9998
0.03	16.91	21.32	0.9993	0.9995
0.05	14.90	19.98	0.9988	0.9992
0.07	13.64	19.00	0.9984	0.9989
0.09	12.68	18.16	09979	0.9987

TABLE II. DENOISING BY UDWT

Noise Level	P.S.N.R (Original)	P.S.N.R (Denoised)	M.S.S.I.M (Original)	M.S.S.I.M (Denoised)
0.01	21.43	**26.70**	0.9997	0.9998
0.03	16.91	**22.90**	0.9993	0.9995
0.05	14.90	**21.40**	0.9988	0.9992
0.07	13.64	**19.90**	0.9984	0.9989
0.09	12.68	**19.01**	09979	0.9987

X. CONCLUSION

In this paper a comparative study is performed for denoising MRI images. Comparison is done using the two very efficient techniques i.e. DWT and UDWT. The results are compared on the basis of the PSNR values obtained from the denoised images. The denoised MRI images obtained by Undecimated discrete wavelet transform are found to be good in terms of quality metric (PSNR).

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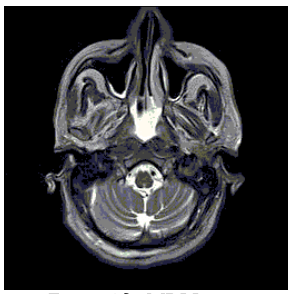

Figure 16. MRI Image

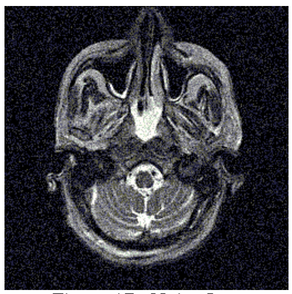

Figure 17. Noisy Image
PSNR = 21.34 db

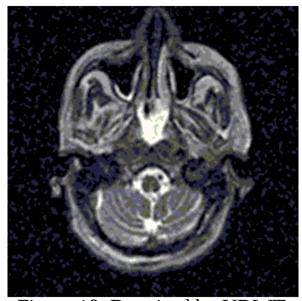

Figure 18. Denoised by UDWT
PSNR = 25.47 db

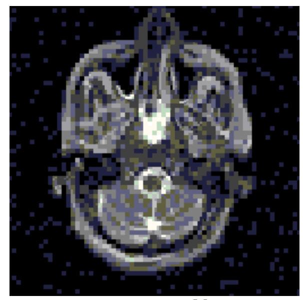

Figure 19. Denoised by DWT
PSNR = 22.32 db