# APPLICATION OF SUBBAND ADAPTIVE THRESHOLDING TECHNIQUE WITH NEIGHBOURHOOD PIXEL FILTERING FOR DENOISING MRI IMAGES

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**Abstract :**
The image de-noising naturally corrupted by noise is a classical problem in the field of signal or image processing. Image denoising has become an essential exercise in medical imaging especially the Magnetic Resonance Imaging (MRI)..We propose a new method for MRI restoration. Because MR magnitude images suffer from a contrast-reducing signal-dependent bias. Also the noise is often assumed to be white, however a widely used acquisition technique to decrease the acquisition time gives rise to correlated noise. Subband adaptive thresholding technique based on wavelet coefficient along with Neighbourhood Pixel Filtering Algorithm (NPFA) for noise suppression of Magnetic Resonance Images (MRI) is presented in this paper. A statistical model is proposed to estimate the noise variance for each coefficient based on the subband using Maximum Likelihood (ML) estimator or a Maximum a Posterior (MAP) estimator. Also this model describes a new method for suppression of noise by fusing the wavelet denoising technique with optimized thresholding function. This is achieved by including a multiplying factor (α) to make the threshold value dependent on decomposition level. By finding Neighbourhood Pixel Difference (NPD) and adding NPFA along with subband thresholding the clarity of the image is improved. The filtered value is generated by minimizing NPD and Weighted Mean Square Error (WMSE) using method of leastsquare.Areduction in noise pixel is well observed on replacing the optimal weight namely NPFA filter solution with the noisy value of the current pixel. Due to this NPFA filter gains the effect of both high pass and low pass filter. Hence the proposed technique yields significantly superior image quality by preserving the edges, producing a better PSNR value. To confirm the efficiency this is further compared with Median filter, Weiner Filter, Subband thresholding technique along with NPFA filter.

***Keywords: Magnetic Resonance Image (MRI); Decomposition Level; Neighbourhood Pixel Difference (NPD); Optimum thresholding.***

## 1. Introduction

Several approaches to noise reduction by wavelet-domain filtering were tested before a viable concept was found: Filtering of (i) k-space data, (ii) data in the complex image space and (iii) in magnitude image space. The final denoising approach presented in this report was preceded by extensive tests of several wavelet-based noise reduction schemes, all similar to the Wiener-like filtering presented by Wirestam & Ståhlberg [Wirestam and Ståhlberg, (2005)], the WienerChop model [Ghael *et. al* (1997), ] Choi and Baraniuk (1892), ] Bruni and Vitulano (2008)], the approximation to a Wiener-like filter by Nowak [Nowak and Baraniuk (1999), Nowak

(1999), Alexander (2000)], denoising of magnitude images after bias-reduction, accomplished by a modification of the method proposed by Gudbjartsson [Gudbjartsson and Patz (1995)] and of course combinations of the above- mentioned methods. MR images are typically corrupted with noise, which hinder the medical diagnosis based on these images. There has been substantial interest in the problem of denoising of images in general. Tools from traditional image processing field have been applied to denoised MR images [Peck (1992)]. However, the process of noise suppression must not appreciably degrade the useful features in an image. In particular, edges are important features for MR images and thus the denoising must be balanced with edge preservation. Wavelets are popular for such image denoising and enhancement applications because they have good localization properties both in space and frequency. Further, use of wavelet packets allows adaptive representation for a given signal. A brief survey of representative techniques for image denoising is now presented. Lee and Tsai discuss the use of wavelets for image enhancement in [Tsai and Lee (2004)]. Zadeh et. al compare various filters (ratio, log ratio and angle image filters) to enhance MR images in [Peck (1992)]. In [Archibald and Gelb (2002)], the authors have looked at noise suppression in MR images using Fourier spectral methods. In [Prager and Singer (1991)], the authors used FIR filters along with wavelet decomposition for image enhancement, specifically edge enhancement and edge detection. Recently, in [Tsai and Lee (2004)] the authors have used wavelets to enhance MR images. They used a mapping function to manipulate the transform coefficients before reconstruction. The mapping function was chosen such that the low frequency coefficients are not affected which prevents distortion. The coefficients with larger absolute values contain more information while the high frequency coefficients contain important edge information. Hence, coefficients belonging to either of these classes were heavily weighted compared to other coefficients. In [Donoho (1995)], the author discusses the use of Softthresholding for image denoising. More recently, denoising using MDL based thresholding was introduced in [Rissanen (2000)]. From the above review of research papers, it is quite clear that wavelet has provided a very handsome amount of contribution in image denoising.

In this paper wavelet shrinkage technique is adopted along with filtering of wavelet coefficients. Wavelet shrinkage is a method of removing noise from images by shrinking the empirical wavelet coefficients in the wavelet domain and it is a non linear image denoising procedure to remove the noise. A common shrinkage approach is thresholding [Donoho and Johnstone (1994), which sets the wavelet coefficients with “small” magnitudes to zero while retains shrinking in magnitude for the remaining ones. Originally, Donoho and Johnstone proposed the use of a universal threshold uniformly throughout the entire wavelet decomposition tree which was found to be more efficient Donoho (1993), Zhong and Cherkassy (2000, Donoho and Johnstone (1994)]. Although thresholding with a uniform threshold per subband is attractive due to its simplicity, the performance is limited and the denoising quality is often not satisfactory. Thus wavelet shrinkage methods using separate threshold in each subband have been developed over recent years. Some methods of selecting thresholds that are adaptive to different spatial characteristics have been recently proposed and investigated [Chang (2000), Chang *et. al* (2000), Chang *et. al* (1997)]. In general, adaptive approaches have found to be more effective than their global counterparts.

A new model is proposed based on wavelet coefficients and noise variance is estimated for each coefficient depending on the subband using Maximum Likelihood (ML) estimator. A multiplying factor ($\alpha$) is included in the optimum threshold formula to make the threshold value dependent on decomposition level. Now NPFA filter is introduced to each coefficient in order to improve the clarity of the resultant image The concept that the low pass filter preserves the energy of signal and attenuates the high pass features at the discontinuities is used in the proposed filter. This NPFA filter considers the neighbouring pixel values and cuts off high frequency signal instead of all noisy signals. A reduction in noise pixel is observed on replacing the optimal weight namely NPFA filter solution with the noisy value of the current pixel. Due to this, NPFA filter gains the effect of both high pass and low pass filter. This filter behaves like a low pass filter in smooth region by decreasing noise variance effectively and giving similar weights to all its neighboring pixels. Also it attenuates the high pass features at the discontinuities by maintaining the sharpness of edges and gives small weight for that pixel. After computing threshold, apply soft thresholding to each noisy coefficient. By inverting the multi scale decomposition, the resultant quality image with less blurring and preserving more detail information is reconstructed.

## 2. Wavelet Coefficient Model

Considering the advantages and limitations of the statistical model a new model is proposed based on the wavelet coefficients. Wavelet coefficients with large magnitudes are representatives of edges or some textures. While those with small magnitudes are associated with smooth regions are the representatives of the background. In this smooth region the signal variance for every sub band are estimated by a ML estimator. This method presents effective results but their spatial adaptivity is not well suited near object edges where the variance field is not smoothly varied. To overcome this the coefficient in each subband except the first fine scale is partitioned into two classes based on the magnitudes of their parents, namely significant class and insignificant class in the corresponding region .The significant class represents high activity regions and insignificant class corresponds to smooth region. The sizes of the two classes are controlled by the significance threshold T. If the magnitude of the parent is larger than T then the coefficient is included in significant class otherwise it is included in insignificant class.

The two classes have different statics. The histogram of the coefficient in insignificant class is highly concentrated around zero while that of significant class is more spread out. Hence the coefficients in significant class are modeled as independent identically distributed (iid) Laplacian with zero mean. For the coefficient in insignificant model which corresponds to homogeneous regions, the usage of intrascale model in Estimation Quantization [EQ] coder is appropriate [Zhong and Cherkassy (2000)]. It provides a good fit for the first order statics of wavelet coefficients and well models the nonstationary nature of low-activity regions.

### 2.1. *Statistical Model*

The observation model is expressed as follows $Y = X + V$, where $Y$ is the wavelet transform of the degraded image, $X$ is the wavelet transform of the original image, $V$ denotes the wavelet transform of the noise components following the Gaussian distribution $N(0,\sigma_V^2)$ Since $X$ and $V$ are mutually independent, the variances of $Y$, $X$ and $V$ are given by

$$\sigma_Y^2 = \sigma_X^2 + \sigma_V^2 \tag{1}$$

## 3. Estimation of Noise Variance

The following steps are used to evaluate the variance estimate for each wavelet coefficients depending on the subband.

**Step 1:** The noise variance $\sigma_V^2$ can be accurately estimated from the first decomposition level diagonal subband $HH_1$ by the robust and accurate median estimator [20].

$$\sigma_V^2 = \left( \frac{median\left| y(V) \right|}{0.6745} \right)^2 \tag{2}$$

Where $y(V)$ represents the coefficients $HH_1$ subband.

**Step 2:** The coarse sub bands are not processed because the coarse subband has very high SNR. These coefficients are considered reliable.

**Step 3:** For each of the three sub bands (horizontal, vertical and diagonal orientations) coefficients within the subband are modeled as identically independently distributed with zero mean and variance $\sigma_{\bar{x},j}^2$ (where $j$ indicates the subband). The variance estimate is computed from the noisy coefficients in subband $j$ as

$$\sigma_{\bar{x},j}^2 = \max\{0, \mathrm{var}\{\overline{y_i}, i \in subbandj\} - \sigma_v^2\} \tag{3}$$

Using MAP, estimation of $\bar{x}$ is obtained by applying a soft threshold $\lambda$ as given in equation (4) to each noisy coefficient.

$$\lambda = \sqrt{2}\sigma_v^2 / \sigma_{\bar{x},j}^2, \, j \in subband \tag{4}$$

**Step 4:** In each of the other high sub bands, coefficients are assigned either to significant or insignificant classes depending on the magnitude of their estimated parent relative to the significance threshold $T$, where

$$T = \sigma\sqrt{2\log N^2} \tag{5}$$

(i) Coefficients in significant class are modelled as iid Laplacian with zero mean and their variance $\sigma_{\bar{x},insig}^2$ is estimated from the noisy coefficients as mentioned in step 3. Again the MAP estimator is a simple soft thresholding scheme where its threshold value is adjusted to the signal variance.

(ii) Coefficients in insignificant class which has small magnitude representing smooth areas, $\sigma_{\bar{x},insig}^2$ is estimated using ML estimator in order to have an estimate for a local neighborhood $\sigma_{\bar{x}}^2$ where variance is assumed to be constant. The estimate of the class coefficient variance is

$$\sigma_{\bar{x},insig}^2 = \frac{1}{M}\left(\sum_{V=1}^{M} y^2(V) - \sigma_V^2\right) \tag{6}$$

where M represents the number of wavelet coefficients residing in local neighborhood *N*. Considering the coefficients belonging to a insignificant class inside the window are used by excluding the one which belong to significant class, the MAP estimator is given by

$$\overline{x} = \frac{\sigma^2_{\bar{x},insig}}{\sigma^2_{\bar{x},insig} + \sigma^2_V}\,\overline{y_i} \tag{7}$$

Thus the coefficient of estimates corresponding to the high subband are obtained by repeating the above steps from parent to child subband, starting from the coarse scale and terminating in the highest subband.

## 4. Neighbourhood Pixel Filtering Algorithm (NPFA) for Denoising

The first step in the algorithm is to detect whether the noisy pixel value input $B_{ij}$ itself is corrupted by a noise or not. The deduction of noise is made by applying the denoising model as shown in Fig. 1 and Fig. 2. After comparing the pixel value of the current pixel $B_{ij}$ to that of the neighboring pixels $B_{i-1,j}$, $B_{i+1,j}$, $B_{i,j-1}$, $B_{i,j+1}$ and co-located pixel $P_{ij}$ in the previous wavelet frame.

Find the Neighbouring Pixel Difference (NPD) by subtracting the neighbouring pixel values namely $B_{i-1,j}$, $B_{i+1,j}$, $B_{i,j-1}$, $B_{i,j+1}$ and current pixel $P_{ij}$ from the pixel value $B_{ij}$. If all the differences are greater than a specified threshold $T$ then the pixel $B_{ij}$ is corrupted by a noise. Otherwise it is not corrupted by a noise. After noise detection in the first step, a filtered value $f_{ij}$ would be assigned for each corrupted noisy pixel as the weighted average of its neighbouring pixel values in the NPFA frame given by Eq. (8):

$$f_{ij} = \frac{B_{i-1,j} + B_{i+1,j} + B_{i,j+1} + B_{i,j+1}}{4} \tag{8}$$

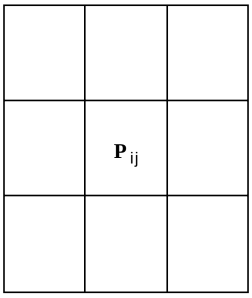



Fig. 1 Wavelet frame

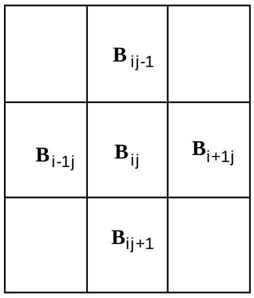



Fig. 2 NPFA frame

The correlation between the noisy pixel value $B_{ij}$ and its original pixel value would be reflected by NPD. For corrupted pixels this correlation between the pixel differences is small and a filtered value $f_{ij}$ is assigned to each current pixel in order to approximate the original pixel value of current pixel. While for each uncorrupted pixels the noisy pixel value is highly correlated with the original pixel value. In this case the filtered value $f_{ij}$ will be generated by minimizing NPD and Weighted Mean Square Error (WMSE) which is given in Eq. (12) using method of Least Squares. For which the weight $W_{ij}$ of each pixel is required which depends on NPD and calculated using Eq. (9) and Eq. (10):

$$W_{ij} = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N} g(i)\left[\left|P_{ij} - B_{ij}\right|\right] * f_{ij}}{\sum_{i=1}^{M}\sum_{j=1}^{N} g(i)\left[\left|P_{ij} - B_{ij}\right|\right]} \tag{9}$$

$$g(i) = \begin{cases} 2^{\left(\lfloor T/8 \rfloor - \lfloor i/8 \rfloor\right)} & i < T \\ 0 & \text{else} \end{cases} \tag{10}$$

where $P_{ij}$ is the current pixel value, $B_{ij}$ is the noisy pixel value, $f_{ij}$ is the filtered value**.**

On replacing the optimal weight namely NPFA filter solution obtained from Eq. (13) with the noisy value of current pixel a reduction in noise pixel is observed. Due to this, NPFA filter gains the effect of both low pass filter and high pass filter. In smooth areas this filter decreases noise variance effectively by giving similar weights to all its neighbouring pixels. Hence in this area the proposed filter behaves like a low pass filter and preserves edge information. In high texture areas, this filter exploits the edge information by using the pixel value difference between the current pixel and its neighbouring pixels (NPD). Because of this in this area NPFA filter attenuates high pass features at the discontinuities and maintains the sharpness of edges by giving small weight for that pixel. Also this filters cuts off only high frequency signal instead of all noisy signals.

Quantitatively the measure of image is given by its PSNR value obtained from Eq. (11) where the minimized WMSE is used. Hence this filter yields a significant PSNR value to that of other wavelet method.

$$PSNR = 10\log_{10}\left[\frac{255^2}{WMSE}\right]dB \tag{11}$$

Minimise $$WMSE = \sum_{i=1}^{M}\sum_{j=1}^{N} W_{ij}\left(B_{ij} - Y_{ij}\right)^2 \tag{12}$$

$Y_{ij}$ is the NPFA filter solution given by the following equation:

$$Y_{ij} = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N} W_{ij} B_{ij}}{\sum_{i=1}^{M}\sum_{j=1}^{N} W_{ij}} \tag{13}$$

## 5. Optimum Value Threshold and Proposed Technique

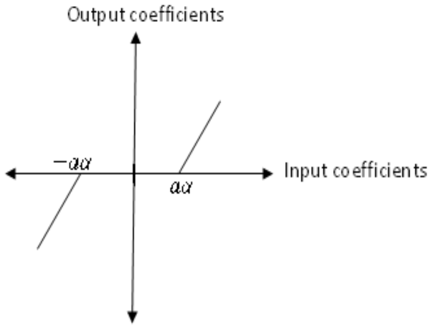
Wavelet thresholding Andrew Bruce *et. al*,(1996), is a signal estimation technique that exploits the capabilities of wavelet transform for signal denoising. It removes noise by killing coefficients that are insignificant relative to some threshold and turns out to be simple and effective which depends heavily on the choice of a thresholding parameter. The choice of this threshold determines the efficacy of denoising to a great extent.

### 5.1 *Threshold Selection*

Finding an optimum value thresholding is not an easy task. A small threshold may yield a result close to the input, but the result may still be noisy. A large threshold on the other hand, produces a signal with a large number of zero coefficients. This leads to a smooth signal. Paying too much attention to smoothness destroys details and it may cause blur and artifacts in image processing.

Soft thresholding method is used to analyze the performance of Denoising system for different levels of DWT decomposition, as it results in better denoising performance than other denoising methods. Also it leads to less severe distortion of the object of interest than other thresholding methods [24]. Several approaches have been suggested for setting the threshold for each band of the wavelet decomposition. A common approach is to compute the sample variance $\sigma^2$ of the coefficients in each band and set the threshold to any multiple of standard deviation $\sigma$ for that band [25]. Thus, to implement a soft threshold of the DWT coefficients for a particular wavelet band, the coefficients of that band should be threshold as shown in Fig. 3 and Fig. 4.The soft thresholding is generally represented by,

$$d_{ik}^{soft} = \begin{matrix} sign(d_{ik})(|d_{ik}| - \lambda^*) if d_{ik} > \lambda^* \\ 0 if d_{ik} \le \lambda^* \end{matrix} \tag{14}$$



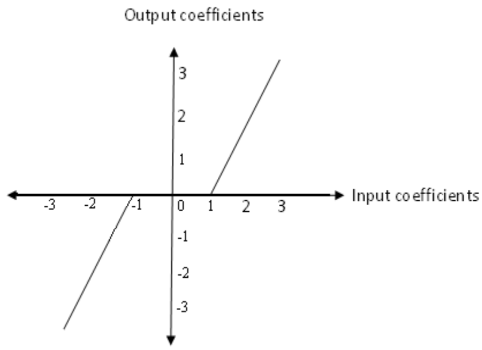




Fig.3 Soft threshold Characteristics with $\lambda = a\sigma$ Fig.4 Soft threshold characteristics with $\lambda = 1$

### 5.2 *Optimum Value Threshold*

An adaptive thresholding is proposed by fixing the optimum thresholding value depending on the decomposition level. At every decomposition level, four frequency sub bands are obtained namely LL, LH, HL, and HH. The next level should be applied to the low frequency subband LL only. This process is continued until a prespecified level (level 2) is reached. In wavelet domain, as the level of sub bands increases its coefficients becomes smoother. That is, subband $HL_2$ is smoother than the corresponding subband in the first level ($HL_1$) and so the threshold value of $HL_2$ should be smaller than that of $HL_1$.
In the wavelet decomposition, the magnitude of the coefficient varies depending on the decomposition level. Therefore, if all levels are processed with one threshold value, the processed image may be overly smoothened so that sufficient information preservation is not possible and the image gets blurred. To overcome this problem and to obtain a significantly superior quality image, the multiplying factor $\alpha$ is included in the threshold formula to get better PSNR value by preserving edges where $\alpha = 2^{L-K}\sqrt{\log M}$ (15)
L is the number of wavelet decomposition level, K is the level at which the subband is available, M is the total number of wavelet coefficients. Using this multiplication factor α the optimum threshold formula for the proposed technique is given by $\lambda^{*} = \alpha\lambda$ (16)
where $\lambda, \sigma$ are calculated using Eq. (4) and Eq.(15) respectively.

### 5.3 *Proposed Algorithm*

There are two stages in this algorithm by which the denoised image of MRI can be obtained. In the first stage the image gets denoised by using Subband adaptive thresholding technique without adding NPFA filter. The qualitative and quantitative measures are given in Table 1 and Fig. 7 based on the following steps involved in this stage of the algorithm

**Stage 1: Analysis of Image Denoising using Wavelet Coefficient and Adaptive Subband Thresholding Technique.**

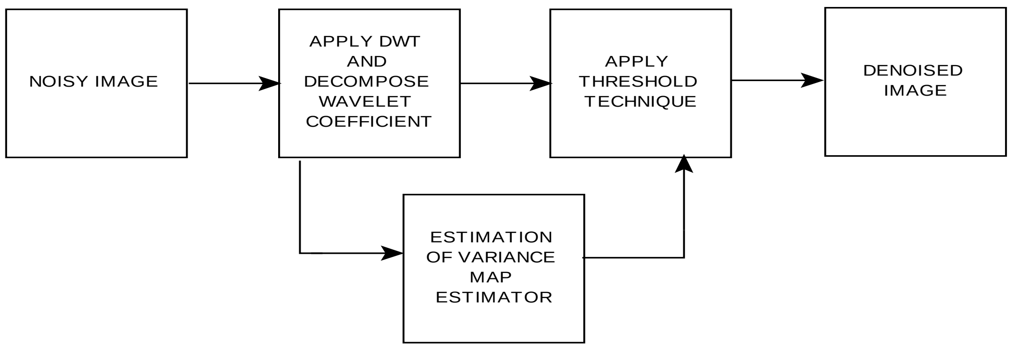



Fig. 5 Block diagram of the proposed method (Stage 1)

**Algorithm:**
The complete algorithm of the proposed wavelet based denoising technique is explained in the following steps:
**Input:** Noisy image
**Output:** Denoised image
Step 1: Perform Multiscale decomposition of the image corrupted by Gaussian noise using wavelet transform.
Step 2: Estimate the noise variance $\sigma_V^2$ using Eq. (1) for each scale and compute the scale parameter.
Step 3: For each of the three sub bands variance estimate is computed from the noisy coefficient in subband j using Eq. (2).
Step 4: In each of the other high sub bands the estimates of the class coefficient variance are estimated using Eq. (2) and Eq. (3).
Step 5: Calculate threshold value using optimum value threshold formula as given in Eq. (16) after finding the multiplying factor $\alpha$ for each subband using the relation given in Eq. (15). After computing threshold for each subband except the low pass or approximation subband, apply soft thresholding to each wavelet coefficient using threshold given in Eq. (14), by substituting the threshold value obtained in Step 5.
Step6: Invert the multiple decomposition to reconstruct the denoised image.

In the second stage NPFA filter is added before applying soft thresholding to the Subband. By adding this filter to each wavelet coefficients in the entire subband except the $LL_1$ subband reduction in noise is observed on replacing the optimal weight namely NPFA filter solution with the noisy values of the current pixel. The qualitative and quantitative measures are given in Table 2 and Fig. 7 based on the following steps involved in this stage of the algorithm.

**Stage 2: Analysis of image denoising using wavelet coefficients and adaptive subband thresholding technique along with NPFA filter.**

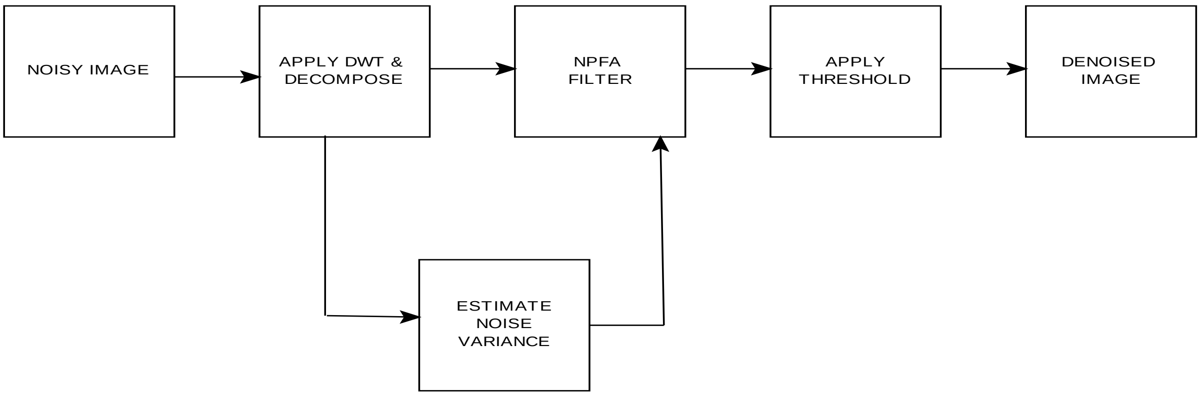



Fig. 6 Block diagram of the proposed method (Stage 2)

**Algorithm:**
**Input:** Noisy image
**Output:** Denoised image

Step 1: Perform Multiscale decomposition of the image corrupted by Gaussian noise using wavelet transform.
Step 2: Estimate the noise variance $\sigma_V^2$ using Eq. (1) for each scale and compute the scale parameter.
Step 3: For each of the three sub bands variance estimate is computed from the noisy coefficient in subband j using Eq. (2).
Step 4: In each of the other high sub bands the estimates of the class coefficient variance are estimated using Eq. (2) and Eq.(3).
Step 5: Add NPFA filter to each coefficient in all the three sub bands except the low pass or approximation subband.
Step 6: Find optimal NPFA filter solution for each coefficient using the Eq. (13).
Step 7: Calculate threshold value using optimum value threshold formula as given in equation (16) after finding the multiplying factor $\alpha$ for each subband using the relation given in Eq.(15).
Step 8: After computing threshold for each subband except the low pass or approximation subband, apply soft thresholding to each wavelet coefficient using threshold given in Eq. (14), by substituting the threshold value obtained in Step 7.
Step 9: Invert the multiple decomposition to reconstruct the denoised image.

## 6. Experiment and Results

The medical image noise reduction algorithm has been implemented in the MATLAB environment. The algorithm was tested with Weiner Filtering, Median Filtering; subband Adaptive Threshold Technique with and without NPFA filtering in wavelet domain. To estimate the performance the reduction algorithm is carried out in two stages.

In the first stage without adding NPFA filter, apply soft thresholding to each wavelet coefficient except in low or approximation band and the algorithm is implemented. In the second stage of the algorithm before applying soft thresholding NPFA filter is added to each coefficient in three bands except the low or approximation band and the steps in the algorithm have been implemented. To estimate the filter performance the quantitative measure such as PSNR of the MRI images have been used, which is calculated by using the Eq. (17) for the first stage of algorithm and by Eq. (18) for the second stage of algorithm.

Stage 1: $$PSNR = 20\log_{10}\left(\frac{255^2}{MSE}\right)dB \tag{17}$$

$$MSE = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}(X_{ij} - Y_{ij})^2$$

Table 1. Comparison Table for PSNR Value using Subband Wavelet Method With Different Noise Level $\sigma^2$

| NOISE VARIANCE | NOISY IMAGE | SUBBAND |
|---|---|---|
| 0.01 | 60.91 | 66.78 |
| 0.015 | 57.05 | 64.88 |
| 0.02 | 54.33 | 61.67 |
| 0.025 | 52.25 | 59.11 |
| 0.03 | 50.56 | 57.03 |
| 0.035 | 49.15 | 55.27 |
| 0.04 | 47.92 | 53.75 |
| 0.045 | 46.85 | 52.43 |
| 0.05 | 45.89 | 51.26 |
| 0.055 | 45.04 | 50.27 |

Stage 2: $$PSNR = 10\log_{10}\left[\frac{255^2}{WMSE}\right] dB \tag{18}$$

where $WMSE = \sum_{i=1}^{M}\sum_{j=1}^{N} W_{ij}\left(B_{ij} - Y_{ij}\right)^2$

Table 2. Comparison Table for PSNR Value using Subband Wavelet Method With NPFA filter and other existing filters for Different Noise Level $\sigma^2$

| NOISE VARIANCE | NOISY IMAGE | MEDIAN | WEINER | NPFA | SUBBAND |
|---|---|---|---|---|---|
| 0.01 | 60.91 | 60.98 | 60.07 | 69.39 | 66.78 |
| 0.015 | 57.05 | 58.53 | 56.19 | 64.95 | 64.88 |
| 0.02 | 54.33 | 56.60 | 53.45 | 63.37 | 61.67 |
| 0.025 | 52.25 | 55.03 | 51.36 | 62.14 | 59.11 |
| 0.03 | 50.56 | 53.68 | 49.66 | 61.04 | 57.03 |
| 0.035 | 49.15 | 52.50 | 48.22 | 60.09 | 55.27 |
| 0.04 | 47.92 | 51.47 | 46.98 | 59.24 | 53.75 |
| 0.045 | 46.85 | 50.53 | 45.89 | 58.44 | 52.43 |
| 0.05 | 45.89 | 49.70 | 44.93 | 57.72 | 51.26 |
| 0.055 | 45.04 | 48.93 | 44.06 | 57.04 | 50.27 |

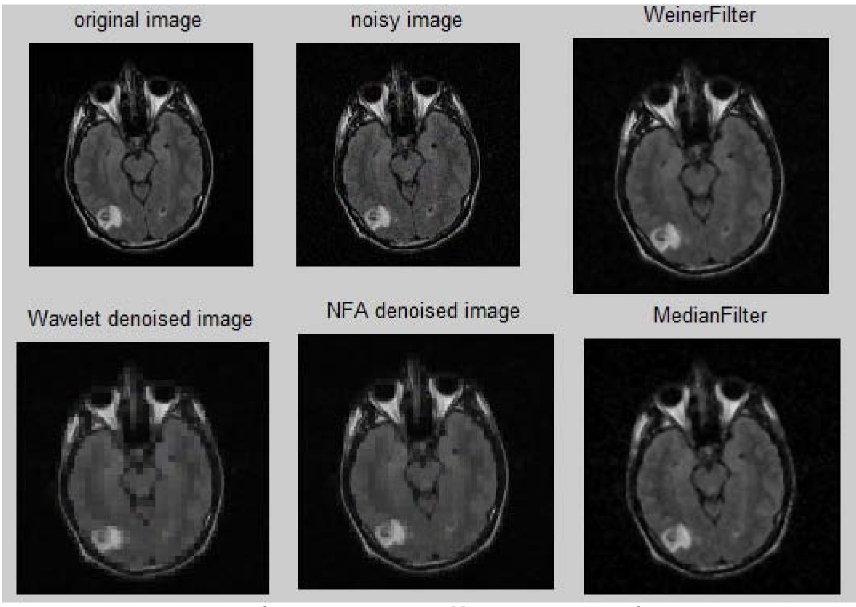



Fig. 7 Denoising of MRI image corrupted by Gaussian noise of variance 0.01

(a)top left-original image (b) top middle-noisy image (60.91 dB), (c) top right-Weiner Filter image (60.07dB) (d) bottom left Subband Wavelet Denoised image (66.78), (e)bottom middle- NPFA image (69.39 dB); (f) bottom right-Median Filter Image (60.98 dB).

The denoising algorithm developed in MATRIX laboratory (MATLAB) environment have been tested in more than 200 MRI images. The performance metrics calculated from the denoised image after implementing subband thresholding technique is given in Table 1. Also another table, Table 2 is given to show the PSNR value of the denoised images obtained after implementing subband thresholding with NPFA filter and for the performance of various filters. The qualitative performance of the images for various filters with the corresponding PSNR value is given in Fig. 7**.** Also graphical representation based on the performance of various filter with the corresponding PSNR value is given in Fig. 8.

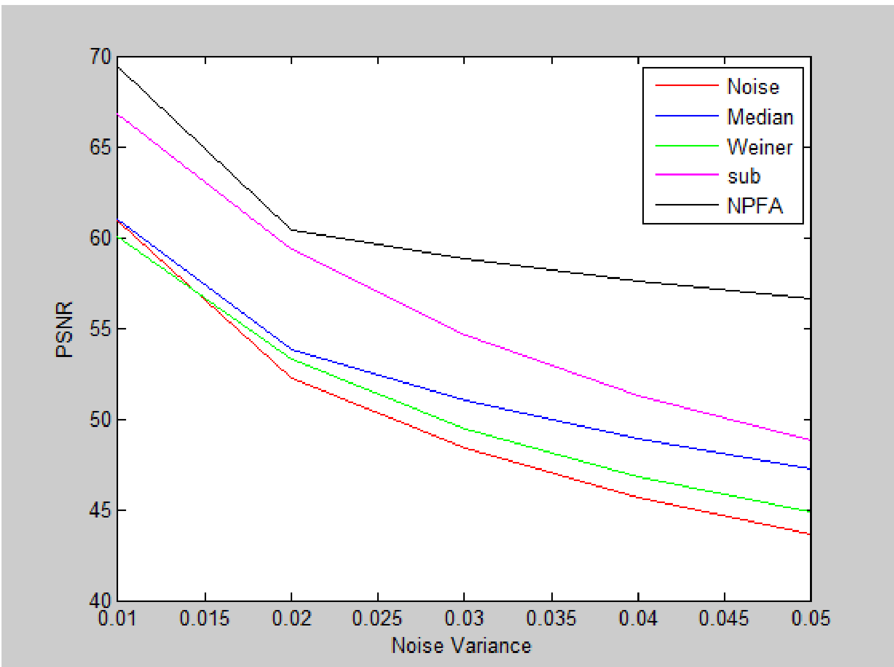



Fig. 8 Comparison chart of PSNR of different noise variance for MRI image

From the graph and the table it is observed that PSNR value obtained with the addition of NPFA filter along with sub band wavelet Thresholding is more. Qualitatively also it is observed that the images are having more clarity without loss of much detailed information. This is due to the addition of NPFA filter which gains the effect of low pass filter and high pass filter which in turn cuts off only high frequency noise signal instead of all noise signals. Also the decomposition level dependent is included as a multiplying factor $\alpha$ in the optimum value threshold formula along with sub band variance estimation

From Fig.8 it is observed that Weiner filter performs little denoising in high activity sub regions to preserve the sharpness of the edges but completely denoise the flat subparts of the image. Median filter preserve edges better than noise removal method using wiener filter. Subband wavelet method yields better results for denoising and also adopt thresholding strategy by preserving edges better than wieners and median filter. The proposed thresholding algorithm gives better performance than other spatial domain filter like weiner, median, subband wavelet giving a better PSNR value. Further it out performs the performance of the above mentioned filtering algorithm by preserving the edges as well as removing the noise, due to the advantages of using the multiplying factor $\alpha$ included in the optimum value threshold formula and subband thresholding, and addition of NPFA filter.

## 7. Conclusion:

The proposed threshold estimation method is based on the analysis of statistical parameters like standard deviation, variance of the sub band coefficients using ML or MAP estimator which is more sub bands adaptive. Since the decomposition level dependent is included as a multiplying factor $\alpha$ in the optimum value threshold formula along with sub band variance estimation, the proposed technique yields significantly superior image quality by preserving edges and a better PSNR value. As the concept low pass filter preserving the energy of signal and attenuating the high pass features at the discontinuities is used this filter gains the effect of both high pass and low pass filter. This filter uses NPD and cuts off only high frequency signal instead of all noisy signals. After implementing and using the results of the NPFA a significant improvement in clarity and sharpness of the image is observed. Comparative studies have been made between Median filter Wiener filter, subband thresholding technique with and without NPFA. The out come of the study revels that NPFA filter with subband thresholding out performs all the other filters in terms of PSNR and visual quality.

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