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# Evaluating Denoising Performances of Fundamental Filters for T2-Weighted MRI Images

Iza Sazanita Isa[1], Siti Noraini Sulaiman[1], Muzaimi Mustapha[2], Sailudin Darus[1]

*Universiti Teknologi MARA, Penang Campus, 13500 Pmtg Pauh, Pulau Pinang, Malaysia[1].*
*Universiti Sains Malaysia, Health Campus, 16150 Kubang Kerian, Kelantan, Malaysia[2].*

**Abstract**

In Magnetic Resonance (MR) images, noise is a common issue which limits the image accuracy of any quantitative measurements. Noise elimination in MRI image pre-processing is an important step to eliminate the noise and to make the image fit for further steps involved in the process of analyzing. However, different types of noises produces ranges of significant impact on image quality, and thus tend to affect human interpretation and performance of computer-aided diagnosis systems. Another issue is about filtering strategies to eliminate noise and preserve high quality image depending on filter reconstruction ability and noise model. In this work three different filtering algorithms such as Median filter (MF), Adaptive filter (ADF) and Average filter (AVF) are used to remove the additive noises present in the MRI images i.e. Gaussian, Salt and pepper and speckle noise. The noise density was gradually added to MRI image up to 90% to compare performance of the filters by qualitative and quantitative evaluation. The performance of these filters are compared using the statistical parameters such as Mean Squared Error (MSE) and Peak Signal-to-Noise Ratio (PSNR). The study shows that Median filter reconstructs a high quality image than other filters in Gaussian and Salt and pepper denoising with 38.3 dB PSNR at 10% noise variance. While for speckle noise removal, Average filter is perform better than others which result of 56.2 dB PSNR at 10% noise variance. A comparison with other well-established methods, this study shows that the Median and Average filter produces better denoising results, preserving the main structures and details.


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*Keywords:* Denoising, Noise, MRI Image, Image Pre-processing

**Nomenclature**

| | |
|---|---|
| *PSNR* | Peak Signal-to-Noise Ratio |
| *MSE* | Mean Squared Error |
| $\sigma$ | Noise variance |
| $\mu$ | Constant Mean |

## 1. Introduction

In medical image processing, poor image quality is insufficient for effective feature extraction, feature analysis, pattern recognition and quantitative measurements. The medical images are normally corrupted by random noise that occurs during the measurement process thus complicating the automatic feature extraction and analysis of clinical data [1]. Therefore, noise elimination is a must for medical images processing to remove such noises while retaining as much as possible the important image features. Numerous methods of noise removal were developed in wide applications such as medical imaging, signal


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processing, RFID, audio and speech processing with the objective to reduce noise and enhance the images [1]–[5]. The numbers of medical imaging modalities that are used for image processing research has been growing rapidly and this includes the magnetic resonance imaging (MRI). MRI is said to be the most powerful among all imaging tools [6] due to its sensitivity and ability to dispose signal abnormalities in complex organs of the human body.

The main purpose of this paper is to evaluate performances of different filtering techniques on different types of noises for MRI images. To evaluate the performances of these filters, a comparison using statistical parameters of MSE and PSNR is computed. Moreover, it is expected that from results of the study, we are able to define the best filtering method for T2-weighted MRI images. In addition to this, the identification of the best filtering method will thus improve and have significant impact on the quality of images.

This paper has been organized as follows; Section 1 and section 2 introduces research background and the related works on previous study. Section 3 constitutes the common noises along with image denoising methods. The proposed approach is covered in section 4. The results and observations are reported and discussed in section 5. Section 6 concludes the paper.

## 2. Related Works

The image processing literature presents a number of denoising methods or noise removal based on MRI medical image to preserve optimum information of an image. A study by Rajeesh *et al* proposed a denoising method in MRI image using Wave Atom Shrinkage[6]. This study was conducted to overcome the problem of magnetic resonance (MR) images which often suffer from low SNR or Contrast-to-Noise Ratio (CNR), especially in cardiac and brain imaging. The implementation of such filtering method had led to the improvement of SNR for images with low and high level of noise. Jose *et al* proposed a parametric filter namely Non-Local Means (NLM) for random noise removal in MR magnitude images[7]. As the filter is highly dependent on the parameters setting, the work has been conducted to find the optimum parameters for different noise levels. In general, this filter is applicable for automatic MR image denoising over synthetic and real images. The same filtering algorithm was proposed by Liu *et al* to remove noise in 3D MRI images so that denoising effect will improve. Experimental results demonstrate that the proposed filter achieved better denoising performance over the other filters being compared[8].

Another approach to MRI noise reduction is the adaptive multiscale data condensation (MDC) strategy using adaptive k-nn approach [3]. The strategy was tested with Rician noise and the performance evaluation was done using Wiener filter and wavelet transformation based noise reduction and reconstruction tools. The results showed that this approach is better on image blurring side effect even at a large mask size. Moreover, the mean-square error of this approach is slightly lesser than the Wiener filter.

In the work by Bhausaheb Shinde *et al*, different types of filtering technique namely median, adaptive and average filter have been tested to remove speckle noise in different medical images including MRI image. As per discussed in the work, the results revealed that noise removal is depending on types of noise and types of filtering technique. The right filter selection will benefit on image processing time and provide easier medical diagnosis [9].

Almost the same approach was taken by Sivasundari *et al* which is conducted to analyze the performance of filtering algorithms for MRI noise denoising. These filtering algorithms have been tested with various types of noisy images using Median filter, Center Weighted Median filter and Weiner filter. From the result analysis, it showed that Weiner filter gave desirable results with large PSNR value thus ensuring high image enhancement[10].

Based on the review of literature, the study presents a numbers of denoising techniques and filtering algorithms supported with significant findings and results as summarized in Table 1. However, no single method has shown to be superior to all others in terms of different types of noise additives as well as noise variance. As such, most study only focused on single noise while some were evaluated performance only on standard deviation. Therefore, this study is proposed to evaluate the performance of different filtering techniques of denoising along with gradually increase the noise density. Through this work, the performance of best filtering techniques is evaluated by qualitative and quantitative method. For qualitative method, the quality of image is examine visually as the noise density increase. Meanwhile, quantitative method is performed by mathematical calculation based on PSNR and MSE value.

Table 1. MRI Noise removal using different filtering method

| Study | | Noise density (%) | PSNR | MSE |
|---|---|---|---|---|
| M.S. Sindasuri, 2014 | Median filter | NA | 7.1991 | 148949.00 |
| | CWM filter | | 16.312 | 2781900.00 |
| | **Weiner filter** | | 17.813 | 8363.60 |
| J.M. Waghmare, 2013 | Standard Median Filter | 10% - 90% | 32.05 | NA |
| | Hybrid Median Filter | | 26.3 | NA |
| | **Relaxed Median Filter** | | 27.49 | NA |
| M. Yousuf, 2010 | **Combined Median & Mean filter** | | 43.68 | 184041 |

| | | | | |
|---|---|---|---|---|
| | Smoothing filter | NA | 43.43 | 194992.9 |
| | Median filter | | 43.64 | 186045.57 |
| | Midpoint filter | | 42.08 | 265998.06 |
| Bhausaheb Shinde, 2012 | Median Filter | Speckle Noise | Standard derivation 62.1669. | |
| | **Adaptive Filter** | | | |
| | Average Filter | | | |
| Balika Tawade, 2013 | Median filter | 3 % - 9% Rician noise | | NA |
| | Pseudo median Filter | | | |
| | Non Local Means Filter | | | |
| | Sparse Code Shrinkage (SCS) Method | | | |
| | **PCA method** | | | |

## 3. Common Noises in MRI

From theoretical expectations, the noise measured in unfiltered images was found to be normally distributed, spatially invariant and white [11]. As in image processing, the digital images are much sensitive to noise which results are due to the image acquisition errors and transmission errors. MRI images captured usually are prone to speckle noise, Gaussian noise and salt and pepper noise which have influence on the image quality [10]. Poor quality of image tends to degrade the performances of further works, e.g. feature extraction, reduction and classification of the processed images. The noises have to be removed before these processing stages as there were many available image filtering algorithms recommended in the literature.

Gaussian noise is a common noise distributed in magnitude MRI images and non-avoidable[12]. Because of its mathematical tractability in both the spatial and frequency domains, Gaussian noise is used frequently in practice [13]. Various filters such as average, median and adaptive Gaussian filter etc. have been proposed to clean the image from unfavourable candidates of noise [14].

Salt and pepper noise also known as impulsive noise will have dark pixels and bright pixels alternate bright and dark regions. Because impulse corruption usually is large compared with the strength of the image signal, impulse noise generally is digitized as extreme values in an image [13].

Speckle noise is a different type of noise in the coherent imaging of objects[2]. Speckle noise is a granular noise which degrades the quality due to transmission errors[10].

## 4. Methodology

### *4.1. MRI Data Set*

In this study, MRI data set of brain T2-weighted MR images are acquired from symptomatic untreated multiple sclerosis (MS) subjects which were downloaded from http://www.medinfo.cs.ucy.ac.cy/ [15]. This data set contains 38 (17 males, and 21 females) MRI images of MS/brain lesions subjects which were scanned twice at 1.5 T with an interval of 6-12 months. Each MRI images depicted 22 to 27 slides per sequence. Since this study focuses on filtering algorithms, only single slide of each MRI image is selected for testing with MATLAB 8.3.0.

### *4.2. Preprocessing Step*

Intensity normalization in image processing is the process of changing the range of pixel intensity values or known as contrast stretching / histogram stretching. The purpose of this process is used to bring the image into a range that is more familiar or normal to the senses. In order to achieve the consistency in dynamic range for a set of data images so that fatigue can be avoided, there are several methods proposed for image intensity normalization. However, it is recommended by [15] to normalize the image intensity using Histogram Normalization (HN) since it gave the best performance compared to other methods. The linear normalization of a grayscale MRI image is given as in (1). The initial image $g(x,y)$ is stretched to new image namely $f(x,y)$. The brightness range of new image are denoted as $g_{HIR}$ and $g_{LIR}$. While $g_{\max}$ and $g_{\min}$ are the initial brightness level of image from minimum to maximum range.

$$f(x,y) = \left(g(x,y) - g_{\min}\right)\left[\frac{g_{HIR} - g_{LIR}}{g_{\max} - g_{\min}}\right] + g_{LIR} \tag{1}$$

### *4.3. Filtering Process*

#### *4.3.1. Median Filter*

Median filter is a sliding window spatial filter, but it replaces the center value in the window with the median of all pixels value in the window. This filter provides noise removal but results in loss of fine details [5]. Median filters are mostly used by researchers because of its capability to provide excellent noise reduction with less blurring for various types of noise. Median filters are also widely used as smoothers for image processing, as well as in signal processing and time series processing. A major advantage of the median filter over linear filters is that the median filter can eliminate the effect of input noise values with extremely large magnitudes. Median filter is advantageous over mean filter and it's a non-linear filtering technique, helps removing noise[10]. It has the ability to remove 'impulse' noise (outlying values either high or low). It also widely claimed to be 'edge-preserving' since it theoretically preserves step edges without blurring. However, in the presence of noise, it does slightly blur edges in images. The standard median filter is given by (2) where $X_i$ and $Y_i$ be the input and the output at location $i$ of the filter [5]. The $[W_i]_r, r = 1,....2N+1,$ the r[th] order statistic of the samples inside the window $W_i$ is $[W_i]_1 < [W_i]_2 < \ldots [W_i]_{2N+1}$. Meanwhile, for this work, the window size of the filters is 3x3. This size is chosen since the increment in mask size will increase the RMSE [16].

$$Y_i = med\{W_i\} = med\{X_i + r : r \in W\} \tag{2}$$

### 4.3.2. Average (Mean) Filter

The Average filter is a simple sliding window spatial filter that replaces the center value in the window with the average (mean) of all pixels values in the window. The main drawback of this filter is that it is poor in edge preserving[10] as the noise reduced will result in blurring. The average filter is given by (3) [13]. The mean filtering process computes the average of the corrupted image $g(x, y)$ in the area $S_{xy}$. The $\hat{f}(x, y)$ represents mean computed using the pixels in region $S_{xy}$ subimage window of size $m \times n$.

$$\hat{f}(x, y) = \frac{1}{mn} \sum_{(s,t)\in S_{xy}} g(s,t) \tag{3}$$

### 4.3.3. Adaptive (Wiener) Filter

The adaptive filtering carries out an optimal tradeoff between inverse filtering and noise smoothing. It removes additive noise and deblurring concurrently [17]. The adaptive filter is given by (4) where $H(m,n)$ and $H^*(m,n)$ is the degradation function and its complex conjugate respectively. While $P_n(m,n)$ and $P_s(m,n)$ is power spectral density of noise and power spectral density of un-degraded image[10].

$$W(m,n) = \frac{H^*(m,n)}{|H(m,n)|^2 + \dfrac{P_n(m,n)}{P_s(m,n)}} \tag{4}$$

The adaptive filter is more selective than a comparable linear filter, preserving edges and other high frequency parts of an image [9]. However, it does require more computations time than linear filtering.

### 4.4. Filters Performance Measurement

There are two types of metric used to evaluate the performance of the filter either by error sensitivity measure or image quality assessment (QA) measure. The most widely used error sensitivity measure are the Mean Squared Error (MSE), Signal-to-Noise Ratio (SNR) and Peak Signal-to-Noise Ratio (PSNR) [18]. MSE is computed by averaging the squared intensity of the original (input) image and the resultant (output) image pixels as in (5). $I$ and $\hat{I}$ are the reference and filtered images of size $M \times N$ respectively[19].

$$MSE = \frac{1}{M \times N} \sum_{i=1}^{i=M} \sum_{j=1}^{j=N} \left(\hat{I}(ij) - I(ij)\right)^2 \tag{5}$$

The SNR and PSNR are very useful in quantifying the image contrast but PSNR is more useful when dealing with contrast adjustment in the region of interest. SNR is badly defined for homogenous images, so for reconstruction evaluation, PSNR is preferred to be used on this study. On the other hand, these measures are popular, simple and easy to evaluate [19]. PSNR is defined as relative to peak dynamic range i.e. 255 for an 8 bit image. The PSNR is used to measure the quality of an image after the reconstruction in which higher a PSNR indicates a good reconstruction and hence, ensuring a high image enhancement. PSNR is expressed in dB and formulated as in (6) where $L$ is the dynamic range of the pixel intensities.

$$PSNR = 10\log_{10}\left[\frac{L^2}{MSE}\right] \tag{6}$$

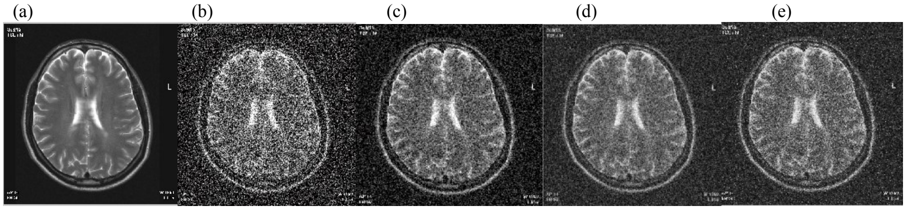
## 5. Results and Discussion

In this section, two analyses are applied namely the qualitative and quantitative analysis. The result for both analyses will be presented in section 5.1 and 5.2.

### *5.1. Qualitative Analysis*

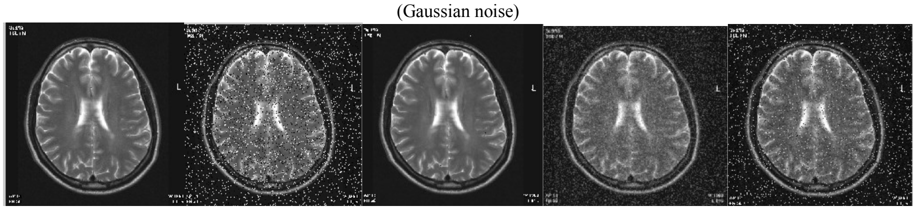
Figures 1(a) – (e) to figure 3(a) – (e) presents MRI image with different noise density (10%, 50% and 90%) and the quality of image reconstruction using Median, Adaptive and Average filters. The MRI image with Gaussian noise depicted better enhancement in all filtered images but Average and Adaptive filters caused blurring to the images. Median filter showed better filtered image quality for Salt and Pepper and Speckle noise removal compared to other filters. The image can be visually evaluated in 10% noise removal as shown in figures 1 (a) – (e) and also, for 50% as well as 90% density of noise removal, Median filter is showing the best performance qualitatively by preserved the edge without blurring. The visual interpretation is supported by quantitative measurement. PSNR as recorded below for each resultant images.

(a) (b) (c) (d) (e)



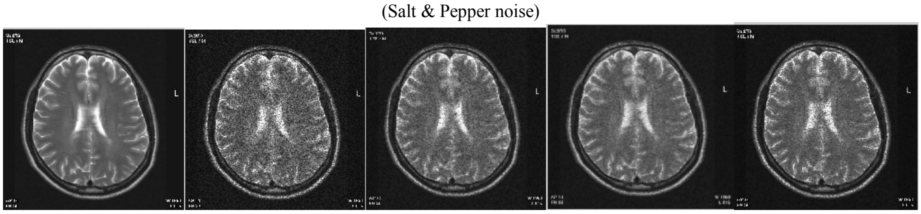
PSNR=38.3dB PSNR=36.34 dB PSNR=34.04dB

(Gaussian noise)



PSNR= 62.25dB PSNR= 43.39 dB PSNR=34.28dB

(Salt & Pepper noise)

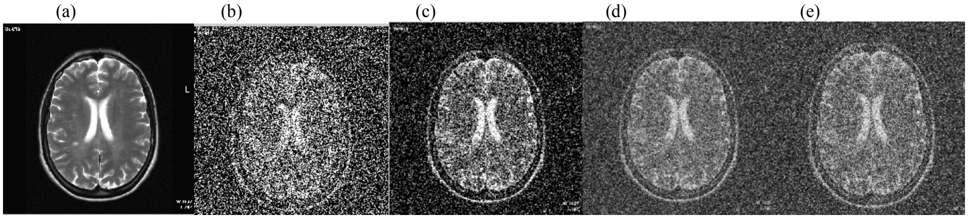


PSNR=52.49dB PSNR= 56.202 dB PSNR=50.521dB

(Speckle noise)

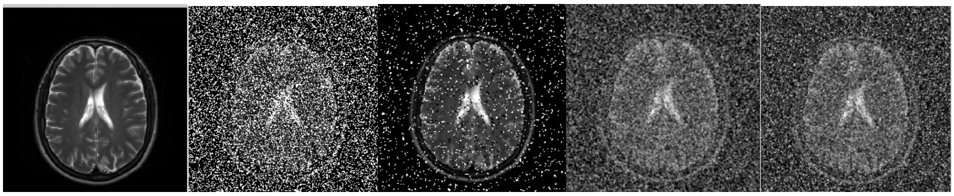
Fig 1 (a) Original MRI image (b) Noisy image (10% noise density) (c) Median filter (d) Average filter (e) Adaptive filter

(a) (b) (c) (d) (e)

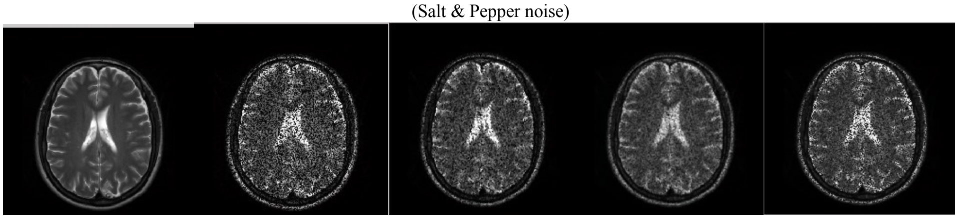


PSNR= 25.94 dB PSNR= 24.98 dB PSNR= 24.17 dB

(Gaussian noise)



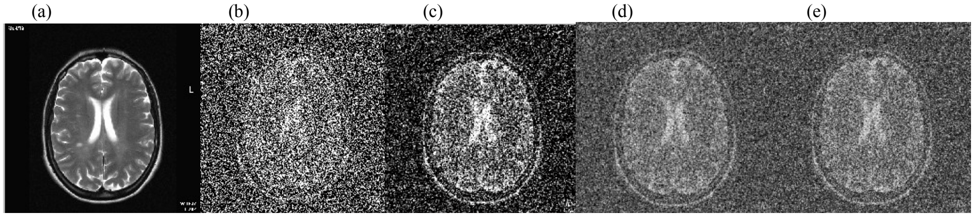
PSNR=27.71dB PSNR= 24.73 dB PSNR=23.62dB
(Salt & Pepper noise)



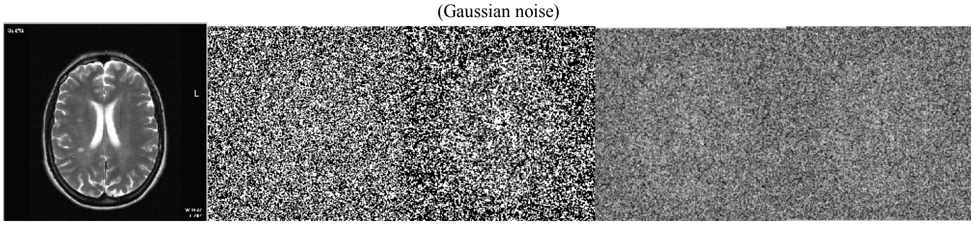
PSNR= 41.29dB PSNR= 46.67 dB PSNR= 37.37 dB
(Speckle noise)

Fig 2 (a) Original MRI image (b) Noisy image (50% noise density) (c) Median filter (d) Average filter (e) Adaptive filter

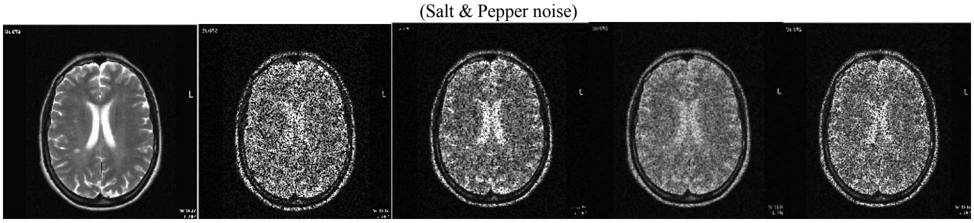
(a) (b) (c) (d) (e)



PSNR= 21.80dB PSNR= 22.23 dB PSNR=21.72dB
(Gaussian noise)



PSNR= 10.30dB PSNR= 16.31 dB PSNR=16.20 dB
(Salt & Pepper noise)



PSNR= 37.02dB PSNR= 43.84 dB PSNR=34.44dB
(Speckle noise)

Fig 3 (a) Original MRI image (b) Noisy image (90% noise density) (c) Median filter (d) Average filter (e) Adaptive filter

### *5.2. Quantitative Analysis*

Table 2 tabulates average PSNR values of each tested filters namely Median filter, Average filter and Adaptive filter. Each filter was used to remove three types of noises that are Gaussian, Salt and pepper and speckle. The noise density was added to MRI image varying from a minimum of 10% to a maximum of 90%. To compare all three filters, Median and Average filter are works better for speckle noise as compared to salt and pepper noise. Moreover, Median filter performs higher PSNR compared to other filters but only for salt and pepper noise density level less than 30%. As mentioned theoretically in sub topic 4.3 above, it does preserve the edges without blurring as shown in figure 1 (salt and pepper noise). As the higher the salt and pepper noise is, the more blurring occurs in the image as shown in figure 2 (salt and pepper noise) and figure 3 (salt and pepper noise).

Table 3 tabulates an average MSE for each tested filters and the results revealed that Average filter produced the lowest MSE compared to other filters. It also explains that speckle noise in MRI images is easier to remove by any types of filter but most workable are Adaptive and Average.

Through this work, even though the MRI image visually shows better enhanced image, as illustrated in figure 1, 2 and 3, the PSNR values do not interpret the similar results. As example, MRI image quality in figure 3(a)(Speckle noise) shown better edge preservation and less blurring by Median filtering as compared to Average filter. However, in terms of PSNR value, Average filter is much higher. This is showing that qualitative and quantitative evaluation are dependable of each other to support the filtering technique.

Table 2. Average PSNR of different filtering methods

| **Noise, $\sigma$** | 10 | 20 | 30 | 40 | 50 | 60 | 70 | 80 | 90 |
|---|---|---|---|---|---|---|---|---|---|
| **Gaussian** | | | | | | | | | |
| Median | **38.300** | **32.916** | **29.790** | **27.619** | **25.937** | **24.623** | **23.549** | 22.614 | 21.798 |
| Adaptive | 34.038 | 29.252 | 26.834 | 25.293 | 24.166 | 23.344 | 22.712 | 22.171 | 21.721 |
| Average | 36.339 | 30.912 | 28.063 | 26.272 | 24.980 | 24.043 | 23.330 | **22.720** | **22.225** |
| **Salt & Pepper** | | | | | | | | | |
| Median | **62.248** | **54.700** | **44.458** | **35.126** | **27.714** | 21.752 | 17.074 | 13.313 | 10.296 |
| Adaptive | 34.275 | 31.101 | 28.309 | 25.821 | 23.621 | 21.535 | 19.632 | 17.856 | 16.204 |
| Average | 43.386 | 36.176 | 31.376 | 27.706 | 24.730 | **22.174** | **19.993** | **18.050** | **16.306** |
| **Speckle** | | | | | | | | | |
| Median | 52.486 | 47.956 | 45.038 | 42.921 | 41.286 | 39.885 | 38.776 | 37.851 | 37.018 |
| Adaptive | 50.521 | 44.492 | 41.048 | 38.786 | 37.374 | 36.367 | 35.587 | 34.972 | 34.444 |
| Average | **56.202** | **52.465** | **49.817** | **47.913** | **46.666** | **45.701** | **44.972** | **44.362** | **43.842** |

Table 3. Average MSE of different filtering methods

| **Noise, $\sigma$** | 10 | 20 | 30 | 40 | 50 | 60 | 70 | 80 | 90 |
|---|---|---|---|---|---|---|---|---|---|
| **Gaussian** | | | | | | | | | |
| Median | **799.69** | **1484.98** | **2127.38** | **2730.26** | **3312.19** | **3852.67** | **4358.62** | 4853.83 | 5331.04 |
| Adaptive | 1306.08 | 2267.77 | 2997.31 | 3580.91 | 4078.87 | 4483.54 | 4824.69 | 5134.53 | 5408.55 |
| Average | 1002.88 | 1874.05 | 2602.89 | 3200.28 | 3715.50 | 4138.31 | 4495.06 | **4821.51** | **5105.52** |
| **Salt & Pepper** | | | | | | | | | |
| Median | **62.78** | **126.58** | **394.37** | **1151.04** | **2700.46** | 5364.63 | 9193.49 | 14174.97 | 20063.66 |
| Adaptive | 1271.16 | 1831.49 | 2527.92 | 3368.98 | 4343.42 | 5526.32 | 6886.22 | 8451.13 | 10228.99 |
| Average | 444.79 | 1020.92 | 1777.13 | 2714.49 | 3826.41 | **5138.35** | **6609.52** | **8267.46** | **10111.57** |
| **Speckle** | | | | | | | | | |
| Median | 168.17 | 280.66 | 391.25 | 498.17 | 601.97 | 706.51 | 801.77 | 892.95 | 982.17 |
| Adaptive | 201.09 | 402.89 | 598.86 | 776.16 | 913.31 | 1024.87 | 1120.07 | 1201.62 | 1276.04 |
| Average | **110.85** | **169.19** | **228.40** | **283.17** | **327.29** | **365.37** | **396.36** | **425.29** | **451.42** |

## 6. Conclusion

This paper investigated the performance of three different filtering methods tested with different noises on MRI images. The Median filter is the most outperformed method as compared to other filters mainly for Gaussian noise denoising. This filter performed best when the noise is constant-power ("white") additive noise, such as speckle noise. From this study, the results showed that Median filter gives desirable results with higher PSNR value for MRI image denoising. The result is also supported by previous related studies which has been tested on different modes of imaging images. As the Average filter removes additive noise and deblurring concurrently, therefore it has a significant ability to optimize the reduction of the overall MSE. Through this work, it has been observed that the choice of filters for de-noising the MRI images depends on the type of noise and type of filtering techniques. As such, Median filter is applicable to remove Gaussian and Salt and pepper noises while Average filter prone to eliminate Speckle noise in MRI images. This experimental analysis will improve the accuracy of MRI images for other processing step such as segmentation and feature extraction.

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