SCIREA Journal of Computer

http://www.scirea.org/journal/Computer

February 27, 2017

Volume 2, Issue 1, February 2017

MRI Medical Image Denoising by Fundamental Filters

Hanafy M. Ali

Computers and Systems Engineering Department, Faculty of Engineering, Minia University, El Minia, Egypt hmali@mu.edu.eg

Abstract

Nowadays Medical imaging technique Magnetic Resonance Imaging (MRI) plays an important role in medical setting to form high standard images contained in the human brain. MRI is commonly used once treating brain, prostate cancers, ankle and foot. The Magnetic Resonance Imaging (MRI) images are usually liable to suffer from noises such as Gaussian noise, salt and pepper noise and speckle noise. So getting of brain image with accuracy is very extremely task. An accurate brain image is very necessary for further diagnosis process.

During this paper, a median filter algorithm will be modified. Gaussian noise and Salt and pepper noise will be added to MRI image. A proposed Median filter (MF), Adaptive Median filter (AMF) and Adaptive Wiener filter (AWF) will be implemented. The filters will be used to remove the additive noises present in the MRI images. The noise density will be added gradually to MRI image to compare performance of the filters evaluation. The performance of these filters will be compared exploitation the applied mathematics parameter Peak Signal-to-Noise Ratio (PSNR).

Keywords: MRI image, De-noising, Non-linear filter, Median filter, Adaptive filter and Adaptive Median filter.

1. Introduction

Image De-noising has been an important problem in the field of image processing. Noise reduction process is an important part of image processing systems. It is a technique removes out noise which is added in the original image. Image quality may get defective while capturing, processing and storing the image. Removing noise from the original images is still a challenging problem for researchers because noise removal introduces artifacts and causes blurring of the images. Nowadays, image de-noising has become an important purpose in medical imaging particularly the Magnetic Resonance Imaging (MRI).Many de-noising and enhancement techniques are applied on MRI images [1-8].

In this paper, a median filter algorithm will be modified. Gaussian noise and Salt and pepper noise will be added to MRI image. A proposed Median filter (MF), Adaptive Median filter (AMF) and Adaptive Wiener filter (AWF) will be implemented. The filters will be used to remove the additive noises present in the MRI images. The noise density will be added gradually to MRI image to compare performance of the filters evaluation. The performance of these filters will be compared exploitation the applied mathematics parameter Peak Signal-to-Noise Ratio (PSNR). After this study, the best filtering method for MRI image will be able to define.

2. IMAGE DENOISING TECHNIQUES

A lot of different Image de-noising techniques are developed so far each having its own advantages and limitation. According this work will prove that, applied the technique depend on the type and amount of noise present in the image. One should also consider the other factors like performance in de-noising the image, computational time, and computational cost [9-12].

De-noising can be exhausted in various domains like Spatial Domain, Frequency Domain and Wavelet Domain. Also, filtering is a technique in image processing which is employed for various tasks like noise reduction, interpolation, and re-sampling. The selection of filter depends upon the type and amount of noise present in an image because different filters can remove different types of noise efficiently.

2.1 Adaptive Wiener Filter

Adaptive Wiener Filter (AWF) is considering frequency domain filter. The adaptive wiener filter changes its behavior based on the statistical characteristics of the image inside the filter region, which is defined by the maximum rectangular window. Adaptive filter performance is commonly superior to non-adaptive counterparts. Mean and variance are two important mathematics measures using which adaptive filters can be designed [13].

The adaptive wiener filter uses a pixel-wise adaptive Wiener method based on statistics estimated from a local neighborhood of each pixel. Its function filters the image using pixel-wise adaptive wiener filtering, using neighborhoods of size M-by-N to estimate the local image mean and standard deviation.

2.2 Non-Linear Filters:

In recent years, a variety of non-linear filters like median filter, adaptive median filter, min filter, max filter have been developed to overcome the defect of linear filter. Non-linear filters give better performance than linear filters [12 and 14]. The non-linear filters are spatial domain filters. In following sections, the median filter and adaptive median filter are discussed.

2.2.1 The Proposal Median Filter

Median filter is spatial domain filter. It is also known as order statistics filter. The median filter is most popular and commonly used nonlinear filter. It removes noise by smoothing the images. This filter also lowers the intensity variation between one and other pixels of an image. The median filter algorithm replaced the pixel value of image with the median value. The median value is calculated in two steps, first arranging all the pixel values in ascending order, second replace the pixel being calculated with the middle pixel value. If the neighboring pixel of image which is to be consider, contains and even no of pixels, then it replaces the pixel with average of two middle pixel values. The mean filter can be represented by the following equation:

$$\mathrm{f}^{\wedge}(\mathrm{x},\mathrm{y}) = \mathrm{median}\,\{\mathrm{g}(\mathrm{s},\mathrm{t})\} \qquad \mathrm{where}\ (\mathrm{s},\mathrm{t}) \in \mathrm{S}_{\mathrm{xy}} \tag{1}$$

Where Sxy corresponds to the set of coordinates in a rectangular sub image window which has center at (x,y). The median filter calculates the median of the corrupted image g(x,y) under the area Sxy. Here f^(x,y) represents the restored image.

In this paper, the median filter algorithm is modified. The restored image pixel at (i,j) equal the median value of (g(i-1,j),g(i,j-1),g(i+1,j),g(i,j+1),g(i+1,j+1),g(i-1,j-1),g(i-1,j+1) and g(i+1,j-1).

Median filters are mostly used by researchers due to its capability to fit out excellent noise reduction with less blurring for various types of noise. Median filters are wide 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.

2.2.2 Adaptive Median Filtering

The Adaptive Median Filtering (AMF) [15] has been applied wide as an advanced de-noising technique compared with standard median filtering. The adaptive Median filter executes spatial processing to determine which pixels in an image have been affected by noise. The Adaptive Median Filter classifies pixels as noise by comparison each pixel in the image to its surrounding neighbor pixels. The size of the neighborhood (window) is adjustable, as well as the threshold for the comparison. A pixel that is different from a majority of its neighbors, as well as being not structurally aligned with those pixels to which it is similar, is labeled as noisy pixel. These noisy pixels are then exchange by the median value of the pixels in the neighborhood that have passed the noise labeling test. Adaptive median filter changes the size of the neighborhood (window) through operation. The standard median filter does not perform well when the impulse noise density is high, while the adaptive median filter can better handle these noises. Also, the adaptive median filter preserves image details such as edges and smooth non-impulsive noise, while the standard median filter does not.

In this work, the adaptive median filter works on a rectangular region Sxy. The adaptive median filter changes the size of Sxy through the filtering operation depending on certain criteria. The adaptive median filter works in two levels denoted Level A and Level B as follows.

Level 1:L11= Zmed - Zmin

L12= Zmed - Zmax

If L11 > 0 AND L12 < 0, Go to level 2

Else increase the window size

If window size <= Smax repeat level 1

Else output Zxy.

Level 2: L21 = Zxy – Zmin

L22 = Zxy – Zmin

If L21 > 0 And L22 < 0 output Zxy

Else output Zmed.

Where:-

Zmin = Minimum gray level value in Sxy.

Zmax = Maximum gray level value in Sxy

Zmed = Median of gray levels in Sxy

Zxy = gray level at coordinates (x, y)

Smax = Maximum allowed size of Sxy

The output of the filter is a single value which the exchange the corrupted pixel value at (x, y), the point on which Sxy is centered at the time.

3. Common Noises in MRI

From theoretical expectations, the noise measured in unfiltered MRI images was found to be usually distributed, spatially invariant and white. As in digital 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 Gaussian noise and salt and pepper noise which have influence on the image quality [4 and 16-22]. Poor quality of image tends to degrade the performances of any works such as feature extraction, reduction and classification of the processed images. The noises go to be removed before these processing stages as there were many available image filtering algorithms recommended in the literature. Gaussian noise and Impulse noise are popular noises distributed in magnitude MRI images and non-avoidable. Because of its mathematical tractability in both the spatial and frequency domains, many of filters are used to remove the Gaussian noise. Salt and pepper noise consider 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, the impulse noise mostly is digitized as extreme values in an image.

3.1 Gaussian Noise or Amplifier Noise

It is conjointly referred to as Gaussian distribution. It has a probability density equation of the normal distribution. The Gaussian noise or amplifier noise is added to image during image acquisition like sensor noise caused by low light, high temperature, transmission e.g. electronic circuit noise. This noise will be removed by using spatial filtering (Adaptive Wiener filter, Median filter and Adaptive Median filter). The Probabilities Density Function (PDF) of Gaussian Noise is shown in the following equation and figure 1:

$$p(z) = \frac{1}{\sqrt{2\pi\sigma}} e^{\frac{-(z-u)^2}{2\sigma^2}} \quad (2)$$

Where: *P(x)* is the Gaussian distribution equation noise in image; μ and σ is the mean and standard deviation respectively.

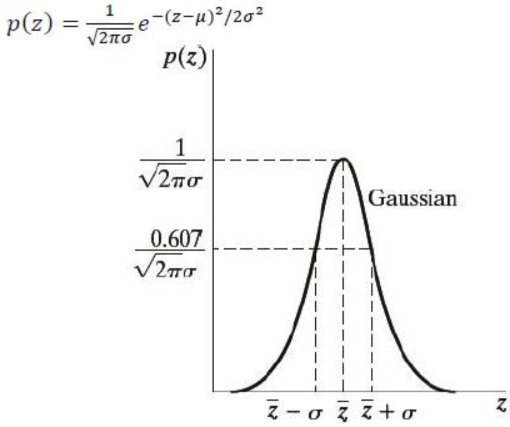

Fig. 1: Gaussian Noise

3.2 Impulse Noise

The Impulse noise is also famous as Salt & Pepper noise or Spike noise. It's caused by malfunctioning pixels in camera sensors, faulty memory locations in hardware, or transmission in a noisy channel. It's forever independent and uncorrelated to image pixels. Its two types are the salt-and-pepper noise and the random-valued noise. In the Salt and Pepper type of noise, the noisy pixels takes either salt value (gray level -225) or pepper value (grey level -0) and it seems as black and white spots on the images In case of random valued impulse noise, noise can take any gray level value from 0 to 225. In this case also noise is randomly distributed over the entire image and probability of occurrence of any gray level value as noise will be same.

The Salt and Pepper noise is shown in following equation and figure 2.

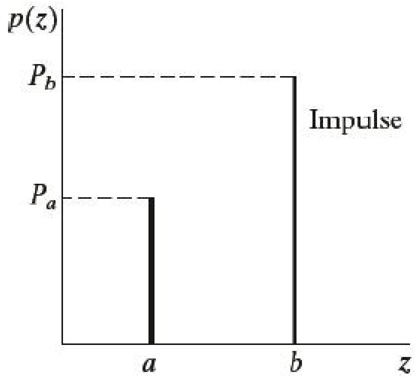

Fig.2: Salt and Pepper Noise

$$P(z) = \begin{cases} p_a & \text{for } z = a \\ p_b & \text{for } z = b \\ 0 & \text{otherwise} \end{cases} \qquad (3)$$

Where: p_a , p_b are the probabilities density equation, *p (z)* is distribution salt and pepper noise in image and *a, b* are the arrays size image.

4. Peak signal-to-noise ratio

The phrase peak signal-to-noise ratio is typically abbreviated PSNR. The peak signal-to-noise ratio (PSNR) is an engineering term defined as the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. Because many signals have a very wide dynamic range, PSNR is typically expressed in terms of the logarithmic decibel scale.

It is most simply defined via the mean squared error (MSE) which for two $m \times n$ monochrome images I and K where one of the images is considered a noisy approximation of the other is defined as:

$$MSE = \frac{1}{mn} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} [I(i,j) - K(i,j)]^2 \qquad (4)$$

The PSNR equation is defined as:

$$PSNR = 20.\log_{10}\left(\frac{MAX}{\sqrt{MSE}}\right) = 10.\log_{10}\left(\frac{MAX^2}{MSE}\right) \qquad (5)$$

Here, MAX is the maximum possible pixel value of the image. When the pixels are represented using 8 bits per sample, this is 255. More generally, when samples are represented using linear PCM with B bits per sample, MAX is $2^B - 1$.

5. **Results and Discussion**

The three filters: the adaptive wiener filter, the median filter and the adaptive median filter were implemented using (MATLAB R22015a) and tested for two types of noise: Gaussian Noise and Salt & Pepper Noise corrupted on the MRI brain image. The following two sections describe the results.

5.1 Qualitative Analysis

Figures 3(A) - (C) and 8(A) – (B) presents MRI image with different noise density (10%, 50% and 90%). The quality of image is rebuilding using Adaptive Wiener, Median and Adaptive Median filters. The Adaptive Wiener filter result is showed bad filter MRI image quality for Salt and Pepper and Gaussian noise. The results of the Median filter showed, its better filter image quality for Gaussian noise. The Adaptive Median results showed, it is better filter for salt and Pepper noise than Median and Adaptive Wiener filter. But, it is gave bad filter quality for Gaussian noise. The PSNR is recorded below for each resultant image as shown in figures (3-8). In this work, the calculation algorithm of median value in median filter is modified. The processing time and memory used for median filter algorithm was increase than the Adaptive Wiener and Adaptive Median filters by 400%.

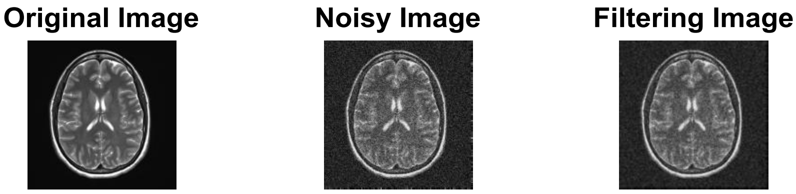

Fig.3-A: Noise Density =10%- PSNR=43.2096

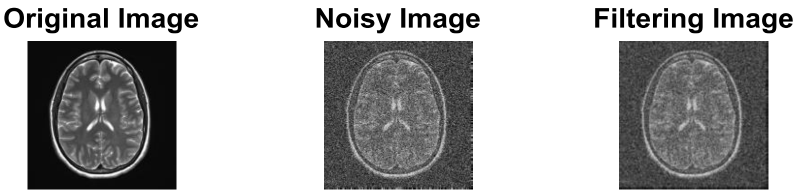

Fig.3-B: Noise Density =50%- PSNR=37.9244

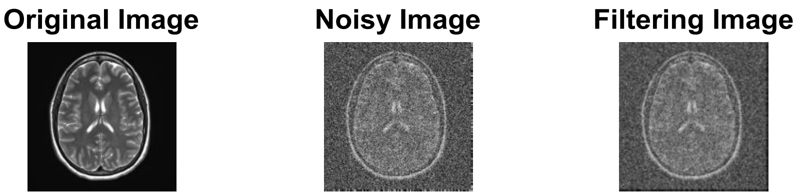

Fig.3-C: Noise Density =90%- PSNR=36.5301

Fig. 3: wiener filter (Gaussian noise)

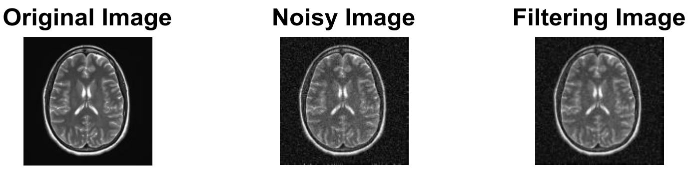

Fig.4-A: Noise Density =10%- PSNR=45.2549

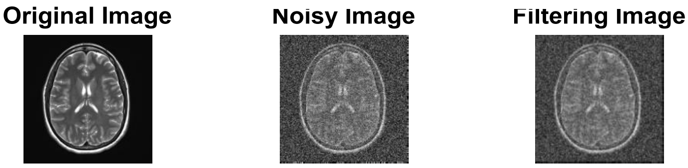

Fig.4-B: Noise Density =50%- PSNR=37.8006

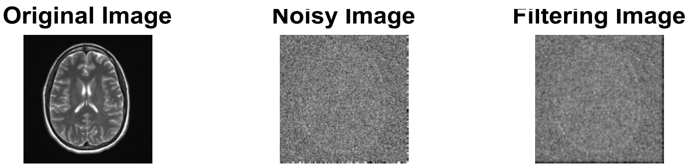

Fig.4-C: Noise Density =90%- PSNR=33.4716

Fig. 4 Wiener filter (Salt & Pepper Noise)

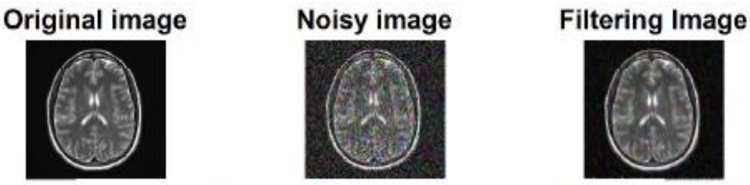

Fig.5-A: Noise Density =10%- PSNR=51.9813

Fig.5-B: Noise Density =50%- PSNR=47.2688

Fig.5-C: Noise Density =90%- PSNR=45.5434

Fig. 5: Median filter (Gaussian noise)

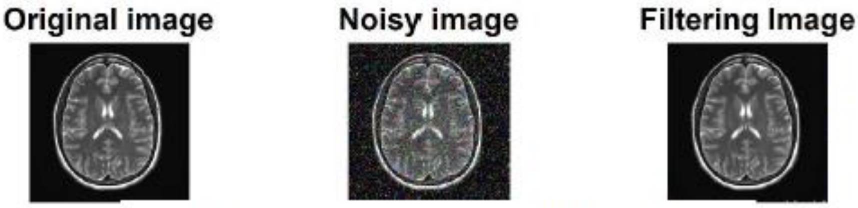

Fig.6-A: Noise Density =10%- PSNR=61.8162

Fig.6-B: Noise Density =50%- PSNR=52.0523

Fig.6-C: Noise Density =90%- PSNR=39.1255

Fig. 6: Median filter (Salt & Pepper Noise)

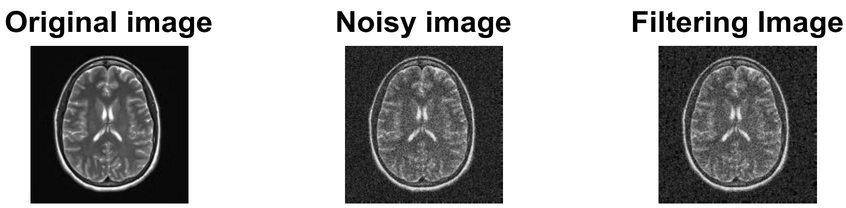

Fig.7-A: Noise Density =10%- PSNR=38.9811

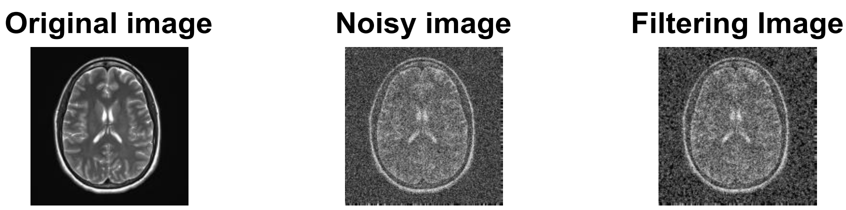

Fig.7-B: Noise Density =50%- PSNR=34.5541

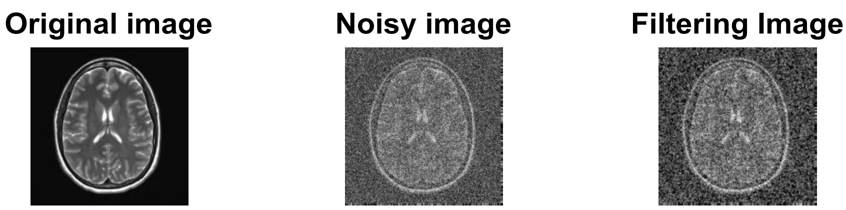

Fig.7-C: Noise Density =90%- PSNR=33.7908

Fig. 7: Adaptive Median filter (Gaussian noise)

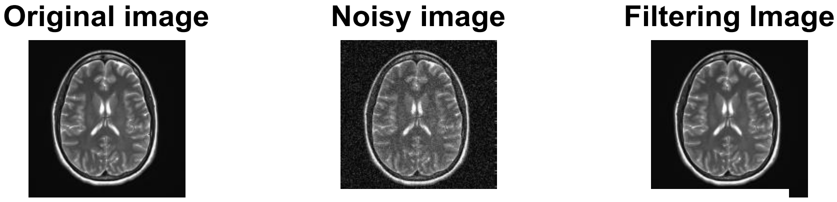

Fig.8-A: Noise Density =10%- PSNR=66.8579

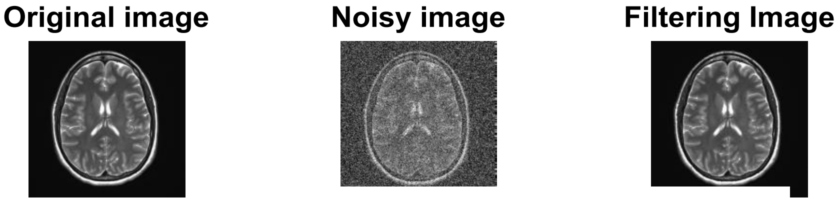

Fig.8-B: Noise Density =50%- PSNR=54.9245

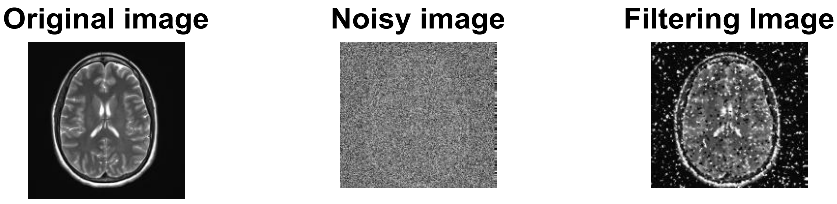

Fig.8-C: Noise Density =90%- PSNR=40.1885

Fig. 8: Adaptive Median filter (Salt & Pepper Noise)

5.2. Quantitative Analysis

Table 1 shows average peak signal-to-noise ratio (PSNR) values of each tested filters (Adaptive Wiener filter, Median filter and Adaptive Median filter). Each filter was used to remove the Gaussian noise. The noise density was added to MRI image varying from a 10% to 90%. To compare all three filters, Median filter works better for Gaussian noise as shown in figure 9. Median filter performs higher PSNR compared to other filters as shown in table 1. Also, the efficiency of Adaptive Median filter is bad in removing Gaussian noise and more blurring occurs in the image as shown in figure 7 and table 1.

Table 2 tabulates average peak signal-to-noise ratio (PSNR) values of each tested filters (Adaptive Wiener filter, Median filter and Adaptive Median filter). Each filter was used to take off the Salt and Pepper noise. The noise density was added to MRI image varying from a 10% to 90%. To compare all three filters, the Adaptive Median filter gave a better result as shown in figure 10 and table 2. The Adaptive Median filter performs higher PSNR compared to the Median filter and the Adaptive Weiner filter

Through this work, the Median filter allowed a high performance in removing two noises (salt and Pepper noise- Gaussian noise). But, the processing time and memory for median filter algorithm was increased than the Adaptive Wiener and Adaptive Median filters by 400%.

Table 1: PSNR of different filtering methods (Gaussian Noise)

Gaussian Noise	10%	20%	30%	40%	50%	60%	70%	80%	90%
Wiener	43.2096	40.7198	39.4058	38.5437	37.9244	37.4609	37.0554	36.7821	36.5301
Median	51.9813	50.0028	48.8096	47.9059	47.2688	46.7664	46.2666	45.9440	45.5434
Adaptive median	38.9811	36.6111	35.5311	34.9378	34.5541	34.2792	34.0766	33.9278	33.7908

Fig. 9: PSNR of different filtering methods (Gaussian Noise)

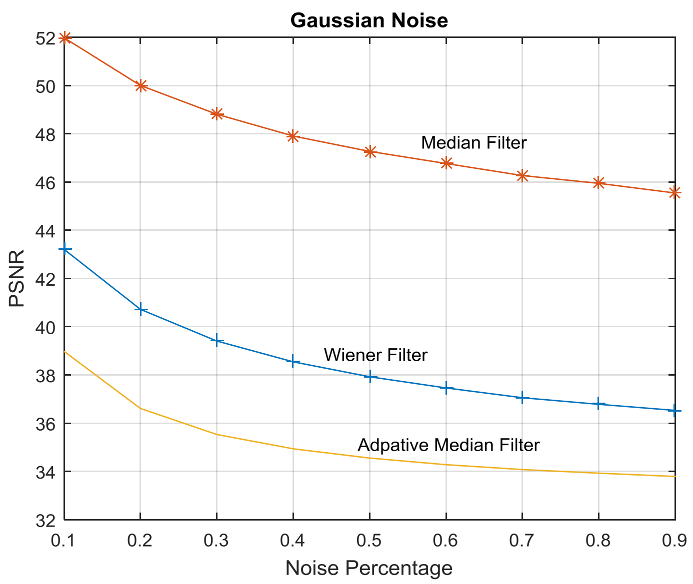

Table 2: PSNR of different filtering methods (Salt & Pepper Noise)

Salt & Pepper Noise	10%	20%	30%	40%	50%	60%	70%	80%	90%
Wiener	45.2549	42.7827	40.8778	39.2039	37.8006	36.5460	35.3685	34.3821	33.4716
Median	61.8162	58.7794	56.6603	54.2224	52.0523	49.3339	46.5512	43.2658	39.1255
Adaptive median	66.8579	62.3232	59.4506	57.2552	54.9245	52.8025	50.6639	45.7517	40.1885

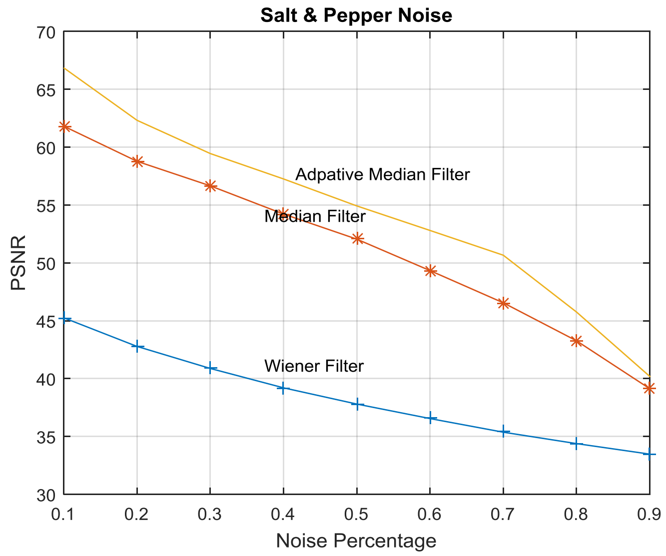

Fig. 10: PSNR of different filtering methods (Salt & Pepper Noise)

6. Conclusion

This paper investigated the performance of three different completely filtering methods tested with different noises on Magnetic Resonance Imaging (MRI) images. The Median filter is the most high performance method as compared to other filters mainly for Gaussian noise de-noising. The Adaptive Median filter is the most outperformed method as compared to other filters mainly for Salt and Pepper noise de-noising.

Through this work proved, the choice of filter depends upon the type and amount of noise present in an image. Also, the de-noising the MRI images performance depends on the type of noise and type of filtering techniques. The Median filter was better filter Magnetic Resonance Imaging images quality Gaussian noise. The Adaptive Median filter was better filter MRI image quality Salt and Pepper noise. The results showed that The Median filter has a better performance than other filters. The computation time and memory for the Median filter algorithm was increased than the Adaptive Wiener and Adaptive Median filters by 400%.

Reference

[1] J.Rajeesh, R.S.Moni, S.Palanikumar and T.Gopalakrishnan “Noise Reduction in Magnetic Resonance Images using Wave Atom Shrinkage” International Journal of Image Processing (IJIP), Volume(4) : Issue(2) 2010, pp: 131-141.

[2] M. Zhang and B.K. Gunturk," Multi resolution bilateral filtering for image de-noising", IEEE Trans. Image Process. 17 (12) (2008),PP. 2324–2333, 2008.

[3] A. Phophalia, A. Rajwade and S.K. Mitra, Rough set based image de-noising for brain MR images, Signal Process. 103(2014), PP.24–35, 2014.

[4] Iza Sazanita Isa, Siti Noraini Sulaiman, Muzaimi Mustapha and Sailudin Darus," Evaluating De-noising Performances of Fundamental Filters for T2-Weighted MRI Images", 19th International Conference on Knowledge Based and Intelligent Information and Engineering Systems, Procedia Computer Science, Vol. 60 , pp. 760 – 768, 2015.

[5] R. Rahmat, A. S. Malik, and N. Kamel," Comparison of LULU and Median Filter for Image De-noising", International Journal of Computer and Electrical Engineering, Vol. 5, No. 6, December 2013.

[6] N. Dey , A. S. Ashour,, S. Beagum, D. Sifaki Pistola , M. Gospodinov , E. Gospodinova and R. S. Tavares," Parameter Optimization for Local Polynomial Approximation based Intersection Confidence Interval Filter Using Genetic Algorithm: An Application for Brain MRI Image De-Noising", www.mdpi.com/journal/jimaging, J. Imaging 2015.

[7] C. Lakshmi Devasena, and M. Hemalatha," Noise Removal in Magnetic Resonance Images using Hybrid KSL Filtering Technique", International Journal of Computer Applications (0975 – 8887), Volume 27, No.8, August 2011.

[8] S. A. Akar, "Determination of optimal parameters for bilateral filter in brain MRimage denoising", Applied Soft Computing 43 (2016) 87–96,2016.

[9] A. Bovik, "Handbook of Image and Video Processing". New York: Academic, 2000.

[10] R. Bourne," Image filters. In Fundamentals of Digital Imaging in Medicine", Springer London, 2010.

[11] K. Patel and H. Mewada, "A Review on Different Image De-noising Methods", International Journal on Recent

[12] M. Erturk," De-noising MRI using spectral subtraction", IEEE Transaction on Bio-Medical Engineering,Vol. 60, No. 6, June 2013.

[13] J. Mohan, V. Krishnaveni, and Y. Guo," A New Neutrosophic Approach of Wiener Filtering for MRI Denoising", MEASUREMENT SCIENCE REVIEW, Volume 13, No. 4, 2013.

[14] Shuqian Luo ," Filtering medical image using adaptive filter" Engineering in Medicine and Biology Society, 2001. Proceedings of the 23rd Annual International Conference of the IEEE,pp. 2727 – 2729, vol.3,2001.

[15] L. Lin , X. Meng , and X. Liang,” Reduction of impulse noise in MRI images using block-based adaptive median filter”, Medical Imaging Physics and Engineering (ICMIPE), 2013 IEEE International Conference on 19-20 Oct. 2013, pp.132-134,2013.

[16] E. Hancer, C. Ozturk, and D. Karaboga, “Extraction of brain tumors from MRI images with artificial bee colony based segmentation methodology,” 2013 8th Int. Conf. Electr. Electron. Eng., pp. 516–520, Nov. 2013.

[17] M. K. S. Sivasundari, and R. Siva Kumar, “Performance Analysis of Image Filtering Algorithms for MRI Images,” Int. J. Res. Eng. Technol., vol. 3, no. 5, pp. 438–440, 2014.

[18] C. P. Loizou, M. Pantziaris, C. S. Pattichis, and I. Seimenis, “Brain MR Image normalization in texture analysis of multiple sclerosis,” J. Biomed. Graph. Comput., vol. 3, no. 1, pp. 20–34, Nov. 2012.

[19] Lijun Bao, W. Liu , Y. Zhu , Z. Pu , and I. E. Magnin,” Sparse representation based MRI de-noising with total variation”, Signal Processing, 2008. ICSP 2008. 9th International Conference on Oct. 2008,pp. 2154 – 2157,2008.

[20] Priyadharsini B.,” A Novel Noise Filtering Technique for De-noising MRI Images”, Proceedings of International Conference On Global Innovations In Computing Technology (ICGICT’14), Vol.2, Special Issue 1, March 2014.

[21] K. Patel and H. Mewada, “A Review on Different Image De-noising Methods”, International Journal on Recent and Innovation Trends in Computing and Communication, Vol. 2 Issue 1, P. 155-159 March 2014.

[22] S. Akar, “Determination of optimal parameters for bilateral filter in brain MR image de-noising”, Elsevier Applied Soft Computing, Vol. 43, pp. 87-96,2016.