
MRI Medical Image Denoising by Fundamental Filters

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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 chapter, 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

Statistical models of signal and noise consider a fundamental role in medical image processing. In particular, many different applications in the magnetic resonance (MR) image processing field rely on a well-defined prior statistical model of the data. Many techniques of these model-based methods may be found in literature: noise removal and signal estimation methods as the conventional approach.

MR image De-noising has been an important research point in the field of MR image processing. Noise reduction and removing process is an important part of MR image processing systems. It is a technique removes out noise which is added in the MR original image. MR Image quality

may get defective while capturing, processing and storing the MR image. Removing noise from the original MR images is still a challenging problem for researchers because noise removal introduces artifacts and causes blurring of the MR images. Nowadays, MR 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].

De-noising is one of the main branches of MR image processing. Basically, it finds its major use in all of the systems that acquire mono-dimensional or multi-dimensional signals. Of course, Magnetic Resonance Imaging (MRI), which plays an important role in clinical diagnosis producing high quality 2-D and 3-D images of the body, is also affected by noise. Several de-noising techniques have been proposed in recent years in literature. The main challenge consists in reducing the amount of noise, i.e. regularize the MR image, while preserving the details, the edges and in general the small structures that could be crucial for a correct diagnosis. Three main MRI de-noising filter families can be identified: methods defined in the spatial domain, methods working in a transformed domain and methods exploiting the statistical properties of the signals. Filters in the spatial domain implement an average of pixels for reducing the amount of noise.

In this chapter, 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 MR 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 MR image. One should also consider the other factors like performance in de-noising the MR 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 MR 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 MR 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 MR image using pixel-wise adaptive Wiener filtering, using neighborhoods of size M-by-N to estimate the local MR 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, 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 define as order statistics filter. The median filter is most common and commonly used nonlinear filter. It removes noise by smoothing the MR images. This filter also lowers the intensity variation between one and other pixels of an MR image. The median filter algorithm replaced the pixel value of MR image with the median value. The median value is calculated in two steps, first step; arranging all the pixel values in ascending order, second step; replace the pixel being calculated with the middle pixel value. If the neighboring pixel of MR 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:

$$f^{\wedge}(x, y) = \text{median} \{g(s, t)\} \quad \text{where } (s, t) \in S_{xy} \quad (1)$$

where S_{xy} is corresponds to the set of coordinates in a rectangular sub MR image window which has center at (x, y) . The median filter calculates the median of the corrupted MR image $g(x,y)$ under the area S_{xy} . Here $f^{\wedge}(x, y)$ represents the restored MR image.

In this chapter, the median filter algorithm is modified. The restored MR 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 MR 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 and remove 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 traditional median filtering. The adaptive Median filter executes spatial processing to determine which pixels in an MR image have been affected by noise. The Adaptive Median Filter classifies pixels as noise by comparison each pixel in the MR 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. But, in classic median filter; the neighborhood window is constant through the operation. For that, 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 MR image details such as edges and smooth non-impulsive noise, while the standard median filter does not.

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

$$\text{Level 1: } L_{11} = Z_{\text{med}} - Z_{\text{min}}$$

$$L_{12} = Z_{\text{med}} - Z_{\text{max}}$$

If $L_{11} > 0$ AND $L_{12} < 0$, Go to level 2

Else increase the window size.

If window size $\leq S_{\text{max}}$ repeat level 1.

Else output Z_{xy} .

$$\text{Level 2: } L_{21} = Z_{xy} - Z_{\text{min}}$$

$$L_{22} = Z_{xy} - Z_{\text{max}}$$

If $L_{21} > 0$ And $L_{22} < 0$ output Z_{xy}

Else output Z_{med} .

Where

Z_{min} is a minimum gray level value in S_{xy} .

Z_{max} is a maximum gray level value in S_{xy} .

Z_{med} is a median of gray levels in S_{xy} .

Z_{xy} is a gray level at coordinates (x, y) .

S_{max} is a maximum allowed size of S_{xy} .

The output of the filter is a single value which the exchange the corrupted pixel MR image value at (x, y) , the point on which S_{xy} is centered at the time.

3. Common noises in MR image

From theoretical expectations, the noise measured in unfiltered MR images was found to be usually distributed, spatially invariant and white. As in MR image processing, the MR images

are much sensitive to noise which results are due to the image acquisition errors and transmission errors. MR images captured usually are prone to Gaussian noise and salt and pepper noise which has influence on the MR image quality [4, 16–22]. Poor quality of MR image tends to degrade the performances of any works such as feature extraction, reduction and classification of the processed MR images. The noises go to be removed before these processing stages as there were many available MR image filtering algorithms recommended in the literature. Gaussian noise and Impulse noise are popular noises distributed in magnitude MR 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. The Gaussian noise has a probability density equation of the normal distribution. The Gaussian noise or amplifier noise is added to MR image during image acquisition such as 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, Wiener filter and Adaptive Median filter). The Probabilities Density Function (PDF) of Gaussian Noise is shown in the following equation and **Figure 1**:

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

where $P_{(x)}$ is the Gaussian distribution equation noise in MR image; μ and σ is the mean and standard deviation respectively.

3.2. Impulse noise

The Impulse noise is also defined by Salt & Pepper noise or Spike noise. It is caused by malfunctioning pixels in camera sensors, faulty memory locations in hardware, or transmission

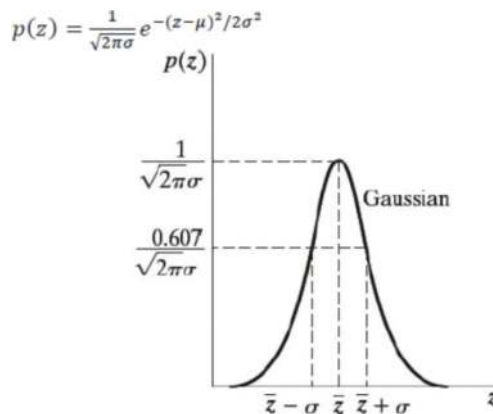


Figure 1. Gaussian noise.

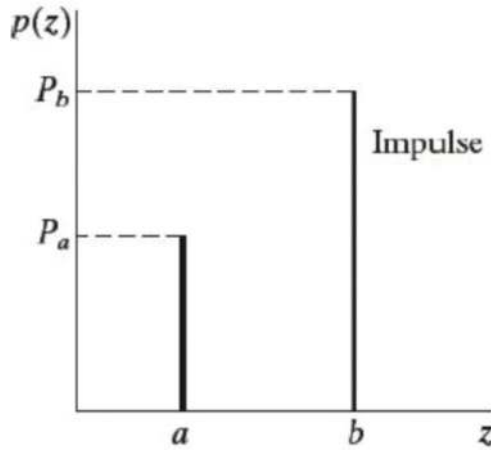


Figure 2. Salt and pepper noise.

in a noisy channel. It is forever independent and uncorrelated to MR 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 (gray level – 0) and it seems as black and white spots on the MR 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 MR 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**.

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

where p_a, p_b are the probabilities density equation, $p(z)$ is distribution salt and pepper noise in MR image and a, b are the arrays size MR 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 MR images I and K where one of the MR images is considered a noisy approximation of the other is defined as:

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

The PSNR equation is defined as:

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

Here, MAX is the maximum possible pixel value of the MR 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) present 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

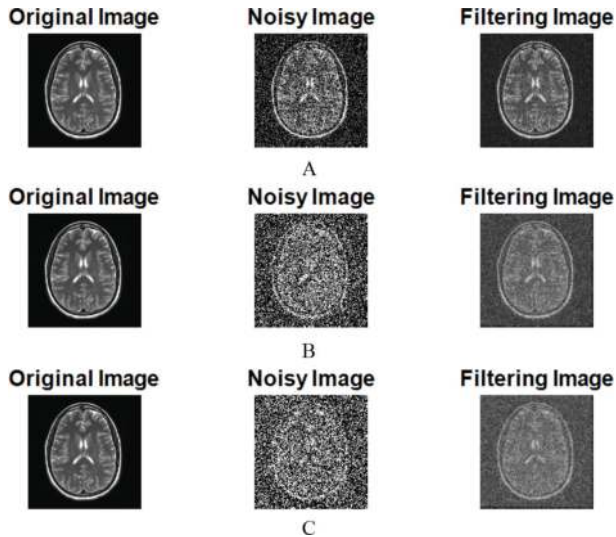


Figure 3. Wiener filter (Gaussian noise). (A) Noise Density =10%- PSNR=43.2096, (B) Noise Density =50%- PSNR=37.9244, (C) Noise Density =90%- PSNR=36.5301.

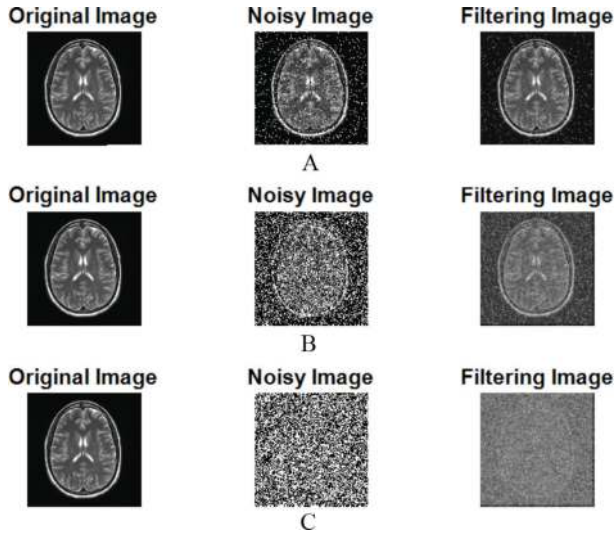


Figure 4. Wiener filter (Salt & Pepper Noise). (A) Noise Density =10%- PSNR=45.2549, (B) Noise Density =50%- PSNR=37.8006, (C) Noise Density =90%- PSNR=33.4716.

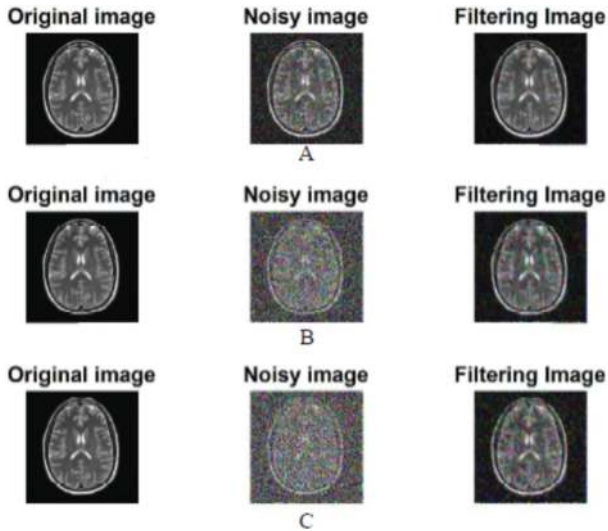


Figure 5. Median filter (Gaussian noise). (A) Noise Density =10%- PSNR=51.9813, (B) Noise Density =50%- PSNR=47.2688, (C) Noise Density =90%- PSNR=45.5434.

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%.

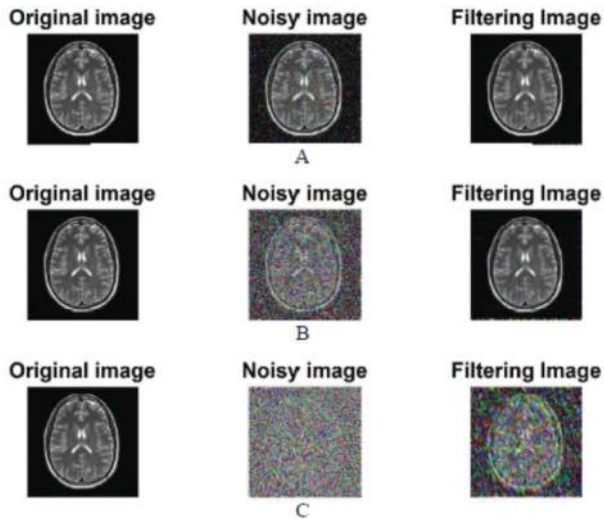


Figure 6. Median filter (Salt & Pepper Noise). (A) Noise Density =10%- PSNR=61.8162, (B) Noise Density =50%- PSNR=52.0523, (C) Noise Density =90%- PSNR=39.1255.

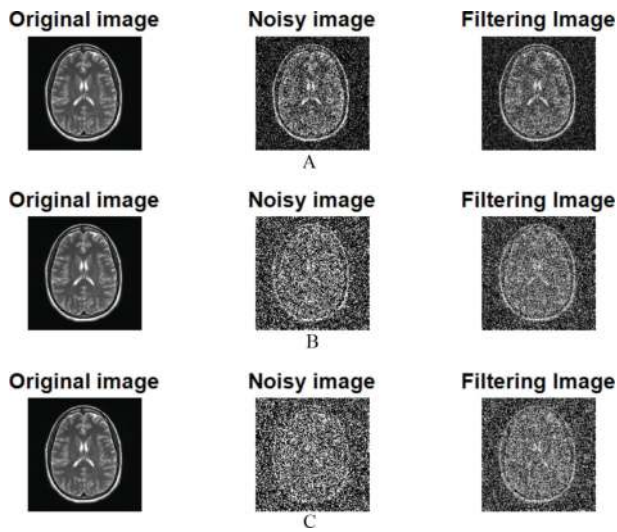


Figure 7. Adaptive median filter (Gaussian noise). (A) Noise Density =10%- PSNR=38.9811, (B) Noise Density =50%- PSNR=34.5541, (C) Noise Density =90%- PSNR=33.7908.

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 10–90%. To compare all three filters, Median filter works better for Gaussian noise as shown in **Figure 9**.

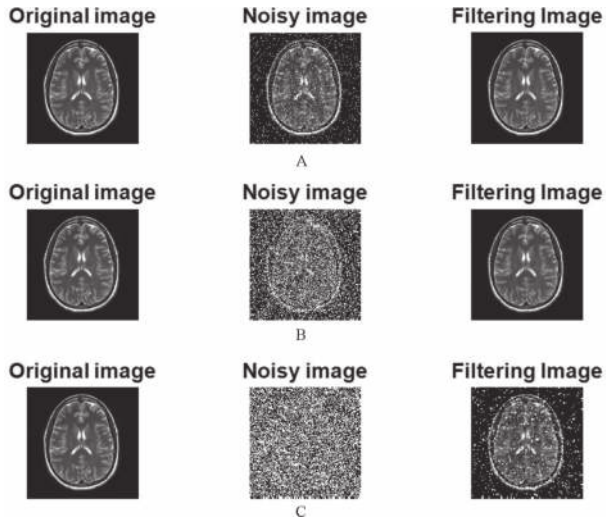


Figure 8. Adaptive median filter (Salt & Pepper Noise). (A) Noise Density =10%- PSNR=66.8579, (B) Noise Density =50%- PSNR=54.9245, (C) Noise Density =90%- PSNR=40.1885.

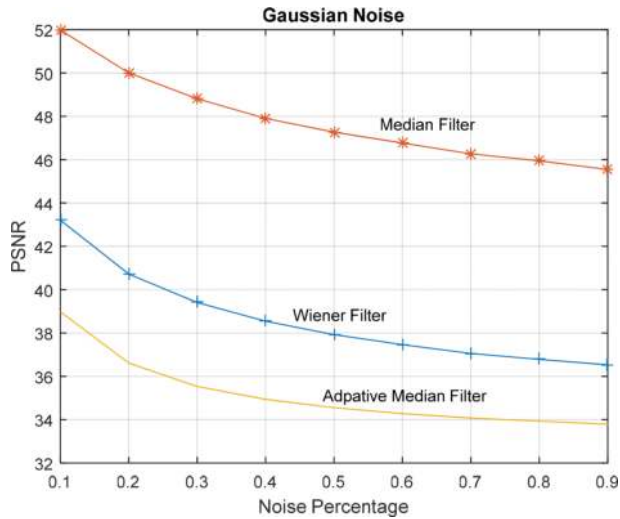


Figure 9. PSNR of different filtering methods (Gaussian noise).

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**.

| 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 |

Table 1. PSNR of different filtering methods (Gaussian 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 |

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

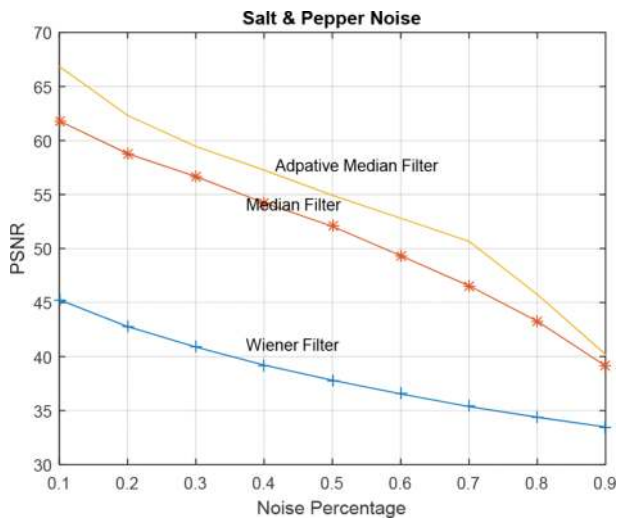


Figure 10. PSNR of different filtering methods (Salt & Pepper Noise).

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 10–90%. 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 Wiener 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%.

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%.

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