

Kernels Analysis in MRI Images Noise Removal Methods

Aye Min, Zin Mar Kyu

University of Computer Studies, Mandalay (UCSM)

ayemin.loikaw@gmail.com, zinmarkyu.pp@gmail.com

Abstract

With advanced imaging techniques, Magnetic Resonance Imaging (MRI) plays an important role in medical environments to create high quality images contained in the human organs. In the processing of medical images, medical images are coordinated by different types of noise. It is very important to acquire accurate images and observe specific applications with precision. Currently, eliminating noise from medical images is a very difficult problem in the field of medical image processing. In this document, three types of noise, Gaussian noise, and salt & pepper noise, uniform noise are tested and the tested variances of Gaussian noise and uniform noise are 0.02 and 10 respectively. We analyze the kernel value or the window size of the median filter and the Wiener filter. All experimental results are tested on MRI images of the BRATS data set, the DICOM data set and TCIA data set. MRI brain images are obtained from the BRATS data set and the DICOM data set, the MRI bone images are obtained from the TCIA data set. The quality of the output image is measured by statistical measurements, such as the peak signal noise ratio (PSNR) and the root mean square error (RMSE).

1. Introduction

In the processing of medical images, it is very significant to acquire accurate images to enable accurate observation of a given application. Therefore, there is an essential need for noise reduction from medical images. In this document, MRI images are experimented to remove noise with variety of kernel in Median filter and Wiener filter. There are some noises occur in MRI images because of its electro-magnetic wave radiation. Especially noises are rician noise, salt & pepper noise (impulse noise or speckle noise) [7], gaussian noise and uniform noise. The properties of rician noise and salt & pepper noise are mostly similar noise distribution [4,7]. In this research, we emphasize on the salt & pepper noise, gaussian noise and uniform noise. We

analyzed the kernels of Median filter and Wiener filter on these noises.

The main purpose of image noise removal technology is to eliminate these noises and at the same time preserve important characteristics of the signal. The average filtering technique can successfully remove distorted image noise, but in this case the filtered image is subjected to a blurring effect. The affected pixels are thought to be calculated as mean and unaffected pixels are also replaced by this calculated average.

The median filter was once the most common nonlinear filter to eliminate noise due to its excellent noise rejection power [5] and computational efficiency [6]. Its main disadvantage is that noisy pixels are replaced with some median values in the vicinity, without considering local features such as the possibility of edge presence [7]. Therefore, especially when the noise level is high, details and edges are not fully recovered. This paper examines the affection of changing kernels value in median filtering and wiener filtering to determine of a more accurate value of pixels of noisy image. The experimental result shows the efficiency of changing kernel value.

2. State of the Arts

Many researchers proposed the methods in MRI images noise removal. S. Jeevakala and B. Therese described the paper title with “Non Local Means Filter Based Rician Noise Removal of MR Images” in 2016. In this paper, the authors proposed a combination of NLM and stationary wavelet transform (SWT) with adaptive thresholding to remove Rician noise and preserve structural information of edges. The proposed noise elimination algorithm will be useful for the subtle analysis of tissue / organ images [1].

M. N. Nobi and M. A. Yousuf proposed the paper title with “A New Method to Remove Noise in Magnetic Resonance and Ultrasound Images”. The proposed method is compared with a smoothing, medium and midpoint filter using quantitative

parameters such as PSNR, SNR, and RMSE. The smoothing filter shows better results, but it is painful because of the blurring effect. In the medium filtering technique, it is considered that each pixel calculates the average and all the pixels are replaced by the calculated average. Therefore, the affected pixels are taken into account to calculate the average, and the unaffected pixels are replaced by this calculated average [2]. B. Shinde and AR Dani have announced a "Filtering Method for Detecting and Removing Noise" in 2012. In this experiment, various medical images, such as MRI, cancer, X-ray, brain, etc. All these medical images, after detection of Gaussian noise, use median filtering techniques to remove noise. The results they have achieved are more useful and found useful for general practitioners to easily analyze the patient's symptoms [3]. Anisha .et.al. presented the comparison paper title with "Comparison of Various Filters for Noise Removal in MRI Brain Image" in 2015. KSL filtering: removal of noise in various types of brain MRI images. Therefore, brain magnetic resonance and Wiener filter for noise elimination are superior. - Noise filtering, inverse filtering, adaptive filter are required. - Less computation time. It is an anisotropic filter; it reduces the high frequency noise. Mean filter - eliminates grain noise in the image [4].

A. Mihailova, V. Georgieva (2016) proposed the paper "Comparative Analysis Various Filters for Noise Reduction in MRI Abdominal Images". To evaluate the proposed methods of automatic analysis and the value of PSNR, which should be greater, and the value of NRR, which should be low, at the same time are compared. The median filter performs better than the Gaussian filter. Wiener filter works best, but the most significant results they get from the seismic pulse and especially the wavelet of the homomorphic filter [5].

Dr. Abdulameer A. Kareem and Dr. Rana F. Ghani proposed the paper "Data Fusion Approach for Image Noise Removing". In this paper, authors present a new method for image noise removal by fusing number of images transmitted through different noisy channels. A new filter has been proposed in this work that is the Mode filter which computes the resulted pixel by taking the corresponding pixels in the source images and consider the resulted pixels value equals to the value of higher frequently occurred pixels value [6].

S. Priyanka, Dr. AS Naven kumar proposed the name of the noise elimination document "Removing the noise of remote sensing images using

the Kalman filter algorithm" in 2016. Remote sensing, in general, using sensors installed on airplanes and space platforms, the authors discussed Gaussian noise and speckle noise (salt and pepper). In this proposed study, authors reduced image noise using the Kalman filter and the Wiener filter. The Kalman filter is suitable for reducing noise while maintaining the basic structure of the image compared to other filters. The Kalman filter shows more filters with improved noise efficiency [7].

B. Shinde et al. MRI, cancer, x-ray, brain and various medical images. Standard deviation and mean deviation are reassessed after removal of noise using moderate filtering techniques. After detecting the salt and pepper noise on the X-ray image, several filtering methods were applied and proved to be most effective for noisy images. The adaptive filter proved to be the most effective for noisy images [8].

3. Background Theory

In this paper, Gaussian noise, Salt & pepper noise and Uniform noise are tested on the Median filter and Wiener filter. In this section, all above theoretical information will be described.

3.1. Gaussian noise

Gaussian noise is inherently statistical with a probability density function equal to the probability density function of a normal distribution. Gaussian noise is usually a set of values taken from the zero mean Gaussian distribution added to each pixel value. The Gaussian noise reduction algorithm should smooth out individual parts of the image. For image processing, we can reduce Gaussian noise using a spatial filter. A particular case of Gaussian noise is white Gaussian noise, the values of which is statistically independent and describes the noise correlation [4].

$$\text{Gaussian} = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-(g-m)^2/2\sigma^2} \quad (1)$$

Where,

g= gray level

m= mean (average)

σ= standard deviation.

3.2. Salt & pepper noise

This type of noise contains random occurrences of both black & white intensity values, and often caused by threshold of Noise image. Salt &

Pepper distribution Noise can be expressed by as follow;

$$P(x) = \begin{cases} p1, & x = A \\ p2, & x = B \\ 0, & otherwise \end{cases} \quad (2)$$

Where,

P1, P2 = the Probabilities Density Function (PDF)

P(x) = the distribution salt and pepper Noise in image

A, B= the array size of image

The main problem of removing salts and pepper noise from images is the sharing of image and noise data with the same small set of values and a violation of the process of detecting and removing noise [7].

3.3. Uniform noise

Uniform noise means that different "values" of are equally probably. For a uniform distribution, the gray level value of the noise is evenly distributed over a certain range and is a full range (0 to 255 for 8 bits) or a small part of the entire range. Visually, Gaussian uniform and noisy images are similar, but the image with salt and pepper added is very distinctive.

$$Uniform = \begin{cases} \frac{1}{b-a}, & a \leq g \leq b \\ 0, & Otherwise \end{cases} \quad (3)$$

Where,

g= gray level

a=low boundary value

b=high boundary value

3.4. Median Filter

The most useful order filter is a median filter, searching for neighboring gray levels in the list, sorting the list in ascending order, and moving the noisy values to the end of the list. The main disadvantage of media filters is that it is not specific; any structure that occupies less than half of the filters neighborhood will tend to be eliminated. Median filtering is therefore well able to remove this outlier without reducing the sharpness of the image.

$$y[m,n]=\text{median}\{x[i,j],(i,j)\in\omega\} \quad (4)$$

Where ω is a neighborhood defined by the user, centered around location [m,n] in the image. An example of median filter of 3*3 kernel or window size is shown below. We take the original values and order the values to 0, 2, 3, 3, 4, 6, 10, 15 and 97. We

find the medium value and fill this value to the center point. So, centered value 97 is replaced by the medium of all nine values 4.

Unfiltered value

6	2	0
3	97	4
19	3	10

Filtered value

*	*	*
*	4	*
*	*	*

3.5. Wiener filter

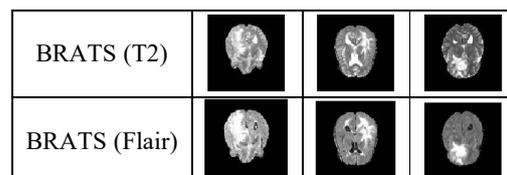
The Wiener filter or adaptive filtering is one of the oldest and best known approaches for updating linear images. The most important technique for eliminating noise in images is due to the linear movement of the Wiener filter. Each pixel has a digital representation of the image that must represent the intensity of a single fixed point in front of the camera. The main improvement is that a short calculation time finds a solution [10]. Its purpose is to reduce the amount of noise in the image [7]. The formulation of wiener filter is shown the following:

$$G(k, l) = \frac{H(k, l)}{|G(k, l)|^2 + S_u(k, l)/S_x(k, l)} \quad (5)$$

Where, $S_x(k, l)$ is the signal of power spectrum, $S_u(k, l)$ is the noise power spectrum and $H(k, l)$ is the Fourier transform of the point-spread function (PSF).

4. Dataset Description

In this research paper, the MRI images for brain are got from Brats dataset and DICOM datasets. T2 and Flair sequence of MRI from BRATS datasets are tested and simple MRI images are got from DICOM. MRI images for Bones images are got TCIA dataset. The figure (1) shows the sample images of BRATS, DICOM and TCIA datasets.



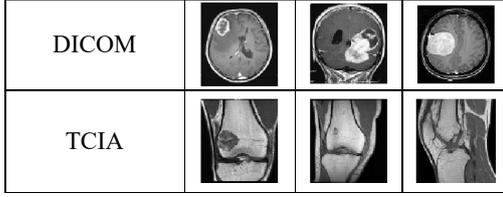


Figure 1. Sample images of Datasets

5. Kernel Values Analysis and Experimental Results

Kernel values of Median filter and Wiener filter are tested with the presented datasets. This paper strongly emphasized on affecting of removal rate when changing on the kernel values or window size. Kernel values (3, 5, 7 and 9) or window size are tested and analyzed. The rates of noise removal are tested with adding Gaussian noise, Salt & pepper noise and Uniform noise. The quality of the output image is measured by statistical measurements, such as the peak signal noise ratio (PSNR) and the root mean square error (RMSE). The formulations of PSNR and RMSE are shown in following and both formulations depend on MSE value. MSE is also described in the following:

$$MSE = \frac{1}{M \times N} \sum_{i=1}^N \sum_{j=1}^M [I(i, j) - I'(i, j)]^2 \quad (6)$$

$$RMSE = \sqrt{MSE} \quad (7)$$

$$PSNR = 10 \log_{10} \left(\frac{255^2}{MSE} \right) \quad (8)$$

The table (1) describes the average results of T2 image in kernel values in salt & pepper noise.

Table 1. Average results of T2 in Salt & pepper noise

Kernels	Median filter		Wiener filter	
	RMSE	PSNR	RMSE	PSNR
3*3	6.223	32.413	30.872	18.374
5*5	9.204	28.968	22.258	21.217
7*7	11.604	26.925	85.855	22.850
9*9	13.335	25.704	16.850	23.635

According to experimental results in T2, smallest window size or kernel value 3 is more effective than other kernel values in Median filter and Wiener filter. In salt & pepper noise, Median filter's results are more satisfied than Wiener filter for all kernels. The table (2) describes the average results of Flair image in kernel values in salt & pepper noise.

The results of Flair images are also similar to T2 results in Salt & pepper noise removal.

Table 2. Average results of Flair in Salt & pepper noise

Kernels	Median filter		Wiener filter	
	RMSE	PSNR	RMSE	PSNR
3*3	6.130	32.781	30.860	18.378
5*5	9.216	29.237	22.518	21.115
7*7	11.268	27.421	18.436	22.852
9*9	12.740	26.322	16.477	23.833

Table 3. Average results of T2 in Gaussian noise

Kernels	Median filter		Wiener filter	
	RMSE	PSNR	RMSE	PSNR
3*3	12.52	26.199	14.73	24.85
5*5	12.32	26.379	13.998	25.245
7*7	13.523	25.570	14.207	25.116
9*9	14.767	24.799	14.548	24.910

Table (3) and (4) describe about the T2 and Flair experiment results of all kernels in Median filter and Wiener filter with Gaussian noise. In Gaussian noise, the performances of Median filter and Wiener filter are slightly difference for all kernels. It means that the kernel values do not affected seriously in Gaussian noise removal.

Table 4. Average results of Flair in Gaussian noise

Kernels	Median filter		Wiener filter	
	RMSE	PSNR	RMSE	PSNR
3*3	12.506	26.240	14.714	24.811
5*5	12.420	26.373	13.939	25.283
7*7	13.378	25.767	14.044	25.218
9*9	14.425	25.118	14.277	25.077

In table (5) and (6), the experimental results are described for all kernels in T2 and Flair with Uniform noise respectively. In Uniform noise, Median filter's results are better than Wiener filter's results in all kernel values. Changing of kernel values are effect on the uniform noise removal and smaller kernel values are better than others sequentially in Median filter. In Wiener filter, the bigger kernel values are better than others and it means the results of Wiener filter are inversely in Median filter results. In testing of T2 and Flair images from BRATS dataset, the Median filter is more effective in Salt & pepper noise and Uniform noise. In Gaussian noise, the results of Median and Wiener filter are mostly equivalent.

Table 5. Average results of T2 in Uniform noise

Kernels	Median filter		Wiener filter	
	RMSE	PSNR	RMSE	PSNR
3*3	6.994	31.343	29.500	18.769
5*5	9.713	28.475	22.919	20.961
7*7	11.856	26.723	20.534	21.916
9*9	13.542	25.559	19.603	22.320

Table 6. Average results of Flair in Uniform noise

Kernels	Median filter		Wiener filter	
	RMSE	PSNR	RMSE	PSNR
3*3	7.035	31.491	29.891	18.654
5*5	9.551	28.854	23.200	20.855
7*7	11.384	27.298	20.643	21.871
9*9	12.799	26.246	19.523	22.356

Table (7), (8) and (9) present about the tested results in DICOM images with Salt & pepper noise, Gaussian noise and Uniform noise respectively. In Salt & pepper noise, Median filter is more satisfied than Wiener filter in all kernel values. The kernel value 3 is the best suitable kernel for Median filter and kernel value 7 is good for Wiener filter. In kernel value 9, Medina filter result and Wiener filter result are almost similar. In Gaussian noise, Wiener filter results are more slightly better than Median filter for all kernels. In, Uniform noise, Median filter are better than Wiener filter for all kernels. In DICOM images, the Median filter are improved than Wiener filter in Salt & pepper noise and Uniform noise. In Gaussian noise, the Wiener filter is better than Median filter.

Table 7. Average results of DICOM in Salt & pepper noise

Kernels	Median filter		Wiener filter	
	RMSE	PSNR	RMSE	PSNR
3*3	5.487	33.557	25.595	20.007
5*5	10.416	27.958	19.359	22.434
7*7	15.534	24.445	17.847	23.151
9*9	20.279	22.105	18.284	22.950

Table 8. Average results of DICOM in Gaussian noise

Kernels	Median filter		Wiener filter	
	RMSE	PSNR	RMSE	PSNR
3*3	13.047	25.864	13.099	25.827
5*5	14.008	25.293	13.358	25.671
7*7	17.664	23.293	14.809	24.786
9*9	21.700	21.498	16.309	23.956

Table 9. Average results of DICOM in Uniform noise

Kernels	Median filter		Wiener filter	
	RMSE	PSNR	RMSE	PSNR
3*3	6.920	31.500	24.364	20.446

5*5	11.244	27.287	19.674	22.298
7*7	16.168	24.095	19.393	22.432
9*9	20.864	21.854	20.413	21.991

The experimental results of MRI images from TCIA dataset are described with table (10), (11) and (12). Table (10) describes the tested result of TCIA image with Salt & pepper noise, table (11) presents the tested result with Gaussian noise and table (12) shows the tested results with Uniform noise. In Salt & pepper noise, Median filter is more satisfied than Wiener filter in all kernel values. The kernel value 3 is the best suitable kernel for Median filter and kernel value 7 is good for Wiener filter. In Gaussian noise, Wiener filter results are more slightly well than Median filter for all kernels. In, Uniform noise, Median filter are better than Wiener filter for all kernels. In TCIA images, the Median filter is better than Wiener filter in Salt & pepper noise and Uniform noise. In Gaussian noise, the Wiener filter is better than Median filter.

Table 10. Average results of TCIA in Salt & pepper noise

Kernels	Median filter		Wiener filter	
	RMSE	PSNR	RMSE	PSNR
3*3	8.615	30.390	26.707	19.645
5*5	12.071	27.143	19.816	22.229
7*7	15.159	25.111	17.873	23.144
9*9	18.14	23.559	17.917	23.164

Table 11. Average results of TCIA in Gaussian noise

Kernels	Median filter		Wiener filter	
	RMSE	PSNR	RMSE	PSNR
3*3	14.744	24.854	13.751	25.418
5*5	15.157	24.734	13.584	25.579
7*7	17.35	23.64	14.514	25.03
9*9	19.735	22.569	15.534	24.45

Table 12. Average results of TCIA in Uniform noise

Kernels	Median filter		Wiener filter	
	RMSE	PSNR	RMSE	PSNR
3*3	9.485	29.365	24.649	20.350
5*5	12.559	26.761	20.138	22.101
7*7	15.488	24.884	19.068	22.585
9*9	18.316	23.434	19.54	22.397

Figure (2), (3) and (4) describe about the tested noise removal in T2 with all of kernels in salt & pepper noise, Gaussian noise and uniform noise respectively. Table (13) and (14) show the average time complexity of all datasets is tested with all kernels of median filter and wiener filter in salt & pepper noise, Gaussian noise and uniform noise

respectively. According to the time complexity result, 5*5 kernel is faster than the other kernels.

Kernel s	Origin al Image	Salt & pepper noise	Median filter	Wiener filter
3*3				
5*5				
7*7				
9*9				

Figure 2. Sample filtered image of T2 with Salt & pepper noise

Kernel s	Origin al Image	Gaussia n noise	Median filter	Wiener filter
3*3				
5*5				
7*7				
9*9				

Figure 3. Sample filtered image of T2 with Gaussian noise

Kernel	Origin al Image	Unifor m noise	Median filter	Wiener filter
3*3				
5*5				
7*7				
9*9				

Figure 4. Sample filtered image of T2 with Uniform noise

Table 13. Average results of Time Complexity with Median filter (sec)

Kernels and noise	3*3	5*5	7*7	9*9
Salt & pepper	0.0854	0.011	0.011	0.012
Gaussian	0.0194	0.010	0.012	0.012
Uniform	0.0094	0.009	0.011	0.013

Table 14. Average results of Time Complexity with Wiener filter (sec)

Kernels and noise	3*3	5*5	7*7	9*9
Salt & pepper	0.018	0.014	0.011	0.012
Gaussian	0.014	0.011	0.0109	0.010
Uniform	0.011	0.011	0.011	0.011

6. Conclusion

In this work, we have in use different MRI images from BRATS datasets, DICOM dataset and TCIA dataset. We have noticed Gaussian noises, Salt & pepper noise and Uniform noise. These noises are removed with the Median filter and Wiener filter. The proposed paper is emphasized on the changes of kernel values in filter methods and finding the best suitable kernel values in MRI images noise removal. The results are evaluated and compared with standard pattern of noises and also evaluated through the quality metrics like RMSE and PSNR. For all of the tested datasets in this paper, Median filter is more operative in Salt & pepper and Uniform noise removing and kernel value 3 is the best suitable in median filter. Wiener filter is more effective in Gaussian noise removal. All kernels of wiener filter got the equivalent results.

References

- [1] S. Jeevakala, B. Therese, "Non Local Means Filter Based Rician Noise Removal of MR Images", *International Journal of Pure and Applied Mathematics*, Volume 109 No. 5 2016.
- [2] M. N. Nobil and M. A. Yousuf, "A New Method to Remove Noise in Magnetic Resonance and Ultrasound Images", *Journal of Scientific Research (JSR) Publication*, 2011.
- [3] B. Shinde and A.R. Dani, "Noise Detection and Removal Filtering Techniques in Medical Images", *International Journal of Engineering Research and Applications (IJERA)*, Vol. 2, Issue 4, pp.311-316, July-August 2012.

- [4] Anisha, S.R PG Scholar, Dr J Venugopala Krishnan, M. V. PG scholar, “ Comparison of Various Filters for Noise Removal in MRI Brain Image”, International Conference on Futuristic Trends in Computing and Communication (ICFTCC), 2015.
- [5] A. Mihailova, V. Georgieva, “Comparative Analysis Various Filters for Noise Reduction in MRI Abdominal Images”, International Journal "Information Technologies & Knowledge, Volume 10, Number 1, © 2016.
- [6] Dr. A.A. Kareem and Dr. R.F. Ghani, “Data Fusion Approach for Image Noise Removing”, IEEE, 2009.
- [7] S. Priyanka, Dr.A.S.N. kumar, “ Noise Removal in Remote Sensing Image Using Kalman Filter Algorithm”, International Journal of Advanced Research in Computer and Communication Engineering Vol. 5, Issue 3, March 2016.
- [8] B. Shinde, D. Mhaske, A.R. Dani, “I.J. Image, Graphics and Signal Processing”, 2012.