Assessment of De-noising Filters for Brain MRI T1-Weighted Contrast-Enhanced Images

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Abstract Noise in the medical images is always of great concern because it can lead to misinterpretation for advance process. With advancements in technology, the quality of image capturing through MRI improved, but noise is still present; therefore, noise present in the MRI images should be removed to get the good quality of images for accurate diseases detection and its diagnosing. In this work, five different filtering algorithms, named as non-local mean (NLM) filter, anisotropic filter, Weiner filter, bilateral filter, and Gaussian filter, used to eradicate the different types of noise named (salt and pepper, speckle, and Gaussian) through brain MRI images. PSNR, SSIM, and MSE are statistical parameters used for analyzing the performance of the filters. The study shows that for Gaussian noise, Weiner filter is considered the most efficient filter. For salt and pepper noise, Gaussian filter work better than other filters. In the case of speckle noise, anisotropic works better on low noise density, whereas for high noise density, Gaussian filter works better.

Keywords NLM · Anisotropic filter · Weiner filter · Bilateral filter · Noises · SSIM · PSNR · MSE

1 Introduction

In the medical field, image quality is vital for the detection of diseases. MRI provides a highly detailed image of human tissue and organs, and it also does not use radiations; therefore, it is a frequently used examination method to find brain diseases. Despite good MRI scanner technology, MRI quality is affected by the noise that occurs during acquisition. The noise in MRI image limits further analysis processes like feature

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extraction, segmentation, and classification. To improve MRI images' quality, noise should be removed while retaining the image features before subsequent analysis [1]. MRI images are prone to salt and pepper, Gaussian**,** and speckle noise [2]. In brain MR images, Gaussian is the most common noise [3], also known as electronic noise, which arises in the MRI machine's detector and amplifier. Salt and pepper noise have black and white pixels, and it is also known as impulse noise [4]. Speckle noise occurs due to the environmental effect on the sensor of an image-capturing device.

This paper's primary purpose is to evaluate different filters' performance in removal of types of noise through brain MRI images. PSNR, MSE, and SSIM parameters are used for assessing the noise filtering quality of these filters.

Paper's organization is as follows: research background in first segment. In segment 2, we discussed the previous work done by the researchers. Segment 3 describes the material and method used in the work. Results are discussed in segment 4, and the outcome of the study is concluded in segment 5.

2 Literature Review

In past few years, many researchers worked on removing noise from the MRI images with preserving the optimum information. Chandrashekar et al. [5] explained the noise model and nonlinear de-noising algorithm such as anisotropic, bilateral, and nonlocal mean (NLM) filter. They found that NLM filter works better than the other two filters in terms of the high value of parameters like PSNR and SSIM, but the execution time of NLM is 200 s which is higher than the anisotropic and bilateral filter. Riji et al. [6] proposed an iterative bilateral algorithm for removing Gaussian noise from the MRI images and compared the results with the NLM, UNLM, and LMMSE de-noising algorithms in terms of statistical parameters such as mean SSIM and PSNR; results confirmed that the proposed filtering algorithm by them has better noise removing quality than the other filters. Nagarjan et al. [7] performed de-noising of the MR images having Gaussian noise with block division-based filtering algorithm. Compared the result with median, bilateral, anisotropic, NLM, IBLF and WBNLM, SANLM algorithm in term of PSNR, SSIM, RMSE and execution time. They found that prosed technique works better than all other algorithms with less execution time, i.e., 26.28 s for T1 weighted, 9.945 s for T2 weighted, and 9.366 s PD-weighted images, respectively. Anitha et al. [8] applied the median and Weiner filter for removing the noise and found that the median filter works better than Weiner filter. Zeng et al. [9] performed the de-noising of brain MR images by hybridizing the Weiner filter, wavelet soft threshold, and wavelet hard threshold and found that hybrid algorithm works better than each method alone. Saladi et al. [10] compared the performance of PCA, NLM, bilateral, and SANLM de-noising algorithm by statistical parameters and found that SANLM works better than other filters. Mundada et al. [11] investigated the noise parameter's effect on the image restoration of brain MRI images and found that change in standard deviation of noise results in change of noise distribution also. For a lower range of standard deviation, i.e., Gaussian distribution for noise range 1–4.27, and for standard deviation 4.51 or greater than this, noise is Rician noise. They found that for de-noising brain MRI images, the Gaussian filter works better for Gaussian noise distribution, whereas for Rician distribution, the hybrid filter works better. Isa et al. [12] evaluated three de-noising algorithms named median, adaptive, and average filter for Gaussian, speckle, and salt and pepper noise. Their work proves that the median filter works better for Gaussian and salt and pepper noises with PSNR value 38.3 dB, whereas the average filter do filtering better for speckle noise with PSNR of 56.2 dB. Rai et al. [13] proposed hybrid algorithm ICA-DWT for removing noise like Gaussian, speckle, and Salt and Pepper with noise variance of 0.1–0.9 and compared this with the traditional algorithms such as ICA, DWT, and UDWT. They found that proposed technique works better for high noise variance levels and preserves the structure of MRI.

3 Methodology

3.1 DataSet

For this work, brain MRI dataset of T1-weighted contrast-enhanced images (3064) are used, which were downloaded from [14]. This dataset contains 3064 MRI images from 233 patients, in axial, sagittal, and coronal view. We have taken 10 images for our work.

3.2 Filters

Non-local mean (NLM) filter performs the mean of all neighboring pixels and put weight to these by the similarity of pixels to the center pixel. Weights are used to determine the closeness of the pixel from the target pixels. Common weighting functions are Gaussian and discrete algorithms. NLM is a powerful method for noise removal, but it is limited by the high execution time [15].

Wiener filter is used to de-noising the image, whose quality is decreased by additive noise and blurring. For calculating assumption requires that the noise and signal both processes are of second order. Zero mean noise is considered [16].

Wiener filters generally apply in the frequency domain [17]. Take a corrupted image, $i(n, m)$, takes DFT to get $I(k, l)$. To estimate the original image spectrum, multiplication of $I(n, m)$ and Weiner filter $W(n, m)$ is taken:

The Wiener filter is as follows:

$$W(k,l) = \frac{H^*(k,l)P_s(k,l)}{|H(k,l)|^2 P_s(k,l) + P_n(k,l)} \tag{1}$$

Bilateral filter is an algorithm for removing noise while protecting the edges. In this, each pixel is replaced by average of the neighboring pixels, so the formulation is easy. It depends on the size and contrast of the feature to protect. Computational speed is high; therefore, it can be used at iterative speed for large size image [18].

Gaussian filter is a linear filter used to reduce noise and blurring from the image. It takes the weighted average of the neighboring pixels. It uses zero mean Gaussian distribution.

Anisotropic diffusion filter is also called Perona–Malik diffusion filter because Peeerona and Malik introduced it in 1987. It removes the noise from the image without distorting the image details like edges. The diffusion process of the filter is space invariant and linear of the original image.

4 Result and Discussion

Performances of the filters are measured using the statistical parameter PSNR, SSIM, and MSE.

Mean square error (MSE) is computed by doing an average of the square of the difference in the input image's intensity and the output image's intensity [19]:

$$MSE = \frac{1}{mn}\sum_{i=0}^{mn-1}\left(d(i) - \hat{d}(i)\right)^2 \tag{2}$$

Peak signal-to-noise ratio (PSNR), and is calculated by [20]:

$$PSNR = 10\log 10\left(\frac{255^2}{MSE}\right) \tag{3}$$

PSNR value must be greater or near 48 dB for better performance of the filter.

SSIM stands for the structure similarity index, and it is calculated by as [21]:

$$SSIM = \frac{\left(2\mu_x\mu_y + C_1\right)\left(2\sigma_{xy}C_2\right)}{\left(\mu_x^2\mu_y^2C_1\right)\left(\sigma_x^2\sigma_y^2 + C_2\right)} \tag{4}$$

Filter having SSIM value near to1 is considered as the most effective filter.

Qualitatively analysis of the different filters using the statistical parameters like MSE, PSNR, and SSIM is shown in Tables 1, 2 and 3, respectively.

Table 1 MSE of different filters

Noise variance	0.05	0.1	0.5	0.9
Gaussian noise				
NLM	1999.0894	3742.1724	11487.058	14643.792
Anisotropic diffusion	500.2552	1059.066	4176.353	5782.596
Weiner	**399.9964**	**790.1641**	**3214.55**	**4508.743**
Bilateral	527.1559	1103.33	4231.541	5868.273
Gaussian	609.7047	1067.795	3611.562	4910.483
Salt and pepper noise				
NLM	1389.8414	2753.3822	13740.169	24635.022
Anisotropic diffusion	249.9103	522.4391	4522.417	11365.16
Weiner	146.6004	286.7802	3177.689	9312.235
Bilateral	242.037	550.3864	4530.614	11483.2
Gaussian	**97.3878**	**219.3397**	**3079.496**	**3104.496**
Speckle noise				
NLM	114.4543	281.9931	1403.0609	2007.9464
Anisotropic diffusion	**18.7696**	34.1259	205.7021	319.7328
Weiner	18.9268	36.3139	159.5432	232.757
Bilateral	21.854	46.5252	236.3332	346.2618
Gaussian	26.2175	**32.9796**	**82.2954**	**117.219**

Table 2 PSNR of different filters

Noise variance	0.05	0.1	0.5	0.9
Gaussian noise				
NLM	15.1225	12.3996	7.5287	6.4743
Anisotropic diffusion	21.1389	17.8816	11.9228	10.5096
Weiner	**22.1102**	**19.1536**	**13.0596**	**11.5902**
Bilateral	20.9114	17.7037	11.8658	10.4457
Gaussian	20.2796	17.8459	12.5497	11.2196
Salt and pepper noise				
NLM	16.7012	13.7321	6.7509	4.2153
Anisotropic diffusion	24.153	20.9504	11.5771	7.575
Weiner	26.4695	23.5553	13.1097	8.4403
Bilateral	24.292	20.7241	11.5692	7.5302
Gaussian	**28.2458**	**24.7196**	**13.246**	**13.2103**

(continued)

Table 2 (continued)

Noise variance	0.05	0.1	0.5	0.9
Speckle noise				
NLM	27.5445	23.6284	16.66	15.1033
Anisotropic diffusion	**35.3963**	32.8	24.9984	23.0829
Weiner	35.36	32.5301	26.102	24.6474
Bilateral	34.7355	31.4539	24.3956	22.7368
Gaussian	33.9449	**32.9484**	**28.977**	**27.4408**

Table 3 SSIM of different filter

Noise variance	0.05	0.1	0.5	0.9
Gaussian noise				
NLM	0.0628	0.0377	0.0119	0.0087
Anisotropic diffusion	0.2663	0.1885	0.0828	0.0593
Weiner	0.333	0.2655	0.1486	0.1171
Bilateral	0.2478	0.1769	0.0795	0.0581
Gaussian	**0.3402**	**0.2812**	**0.1595**	**0.1267**
Salt and pepper noise				
NLM	0.285	0.1225	0.0132	0.0028
Anisotropic diffusion	0.3638	0.2508	0.078	0.0182
Weiner	0.4692	0.3701	0.163	0.0556
Bilateral	0.3797	0.2565	0.0803	0.0169
Gaussian	**0.5352**	**0.402**	**0.1683**	**0.1611**
Speckle noise				
NLM	0.8513	0.7734	0.6656	0.646
Anisotropic diffusion	**0.966**	0.9423	0.82	0.7853
Weiner	0.1025	0.0857	0.0509	0.0448
Bilateral	0.9505	0.9157	0.8058	0.7752
Gaussian	0.9619	**0.9501**	**0.8912**	**0.8626**

5 Conclusion

In this paper, the performance of de-noising filters evaluated for three different types of noise on brain MRI images. Performance is evaluated on the basis of statistical parameters such as PSNR, MSE, and SSIM. From results, it is observed that for Gaussian noise, Weiner filter works more prominent than other filters. In case of salt and pepper noise, Gaussian filter works better. For speckle noise, anisotropic diffusion filter works better on low noise density with MSE 18.7696 at 5% noise density, whereas for high noise density, Gaussian filter works better with MSE value 117.219 at 90% noise density.

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