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Noise Removal from MRI Brain ImagesUsing Median-Filtering Techniques

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Abstract
Noise removal techniques in medical image processing are important practices for analyzing anatomical structures. Researchers have been utilizing several noise removal filters, namely, Adaptive filter, Mean filter, Gaussian filter, Median filter, etc. to diminish noises from the images. In this research, we have proposed a MatLab-based noise removal technique for removing salt and pepper noise from brain MR images. We have employed different types of median filtering techniques along with the aforementioned filtering techniques. Several performances measuring metrics such as MSE, PSNR, and SSIM have been calculated to compare the results. The study reveals that the weighted median filter outperforms the other filters in terms of MSE, PSNR, and SSIM. The weighted median filter obtained 0.0876, 58.9325, and 0.9893 MSE, PSNR, and SSIM values, respectively. In comparison with the other filtering techniques, the median filter with kernel size 3 outperforms the others in terms of similar performance metrics.

Keywords:*Magnetic Resonance Imaging, Median Filter, Salt and Pepper Noise, PSNR, SSIM.*

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I. INTRODUCTION

Brain tumors, the abnormal growths of cells in the human brain, can be cancerous or noncancerous. When tumors grow, they usually create pressure inside the skull of the brain which can cause brain damage, and be life-threatening. Over 600,000 individuals in the United States, have primary-stage brain tumors according to the National Brain Tumor Society.There are 28,000 young persons under the age of 20.Metastatic brain tumors are the most frequent types of brain tumors accounting for 20-40% of all cancer cases [1, 2]. Therefore, medical imaging techniques are highly utilized to diagnose these abnormalities in advance and provide proper treatment. Brain tumors are currently diagnosed using a variety of medical imaging techniques, including magnetic resonance imaging (MRI), computed tomography, and positron emission tomography [3]. Among them, MRI in the medical field plays a significant role in creating high-quality images of the human brain because of its some well-known features, including no radiation exposure, adjustable thickness in any plane, greater contrasting resolution, and numerous details without intravenous contrast. In general, every medical imaging technique, as well as MRI, is liable to suffer from salt and pepper noise, Gaussian noise, speckle noise, uniform noise, and other types of noise [4]. Therefore, noise removal is very important for proper diagnosis [5, 6]. Different filtering techniques, namely adaptive, mean, Gaussian, median, weighted median, adaptive median, 3D median filters, and median filters with different kernel sizes are utilized to remove the high-frequency components and the noises [7, 8]. Deepa et al. in [9], introduced noise reduction strategiesfor the examination of anatomical structure as a necessary exercise in medical imaging applications.Logeswari and Karnanin [2], used a weighted median filter for reducing the noises from the MRI images. Yousuf et al. in the study [10], suggested a new approach for removing noise from magnetic resonance and ultrasound images. Their experimentsshowed that the suggested filter outperformed PSNR in terms of MSE. Isa et al. in the work [11], proposed a noise removal approach to remove the salt and pepper noise in different medical images including MRI, and evaluated the denoising performances of fundamental filters such as median, adaptive and average filter. Kankariya et al. [4], suggested time-saving techniques for removing salt and paper noise. PSNR for pictures with low and high levels of noise has improved as a result of the use of such algorithms.Shinde et al. in [12], employed several filtering approaches, including median, adaptive and average filters to reduce speckle noise in various medical images including MRI. Sivasundari et al. [13], employed several filtering approaches namely median filter, center-weighted median filter, and wiener filter to analyze the performance of filtering algorithms for MRI noise demising. The result showed that the Weiner filter performed better with a large PSNR value.

In this research, we proposed a MatLab-based noise removal approach to remove the salt and pepper noise from brain MRIs. Several filtering methods like adaptive filter, mean filter, Gaussian filter, median filter, weighted median filter, adaptive median filter, 3D median filter, and median filter with different kernel sizes have been utilized for salt and pepper noise removal. Finally, the performance of the filters is commensurate by determining numerical values including mean squared error (MSE), peak signal-to-noise ratio (PSNR), and structural similarity index measure (SSIM) from each type of the filtered image. Further arrangements are designed as follows: Section II presents the material and methods of this research; Section III presents results and discussion; and finally, in Section IV we have made a concluding remark.

II. MATERIALS AND METHODS

The overall research work is shown in Fig. 1.

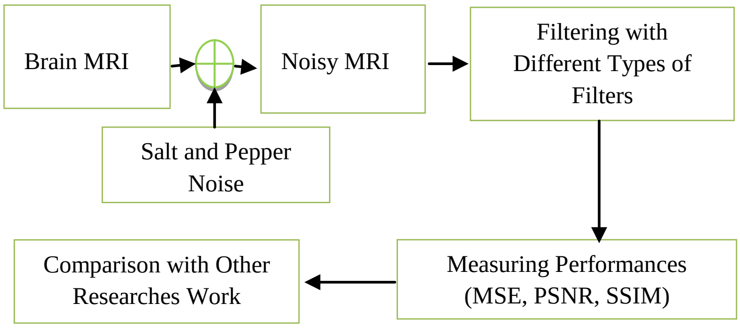


Fig. 1.Overall working block diagram.

A. *Data Description*

We have collected five MRI data from the Kaggle database [14] for this research. Images are three types: (i) binary, (ii) grayscale, and (iii) color images. In this research, we utilized grayscale or intensity images with the default size of 256 × 256.

B. *Noisy Brain MRI*

In this experiment, we have added the salt and pepper noise with the original image for filtering purposes. The adding formula is expressed as follows:

$$C(x,y) = A(x,y) + B(x,y) \qquad (1)$$

Here, $C(x,y)$, $A(x,y)$, and $B(x,y)$ present the real output, original, and noisy images, respectively.

C. *Salt and Pepper Noise*

Salt and pepper noise, additionally known as impulse noise or spike noise is arbitrarily scattered with white, black, or each constituent over the images. Salt and pepper noises result from memory cell failure, out-of-whack of the camera's detector cells, and timing errors when scanning or transmitting images.

D. *Filtering Process*

In this process, firstly the collected data is sampled by removing noises. Several methods of image intensity normalization have been proposed to achieve vigorous range consistency for several data images to avoid fatigue. This process will be employed by the open-source toolbox in MatLab and will store the image data pre-processed in MatLab files.

E. *Performance Evaluation*

Filter performance was evaluated using the following metrics.

- ***Mean Squared Error (MSE):*** Mean squared error (MSE) determines the mean square of the error in the desired signal $x\,(n)$ and the primary signal $\tilde{x}(n)$that supplied to the filter. Mathematically, the formula for MSE is obtained from the following equation:

$$MSE = \sqrt{\frac{1}{N}\sum_{n=0}^{N}(x(n) - \tilde{x}(n))^2} \qquad (2)$$

- ***Peak Signal to Noise Ratio (PSNR):*** Peak signal-to-noise ratio (PSNR), the ratio of the maximum possible power of a signal to the power of corrupting noise that detriment the accuracy of its illustration. Mathematically, PSNR is expressed in terms of the logarithmic decibel scale [15].

$$PSNR = 10log_{10}[\frac{MAX^2}{MSE}] \qquad (3)$$

Here, MAX is the maximum possible pixel value of the MRI.

- ***Structural Similarity Index Measure (SSIM):*** The structural similarity index measure (SSIM), utilized for predicting the perceived quality of images, is based on the multiplication of 3 terms: luminance, contrast, and structural terms [16]. The similarity index is simplified as follows:

$$SSIM = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\delta_x^2 + \delta_y^2 + C_2)} \quad (4)$$

Where, μ_x and μ_y are the local means of x and y, and σ_{xy} is the cross-covariance of x, y for the image.

III. RESULT AND DISCUSSION

Original, noisy, and filtered MRI images are shown in Fig. 2. The adaptive, mean, Gaussian, and median filter's filtered images are displayed progressively and clearly.

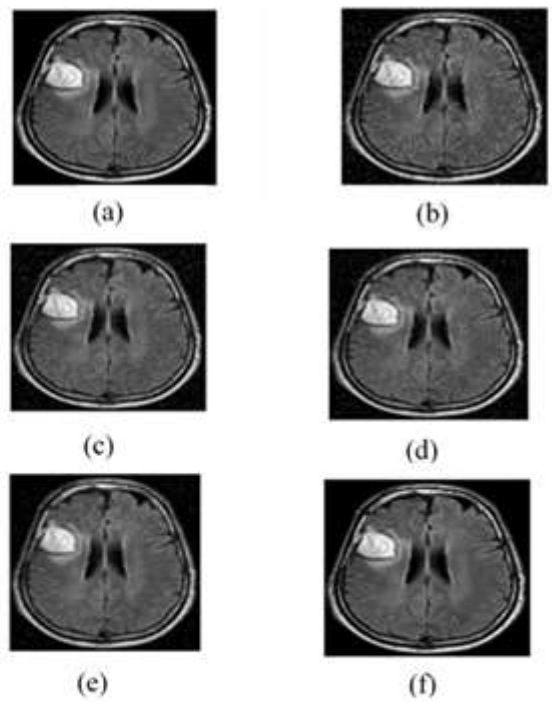


FIG 2 Examples of (a) original image, (b) noisy image, (c) adaptive filtered image, (d) mean filtered image, (e) Gaussian filtered image, and (f) median filtered image.

The statistic clearly illustrates that the applied filters effectively suppress the salt and pepper noise.Several performances evaluation metrics, including MSE, PSNR, and SSIM for four types of filters are calculated using five images of the Kaggle dataset, and, the average values are shown in Table 1.MSE, PSNR, and SSIM estimated average values for the adaptive filtered image are 17.3977, 36.1424 dB, and 0.5566, respectively, as shown in the table. The values are 18.0905, 35.8594 dB, and 0.5775 for the mean filtered image, respectively. For Gaussian filtered images, the computed values of MSE, PSNR, and SSIM are 18.9751, 35.9120 dB, and 0.7127, respectively. The results are 7.2034, 41.0498 dB, and 0.9632, respectively for the median filtered image.

Table 1. Average values of MSE, PSNR, and SSIM for different

Filter Types	MSE	PSNR	SSIM
Adaptive	17.3977	36.1424	0.5566
Mean	18.0905	35.8594	0.5775
Gaussian	18.9751	35.9120	0.7127
Median	7.2034	41.0498	0.9632

The original, noisy (salt and pepper noise), and filtered MRI images are shown in Fig. 3, utilizing several types of median filters including median, weighted, adaptive, and 3D median filters. The statistic clearly illustrates that the applied filters effectively reduce the salt and pepper noise. Performance measuring metrics, namely MSE, PSNR, and SSIM for four types of median filters are calculated using five images of the Kaggle dataset, and, the average values are shown in Table 2.

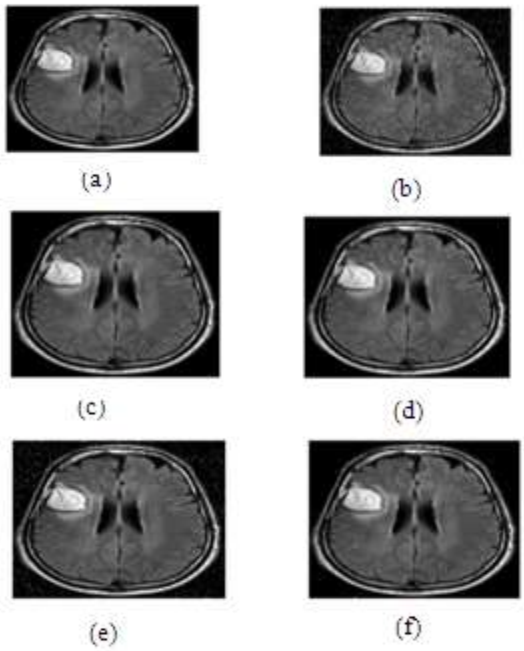


FIG 3Examples of (a) original, (b) noisy (salt and pepper), (c) median filtered image, (d) weighted median filtered image, (e) adaptive filtered image, (f) 3D median filtered image.

Fig. 4 displays the median filtered MRI images for various kernel size values. The genuine and noisy (spike noise/ salt and pepper) images are shown in Figs. 2 and 3. For kernel values of 3, 5, 7, 9, 11, 13, 15, 17, 19, and 21, thefiltered images are identified, respectively. Table 3 evaluates and displays the numerical values of MSE, PSNR, and SSIM, respectively. As seen in the figures as well as in the table, kernel 3 is better than other kernels, in terms of MSE, PSNR, and SSIM.

Table 2. Average values of MSE, PSNR, and SSIM for different types of median filters

Filter Types	MSE	PSNR	SSIM
Median Filter	7.2034	41.0498	0.9632
Weighted Median	0.0876	58.9325	0.9893
Adaptive Median	1.7556	47.8022	0.8708
3D Median	5.4147	43.1613	0.9727

A combined graphical interpretation of MSE, PSNR, and SSIM for adaptive, mean, Gaussian, and median filters are also given in Fig. 5(a), which complies with Fig. 2 and Table 1. From Fig. 5(a), we can see that the values of MSE, PSNR, and SSIM of the median filter are lower, higher, and higher than other filters of the same patterns. It indicates that the median filter performs better than other filters.

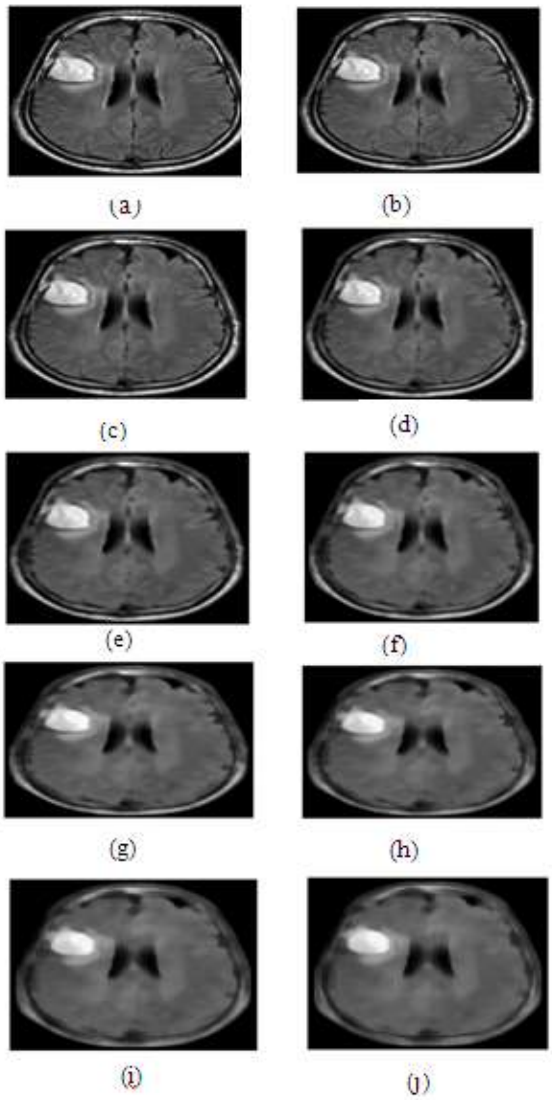
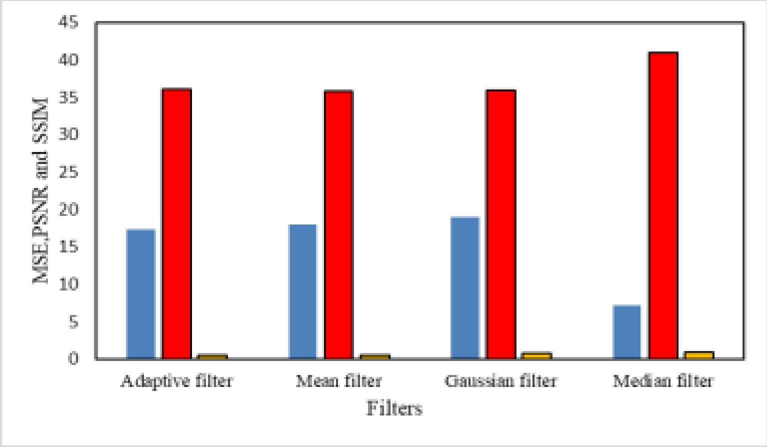


Fig. 4. Median filtered images with kernel size (a) 3, (b) 5, (c) 7, (d) 9, (e) 11, (f) 13, (g) 15, (h) 17, (i) 19, and (j) 21.

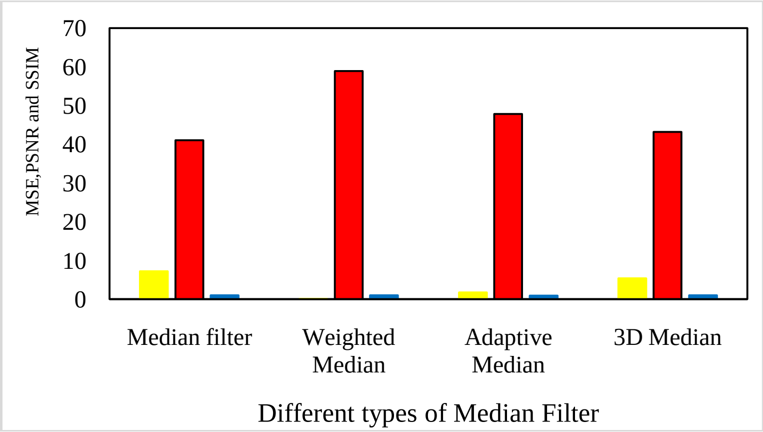
Table 3. Values of MSE, PSNR, and SSIM of median filters with kernel size

Kernel Size	MSE	PSNR	SSIM
3	6.1791972	40.2554788	0.978290
5	14.5344017	36.5408277	0.9412496
7	22.9476733	34.5574127	0.8795178
9	30.1917335	33.3659188	0.8126552
11	35.9167253	32.6118320	0.7557215
13	39.7082043	32.1759968	0.7112104
15	43.3951238	31.7903900	0.6761664
17	46.3159185	31.5074965	0.6507547
19	49.3574913	31.2312685	0.6287277
21	52.0278638	31.0024394	0.6112367

The same graphical interpretation for the median, weighted median, adaptive median, 3D median filters are also depicted in Fig. 5(b), which also resemblance with Fig. 3 and Table 2. The figure shows that the MSE value of the weighted median filter is lower than other median filters.Both the values of PSNR and SSIM of the weighted median filter are also higher than other median filters, revealing thatthe weighted median filter performs better than other median filters.



(a)



(b)

Fig.5. Graphical presentations of MSE, PSNR, and SSIM values of (a) adaptive, mean, Gaussian, and median filters, and (b) median, weighted, adaptive, and 3D median filters.

Fig. 6 represents the bar graph of MSE, PSNR, and SSIM of the median, weighted median, and median filter with kernel size 3. As seen in the graph, the weighted median is better than other types of median filters, in terms of MSE, PSNR, and SSIM.

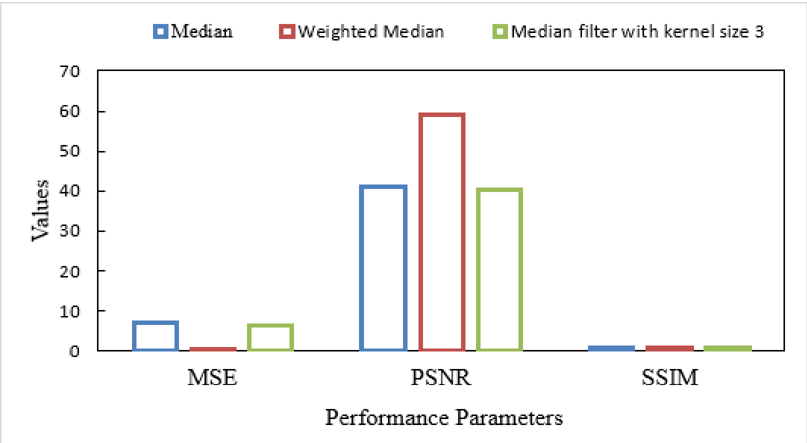


Fig. 6. A bar graph of MSE, PSNR, and SSIM values of the median, weighted, and median filter with kernel size 3.

Table 4 summarizes these findings as well. In comparison to the median and median filter with kernel size 3, the weighted median filter displays strong PSNR, and low MSE with 98.93% average values of SSIM, as shown in the table.

Table 4. Comparison of MSE, PSNR, and SSIM of Median filter, Weighted Median, and Median filter with kernel size 3.

Filters	MSE	PSNR	SSIM
Median	7.2034	41.0498	0.9632
Weighted Median	0.0876	58.9325	0.9893
Median filter with kernel size 3	6.1791	40.2554	0.9782

Finally, Table 5 presents the comparison of the results of our study with the other studies. In this table, we can see that the median filter with kernel size 3 outperforms the other filtering techniques in terms of MSE, PSNR, and SSIM respectively.

Table 5. Comparison with other researches

Researches	Kernel Size	MSE	PSNR	SSIM
[5]	3	30.61	33.499	-
	5	79.92	29.221	-
	7	129.04	27.107	-
	9	173.44	25.810	-
[8]	3	10.6754	35.6754	0.9365
	5	38.2288	32.3069	0.9265
	7	164.335	25.9735	0.8136
	9	351.632	22.6699	0.7205
Our Work	3	6.1791	40.2554	0.9782
	5	14.5344	36.5408	0.9412
	7	22.9476	34.5574	0.8795
	9	30.1917	33.3659	0.8126
	11	35.9167	32.6118	0.7557
	13	39.7082	32.1759	0.7112
	15	43.3951	31.7903	0.6761
	17	46.3159	31.5074	0.6507
	19	49.3574	31.2312	0.6287
	21	52.0278	31.0024	0.6112

Fig. 7 (a), 7(b), and 7(c) represent the graphical interpretation of MSE, PSNR, and SSIM of Median, Weighted Median, Adaptive Median, and 3D median filter, respectively. From this figure, we see that the Weighted Median filter outperforms the other filters in terms of MSE, PSNR, and SSIM, respectively.

IV. CONCLUSION AND FUTURE WORK

In this research, we have utilized brain MRI for filtering purposes. The salt and pepper noise was added to the original images. Then different filtering methods like adaptive, mean, Gaussian, median weighted median, adaptive median, 3D median filters, and median filter with different kernel sizes (3, 5, 7, 9, 11, 13, 15, 17, 19, and 21) have been employed in this study. The median filter provides a higher quality of images by reducing the salt and pepper noise. It shows high values of PSNR and low values of MSE with 96.32% average values of SSIM, compared to adaptive, mean, and Gaussian filters. In addition, the weighted median filter provides a higher quality of images by reducing the salt and pepper noise. It shows high values of PSNR and low values of MSE with 98.93% average values of SSIM, compared to median, adaptive median, and 3D median filters. On the contrary, the median filter with kernel size 3 provides a higher quality of images by reducing the salt and pepper noise. It shows high values of PSNR and low values of MSE with 97.82% values of SSIM, compared to kernel size 5, 7, 9, 11, 13, 15, 17, 19, 21 respectively. The weighted median is better than other median and the median filter with kernel size 3, in terms of MSE, PSNR, and SSIM.

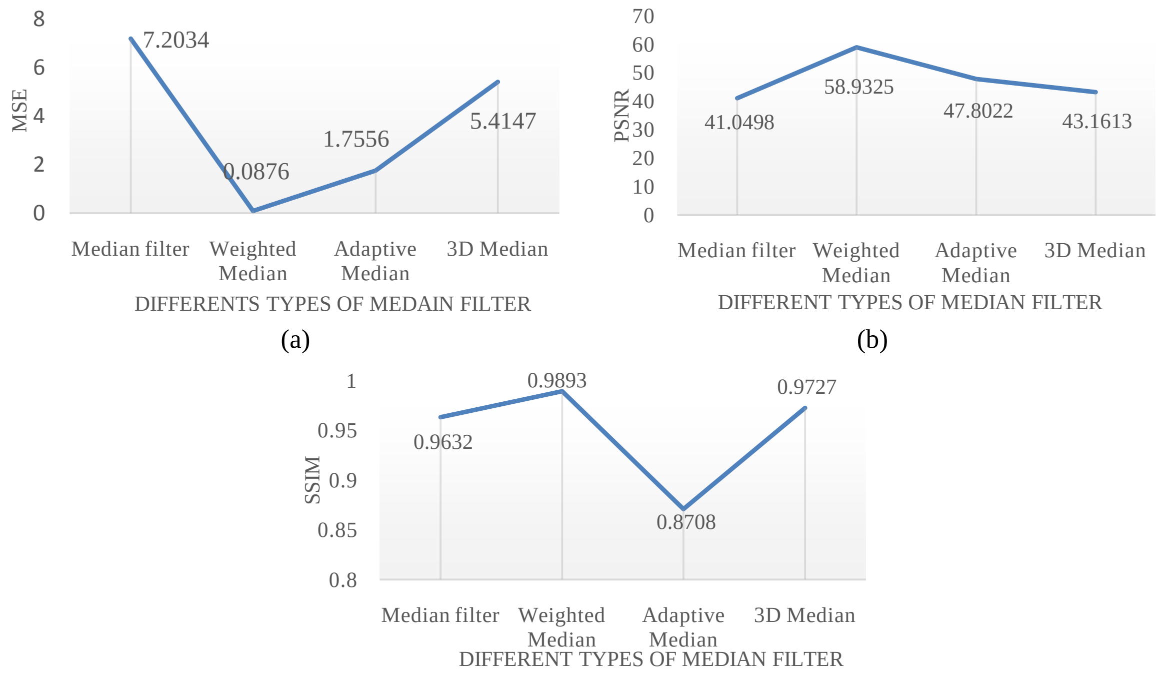


Fig. 7. Graphical presentation of performance matrices obtained by applying Median, Weighted, Adaptive, and 3D median filters: (a) MSE, (b) PSNR and (c) SSIM.

In the future, we will apply the median filter, weighted median filter, and the median filter with kernel size 3 at the preprocessing stage of the brain MR images for classifying tumors in the human brain by employing machine-learning techniques.

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