ORIGINAL ARTICLE

High Impulse Noise Removal and Edge Detection in MRI Images Using Advanced Filtering Techniques

T Shravan Kumar[1, *] and Bhukya Madhu[2]

[1]*Research Scholar, Computer Science and Engineering, Bharatiya Engineering Science and Technology Innovation University, Andhra Pradesh, India.*

[2]*Associate Professor, Department of Computer Science and Engineering, Malla Reddy (MR) Deemed to be University, Telangana, India.*

(**Received** 23 December 2025, **Revised** 31 January 2026, **Accepted** 28 March 2026)

*Corresponding author: 2023scse016@bestiu.edu.in

DOI: 10.5875/853y5407

Abstract: Medical imaging plays a critical role in disease diagnosis and treatment planning, with Magnetic Resonance Imaging (MRI) being a cornerstone in capturing detailed anatomical structures. However, MRI images often suffer from high impulse noise, such as salt-and-pepper noise, introduced during acquisition and transmission, which compromises image quality and diagnostic accuracy. Additionally, precise edge detection is essential to delineate anatomical boundaries and regions of interest. This research proposes a novel two-stage approach combining advanced denoising and edge detection techniques. The first stage employs an Adaptive Modified Weighted Median Filter (AMWMF) to efficiently remove high impulse noise while preserving image details. The second stage integrates Rough Set Theory (RST) for accurate edge detection by leveraging intensity-based local variations and approximations. Extensive experiments were conducted to evaluate the proposed method against existing techniques, using metrics such as Peak Signal-to-Noise Ratio (PSNR) and Mean Squared Error (MSE). Results demonstrate significant improvements in noise suppression, edge preservation, and feature enhancement, offering a robust framework for enhanced MRI image analysis. The proposed method provides a reliable solution for medical imaging applications, aiding in improved visualization, classification, and diagnosis of complex medical conditions.

Keywords: MRI Image Processing, High Impulse Noise Removal, Edge Detection, Adaptive Weighted Median Filter, Rough Set Theory.

Introduction

Noise is not something that can be added to a visual medium like an image or any other kind of pictorial representation and can thus be taken away. It represents a lack of data in the image itself. It is usually created by using high ISO levels in low light. In general, this is only after applying the Gaussian filter [20]; the image becomes the better version of it. However, Gaussian Filter has its own limitations as it fails to resolve the issues with some noise types. For example, salt and pepper noise doesn’t get affected by the filter and hence remains the same. Image enhancement and registration is another main challenge in the medical field for doctors. During the last two decades, various new innovative techniques have emerged for image enhancement. The objective of this approach is to prevent MRI brain pulse noise to better capture and classify the image. This shows an effective model in the form of a filter that can eliminate the danger of noise and impulse noise. Various experiments with different noise levels were performed to test the effectiveness of the proposed model. The proposed method was compared with existing denoising methods in terms of diagnostics of parameters. And the experimental results showed that the proposed filter works as other methods.

Over the past two decades, digital image and communication technology have evolved developments in all fields. In today's digital world, digital images are recorded using various electronic devices to better visualize and classify diseases in medical image processing. Sending and classifying images in medical image processing [21] has become a very important task, even for the detection of a disease problem. In this phase of image acquisition, transmission and even before segmentation, the image is damaged by noise. Salt and Pepper noise is one of the sounds of the image. This noise is generated by image pixel distortion, damaged memory space in the hardware, or transmission to a noisy channel [1, 8], average switching filter [9], decision-based algorithm (DBA) [2]. Primary multimedia filters first identify pixel to pixel-positive noise pixels in a given input image and then replace pixel values with a mean-value filter. In an equivalent case, the remaining pixels remain unchanged. They are effective to detect and eliminate noise even at high noise levels.

MRI Image with Noise Characteristics

In medical image applications, as theoretical expectations, noise is measured in the MRI image of the brain to be divided into invariant and white. When taking MRI the images are very sensitive more chances for adding noise, which ends with errors in obtaining and sending an image. Medical images recorded with MRI are pruned for noise, and due to the overlapped noise the trained model will get biased.

In the processing of medical image, the MRI or CT or X-ray images are more sensitive to noise and the results refer to image acquisition and transmission errors [2]. If the image poor quality tends to reduce the performance of certain characteristic values, such as obtaining, reducing, and classifying the properties of the processed images. Since noisy image contains noise, noise must be removed before further processing operations, using many algorithms available for literature filtering. Gaussian noise and impulse noise are noises that are well known in medical MRI image. Pulse and Gaussian noises are divided into size values in MRI images and cannot be avoided. To prevent Gaussian noise as well as other small noise. The impulsive noise that appears in the MRI image is dark and bright patch.

Image denoising is a very important part in the process of medical image processing [3]. The goal is to eliminate noise that can damage the image label by recording or sending a picture while maintaining its good quality. Medical images obtained using the MRI technique is an important tool for diagnosing diseases in the medical world. Medical images are often affected by accidental noise resulting from the process of image acquisition and subsequent processing. The effect of noise on the MRI image not only reduce the quality [22], but also affects the low visibility of the image and low contrast values. It should be noted that noise prevention is a major problem in medical image applications to improve and restore accurate information that may be hidden in the image. The noise reduction process should not significantly alter the useful properties of the image. In addition, the main features of the MRI image are the features of the device. Therefore, noise reduction should be balanced with edge protection. The MRI method has two important features that affect the ability to visualize the anatomical structure and the abnormal parts of the human body:

a. Blurring image, which affects the visibility of small features of image detailed
b. Noise image, which reduces visibility of the low-contrast value of the image.

2. Related work

Medical image processing uses edge detection techniques to obtain sharp and defined edges. Sobel Edge Detector is a standard edge detection method commonly used at the edges of an image. It is a simple edge detection method that uses 3x3 window-size convolutional masks to determine the edge of the image horizontally and vertically. Both window masks are used to calculate the size and direction of the gradient. Another method of edge detection is Laplacian Edge Detection Operator [4]. It is a second-order derived operator that is also used to determine edge boundaries. This operator provides better edge positioning compared to first-order derivation methods, but is very sensitive to noise.

Laplace Gaussian edge detector is the edge detection method. This method first eliminates the noise of this image using Gaussian operator [5] [23], and then detects the contours with the Laplace operator. Robert's operator performs a two-dimensional spatial measurement of the gradient. Digital and medical image. This method focuses on high spatial frequency zones corresponding to the edges of the image. The calculated sets provide a unique approach to nodes using granular information. Provides a difference between the coverage limits of a particular data domain [6]. Estimated ensemble methods [7] have been used in the context of hybrid methods like neural networks and simple ML models. Approximate kits have been found to be particularly useful for creating rules and selecting features. The concept of an approximate set can be quite broadly distinguished by the use of topology, internal and closing operations called approximation.

The term Granular Computing (GrC) [8], [9] provides uncertainty, partial truth, and impreciseness under the granule space. Granules at the lowest level are composed of atomic particle of the universe of discourse. The mathematical morphology works on the basis of the structuring element of the particular image. In morphological operations, [10] the image and the structuring element of the images are considered clusters, and this series of operations is performed using the basic concepts of basic cluster theory. The main activities of mathematical morphology are expansion and erosion. Based on these basic concepts, some edge-determining algorithms have been developed as part of the expansion and erosion operations when structuring image elements. Using these operations, a matrix is created. This matrix has only 0 and 1, which can have any shape and size. Pixels with a value of 1 determine the value of the pixels around the image.

Enlargement is one of the two basic operators of mathematical morphology technique [11]. In general, it refers to binary images and grayscale images. The main effect of binary image dilatation is to slowly expand the boundaries of pixel areas in the foreground pixels. As a result, areas with foreground pixels become larger in areas that become smaller. Erosion is another operator of the concept of mathematical morphology concepts. The main effect of the operator on the binary image is to remove the zone boundaries with the pixels in the foreground pixels. For this reason, areas with visible pixels have been reduced and enlarged.

In medical imaging applications, different types of edge detectors are used in the magnetic resonance imaging of the brain. Defining the bases is the is 'Sobel', 'Prewitt', 'Robert', 'Laplacian of Gaussian' and 'Canny' edge detector algorithms [14]. The Canny peripheral operator algorithm gave better results with less noise in the medical image. This algorithm provided sophisticated and complete edges with other existing algorithms. Mathematical morphological algorithms, such as the Zhao Yu-Quain slope [15] and algorithm, are no better for edge detection. The morphological edge detection method is recommended for salt and pepper noise containing a medical image. When analyzing medical images, it is possible that the edge detectors do not contain any edges near the edge and can also not create borders for the region. In MRI images, the ideal contours (closed curves) are more important for contouring and classification. Methods based on the Region Growing (RG) [16] and [17] Active Contour (AC) contain many changes compared to the AC method [4], and the method of determining boundaries remains. stronger objects especially in medical imaging. The Snake model is based on AC-based methods. This model is more resistant to noise and other artifacts.

Another method is Chan and Vese, which is based on Snake models [18] and [19] that work according to the binary concept as object boundaries in terms of foreground segmentation and background segmenting of image. For the first time, a multi-phase pipe model was proposed to generalize the idea of establishing multiple detection limits. This [24][25]method refers to the distribution of the image in two objects N, taking into account the N-level sets. In medical imaging applications, contour detection and classification concepts allow experimentally to focus on the Canny edge detector, the morphological actions that create a lot of false contours in a noisy environment. The edge of the object Canny thus obtained is meaningless in the closed curve of the image in the object. The Chan-Vese Active Contour method and current version seemed strong in terms of noise.

3.Methodology

The proposed methodology focuses on the edges of closed curves. The method of determining the edge of a closed curve is recommended based on the calculated set theory. To capture closed edges of the objects which is not performed in previous methods? In this process first active contour methods are detected with the boundaries of this object, but not within the boundaries of the closed object. The Chan-Vese multi-phase active contour method is limited to the number of images in the object. The granular information overcomes the constraint object and captures closed boundaries around the image. This closed curve edge provides additional information that can be used to select comparable pixel values are used for image deletion, increase resolutions, and segmentation.

The proposed methodology 1 is the edge detection method tested in the presence of noise in the image. The experiment was carried out by computerized images as well as MRI imaging in the brain. The performance of the proposed method has been found to be optimistic and allows a better comparison of existing edge detection methods. It stimulated the best results in the proposed algorithm working with contour detection using different boundaries, without any conditions for the amount of objects in the image. The concept of approximate set theory uses the concept of better processing of image uncertainty. The active curve methods divide the foreground and the background area from the original contour. RST defines the lower and upper approximation to a particular object using small information. The boundaries of the sample are taken by obtained by different approximations.

Procedure for RST methodology:

The relation r of the class r is determined by the element x with r (x). Indispensability relation to some certain it describes the lack of knowledge of the universe. Equivalence classes, made up of by indispensability relation, called granules, represent an elementary of the observed knowledge. Formal definitions of approximations are:

$$\underline{r}(x) = \bigcup_{x \in U} r(x) : r(x) \subseteq X \quad (1)$$

$$\bar{r}(x) = \cup_{x \in S} r(x) \cap X \neq \emptyset \quad (2)$$

$$Br(X) = \bar{r}(x) - \underline{r}(x) \quad (3)$$

The lower approximation to the set is the whole set of grains that are fully included in the set; the highest approach is the combination of all the grains that have 0 empty sets, with the sequence; The border area of the set corresponds to the difference between the upper and lower approximation. The edge information can be used to cross borders. This prompted the current job to choose an approximate set of theory for capturing edge features and is included actual edges. The proposed method is used to reduce the number of conflicting objects. Processing of grain information from raw material set theory (RST) allows visualizing the possible edges or heterogeneity of granules. The filters size is 2 × 1, 1 × 2 or 2 × 2, etc.

The proposed RST approach using small patches provides partitions in the image to lower and upper approximations of objects. The lowest approximation is fully included in upper approximation set. The difference between the two approximations provides a possible boundary area for a particular object or image.

The entire procedure for proposed method:

- First estimate approximation values from the noisy samples, and performs optimizations.
- After optimizing each threshold value, the Binary weighted median filters applied the image to captures binary values.
- The vector with 1's or 0's of each pixel for all threshold value. Will represents the Category of all binary strings and there by pixel values shown in figure 1 and figure 2.

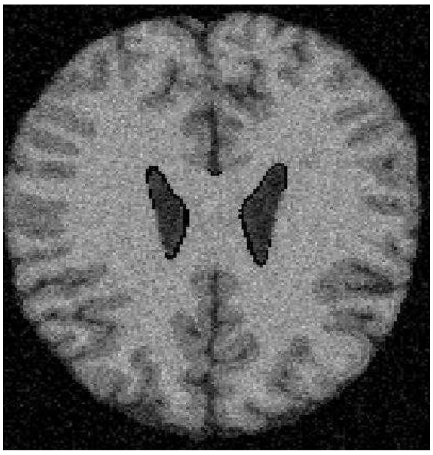

Figure 1 Noise free MR Image

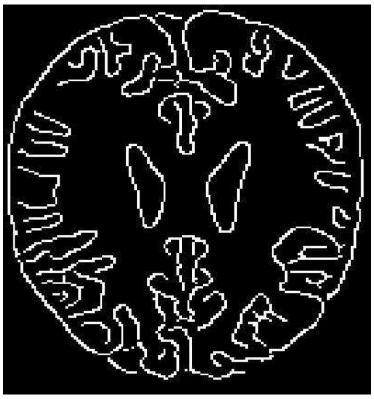

Figure 2 Canny edge detection on noisy image

Common Noises in MRI images

Theoretical medical expectations showed that the noise percent in MRI images is divided, invariant and white. When captured magnetic resonance images are usually sensitive to Gaussian noise and salt and pepper noise or impulsive noise. This noise is affected by poor image quality, which reduces performance, such as acquisition, reduction and classification of processed images. Noise was eliminated before to these post processing steps because the literature suggested a lot of available image filtering algorithms.

Gaussian and impulse noise are most added noises that are widely used in MRI samples and non-avoidable. Impulse noise is also called salt and pepper noise. Gaussian noise is a mathematical opportunity both in the space domain and in the frequency domain. Salt and pepper noise is also an impulsive noise, this type of noise occurs between the pixels of the image. The impulse noise when gloomy and brilliant pixels change between light and dark places. In this case, the pulse noise was damaged and impulse noise digitized by the extreme value in the image.

Gaussian Noise or Amplifier Noise

This kind of noise is called Gaussian distribution. Gaussian noise or amplifier noise contains the normal distribution probability distribution equation. Gauja noise is added to samples when an sensor head, is obtained. This Gaussian noise is due to low sensor brightness, high temperature and electronic circuitry. The spatial filtering and Gaussian noise is performed with equation (4).

$$P(z) = \frac{1}{\sqrt{2\pi\sigma}} e^{\frac{-(z-u)^2}{2\sigma^2}} \quad (4)$$

Impulse Noise or salt and pepper noise

Impulses are also called salt and pepper noise or Spike noise. This type of noise is caused by camera sensor pixel failure, faulty locations, or transmission to the noise channel. Impulse noise is always separated and not related to the pixels of the image. This type of noise can be divided into two types: salt and pepper noise and noise at random. In the form of noise, the pixels of the noisy image take the salt value is -225 or the pepper value -0. This type of noise is seeming to black and white points. In the event of accidental pulse noise, noise can be inferred from any value between 0 and 225.

Operational Structure of Proposed System

The Proposed filtering technique is the Operational Structure classified in 3 stages-

- Stage: 1-Adaptive median Filter:
- Stage: 2-Shrinkage Window
- Stage: 3-Weighted Mean Filter

In the proposed method of the process are defined in stage 1, stage 2 and stage 3. In stage 1 is the procedure for the Adaptive median filter.

Stage 1: Adaptive Median filter

The step by step procedure for the Adaptive median filter is given below:

Step 1:Initally taken an input noisy image.then the filtering is applied input image of the pixel values,and changed the pixel values as a 0’s or 1’s.

Step 2:After the step 1 process,thenset the window size as 3×3 and maximize the sliding window size is low.

Step 3:The sliding window process across the entire image and all pixel values are 0’s and 1’s.otherwise remove all 0’s and 1’s in the window and measure the median value of remaining pixels,and replace the under processed pixel value with the median.

In the above 3 steps are scanning the entire image with sliding window for given noisy image.This steps are performed in Adaptive median filter.

Stage 2: *Shrinkage Window*

The proposed method of the stage 2 process is the shrinkage window.It is also step by step procedure.

Step 1: Initally set the predefined maximum sliding window size(2×2)

Step2: The sliding window scans the all pixel values 0’s or 1’s are on the boundary of the image or not. If pixel values are on the boundary then go to step 3, otherwise the window size shrunk by 1.

Step 3: In this step, the boundary pixel values all are 1, then the center pixels vlaues will changes like 0’s to 1 and 1 to 0.

The entire process is done for shrinkage the window for scans the pixel through noisy image.

Stage:3-Weighted Mean Filter

This is the last stage of the proposed technique for detecting noise through the entire Brain MRI images

Step 1: The sliding window, check the entire image the under processed pixel values or not(pixel values are 1’s or 0’s).if the under processed pixels are 0’s or 1’s then goes to step 3. Otherwise, leave it.

Step 2: Set (2×2) level sliding window size and also set the weight values of the each pixel.

Step 3: Scan the entire image with sliding window, when the resulted image is the denoised image.

The middle filtering method replaces each pixel value in an image with the median value of its neighbors, including itself. median filters are applied to an image, pixel values of adjacent pixels are taken into account and the remaining pixels are removed. By removing these odd features, the values are assigned to the pixels with the values of the neighboring pixels in the original image. A square core of a 3 x 3 kernel sliding window is used, although larger cores (e.g a 5 × 5 square) can also be used, which causes a larger flattening of the image. performance in terms of noise elimination. The median value is calculated by sorting all the pixel values according to their size, then selecting the value of the median as a new value for the pixel. The number of classification pixels must be taken into account when calculating the median.

In this a weighted media filtering technique to eliminate noise from brain MRI images without modifying the contrast value. The weights of the proposed filtering technique are determined on the basis of the pixel intensity value of the MRI image. In this method, four types of weights like 0, 0.1, 0.2 and 0.3 have been used. The weights of the preceding pixels are multiplied by the pixel intensity value used by the median filter to calculate the weighted median filter.

4. Results and analysis

To evaluate the proposed method for removing noise from MRI images of the brain, MRI images have also been implemented for better evaluation compared to other imaging techniques. The results are captured for all filters, such as the all parameters, the weights and the dimensions of the windows, are determined on the basis of the optimal values that have been proposed for the specific noise level. Table 1 presents the results obtained with the different existing methods, as well as the method proposed for 20%, 40%, 60% and 80% and 90% of the impulsive noise in different MRI images. The proposed algorithm offers better results in terms of detail and better similarity, least noise value and edge retention, especially for MRI images in the brain.

In this proposed method, the measurement parameters PSNR, MSE are the same as those used in the previous experiments, each of which is described below. The PSNR calculates the peak signal-to-noise ratio between two images in the intensity value unit. This PSNR relationship is often used as a measure of quality between the original image and the noiseless image. The highest PSNR values for images without noise, the best image quality

$$PSNR = 20\log_{10}\left(\frac{MAX_I}{\sqrt{MSE}}\right) \quad (5)$$

Where, the MSE is the collective squared error between the de noised image and the original image.

Table 1 Comparison and performance of proposed and existing filtering technique with evaluation parameters PSNR and MSE.

Window Size	SMF (MRI)		AMF (MRI)		MFWMF (MRI)		AMFWMF (MRI)	
	PSNR	MSE	PSNR	MSE	PSNR	MSE	PSNR	MSE
2×2	38.6973	8.77786	29.6595	70.3383	28.0279	102.426	42.3894	3.75203
3×3	38.1993	9.84584	28.4252	93.5027	26.0145	162.813	41.5808	4.51929
4×4	37.6132	11.2736	36.272	15.342	28.54	91.2022	40.3508	5.9979
5×5	37.173	12.498	35.3671	18.8961	28.152	99.8219	39.8668	6.70501

Form the Table 1. The table shows the comparison of the proposed and existing filtering techniques and the performance with the parameters of the PSNR and MSE evaluation. The table shows that the proposed method works better for low and high noise levels. Based on qualitative and quantitative results, it can be concluded that the use of the proposed method for noise prevention improves the MRI input image equivalence structure. The proposed method maintains performance and keeps the image structure at a low level and increases noise level.

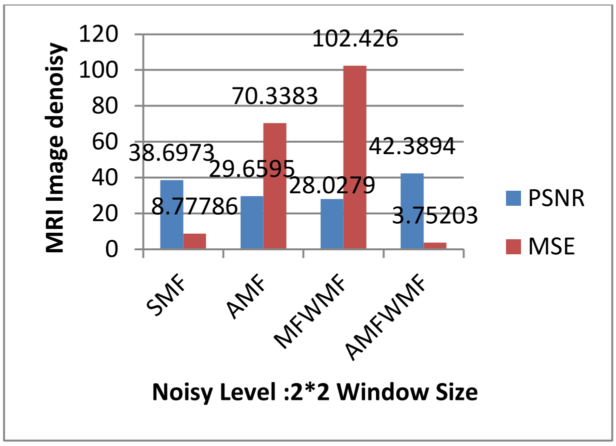

Figure 3: Denoisy Performances with PSNR and MSE (2*2 Window Size)

The comparative performance of the four filtering techniques—Standard Median Filter (SMF), Adaptive Median Filter (AMF), Modified Filtered Weighted Median Filter (MFWMF), and Adaptive Modified Filtered Weighted Median Filter (AMFWMF)—was evaluated using bar charts for different window sizes (2×2, 3×3, 4×4, and 5×5). The figures highlight the variation of Peak Signal-to-Noise Ratio (PSNR) and Mean Square Error (MSE) for MRI images corrupted with high impulse noise, thereby providing a clear understanding of the effectiveness of each method in terms of noise suppression and edge preservation.

The figure 3 illustrates a 2×2 window size and demonstrates a stark contrast in the denoising performance across the filters. SMF achieves a PSNR of 38.6973 with an MSE of 8.77786, suggesting a reasonable balance between noise removal and structural preservation. AMF, however, exhibits weaker results at this small window size, recording a PSNR of 29.6595 with a significantly higher MSE of 70.3383. This indicates that while AMF adapts to local noise density, it is less effective with smaller neighborhoods. MFWMF performs even worse under this setting, with a PSNR of 28.0279 and the highest MSE of 102.426, clearly showing its inability to handle dense noise at small scales. By contrast, AMFWMF outperforms all other methods with a PSNR of 42.3894 and the lowest MSE of 3.75203. This strong performance at 2×2 indicates the capability of AMFWMF to effectively suppress noise while maintaining edge clarity, even under extreme noise conditions.

The figure 4 illustrates a 3×3 window size, provides further evidence of the relative strengths and weaknesses of the methods. SMF maintains a fairly stable performance with a PSNR of 38.1993 and MSE of 9.84584, showing only a slight decline compared to its 2×2 results. AMF again shows limited effectiveness, producing a PSNR of 28.4252 with a high MSE of 93.5027, suggesting that its adaptive strategy does not adequately preserve edges when noise levels are high. MFWMF performs poorly at this scale, with a PSNR of 26.0145 and a dramatically increased MSE of 162.813, making it unsuitable for practical MRI denoising at this window size. AMFWMF, however, once again demonstrates superior performance with a PSNR of 41.5808 and a low MSE of 4.51929. This consistent superiority reinforces the conclusion that the adaptive and weighted combination allows AMFWMF to handle impulse noise effectively without blurring important image details.

In figure 5 illustrates the 4×4 window size, the results highlight the trade-offs inherent in larger neighborhood processing. SMF achieves a PSNR of 37.6132 with an MSE of 11.2736, reflecting a gradual deterioration as window size increases, largely due to oversmoothing. Interestingly, AMF shows significant improvement at this scale, with a PSNR of 36.272 and MSE of 15.342, suggesting that larger neighborhoods improve its adaptivity. MFWMF achieves a PSNR of 28.54 with an MSE of 91.2022, which, although better than its performance at 3×3, still indicates insufficient robustness to high impulse noise. AMFWMF again emerges as the best-performing filter, with a PSNR of 40.3508 and an MSE of 5.9979, highlighting its ability to sustain high-quality denoising even at larger windows. Importantly, AMFWMF manages to preserve edges more effectively than the other filters, which tend to lose structural details as the window size increases.

The figure 6 illustrates the 5×5 window size, further validates these observations. SMF records a PSNR of 37.173 and MSE of 12.498, continuing its trend of gradual degradation with larger windows. AMF produces a PSNR of 35.3671 and MSE of 18.8961, indicating that while it benefits somewhat from larger window sizes, its overall performance remains inferior compared to more advanced methods. MFWMF shows limited improvement, with a PSNR of 28.152 and MSE of 99.8219, suggesting persistent difficulties in balancing denoising with edge preservation. In contrast, AMFWMF demonstrates remarkable consistency, with a PSNR of 39.8668 and MSE of 6.70501, sustaining its superior performance across all window sizes. This stability underlines the robustness of AMFWMF in adapting to noise density while minimizing distortions, making it the most effective technique for MRI denoising.

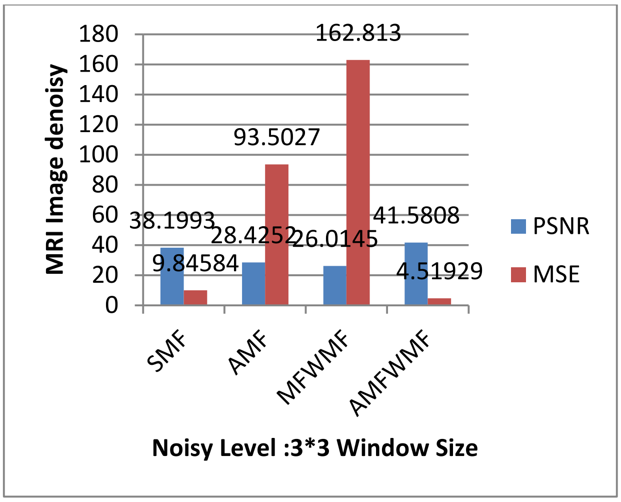

Figure 4: Denoisy Performances with PSNR and MSE (3*3 Window Size)

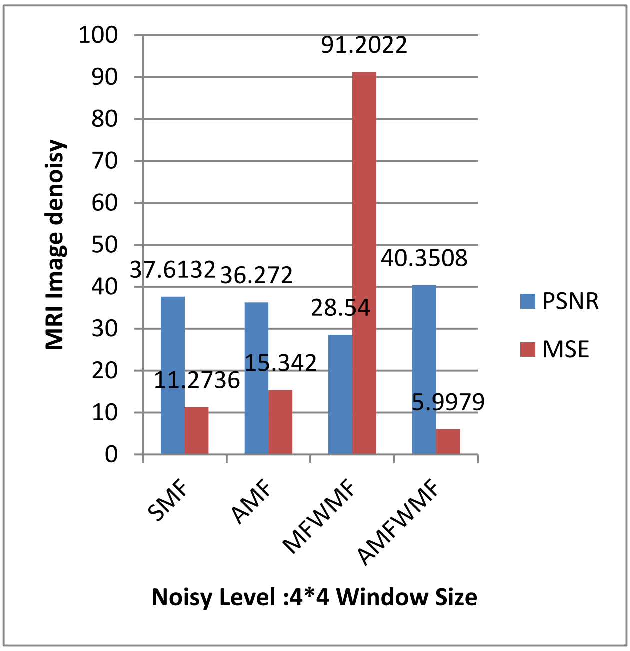

Figure 5: Denoisy Performances with PSNR and MSE (4*4 Window Size)

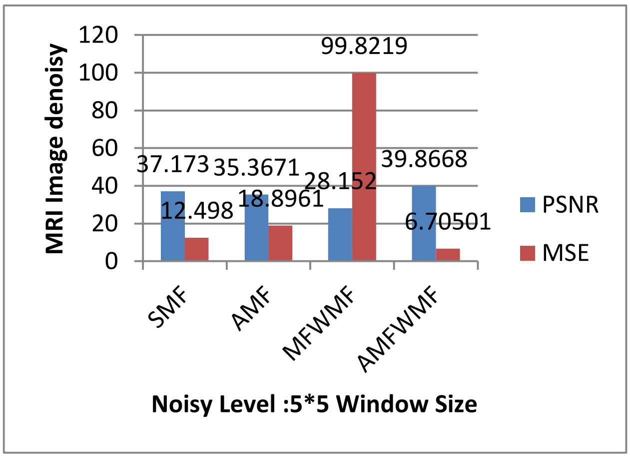

Figure 6: Denoisy Performances with PSNR and MSE (5*5 Window Size)

5. Conclusion

The filtering technique proposed in this chapter, namely the AMFWM, is introduced as a new leveling filter to optimize a lot of noise, even if it is high density. This combination of filters has better structural characteristics than another filter to reduce noise of different pulse noise at various stages. This method prevents noise to maintain image details and edges. These elements are very important to prevent MRI images. Using the filtering method of proposed in this paper, it provides optimal performance with existing filters to suppress embedded MRI images; the roughest offer based edge detection method also works well to identify or classify the original object area.

Declarations

Funding: There is no specific funding to support this research.

Conflict of Interest: The authors declare that they have no conflicts of interest regarding this work.

Data Availability: The data that support the findings of this study are not publicly available due to confidentiality agreements but are available from the corresponding author upon reasonable request.

Code Availability: Not applicable.

Author Contributions: All authors contributed to the design and methodology of this study, the assessment of the outcomes, and the writing of the manuscript.

References

[1] Besov, O. V., Lozinskii, V. P., & Stepanov, S. I. (2019). *Function spaces and their applications*. Springer. https://doi.org/10.1007/978-3-030-06179-1

[2] Bhadoria, R. S., & Fernandes, B. G. (2013). Hybrid median filter for impulse noise removal. *International Journal of Image Processing, 7*(1), 45–56.

[3] Chan, R. H., Ho, C.-W., & Nikolova, M. (2005). Salt-and-pepper noise removal by median-type noise detectors and edge-preserving regularization. *IEEE Transactions on Image Processing, 14*(10),1479–1485. https://doi.org/10.1109/TIP.2005.852196

[4] Dabov, K., Foi, A., Katkovnik, V., & Egiazarian, K. (2007). Image denoising by sparse 3D transform-domain collaborative filtering. *IEEE Transactions on Image Processing, 16*(8), 2080–2095. https://doi.org/10.1109/TIP.2007.901238

[5] Gonzalez, R. C., & Woods, R. E. (2018). *Digital image processing* (4th ed.). Pearson.

[6] Jain, A. K. (1989). *Fundamentals of digital image processing*. Prentice Hall.

[7] Kass, M., Witkin, A., & Terzopoulos, D. (1988). Snakes: Active contour models. *International Journal of Computer Vision, 1*(4), 321–331. https://doi.org/10.1007/BF00133570

[8] Kaur, M., Kaur, J., & Singh, J. (2014). MRI image denoising and segmentation techniques. *International Journal of Engineering Research and Applications, 4*(4), 61–68.

[9] Khare, A., & Kumar, U. (2015). A review of medical image denoising methods. *Biomedical Signal Processing and Control, 16*, 39–45. https://doi.org/10.1016/j.bspc.2014.11.006

[10] Koenderink, J. J. (1984). The structure of images. *Biological Cybernetics, 50*(5), 363–370. https://doi.org/10.1007/BF00336961

[11] Lakshmanaprabu, S. K., Mohanty, S. N., Krishnamoorthy, S., Uthayakumar, J., & Shankar, K. (2020). An optimal rough set-based MRI image segmentation and classification approach. *Soft Computing, 24*(10), 7769–7781. https://doi.org/10.1007/s00500-019-04242-9

[12] Lee, J.-S. (1980). Digital image enhancement and noise filtering by use of local statistics. *IEEE Transactions on Pattern Analysis and Machine Intelligence, PAMI-2*(2), 165–168. https://doi.org/10.1109/TPAMI.1980.4766994

[13] Mallat, S. (2008). *A wavelet tour of signal processing* (3rd ed.). Academic Press. https://doi.org/10.1016/B978-0-12-374370-1.X0001-8

[14] Mamun, M. A., Rahman, M. M., & Hossain, M. A. (2011). A new switching weighted median filter for impulse noise removal. *International Journal of Advanced Computer Science and Applications, 2*(7),34–38. https://doi.org/10.14569/IJACSA.2011.020706

[15] Pitas, I., & Venetsanopoulos, A. N. (1992). Order statistics in digital image processing. *Proceedings of the IEEE, 80*(12), 1893–1921. https://doi.org/10.1109/5.192894

[16] Pratt, W. K. (2007). *Digital image processing: PIKS scientific inside* (4th ed.). Wiley.

[17] Sheikh, H. R., Sabir, M. F., & Bovik, A. C. (2006). Image and video quality assessment research at LIVE. *IEEE Transactions on Image Processing, 15*(1), 3440–3450. https://doi.org/10.1109/TIP.2006.881959

[18] Shrivastava, C. S., Londhe, N. D., & Sonawane, R. S. (2014). Comparative analysis of various filters for MRI image noise removal. *International Journal of*

Computer Applications, 103(7), 20–25. https://doi.org/10.5120/18127-9154
[19] Singh, G., Kaur, L., & Singh, K. (2016). Edge detection techniques for MRI image analysis: A review. *Biomedical Research, 27*(1), 22–31.
[20] Szeliski, R. (2021). *Computer vision: Algorithms and applications* (2nd ed.). Springer. https://doi.org/10.1007/978-3-030-34372-9
[21] Tomasi, C., & Manduchi, R. (1998). Bilateral filtering for gray and color images. In *Proceedings of the Sixth International Conference on Computer Vision* (pp. 839–846). IEEE. https://doi.org/10.1109/ICCV.1998.710815
[22] Turk, M., & Pentland, A. (1991). Eigenfaces for recognition. *Journal of Cognitive Neuroscience, 3*(1), 71–86. https://doi.org/10.1162/jocn.1991.3.1.71
[23] Wang, Z., Bovik, A. C., Sheikh, H. R., & Simoncelli, E. P. (2004). Image quality assessment: From error visibility to structural similarity. *IEEE Transactions on Image Processing, 13*(4), 600–612. https://doi.org/10.1109/TIP.2003.819861
[24] Weszka, J. S., Rosenfeld, A., & Nagel, R. (1974). A comparative study of threshold selection techniques. *IEEE Transactions on Computers, C-23*(3), 294–303. https://doi.org/10.1109/T-C.1974.224122
[25] Zhang, L., Dong, W., Zhang, D., & Shi, G. (2006). Image denoising with symmetric principal component analysis. *Pattern Recognition Letters, 27*(9), 894–899. https://doi.org/10.1016/j.patrec.2005.11.014