Enhancing Diagnostic Accuracy: A Hybrid Approach to Mitigate Speckle and Rician Noise in Medical Images

Abstract: - This research explores the detrimental effects of Rician and speckle noise in medical imaging, particularly within MRI and radiographic modalities. Such noise can significantly obscure critical details, potentially leading to misdiagnoses and inaccurate measurements. Rician noise candidly dangles on the signal strength. Removing this noise affects the original information in image that makes this noise removal perplexing. On other hand speckle noise is visualised like granular clog in ultrasound imageries. It creates ambiguous details and edges in the images. To address this challenge, the study introduces a novel hybrid method implemented in Java. The method employs a frequency-based decomposition approach for speckle noise and separates images into magnitude and phase components for Rician noise. This allows for targeted filtering, utilizing customized versions of median and Gaussian filters, to effectively remove noise while preserving crucial image features. The proposed method was rigorously assessed using 200 contaminated brain and lung MRIs and radiographs, demonstrating superior performance compared to traditional filters based on crucial system of measurement like Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and Mean Squared Error (MSE). This research presents a promising solution for enhancing the quality and reliability of medical images, potentially leading to improved diagnostic accuracy and patient outcomes.

Keywords: Medical Images, Median Filter, Gaussian Filter, Speckle Noise, Rician Noise

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I. INTRODUCTION

Medical imaging plays a pivotal role in prevailing medical services, offering a minimally or no intrusive approach for detecting and observing assorted health ailments. However, image noise, such as Rician and speckle noise, can hinder accurate interpretation and limit the effectiveness of imaging techniques. Rician noise, prevalent in MRI scans, arises from the interference of two independent Gaussian noise sources, obscuring subtle details and potentially leading to misdiagnoses. It also impedes precise measurements crucial for assessing disease progression or treatment outcomes. Speckle noise, characteristic of radar and ultrasound images, manifests as a grainy disturbance that blurs details, making it challenging to distinguish between healthy and diseased tissue. This compromises diagnostic accuracy and restricts the applicability of ultrasound. In response to these challenges, this research presents a hybrid method for reducing noise in MRI and radiographic images. For speckle noise, the method employs a frequency-based decomposition approach to simplify the image and facilitate efficient processing. It then utilizes a noise reduction technique that preserves essential edge and texture information. To address Rician noise in MRI, the method separates the image into magnitude and phase components. Specific filters are applied to each component to remove noise without compromising critical edge details, ensuring image clarity while diminishing noise levels.

Developed using Java programming, this method was evaluated using ethically sourced hospital data. Its performance was compared against traditional filters using three quality metrics: peak signal-to-noise ratio, Mean Square Error, and Structural Similarity Index.

1.1 Literature Review

This research [1] explores noise’s complex nature in terms of magnitude MR images. The main goal is to develop a precise and consistent language for discussing this issue, specifically discouraging the use of phrases such as “Rician noise” and “Rician noise bias.” The researchers argue that it’s not the noise, however, the measured intensities adhere to the Rician distribution. They caution against the phrase “Rician noise,” as it suggests attributes not usually linked with noise, like dependence on signal strength, which can cause misunderstandings. Diverging from previous attributions, the authors posit that image noise stems from inherent Gaussian noise within the signals themselves. The researchers hope that their work will lead to more accurate and clear language when discussing these concepts in the future.

The research [2] delves into the theoretical underpinnings and mathematical methods used to tackle the challenges of stochastic data analysis within the Rice statistical model. In this model, the amplitude of the output signal consists of an initial desired value overlaid with a random Gaussian noise component. The study reveals that key features of the Rician signal, such as its average value and noise spread, are not directly related to the parameters of the Rice distribution. This insight led to the creation of a new method for analyzing stochastic Rician data, which focuses on the simultaneous and accurate estimation of both the signal and noise components. By estimating the parameters of the Rice distribution together, this method effectively recovers the underlying significant signal in the presence of noise. Importantly, this method avoids the constraints associated with assumptions in traditional techniques. Numerical experiments validate the efficacy of this new method for analyzing stochastic data within the Rice statistical model.

Research papers [3] and [4] explore various strategies for reducing noise in low-dose CT imaging. They thoroughly investigate several techniques, including filtered back projection, denoising in the image-space, denoising in the projection-space, and iterative reconstruction. Both papers conduct a rigorous evaluation of these methods using a mix of quantitative and qualitative metrics. They also incorporate input from radiologists and real clinical cases to offer a well-rounded evaluation of the advantages and drawbacks of each technique. The papers probe the fine line between reducing noise and preserving the visibility of low-contrast lesions. They illustrate that while noise reduction techniques can significantly improve image quality, overdoing noise reduction might hide subtle details and potentially result in overlooked diagnoses. Hence, fine-tuning noise reduction algorithms to achieve the right balance is essential for effective low-dose CT imaging. The papers present the results of noise reduction at various levels, demonstrating the effect of different noise reduction intensities on image quality and diagnostic accuracy. They underscore the need to customize noise reduction strategies to specific clinical applications and patient characteristics.
The research [5] explores the extensive field of noise reduction methods in medical imaging, providing a detailed examination of the current state of research in this area. The authors carried out a comprehensive review of existing studies and commonly used algorithms for noise reduction, with a special emphasis on the anatomical areas targeted and the use of parallel techniques in research published from 2010 to 2022. Their analysis revealed a significant focus on anatomical areas such as the brain, bones, heart, breast, lungs, and visual system, indicating the primary areas of interest in noise reduction research. They also found 14 articles that employed parallel computing techniques for noise reduction, pointing to an emerging trend of harnessing computational power to address this issue. The authors conclude by highlighting the significant role of effective noise reduction in improving image quality, which in turn leads to more accurate and reliable diagnoses in medical imaging.

The paper [6] underscores the importance of Magnetic Resonance Imaging (MRI) in medical diagnostics and different types of noise like speckle, salt and pepper and Gaussian manifest in unique ways, posing diverse problems for image processing applications. To tackle these issues, the author introduces a modified median filter algorithm specifically tailored to eliminate noise from MRI images. The paper also investigates the use of the Adaptive Median filter (AMF) and the Adaptive Wiener filter (AWF) for noise reduction. The effectiveness of these filters is evaluated using the statistical metric Peak Signal-to-Noise Ratio (PSNR), while progressively increasing the noise density within the MRI image. The paper stresses that successful noise reduction in MRI images can significantly improve image quality, leading to more precise and efficient diagnoses in medical practice.

Reducing noise in MRI is a nuanced task that necessitates a tailored strategy based on the specific context. Acknowledging this complexity, the authors [7] delve deep into the details of noise filtering methods, offering a thorough analysis and classification. They provide valuable insights on choosing the most suitable technique for different situations. Furthermore, they present a case study illustrating the adaptation of an existing filter to enhance its efficacy in a particular MRI environment.

The research presented in [8] unveils an enhanced, unbiased non-local mean (NLM) filter specifically developed to address the challenge of noise removal in MRI images. The authors refine the NLM filter by integrating local noise statistics into its structure, resulting in an unbiased variant. They initiate the process by using wavelet decomposition to extract Gaussian noise details from the noisy image. Subsequently, they statistically model the wavelet coefficients leveraging the diagonal sub-band, to estimate the noise variance using the MAD estimator. The NLM filter is then applied to eliminate Rician noise by averaging boisterous pixels with a Gaussian weight factor. Lastly, they implement a noise bias subtraction method on the NLM-filtered pixels to restore the original values, yielding an unbiased output. Through experiments conducted on both real MRI and synthetic images, the authors demonstrate the efficacy of their approach. Their method surpasses existing non-local mean filtering schemes, delivering significantly improved results.

In their research [9], the authors devised a method using MATLAB to eliminate salt-and-pepper noise from brain MRI images. They conducted a comparative analysis of various median filtering techniques and discovered that the weighted median filter surpassed the others, exhibiting superior performance based on system of measurements like MSE (Mean Square Error), PSNR (Peak Signal-to-Noise Ratio), and SSIM (Structural Similarity Index). The weighted median filter achieved remarkable results with respective values of 0.0876, 58.9325, and 0.9893. Furthermore, the authors noted a robust performance from a median filter utilizing a kernel size of 3. A tabulated summary of pertinent literature is provided for reference.

<table>
<thead>
<tr>
<th>Article Reference No.</th>
<th>Problem Addressed</th>
<th>Methodology</th>
<th>Pros</th>
<th>Cons</th>
<th>Future Scope</th>
</tr>
</thead>
<tbody>
<tr>
<td>[6]</td>
<td>Noise in MRI images</td>
<td>Modified median filter algorithm</td>
<td>Effective at removing Gaussian noise and Salt and pepper noise from MRI images</td>
<td>Limited to specific types of noise</td>
<td>Further research can be done to improve the algorithm and make it applicable to other types of noise</td>
</tr>
</tbody>
</table>
Reducing noise in medical images, specifically in magnetic resonance imaging (MRI), continues to be a hurdle due to the existence of speckle and Rician noise. While current methods such as modified median filters, adaptive filters, and enhanced unbiased NLM filters show potential, they often struggle with certain types of noise or lack adaptability across various situations. This indicates an exciting direction for future research: design and development of a fusion filter that syndicates the strengths of Gaussian and median filters. This hybrid approach seeks to benefit from the Gaussian filter’s capacity to smooth noise while maintaining edges, along with the median filter’s proficiency in eliminating noise bursts. Such a hybrid filter could provide a more resilient solution for managing the diverse noise patterns found in medical imaging.

## II. METHOD

This research presents a unique hybrid filtering system designed to tackle two usual forms of noise in clinical Radiological or scan images: speckle noise and Rician noise. In contrast to conventional methods, this system uses order statistics filters, showing superior performance in reducing these noise artifacts. It works on Radiographic and MRI images of the human body, using standard Median and Gaussian filters along with newly developed “Advanced Median” and “Advanced Gaussian” filters. These advanced filters are customised to yield more precise results by incorporating specific characteristics of medical images. This groundbreaking system offers a promising solution for improving the quality of medical images, potentially leading to more accurate diagnoses and enhanced clinical outcomes.

### 2.1 Proposed Approach Flow

<table>
<thead>
<tr>
<th>Reference</th>
<th>Title</th>
<th>Description</th>
<th>Approach</th>
<th>Method Focus</th>
</tr>
</thead>
<tbody>
<tr>
<td>[7]</td>
<td>Noise in MRI images</td>
<td>Various filtering methods</td>
<td>Comprehensive review of different noise filtering approaches</td>
<td>Does not propose a new method</td>
</tr>
<tr>
<td>[8]</td>
<td>Noise in MRI images</td>
<td>Improved unbiased NLM filter</td>
<td>Effective at removing salt and pepper noise from brain MR images</td>
<td>Limited to specific types of noise</td>
</tr>
<tr>
<td>[10]</td>
<td>Noise in MRI images</td>
<td>Average, median, and wiener filtering</td>
<td>Proposes a new technique to enhance the quality of MRI image by de-noising</td>
<td>Limited to Gaussian noise</td>
</tr>
<tr>
<td>[11]</td>
<td>Noise in MRI images</td>
<td>Median and Gaussian filter, Max filter, Min filter, and Arithmetic Mean filter</td>
<td>Comprehensive review of different noise filtering approaches</td>
<td>Does not propose a new method</td>
</tr>
<tr>
<td>[9]</td>
<td>Noise in MRI images</td>
<td>Different types of median filtering techniques</td>
<td>Effective at removing salt and pepper noise from brain MR images</td>
<td>Limited to specific types of noise</td>
</tr>
</tbody>
</table>
This research introduces a new hybrid method designed to improve the quality of radiographic images and facilitate accurate diagnoses. The process, as illustrated in Figure 1, consists of several key stages:

1. **Input Image**: The system begins by obtaining a radiographic image, which is often tainted with speckle noise that can mask important details and hinder accurate diagnosis. The type of image (radiographic) determines the characteristics of the noise and requires specific filtering techniques. This stage may include pre-processing steps, such as converting to grayscale, to prepare for the following stages.

2. **Image Decomposition**: This step involves dividing the input image into multiple frequency-based sub-bands using methods like wavelet decomposition. Low-frequency bands capture smoother variations, while high-frequency bands contain edge and texture details. By focusing noise reduction efforts on the affected high-frequency bands, unnecessary processing is minimized, preserving vital details in the low-frequency bands.

3. **Total Variation (TV) Minimization**: This phase aims to maintain the true structure of the denoised image without introducing unwanted artifacts. It involves minimizing total variation, which measures changes in pixel values across the image. This process ensures a smooth, consistent processed image while effectively removing noise. Algorithms like Bregman iteration facilitate TV minimization.

4. **Speckle Noise Identification and Filtering**: To eliminate speckle noise, this phase uses a Rician distribution function to accurately model the behavior of speckle noise. Statistical analysis identifies pixels affected by speckle noise, preserving genuine image details while filtering noise using techniques like adaptive Wiener filtering or non-local means filtering.

5. **Noise Addition**: This phase simulates real-world scenarios by artificially adding noise to the original image, allowing the system to evaluate noise reduction algorithms under practical conditions. Noise levels are controlled within a range (1% to 100%).

6. **Filter Application**: This stage compares the performance of three different filters on the noisy image:
   a) **Gaussian filter**: A standard technique for smoothing noise, but it can blur edges and details.
   b) **Median filter**: Effective against impulsive noise but can also blur edges.
   c) **Advanced filter**: A novel proposal that combines the benefits of Gaussian and median filters while minimizing drawbacks, preserving edges and textures.

7. **Results Evaluation**: This phase assesses filter performance by calculating two key metrics:
   a) **Peak Signal-to-Noise Ratio (PSNR)**: Quantifies the improvement of the denoised image compared to the original, where greater values signify superior noise removal.
   b) **Structural Similarity Index (SSIM)**: Assesses the structural similarity between the original and denoised images, with higher values signifying better preservation of image details and structures.

By comparing the PSNR and SSIM values for each filter, the system determines the filter that achieves the best balance between noise reduction and preservation of image details.
2.2 Proposed Advanced Filter Working

The advanced filter operates by examining the relationships between adjacent pixels in an image to eliminate speckle noise while maintaining edges and textures. It follows these steps:

a. Initialisation: The filter accepts the original noisy image as input and extracts the pixel values for the entire image.

b. Processing: The filter concentrates on the central part of the image, excluding the first and last rows and columns. It then processes each remaining pixel \((x, y)\) individually.

c. Disparity Calculation: For each pixel, the filter calculates the difference between its value \((G(x, y))\) and the value of the pixel in the previous row and column \((G(x-1, y-1))\). This difference, or disparity, indicates the potential presence of speckle noise at the current pixel.

d. Weighted Disparity Application: To balance noise reduction with edge preservation, the filter multiplies the calculated disparity by a factor of 0.5. This weighted disparity is then added to the unprocessed pixel value at coordinate \((x, y)\) in the reference image \([G(x, y)]\).

e. Updated Pixel Value: The filter replaces the original pixel value \((G(x, y))\) with the newly computed value, incorporating both noise reduction and edge preservation.

f. Image Updating: The filter repeats steps 3 to 5 for all pixels within the central part of the image.

g. Output: The filter produces a denoised image where each pixel value has been adjusted based on the advanced filter formula.

The advanced filter effectively removes speckle noise while maintaining edges and textures in medical images, leading to improved image quality and potentially more accurate diagnoses. The above key steps are shown in the below table 2

2.3 Implementation of Proposed Approach and Filter
Initially, the system selects an MRI image from a dataset comprising brain MRIs and radiographs. This image serves as the basis for demonstrating the noise removal process using various filters. To showcase the system’s flexibility, noise can be introduced, adjusting it from 1% to a noisy 100%. For this testing, it is ramped up to 70%. Once the image is sufficiently noisy, the system applies different filters, presenting the processed versions alongside the original for a direct comparison. This allows to observe how each filter handles the noise and impacts the image. To rigorously evaluate the proposed method, 200 brain and lung MRIs and radiographic images were utilized, each contaminated with both Rician and speckle noise. Further three different filters were applied to each image and measured three key metrics: Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and Mean Squared Error (MSE). This system of measurement aided in analyzing the effectiveness of each filter in eliminating the noise while preserving image details.

### Table 2: Key Steps implemented

<table>
<thead>
<tr>
<th>Step</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initialization</td>
<td>Input noisy image and extract pixel values.</td>
</tr>
<tr>
<td>Processing</td>
<td>Focus on inner portion of the image and process each pixel.</td>
</tr>
<tr>
<td>Disparity Calculation</td>
<td>Calculate difference between current pixel and previous row and column pixel.</td>
</tr>
<tr>
<td>Weighted Disparity Application</td>
<td>Apply balancing weight to disparity and add it to original pixel value.</td>
</tr>
<tr>
<td>Updated Pixel Value</td>
<td>Replace original pixel value with newly computed value.</td>
</tr>
<tr>
<td>Image Updating</td>
<td>Repeat steps 3-5 for all pixels within the inner image portion.</td>
</tr>
<tr>
<td>Output</td>
<td>Generate denoised image with adjusted pixel values.</td>
</tr>
</tbody>
</table>

### III. RESULT

To assess the efficacy of the implemented noise removal filters, 100 MRI images and 100 radiography images were processed to eliminate Speckle noise and Rician noise. Three filters—Median, Gaussian, and the newly proposed advanced filter—were developed using the Java programming language and applied to all images. The performance of these filters was assessed using three system of measurements: Peak Signal-to-Noise Ratio (PSNR), Mean Squared Error (MSE), and Structural Similarity Index (SSIM).

Peak Signal-to-Noise Ratio (PSNR) - acts as a window into the quality of a filtered image compared to its pristine counterpart. It offers a quantitative measure of how adeptly the filtering process has been in preserving the original signal while effectively removing unwanted noise. The PSNR value, expressed in decibels (dB), has a direct correlation with quality. Higher values indicate better preservation of the original image and less noticeable noise. Generally, a PSNR value of 30 dB or above is considered good, while values below 20 dB may suggest significant image degradation. The PSNR is calculated using the following formula:

$$PSNR = 10 \times \log_{10}\left(\frac{MAX_I^2}{MSE}\right)$$

where:
The variable MAX_I represent the pinnacle of possible pixel values within the image. Imagine a ladder representing all possible brightness levels a pixel can hold, with MAX_I perched at the very top. In an 8-bit image, where each pixel can take on 256 distinct shades, MAX would be 255, representing the brightest possible pixel.

Secondly, MSE or Mean Squared Error, delves into the heart of the difference between the original and filtered images. Imagine each image as a vast landscape, each pixel representing a tiny piece of the terrain. MSE calculates the average squared difference in elevation between these two landscapes. The Mean Squared Error (MSE) formula serves as a magnifying glass, allowing us to examine the discrepancies between the original and filtered images at a pixel-by-pixel level. Imagine both images as intricate mosaics, each pixel a unique tesserae contributing to the overall composition. The MSE formula as shown below delves into the heart of the difference by calculating the average squared difference in intensity between corresponding tesserae in the two mosaics. This process essentially measures how much each pixel in the filtered image deviates from its original counterpart.

\[
MSE = \frac{1}{MN} \sum (I_{\text{original}} - I_{\text{denoised}})^2
\]

where:

M and N Indicate the horizontal and vertical extent of the image.

\(I_{\text{Original}}\) denotes the original image.

\(I_{\text{denoised}}\) denotes the denoised image.

Thirdly, Structural Similarity Index (SSIM) - SSIM evaluates the structural likeness amongst unprocessed image and Transformed image. Higher SSIM values indicate superior preservation of image details and structures. It is calculated using the following formula:

\[
SSIM = \frac{(2 \mu_x \mu_y + C1) * (2 \sigma_{xy} + C2)}{((\mu_x^2 + \mu_y^2) + C1) * (\sigma_x^2 + \sigma_y^2 + C2)}
\]

where:

\(\mu_x\) and \(\mu_y\) represents the mean values of the original and denoised images

\(\sigma_x^2\) and \(\sigma_y^2\) are their respective variances

\(\sigma_{xy}\) is their covariance

C1 and C2 are constants stabilizing the SSIM metric.

These metrics provide a comprehensive assessment of the noise removal capabilities of the different filters, allowing for a comparison of their effectiveness in preserving image quality and structural details.

3.1. Discussion

3.1.1 Analysis and Inference of removing Rician noise from MRI images.

50 images were used as input for all three filters, and the results are visually depicted in the Radar with marker graph shown in the figure 3. Upon examining the graph and the table, the Proposed Filter demonstrates superior performance compared to the other filters across all three measures, indicating its superior effectiveness in removing Rician noise from MRI images while preserving image details and structures.
For an instance as shown in below table 3, the Proposed Filter displays a PSNR value that is 3.4894 dB higher than the original image and an MSE value that shows a significant reduction of 1086.5212 compared to the original image. These results highlight the significant improvements achieved in noise removal and image preservation by using the Proposed Filter. Furthermore, the Proposed Filter shows an SSIM value 0.0254 higher than the original image, indicating its ability to better maintain structural similarity between the original and filtered images.

The comprehensive data from the graph above confirm that the Proposed Filter has high efficacy towards reducing Rician noise in MRI images while skillfully preserving image details and structures.

**Table 3: Proposed Filter Metrics value compared with other filters for one image**

<table>
<thead>
<tr>
<th>Filter</th>
<th>PSNR (dB)</th>
<th>MSE</th>
<th>SSIM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Original image</td>
<td>15.1921</td>
<td>1967.292</td>
<td>0.9496</td>
</tr>
<tr>
<td>Proposed Filter</td>
<td>18.6822</td>
<td>880.7708</td>
<td>0.975</td>
</tr>
<tr>
<td>Gaussian Filter</td>
<td>17.8208</td>
<td>1073.997</td>
<td>0.9711</td>
</tr>
<tr>
<td>Median Filter</td>
<td>18.2226</td>
<td>979.0787</td>
<td>0.9744</td>
</tr>
</tbody>
</table>

3.1.2. Analysis and Inference of removing Speckle noise from MRI images.

Fifty images were processed using three filters, and the results were visually represented in a Radar with marker graph shown in the figure 4. Upon analysis and for an instance as shown in table 4 the proposed Filter demonstrated remarkable performance metrics: it achieved a PSNR value 4.405 dB higher than the original image and showed a decrease of 47.01 in MSE compared to the original image. These outcomes underscore significant improvements in noise reduction and image preservation achieved through the use of the Proposed Filter. Furthermore, the Proposed Filter exhibited an SSIM value 0.0419 higher than the original image, indicating its superior capability in preserving structural similarity between the original and filtered images.

**Table 4: Proposed Filter Metrics value compared with other filters for one image**

<table>
<thead>
<tr>
<th>Filter</th>
<th>PSNR (dB)</th>
<th>MSE</th>
<th>SSIM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Original image</td>
<td>30.365</td>
<td>72.02</td>
<td>0.9234</td>
</tr>
<tr>
<td>Proposed Filter</td>
<td>34.770</td>
<td>25.01</td>
<td>0.9653</td>
</tr>
<tr>
<td>Gaussian Filter</td>
<td>33.852</td>
<td>32.07</td>
<td>0.9598</td>
</tr>
</tbody>
</table>
3.1.3. Analysis and Inference of removing Rician noise from Radiography images

The radar with marker graph is shown for all the instance in figure 5. Considering an instance and its value the Proposed Filter outperforms the Median Filter and Gaussian Filter on all three metrics. The Proposed Filter achieves the highest PSNR of 22.7166 dB, the lowest MSE of 347.8762, and the highest SSIM of 0.9968. The Median Filter and Gaussian Filter perform similarly, while the Median Filter exhibits marginally greater PSNR while Gaussian Filter yields marginally lesser MSE.

3.1.4. Analysis and Inference of removing Speckle noise from Radiography images

The radar with marker graph is represented in the below figure 6 for the 50 radiography images. The graph in figure 6 shows that the proposed filter outperforms the median filter and Gaussian filter on all three metrics. For example, the proposed filter achieves a PSNR of 22.7166 dB, while the median filter and Gaussian filter achieve PSNR values of 21.4608 dB and 21.4992 dB, respectively. Similarly, the proposed filter achieves a MSE of 347.8762, while the median filter and Gaussian filter achieve MSE values of 446.1414 and 443.3416, respectively. Finally, the proposed
The presented findings suggest that the proposed filter surpasses other denoising filters in effectiveness for Speckle and Rician noise. It outperforms the median filter and Gaussian filter on all three metrics, indicating that it can remove noise while preserving the image's structural features.

IV. CONCLUSION

This study presents a unique hybrid filtering system designed to combat Rician and speckle noise in medical images. The system demonstrates superior performance in reducing these noise artifacts compared to traditional filtering methods. Considering MRI images, the proposed filter achieves a significantly higher PSNR (3.49 dB and 4.40 dB higher than the original image in two instances) and lower MSE (1086.52 and 47.01 lower than the original image in two instances) compared to the other filters. It also exhibits a higher SSIM (0.0254 and 0.0419 higher than the original image in two instances), indicating better preservation of structural similarity. Likewise for radiography images, the proposed filter achieves the highest PSNR (22.72 dB), the lowest MSE (347.88), and the highest SSIM (0.9968) compared to the other filters. These results demonstrate a clear advantage in noise removal and image preservation offered by the proposed filter. This research offers a promising avenue for improving the quality of medical images, potentially leading to more accurate diagnoses and better patient care. Future directions include the development of a hybrid filter combining the strengths of both Gaussian and median filters for increased resilience in managing diverse noise patterns and investigating the clinical impact of the proposed method by integrating it into diagnostic workflows.

REFERENCES


