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Fuzzy Logic-Based Mixed Noise Reduction in Ultrasound Images

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Abstract

Ultrasound (US) imaging is widely employed in medical diagnostics due to its non-invasive nature and real-time imaging ability. The existence of mixed noise, consisting of Gaussian and speckle noise, significantly impairs image quality, hindering accurate diagnosis. This study introduces an advanced fuzzy logic-based technique for noise reduction to enhance US image quality while preserving essential structural information. The proposed approach utilizes a modified Gaussian membership function to improve the filtering process, ensuring adaptive noise reduction across varying noise levels. The system is evaluated on synthetic and clinical US images using diverse image quality assessment metrics. The experimental results demonstrate that the proposed method exceeds existing top denoising techniques in terms of noise reduction, edge preservation, and image clarity. This work presents a systematic and effective approach for improving US image quality, hence augmenting medical analysis and diagnosis.

Keywords: ultrasound imaging, speckle noise, gaussian noise, fuzzy filtering, restored image.

1 Introduction

Medical imaging techniques have become essential for advanced medical assessments today. The remarkable progress in atomic physics during the 20th century has allowed doctors to visualize internal body structures, enabling the detection of anatomical features and the diagnosis of congenital abnormalities [1, 2]. Medical imaging has become a vital research area that integrates various scientific disciplines. It plays a key role in measuring and diagnosing diseases, as well as guiding treatment [3]. In recent years, several scholars have become interested on using US image analysis for various purposes and utilizing a variety of approaches. Various applications showed how the US imaging has advanced over time, for example, in the field of radiation therapy, high-energy radiation is targeted to specific regions of the body to destroy cancer cells [4]. In interventional radiology, imaging is used to guide minimally invasive procedures, such as the delivery of drugs or other therapeutic agents directly to the site of a disease. These advancements in medical imaging have improved patient outcomes

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and expanded the capabilities of healthcare providers.

In order to minimize noise in images impacted by various types of noise, such as Gaussian noise, salt-and-pepper noise, and speckle noise, Iftimia et al. [5] presented two filtering techniques: the median filter and the Wiener filter. This type of noises may be present in the image at the time of capture or introduced to the image later on during transmission. The authors derive the conclusion that the median filter outperforms the Wiener filter after denoising for speckle and Gaussian noisy images. Also, to denoise an image, the Wiener filter is outperformed by the median filter on a salt & pepper noisy image. Kumain et al. [6] proposed an innovative method for reducing Gaussian noise in visuals. Chowdhury et al. [7] originated a filtering approach based on fuzzy logic, utilizing a triangular-shaped fuzzy membership function to determine fuzzy membership values.

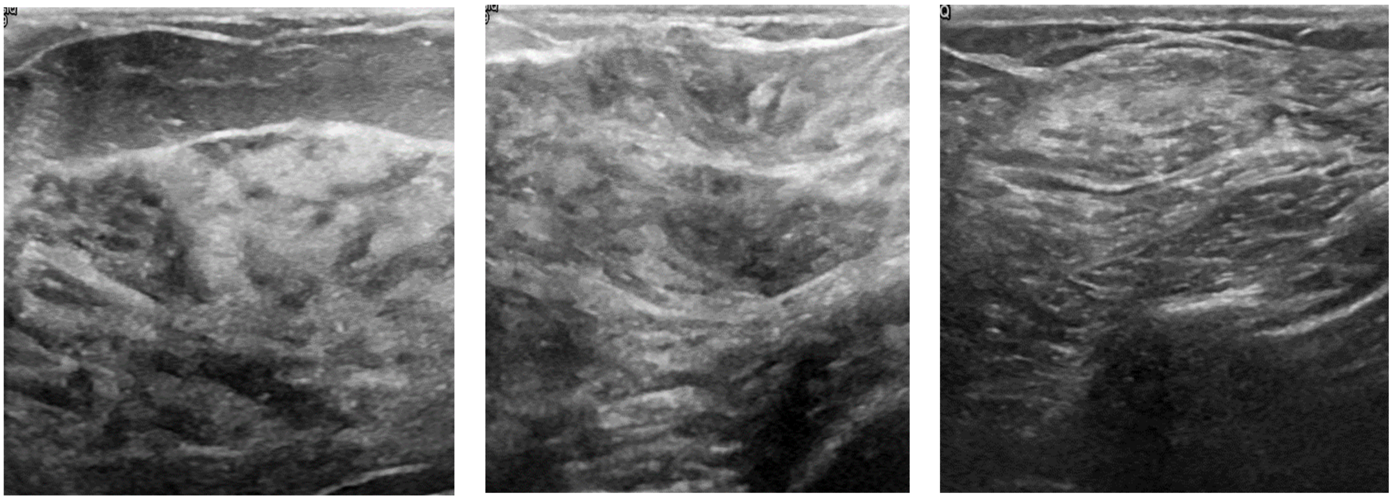
Uddin et al. [8] introduced an image denoising technique based on Artificial Neural Networks (ANN) in. This ANN-based method efficiently eliminates noise while retaining crucial details of the original image, making it a robust solution for image denoising. An alternative approach involves utilizing information from surrounding pixels to compute a new gray-level value for each noisy pixel. A similar method is presented in [9], where the authors employed a type-II fuzzy set to predict a new gray-level value for each noisy pixel, which is then utilized to generate a filtered image. Zhang et al. [10] also emphasize the effectiveness of fuzzy logic techniques in minimizing speckle noise in images, suggesting their potential applicability across various medical imaging domains. Additionally, Rubanee et al. [11] introduced a speckle noise reduction technique for ultrasound images using fuzzy logic, contributing to the development of an innovative fuzzy histogram adaptive filter designed to reduce noise in digital images. Improving the spatial resolution of US images remains an active area of research, and new methods are being developed to provide high-quality images for medical diagnosis and treatment. These includes digital adaptive filters [12, 13], transformation of wavelets including different configurations [14], moving-average techniques [15]. Starck et al. [16] described the second generation of the curvelet transform for image representation in two and three dimensions. They have shown two techniques for transformation, the first digital transformation is based on FDCT via unequally spaced fast Fourier transforms, and the second digital transformation is based on FDCT via wrapping. Both of these transformations are based on the FDCT algorithm. These are distinguished from one another by the spatial grid that was utilized in the translation of curvelets at each scale and angle. On the other hand, wrapping is preferable to USFFT due to the fact that the wrapping approach requires fewer processing resources than USFFT does.

Mahallati et al. [17] developed a method to reconstruct digital images by applying fuzzy filtering, where the value of the corrupted pixel is substituted with the average of the surrounding noise-free pixels. These methods have a precise reconstruction feature, which is suitable for clinical studies. Krishnan et al. [18] organized a study on image thresholding techniques. The image denoising-based approaches of Kapur, Sahoo, and Wong, as well as Pavlin, and Stuart, as well as the clustering-based method of Kittler and Illingworth, are the thresholding algorithms that perform the best in this body of research [19, 20]. However, here only text document images with noise and blurry deterioration were used to get these results. If an image is corrupted by mixed noise, then the Wiener filter, median filter, and rank filter do not completely remove the noise. Therefore, the reduction of multiple terms of noise, or simply mixed noise, in the machine vision applications is growing over the period [21–23].

The main contribution of this study is an improved technique for eliminating mixed noise from ultrasonography images, which enhances image quality for more accurate medical analysis and diagnosis. The proposed approach introduces a fine-tuned Gaussian fuzzy logic-based filtering algorithm that effectively reduces Gaussian and speckle noise while preserving important structural information.

2 Proposed Method

This study presents a systematic approach to image denoising, with the primary objective of improving image quality to enhance visual clarity and interpretability. Image noise may stem from various sources, including sensor limitations during acquisition, compression artifacts, or interference during transmission over unreliable channels. A wide range of denoising techniques has been explored in the literature; however, an ideal denoising framework must not only suppress noise effectively but also preserve critical structural and textural details essential for clinical interpretation or scientific analysis. In this work, we employ MATLAB as the simulation environment to implement and evaluate



(i) (ii) (iii)

Figure 1. Examples of ultrasound (i) Normal, (ii) Benign, and (iii) Malignant images that were used in the study to show how different amounts of noise affect image quality.

the performance of denoising models in mitigating both single-type and mixed noise across a variety of benchmark test images.

2.1 Image Acquisition

Image acquisition is the procedure of forming a digital representation of an object's visual qualities, such as a physical scene or the internal arrangement of the object image through a device (e.g., camera, scanner, or medical imaging equipment). It involves capturing or retrieving an image and storing it in a suitable format for use in the model. The standards and characteristics of the acquired image can have a profound influence on the performance of the model; hence, it is crucial to consider the particular requirements of the model and account for the appropriate image acquisition tools and techniques accordingly. Three sample US (breast) images are presented in Figure 1 [24].

212	89	37	89	123	76	42
245	11	90	21	81	198	211
131	191	22	125	250	156	189
34	101	134	42	198	43	167
190	55	121	110	134	87	27
123	99	78	98	62	234	24

Figure 2. The central pixel is processed using a 3×3 filtering kernel applied over its neighborhood.

2.2 Proposed Denoising Method

An image influenced by multiple noises can be represented as

$$I'(i,j) = I(i,j) \cdot B(i,j) + C(i,j), \tag{1}$$

where the noisy image is denoted as $I(i,j)$, the original image as $I(i,j)$, the multiplicative noise as $B(i,j)$, and the Gaussian noise as $C(i,j)$. Image denoising is the process of recovering the original image from a noisy image through the elimination of the noise. This study employs a modified Gaussian fuzzy logic approach that eradicates both single and mixed types of noise from a damaged US image and offers an efficient filtering technique for image denoising.

Figure 2 presents a segment of a noisy image in which a 3×3-pixel window highlighted with a bold boundary is centered around the target pixel with an initial intensity value of 11. The surrounding neighboring pixel intensities are 212, 89, 37, 245, 90, 131, 191, and 22. To initiate the filtering process, the minimum, maximum, and mean values of these neighboring pixels are computed. Subsequently, a Gaussian membership function, as depicted in Figure 3, is utilized to derive a new intensity value for the center pixel, effectively replacing its original value.

In image processing, a fuzzy set often referred to as fuzziness represents a framework that integrates

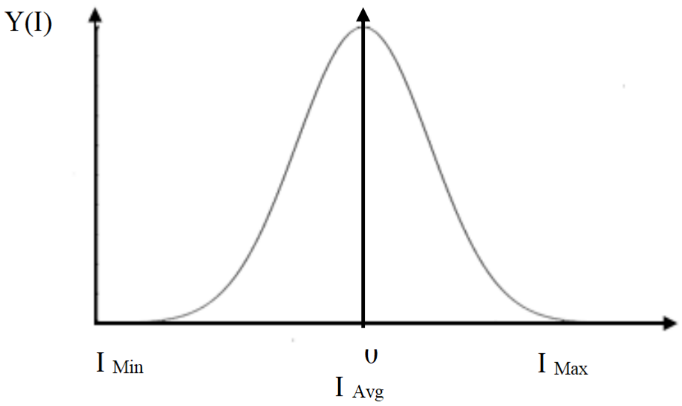


Figure 3. Depiction of the Gaussian membership function at various pixel intensities.

various techniques for analyzing, interpreting, and representing image features and segments. Fuzzy logic emulates human reasoning and perception, making it particularly effective for handling uncertainty and imprecision. A critical aspect of fuzzy-based methodologies is the structure of the membership function, as it defines the degree of association between each element and the fuzzy set.

A Gaussian fuzzy mathematical model is a representation of Gaussian functions that use fuzzy logic to process and analyze data. The membership function can take on values between 0 and 1, with 0 representing the absence of membership and 1 representing full membership. This technique calculates the fuzzy membership values of individual pixels by employing a boundary-aware, non-linear Gaussian function, defined as follows:

$$Y_A(l) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(\frac{-(M-l)^2}{2\sigma^2}\right), \tag{2}$$

$$Y_B(l) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(\frac{-(l-A)^2}{2\sigma^2}\right). \tag{3}$$

In this case, M, A, and l denote the maximum pixel value, the mean of the neighborhood, and the original pixel intensity, respectively, while σ represents the standard deviation that defines the width of the Gaussian membership function. The Gaussian membership function specified in Equation (2) is applied to neighboring pixels with intensities greater than the local mean, whereas Equation (3) is utilized for those with intensities below the mean.

Figure 4 demonstrates a complete block diagram of our proposed approach. It demonstrates how the algorithm was set up. It consists of six steps, as detailed below. Algorithm 1 elucidates the methodology of fuzzy logic-based noise reduction for US Images. The input is a noisy US image I, and the output is a denoised US image I′.

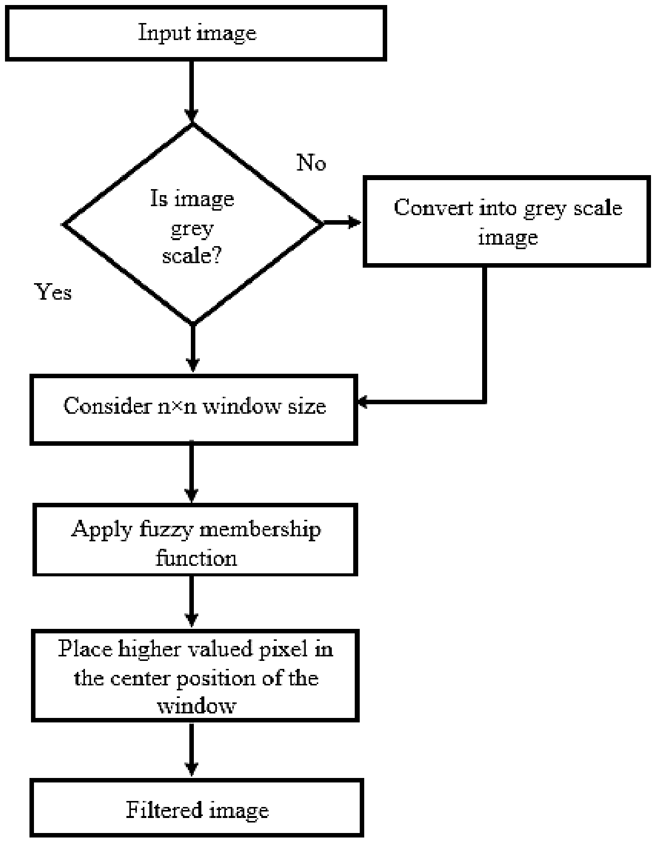


Figure 4. Flow diagram for fuzzy-based image restoration process.

3 Experimental Result and Discussion

The system described in this research has made a contribution to the advancement of US imaging technology. The method proposed work was executed in MATLAB and tested in an Intel (R) Core (TM) i5-7200U CPU 2.50 GHz machine with 8 GB RAM. For evaluating the performance of the proposed method, several single noise and mixed noise images of sizes 512×512 and 256×256 pixels are used. The Gaussian noise and speckle noise are imposed artificially using the in-built functions in MATLAB software. Each image is contaminated with Gaussian noise and speckle noise of densities 2%, 5%, 10%, 15%, 20%, 25%, and so on. We presented a methodical comparison with the five popular filters from the literature to illustrate the effectiveness of the suggested modified Gaussian fuzzy logic filter: triangle fuzzy filter, rank filter, Wiener filter, median filter, and mean filter. The performance of the recommended and juxtaposed

Algorithm 1: Fuzzy Logic-Based Noise Reduction for US Images

Input: Input image I
Output: Denoised image I_{denoised}
Step 1: Import the input image.
Step 2: If the image is in color, convert it to grayscale.
Step 3: For each pixel $l(i,j)$ in the image:
a. Select a 3×3 square window centered at $l(i,j)$.
b. Compute the average intensity value (l_{avg}) within the window.
c. Determine the maximum (l_{max}) and minimum (l_{min}) intensity values in the window.
Step 4: Utilize the modified Gaussian fuzzy membership functions to compute the membership values for each pixel within the window.
Step 5: Substitute the pixel of interest with the pixel value possessing the highest membership value.
Step 6: Execute Steps 3 to 5 for each pixel in the image.
Step 7: Output the denoised image.

approaches is determined using various picture quality metrics, including MSE (mean squared error), PSNR (peak signal to noise ratio), NAE (normalized absolute error), and SSIM (structural similarity). A number of actual US images are then used to test the suggested approach, which is assessed using the BRISQUE (blind/reference less image spatial quality evaluator) and NIQE (naturalness image quality evaluator) quality scores.

3.1 Experimental Result I: Single Noise Reduction with 'Lena' Image

To assess the performance of the proposed filter, we initially selected a 512×512-pixel grayscale 'Lena' image and added 10% speckle noise to it. The proposed filter, along with several existing filters like the Wiener filter, median filter, and triangular fuzzy filter, was applied to the noisy 'Lena' image. Figures 5 (i) and 5 (ii) display the original 'Lena' image and the tainted version, respectively. The results of various filtering techniques are shown in Figures 5 (iii)–5 (vi). A detailed comparison reveals that the implied Gaussian fuzzy filter offers superior sharpness compared to the others.

Table 1. Evaluation of image quality metrics applied to the standard 'Lena' test image.

Analytical Approach	MSE	PSNR	NAE
Wiener	20.03	35.38	0.0218
Median	29.80	34.03	0.0258
Fuzzy tri.	23.34	35.29	0.0288
Proposed	11.75	38.34	0.0179

Table 1 provides a quantitative comparison of the outcomes from Experiment I. In this context, lower values of MSE and NAE signify improved accuracy, whereas a higher PSNR indicates superior image quality. As evidenced in Table 1, the proposed filter achieves reduced MSE and NAE values alongside an enhanced PSNR, outperforming traditional filtering techniques.

3.2 Experimental Result II: Single Noise Reduction with 'Kingfisher' Image

To further assess the performance of the proposed filtering technique in noise reduction and image quality preservation, an additional test image, "Kingfisher" was utilized. Figure 6(i) presents the ground truth image, while Figure 6(ii) shows the noise-contaminated version. The denoised outputs achieved using the Wiener filter, median filter, fuzzy triangular filter, and the proposed method are displayed in Figures 6(iii) - 6(vi), respectively. The corresponding quality metrics for the restored images are provided in Table 2. Both subjective visual assessments and objective quantitative comparisons indicate that the proposed method outperforms existing techniques in effectively suppressing single and mixed noise.

Table 2. Analysis of image quality metrics for the 'Kingfisher' image.

Analytical Approach	MSE	PSNR	NAE
Wiener	23.89	35.09	0.0189
Median	36.55	34.76	0.0257
Fuzzy tri	28.80	34.78	0.0319
Proposed	**13.48**	**35.78**	**0.0187**

3.3 Experimental Result III: Mixed Noise Reduction with 'Apple' Image

In general, mixed noise exaggerates medical US visualizations. Misdiagnosis can result from mixed noise, which can make it challenging to comprehend US images. Therefore, it is important to remove or

Figure 5. Performance Comparison of Noise Reduction Filters on "Lena" Image: (i) Original image, (ii) Image affected by 10% speckle noise, (iii) Denoised using the wiener filter, (iv) Denoised using the median filter, (v) Denoised using the triangular fuzzy filter, and (vi) Denoised using the proposed fuzzy filter.

minimize the noise in US images to enhance their caliber and rendering them easier to interpret. Using a modified Gaussian fuzzy filter, it is expected that it can reduce the mixed noise while maintaining the perimeters and important highlights in the image. In that case, a noise-free 'Apple' image is taken as the source image as shown in Figure 7(i).

Figure 7(ii) displays the noisy version of the image. Figures 7(iii) to 7(vi) represent the filtered images derived from the Wiener filter, median filter, rank filter, fuzzy logic method with a triangular membership function, and the proposed method, respectively. Table 3 provides a comparison of various image quality metrics for the proposed and the compared methods. In this context, lower MSE and BRISQUE values indicate better image quality. However, higher PSNR and SSIM values indicate the best performance of a method which leads to the best image quality. The numerical comparison in Table 3 further supports the visual comparison, which shows that the suggested method generates a more distinct outcome than the other approaches.

Table 3. Performance comparison of different denoising approaches on a sample image.

Analytical Approach	MSE	PSNR	SSIM	BRISQUE
Wiener filter	72.57	28.76	0.581	35.03
Median filter	35.07	31.51	0.630	38.17
Rank filter	37.36	31.97	0.628	39.78
Fuzzy tri	28.77	32.51	0.627	41.98
Proposed	**20.56**	**35.73**	**0.849**	**35.48**

3.4 Experimental Result IV: Mixed Noise Reduction with 'Baboon' Image

Lastly, in the experiment IV the reference image is yet another "Baboon" picture without any noise. Figure 8 is a visual representation of the results of the image filtering experiment. It exhibits the noisy "Baboon" image as well as the filtered versions of the image generated via the Wiener filter, median filter, rank filter, triangular fuzzy logic method, and the proposed method.

This figure's objective is to visually compare the various filtering methods and their effectiveness in eliminating noise from the noisy image. Table 4

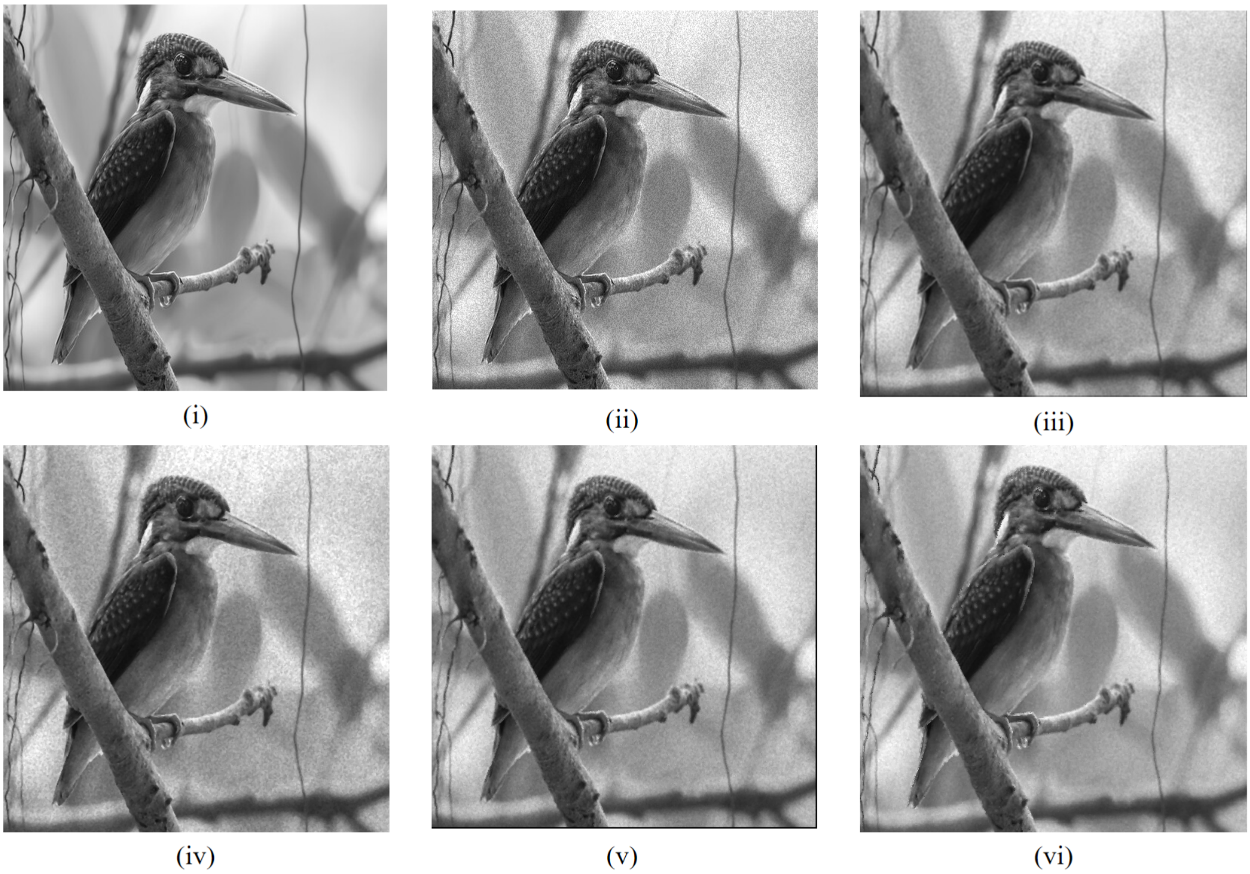


Figure 6. Performance Comparison of Noise Reduction Filters on "Kingfisher" Image: (i) Original Kingfisher image, (ii) Image corrupted by 20% speckle noise, (iii) Denoised using the wiener filter, (iv) Denoised using the median filter, (v) Denoised using the triangular fuzzy filter, and (vi) Denoised using the proposed fuzzy filter.

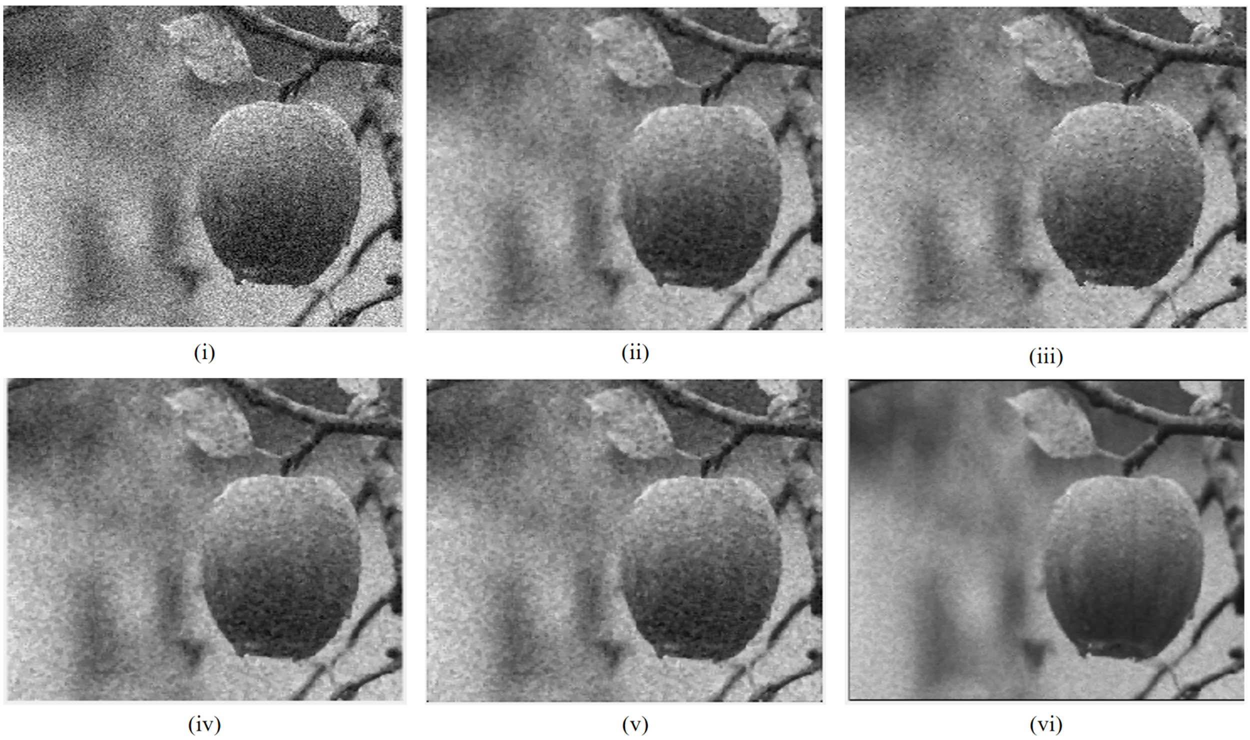


Figure 7. Performance Comparison of Noise Reduction Filters on "Apple" Image: (i) Original image, (ii) image corrupted by 20% speckle noise, (iii) Denoised using the wiener filter, (iv) Denoised using the median filter, (v) Denoised using the triangular fuzzy filter, and (vi) Denoised using the proposed fuzzy filter.

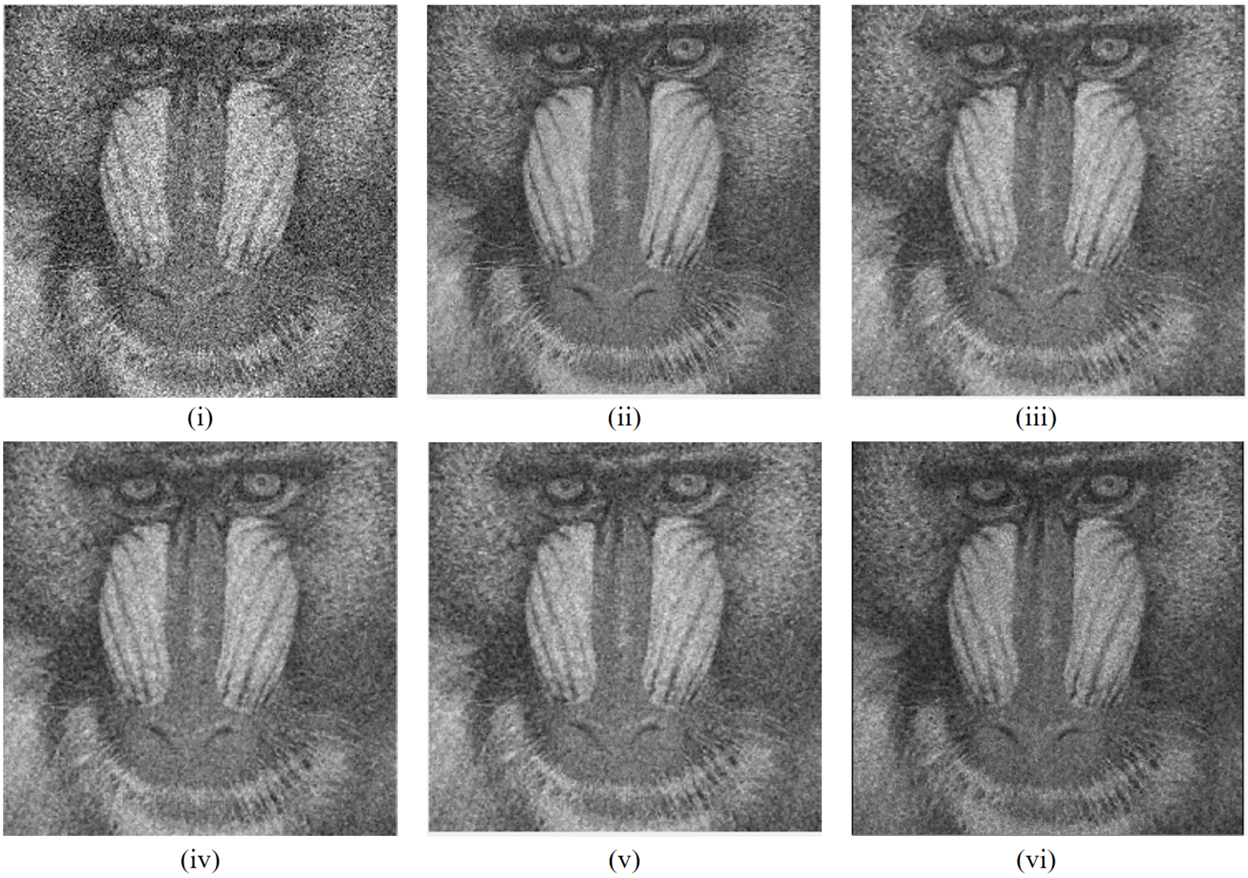


Figure 8. Performance Comparison of Noise Reduction Filters on "Baboon" Image: (i) noisy image, and image restored using, (ii) Denoised using the wiener filter, (iii) Denoised using the median filter, (iv) Denoised using the rank filter, (v) Denoised using the fuzzy triangular logical method, and (vi) Denoised using the proposed method.

is a summary of the results of the image filtering experiment and it contains numerical values of the image quality metrics. The suggested solution performs more proficiently than the other approaches for mixed noise, according to both quantitative and visual assessments.

Table 4. Comparison of image quality metrics for the 'Baboon' image.

Analytical Approach	MSE	PSNR	SSIM	BRISQUE
Wiener filter	53.76	29.48	0.625	20.76
Median filter	37.75	31.85	0.616	32.43
Rank filter	41.67	31.79	0.609	38.09
Fuzzy tri.	30.15	31.78	0.630	38.34
Proposed	**18.89**	**36.76**	**0.713**	**32.35**

3.5 Quantitative Analysis

This section describes some methods of evaluating the quality of image filtering using numerical metrics. The metrics mentioned MSE, PSNR, NAE, and SSIM are commonly used in image processing to evaluate the quality of filtered images. Let's first analytically describe these measures and then see how the filters work compare to one another.

3.5.1 Mean squared error (MSE)

Figure 9(i) shows the variation of the MSE values with respect to the speckle noise density for the proposed approach using the modified Gaussian fuzzy logic technique and the other three compared techniques. Figure 9(ii) is for mixed noise where the Gaussian noise is kept fixed but the speckle noise is varied. From the numerical comparison, it can be inferred that the MSE values for the proposed method are lower than the MSE values for the other four techniques, indicating that the recommended method has better performance in terms of noise elimination. This also suggests that the speculative method is more efficacious at removing noise from US images, resulting in a higher quality image and thus better diagnostic results.

3.5.2 Peak Signal to Noise Ratio (PSNR)

PSNR is another commonly used image quality metric that compares the peak signal strength of the original image to the peak signal strength of the denoised

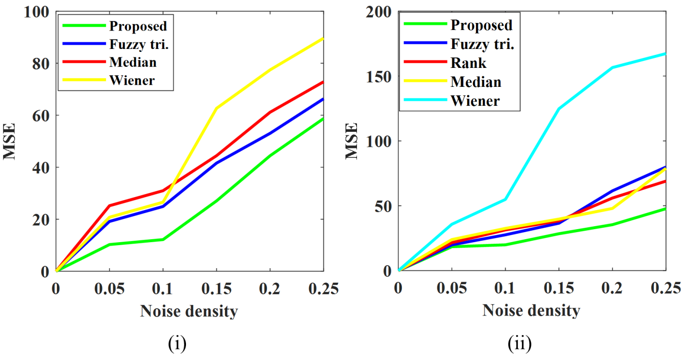


Figure 9. Performance analysis of MSE vs Noise Density on (i) 'Lena' image for single noise reduction, (ii) 'Apple' image for mixed noise reduction.

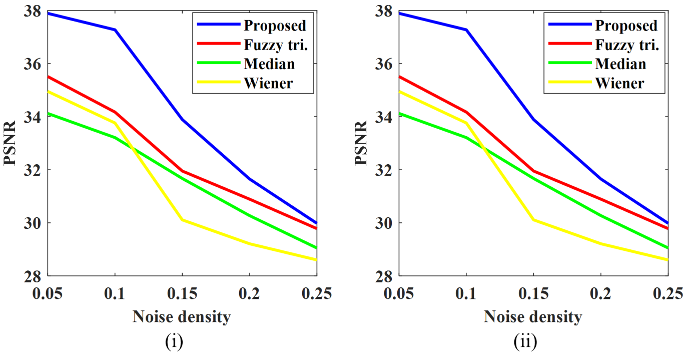


Figure 10. Performance analysis of PSNR vs Noise Density on (i) 'Lena' image for single noise reduction, (ii) 'Apple' image for mixed noise reduction.

image. Figure 10(i) shows the variation of the PSNR values with the variation of speckle noise density for the proposed approach and three other compared techniques. Figure 10(ii) is for mixed noise, where again the Gaussian noise is kept fixed but the speckle noise is varied. The visual quality improves with a greater PSNR value. According to the graph, the recommended approach has a greater PSNR value than the current approaches, suggesting that it is superior in terms of reducing noise.

3.6 Structural similarity (SSIM)

Figures 11(i) and 11(ii) show the dependency of SSIM on noise density with the 'Lena' and 'Apple' images for the suggested method and the compared methods. For all the tested datasets, the SSIM of the restored images obtained from the proposed method is always higher than that of the compared methods.

3.7 Performance Comparison on a Real Ultrasound Imaging Dataset

As a result, US imaging is increasingly being used as a real-time source of imaging in a wide range of clinical applications. The findings of experiments I, II, III, and

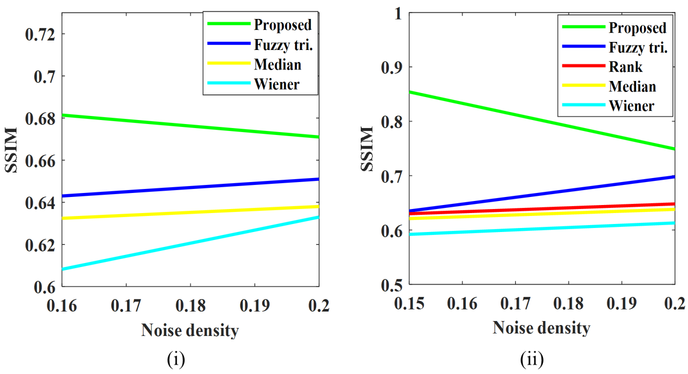


Figure 11. Performance analysis of SSIM vs Noise Density on (i) 'Lena' image for single noise reduction, (ii) 'Apple' image for mixed noise reduction.

IV reveal that, out of the four approaches examined in this work, the suggested approach prevails over the others by a large margin.

Therefore, the proposed approach is additionally implemented on actual US images, and the quality of the resulting images is assessed through blind image quality metrics. The dataset [24] refers to a collection of US images obtained from real patients. This dataset comprises various types of breast US images, of which three are selected at random for the purposes of the study. The attributes of an authentic US imaging dataset may differ based on the origin of the images (e.g. hospital, clinic, research facility), the type of US imaging modality used (e.g. abdominal, cardiac, obstetrical), and the demographics of the patient population (e.g. age, gender, health status). Figure 12 displays the clinical US visuals alongside their filtered counterparts utilizing the proposed and comparative methodologies.

Table 5 illustrates the statistical calculation of different methods utilizing the non-reference image quality metrics: blind/referenceless image spatial quality evaluator (BRISQE) and naturalness image quality evaluator (NIQE). For both metrics, lower scores indicate higher image quality. The positive impact of the suggested technique in terms of minimizing noise has been demonstrated by the lower scores it attains for all three images compared to the other techniques, as shown in Table 5. From the experimental findings shown so far, it can be concluded that the suggested modified Gaussian function-based filter outperforms to the traditional denoising techniques.

4 Conclusion

Denoising of US images is an important task in the diagnosis and treatment of breast cancer. It might

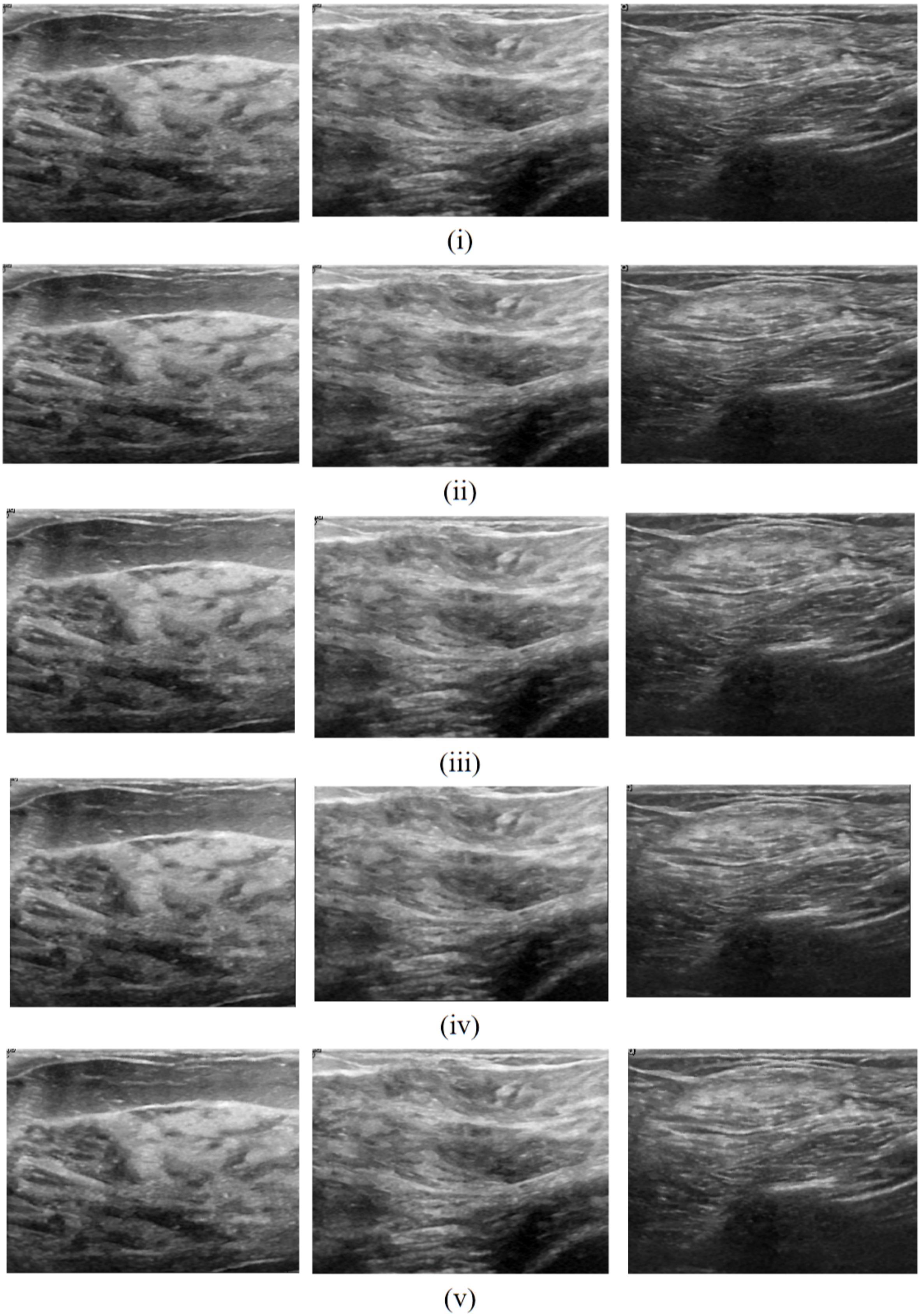


Figure 12. Evaluation of Noise Reduction Techniques on US Images dataset: (i) Original real US images, (ii) Image processed with the wiener filter, (iii) Image processed with the median filter, (iv) Image processed with the triangular fuzzy filter, and (v) Image processed with the proposed fuzzy filter.

Table 5. Experimental outcomes for real ultrasound images.

Analytical Approach	Image 1		Image 2		Image 3	
	BRISQUE	NIQE	BRISQUE	NIQE	BRISQUE	NIQE
Wiener	43.45	7.98	44.78	7.07	43.43	6.91
Median	44.76	8.87	45.09	8.76	43.92	7.15
Fuzzy tri	42.76	6.99	45.97	6.37	42.35	6.54
Proposed	**40.09**	**5.86**	**39.34**	**5.87**	**41.26**	**5.84**

be challenging to properly diagnose and treat breast cancer when speckle noise and Gaussian noise, two prevalent forms of noise, can be observed in US images. The use of a modified Gaussian fuzzy logic technique in US images is an efficient way for removing this type of noise. The presence of mixed noise can make it more challenging to remove noise from images as different types of single noise may require different methods for removal. US images with reduced noise can be easier to interpret and can reveal important details that may have been obscured by noise. Radiologists may find the recommended modified Gaussian fuzzy logic strategy for noise elimination from US visuals to be an invaluable tool for clinical diagnosis. Finally, the proposed scheme in this research is a relatively simple method to implement and has a lower or closer computational burden compared to other denoising methods. This can be an important consideration when working with medical images, as the denoising process should be fast and efficient to minimize the delay in the diagnosis and treatment of patients. Additionally, a simpler implementation with less computational time can be beneficial for real-time applications, where a delay in processing could have serious consequences. The simplicity and efficiency of this method make it a promising option for denoising US images in a clinical setting.

Data Availability Statement

Data will be made available on request.

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Conflicts of Interest

The authors declare no conflicts of interest.

Ethical Approval and Consent to Participate

Not applicable.

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