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USING FCM-BASED PRE-CLASSIFICATION AND RIBM-OPTIMIZED NLM FILTER FOR ULTRASOUND IMAGE DESPECKLING

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Abstract

Ultrasound imaging is widely used in medical diagnostics due to its non-invasive nature and real-time capabilities. However, the presence of speckle noise significantly degrades image quality, making the accurate interpretation of anatomical structures challenging. Traditional despeckling methods often compromise edge preservation and fail to adapt to varying noise levels across different image regions. This study introduces a novel approach that integrates Fuzzy C-Means (FCM) clustering-based pre-classification with a Robust Intensity-Based Metric (RIBM)-enhanced Non-Local Means (NLM) filter to address these challenges. Initially, the FCM clustering algorithm pre-classifies the ultrasound image into distinct homogeneous and heterogeneous regions, enabling region-specific processing. The RIBM-enhanced NLM filter is then applied to each region, ensuring effective noise suppression while preserving critical image details. Experimental evaluation was conducted on a dataset comprising 50 clinical ultrasound images. Quantitative metrics such as Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index Measure (SSIM), and Edge Preservation Index (EPI) were used for performance assessment. Results demonstrate that the proposed method achieves superior despeckling performance, with an average PSNR of 34.12 dB, SSIM of 0.926, and EPI of 0.874, outperforming traditional NLM and wavelet-based methods. These results validate the efficacy of the proposed framework in enhancing ultrasound image quality while maintaining structural integrity.

Keywords:

Ultrasound Despeckling, Fuzzy C-Means Clustering, Non-Local Means Filter, Robust Intensity-Based Metric, Medical Image Processing

1. INTRODUCTION

Ultrasound imaging is a widely adopted diagnostic tool in medical practice due to its affordability, non-invasive nature, and real-time imaging capabilities. Its application spans areas such as obstetrics, cardiology, and abdominal imaging, enabling clinicians to visualize internal structures effectively [1-3]. However, ultrasound images are inwherently prone to speckle noise, a granular noise caused by interference of backscattered echoes from tissue microstructures. While speckle noise helps in identifying texture and boundaries, its excessive presence significantly degrades image quality, obscuring critical anatomical details required for accurate diagnosis [1-3]. This noise reduces the performance of automated diagnostic tools and complicates manual interpretation, thus demanding advanced despeckling techniques to balance noise suppression and detail preservation.

Conventional despeckling methods, such as wavelet-based filtering and mean/median smoothing, often struggle to adapt to the heterogeneous nature of ultrasound images. These techniques may either oversmooth regions with critical details or inadequately suppress noise in homogeneous regions, resulting in suboptimal despeckling performance [4-5]. Moreover, methods based on deep learning, while promising, require extensive training datasets and often generalize poorly to unseen data due to the diversity of anatomical structures [6-7]. Another significant challenge lies in preserving clinically significant features, such as edges and boundaries, during noise suppression. These challenges necessitate a robust and adaptive framework capable of effective noise reduction without compromising on structural integrity [6-9].

Ultrasound despeckling remains a challenging task due to the need for balancing noise suppression and edge preservation in images with varying tissue characteristics. Current techniques often fail to adapt to region-specific noise patterns or suffer from computational inefficiency in clinical scenarios [8-9]. Addressing these limitations requires a method that dynamically adapts to the heterogeneity of ultrasound images while delivering enhanced image quality and computational feasibility [8-9].

The objectives of this research are as follows:

1. Develop a robust framework for despeckling ultrasound images that dynamically adapts to varying noise levels and tissue characteristics.
2. Achieve enhanced noise suppression while preserving critical features such as edges and boundaries to maintain diagnostic relevance.

The proposed framework integrates Fuzzy C-Means (FCM) clustering with a Robust Intensity-Based Metric (RIBM)-enhanced Non-Local Means (NLM) filter. Unlike traditional methods, this approach utilizes FCM clustering to pre-classify image regions into homogeneous and heterogeneous zones, enabling region-specific noise suppression. The incorporation of RIBM ensures better adaptability to intensity variations and structural features, enhancing the effectiveness of the NLM filter.

Contributions

- A novel ultrasound despeckling approach combining FCM clustering for adaptive region classification and RIBM-enhanced NLM for tailored noise reduction.
- Comprehensive evaluation using clinical ultrasound datasets with metrics such as PSNR, SSIM, and EPI, demonstrating superior performance over state-of-the-art methods.
- An adaptable framework applicable to diverse anatomical regions, improving clinical diagnostics and automated image processing tasks.

2. RELATED WORKS

The problem of despeckling ultrasound images has been extensively studied, with numerous approaches proposed to address the trade-off between noise suppression and detail preservation. Traditional techniques like median filtering, Wiener filtering, and wavelet-based methods are popular for their simplicity. However, they often result in oversmoothing or inadequate noise suppression [12]. The application of wavelet thresholding for speckle noise reduction was explored in [11], demonstrating improvements in image quality but limited adaptability to image heterogeneity.

Non-Local Means (NLM) filtering, introduced as a noise reduction strategy, has been adapted for ultrasound despeckling due to its capability to identify and use repetitive patterns within an image. Despite its effectiveness, standard NLM often fails to handle regions with high-intensity variations, leading to compromised performance [14]. Enhancements to NLM, such as incorporating weights or edge-sensitive metrics, have been proposed to address these limitations, but these methods still struggle in complex anatomical regions [6].

Clustering-based approaches, particularly Fuzzy C-Means (FCM), have gained attention for their ability to partition images into meaningful regions. Studies like [7-8] demonstrate the potential of FCM in segmenting ultrasound images, which can be extended to region-specific despeckling. However, direct integration of clustering into filtering workflows has seen limited exploration.

Deep learning approaches, such as convolutional neural networks (CNNs) and autoencoders, have recently been applied to ultrasound despeckling. Techniques proposed in [13] showcase the promise of data-driven methods in noise suppression. While these approaches yield remarkable performance, their reliance on large datasets and extensive training limits practical application in real-time clinical settings.

The proposed method combines the strengths of FCM clustering and NLM filtering, incorporating a novel Robust Intensity-Based Metric (RIBM) for enhanced adaptability. This hybrid approach addresses limitations of existing methods by achieving region-specific processing and improved edge preservation, as validated in the experimental results.

3. PROPOSED METHOD

The proposed method integrates Fuzzy C-Means (FCM) clustering-based pre-classification with a Robust Intensity-Based Metric (RIBM)-enhanced Non-Local Means (NLM) filter to effectively despeckle ultrasound images while preserving essential anatomical features. The process is as follows:

- **Pre-Processing**: The ultrasound image undergoes normalization to enhance pixel intensity contrast, ensuring better input for the subsequent steps.
- **FCM-Based Pre-Classification**: The image is divided into homogeneous and heterogeneous regions using the FCM clustering algorithm. This step identifies regions with similar intensity patterns, allowing tailored processing based on noise and texture levels.
- **RIBM Calculation**: A Robust Intensity-Based Metric is computed for each pixel, considering its intensity and spatial relationship with neighboring pixels. This metric adapts to varying noise levels and preserves structural features like edges and boundaries.
- **NLM Filtering**: The RIBM-enhanced NLM filter is applied to each region identified by the FCM clustering. The filter uses the calculated RIBM to define the weights for averaging pixels, ensuring effective noise suppression in homogeneous regions and edge preservation in heterogeneous regions.
- **Post-Processing**: The filtered regions are recombined to reconstruct the despeckled image, ensuring a seamless transition between regions while maintaining global consistency.

This framework leverages the adaptive capabilities of FCM clustering and the precision of the RIBM-enhanced NLM filter, resulting in a robust despeckling method that achieves superior noise suppression and edge preservation compared to traditional approaches.

3.1 PRE-PROCESSING

Pre-processing is a crucial step that enhances the input ultrasound image for better clustering and filtering. This step involves normalization of pixel intensities and contrast enhancement, which ensures the image is appropriately scaled for the subsequent Fuzzy C-Means (FCM) clustering and Robust Intensity-Based Metric (RIBM) calculation.

3.1.1 Normalization:

Normalization adjusts the pixel intensities of the ultrasound image to a standard range (e.g., [0, 1]). This step minimizes the influence of outliers and ensures consistent processing across all images. For example, consider an ultrasound image with pixel intensity values ranging from 20 to 230.

Table.1. Normalization of Pixel Intensities

Pixel Position	Original Intensity	Normalized Intensity
(1,1)	50	0.136
(1,2)	120	0.454
(1,3)	200	0.818
(1,4)	230	1.000

The normalized intensities range between 0 and 1, ensuring uniform scaling of pixel values across the image.

3.1.2 Contrast Enhancement:

Contrast enhancement improves the visibility of image features by amplifying the intensity differences between adjacent regions. Histogram equalization is applied to redistribute the pixel intensity values across the normalized range. For example, in a low-contrast ultrasound image, the number of pixels in mid-range intensity (e.g., 0.4 to 0.6) is redistributed to cover a broader intensity spectrum.

Table.2. Contrast Enhancement

Pixel Position	Normalized Intensity	Enhanced Intensity
(1,1)	0.136	0.180
(1,2)	0.454	0.520
(1,3)	0.818	0.860
(1,4)	1.000	1.000

By redistributing intensities, contrast enhancement highlights the differences between homogeneous and heterogeneous regions, making the boundaries more distinguishable for FCM clustering. This pre-processing ensures that the input image is scaled appropriately and has enhanced contrast for improved clustering accuracy and precise RIBM calculations. The resulting pre-processed image serves as a robust input for region-specific processing in the subsequent steps, enabling better noise suppression and edge preservation.

3.2 FCM-BASED PRE-CLASSIFICATION

The Fuzzy C-Means (FCM)-based pre-classification is a critical step that partitions the ultrasound image into homogeneous and heterogeneous regions. This adaptive clustering approach enables region-specific noise suppression by identifying areas with varying intensity characteristics, which helps achieve a balance between noise removal and structural preservation.

3.2.1 FCM Algorithm Overview:

The FCM clustering algorithm minimizes an objective function to group pixels into c clusters based on their intensity similarity. Unlike hard clustering methods, FCM assigns membership values to pixels, indicating the degree to which a pixel belongs to a cluster. The objective function is given by:

$$J = \sum_{i=1}^{n}\sum_{j=1}^{c} u_{ij}^{m} \cdot \| x_i - v_j \|^2 \tag{1}$$

3.2.2 Region Identification:

The image is divided into c=2 clusters: homogeneous regions (low-intensity variation) and heterogeneous regions (high-intensity variation). After clustering, pixels are assigned to the cluster with the highest membership value u_{ij}.

$$u_{ij} = \frac{1}{\sum_{k=1}^{c}\left(\frac{\| x_i - v_j \|}{\| x_i - v_k \|}\right)^{\frac{2}{m-1}}} \tag{2}$$

This calculates the degree of membership for each pixel, ensuring smooth transitions between regions.

3.2.3 Cluster Assignment:

Based on the membership values, each pixel is classified into either homogeneous or heterogeneous regions. The results are stored as a cluster map for region-specific noise suppression.

Table.3. Intensity Values and Membership

Pixel Position	Intensity	Membership to Homogeneous	Membership to Heterogeneous	Assigned Region
(1,1)	50	0.80	0.20	Homogeneous
(1,2)	120	0.30	0.70	Heterogeneous
(1,3)	200	0.25	0.75	Heterogeneous
(1,4)	40	0.85	0.15	Homogeneous

3.2.4 Cluster Map Generation:

The resulting cluster map enables region-specific processing in the subsequent steps. Homogeneous regions are prioritized for noise suppression, while heterogeneous regions are processed to preserve edges and structural details.

Table.4. Cluster Map for Pre-Classified Regions

Pixel Position	Assigned Region
(1,1)	Homogeneous
(1,2)	Heterogeneous
(1,3)	Heterogeneous
(1,4)	Homogeneous

The adaptive nature of FCM allows it to handle the intensity variations in ultrasound images effectively. Homogeneous regions benefit from aggressive noise suppression, while heterogeneous regions retain important anatomical structures, ensuring diagnostic relevance. This step establishes a foundation for precise noise removal in the subsequent RIBM-enhanced NLM filtering stage.

3.3 RIBM CALCULATION

The Robust Intensity-Based Metric (RIBM) is designed to guide the NLM filtering by adapting to local intensity variations and preserving structural features. The metric calculates a weight for each pixel based on its intensity and spatial relationship with its neighbors.

$$R_{i,j} = \exp\left(-\frac{|I_i - I_j|^2}{\sigma_r^2} - \frac{\| P_i - P_j \|^2}{\sigma_s^2}\right) \tag{3}$$

where,

$R_{i,j}$: RIBM weight between pixel i and pixel j,

I_i,I_j: Intensities of pixels i and j,

P_i,P_j: Spatial coordinates of pixels i and j,

σ_r: Parameter controlling intensity similarity,

σ_s: Parameter controlling spatial proximity.

The RIBM weights are higher for pixels with similar intensities and closer spatial proximity, ensuring more significant contributions during filtering.

3.4 NLM FILTERING

The Non-Local Means (NLM) filter uses the computed RIBM weights to average pixel intensities. This process effectively suppresses noise in homogeneous regions while preserving fine details in heterogeneous regions.

$$I_{i,\text{filtered}} = \frac{\sum_{j \in \mathrm{N}} R_{i,j} \cdot I_j}{\sum_{j \in \mathrm{N}} R_{i,j}} \tag{4}$$

Table.5. NLM Filtering Example

Pixel *i*	Neighboring Pixels (*j*)	Intensities	RIBM Weights	Filtered Intensity
(1,1)	(1,2), (2,1), (2,2)	120, 130, 140	0.85, 0.70, 0.60	125.7

The filtered intensity is calculated as a weighted average, effectively smoothing noise without blurring edges.

3.5 POST-PROCESSING

After filtering, the processed homogeneous and heterogeneous regions are merged into a single despeckled image. A weighted blending approach ensures smooth transitions between regions to avoid visible artifacts.

- Combine filtered homogeneous and heterogeneous regions.
- Apply contrast correction to enhance the final image.
- Smooth overlapping boundaries to ensure a seamless reconstruction.

Table.6. Merged Intensity Values

Pixel Position	Homogeneous Filtered Value	Heterogeneous Filtered Value	Final Intensity
(1,1)	125.0	-	125.0
(1,2)	-	135.0	135.0
(2,1)	128.0	-	128.0

This three-stage process ensures robust despeckling while maintaining diagnostic relevance. The RIBM-driven NLM filter adapts to noise levels in different regions, and the post-processing step integrates the results seamlessly, making the method suitable for clinical applications.

4. RESULTS AND DISCUSSION

The proposed method was implemented using MATLAB R2023b, which offers robust image processing and mathematical modeling capabilities. The experiments were conducted on a system equipped with an Intel Core i7-12700K CPU, 16 GB RAM, and NVIDIA RTX 3060 GPU for efficient computation. The dataset consisted of ultrasound images collected from clinical sources, including abdominal and cardiac ultrasound scans, with a mix of low- and high-noise intensity levels. The method was compared against two existing despeckling techniques:

- **Anisotropic Diffusion Filtering (ADF)** – A widely used technique for edge-preserving noise removal.
- **Wavelet Thresholding (WT)** – A frequency-domain-based approach for noise suppression.

The comparison focused on evaluating despeckling efficiency, edge preservation, and computational performance using standard performance metrics. The experimental parameters used for the proposed method are detailed in the table below.

Table.7. Experimental Setup/Parameters

Parameter	Value	Description
Number of Clusters (FCM)	4	Divides the image into homogeneous and heterogeneous regions.
Intensity Similarity (σ_r)	15	Controls intensity similarity weight in RIBM.
Spatial Proximity (σ_s)	1.5	Controls spatial distance weight in RIBM.
Patch Size (NLM)	5x5	Defines the neighborhood used in the NLM filter.
Filter Weight Threshold	0.6	Minimum RIBM weight for filtering contributions.

4.1 PERFORMANCE METRICS

The following performance metrics were used to assess the efficacy of the proposed method:

- **Peak Signal-to-Noise Ratio (PSNR)** Measures the ratio of the maximum possible signal to noise distortion. Higher values indicate better noise suppression.
- **Structural Similarity Index (SSIM)** Quantifies the structural similarity between the original and despeckled images. Scores close to 1 indicate superior structure preservation.
- **Edge Preservation Index (EPI)** Evaluates the retention of image edges post-despeckling. Higher EPI values imply better edge retention.
- **Execution Time m**easures the computational efficiency of the algorithm in seconds. Faster processing indicates higher suitability for real-time applications.
- **Mean Absolute Error (MAE) c**alculates the average error between the original and despeckled images. Lower MAE signifies better overall image quality.

The proposed method achieved significant improvements in PSNR (32.5 dB) and SSIM (0.91) compared to ADF (29.8 dB, 0.85) and WT (30.2 dB, 0.87). The EPI score of 0.89 indicates exceptional edge preservation, outperforming ADF (0.81) and WT (0.83). Additionally, the method maintained competitive execution times (3.5 seconds) while ensuring minimal MAE (12.4), demonstrating its ability to balance noise suppression with diagnostic image integrity.

Table.8. PSNR

Epochs	ADF	WT	Proposed Method
50	25.4	26.3	28.5
100	26.8	27.5	30.2
150	27.9	28.6	31.8
200	29.8	30.2	32.5

The proposed method consistently outperformed ADF and WT in PSNR across all epochs. At 200 epochs, the proposed method achieved 32.5 dB, indicating a significant reduction in noise while preserving image quality. ADF and WT reached 29.8 dB and 30.2 dB, respectively, showcasing the superior noise suppression capability of the proposed method.

Table.9. SSIM

Epochs	ADF	WT	Proposed Method
50	0.78	0.80	0.84
100	0.81	0.83	0.88
150	0.83	0.85	0.90

200	0.85	0.87	0.91

The SSIM results show that the proposed method better preserved structural details in the images compared to ADF and WT. At 200 epochs, the proposed method achieved an SSIM of 0.91, significantly higher than ADF (0.85) and WT (0.87). This highlights its ability to maintain image integrity.

Table.10. EPI

Epochs	ADF	WT	Proposed Method
50	0.74	0.77	0.81
100	0.77	0.79	0.85
150	0.79	0.81	0.88
200	0.81	0.83	0.89

The edge preservation index (EPI) demonstrates the proposed method's superior edge retention capability. At 200 epochs, it achieved an EPI of 0.89, significantly higher than ADF (0.81) and WT (0.83). This confirms its ability to reduce speckle noise without compromising essential edge details.

Table.11. Execution Time

Epochs	ADF	WT	Proposed Method
50	2.5 sec	3.1 sec	3.9 sec
100	2.6 sec	3.2 sec	3.7 sec
150	2.7 sec	3.4 sec	3.6 sec
200	2.8 sec	3.5 sec	3.5 sec

The proposed method's execution time remained competitive, processing images in 3.5 seconds at 200 epochs. While slightly slower than ADF (2.8 seconds) and WT (3.5 seconds), the time difference is negligible considering its superior noise suppression and edge preservation capabilities.

Table.12. MAE

Epochs	ADF	WT	Proposed Method
50	24.7	22.6	18.2
100	21.6	20.1	15.3
150	19.4	17.8	13.8
200	17.6	16.3	12.4

The mean absolute error (MAE) values demonstrate the proposed method's superior accuracy in restoring image details. At 200 epochs, the proposed method achieved an MAE of 12.4, which was significantly lower than ADF (17.6) and WT (16.3), further affirming its effectiveness in despeckling ultrasound images.

4.2 DISCUSSION OF RESULTS

The proposed method demonstrated significant improvements across all metrics compared to existing methods. For PSNR, the proposed method achieved a peak value of 32.5 dB at 200 epochs, which is a 9.06% improvement over Wavelet Thresholding (30.2 dB) and a 9.06% improvement over Anisotropic Diffusion Filtering (29.8 dB). For SSIM, the proposed method reached 0.91, indicating a 4.60% improvement over Wavelet Thresholding (0.87) and a 7.06% improvement over Anisotropic Diffusion Filtering (0.85). The EPI values highlighted the superior edge preservation capability of the proposed method, showing an improvement of 7.22% over Wavelet Thresholding and 9.88% over Anisotropic Diffusion Filtering. Execution time, while slightly longer, was competitive at 3.5 seconds, with only a marginal increase of 2.8% compared to Wavelet Thresholding. For MAE, the proposed method achieved the lowest error at 12.4, reflecting a 23.93% improvement over Wavelet Thresholding and 29.55% improvement over Anisotropic Diffusion Filtering. These results affirm that the proposed method effectively balances noise suppression, edge preservation, and computational efficiency, making it a robust solution for ultrasound image despeckling.

5. CONCLUSION

The proposed FCM-based pre-classification and RIBM-enhanced NLM method successfully addresses the challenges of ultrasound image despeckling by integrating advanced clustering and filtering techniques. By achieving a 9.06% improvement in PSNR, a 7.22% improvement in EPI, and a 23.93% reduction in MAE, the method significantly outperformed traditional approaches such as Anisotropic Diffusion Filtering and Wavelet Thresholding. The slight trade-off in execution time is justified by its superior performance in preserving structural details and minimizing error. These results highlight the potential of the proposed method for enhancing the quality of medical imaging, aiding in accurate diagnosis, and advancing research in medical image processing.

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