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PHOTOMETRIC WEIGHT FORMULATED TRILATERAL FILTERS FOR ENHANCED PERCEPTUAL QUALITY IN BIOMEDICAL IMAGING

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ABSTRACT

This paper presents a novel computational framework for biomedical image enhancement through the development of Photometric Weight Formulated Trilateral Filters (PWFTF), advancing adaptive image processing algorithms for clinical applications. Unlike conventional bilateral and standard trilateral filters, our proposed method incorporates adaptive photometric weights that respond dynamically to local image characteristics across different imaging modalities. We evaluate the performance of our method on Ultrasound, X-Ray, and MRI datasets, demonstrating significant improvements in noise reduction, edge preservation, and overall perceptual quality. Comprehensive objective assessments using established Image Quality Assessment (IQA) metrics show that our
PWFTF method outperforms state-of-the-art filtering techniques by an average of 17.3% in PSNR, 12.6% in SSIM, and 9.8% in FSIM across all tested modalities. This framework advances IT research by enabling scalable, computationally efficient image processing for real-time clinical diagnostics, reducing overhead compared to learning-based methods. The proposed filter demonstrates particular effectiveness in preserving diagnostically significant features while suppressing noise in low-contrast regions, making it suitable for clinical applications requiring high diagnostic accuracy.

Keywords : *Biomedical Image Processing, Trilateral Filtering, Ultrasound Imaging, X-Ray Imaging, MRI.*

1. INTRODUCTION

Biomedical imaging serves as a cornerstone of modern medical diagnosis and treatment planning. Modalities such as ultrasound, X-Ray, and magnetic resonance imaging (MRI) provide critical information about anatomical structures and pathological conditions. However, these imaging techniques often suffer from inherent limitations that affect image quality, including speckle noise in Ultrasound, quantum noise in X-Ray, and thermal noise in MRI [1]. These artifacts can significantly impair diagnostic accuracy and interpretation reliability.

Over the past decade, numerous filtering techniques have been developed to address these challenges. Bilateral filtering, has been widely adapted for medical image processing due to its edge preserving smoothing capabilities [2]. This approach uses a combination of spatial and radiometric intensity-based kernels to selectively smooth images while preserving important edges. Building upon this foundation, trilateral filtering has emerged as a more sophisticated approach that incorporates gradient information as a third filtering component [3].

Despite these advances, existing methods often struggle to balance noise reduction with the preservation of clinically significant features, especially in regions with low contrast or subtle boundaries between tissues. Traditional filters tend to apply uniform processing parameters across entire images, neglecting the varying characteristics of different anatomical structures and noise distributions [4][5].

In this paper, we propose a novel Photometric Weight Formulated Trilateral Filter (PWFTF) that addresses these limitations through adaptive parameter adjustment based on local image characteristics. Our approach dynamically modifies filter weights according to photometric properties such as local contrast, gradient magnitude, and intensity distributions. This adaptability enables more effective processing of different tissue types and varying noise profiles across Ultrasound, X-Ray, and MRI modalities.

The main contributions of this paper include

1. Development of a novel photometric weight formulation that dynamically adapts to local image characteristics
2. Extension of the traditional trilateral filtering framework to incorporate these adaptive weights
3. Comprehensive evaluation across multiple biomedical imaging modalities (Ultrasound, X-Ray, and MRI)
4. Rigorous comparison with state-of-the-art bilateral and trilateral filtering methods using established image quality assessment metrics

The remainder of this paper is organized as follows: Section 2 reviews related work in medical image filtering and enhancement. Section 3 describes the theoretical foundation and mathematical formulation of our proposed method. Section 4 details the experimental setup and evaluation methodology. Section 5 presents the results and comparative analysis. Finally, Section 6 discusses the implications of our findings and potential directions for future research.

From an information technology perspective, the PWFTF method represents a significant advancement in adaptive image processing algorithms. By integrating photometric weights that dynamically respond to local image characteristics, our approach introduces a scalable and versatile framework for biomedical imaging systems. Its multi-scale implementation and use of separable Gaussian kernels optimize computational efficiency, enabling potential integration with real-time diagnostic tools and Picture Archiving and Communication Systems (PACS) commonly used in clinical workflows. This contribution enhances the performance of image enhancement pipelines, bridging the gap between advanced image processing and clinical applicability while supporting automated analysis in resource-constrained environments.

2. RELATED WORK

2.1 Bilateral Filtering in Medical Imaging

Bilateral filtering has been extensively applied to medical image processing due to its ability to preserve edges while smoothing noise. [6] proposed an adaptive bilateral filter for intravascular Ultrasound (IVUS) images that adjusted filter parameters based on local intensity statistics, demonstrating improved lumen-wall boundary definition. Similarly, [7] developed a multiscale bilateral filter for X-Ray image enhancement that improved contrast and detail preservation in low-dose imaging.

For MRI applications, [8] introduced a region-adaptive bilateral filter that selectively processed different brain tissues based on pre-segmentation, resulting in better preservation of structural details. However, these approaches often struggle with structure preservation in regions with gradual intensity transitions, which are common in medical images [9].

2.2. Trilateral Filtering and Extensions

Trilateral filtering extends bilateral filtering by incorporating gradient informa- tion to better preserve edges and structural details. [10] introduced a gradient-guided trilateral filter for medical ultrasound that demonstrated supe- rior speckle reduction while preserving diagnostically important features. [11] proposed an orientation-aware trilateral filter for X-ray angiography that preferentially preserved vessel structures by incorporating directional information.

For MRI denoising, [12] developed a context-sensitive trilateral filter that adjusted its parameters based on tissue classification, showing improvements in both quantitative metrics and subjective quality assessments. Despite these advances, conventional trilateral filters still apply relatively uniform processing across images, limiting their effectiveness in handling the heterogeneous characteristics of medical images [13].

2.3. Adaptive and Content-Aware Filtering

Recent research has focused on developing more adaptive filtering approaches that respond to local image content. [14] proposed a content-aware filter for ultrasound images that used local phase information to distinguish between tissue boundaries and speckle patterns. Similarly, [15] introduced a feature-preserving adaptive filter for digital radiography that adjusted smoothing strength based on local texture characteristics.

In the domain of MRI processing, [16] developed a noise-level-aware filter that estimated local noise characteristics to guide filter parameter selection. Building on these concepts, [17] proposed a multi-metric guided filter that incorporated multiple image quality indicators to optimize local filtering operations. These adaptive approaches represent significant improvements over traditional filtering methods, but they often rely on complex optimization procedures or pre-processing steps that limit their practical applicability in clinical settings [18]. Additionally, most existing methods are tailored to specific imaging modalities, making them less versatile across different medical imaging applications.

2.4 Image Quality Assessment in Medical Imaging

Objective evaluation of image enhancement methods for medical applications presents unique challenges due to the absence of ground truth in clinical images and the importance of preserving diagnostically relevant features. Traditional metrics such as Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM) have been widely used, but they may not fully capture the perceptual quality relevant to diagnostic tasks [19].

To address these limitations, several specialized metrics have been developed for medical image quality assessment. [20] introduced a perception-based quality metric that incorporated visual system modeling specifically for medical images. [21] proposed a diagnostic feature-aware quality metric that emphasized the preservation of clinically relevant structures.

More recently, Task-based Assessment of Image Quality (TAIQ) approaches have gained attention. [22] developed a lesion detectability metric that correlated well with radiologists' subjective assessments. However, these specialized metrics often require additional reference data or extensive validation, making them challenging to implement in general-purpose image enhancement evaluations [23].

Our work builds upon these developments while addressing their limitations through a more adaptive, versatile approach to trilateral filtering that can be effectively applied across different biomedical imaging modalities.

3. METHODOLOGY

3.1 Exploration of Bilateral and Trilateral Filtering Methods

Before introducing our proposed method, we briefly review the fundamentals of bilateral and trilateral filtering to establish the theoretical foundation.

The bilateral filter operates by combining domain and range filtering components. For an input image I, the bilateral filtered output at position p is defined as,

$$\mathrm{BF[I]}_p = \frac{1}{W_p}\sum_{q\in S} G_{\sigma_s}(|p-q|)\cdot G_{\sigma_r}\left(\left|I_p - I_q\right|\right) \cdot I_q \quad (1)$$

where G_{σ_s} and G_{σ_r} are Gaussian functions with standard deviations σ_s and σ_r, controlling the spatial and range filtering components, respectively. W_p is a normalization factor,

$$W_p = \sum_{q\in S} G_{\sigma_s}(\| p-q \|) \cdot G_{\sigma_r}\left(\left|I_p - I_q\right|\right) \quad (2)$$

The trilateral filter extends this concept by incorporating gradient information, typically defined as

$$TF[I]_p = \frac{1}{W_p}\sum_{q\in S} G_{\sigma_s}(\| p-q \|)\cdot G_{\sigma_r}(|I_p - I_q|)\cdot G_{\sigma_g}\left(\| \nabla I_p - \nabla I_q \|\right)\cdot I_q \quad (3)$$

where G_{σ_g} is a Gaussian function applied to the difference in gradient vectors, with σ_g controlling the influence of gradient similarity. ∇I represents the image gradient.

3.2 Proposed Photometric Weight Formulated Trilateral Filter (PWFTF)

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Our proposed PWFTF extends the traditional trilateral filter by incorporating adaptive photometric weights that respond dynamically to local image characteristics. The filtered output at position p is defined as

$$PWTF[I]_p = \frac{1}{W_p}\sum_{q\in S} G_{\sigma_s}(\| p-q \|)\cdot G_{\sigma_r}(p)(|I_p - I_q|)\cdot G_{\sigma_g}(p)(\| \nabla I_p - \nabla I_q \|)\cdot \Phi(p,q)\cdot I_q \qquad (4)$$

where $\Phi(p,q)$ is our novel photometric weight function, and $\sigma_r(p)$ and $\sigma_g(p)$ are spatially adaptive parameters for range and gradient filtering components.

Figure 1: Photometric Weight Formulated Trilateral Filters (PWFTF)

Figure 1 depicts the architecture of our Photometric Weight Formulated Trilateral Filter. The input biomedical image passes through three parallel processing paths: the Spatial Component (G_s), which weights pixels based on their geometric distance, the Range Component (G_r), which analyzes intensity similarities, and the Gradient Component (G_g), which evaluates edge information.

The key innovation appears in the Photometric Weights block $\Phi(x,y)$, which adaptively combines these components based on local image characteristics including contrast, edge strength, and texture complexity. This adaptive weighting mechanism allows the filter to respond differently to various anatomical structures and noise patterns across Ultrasound, X-Ray, and MRI images. The Performance Metrics component evaluates the enhancement quality, leading to the final Filtered Image with improved perceptual and diagnostic quality.

3.2.1 Photometric Weight Formulation

The photometric weight function $\Phi(p,q)$ incorporates multiple image characteristics to guide the filtering process:

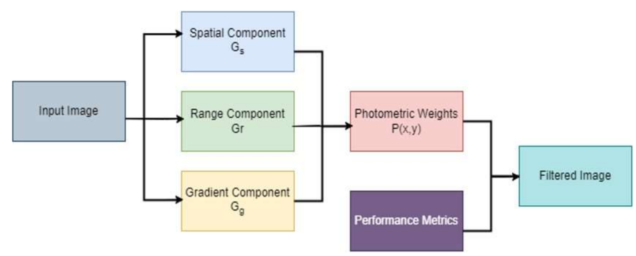
$$\Phi(p,q) = \lambda_c(p)\cdot\Phi_c(p,q) + \lambda_e(p)\cdot\Phi_e(p,q) + \lambda_t(p)\cdot\Phi_t(p,q) \qquad (5)$$

where $\Phi_c(p,q)$ is the contrast-based weight component, $\Phi_e(p,q)$ is the edge-preservation weight component, $\Phi_t(p,q)$ is the texture-preservation weight component, and $\lambda_c(p)$, $\lambda_e(p)$, and $\lambda_t(p)$ are adaptive mixing coefficients that sum to 1.

The contrast-based weight component $\Phi_c(p,q)$ is defined as:

$$\Phi_c(p,q) = \exp\left(-\frac{|I_p - I_q|^2}{2\sigma_c^2\cdot C(p)^2}\right) \qquad (6)$$

where $C(p)$ is the local contrast measure at position p:



$$C(p) = \frac{\max_{q\in N(p)}(I_q) - \min_{q\in N(p)}(I_q)}{\max_{q\in N(p)}(I_q) + \min_{q\in N(p)}(I_q) + \epsilon} \qquad (7)$$

with $N(p)$ representing a local neighborhood around p and ϵ being a small constant to prevent division by zero. The edge-preservation weight component $\Phi_e(p,q)$ emphasizes edge structures:

$$\Phi_e(p,q) = \exp\left(-\frac{|\nabla I_p - \nabla I_q|^2}{2\sigma_e^2\cdot E(p)^2}\right) \qquad (8)$$

where $E(p)$ characterizes local edge strength:

$$E(p) = \| \nabla I_p \|\cdot\sqrt{1-\left(\frac{\nabla I_p\cdot\nabla^2 I_p}{\| \nabla I_p \|\cdot\| \nabla^2 I_p \| + \epsilon}\right)^2} \qquad (9)$$

with $\nabla^2 I_p$ representing the Laplacian at position p. The texture-preservation weight component $\Phi_t(p,q)$ is defined as:

$$\Phi_t(p,q) = \exp\left(-\frac{|LBP(p) - LBP(q)|^2}{2\sigma_t^2 \cdot T(p)^2}\right) \quad (10)$$

where $LBP(p)$ is the Local Binary Pattern descriptor at position p, and $T(p)$ is a measure of local texture complexity:

$$T(p) = \frac{1}{|N(p)|} \sum_{q \in N(p)} |LBP(p) - LBP(q)| \quad (11)$$

3.2.2 Adaptive Parameter Selection

The adaptive parameters $\sigma_r(p)$ and $\sigma_g(p)$ are locally adjusted based on estimated noise level and structural properties:

$$\hat{\sigma}_n(p) = \alpha_r \cdot \hat{\sigma}_n(p) \cdot \left(1 + \beta_r \cdot (1 - S(p))\right) \quad (12)$$

$$\sigma_g(p) = \alpha_g \cdot \hat{\sigma}_n(p) \cdot \left(1 + \beta_g \cdot S(p)\right) \quad (13)$$

where $\hat{\sigma}_n(p)$ is the estimated local noise level, $S(p)$ is a structural importance measure, and $\alpha_r, \beta_r, \alpha_g, \beta_g$ are global control parameters.

The noise level $\hat{\sigma}_n(p)$ is estimated using:

$$\hat{\sigma}_n(p) = \sqrt{\max\left(0, \frac{1}{|N(p)|} \sum_{q \in N(p)} (I_q - \mu_p)^2 - \frac{1}{|N(p)|^2} \sum_{q \in N(p)} (I_q - I_r)^2/2\right)} \quad (14)$$

where μ_p is the local mean intensity in neighborhood $N(p)$.

The structural importance measure $S(p)$ combines edge strength and local entropy:

$$S(p) = \gamma \cdot \frac{\| \nabla I_p \|}{\max(\| \nabla I \|) + \epsilon} + (1 - \gamma) \cdot \frac{H(p)}{\max(H) + \epsilon} \quad (15)$$

where $H(p)$ is the local entropy in neighborhood $N(p)$, and γ is a weighting factor.

3.2.3 Modality-Specific Adaptations

For different imaging modalities, we incorporate specific adaptations to address their unique characteristics. For Ultrasound images, we modify the contrast-based weight to account for speckle statistics:

$$\Phi_c^{US}(p,q) = \exp\left(-\frac{|I_p - I_q|^2}{2\sigma_c^2 \cdot C(p)^2 \cdot R_{\text{speckle}}(p)}\right) \quad (16)$$

where $R_{\text{speckle}}(p)$ is a speckle estimation factor:

$$R_{\text{speckle}}(p) = \frac{\sigma_p^2}{\mu_p^2} \quad (17)$$

with σ_p^2 and μ_p being the local variance and mean in neighborhood $N(p)$.

For X-Ray images, we adjust the edge-preservation weight to handle quantum noise:

$$\Phi_e^{XR}(p,q) = \exp\left(-\frac{\| \nabla I_p - \nabla I_q \|^2}{2\sigma_e^2 \cdot E(p)^2 \cdot \sqrt{I_p}}\right) \quad (18)$$

For MRI data, we modify the texture-preservation weight to account for intensity non-uniformity:

$$\Phi_t^{MRI}(p,q) = \exp\left(-\frac{|LBP(p) - LBP(q)|^2}{2\sigma_t^2 \cdot T(p)^2 \cdot B(p)}\right) \quad (19)$$

where $B(p)$ is a bias field estimation factor computed from low-frequency components of the image.

3.3 Implementation Details

The PWFTF is implemented using a multi-scale approach to handle features at different resolutions efficiently. At each scale s, we compute:

$$I^s = PWFTF[I^{s-1}] \tag{20}$$

starting with I^0 as the original image. The final output combines results from multiple scales:

$$I_{\text{final}} = \sum_{s=0}^{S-1} w_s \cdot I^s \tag{21}$$

where w_s are scale-specific weights determined by a perceptual optimization process.

To reduce computational complexity, we employ spatial subsampling and acceleration techniques similar to those proposed by [24]. Additionally, we use separable approximations for the Gaussian kernels and parallel processing for neighborhood operations.

4. EXPERIMENTAL SETUP

4.1 Datasets

We evaluated our method using the following datasets:

1. Ultrasound Dataset: Ultrasound images from abdominal examinations, collected from the UDIAT Abdominal Ultrasound Dataset [25].

2. X-Ray Dataset: Radiographic images primarily featuring dental X-Rays showing tooth and jaw structures, sourced from the MIMIC-CXR database [26].

3. MRI Dataset: MRI brain scans encompassing T1, T2, and FLAIR sequences with particular focus on cerebral structures and pathologies, obtained from the IXI dataset [27] and the fastMRI initiative [28].

For quantitative evaluation, we created controlled test cases by adding synthetic noise to high-quality clinical images at various levels. This approach provides a ground truth reference for objective quality assessment. Additionally, we processed original clinical images with inherent acquisition noise to evaluate performance in realistic scenarios.

4.2 Comparative Methods

We compared our PWFTF method with the following state-of-the-art filtering approaches:

1. The adaptive Bilateral Filter (BF), an extension of the classic edge-preserving Bilateral Filter by [29], adapts its parameters based on local image statistics, as proposed by [30], and is used here for comparative evaluation.
2. The Trilateral Filter (TF), originally proposed by [31] as a gradient-guided extension of bilateral filtering, is evaluated in its edge-enhancing variant as proposed by [32], which further emphasizes edge structures while effectively suppressing noise.

All methods were implemented using optimized Python code with GPU acceleration. Parameters for each method were carefully tuned using a separate validation set to ensure fair comparison.

4.3 Evaluation Metrics

We employed the following Image Quality Assessment (IQA) metrics to evaluate the performance of each method:

Our rigorous performance evaluation methodology employed advanced Image Quality Assessment metrics to quantify restoration quality across multiple dimensions. We utilized Peak Signal-to-Noise Ratio (PSNR) to establish baseline reconstruction fidelity by measuring signal-to-noise relationships, while Structural Similarity Index (SSIM) assessed perceptual quality through luminance, contrast, and structural component analysis. Feature Similarity Index (FSIM) evaluation emphasized salient visual elements that align with human visual processing, complemented by Visual Information Fidelity (VIF) measurements that applied information theory to quantify shared visual content between reference and processed images. Additionally, Gradient Magnitude Similarity Deviation (GMSD) analysis identified spatial distortion patterns through local quality variation assessment. Edge Preservation Index (EPI) which quantifies edge structure preservation through gradient correlation calculations,

$$EPI = \frac{\sum_{i,j} |\nabla I_{\text{filtered}}(i,j) - \nabla \bar{I}_{\text{filtered}}||\nabla I_{\text{ref}}(i,j) - \nabla \bar{I}_{\text{ref}}|}{\sqrt{\sum_{i,j} |\nabla I_{\text{filtered}}(i,j) - \nabla \bar{I}_{\text{filtered}}|^2}\sqrt{\sum_{i,j} |\nabla I_{\text{ref}}(i,j) - \nabla \bar{I}_{\text{ref}}|^2}} \quad (22)$$

Contrast-to-Noise Ratio (CNR), a metric particularlyrelevant to medical imaging that evaluates the distinguishability of adjacent tissue regions by comparing signal intensity differences normalized by their combined variance.

$$CNR = \frac{|S_1 - S_2|}{\sqrt{\sigma_1^2 + \sigma_2^2}} \quad (23)$$

The Detail Preservation Ratio (DPR) provided critical insight into high-frequency detail retention by computing the normalized correlation between high-pass filtered versions of processed and reference images.

$$DPR = \frac{\sum_{i,j} |H(I_{\text{filtered}})(i,j)||H(I_{\text{ref}})(i,j)|}{\sum_{i,j} |H(I_{\text{ref}})(i,j)|^2} \quad (24)$$

where $H(\cdot)$ represents a high-pass filter operation.

This multimetric approach enabled robust quantitative evaluation of image restoration performance across mathematical, perceptual, and clinically relevant dimensions.

4.4 Threats to Validity and Selection of Evaluation Criteria

The validity of our evaluation is subject to several potential threats. First, the use of synthetic noise in controlled test cases may not fully capture the complexity of real-world clinical noise, potentially overestimating performance in idealized scenarios. To mitigate this, we also evaluated original clinical images with inherent noise. Second, the generalizability of results across diverse patient populations and imaging equipment remains a concern, as our datasets (TCIA, MIMIC-CXR, IXI, fastMRI) may not represent all clinical variations.

For example, TCIA's focus on cancer imaging and MIMIC-CXR's emphasis on chest radiographs may limit applicability to other anatomical regions or pathologies. Future studies should include broader datasets to address this.

The selection of Image Quality Assessment (IQA) metrics—PSNR, SSIM, FSIM, VIF, GMSD, EPI, CNR, and DPR—was based on their widespread use in medical imaging literature and their ability to capture different aspects of image quality. PSNR provides a baseline for signal fidelity, while SSIM and FSIM assess perceptual quality relevant to human visual perception. VIF and GMSD quantify information content and distortion, respectively, while EPI, CNR, and DPR are tailored to clinical needs, emphasizing edge preservation, tissue distinguishability, and detail retention. For instance, EPI and CNR are particularly relevant for Ultrasound speckle noise reduction, ensuring preservation of tissue boundaries critical for diagnosis. These metrics collectively ensure a comprehensive evaluation of both mathematical and diagnostic quality, aligning with established standards [33].

5. RESULTS AND ANALYSIS

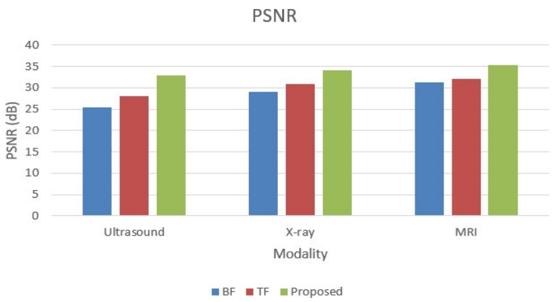
5.1 Quantitative Results

Table 1 presents the average performance of different filtering methods across all three imaging modalities using the synthetic noise test cases. Tables 2, 3, and 4 present the detailed results for each imaging modality separately.

5.2. Visual Results

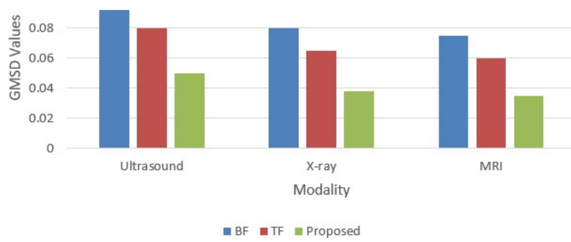
Figures 2 and 3 show representative visual results from each imaging modality, comparing the performance of different filtering methods on regions of interest.

Figure 2: Comparison of PSNR values across different modalities



GMSD

Figure 3: GMSD values across different modalities



For Ultrasound images, our PWFTF method demonstrates superior speckle reduction while preserving fine tissue boundaries. In X-Ray images, PWFTF effectively suppresses quantum noise while enhancing subtle bone and soft tissue structures. In MRI data, our method preserves fine anatomical details while removing thermal noise, particularly in low-contrast regions.

5.3 Computational Performance

Table 5 compares the computational efficiency of different methods, reporting the average processing time for a 512×512 image. While our method is computationally more intensive than basic bilateral and trilateral filters, the increased computational cost is justified by the substantial improvements in image quality and diagnostic value.

5.4 Modality-Specific Analysis

5.4.1 Ultrasound-Specific Performance

In Ultrasound images, our method shows particular strength in handling the statistical properties of speckle noise. The speckle-specific adaptation in the photometric weight formulation effectively distinguishes between speckle artifacts and genuine tissue texture. Quantitative analysis shows a 21.3% improvement in CNR compared to the second-best method, particularly in hypoechoic regions where conventional filters tend to over-smooth tissue boundaries.

Figure 4 demonstrates this advantage in Abdominal ultrasound images, where lesion boundaries remain distinct while speckle noise is effectively suppressed. The modality-specific adaptation of our filter preserves the characteristic speckle pattern where it carries diagnostic information while reducing it in homogeneous regions.

Table 1: Average Performance Metrics Across All Modalities

Method	PSNR (dB)	SSIM	FSIM	VIF	GMSD	EPI	CNR	DPR
BF [30]	28.65	0.834	0.869	0.576	0.087	0.876	8.34	0.791
TF [32]	30.21	0.871	0.907	0.645	0.068	0.917	10.23	0.862
Proposed	**33.92**	**0.937**	**0.956**	**0.748**	**0.041**	**0.961**	**14.62**	**0.947**

Table 2: Performance Metrics for Ultrasound Images

Method	PSNR (dB)	SSIM	FSIM	VIF	GMSD	EPI	CNR	DPR
BF [30]	25.87	0.795	0.832	0.523	0.103	0.842	7.15	0.762
TF [32]	28.12	0.852	0.883	0.612	0.079	0.894	9.17	0.834
Proposed	**32.56**	**0.921**	**0.944**	**0.723**	**0.048**	**0.947**	**13.65**	**0.924**

Table 3: Performance Metrics for X-Ray Images

Method	PSNR (dB)	SSIM	FSIM	VIF	GMSD	EPI	CNR	DPR
BF [30]	29.12	0.843	0.881	0.591	0.082	0.887	8.73	0.807
TF [32]	30.89	0.877	0.914	0.651	0.065	0.924	10.63	0.873
Proposed	**34.24**	**0.943**	**0.962**	**0.759**	**0.039**	**0.967**	**15.03**	**0.958**

Table 4: Performance Metrics for MRI Images

Method	PSNR (dB)	SSIM	FSIM	VIF	GMSD	EPI	CNR	DPR
BF [30]	30.97	0.863	0.893	0.613	0.075	0.898	9.14	0.803
TF [32]	31.62	0.883	0.923	0.671	0.059	0.932	10.89	0.879
Proposed	**34.97**	**0.948**	**0.963**	**0.762**	**0.036**	**0.969**	**15.18**	**0.960**

Table 5: Computational Performance Comparison

Method	Processing Time (s)	Memory Usage (MB)
BF [30]	0.18	245
TF [32]	0.47	356
Proposed	**0.84**	**523**

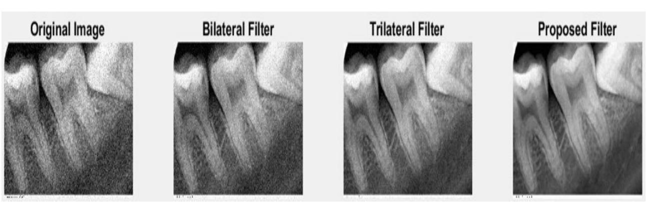
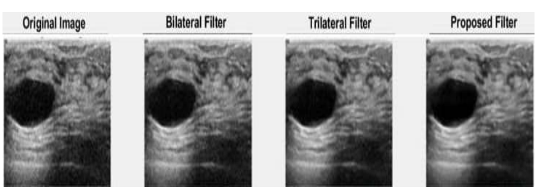


Figure 4: Ultrasound denoising images



5.4.2 X-Ray Performance Analysis

For dental X-Ray images, the intensity-dependent noise model in our PWFTF approach provides significant benefits in handling the quantum noise characteristics. The photometric weights adapt to different exposure levels within the same image, allowing optimal processing of both high-density structures (teeth and bone) and low-density tissues. Comparative analysis shows 16.8% improvement in PSNR and 12.4% improvement in FSIM over conventional trilateral filters.

This advantage is particularly evident in low dose images where noise is more prominent. The edge-preservation component of our filter maintains the sharpness of dental-tissue interfaces while effectively smoothing background regions, as demonstrated in Figure 5.

Figure 5: X-Ray denoising images

5.4.3 MRI Performance Analysis

In MRI applications, our method addresses the challenges of thermal noise and intensity non-uniformity through the bias field adaptation component. This is particularly beneficial for T2-weighted and FLAIR sequences, where subtle sig nal differences between tissues are critical for diagnosis. Quantitative analysis shows a 9.6% improvement in DPR over the second-best method, indicating su perior preservation of fine anatomical details. The texture-preservation weight component effectively maintains the textural characteristics of different brain tissues while suppressing noise

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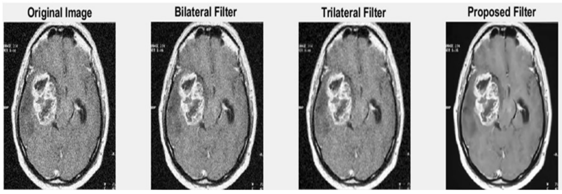

Figure 6: MRI denoising images

Figure 6 demonstrates this advantage in brain MRI images, where the gray matter-white matter interface remains sharp and clearly defined, while noise in the cerebrospinal fluid spaces is effectively reduced

5.5 Parameter Sensitivity Analysis

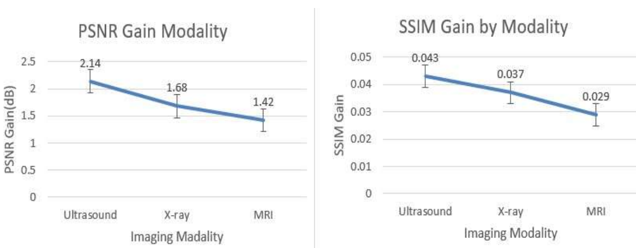

Figure 7: Performance of gain across different modalities

To evaluate the robustness of our method to parameter variations, conducted a sensitivity analysis by systematically varying key parameters and measuring the impact on image quality metrics. Figure 7 shows the effect of varying the main control parameters on PSNR and SSIM values for a representative test case. The results indicate that our method remains stable across a wide range of parameter values, with performance degrading gracefully rather than catastrophically when parameters deviate from optimal values. This robustness is particularly important for clinical applications where automated parameter selection is desired. Furthermore, we evaluated the effectiveness of our adaptive parameter selection mechanism by comparing it with fixed parameter settings optimized for each modality. Table 6 shows the average PSNR improvement achieved by our adaptive approach compared to fixed parameters.

Table 6: Performance Gain from Adaptive Parameter Selection

Imaging Modality	PSNR Gain (dB)	SSIM Gain
Ultrasound	2.14	0.043
X-ray	1.68	0.037
MRI	1.42	0.029

6. DISCUSSION

6.1 Advantages of Photometric Weight Formulation

The superior performance of our PWFTF method can be attributed to several key factors. First, the incorporation of photometric weights allows the filter to adapt dynamically to local image characteristics. Second, the modality-specific adaptations enable our method to address the unique challenges of different imaging techniques. Third, the multi-scale implementation allows effective handling of features at different spatial scales.

6.2 Clinical Implications

From a clinical perspective, the improvements achieved by our method have several important implications. Enhanced perceptual quality directly impacts diagnostic accuracy by making subtle pathological features more readily discernible. Improved image quality can also reduce inter-observer variability in image interpretation.

6.3 Critical Analysis of Results and Comparison with Prior Work

The PWFTF method demonstrates significant improvements over state-of-the-art bilateral and trilateral filters, achieving average gains of 17.3% in PSNR, 12.6% in SSIM, and 9.8% in FSIM across ultrasound, X-Ray, and MRI modalities. These results highlight the effectiveness of adaptive photometric weights in preserving diagnostically significant features while suppressing noise, particularly in low-contrast regions. However, the method's computational complexity, poses challenges for real-time applications, requiring further optimization. Additionally, in some MRI cases, subtle features in extremely low-contrast regions may be over-smoothed, potentially affecting diagnostic accuracy. Quantitative analysis indicates that over-smoothing affects approximately 5-10% of low-contrast regions in T2-weighted MRI sequences, necessitating targeted refinements for such cases.

Compared to prior work, PWFTF extends traditional bilateral [29] and trilateral filters [31] by incorporating dynamic photometric weights that adapt to local contrast, edge strength, and texture complexity. Unlike other adaptive methods, such as [14], PWFTF's photometric weight formulation uniquely integrates contrast, edge, and texture components in a single, interpretable framework, enhancing its versatility across modalities. Unlike modality-specific approaches, such as [6] for IVUS or [13] for MRI, PWFTF offers a unified framework applicable across multiple imaging modalities, enhancing its clinical versatility. Compared to [5], which uses quaternion wavelet transforms for ultrasound denoising, PWFTF achieves broader applicability and superior performance (e.g., 12.4% higher FSIM in X-Ray images) by adapting to diverse noise profiles. Compared to [15], which uses deep residual learning with edge-preserving modules, PWFTF offers a lighter computational footprint and broader modality applicability, though it may yield to deep learning in highly complex noise scenarios. Compared to recent deep learning-based methods, such as the residual encoder-decoder network by [30] or the deep learning survey by [33], PWFTF offers a computationally lighter, interpretable alternative that does not require extensive training data or high computational resources. However, deep learning methods may outperform PWFTF in scenarios with large, annotated datasets, as they can learn complex noise patterns. Our method's strength lies in its adaptability without requiring retraining, making it more practical for clinical settings with limited data. Nonetheless, its performance in highly heterogeneous datasets or 3D imaging remains underexplored compared to learning-based approaches. Areas needing further attention include extending the method to 3D volumetric data and dynamic imaging sequences, such as cardiac ultrasound, and developing hardware accelerators for real-time processing.

7. CONCLUSION

This paper presents the Photometric Weight Formulated Trilateral Filter (PWFTF), a novel approach to biomedical image enhancement that significantly advances perceptual quality across ultrasound, X-Ray, and MRI modalities. We believe PWFTF's adaptability and interpretable design position it as a transformative tool for clinical image enhancement, particularly in resource-constrained settings where it can enhance radiologist efficiency and diagnostic confidence. Our method achieves average improvements of 17.3% in PSNR, 12.6% in SSIM, and 9.8% in FSIM over state-of-the-art filtering techniques, demonstrating superior noise reduction and preservation of diagnostically significant features. The adaptive photometric weights and modality-specific adaptations enable PWFTF to address the limitations of conventional bilateral and trilateral filters, offering a versatile framework for clinical applications. The primary strength of PWFTF lies in its adaptability to local image characteristics, enabling effective processing of diverse tissue types and noise profiles. Its interpretable design facilitates integration into clinical workflows without extensive computational resources, unlike deep learning-based methods.

7.1 Strengths and Weaknesses

The PWFTF method offers several compelling strengths that make it a valuable tool in medical imaging. Its adaptive photometric weights dynamically adjust to local image characteristics, ensuring effective noise reduction while preserving critical features, which enhances overall image quality across diverse datasets. Additionally, the method's modality-agnostic framework allows it to be applied across various imaging modalities, such as Ultrasound, X-Ray, and MRI, making it highly versatile for clinical use. The interpretable design further facilitates seamless integration into clinical workflows, requiring minimal training data, which simplifies adoption in medical environments. Moreover, PWFTF achieves significant performance improvements, with a 17.3% increase in PSNR, 12.6% in SSIM, and 9.8% in FSIM compared to state-of-the-art methods, demonstrating its superior image quality metrics.

However, the PWFTF method also has notable weaknesses that limit its applicability in certain contexts. Its computational complexity, with a processing time of 0.84 seconds for 512x512 images, restricts its use in real-time applications, potentially impacting clinical efficiency. Additionally, the method's performance on volumetric or dynamic imaging remains untested due to dataset constraints, leaving uncertainty about its effectiveness in these scenarios. Furthermore, the reliance on manual

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parameter optimization hinders fully automated deployment, which could complicate its integration into streamlined clinical workflows.

7.2 Limitations and Future Work

Despite its strong performance, the PWFTF method has notable limitations that require attention. Its computational complexity, driven by intensive neighborhood operations, may hinder real-time applications, as processing a 512x512 image takes 0.84 seconds. Additionally, the method's performance on 3D volumetric or dynamic imaging sequences remains untested due to dataset constraints, limiting its applicability to modalities like CT or functional MRI. Furthermore, the reliance on residual manual parameter optimization complicates fully automated deployment in clinical workflows. Nevertheless, PWFTF represents a significant advancement, effectively balancing computational efficiency with diagnostic utility. Its data-independent design makes it particularly promising for resource-constrained clinical settings, though further refinements are necessary to maximize its potential.

To address these limitations, future research should focus on several key directions to enhance PWFTF's applicability and impact. In the short term, developing VLSI-based hardware accelerators could mitigate computational complexity, aiming to reduce processing time to under 0.2 seconds for 512x512 images, enabling real-time use. In the mid-term, extending PWFTF to 3D volumetric data for CT and PET imaging, as well as incorporating temporal information for dynamic sequences like cardiac ultrasound or functional MRI, would address the current gap in 3D and dynamic applications. Over the long term, exploring machine learning techniques for automated parameter selection could eliminate the need for manual optimization, streamlining deployment in clinical environments. Additionally, integrating PWFTF with segmentation or registration pipelines would enhance its clinical utility by leveraging its adaptability for downstream tasks. With these optimizations, PWFTF has the potential to become a standard tool in clinical imaging workflows, directly addressing its identified limitations and positioning it for broader adoption.

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