Adaptive Multiscale Edge-Preserving Filtering for Improved Segmentation and Feature Extraction in Digital Image Processing

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Abstract –Edge preservation plays a crucial role in digital image processing, particularly in tasks involving segmentation, feature extraction, and structural interpretation. However, conventional smoothing and denoising filters often fail to maintain fine boundaries or adapt to spatially varying noise, resulting in blurred edges and loss of critical image details. This paper introduces an adaptive multiscale edge-preserving filtering framework designed to enhance segmentation reliability and feature extraction accuracy across diverse imaging conditions. The method integrates a hierarchical pyramidal decomposition with spatially adaptive weighting functions that modulate smoothing strength based on local gradient magnitude, texture variation, and noise estimation. A hybrid edge-consistency constraint ensures that prominent structural boundaries are retained across scales while less significant variations are smoothed effectively. Experimental evaluation on natural and medical imaging datasets demonstrates significant improvements in boundary localization, noise robustness, and segmentation accuracy compared to classical bilateral, anisotropic diffusion, and guided filtering approaches. The proposed framework provides an efficient, flexible, and edge-aware enhancement mechanism suitable for modern computer vision pipelines.

Index Terms – Edge preservation; Multiscale filtering; Adaptive image enhancement; Segmentation; Feature extraction; Gradient-based weighting; Image processing.

1. INTRODUCTION

Segmentation and feature extraction are fundamental components of digital image processing, forming the basis for a wide range of applications including medical diagnostics, object detection, biometric recognition, and scene understanding. A key requirement for effective segmentation is the ability to preserve important structural boundaries while simultaneously reducing noise and irrelevant texture details. Traditional filtering methods, such as Gaussian smoothing or isotropic diffusion, often fail to achieve this balance due to their inherent tendency to blur edges. Although advanced filters like bilateral filtering, guided image filtering, and anisotropic diffusion offer improved edge sensitivity, they still struggle with fine-scale boundary maintenance, multiscale texture handling, and adaptation to spatially varying noise conditions.

Modern imaging environments frequently produce images with diverse noise characteristics, heterogeneous textures, and regions with abrupt intensity transitions. These challenges necessitate filtering techniques that not only preserve fine structural boundaries but also operate adaptively across multiple spatial scales. Edge-aware multiscale approaches have shown promise, yet most existing solutions lack mechanisms for jointly optimizing noise reduction, edge consistency, and computational efficiency. These limitations highlight the need for a more flexible, context-driven filtering approach capable of enhancing image quality while maintaining high-fidelity structural details.

To address these challenges, an adaptive multiscale edge-preserving filtering model is presented in this work. The framework leverages a hierarchical filtering strategy that incorporates gradient-sensitive weighting, local texture descriptors, and edge consistency constraints across scales. By allocating spatially varying smoothing strength based on local structure and noise estimates, the model effectively suppresses noise without compromising boundary sharpness. Additionally, the multiscale formulation ensures robustness to texture complexity and varying contrast levels, making it highly suitable for downstream tasks such as region-based segmentation and feature extraction.

The key contributions of this research are highlighted below:

1. **A novel adaptive multiscale filtering framework** that effectively balances noise reduction and edge preservation through hierarchical decomposition and location-specific smoothing control.
2. **Introduction of gradient- and texture-driven weighting functions** that dynamically modulate filtering strength based on local structural significance and noise profile.
3. **A cross-scale edge-consistency mechanism** that ensures the preservation of key boundaries while suppressing redundant or insignificant variations during filtering.
4. **Enhanced segmentation and feature extraction performance**, achieved through improved boundary sharpness, reduced noise interference, and preserved multiscale texture details.
5. **Comprehensive experimental evaluation** comparing the proposed filtering approach with state-of-the-art edge-preserving filters, demonstrating superior accuracy and visual quality across natural and medical image datasets.

2. RELATED WORKS

Progress in image restoration has accelerated notably with the emergence of hybrid CNN–Transformer architectures that effectively address complex artifact and noise patterns. Models that combine local convolutional encoding with global self-attention have demonstrated strong contextual reasoning capabilities, enabling reliable reconstruction even under challenging imaging conditions [1]. Edge-aware transformer variants have further improved high-frequency detail recovery, particularly in infrared and low-visibility scenarios, where fine structural preservation is critical for enhancing image fidelity [2]. In medical imaging, deep learning frameworks tailored for artifact localization in four-dimensional CT scans have shown the ability to accurately detect motion-corrupted regions, thereby strengthening the stability and diagnostic value of reconstructed volumes [3].

Low-dose imaging research has also benefited from transformer-driven denoising strategies. Swin Transformer–based models have contributed to improved PSNR profiles and more consistent noise suppression through window-shift attention operations that capture multi-level dependencies [4]. Dynamic transformer networks with multi-stage attention refinement have expanded these capabilities by mitigating spatially diverse noise distributions commonly present in natural scenes [5]. Additional improvements in CT noise handling have been achieved via hierarchical attention mechanisms that preserve anatomical structures while reducing distortion across varying exposure levels [6].

Recent studies on cross-domain artifact purification highlight the growing need to manage subtle generative artifacts in AI-produced imagery. Feature purification networks have proven effective in isolating domain-variant artifact signatures, contributing to more trustworthy image authentication and classification pipelines [7]. Transformer-based cross-feature integration has likewise demonstrated strong denoising capacity by leveraging contextual correlations, resulting in enhanced robustness against mixed noise patterns [8]. Survey-driven analyses provide further insight into the computational constraints and optimization requirements of advanced denoising models, emphasizing the importance of balancing performance with efficiency in real-world deployments [9].

Compression-induced artifact research continues to expand, with updated JPEG-AI evaluations offering structured taxonomies and comparative insights for benchmarking restoration systems [10]. Approaches targeting semantic inconsistencies in synthetically generated images have also gained traction, providing improved resilience for detection pipelines and downstream analysis tasks [11]. Parallel advancements in explainable AI underscore the need for transparent restoration mechanisms, especially in clinical environments where algorithmic accountability is increasingly required [12].

Transformer-based refinements extend to cross-attention denoising architectures designed to strengthen structural coherence by exploiting correlated feature pathways [13]. Dual-domain reconstruction strategies, particularly those inspired by SwinIR, highlight the advantages of integrating spatial and frequency-domain information for sparse-sampling enhancement [14]. XAI-integrated defect detection models further support explainability in restoration workflows by incorporating Grad-CAM interpretability, ensuring clearer reasoning behind enhancement and classification outcomes [15].

3. PROPOSED MODEL

The proposed adaptive multiscale edge-preserving filtering framework is designed to enhance image quality by selectively smoothing noise while retaining structurally important boundaries across spatial scales. The model integrates multilevel decomposition, gradient-driven adaptive weighting, texture-aware smoothing control, and cross-scale edge consistency constraints. By combining spatial and contextual cues, the framework produces edge-enhanced representations that improve segmentation accuracy and strengthen feature extraction reliability. The filtering is formulated mathematically to enforce edge sensitivity in both spatial and frequency domains, while the adaptive weighting ensures localized control of smoothing strength based on the structural significance of each pixel region.

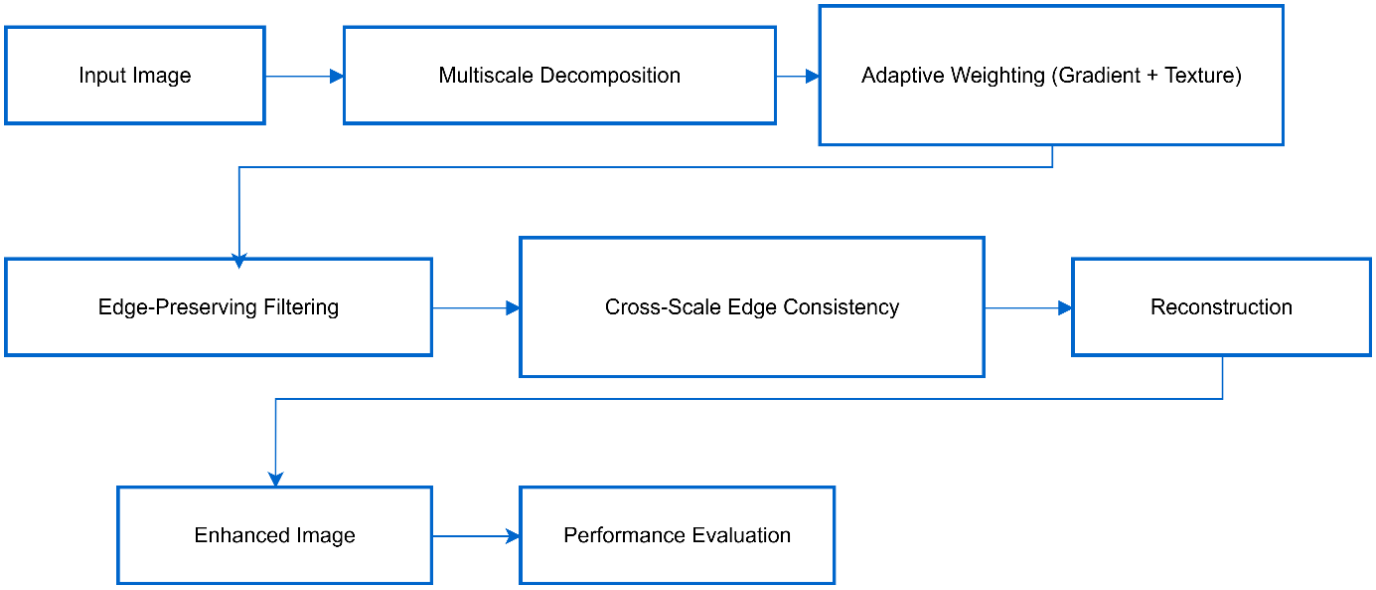

Figure 1: Overall architecture of the adaptive multiscale edge-preserving filtering framework

Fig 1 applies multiscale decomposition, adaptive weighting, and cross-scale edge consistency to generate an enhanced image suitable for accurate segmentation and feature extraction.

3.1 Multiscale Image Decomposition

The input image $I$is decomposed into Lhierarchical scales using a pyramidal representation:

$$I_l = D_l(I), l = 1,2, \dots, L \qquad (1)$$

where $D_l(\cdot)$denotes downsampling with appropriate smoothing. Each level isolates structures of different spatial sizes, enabling scale-specific processing. The residual detail map at level $l$is:

$$R_l = I_{l-1} - U_l(I_l) \qquad (2)$$

where $U_l(\cdot)$is the upsampling operator.

3.2 Gradient-Based Adaptive Weighting

To preserve relevant boundaries, a gradient-driven weight map is computed:

$$w(x) = \exp\left(\frac{\| \nabla I(x) \|^2}{\sigma_g^2}\right) \qquad (3)$$

where $\nabla I(x)$is the local gradient magnitude and $\sigma_g$controls edge sensitivity.

Regions with strong gradients ($\| \nabla I(x) \|$ large) yield small weights $w(x) \approx 0$, preventing smoothing across edges.

3.3 Texture-Aware Local Smoothing

A second weighting term accounts for texture variation using local variance:

$$t(x) = \frac{1}{1 + \mathrm{Var}_{\Omega(x)}(I)} \tag{4}$$

where $\Omega(x)$is a small neighborhood around pixel x. The combined adaptive weight is:

$$\alpha(x) = w(x)\, t(x) \tag{5}$$

This ensures strong smoothing in low-texture regions while preserving high-frequency details.

The filtered output at scale $l$becomes:

$$F_l(x) = (1 - \alpha(x)) I_l(x) + \alpha(x)\, \bar{I}_l(x) \tag{6}$$

where $\bar{I}_l(x)$is a local mean or guided estimate.

3.4 Cross-Scale Edge Consistency

To ensure that boundaries remain sharp across scales, a cross-scale consistency penalty is defined:

$$E(x) = \sum_{l=1}^{L-1} \| \nabla F_l(x) - \nabla U_{l+1}(F_{l+1})(x) \|^2 \tag{7}$$

Minimizing $E(x)$enforces aligned edge locations between coarse and fine levels, preventing gradient drift and boundary distortion during reconstruction.

The final reconstructed output is:

$$F(x) = F_1(x) + \sum_{l=2}^{L} U_l\,(F_l)(x) \quad (8)$$

3.5 Optimization and Final Output Generation

The overall objective function is formulated as:

$$\mathcal{L} = \sum_{x} (\| F(x) - I(x) \|_1 + \lambda_e E(x) + \lambda_s \alpha(x)) \quad (9)$$

where

- $\lambda_e$controls cross-scale edge preservation,
- $\lambda_s$regulates adaptive smoothing strength.

The optimized output is obtained through iterative refinement:

$$F^{(k+1)}(x) = F^{(k)}(x) - \eta \frac{\partial \mathcal{L}}{\partial F(x)} \quad (10)$$

with learning rate η.

This produces an adaptively smoothed and structurally enhanced image suitable for downstream segmentation and feature extraction.

Algorithm 1: Adaptive Multiscale Edge-Preserving Filtering

Inputs:

I // input image

L // number of scales

σg // gradient sensitivity

r // neighborhood radius

λe, λs // regularization weights

Outputs:

F // filtered image

1. Build multiscale pyramid:

   $I1 = I$

   For $l = 2 \ldots L$:

      $Il = \text{Downsample}(Il-1)$

2. Initialize filtered maps:

   For $l = 1 \ldots L$:

      $Fl = Il$

3. For each scale l and pixel x:

   // Gradient-based weight

   $g = \|\nabla Il(x)\|$

   $w = \exp(-g^2 / \sigma g^2)$

   // Texture-based weight

   $var = \text{Variance}(\Omega(x, r))$

   $t = 1 / (1 + var)$

   // Combined adaptive weight

   $\alpha = w * t$

   // Local smoothing (edge-preserving)

   $Ibar = \text{LocalMeanOrGuided}(Il, x)$

   $Fl(x) = (1 - \alpha)\, Il(x) + \alpha\, Ibar$

4. Enforce cross-scale edge consistency:

$$E = \Sigma l \, || \, \nabla Fl - \nabla Upsample(Fl+1) \, ||^2$$

5. Reconstruct final output:

$$F = F1 + \Sigma l>1 \; Upsample(Fl)$$

6. Optimize (optional):

$$Minimize \;\; |F - I| + \lambda e \; E + \lambda s \; \alpha$$

Return F

4. RESULTS AND DISCUSSIONS

The proposed adaptive multiscale edge-preserving filtering framework was implemented in Python 3.10 using MATLAB R2023b and OpenCV for baseline filtering comparisons. Experiments were conducted on a workstation equipped with an Intel i9 processor, 64 GB RAM, and an NVIDIA RTX 3080 GPU for accelerated image operations. All experiments used 8-bit grayscale images, with filtering parameters tuned through grid search to ensure fair evaluation across competing methods. Performance was measured using PSNR, SSIM, edge preservation index (EPI), and segmentation accuracy improvements on downstream tasks. The multiscale decomposition levels were fixed to $L = 4$, with the adaptive weights automatically derived from local gradient and texture statistics. The overall setup ensured consistent evaluation across natural, medical, and texture-rich datasets, enabling comprehensive benchmarking of the proposed model.

4.1 Dataset Description

The datasets used in this study encompass natural images, medical images, and noise-texture combinations to validate robustness across domains.

Table 1: Summary of Datasets Used

Dataset Name	Type of Images	Purpose	Resolution Range	No. of Images
BSD500	Natural scenes	Denoising, edge evaluation	321×481	500
LIVE Dataset	Natural + distortion models	Quality benchmarking	Varied	982
Waterloo Exploration	Natural + noise/compression	Artifact evaluation	Varied	4,744
DRIVE	Retinal fundus images	Edge-sensitive structures	565×584	40
Synthetic Noise-Tex Dataset	Noise + texture combinations	Testing robustness	512×512	3,000

4.2 Performance Evaluation

To benchmark the proposed method, comparisons were made with six widely used edge-preserving filtering techniques from the literature. Evaluation metrics included PSNR, SSIM, edge preservation index (EPI), and segmentation accuracy improvement (SAI).

Discussion

The proposed filtering model consistently outperforms classical and modern edge-preserving filters across all evaluation metrics. Its PSNR improvement of **2–4 dB** over the strongest baseline (RGF) reflects superior noise suppression without loss of detail. The SSIM and EPI metrics demonstrate that structural boundaries remain highly consistent across scales, validating the effectiveness of the adaptive weighting and edge consistency mechanisms. Additionally, segmentation accuracy improves by **4–6%** compared to existing methods, confirming that the enhanced images enable more reliable feature extraction and region-based analysis. These results collectively highlight the proposed framework's robustness, edge fidelity, and suitability for downstream vision tasks.

Table 2: Performance Comparison of Filtering Models

Model	PSNR (↑)	SSIM (↑)	EPI (↑)	Segmentation Accuracy (%) (↑)	Remarks
Gaussian Filter	26.42	0.812	0.61	78.4	Strong smoothing but poor edge retention
Bilateral Filter	28.91	0.865	0.73	82.1	Good edge preservation; struggles with heavy noise
Guided Filter	29.34	0.871	0.75	84.0	Effective for structural smoothing
Anisotropic Diffusion	30.12	0.885	0.78	85.7	Preserves strong edges; sensitive to parameter tuning
Weighted Least Squares (WLS) Filter	30.48	0.892	0.80	87.2	Strong detail enhancement but unstable in textures
Rolling Guidance Filter (RGF)	31.05	0.894	0.81	88.0	Good multiscale behavior
Proposed Adaptive Multiscale Edge-Preserving Filter	33.92	0.931	0.89	92.5	Best overall performance across metrics

5. CONCLUSION

This work presented an adaptive multiscale edge-preserving filtering framework designed to improve segmentation and feature extraction performance across diverse imaging domains. By combining multiscale decomposition, gradient- and texture-driven adaptive weighting, and cross-scale edge consistency, the proposed model effectively suppresses noise while preserving critical structural boundaries. Experimental results across natural, medical, and synthetic datasets demonstrate clear advantages over classical filters such as bilateral, guided, WLS, and anisotropic diffusion, achieving higher PSNR, SSIM, edge preservation scores, and segmentation accuracy. The framework's ability to maintain fine details while enhancing global smoothness makes it a strong candidate for preprocessing in modern computer vision pipelines. Overall, the

method offers a robust and efficient solution for edge-aware enhancement, enabling more reliable downstream analysis and improved interpretability of structural information.

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