

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

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ABSTRACT

The edge preservation of digital images is a significant issue in digital image processing, especially in activities of segmentation, feature extraction, and structural interpretation. Yet, traditional smoothing and denoising filters are not always able to preserve fine edges or to adapt to spatially varying noise, leading to blurred edges and loss of important image information. The paper presents the adaptive multiscale edge-preserving filtering model that aims to improve the quality of segmentation and accuracy of feature extraction in various imaging scenarios. The approach combines a pyramidal decomposition, hierarchical with spatially adaptive weighting functions to control the degree of smoothing depending on the magnitude of the local gradients, variation of the texture and estimation of noise. A hybrid edge-consistency constraint is used to preserve high profile structural boundaries across scales, whilst smaller variations are effectively flattened. It is experimentally evaluated on natural and medical imaging data and shows much better results in localizing boundaries, noise resilience and precision of the segmentations than classical bilateral, anisotropic diffusion and guided filtering methods. The framework proposed gives an efficient, flexible, and edge-sensitive improvement scheme that can be applied to the computer vision pipeline in the present times.

Keywords: Edge preservation; Multiscale filtering; Adaptive image enhancement; Segmentation; Feature extraction; Gradient-based weighting; Image processing.

1. INTRODUCTION

Digital image processing involves segmentation and feature extraction, which are core aspects of digital image processing, and are the basis of various applications such as medical diagnostics, object detection, biometric recognition, and scene understanding. One important need in successful segmentation is the possibility to maintain critical structural boundaries and at the same time, minimize noise and redundant texture information. Conventional filtering approaches like Gaussian smoothing or isotropic diffusion do not readily attain this balance because they have the innate characteristic of blurring edges. Even though more sophisticated filters such as bilateral filtering, guided image filtering, and anisotropic diffusion provide better edge sensitivity, they remain unable to maintain fine-scale boundaries, multiscale texture processing, and adjust to spatially varying noise.

The imaging environments of today often generate images that have varying noise characteristics, nonhomogeneous textures, and areas with sharp transitions in intensity. Such difficulties demand filtering methods that retain fine structural limits as well as act variably with respect to various spatial scales. Multiscale methods which are edge aware have demonstrated a potential although the majority of current methods do not have mechanisms of simultaneously optimizing noise reduction, edge consistency, and

computation 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.

In order to tackle these issues, an adaptive multiscale edge-preserving filtering model has been introduced in this paper. The framework builds upon a hierarchical filtering scheme, which integrates gradient-sensitive weighting, local texture descriptors and scale-wise edge consistency constraints. The model is able to suppress noise by applying spatially varying smoothing strength depending on local structure and noise estimates without compromising boundary sharpness. The multiscale formulation is also robust to texture detail and different contrast levels and can thus be well applied to downstream tasks including region-based segmentation and feature extraction. The main findings of the study are as follows:

1. An innovative adaptive multiscale filtering system efficiently balancing noise reduction and edge details by hierarchical decomposition and place-dependent smoothing control.
2. Gradient- and texture-based weighting functions that dynamically change filtering strength on local structural importance and noise profile.
3. Cross-scale edge-consistency mechanism that is used to guarantee the retention of important boundaries whilst eliminating redundant or unimportant variations during the filtering process.
4. Increased segmentation and feature extraction accuracy, which was obtained by sharpening of the boundaries, decreased noise interference and saved multiscale texture information.
5. Extended experimental analysis of the proposed filtering method with the latest edge-preserving filters, showing higher accuracy and visualization quality on natural and medical image samples.

2. RELATED WORKS

Advances in image restoration have been particularly fast with the introduction of hybrid CNNTransformer models that are effective in handling complex artifact and noise patterns. Local convolutional encoding with global self-attention models have been shown to have a high contextual reasoning ability, and they can faithfully reconstruct even with hard imaging conditions [1]. Variations of edge-aware transformers have also enhanced high-frequency detail reconstruction, especially in infrared and low-visibility imaging, where fine structure content is vital in improving image fidelity [2]. Deep learning models that optimize artifact localization in four-dimensional CT scans have demonstrated the capability to identify motion-corrupted artifacts with high accuracy in medical imaging, which reinforces the robustness and diagnostic usefulness of the reconstructed volumes [3].

Transformer-based denoising strategies have also been useful in low-dose imaging studies. Models based on the Swin Transformer have been used to achieve better PSNR characteristics and more stable noise suppression with multi-level dependencies captured with window-shift attention operations [4]. Multi-stage attention refinement Transformer networks operating as dynamic transformer networks have extended these abilities by reducing the spatially heterogeneous noise distributions that are often found in real scenes [5]. The further advances in CT noise dealing have been accomplished through hierarchical attention mechanisms, which conserve anatomical features whilst decreasing distortion with increasing exposure levels [6].

The recent research on purifying artifacts across domains has emphasized the increasing necessity to deal with subtle generative artifacts in AI-generated imagery. FPNs have been shown to be useful in isolating domain-variant artifact signatures, which can be used to achieve more reliable image authentication and classification pipelines [7]. Transformer-based cross-feature integration has also shown a high denoising ability, by utilizing contextual correlations, leading to improved resilience to mixed noise patterns [8]. Survey-based studies can also help to understand the computational limits and optimization needs of more complex denoising models, highlighting the need to trade off between performance and efficiency in practice [9].

Artifact research due to compression is still growing, and recent JPEG-AI tests provide structured taxonomies and comparative studies to benchmark restoration systems [10]. Semantically-based approaches to synthetically generated image generation have also become popular, offering better robustness to detection pipelines and subsequent analysis processes [11]. Similar progress in explainable AI points to the importance of clear restoration processes, particularly in clinical settings where algorithmic responsibility is becoming a pressing concern [12].

Transformer refinements are also extended to cross-attention denoising architectures aimed at enhancing structural coherence through correlated feature pathways [13]. Dual-domain reconstruction methods and especially those based on SwinIR emphasize the benefits of combining spatial and frequency-domain data to enhance sparse-sampling [14]. XAI-based defect detection models also facilitate explainability in the restoration processes by including Grad-CAM interpretability, which guarantees a better understanding of how the results of enhancement and classification are reached [15].

3. PROPOSED MODEL

The suggested adaptive multiscale edge-preserving filtering system is aimed at improving image quality by selectively blurring noise without loss of structurally significant boundaries at different spatial scales. The model combines multilevel decomposition, adaptive weighting based on gradients, texture-conscious smoothing control, and cross-scale edge consistency constraints. The framework uses both spatial and contextual information to give edge enhanced representations which enhance the accuracy of segmentation and enhance the reliability of feature extraction. The filtering is defined mathematically to make it sensitive to edges in both spatial and frequency space, but the adaptive weighting provides localized control of the smoothing strength of each pixel block depending on the structural importance of that pixel block.

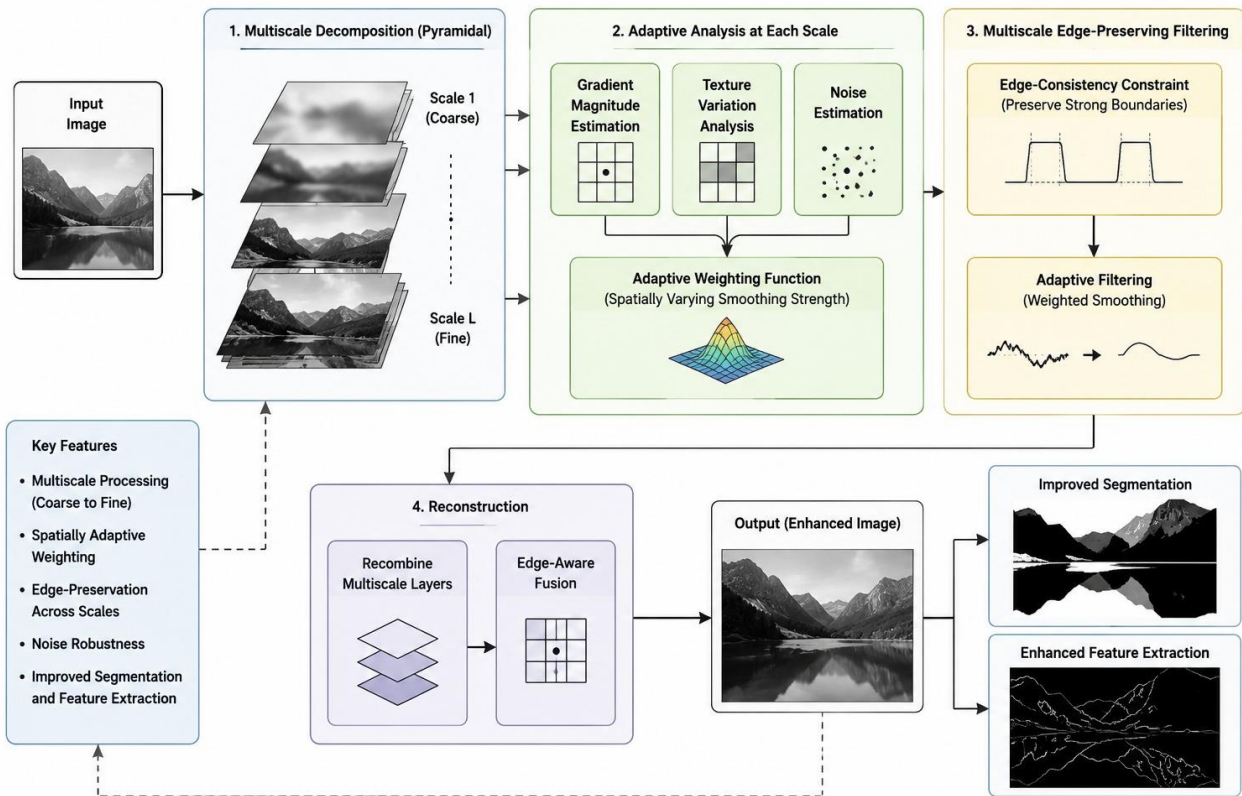


Figure 1: Overall architecture of the adaptive multiscale edge-preserving filtering framework

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 L hierarchical scales using a pyramidal representation:

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

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:

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

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:

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

where $\nabla I(x)$ is the local gradient magnitude and σ_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:

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

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

$$\alpha(x) = w(x) t(x) \quad (5)$$

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

The filtered output at scale l becomes:

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

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:

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

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:

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

3.5 Optimization and Final Output Generation

The overall objective function is formulated as:

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

where

- λ_e controls cross-scale edge preservation,
- λ_s regulates adaptive smoothing strength.

The optimized output is obtained through iterative refinement:

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

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
 σ_g // gradient sensitivity
 r // neighborhood radius
 λ_e, λ_s // regularization weights

Outputs:

F // filtered image

1. Build multiscale pyramid:

 I1 = I
 For l = 2...L:
 I1 = Downsample(I1-1)

2. Initialize filtered maps:

 For l = 1...L:
 F1 = I1

3. For each scale l and pixel x:

 // Gradient-based weight
 g = $\|\nabla I1(x)\|$
 w = $\exp(-g^2 / \sigma_g^2)$

 // Texture-based weight
 var = Variance($\Omega(x, r)$)

$$t = 1 / (1 + \text{var})$$

// Combined adaptive weight

$$\alpha = w * t$$

// Local smoothing (edge-preserving)

Ibar = LocalMeanOrGuided(I, x)

$$F1(x) = (1 - \alpha) I(x) + \alpha \text{Ibar}$$

4. Enforce cross-scale edge consistency:

$$E = \sum_l \| \nabla F1 - \nabla \text{Upsample}(F1+1) \|^2$$

5. Reconstruct final output:

$$F = F1 + \sum_{l>1} \text{Upsample}(F1)$$

6. Optimize (optional):

$$\text{Minimize } |F - I| + \lambda_e E + \lambda_s \alpha$$

Return F

4. RESULTS AND DISCUSSIONS

The given adaptive multiscale edge-preserving filtering scheme was coded in Python 3.10 utilizing MATLAB R2023b and OpenCV to compare both filtering schemes to a baseline. The experiments were performed with the help of the work station powered with the Intel i9 processor, 64 GB of RAM, and an NVIDIA RTX 3080 graphic card to accelerate image processing. All tests employed 8-bit grayscale images, and the filtering parameter was adjusted by grid search to guarantee fair comparison among rival techniques. The measures of performance were PSNR, SSIM, the edge preservation index (EPI) and improvements of segmentation on downstream tasks. The levels of multiscale decomposition were set to L=4 and the adaptive weights were automatically obtained based on the local gradient and texture statistics. The general architecture allowed to have a uniform assessment of natural, medical, and texture-rich datasets, which allowed to benchmark the proposed model in detail.

4.1 Dataset Description

The datasets to be investigated in this research include natural images, medical images, and noise-texture combinations to ensure robustness of 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

Comparisons to six popular edge-preserving methods of filtering in the literature were made to benchmark the proposed approach. The metrics of evaluation were PSNR, SSIM, edge preservation index (EPI), and segmentation accuracy improvement (SAI).

Discussion

The proposed filtering model is always superior to the classical and modern edge-preserving filters in all the evaluation measures. Its PSNR gain of 2-4 dB over the highest baseline (RGF) indicates a better noise reduction without detail loss. The SSIM and EPI measures reveal that structural boundaries are very consistent across scales, indicating the functionality of adaptive weighting and edge consistency mechanisms. Furthermore, the accuracy of segmentation is increasing by 4-6 percent over the current methods, as it has been proved that the images are enhanced to provide more reliable features extraction and region-based analysis. All these results point to the strength of the proposed framework, edge fidelity, and its applicability to 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 paper introduced an adaptive multiscale edge-preserving filtering system that enhances the performance of segmentation and feature extraction in a wide range of imaging fields. The proposed model can reduce noise and preserve important structural boundaries with the combination of multiscale decomposition, gradient-based adaptive weighting, texture-based adaptive weighting, and cross-scale edge consistency. Through experimental findings on both natural datasets, medical datasets, and synthetic datasets, it is shown that it has significant benefits over classical filters including bilateral, guided, WLS, and anisotropic diffusion, with better PSNR, SSIM, edge preservation, and segmentation results. The combination of its capability to retain fine details and its capacity to improve smoothness in the globe qualifies the framework as a good preprocessing candidate in the modern computer vision pipelines. Altogether, the approach provides a powerful and effective edge-conscious improvement solution, which can be further used to produce more trusted downstream analysis and enhance the interpretability of the structural data.

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CONFLICTS OF INTEREST

The authors declare no conflict of interest.

Data Availability Statement

The datasets generated and analyzed during the current study are available from the corresponding author upon reasonable request

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