

Adaptive Parameter Selection in Perona–Malik Anisotropic Diffusion for MRI Image Denoising

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Abstract - Magnetic Resonance Imaging (MRI) is a widely used diagnostic modality, but acquired scans are frequently corrupted by acquisition noise that degrades clinical interpretability and downstream automated analysis. This paper presents an Adaptive Perona–Malik (APM) anisotropic diffusion framework for MRI denoising that removes the dependence of the classical algorithm on manually tuned diffusion parameters. The proposed framework couples automatic image-noise estimation with adaptive selection of the conductance coefficient and an adaptive convergence criterion that halts diffusion once pixel-wise change falls below a data-driven threshold. Six denoising strategies — Gaussian filtering, Median filtering, Bilateral filtering, Non-Local Means (NLM) filtering, the classical Perona–Malik (PM) algorithm, and the proposed APM framework — were implemented in Python and benchmarked on grayscale brain MRI images corrupted with synthetic Gaussian and Speckle noise. Performance was quantified using Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index Measure (SSIM), Mean Squared Error (MSE), an Edge Preservation Index (EPI), and computational runtime. Bilateral filtering attained the highest PSNR (26.17 dB) and the Median filter produced the best SSIM (0.6766), lowest MSE (49.38), and shortest runtime (1.1 ms) on the evaluated dataset. While the proposed APM framework did not surpass the classical baselines on every metric, it eliminated manual parameter tuning entirely and produced a stable, reproducible diffusion pipeline, establishing a foundation for optimization-driven and hybrid extensions.

Keywords - MRI Denoising, Anisotropic Diffusion, Perona–Malik, Adaptive Parameter Selection, Noise Estimation, Image Quality Assessment.

I. INTRODUCTION

Magnetic Resonance Imaging occupies a central role in modern diagnostic radiology because it resolves soft-tissue contrast without ionizing radiation, making it indispensable for detecting neurological disorders, brain tumors, and other structural abnormalities [1]. Despite this advantage, MRI acquisition and reconstruction pipelines introduce noise — predominantly thermal and Rician-distributed magnitude noise — that lowers contrast, obscures fine anatomical boundaries, and can bias both radiologist interpretation and automated analysis pipelines such as segmentation and registration.

Denoising algorithms therefore form an essential pre-processing stage in medical image analysis. The central difficulty is balancing noise suppression against structural fidelity: aggressive smoothing erases diagnostically relevant edges, while conservative smoothing leaves residual noise. Spatial filters such as Gaussian, Median, Bilateral, and Non-Local Means filtering offer different trade-offs along this axis. Among diffusion-based approaches, the Perona–Malik anisotropic diffusion model [1] remains influential because it smooths homogeneous regions while inhibiting diffusion across strong gradients, effectively preserving edges.

The practical drawback of the classical PM algorithm is its reliance on a manually chosen conductance coefficient K and a fixed iteration count, both of which are usually tuned empirically per image. This dependence limits reproducibility and makes the algorithm difficult to deploy consistently across MRI datasets with heterogeneous noise characteristics. This paper investigates an adaptive parameter-selection strategy that estimates image noise directly from pixel statistics and derives the conductance coefficient and stopping criterion automatically, removing the need for manual tuning while retaining the edge-preserving character of anisotropic diffusion.

The remainder of this paper is organized as follows. Section II reviews related work on classical and learning-based denoising. Section III describes the proposed Adaptive Perona–Malik methodology. Section IV details the experimental dataset and setup. Section V presents quantitative and qualitative results with discussion, and Section VI concludes the paper and outlines future directions.

II. LITERATURE SURVEY

Perona and Malik [1] introduced anisotropic diffusion for edge-preserving smoothing using a gradient-dependent partial differential equation, establishing the mathematical basis for diffusion-based denoising but leaving parameter selection to manual trial and error. Weickert [5] extended this theory with more general diffusion tensors and adaptive conductance functions, providing a stronger mathematical treatment of edge preservation under diffusion.

Tomasi and Manduchi [2] proposed the Bilateral filter, which combines spatial and intensity-domain weighting to smooth homogeneous regions while retaining edges; its performance, however, is likewise sensitive to kernel-parameter choice and incurs higher computational cost than linear filters. Buades et al. [3] introduced Non-Local Means filtering, which denoises

by averaging over similar image patches rather than local neighborhoods, improving texture preservation at the expense of computational overhead on large medical images.

Gudbjartsson and Patz [4] showed that magnitude MRI images follow a Rician rather than Gaussian noise distribution, a finding that later informed statistically grounded noise-estimation methods for MRI-specific denoising [6],[7]. Building on this line of work, several studies have argued that automatic, statistically driven noise estimation is essential for adapting classical filters to real acquisition conditions rather than relying on fixed or manually tuned parameters.

Deep-learning approaches such as U-Net [8], residual learning [10], and self-configuring frameworks like nnU-Net [9] have demonstrated strong performance on biomedical image restoration and segmentation tasks, but they require large annotated datasets, substantial computational resources, and lose interpretability relative to model-based diffusion methods. Standard references [6],[11],[13],[14] provide the classical

image-processing and optimization background used in this work. Motivated by this literature, the present study focuses on retaining the interpretable, edge-preserving structure of Perona–Malik diffusion while removing its dependence on manual parameter tuning through automatic, statistics-driven adaptation.

III. PROPOSED METHODOLOGY

A. System Overview

The proposed pipeline consists of five stages: (i) MRI image acquisition and pre-processing, (ii) synthetic noise injection for controlled evaluation, (iii) application of six denoising algorithms under identical conditions, (iv) quantitative performance evaluation, and (v) comparative and visual analysis. Fig. 1 illustrates the internal workflow of the proposed Adaptive Perona–Malik (APM) module, which forms the core contribution of this work.

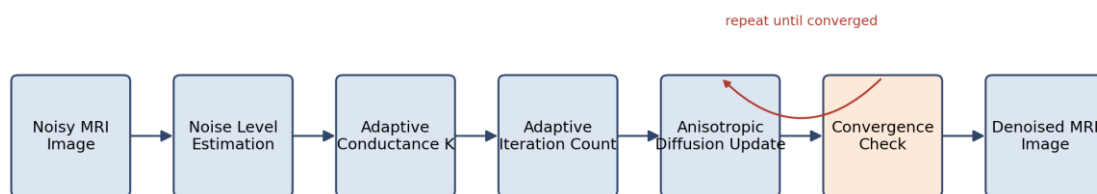


Fig. 1. Workflow of the proposed Adaptive Perona–Malik denoising framework.

B. Noise Model

To evaluate robustness under controlled conditions, grayscale brain MRI images were corrupted with two synthetic noise models. Gaussian noise was added as $I_n(x,y) = I(x,y) + N(0,\sigma^2)$, simulating thermal and electronic disturbances typical of MRI acquisition hardware. Speckle (multiplicative) noise was added as $I_n = I + I \cdot n$, where n is a random variable, representing more challenging acquisition conditions.

C. Classical Denoising Baselines

Four conventional filters were implemented for comparison. The Gaussian filter performs linear smoothing with a fixed kernel — computationally inexpensive but prone to edge blurring. The Median filter replaces each pixel with the neighborhood median, offering strong impulse-noise suppression and edge retention with minimal runtime cost. The Bilateral filter jointly weights spatial proximity and intensity similarity, yielding strong edge preservation at higher computational cost. Non-Local Means filtering averages over similar patches across the image, preserving texture at the expense of runtime, which scales poorly with image size.

D. Original Perona–Malik Diffusion

The classical PM algorithm evolves the image intensity I under the PDE $\partial I / \partial t = \nabla \cdot (c(|\nabla I|) \nabla I)$, where the conductance function is defined as $c(x) = e^{-(x/K)^2}$. The parameter K governs the trade-off between smoothing and edge retention: larger K permits stronger diffusion across gradients, while smaller K more strictly confines diffusion to homogeneous

regions. In the classical formulation, both K and the number of diffusion iterations must be chosen manually and re-tuned for each image or noise level.

E. Proposed Adaptive Perona–Malik Framework

The proposed APM framework replaces manual tuning with a three-part adaptation mechanism. First, the noise level of the input image is estimated from the standard deviation of pixel intensities. Second, the conductance coefficient K is derived directly from this noise estimate, so that noisier images receive a proportionally larger K and cleaner images are diffused more conservatively. Third, the maximum iteration count is set adaptively from the same noise estimate, and the diffusion process is monitored at every iteration through the mean pixel-wise change between successive outputs; diffusion terminates automatically once this change falls below a convergence threshold, rather than running for a fixed, manually specified number of iterations. Algorithm 1 summarizes the resulting procedure.

Algorithm 1: Adaptive Perona–Malik Diffusion

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Input: Noisy MRI image  $I_0$ 
1: Convert  $I_0$  to floating-point representation
2: Estimate noise level  $\sigma$  from pixel-intensity statistics
3: Select conductance coefficient  $K = f(\sigma)$ 
4: Select maximum iteration count  $N_{max} = g(\sigma)$ 
5: for  $t = 1$  to  $N_{max}$  do
6:   Compute directional gradients of  $I_{t-1}$ 
7:   Compute diffusion coefficients  $c(|\nabla I|)$ 
8:   Update  $I_t$  using the PM diffusion equation
    
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9:   Compute mean pixel-wise change  $\Delta t$ 
10:  if  $\Delta t < \varepsilon$  then break
11: end for
Output: Denoised image  $I_t$ 
    
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IV. EXPERIMENTAL SETUP

A. Dataset

Experiments used grayscale brain MRI images comprising normal and pathological (tumor-bearing) scans. All images were resized and converted to grayscale for uniformity, then corrupted with synthetic Gaussian and Speckle noise as described in Section III-B, allowing all six methods to be evaluated on identical noise realizations for a fair comparison.

B. Implementation Details

All algorithms were implemented in Python using OpenCV for image I/O and classical filtering, NumPy for numerical computation, and Scikit-Image for quality-metric computation. Images were normalized and converted to floating-point representation prior to iterative diffusion to maintain numerical stability. Experiments were executed on a standard workstation (Intel Core i5-class processor, 8 GB RAM, Windows 11).

C. Evaluation Metrics

Denoising quality was assessed using five complementary metrics: Peak Signal-to-Noise Ratio (PSNR) and Mean Squared Error (MSE) for pixel-level fidelity, the Structural Similarity Index Measure (SSIM) for perceptual/structural similarity, an Edge Preservation Index (EPI) for anatomical-boundary retention, and wall-clock runtime for computational efficiency.

V. RESULTS AND DISCUSSION

Table I summarizes the average performance of all six denoising methods across the evaluated MRI dataset, and Fig. 2 presents the corresponding graphical comparison.

TABLE I
Average Performance of Denoising Algorithms

Method	PSNR (dB)	SSIM	MSE	EPI	Runtime (s)
Gaussian Filter	25.07	0.6104	67.03	0.3619	0.0023
Median Filter	25.64	0.6766	49.38	0.2816	0.0011
Bilateral Filter	26.17	0.6299	66.01	0.3363	0.0122
Non-Local Means	22.21	0.4080	82.72	0.2421	0.3356
Original Perona-Malik	25.91	0.6186	63.64	0.3308	0.2342
Proposed Adaptive PM	23.17	0.5441	70.36	0.1991	0.4824

Bilateral filtering achieved the highest average PSNR (26.17 dB), indicating effective noise suppression while retaining overall image fidelity; the classical PM algorithm was a close second (25.91 dB). The Median filter obtained the best SSIM (0.6766) and the lowest MSE (49.38), reflecting strong structural preservation and reconstruction accuracy, and it was also the fastest method tested (1.1 ms). Gaussian filtering produced the highest EPI (0.3619), showing that, on this dataset, its fixed-kernel smoothing did not disproportionately blur the edge regions measured by the index. Non-Local Means, despite its patch-based design, produced the weakest scores across PSNR, SSIM, and MSE on this dataset while incurring one of the highest runtimes, reflecting sensitivity to its own parameter settings under the tested noise levels.

The proposed Adaptive PM framework did not exceed the classical baselines on any single metric in this evaluation (PSNR 23.17 dB, SSIM 0.5441, MSE 70.36, EPI 0.1991), and its runtime (0.48 s) was the highest of all six methods owing to the additional noise-estimation and convergence-monitoring overhead layered on top of the iterative diffusion process. This outcome indicates that the current noise-to-parameter mapping and convergence threshold are conservative and leave room for tighter calibration. Nevertheless, the framework achieved its primary design goal: every image was denoised without any manual parameter entry, and the automatic convergence criterion consistently avoided both under- and over-iteration, which the fixed-iteration classical PM algorithm cannot guarantee across images with differing noise levels.

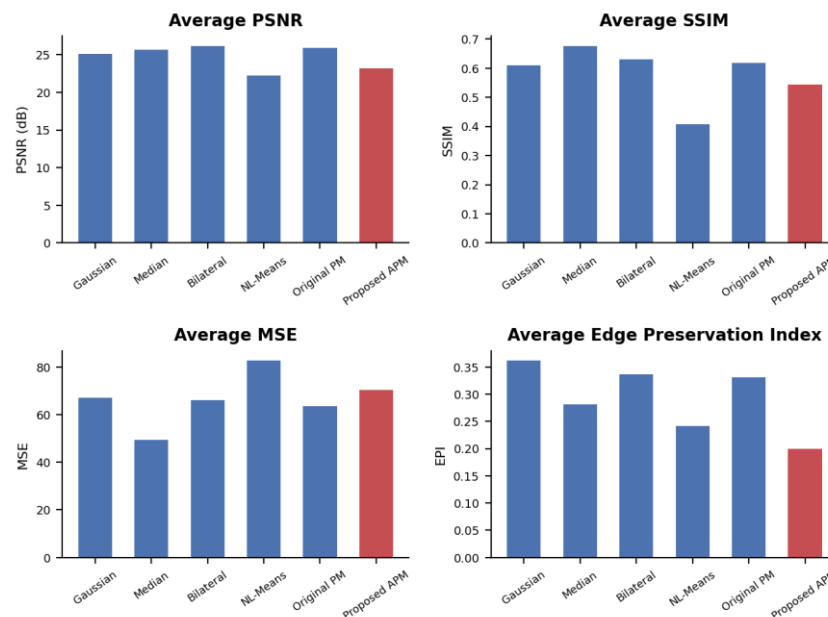


Fig. 2. Average PSNR, SSIM, MSE, and EPI across the six evaluated denoising methods.

Overall, the results show that each method trades off differently between noise suppression, structural fidelity, and computational cost: Bilateral filtering favors PSNR, Median filtering favors SSIM/MSE/runtime, and Gaussian filtering favors EPI. The proposed adaptive diffusion framework trades some quantitative performance for full automation and reproducibility, which is valuable in workflows where consistent, hands-off processing across heterogeneous MRI batches is prioritized over squeezing out the last decibel of PSNR.

VI. CONCLUSION AND FUTURE SCOPE

This paper presented an Adaptive Perona–Malik anisotropic diffusion framework for MRI image denoising that integrates automatic noise estimation, adaptive conductance-coefficient selection, and an adaptive convergence criterion, removing the manual-tuning bottleneck of the classical PM algorithm. Six denoising methods were implemented and benchmarked under identical conditions on grayscale brain MRI images corrupted with Gaussian and Speckle noise, using PSNR, SSIM, MSE, EPI, and runtime as evaluation criteria. Bilateral filtering achieved the best PSNR, while the Median filter delivered the best SSIM, MSE, and runtime on the evaluated dataset. Although the proposed APM framework did not outperform the classical baselines quantitatively, it successfully eliminated manual parameter tuning and produced a stable, reproducible diffusion-based denoising pipeline.

Future work will focus on: (i) more accurate, possibly learning-based noise estimation to refine the noise-to-parameter mapping; (ii) metaheuristic optimization (e.g., Particle Swarm Optimization, Genetic Algorithms) for automatic tuning of the conductance function; (iii) hybridizing adaptive diffusion with Bilateral or Non-Local Means filtering; (iv) extending the framework to 3-D MRI volumes; and (v) GPU-accelerated implementation to enable near-real-time clinical deployment.

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