PSO-Tuned Anisotropic Diffusion Model for Enhanced Denoising and Edge Preservation in Medical Imaging

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Abstract: Speckle noise is an inherent multiplicative distortion in medical ultrasound imaging that significantly degrades image quality by reducing contrast, blurring structural boundaries, and lowering the signal-to-noise ratio (SNR). This adversely affects diagnostic accuracy and the performance of computer-aided analysis systems. This paper proposes a hybrid denoising framework that integrates anisotropic diffusion with Particle Swarm Optimization (PSO) for optimal gradient threshold selection. The anisotropic diffusion process preserves edges while smoothing homogeneous regions, with its performance highly dependent on the gradient threshold parameter. PSO is employed to adaptively determine the optimal threshold, maximizing the Peak Signal-to-Noise Ratio (PSNR) while minimizing the Mean Squared Error (MSE). Two conduction functions are investigated to evaluate their impact on denoising performance. Experimental results on speckle-contaminated brain images demonstrate that the proposed method achieves superior noise suppression and edge preservation compared to conventional filters such as median, Lee, and Frost filters, yielding a maximum PSNR of 26.14 dB at a noise density of 0.04. The approach eliminates the need for local threshold estimation for each scan, thereby improving computational efficiency while maintaining high restoration quality.

Keywords: speckle noise, Medical Image denoising, anisotropic diffusion. Particle Swarm Optimization.

1. Introduction

1.1 Background

Digital Signal Processing (DSP) techniques are widely employed in sonar imaging, underwater imaging, and medical imaging systems. A common challenge in these domains is the presence of noise, which degrades image quality and obscures fine details. In medical imaging—such as X-ray, ultrasound imaging, magnetic resonance imaging (MRI), and computed tomography (CT)—noise significantly impacts diagnostic accuracy. Since internal organs and skeletal structures are not visible to the naked eye due to overlying tissues, medical imaging provides a non-invasive means to visualize and analyze internal anatomy for diagnosis, treatment planning, and monitoring of disease progression.

Medical imaging modalities, including mammography, ultrasound, fluoroscopy, and positron emission tomography (PET), operate by transmitting energy (acoustic waves, magnetic fields, or electromagnetic radiation) through the body and detecting the attenuated or reflected signal. Variations in tissue absorption generate images representing internal structures. While earlier imaging relied on film-based detectors requiring physical processing, modern systems employ digital detectors, enabling real-time visualization and storage.

Although primarily used for diagnostics, medical imaging serves additional purposes such as targeted treatment planning, evaluation of therapeutic efficacy, and detection of age-related medical conditions. Ultrasound imaging, in particular, inherently suffers from speckle noise—a multiplicative noise that degrades contrast, reduces signal-to-noise ratio (SNR), and blurs structural boundaries. This impairs feature extraction, edge detection, image registration (e.g., between MRI and ultrasound), and computer-assisted diagnostic accuracy.

1.2 Literature Review

Given the multiplicative nature of speckle noise, early denoising techniques focused on spatial and transform-domain methods. Spatial-domain filters include mean, median, Wiener, Lee, and Frost filters [2–4]. The median filter's performance depends heavily on window size—larger windows improve noise suppression but increase blurring, while smaller windows preserve detail but reduce noise suppression efficiency. Loupas [5] proposed an adaptive weighted median filter for ultrasound speckle reduction, which improved performance but occasionally removed important features due to unreliable modelling.

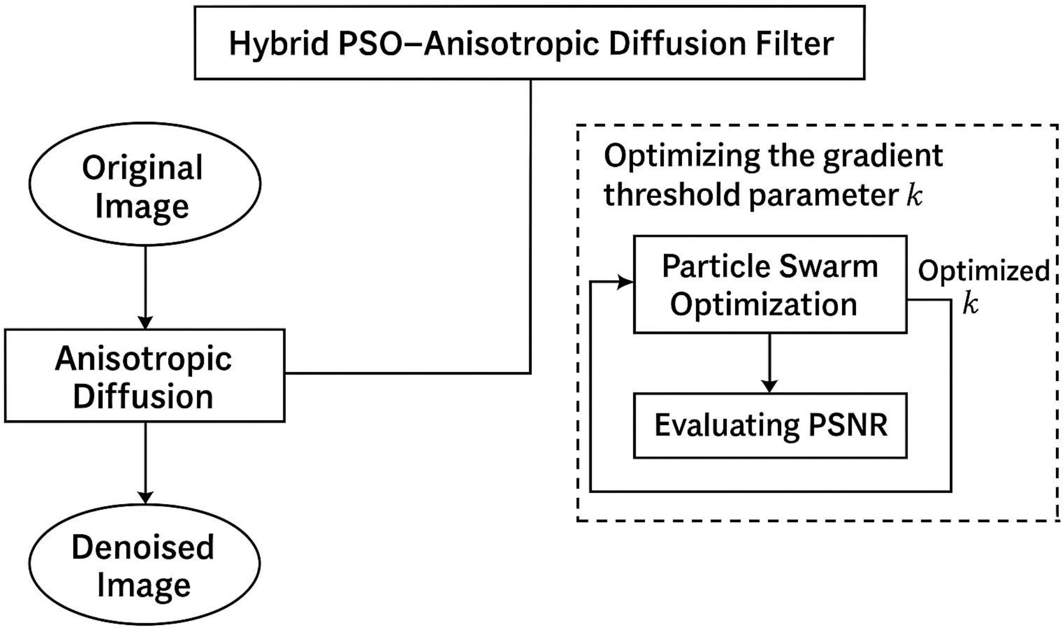
Tomasi [6] introduced the bilateral filter, which assumes local geometric similarity for noise suppression, while the non-local means (NLM) method [7] preserves edges by averaging structurally similar patches, albeit at high computational cost. Transform-domain approaches include Fourier, wavelet [8], contourlet, and cosine transforms. In [9], a two-stage denoising method first removed bias from squared-magnitude images, then applied wavelet-domain denoising to the square root of the image.

Particle swarm optimization (PSO) has been explored for parameter tuning in denoising algorithms [10–12]. Hybrid PSO approaches have been used for underwater speckle reduction [13]. Guillen et al. [14] introduced a stopping criterion for anisotropic diffusion based on inter-image variance ratios, enabling automation. In medical decision-support contexts, PSO has been integrated with K-means clustering and statistical analysis for heart disease modelling [15] and optimized SVM classification for rheumatoid arthritis diagnosis [16].

Anisotropic diffusion has demonstrated superior PSNR performance compared to other filters [17], with strong edge-preservation properties [18]. Shamla Beevi et al. [19] evaluated multiple spatial and transform-domain denoising methods, showing that SRAD outperforms other spatial filters based on SSI, PSNR, and SSIM. Deep learning-based approaches, such as content-noise complementary learning (CNCL) [20], use adversarial frameworks to jointly model structural content and noise for improved denoising performance.

1.3 Proposed Method

This work proposes a hybrid denoising model integrating anisotropic diffusion with PSO-based optimization. The PSO algorithm adaptively tunes the gradient threshold parameter in the diffusion process, enabling effective noise suppression while preserving structural edges. The model is evaluated using PSNR and MSE metrics, demonstrating improved denoising quality compared to conventional methods.



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A. Anisotropic Diffusion

Anisotropic diffusion, introduced by Perona and Malik [1], is a partial differential equation (PDE)-based technique for image processing that produces a scale-space representation of the image—ranging from fine to coarse resolutions—without introducing bias. It is widely employed for simultaneous denoising and edge enhancement.

In this work, anisotropic diffusion is utilized to smooth homogeneous regions while preserving and enhancing structural edges. The method restricts diffusion across edges, thus retaining critical diagnostic information. Instead of applying fixed hard thresholds, an adaptive threshold selection mechanism is employed to ensure optimal performance in fine-detail regions and near boundaries.

The anisotropic diffusion process is governed by:

$$\frac{\partial J(p,q,t)}{\partial t} = \nabla \cdot \left[c_f\left(\|\nabla J(p,q,t)\|\right) \nabla J(p,q,t)\right] \tag{1}$$

where:

- $J(p,q,0)$: Original image,
- $J(p,q,t)$: Image at time t,
- $c_f(\cdot)$: Conductance (diffusivity) function,
- ∇: Gradient operator,
- $\nabla.$: Divergence operator.

The conductance function $c_f(\cdot)$ controls the degree of diffusion:

- $c_f(\cdot)=0 \rightarrow$ No diffusion across edges (maximal edge preservation).
- $c_f(\cdot)=1 \rightarrow$ Maximum diffusion in homogeneous regions.

Two common formulations of $c_f(\cdot)$are:

$$c_{f1}(p) = \exp\left(-\left(\frac{p}{k}\right)^2\right)$$

$$c_{f2}(p) = \frac{1}{1+\left(\frac{p}{k}\right)^2}$$

where k is the gradient threshold parameter, adaptively optimized using PSO in this study.

B. Particle Swarm Optimization (PSO)

PSO, proposed by Kennedy and Eberhart [3], is an evolutionary computation technique inspired by swarm intelligence observed in bird flocking, fish schooling, and human social behavior. Unlike traditional evolutionary algorithms, PSO emphasizes social collaboration over strict fitness competition.

A swarm consists of particles, each representing a candidate solution. The position and velocity of each particle are iteratively updated based on:

1. Personal best position (p_{best}), and
2. Global best position (g_{best}) found by the swarm.

The velocity and position update equations are given by:

$$v_i^{t+1} = wv_i^t + c_1 r_1 (p_{\text{best},i} - x_i^t) + c_2 r_2 (g_{\text{best}} - x_i^t) \tag{2}$$

$$x_i^{t+1} = x_i^t + v_i^{t+1} \quad (3)$$

where:

- w : Inertia weight (controls exploration/exploitation),
- c_1,c_2 : Cognitive and social acceleration coefficients,
- r_1,r_2: Uniformly distributed random numbers in [0,1],
- x_i^t ,v_i^t : Position and velocity of particle iii at iteration t.

1) Parameter Selection in PSO

- Inertia Weight (**www**)**:**
  - w≈1 → Global exploration.
  - w∈[0.2,0.5] → Local exploitation.
  - Time-varying inertia weight (PSO-TVIW) transitions from global to local search.
- Maximum Velocity (**Vmax**)**:**
  - Limits position updates to prevent divergence.
  - Example: xi∈[−10,10],
  - Set Vmax=20.
- Constriction Factor (**χ**)**:**
  - Enhances convergence stability by controlling particle oscillations.
- Swarm Size (**S**)**:**
  - Typically, 20≤S≤60.

C. Integration of PSO with Anisotropic Diffusion

In the proposed Hybrid PSO–Anisotropic Diffusion Filter**:**

1. PSO optimizes the gradient threshold parameter **k** for the conductance function.
2. The optimized kkk value is applied in the anisotropic diffusion process for denoising.
3. The Peak Signal-to-Noise Ratio (PSNR) is used as the objective function for optimization, while Mean Squared Error (MSE) validates performance.

4.Adaptive or Dynamic Weight Particle Swarm Optimization:

An approach to computation is particle swarm optimization. This problem has a few alternative solutions that are thought of as the beginning population. In the search space, this is utilized to locate a solution to the issue. This involves a problem which has a set of potential solutions. Initial population is set to find solution. Each solution has a rate of adaptation during which each person's position modifies and the optimal position is selected. Estimated previous best position and its surroundings. Consider the ith swarm particle in a D-dimensional search space, represented by a D-dimensional vector.

$$X_i = [x_{i1}, x_{i2}, \ldots x_{iD}] \tag{4}$$

Using a D-dimensional vector, the new particle velocity with positional changes is depicted., as shown in Figure 1.

$$V_i = [v_{i1}, v_{i2} \ldots\ldots v_{iD}] \tag{5}$$

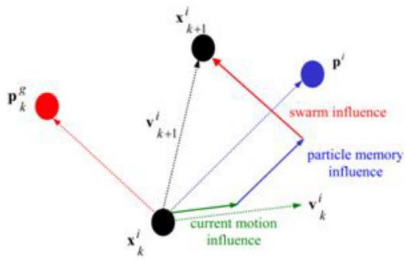

Figure 1: Illustration of the updated velocity and position in PSO

Flowchart Dynamic Weight Particle Swarm Optimization

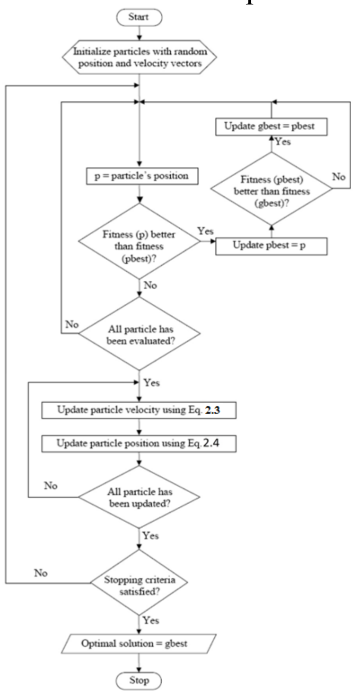

Figure 2. Flowchart of DWPSO

The parameters inertia weights (w), maximum value of velocity (Vmax), social and cognitive constants (cc1 and cc2), , and population size (S) all affect how well APSO performs. Creating particle locations and velocities, updating their velocities, and updating their positions are the steps as shown in Figure 2.

2.Methodology

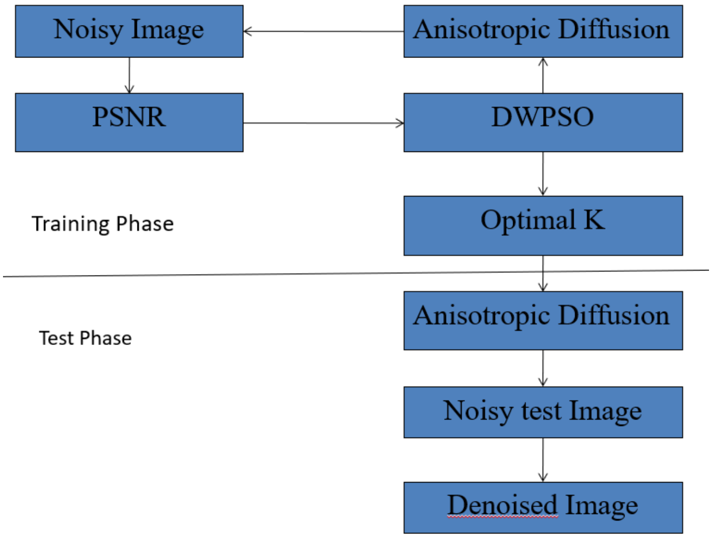

Figure 3. Methodology of Algorithm

The population of PS0 is set to 50, the highest inertia weight is 1.2, the lowest inertia weight is 0.1, and the constriction factor is 0.72. From figure 3, during the training phase, a test image is read. Global value of k is used to calculate PSNR's maximum value. The five iterations required to arrive at this global value of k A test image is then captured. Using k value and the conduction function cf1 in anisotropic diffusion, the PSNR for this test image is determined after 12 iterations. Then, using anisotropic diffusion, the denoised image is restored to its best possible state. This procedure is repeated for anisotropic diffusion's conduction function cf2. From cf1 to cf2, it is seen that PSNR improves.

3.Simulation results

A.

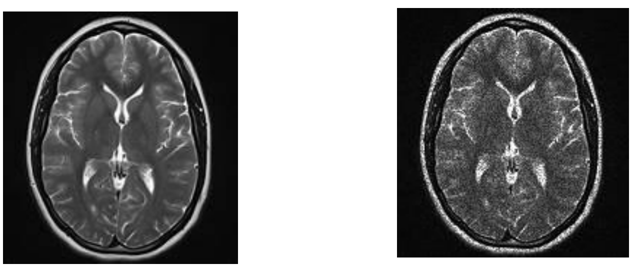

Figure 4. Original Brain image **Figure 5.Image with speckle noise**

B.Training Phase:PSO based gradient threshold using first conduction function.

The optimal gradient Threshold is obtained by training the image with 5 iterations.

ans = 1.0000 2.0000 25.1151 47.9726
ans = 1.0000 3.0000 25.1212 48.1423
ans = 1.0000 4.0000 25.1171 48.0285
ans = 1.0000 5.0000 25.1157 47.9903
FINAL Gradient Threshold value--- 47.9903
PSNR--- 25.1157

C. Test Phase: Test of restoration using first conduction function- Overscanning effect can be seen by performing 15 iterations for test to obtain the highest PSNR.

ans = 1.0000 23.7092 25.1157
ans = 2.0000 23.7092 25.5769
ans = 3.0000 23.7092 25.5209
ans = 4.0000 23.7092 25.2932
ans = 5.0000 23.7092 25.0111
ans = 6.0000 23.7092 24.7206
ans = 7.0000 23.7092 24.4380
ans = 8.0000 23.7092 24.1691
ans = 9.0000 23.7092 23.9159
ans = 10.0000 23.7092 23.6773
ans = 11.0000 23.7092 23.4546
ans = 12.0000 23.7092 23.2497
ans = 13.0000 23.7092 23.0616
ans = 14.0000 23.7092 22.8890
ans = 15.0000 23.7092 22.7301

Figure 6. Noisy Image

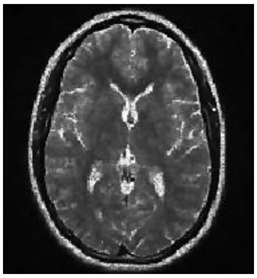

Figure 7.Filtered Image

D. Optimum solution from first conduction function

1.0000 23.7092 25.1157
ans = 2.0000 23.7092 25.5769

Second conduction function

E. Training Phase: PSO based gradient threshold using second conduction function

ans = 1.0000 2.0000 25.7781 49.6908
ans = 1.0000 3.0000 25.7784 49.7025
ans = 1.0000 4.0000 25.7734 49.5303
ans = 1.0000 5.0000 25.7717 49.4725
FINAL Gradient Threshold value--- 49.4725
PSNR--- 25.7717

F. Test Phase: Test of restoration using second conduction function

ans = 1.0000 23.6143 25.7717
ans = 2.0000 23.6143 26.1489
ans = 3.0000 23.6143 25.5946
ans = 4.0000 23.6143 24.7992
ans = 5.0000 23.6143 24.0048
ans = 6.0000 23.6143 23.2775
ans = 7.0000 23.6143 22.6292
ans = 8.0000 23.6143 22.0541
ans = 9.0000 23.6143 21.5402
ans = 10.0000 23.6143 21.0755
ans = 11.0000 23.6143 20.6501
ans = 12.0000 23.6143 20.2583
ans = 13.0000 23.6143 19.8970
ans = 14.0000 23.6143 19.5650
ans = 15.0000 23.6143 19.2617

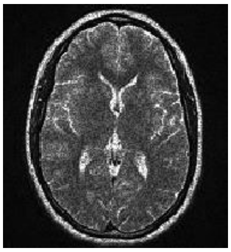

Figure 8. Denoised Image

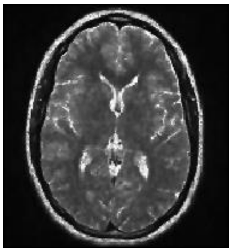

Figure 9. Denoised Image proposed filter

ans = 1.0000 23.6143 25.7717
ans = 2.0000 23.6143 26.1489

PSNR=26.1489

Comparison of different filters—noise density-0.04

Table 1. Table Styles

S.No	Filter	PSNR
1	Median filter	15.08
2	Lee Filter	23.22
3	Frost Filter	24.23
4	Hybrid filter	26.14

Hence from the above table it is observed that PSNR is high in proposed filter.

4.Conclusion

The gradient threshold in anisotropic diffusion plays a critical role in controlling the extent of smoothing and edge preservation. In the proposed method, particle swarm optimization (PSO) is used to determine the optimal threshold value. During a training phase, PSO searches for the threshold that maximizes the peak signal-to-noise ratio (PSNR) for a noisy reference image. This optimized threshold is then applied in the anisotropic diffusion process to denoise test images.

Experimental results show that the proposed approach is both computationally efficient and highly effective in suppressing noise, as it removes the need for local threshold estimation for each scan or image. Furthermore, results indicate that when the threshold is optimally selected, a simple conduction function produces superior performance.

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