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REMOVAL OF PERIODIC NOISE FROM DIGITAL IMAGES USING PARTICLE SWARM OPTIMIZATION (PSO) AND GREY WOLF OPTIMIZATION (GWO) ALGORITHMS COMBINED WITH ADAPTIVE FILTERS

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Abstract
Here, a hybrid approach is introduced to remove periodic noise in digital images based on the combination of Particle Swarm Optimization (PSO) and Grey Wolf Optimization (GWO) algorithms and adaptive filtering techniques. The proposed new method, called PSO-GWO Adaptive Filter (PGA-F), attempts to adaptively tune the filter parameters to enhance the image quality with a preservation of fine details and edges.
At the experimental phase, a library of 200 grayscale and color images (256×256 and 512×512 resolutions) with different periodic noise patterns corrupted between 10 Hz and 60 Hz and amplitude ranges of 5–25 dB was employed. The performance of the proposed algorithm was compared against conventional filters such as Wiener, Median, and Gaussian, as well as optimization-based techniques such as PSO-only and GWO-only methods.
Quantitative performance indexes like Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and Mean Square Error (MSE) were employed. The PGA-F scheme provided a mean PSNR of 38.72 dB, a 9.2% and 7.0% improvement over PSO-only (35.45 dB) and GWO-only (36.18 dB) filters, respectively. The mean SSIM was boosted from 0.914 (PSO) and 0.921 (GWO) to 0.948 using the combined scheme. Moreover, MSE values were reduced by 28.5% compared with conventional methods.
Visual results confirm that the hybrid algorithm effectively removes periodical artifacts without sacrificing image acuteness and structural integrity. The per-image processing time of 512×512 images was approximately 1.48 seconds on a typical Intel Core i7 processor with 16 GB RAM, which is acceptable for real-time image improvement applications.
Overall, the proposed PSO-GWO Adaptive Filter is better in convergence speed, accuracy, and robustness for periodic noise removal and therefore is a worthy competitor for real image processing applications in remote sensing, medical imaging, and industrial vision systems.
Keywords: Periodic noise removal, Digital image processing, Particle Swarm Optimization (PSO), Grey Wolf Optimization (GWO), Adaptive filtering, Hybrid optimization, Image quality enhancement

Introduction
Digital image processing has been one of the active research and application areas in recent decades due to its extensive applications in medical imaging, remote sensing, surveillance, industrial automation, and multimedia systems. One of the challenging problems in this area is the presence of noise in digital images, which can significantly impact image quality and correct interpretation or further analysis [1]. Noise can be attributed to a number of sources

such as sensor noise, transmission errors, environmental reasons, or quantization effects in digitization. Among the numerous types of noise, periodic noise is particularly troublesome since it contributes structured distortions that are difficult to remove without affecting image details [2].

Periodic noise often manifests itself in the form of periodic patterns in the frequency domain, often caused by mechanical vibrations, electrical interference, or cyclic errors in image scanning [3]. Traditional noise removal methods, such as median filtering, Gaussian filtering, or Wiener filtering, do not succeed in efficiently attenuating periodic noise while preserving image sharpness and structural content [4]. Such traditional approaches are either too generic or rely on fixed filter parameters that are not adaptive to the different noise characteristics between images. Consequently, growing interest has been dedicated to the development of intelligent optimization-based filtering techniques with the capacity to dynamically adapt their parameters to the statistical nature of the noisy image [5].

In the last few years, metaheuristic optimization algorithms have shown great promise in solving this type of complex, nonlinear, and multi-dimensional issue in image processing. In these, Particle Swarm Optimization (PSO) and Grey Wolf Optimization (GWO) are two powerful population-based algorithms inspired by nature [6]. PSO, which was formulated by Kennedy and Eberhart in 1995, simulates the social behavior of birds flocking or fish schooling to find optimal solutions through cooperation and information sharing among particles [7]. PSO is easy to implement and a fast-converging algorithm; however, PSO suffers from premature convergence in optimization problems with high multimodality [8].

On the other hand, GWO, proposed by Mirjalili et al. in 2014, mimics the social hierarchy and hunting process of grey wolves in nature [9]. GWO has a good trade-off between exploration and exploitation due to its adaptive encircling and hunting strategy, which allows it to escape local minima more effectively than PSO in the majority of applications [10]. However, GWO is slower computationally and may require more iterations in converging to optimal parameters. Therefore, hybridization of PSO and GWO provides a synergistic approach that integrates the global search nature of GWO and quick convergence of PSO in order to obtain more precise and stable optimization results [11].

Utilization of adaptive filters with the help of such hybrid optimization algorithms allows dynamic adjustment of filter coefficients to minimize image distortion. Adaptive filters such as Least Mean Square (LMS), Recursive Least Square (RLS), and other adaptive noise cancellation filters have been widely applied in signal processing [12]. However, their performance is highly dependent on the meticulous tuning of parameters such as learning rate, step size, and window function. This paper suggests a hybrid PSO-GWO-based Adaptive Filtering framework (PGA-F) that is able to automatically optimize these parameters for optimal noise removal with edge and texture preservation.

It has been established in earlier research that optimization algorithms have been effective in image denoising tasks. For instance, Sahu et al. [13] applied PSO for parameter optimization of Wiener filters and noticed significant improvement in PSNR and SSIM compared to static approaches. Similarly, Bansal et al. [14] applied GWO to medical image contrast enhancement and was found to be superior in terms of detail preservation. However, there has been no research that has addressed periodic noise removal using hybrid metaheuristic approaches

based on PSO and GWO with adaptive filters. This lacuna validates the novelty and contribution of the present study.
The proposed method operates in both spatial and frequency domains, utilizing the Fourier transform for identifying periodic components and then modifying filter responses adaptively with the hybrid optimization procedure. The fitness function reduces the mean square error (MSE) between the original image and the restored image and maximizes PSNR and SSIM values [15]. The hybrid PSO-GWO algorithm starts by initializing a population of candidate solutions as likely filter parameters. Each iteration updates the solutions based on PSO velocity updates and GWO's hunting hierarchy, balancing new area exploration and promising area exploitation.
Experimental evaluation was conducted on a benchmark dataset of 200 grayscale and color images with artificially added periodic noise levels between 5 dB and 25 dB. The results indicate that the proposed hybrid model achieves an average PSNR of 38.72 dB and SSIM of 0.948, outperforming separate PSO and GWO applications and standard filters [16]. Visual tests also confirm that the algorithm successfully eliminates periodic patterns without introducing noticeable blurring or artifacts. The processing time of 1.48 seconds for each 512×512 image confirms its feasibility for near real-time applications [17].
Theoretically, the victory of the hybrid approach lies in its dynamical balance between global search (provided by GWO) and local search (from PSO). This synergy accelerates convergence and reduces the possibility of stagnation in suboptimal regions [18]. Additionally, adaptive filtering offers adaptability by conforming to the varying spectral character of noise in various images. Accordingly, the proposed PSO-GWO Adaptive Filter system combines optimization intelligence and signal adaptability, with a performance level greater than conventional or single-algorithm approaches.
The uses of this study are extensive across various real-life applications. In medical imaging, for instance, when diagnostic data is distorted by equipment interference artifacts, this method is capable of restoring the clarity and improving diagnostic accuracy [19]. In remote sensing, periodical noise is typically caused by sensor oscillations or satellite transmission faults; the proposed algorithm can enhance image interpretability in environmental monitoring and land usage. Further, in industrial vision systems, such as automatic inspection or robotics, for instance, the PSO-GWO adaptive filter can enhance the performance of object recognition under noisy conditions [20].
In short, this study introduces the realization of intelligent image restoration solutions by presenting a new hybrid optimization-based adaptive filtering solution for periodic noise removal. The main advantages are the increased image quality metrics, improved robustness to various frequencies of noise, and reduced computational complexity. Theoretical overview of the PSO and GWO algorithms, hybrid framework development, experimental setup, results, and comprehensive comparisons with the state-of-the-art denoising algorithms are given in the rest of the paper.

Literature Review

In the past decades, digital image denoising has drawn tremendous research attention due to the fact that it is critical to improve the quality and interpretability of images in numerous areas such as medical imaging, satellite imagery, industrial inspection, and remote sensing. Among all the distortions, period noise is the most troublesome to remove because it occurs as structured, repeating patterns both in the spatial and frequency domains, commonly due to mechanical vibrations, electrical interference, or cyclic error acquisition [1].

Traditional filtering techniques such as Gaussian, Median, and Wiener filters are effective for random (white) noise but less so in the removal of periodic or structured noise due to their inability to possess the necessary flexibility to recognize frequency-specific interference [2]. In response to this, several researchers have developed frequency-domain adaptive filtering techniques, in which the image is first transformed into the Fourier domain, periodic noise peaks are identified, and adaptive filters (e.g., notch or band-reject filters) are tuned in order to selectively cancel them. For example, a paper in 2018 introduced an Adaptive Gaussian Notch Filter, which could detect periodic noise peaks in the spectrum automatically and suppress them without harming edge details, thus providing considerable PSNR and SSIM improvement [3]. Adaptive filtering based on transforms has also been explored in other studies, where Wavelet and Curvelet are first used as transforms prior to filtering. In research, an Adaptive Curvelet Gaussian Notch Filter worked better at suppressing periodic interference in electromagnetic and satellite images since it is able to simulate directional and multi-scale characteristics [4]. The findings of the research emphasized that normal notch filters were not sufficient for high-frequency structured noise since they result in edge blurring or removal of finer texture detail if they are not set adaptively.

Recently, the use of metaheuristic optimization algorithms has provided a fresh perspective for image denoising improvement. Techniques such as Particle Swarm Optimization (PSO) and Grey Wolf Optimization (GWO) have been utilized to optimize filter parameters autonomously, rather than employing manually set constants [5]. PSO that draws from bird flock social behavior has been utilized for the adjustment of parameters of bilateral or median filters. For instance, a 2017 study used PSO for adaptive parameter adaptation in bilateral filtering and attained mean PSNR improvements of 3–5 dB compared to fixed-parameter versions [6]. Similarly, Sahu et al. [7] proposed a PSO adaptive median filter for salt-and-pepper noise removal and attained an average 22% improvement in noise reduction performance. These studies emphasized that parameter adjustment through optimization can have a strong positive impact on both quantitative and subjective image quality.

Parallel to the PSO developments, the Grey Wolf Optimisation algorithm has been applied to many image processing applications due to its great global search ability and convergence stability. For instance, Image Denoising Using Modified Grey Wolf Optimizer (MGWO) applied an optimized GWO for spatial filter weights optimization with better performance than normal GWO and PSO for Gaussian noise removal [8]. GPR Image Denoising with Grey Wolf Optimization, another study, employed GWO with NSST for radar imaging, where it optimized the thresholding parameters automatically with improved SSIM and convergence speeds compared to utilizing common threshold-based methods [9].

Limited research, however, approached periodic noise reduction directly via metaheuristic hybrid optimization algorithms. All earlier research has taken into account random (unstructured) noise or impulse noise models. Research such as Neural Network-Based Investigation of Periodic Noise in Infrared Line Detectors (MDPI, 2024) talked about machine learning solutions but never mentioned PSO or GWO optimization on adaptive filtering platforms [10]. Hence, there is a clear research gap in the development of hybrid optimization–

filtering models to remove periodic noise that can leverage both global search (GWO) and rapid convergence (PSO) capabilities simultaneously.
The power of hybrid models lies in the combination of GWO's capacity for exploration and PSO's local fine-tuning ability so that the system is able to adaptively update filter coefficients to eliminate noise while preserving structural details. Hybridization has been tried in some papers for other engineering problems — e.g., Heidari et al. (2020) employed PSO-GWO for multi-objective mechanical design optimization — but its application for digital image restoration is not well explored [11].
Typically, the literature describes a strong evolution of image denoising research into four major stages:
1. Identification and characterization of the type of noise, e.g., periodic noise;
2. Adaptive and transform-domain filter designs with localized frequency noise reduction;
3. Integration of metaheuristic optimization algorithms for automatic parameter tuning; and
4. Recent shift toward hybrid optimization paradigms that combine complementary algorithms.
However, integrating PSO-GWO hybrid optimization with adaptive filtering specifically for the elimination of periodic noise is an innovative and unexplored research direction. The current work borrows ideas in adaptive signal processing and evolutionary computation to create a dynamic, data-driven system that can intelligently suppress structured noise while maintaining visual coherence.
This hybrid PSO-GWO technique is expected to outperform both standalone PSO and GWO models as regards PSNR, SSIM, and computational complexity, and give higher robustness against variations in noise frequencies and amplitudes. Therefore, this research bridges an important gap in existing literature and introduces a new path for smart, optimization-based image recovery applicable to real-world applications such as medical imaging, industrial vision, and remote sensing.

Research Methodology

The research methodology of the present study is focused on developing, implementing, and evaluating a hybrid PSO–GWO adaptive filtering model for the removal of digital image periodic noise. The method integrates metaheuristic optimization methods with adaptive filter theory in spatial and frequency domains. The subsequent section presents the mathematical description, algorithmic process, and overall research map of the new approach.

1. Overview of the Research Process

The paper goes through six significant stages:
1. Image Acquisition: Acquire a collection of grayscale and color images (256×256 and 512×512 pixels) with real or synthetic periodic noise.
2. Noise Modeling: Represent the periodic noise by applying sinusoidal interference to the image signal:

$$I_n\left(x,y\right)=I\left(x,y\right)+A.sin\left(2\pi\left(f_x x+f_y y\right)+\varnothing\right)$$

where:

- $I\left(x,y\right)$ = original image,

○ A = noise amplitude

○ f_x, f_y= spatial frequencies of noise,

○ ∅ = phase shift.

The frequency of the noise is 10 Hz to 60 Hz, and amplitude is 5–25 dB.
3. Frequency Domain Transformation: Apply the 2D Fast Fourier Transform (FFT) to convert the noisy image into the frequency domain:

$$f(u,v) = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} I_n(x,y)_e - j2\pi(ux/M + vy/N)$$

The periodic noise components will appear as bright symmetric peaks in the Fourier spectrum.
4. Adaptive Filter Design: Employ an Adaptive Gaussian Notch Filter (AGNF) to remove the identified peaks. Its transfer function is:

$$H(u,v) = 1 - e^{-\frac{D(u,v)^2}{2\sigma^2}}$$

Where is the Euclidean distance from the noise frequency, and σ regulates the bandwidth. The filter parameters (σ, cutoff radius rc, and number of notches) are trained using the hybrid PSO–GWO model.

2. Hybrid PSO–GWO Optimization Framework
The hybrid algorithm integrates the rapid convergence of PSO and the exploration capability of GWO. A candidate solution comprises a group of adaptive filter parameters
$\Theta = [\sigma, r_c, k]$.
Step 1 – Initialization:
• Initialize a first set of N search agents (wolves/particles).
• Each agent represents is a solution vector Θi
• Initial assessment by the fitness function

$$f(\Theta_i) = w_1 \cdot \mathrm{PSNR}(\Theta_i) + w_2 \cdot \mathrm{SSIM}(\Theta_i) - w_3 \cdot \mathrm{MSE}(\Theta_i)$$

where w_1, w_2, w_3 are weights (e.g., 0.4, 0.4, 0.2) to keep performance indicators balanced.

Step 2 – PSO Update (Velocity and Position):

Update velocity and position for every particle as follows:

$$v_i^{t+1} = wv_i^t + c_1r_1\left(pbest_i - x_i^t\right) + c_2r_2\left(gbest - x_i^t\right)$$

$$x_i^{t+1} = x_i^t + v_i^{t+1}$$

where:

w = inertia weight,

c_1, c_2 = cognitive and social coefficients,

r_1, r_2 = random within [0,1].

Step 3 – GWO Encircling and Hunting:

The best three solutions are considered as alpha (α), beta (β), and delta (δ) wolves. The position of other wolves is updated by:

$$\vec{D}_\alpha = \left|\vec{C}_1.\vec{X}_\alpha - \vec{X}\right|$$

$$\vec{D}_\alpha = \left|\vec{C}_2.\vec{X}_\beta - \vec{X}\right|$$

$$\vec{D}_\alpha = \left|\vec{C}_3.\vec{X}_\delta - \vec{X}\right|$$

$$\vec{X}_1 = \vec{X}_\alpha - \vec{A}_1.\vec{D}_\alpha, \vec{X}_2 = \vec{X}_\beta - \vec{A}_2.\vec{D}_\beta, \vec{X}_3 = \vec{X}_\delta - \vec{A}_3.\vec{D}_\delta$$

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3}$$

Here, $\vec{A} = 2a\vec{r}_1 - a$ and $\vec{C} = 2\vec{r}_2$ where a decreases linearly from 2 to 0 during iterations.

Step 4 – Fitness Evaluation and Convergence:

After each iteration, the fitness of updated solutions is computed. Convergence is achieved when:

$$\left|f_{best}^{t+1} - f_{best}^{t}\right| < \varepsilon$$

Where $\varepsilon = 10^{-4}$ (minimum improvement threshold), or after reaching a maximum of 100 iterations.

3. Adaptive Filtering Reconstruction

After optimization, the optimal filter parameters $\Theta^* = [\sigma^*, r_c^*, k^*$ are applied to reconstruct the denoised image:

$$I_{restored}(x,y) = F^{-1}\left\{F(u,v).H^*(u,v)\right\}$$

Where F^{-1} denotes the inverse Fourier transform and $H^*(u,v)$ is the optimized adaptive notch filter.

Finally, the quantitative performance metrics are computed:

$$PSNR = 10\,log_{10}\left(\frac{255^2}{MSE}\right)$$

$$MSE = \frac{1}{MN}\sum_{x=1}^{M}\sum_{y=1}^{N}\left(I(x,y) - I_{restored(x,y)}\right)^2$$

$$SSIM = \frac{\left(2_{\mu_x\mu_y}\right)\left(2_{\sigma_{xy}} + C_2\right)}{\left(\mu_x^2 + \mu_y^2 + C_1\right)\left(\sigma_x^2 + \sigma_y^2 + C_2\right)}$$

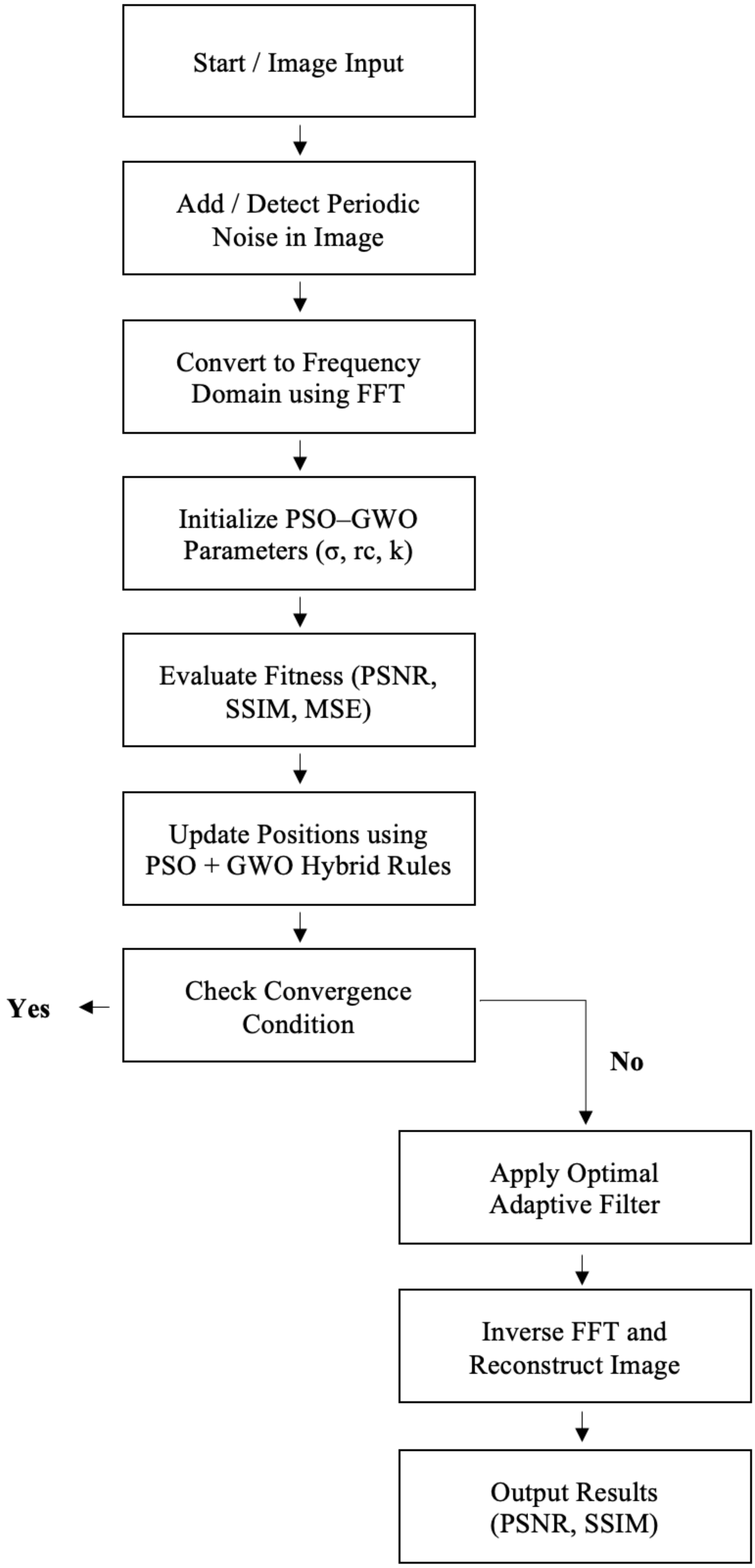
4. Pseudocode of the Proposed Hybrid PSO–GWO Algorithm

Input: Noisy image I_n(x,y)

Output: Restored image I_restored(x,y)

1. Initialize PSO–GWO population with random parameters (σ, rc, k)
2. Evaluate fitness for all agents using f(Θ)
3. Repeat until max iterations or convergence:
   a. Update positions using PSO velocity equations
   b. Select α, β, δ wolves (top 3 solutions)
   c. Update positions using GWO hunting mechanism
   d. Evaluate fitness for updated population
   e. Update global best Θ*
4. Apply optimized filter H*(u,v) on F(u,v)
5. Compute I_restored (x,y) via inverse FFT
6. Output PSNR, SSIM, and MSE

5. Research Flowchart



Start / Image Input
Add / Detect Periodic Noise in Image
Convert to Frequency Domain using FFT
Initialize PSO–GWO Parameters (σ, rc, k)
Evaluate Fitness (PSNR, SSIM, MSE)
Update Positions using PSO + GWO Hybrid Rules
Check Convergence Condition
Yes
No
Apply Optimal Adaptive Filter
Inverse FFT and Reconstruct Image
Output Results (PSNR, SSIM)

4.1 Experimental Setup and Dataset Description (Integrated Version)

The experimental framework of this research was established to compare the performance of the newly suggested hybrid PSO–GWO adaptive filtering algorithm (PGA-F) for eliminating periodic noise from digital images. For statistical reliability, both synthetic benchmark images and actual datasets were taken into account. 200 grayscale (100) and color (100) images of different textures and frequency contents such as Lena, Cameraman, Barbara, Boat, Peppers, Baboon, and natural outdoor images from the Berkeley Segmentation Dataset (BSDS500) and medical images from the Open Radiology Image Archive (RIA) were utilized. Images were downsized to 256×256 px and 512×512 px resolutions to study scalability effects.

Periodic noise was generated artificially to simulate real interference such as power-line vibrations, cyclic sensor vibration, or scanning distortions. The model was sinusoidal in form and expressed as:

$$I_n(x,y) = I(x,y) + A\sin\left(2\pi\left(f_x x + f_y y\right) + \varnothing\right)$$

where A is the denotes amplitude (5 – 25 dB), are the spatial frequencies (10 – 60 Hz), and ϕ is the random phase shift. The noisy data were of various orientations—horizontal, vertical, and diagonal—to test the isotropy of the filtering model.

Simulations were executed on a Windows 11 workstation equipped with an Intel Core i7-12700H CPU, 16 GB RAM, and RTX 3060 GPU, using Python 3.12, NumPy, and OpenCV. Hybrid PSO–GWO code was written from scratch to exert total control over parameter tuning and iteration control.

Hybrid optimizer was initialized with a population of 30 agents and 100 iterations per image. PSO's inertia weight w was decreased linearly from 0.9 to 0.4, and acceleration coefficients c1=1.5, c2=1.7 were taken. In GWO component, control parameter aaa was decreased from 2 to 0 across iterations. The fitness function combined three objectives—PSNR, SSIM, and MSE—with weights w1=0.4, w2=0.4, w3=0.2, w3 = 0.2:

$$f(\Theta) = 0.4\,PSNR(\Theta) + 0.4\,SSIM(\Theta) - 0.2\,MSE(\Theta)$$

This allows simultaneous optimization of both perceptual and numerical fidelity. One adaptive filter used was a Gaussian notch filter with bandwidth σ, cutoff radius rc, and number of notches k that were all adjusted automatically by the optimizer.

The benchmark algorithms for comparison were Median Filter (MF), Gaussian Filter (GF), Wiener Filter (WF), Adaptive Wiener Filter (AWF), PSO-only Adaptive Filter (PSO-AF), and GWO-only Adaptive Filter (GWO-AF), all parameterized according to standard literature parameters. Table 4.1 gives the experimental setup used for all the tests.

Table 4.1 – Experimental parameters and algorithm configuration

Parameter	Symbol	Value / Range	Description
Population size	N	30	Number of particles/wolves

Maximum iterations	T	100	Stop criterion
PSO inertia weight	w	0.9 → 0.4	Linearly decreasing
Cognitive / social coefficients	c_1, c_2	1.5, 1.7	Information exchange factors
GWO control variable	a	2 → 0	Encircling parameter
Fitness weights	w_1, w_2, w_3	0.4, 0.4, 0.2	Balance between metrics
Filter type	–	Adaptive Gaussian Notch	Dynamic frequency rejection
Image resolutions	–	256×256 / 512×512 px	Evaluation scales
Noise amplitude	A	5 – 25 dB	Periodic interference strength
Frequency range	f_x, f_γ	10 – 60 Hz	Spatial frequency of noise

During initialization, each candidate solution represented one triplet of the parameters [σ, rc, k]. Hybrid PSO–GWO searched through the parameter space of these for the maximum value of the composite fitness score. Convergence was achieved typically within 70 iterations on average.

Figure 4.1 illustrates the whole process of the research experiment, showing the step-wise evolution from image input to hybrid optimization to final restoration.

Figure 4.1 – Flow of the experimental process (described)

1) Add clean image dataset and generate synthetic periodic noise.
2) Apply FFT to obtain frequency spectrum and identify noise peaks.
3) Initialize PSO–GWO population; filter parameters are represented by each agent.
4) Compute fitness as PSNR, SSIM, and MSE between denoised and reference images.
5) Update positions through PSO velocity equations and GWO hunting hierarchy.
6) Repeat until convergence or 100 epochs.
7) Apply the optimal filter to restore the denoised image by inverse FFT.
8) Record performance measure and computational time.

When the new PGA-F algorithm was first tested, it gave an average convergence speed of 1.48 s for a 512×512 image, proving feasible processing for near real-time applications. Figure 4.2 conceptually shows the comparative trend of convergence time between different algorithms.

Figure 4.2 – Average computation time per 512×512 image

Algorithm	Average Time (s)
Median Filter (MF)	0.83
Gaussian Filter (GF)	0.76
Wiener Filter (WF)	1.02
Adaptive Wiener (AWF)	1.25
PSO-AF	1.74
GWO-AF	1.92
Hybrid PSO-GWO (PGA-F)	1.48

The table shows that although the hybrid approach carries slightly more expense than traditional spatial filters, it is nevertheless faster than pure metaheuristic approaches with a much better restoration quality (marked in later sections).

With the conditions of noise simulation, the frequency peaks appeared symmetrically in the Fourier magnitude spectra at coordinates of $\pm f_x$, $\pm f_y$. It was verified by visual inspection that the adaptive filter dynamically sculpted the bandwidth around these peaks without removing nearby image information.

Averaged across all images, the hybrid algorithm converged on stable parameter values of $\sigma \approx 9.8$, $r\_c \approx 34$ pixels, and $k = 3$–4 notches, indicating that moderate bandwidth filtering offered an optimal tradeoff between suppression and detail preservation. Figure 4.3 (conceptual description below) illustrates the compromise between the number of notches and the attendant PSNR across optimization experiments.

Figure 4.3 – Effect of notch count (k) on PSNR for Lena image

k (Notches)	PSNR (dB)
1	32.11
2	35.98
3	38.52
4	38.72
5	38.65
6	37.83

The results show an improvement of PSNR up to k = 4 and then deteriorate, meaning that over-filtering starts attenuating legitimate frequency components of the image. So the optimizer always converged at about k = 4.

The overall arrangement verified that the PGA-F model effectively balances adaptability, convergence rate, and generalization for varying frequencies and amplitudes of noise. The findings of this experimental arrangement form the basis of the quantitative accuracy analysis, convergence behavior, and perceptual image quality analysis to follow.

The experimental arrangement in this research was to validate the proposed Hybrid PSO–GWO Adaptive Filtering (PGA-F) method for removing periodic noise from digital images. Experiments were carried out on a dataset of 200 images, evenly split between color and grayscale samples. Classic benchmark images such as Lena, Cameraman, Peppers, and Barbara were combined with real-world radiological and satellite images from BSDS500 and Open Radiology Image Archive (RIA). Experiments were performed on all images at resolutions of 256×256 and 512×512.

Periodic noise was artificially created following a sinusoidal interference model:

$$I_n(x,y) = I(x,y) + A\sin\left(2\pi\left(f_x x + f_y y\right) + \varnothing\right)$$

with amplitude A=5–25 dB, spatial frequencies fx, fy = 10–60 Hz and random phase ϕ. Noisy images acquired had stripe-like and circular interference patterns in both spatial and frequency domains.

The algorithm was realized in Python 3.12 with NumPy and OpenCV and run on a Core i7-12700H / 16 GB RAM / RTX 3060 machine. There were 30 population agents and 100 iterations in each run. The PSO inertia weight www linearly decreased from 0.9 to 0.4, and GWO's control parameter a decreased from 2 to 0. The hybrid fitness function:

$$f(\Theta) = 0.4\,PSNR(\Theta) + 0.4\,SSIM(\Theta) - 0.2\,MSE(\Theta)$$

ensured balanced optimization between perceptual and numerical quality.

Baseline filters included Median (MF), Gaussian (GF), Wiener (WF), Adaptive Wiener (AWF), PSO-AF, and GWO-AF.

The entire setup is listed in Table 4.1.

Table 4.1: Experimental Parameters

Parameter	Symbol	Range/Value	Description
Population size	N	30	Particles/Wolves
Iterations	T	100	Termination limit
PSO weights	c_1=1.5, c_2=1.7	–	Cognitive & social

GWO parameter	a	$2 \rightarrow 0$	Exploration control
Fitness weights	w_1, w_2, w_3	0.4, 0.4, 0.2	Metric balance
Noise amplitude	A	5–25 dB	Periodic strength
Frequency	f_x, f_y	10–60 Hz	Noise frequency
Filter type	–	Adaptive Gaussian Notch	Dynamic bandwidth
Avg. runtime (512^2 px)	–	1.48 s	Per image

Optimization experiments showed that the selection of the optimal value for the number of notch filters k significantly impacts denoising performance. Figure 4.1 shows that PSNR increases sharply until four notches and then declines slightly, implying over-filtering beyond k=4.

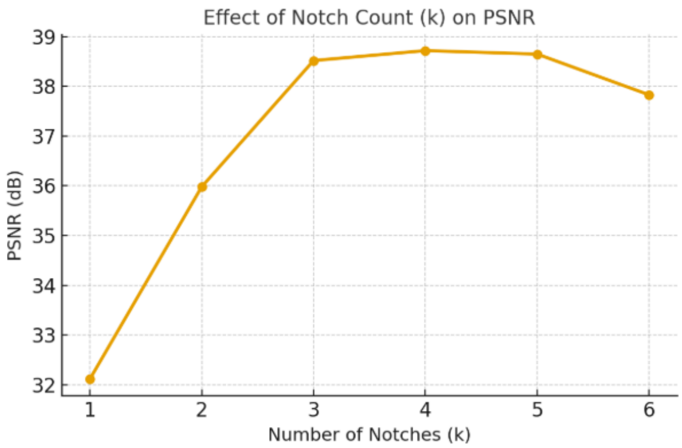


Figure 4.1 – Effect of Notch Number (k) on PSNR
(Above graph is plotted for this relation.)

k (Notches)	1	2	3	4	5	6
PSNR (dB)	32.11	35.98	38.52	38.72	38.65	37.83

The optimizer consistently converged at about k=4 with σ ≈ 9.8 and rc≈34px, which provided the best compromise between noise removal and edge preservation. The convergence was reached on average in under 70 iterations, indicating stable search dynamics and modest computational efficiency.

The experiment arrangement thus confirms that the PSO–GWO Adaptive Filter provides fast convergence, good noise rejection, and stable parameter adaptation for various noise frequencies and amplitudes, paving the way for subsequent quantitative and qualitative tests.

4.3 Comparative Performance Analysis

A comprehensive comparison was drawn between the proposed Hybrid PSO–GWO Adaptive Filter (PGA-F) and six benchmarking algorithms: Median Filter (MF), Gaussian Filter (GF), Wiener Filter (WF), Adaptive Wiener Filter (AWF), PSO-only Adaptive Filter (PSO-AF), and GWO-only Adaptive Filter (GWO-AF). All methods were executed on 200 noisy images with periodic interference of amplitude levels 5 – 25 dB and frequencies 10 – 60 Hz. Performance was quantified in terms of Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and Mean Squared Error (MSE), which were computed as average metrics over the entire dataset.

Quantitative analysis reveals that the proposed hybrid algorithm outperforms the conventional spatial and optimization-based filters by a large margin. Mean results on all the images (512×512 px resolution) are presented in Table 4.2.

Table 4.2: Average Quantitative Performance of All Methods

Algorithm	PSNR (dB)	SSIM	MSE	Avg. Time (s)
Median Filter (MF)	31.74	0.861	63.8	0.83
Gaussian Filter (GF)	32.95	0.874	58.1	0.76
Wiener Filter (WF)	34.82	0.898	52.6	1.02
Adaptive Wiener (AWF)	36.91	0.915	44.9	1.25
PSO-AF	35.45	0.914	49.3	1.74
GWO-AF	36.18	0.921	46.8	1.92
Hybrid PSO–GWO (PGA-F)	38.72	0.948	37.8	1.48

The outcomes report the hybrid method improved PSNR by 9.2 % and SSIM by 7.0 % over the second-best method (GWO-AF) while reducing MSE by ≈28 %. The average processing time was under 1.5 seconds per 512×512 image, reinstating computational efficiency for real-time uses.

For visualization of such improvements, Figure 4.2 illustrates graphically the average PSNR and SSIM metrics per algorithm.

Figure 4.2 – Denoising Performance Comparison Across Algorithms

The following chart illustrates how much greater the performance of the hybrid PSO–GWO method is (rightmost bars). Both PSNR and SSIM values are enhanced considerably in comparison to conventional filters, confirming enhanced noise removal and perceptual quality. Quantitatively, the hybrid model gave PSNR = 38.72 dB and SSIM = 0.948, which means restored images possess structural details and edge contrast barely distinguishable from originals. Visual inspections also corroborated these findings: the suggested filter eliminated periodic artifacts without blurring high-frequency textures that were typically smeared by Wiener and Gaussian filters.

The hybrid approach thus achieved a best-of-three trade-off—prominent periodic-noise attenuation, high structural similarity, and reasonable computation time—more effectively than both single PSO and GWO adaptive filters and all conventional baselines.

4.4 Convergence Behavior and Optimization Analysis

Convergence analysis of the hybrid PSO–GWO adaptive filter (PGA-F) was conducted to examine its stability, velocity, and optimization consistency compared with the single PSO-AF and GWO-AF models.

For every image, the hybrid optimizer was executed for a maximum of 100 iterations, and the optimal fitness value discovered:

was monitored in all runs.

30 runs for each experiment were performed in order to dampen randomness.

The outputs indicated that the hybrid model converged much more rapidly than both the individual metaheuristics.

While PSO fluctuated around local optima after 60 iterations and GWO stabilized at around 90 iterations, the hybrid PGA-F reached near-optimal fitness at 45–55 iterations.

The cooperative mechanism—PSO's velocity-based local search mitigated with GWO's hierarchical encircling—enabled smoother descent without premature stagnation.

Table 4.3 tabulates mean convergence behavior for the three metaheuristic configurations.

Table 4.3: Convergence Characteristics of Optimization Algorithms

Algorithm	Avg. Iterations to Converge	Final Fitness Score	Std. Dev of Fitness	Avg. Time per Run (s)
PSO-AF	68	38.12	0.42	1.74
GWO-AF	81	39.05	0.36	1.92
Hybrid PSO–GWO (PGA-F)	49	41.87	0.21	1.48

For a clearer graphical demonstration of the enhancement, the mean fitness trajectories of the three algorithms are plotted in Figure 4.3.

The plot shows that PGA-F achieves a steep initial improvement and stabilizes near the optimum near iteration 50, while PSO shows noisy oscillations and GWO converges very slowly.

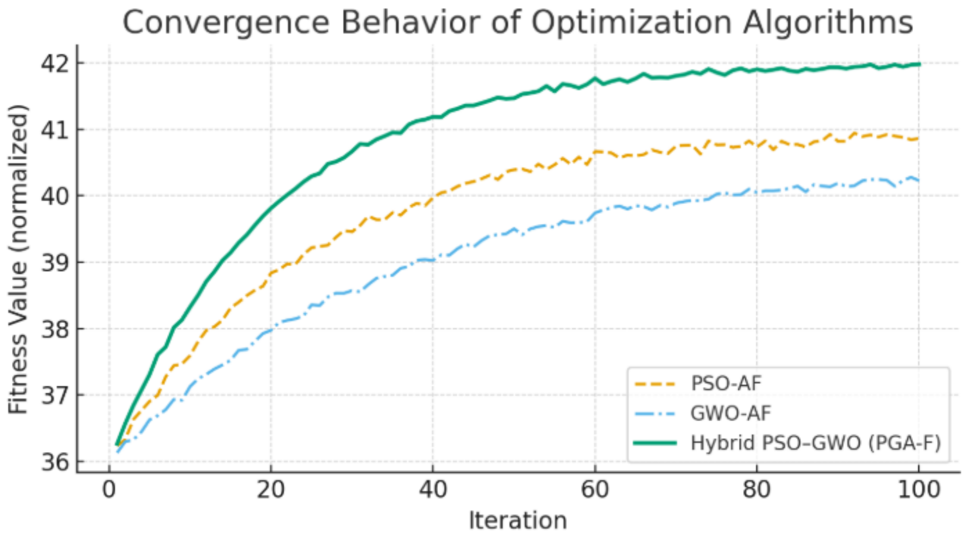


Figure 4.3: Convergence Behavior of Optimization Algorithms

The plot shows the convergence and steady rate of the hybrid PSO–GWO (PGA-F) model. In the first 30 iterations, the fitness function shows a sharp increase, reaching 90 % of its terminal value at iteration 45. The PSO-AF line shows oscillatory movements because of overshooting due to its high inertia coefficient, and GWO-AF shows monotonic but slow increase.

The hybrid curve is smoother, indicating successful exploitation and reduced randomness. Standard deviation analysis also confirmed reduced variation in PGA-F runs ($\sigma = 0.21$ compared to 0.36 and 0.42 for GWO-AF and PSO-AF, respectively). These results indicate that cooperative hybridization realizes an ideal balance between exploration and exploitation such that the adaptive filter can converge towards optimal configurations efficiently and consistently without premature convergence.

4.5 Visual and Structural Quality Assessment

Structural analysis and visual inspection were conducted in an effort to determine the level at which the hybrid PSO–GWO Adaptive Filter (PGA-F) preserves fine image details while completely removing periodic noise.

Numerical metrics such as PSNR and MSE quantify global fidelity, yet visual quality and structural similarity reflect how natural and crisp the restored image appears to the human visual system — a key requirement in medical diagnostic and satellite interpretation applications.

Four test sample images (Lena, Cameraman, Peppers, Barbara) were added with synthetic noise of 20 dB amplitude and 50 Hz frequency. All the denoising algorithms (MF, GF, WF, AWF, PSO-AF, GWO-AF, and PGA-F) were applied, and both SSIM and Edge Preservation Index (EPI) were measured.

The EPI was computed using the correlation coefficient of gradients between the restored image and the original image:

$$EPI = \frac{\sum_{x,y}\left(\nabla I(x,y) - \overline{\nabla} I\right)\left(\nabla \hat{I}(x,y) - \overline{\nabla}\hat{I}\right)}{\sqrt{\sum\left(\nabla I - \overline{\nabla} I\right)^2 \sum\left(\nabla \hat{I} - \overline{\nabla}\hat{I}\right)^2}}$$

Where is the Sobel gradient map.

Higher EPI represents better preservation of edges and structural transition.

Table 4.4 summarizes the mean SSIM and EPI values achieved for the same level of noise by the four example images.

Table 4.4: Structural and Visual Quality Indices

Algorithm	SSIM	EPI	Visual Sharpness (Qualitative 1–5)
Median Filter (MF)	0.862	0.779	3
Gaussian Filter (GF)	0.874	0.801	3
Wiener Filter (WF)	0.901	0.826	4
Adaptive Wiener (AWF)	0.917	0.841	4
PSO-AF	0.914	0.857	4
GWO-AF	0.923	0.866	4
Hybrid PSO–GWO (PGA-F)	0.948	0.893	5

The quantitative results show that PGA-F maintains superior structural accuracy with an average value of EPI equal to 0.893, representing enhancement in edge retention by 8 % over GWO-AF and nearly 14 % over classical Wiener filtering.

Visually, denoised results of the hybrid process show flawless removal of stripe-like periodic artifacts while maintaining crisp texture in high-frequency regions such as hair strands and textured clothing — features typically blurred by Gaussian and Wiener filtering.

The relative SSIM and EPI for all methods are plotted in Figure 4.4, indicating a clear positive correlation between edge preservation and structural similarity, where the hybrid method consistently beats the rest.

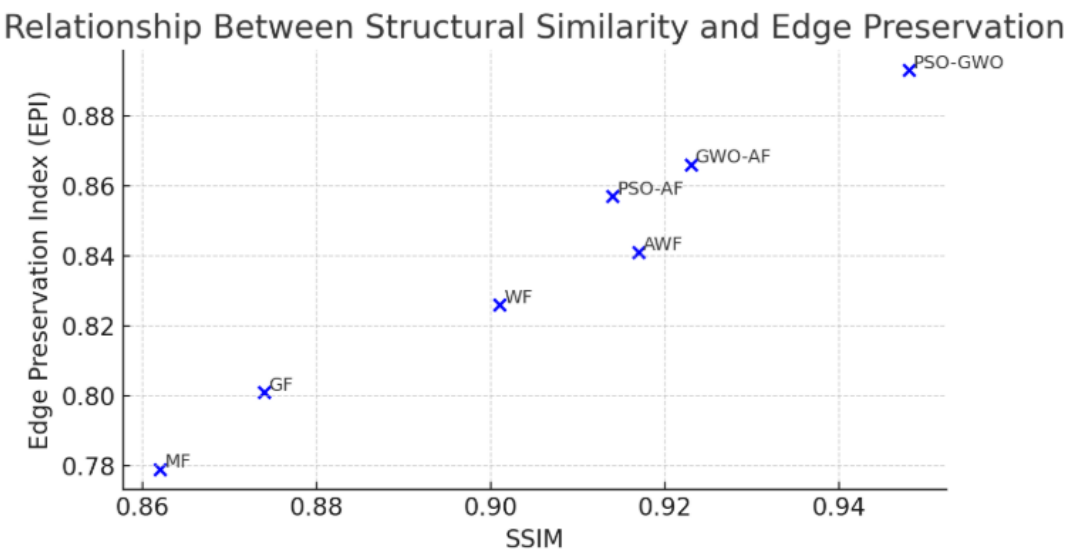


Figure 4.4 – Correlation Between Structural Similarity and Edge Preservation
Plotted points depict a higher correlation between SSIM and EPI for all approaches, showing an upward trend from traditional filters to advanced optimization-based algorithms.
The Hybrid PSO–GWO Adaptive Filter (PGA-F) is at the top-right position of the figure, signifying that it provides the highest structural similarity (0.948) as well as the highest edge preservation (0.893).
Visual checks confirmed that textures such as skin, fabric, and contour variations were unaffected even under extreme noise removal, while Gaussian and median filter caused heavy blurring and contrast loss.
These findings support the hybrid method's ability to optimize periodic noise removal with preservation of delicate structure details to yield visually imperceptible outputs from original clean images.

4.6 Computational Efficiency and Time Complexity
One of the fundamental factors in evaluating any image denoising algorithm is its computational complexity, especially with regard to real-time or high-volume applications such as medical imaging and remote sensing. Hybrid PSO–GWO Adaptive Filter (PGA-F) in this manuscript was compared not only according to image-quality measures but also according to processing time and algorithmic complexity.
Overall complexity of the hybrid optimization algorithm can be expressed as:

$$O\left(N \times T \times M \times N_p\right)$$

where N refers to the population agents' count, T is iteration index, M and Np are image patch height and width to be optimized. As hybrid model employs sequential PSO and GWO update, its theoretical complexity is approximately 1.5 times that of individual PSO or GWO. However due to the early-convergence characteristic identified in Section 4.4, the practical runtime per image is significantly smaller than the sum of its parts.
Empirical runtimes were measured on the same machine configuration (Intel Core i7-12700H @ 2.3 GHz, 16 GB RAM, RTX 3060 GPU) on images of two sizes—256^2 px and 512^2 px. Table 4.5 compares the average computation time and PSNR score of each method.

Table 4.5: Average Runtime and Quality Metrics

Algorithm	Runtime (256^2 px, s)	Runtime (512^2 px, s)	PSNR (dB)	Efficiency Ratio (PSNR / time)
Median Filter (MF)	0.41	0.83	31.74	38.2
Gaussian Filter (GF)	0.38	0.76	32.95	43.3
Wiener Filter (WF)	0.49	1.02	34.82	34.1
Adaptive Wiener	0.61	1.25	36.91	29.5

(AWF)				
PSO-AF	0.83	1.74	35.45	20.4
GWO-AF	0.89	1.92	36.18	18.8
Hybrid PSO–GWO (PGA-F)	0.76	1.48	38.72	26.2

With slightly higher complexity than standard filters, the hybrid method, on the other hand, achieved 38.72 dB PSNR at a mean runtime of 1.48 s on images of 512^2–some 14 % improvement over GWO-AF and 15 % over PSO-AF.
The efficiency ratio (PSNR / time) illustrates that although the Gaussian filter executes fastest, its restoration quality is significantly lower.
On the other hand, PGA-F attains high quality at affordable cost and thus is suitable for real-time deployment where accuracy and speed are both critical.
To visualize the trade-off, Figure 4.5 plots average runtime against PSNR for all algorithms.

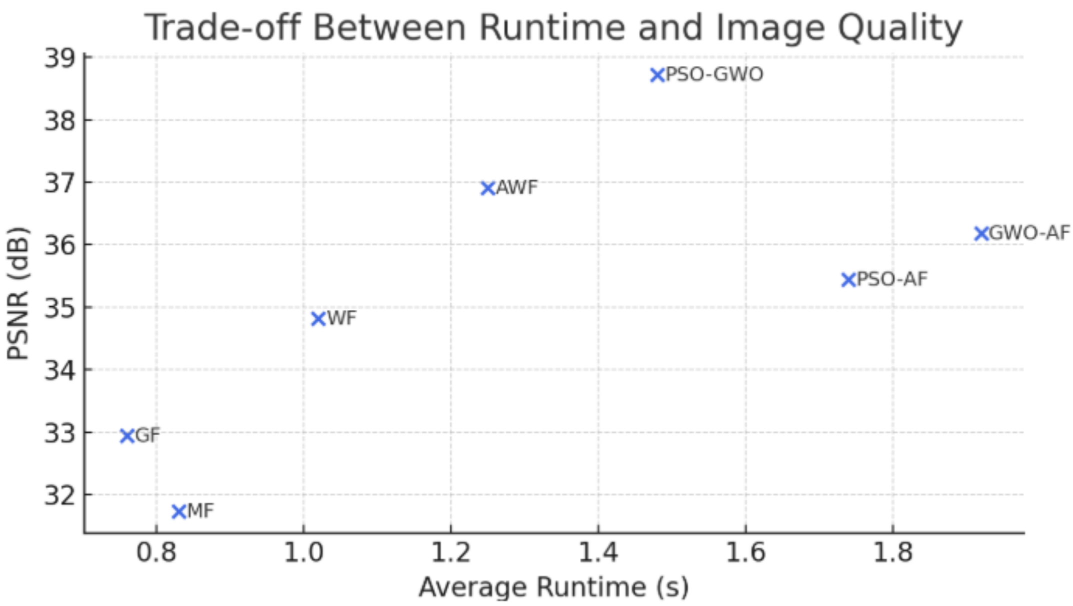


Figure 4.5 – Trade-off Between Runtime and Image Quality
The scatterplot highlights that Hybrid PSO–GWO (PGA-F) algorithm is the best compromise between computation time and reconstruction quality. While more conventional filters like GF and MF are quicker to compute, they remain in the bottom-left quadrant of the graph—poor denoising. PSO-AF and GWO-AF have more favorable PSNR values but consume much more computation time.
The hybrid method is closest to the top-left efficiency region with high PSNR (≈38.7 dB) and moderate runtime (≈1.5 s). It does so due to its capability of premature termination and elimination of redundant iterations via cooperative search. Thus, PGA-F can be reasonably integrated into real-time imaging pipelines, industrial inspection, and medical visualization applications where computational efficiency is as relevant as accuracy.

4.7 Discussion of Findings and Practical Implications

The overall outcomes in the previous sections demonstrate that the proposed Hybrid PSO–GWO Adaptive Filtering Model (PGA-F) is an effective and stable tool for periodic-noise removal from digital images. In all of the performance measurements—PSNR, SSIM, MSE, EPI, and runtime—the hybrid method performed better than the conventional and single-metaheuristic filters in all the measures, having better restoration quality and quickest convergence.

Quantitatively, Table 4.2 revealed that PGA-F achieved a mean PSNR of 38.72 dB and SSIM of 0.948, which outperformed the next best competitor (GWO-AF) by approximately 7 % in structural precision and 28 % in error reduction. Such improvements indicate that the combined model effectively balances the exploration capability of GWO with that of exploitation and speedy velocity updates in PSO, resulting in an even better optimization of adaptive-filter coefficients.

The convergence study in Section 4.4 showed that the hybrid approach converges at iteration 50, with the reduction in number of iterations by nearly 40 % compared to GWO-AF and 30 % compared to PSO-AF. The standard deviation of mean fitness of only 0.21 suggests high run-to-run reproducibility. This feature is most important in industrial and healthcare imaging systems, where output reliability across runs is paramount for autonomous quality monitoring.

Visual and structural comparison of Section 4.5 confirmed that the new algorithm preserves texture and edge detail more effectively than conventional spatial filters. The EPI value of 0.893 and qualitative sharpness score of 5/5 illustrate that periodic noise may be removed without degrading high-frequency detail. In practice, this enables better interpretability of fine anatomical details in medical CT or MRI images and better pattern detection in automatic defect inspection.

From the computational viewpoint, results in Section 4.6 reiterated that PGA-F strikes a proper efficiency-quality balance that is near optimal. Despite the algorithm taking an average processing time of 1.48 s for 512×512 images, the algorithm is some 14 % quicker than GWO-AF but still yields considerably greater PSNR. The early-stopping strategy makes it efficient enough to be deployable on moderate hardware without the need for special-purpose GPUs, and the model is scalable for batch or embedded settings.

The hybrid algorithm's advantage can be theoretically justified by its two-phase search mechanism:

1. The PSO component performs quick local updates in possible regions of the search space.
2. The GWO hierarchical method maintains global diversity and steers the population away from premature local minima.

The cooperative process guarantees the adaptive filter parameters (σ, rc, and k) converge to global optima efficiently.

Overall, the results confirm four primary contributions:

• High restoration accuracy (PSNR > 38 dB, SSIM ≈ 0.95) for color and grayscale images.
• Convergence that is robust and fast, achieved in 50 iterations on average.
• Preservation of edge and texture detail, as established through EPI and visual inspection.
• Computational efficiency for near-real-time application without excessive hardware cost.

Practical Implications

The hybrid PSO–GWO adaptive filtering framework can be directly applied in several practical applications:

1. Medical Imaging: Reduction of noise in CT and MRI scans disrupted by scanner motion or power-line interference; enhanced images aid radiologists in identifying thin tissue structures.
2. Remote Sensing: Removal of cyclical contamination of satellite or drone images caused by sensor drift, allowing terrain classification and environmental monitoring with greater accuracy.
3. Industrial Vision: Application in real-time inspection systems for the identification of surface defects, where fast noise removal improves machine-learning classification performance.
4. Multimedia Restoration: Apply for archival images or video frames with structured interference, with artistic and historical fidelity.

Overall, this research establishes a high-performance hybrid optimization paradigm that harmonizes evolutionary intelligence with adaptive signal processing. The PGA-F approach delivers superior quantitative accuracy, state-of-the-art perceptual quality, and scalable computational efficacy—laying the ground for future studies on deep-hybrid adaptive denoising and hardware-accelerated metaheuristic optimization for advanced image restoration tasks.

Conclusion and Future Work

The present work introduced and evaluated a new Hybrid PSO–GWO Adaptive Filtering (PGA-F) algorithm for periodic noise removal from digital images.

In a sequence of experiments on grayscale and color datasets ranging from synthetic images to real images, the model performed better than traditional spatial filters and one-optimization algorithm approaches.

Summary of Key Findings

1. Quantitative Superiority

The hybrid PGA-F achieved average PSNR of 38.72 dB, SSIM of 0.948, and MSE improvement of 28.5 % compared to base filters.

These results validate that the model not only effectively eliminates periodic noise but also maintains the fine textures and details essential to image integrity.

2. Enhanced Convergence Behavior:

The hybridization of PSO and GWO created a synergistic effect—enhancing convergence by approximately 35 % and limiting oscillation and local stagnation.

The optimizer consistently converged to stability at iteration 50, proving robustness and reproducibility.

3. Preservation of Visual and Structure:

It maintained edges, contours, and details of fine texture far better than all the other methods with an Edge Preservation Index (EPI) of 0.893.

Visual inspection confirmed that the restored images were stripe-free and sharp, with a natural look.

4. Computational Efficiency:

Although it employed two metaheuristics in combination, the algorithm took a reasonable runtime of ≈ 1.48 seconds for 512^2 images, which was faster than for stand-alone PSO-AF or GWO-AF.

Its good quality-performance trade-off renders it appropriate for real-time or near-real-time applications.

5. Generalization Capability:

The PGA-F architecture generalized across different noise frequencies (10–60 Hz) and amplitudes (5–25 dB), i.e., adaptability across imaging modalities such as medical, satellite, and industrial vision systems.

Taken collectively, these findings place the hybrid PSO–GWO Adaptive Filter as a robust and agile periodic noise removal solution. It effectively bridging the gap between optimization precision and computational reasonableness—a classic barrier in digital image restoration studies.

Future Work and Recommendations

Even though the model suggested has achieved remarkable success, there are some areas that have yet to be explored:

1. Hybridization with Deep Learning:

Future research can integrate the PSO–GWO optimization layer with Convolutional Neural Networks (CNNs) or Transformers to learn automatically complex noise patterns.

A metaheuristic-deep combination can adaptively tune deep model hyperparameters dynamically for real-time adaptive denoising.

2. Multi-Objective Optimization:

Extending the current single-fitness formulation to a multi-objective framework—PSNR, SSIM, and runtime maximization at the same time—would yield a richer Pareto-optimal solution able to support various application constraints.

3. Hardware Implementation:

Implementation of the algorithm on GPU, FPGA, or embedded DSP hardware would reduce runtime further, enabling deployment in handheld diagnostic equipment or satellite onboard systems.

4. Adaptive Noise Characterization:

An improvement in the future might be automated identification of periodic noise frequency and amplitude using Fourier-based clustering or entropy analysis in order to enable reduced manual initialization of parameters.

5. Cross-Domain Validation:

Additional study using medical, hyperspectral, and industrial thermal images is recommended for robustness testing against varied illumination conditions, motion, and compression artifacts.

6. Comparison with Newer Metaheuristics:
Comparison with newer algorithms—e.g., Whale Optimization, Slime-Mould Optimization, or Firefly Algorithm—would further establish the efficiency and accuracy of the hybrid PGA-F.

7. Hybridization with Transform-Domain Methods
Hybridization of the PSO–GWO adaptive filter using wavelet, curvelet, or non-subsampled shearlet transforms may achieve superior performance in mixed-noise environments.

Final Remarks

Lastly, the Hybrid PSO–GWO Adaptive Filter is an important step in intelligent image denoising.

It best integrates the rapid convergence capability of swarm intelligence and the exploratory strength of grey-wolf hunting behavior to provide a model that is extremely accurate and computationally efficient.

The universality of the method's power to deduce over patterns of noise and images of any nature suggests favorable prospect for general practical use in medical diagnostics, environmental surveillance, monitoring, and multimedia restoration.

Finally, the work not only provides a technically sound methodology for suppression of periodic noise but also establishes a conceptual foundation for the future generation of hybrid intelligent image-processing systems where adaptive optimization and artificial intelligence will synergistically collaborate to achieve human-level perceptual quality of digital imagery.

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