

Article

A Novel Guided Box Filter Based on Hybrid Optimization for Medical Image Denoising

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Abstract: Medical image denoising is a crucial pre-processing task in the medical field to ensure accurate analysis of anomalies or sicknesses in the human body. Digital filters are popular for reducing undesired noise as they provide reliability, high accuracy, and reduced sensitivity to component tolerances compared to analog filters. However, conventional digital filter design approaches lack efficiency in achieving global optimization robustness. To overcome these incapacities, this paper adopted bio-inspired optimization algorithms to offer viable digital filter designing tools because of their simple implementation and requirement of a few parameters to control their convergence. This research article explores a hybrid strategy that combines a novel guided decimation box filter (GDBF) with a hybrid cuckoo particle swarm optimization (HCPSO) algorithm to design a denoising filter for medical images. It is the first time a decimation box filter has been used for denoising, leading to novelty. The HCPSO algorithm is applied to obtain the filter parameters optimally. Medical images mostly suffer from four types of noises. The performance of the proposed filter is analyzed for these types of noise. To highlight the importance of parameter selection, the results of the proposed method are compared with other recently utilized bio-inspired genetic algorithms, such as PSO (particle swarm optimization), CS (cuckoo search), and FF (firefly). The superiority (potency) of the proposed method has been established by calculating the improvement in quality parameters such as the peak signal-to-noise ratio (PSNR), structure similarity index (SSIM), and feature similarity index (FSIM). The proposed filter achieved the highest PSNR (~35.7 dB), SSIM (~0.95), and FSIM (~0.92) and proved its numerical and visual quality efficacy over state-of-the-art models.



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Keywords: digital filters; medical images; denoising; bio-inspired optimization

1. Introduction

The medical field has entered its digital era. The usage of digital image processing in the medical field has increased in the last two decades. It has been utilized in image acquisition, image transfer, noise removal, pre-processing, channel equalization, image restoration, interference identification, the detection of diseases, etc. In biomedical applications such as CT scans, X-rays, magnetic resonance imaging (MRI), etc., digital filters are commonly used [1,2]. Digital filters are applied in several application areas, such as denoising [3], super-resolution [4], image enhancement [5], and EEG signal processing [6]. Medical images are acquired by different methods such as X-rays, MRI, CT scans, and ultrasounds to identify a disease or its severity. Correct information leads to correct prognosis and treatment. Noise may occur in medical images during the capture phase. This can be caused by environmental impacts or faults in the image acquisition system, such as changes in sensor's sensitivity with varying temperatures. It is quite a challenging task to eliminate noise from the captured medical images without knowledge of which type of noise has occurred. Gaussian noise, Poisson noise, salt and pepper noise (impulse noise), and speckle noise are some examples of noise that distorts the textural information in images.

There are different techniques for designing digital filters, and each one has its pros and cons. Conventional methods such as the least squares (LS) technique [7] are used to design a digital filter for error reduction, but it results in some discontinuity. To further minimize these problems, Chebyshev approximation-based filters were introduced [8]. The error surfaces that are produced by digital filter architectures are often multimodal with regard to the filter coefficients. Because of this characteristic, traditional derivative-based learning algorithms, such as least mean squares, have a high likelihood of being stuck in local minima when attempting to solve optimization problems of this kind. Traditional recursive approaches not only converge to a local minimum, but they also have difficulty with stability and a slow convergence rate and see their performance drastically worsen [9]. Therefore, bio-inspired algorithms are the best approach for better convergence towards local minima and global minima [10]. Ramon et al. [11] presented a model for modifying the traditional reconstruction filters for medical image denoising. However, the designed filter cannot handle quantization noise. Sridhar et al. [12] proposed an adaptive bilateral filter using the backtracking optimized search algorithm in which the sharpness of edges is considered as the optimization parameter. Bhonsle et al. [13] used enhanced grasshopper optimization for denoising medical images. However, this approach was computationally expensive when compared to edge-preserving smoothing. Then, Sam and Fred [14] designed hybrid filters with a combination of filters. The firefly technique was then used to evaluate the filtered output image of artificial neural network systems to determine the precise image information. The lack of internal memory was a drawback since it may cause an early convergence to the local optimum. Other hybrid-optimization-based filters are designed by combining the swarm-based dragonfly (DF) and modified firefly (MFF) algorithms [15]. Malekzadeh et al. [16] proposed an algorithm based on shared latent space specifically for PET images. Boudjelaba et al. [17] presented a hybrid genetic algorithm (HGA) for creating digital filters. HGA filters may incur the drawback of requiring additional memory and/or computation to produce a certain filter response characteristic. Another hybrid-optimization-based filter was designed by utilizing genetic and particle swarm optimization (PSO) [18]. The shift and spacing in the model space were optimized using a particle swarm technique [19]. Instead of partitioning the model space progressively into smaller meshes, this approach searches the model space using a set of particles. It has been used to quickly converge to the best spacing and shift for pairs of analytical functions. Dash et al. [20] designed three distinct kinds of digital linear phase multiband stop filters using the swarm and evolutionary methods. The filter used in the work has limitations in that it attenuates the frequencies that are below the cutoff range. Ababneh and Khodier [21] proposed the cuckoo search (CS) optimization technique to improve the magnitude and linearity of the phase response, leading to better denoising of medical images. The main issue in medical image denoising is to preserve the feature quality for disease diagnosis, such as tumor detection [22]. Some researchers have also presented hybrid bio-inspired algorithms [23–27] for image denoising. Javaid et al. [23] explored the use of a hybrid approach of bio-inspired algorithms such as cuckoo's search and curvelet transform. Curvelet transform was adopted to represent the sparse pixel information and edges. Then, the CS algorithm was used to optimize the denoising coefficients while preserving the structural and morphological information of the images. Li et al. [28] introduced the guided digital filter. Motivated by these filters, the researcher used the digital filter for medical images such as retinal images [29], MRI [30], and ultrasound images [31]. Zhang et al. [32] then presented a hybrid CNN model for removing Gaussian noise. Vasudevan et al. [33] presented a hybrid approach modified cuckoo search algorithm. Asokan and Anitha [34] also hybridized the cuckoo search algorithm with a bilateral filter for medical image denoising. Sun et al. [35] presented PET image denoising using a deep-learning denoising method known as DeepRED. Gong et al. [36] presented unsupervised deep learning using deep neural networks (DNN) for MR image denoising. Miri et al. [37] used ant colony optimization (ACO) with two-dimensional discrete cosine transform for medical denoising. Satapathy and Das proposed medical denoising using Bi-dimensional Empirical Mode De-

composition (BEMD) [38]. S. A. Akar used a bilateral filter with a genetic algorithm (BF-GA) for MR image denoising [39]. Sudeep et al. [40] used the linear minimum mean square error method (LMMSE) for principal component analysis (PCA) to remove noise from an image. Therefore, motivated according to the research contributions provided by researchers, this paper explored bio-inspired optimization algorithms to provide edge-preserved denoising for medical images as a feasible solution. In this regard, the key contributions of this paper are:

- This paper presented a novel hybrid optimization-guided decimation box filter for image denoising filters. Till now, a decimation box filter has never been used for denoising and this leads to novelty.
- The designed HCPSO is application independent approach that is capable of handling multiple noise types, such as Gaussian, Poisson, Speckle, and salt and pepper noises.
- The use of HCPSO in noise removal ensures improved efficiency, as HCPSO facilitates optimization.
- The resulting analysis shows the ablation study on convergence criteria of different bio-inspired optimization algorithms. This paper also presents a result analysis with the variable noise level and decimation box size.
- The proposed algorithm has low computational complexity because it only involves basic arithmetic operations on the image pixels.

Therefore, this paper aims to design a denoising filter for medical images using a novel decimation box filter guided using a bio-inspired optimization hybrid algorithm to reduce the error caused by different noises. The design of the filter and optimization algorithm is achieved in MATLAB. The complete framework is discussed. The proposed novel filter is tested on three different datasets and four different noises to show its better performance over other existing states-of-art denoising filters.

The remaining paper is divided into the following sections: Section 2 provides a brief description of digital FIR filters and the application of bio-inspired optimization algorithms for designing digital filters. Additionally, different noises present in medical images are discussed. Section 3 presents the proposed hybrid model to design an optimization-based guided decimation box filter (GDBF) for medical image denoising. Section 4 presents the implementation details and the results of the analysis for the implemented model. This section also presents the ablation study and comparative state-of-the-art models. Finally, in Section 5, the conclusion and future scope of the paper are presented.

2. Digital Filter as Bio-Inspired Optimization Problem

Multi-rate systems are those that function normally but sample data at a variety of different rates at various points during processing. The sampling frequency can change dynamically during signal processing in multi-rate systems [2]. Decimation and interpolation are the two primary procedures utilized by multi-rate systems. The process of decreasing the sampling frequency to a lower sample frequency that is distinct from the initial frequency by an integer value is referred to as decimation. The process of decimation is often referred to as down-sampling. Below, in Figure 1, the p -fold decimation filter is presented. The filter is designed using a low-pass filter (such as FIR filter) for anti-aliasing followed by p -fold decimators to suppress the frequency $f_s/2p$, termed the Nyquist frequency. Every p_{th} sample is passed through the filter and others are discarded. Afterward, the sampling frequency is changed to f_s/p and returns output as y_n , where f_s is the sampling frequency of the input signal, i.e., x_n .

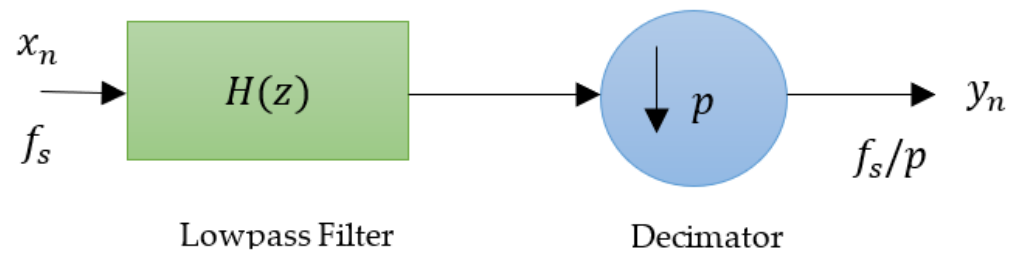


Figure 1. Decimation filter.

The bio-inspired optimization algorithm aims to determine a set of coefficients (c), $c \in R^M$, for achieving desired characteristics by specifically designed filters. The main objective of an optimization-based filter is to find and reduce the error between the filter's ideal frequency response (F_I) and the desired frequency response (F_D) by updating the coefficient iteratively. Mathematically, it is represented as

$$Err_c(e^{j\omega}, c) = F_I(e^{j\omega}) - F_D(e^{j\omega}) \quad (1)$$

As calculated, Err_c is complex.

There are several conventional approaches for designing digital decimation filters, such as windowing techniques, but the limitation of this system is that it does not provide accurate control of transition bandwidth and cutoff frequencies. Another issue in digital filters is ripple and discontinuity near band edges [7]. The weighted Chebyshev approximation technique [8] can address issues related to local minima, slow convergence, and suboptimal results in conventional filter optimization methods. Researchers are now using bio-inspired optimization algorithms to achieve faster exploration and tuning of parameters for multiple filter requirements. The design of digital FIR filters through bio-inspired optimization algorithms involves minimizing an objective or error fitness function, and the choice of the fitness function plays a crucial role in achieving an ideal filter response. Recent research has shown significant progress in digital FIR filter design using bio-inspired optimization algorithms. In this section, this paper discussed the most promising bio-inspired optimization algorithms, such as particle swarm optimization (PSO) [19], cuckoo search (CS) optimization [21], and firefly optimization (FF) [15] for designing decimation filters.

2.1. Particle Swarm Optimization

The particle swarm algorithm was initially proposed to optimize nonlinear continuous functions [19]. It uses a group of particles, where each particle remembers the best solution it has found (the best position of an individual), and the algorithm tracks the optimal location for the entire group. The effectiveness of the particle swarm algorithm depends on the choices made during the process. The algorithm begins with a group of particles that have random starting positions and velocities in the n -dimensional parameter space. This collection of particles is made up of n different individuals or models. During each iteration, a particle's movement is influenced by its previous best position p_best , and the global best is represented as g_best . The updating of velocity, vel_n , and position, pos_n , for each particle is mathematically expressed as

$$vel_n = \omega * el_n + C_1 * r1_n * (p_best_n - pos_n) + C_2 * r2_n * (g_best_n - pos_n) \quad (2)$$

$$pos_n = pos_n + vel_n \quad (3)$$

Here, inertia weight is represented by ω ; learning factors are represented as C_1 and C_2 , respectively; these are used to determine the convergence speed towards local (p_best_n) and global optimal (g_best_n) value for the n_{th} particle in the respective iteration. For the optimal solution, ω , C_1 , and C_2 decrease linearly. The overall processing of the PSO algorithm is represented in Algorithm 1. Once the optimal spacing and shift are obtained, the filter response is evaluated.

Algorithm 1. Particle Swarm Optimization

Input: Minimization criteria function $f(X)$, the domain of sampling interval or the spacing is represented as Δ and shift represented as δ

Output: Δ, δ

Initialize : $pos_0 \leftarrow$ random points in domain of Δ & δ

Initialize : $vel_0 \leftarrow$ random velocity

$p_best \leftarrow pos_0$

$g_best \leftarrow pos_{best}[\text{argmin}(f(p_best))]$

for $i = 1, 2, \dots, T$ do

if g_best does not change for i_{max} iterations, then

return Δ, δ, g_best

end if

update vel_n and pos_n according to Equations (2) and (3)

Update ID $\leftarrow$ is Smaller($f(X_i), f(p_best)$)

$p_best[\text{updateID}] \leftarrow X_i[\text{updateID}]$

$g_best \leftarrow p_best[\text{argmin}(f(p_best))]$

end for

2.2. Cuckoo Search Optimization

The cuckoo search (CS) algorithm is a metaheuristic global optimization approach inspired by the breeding habits of cuckoo species that steal eggs from other birds' nests to hatch them [21]. Algorithm 2 describes the CS algorithm. The host bird will either quit the nest or discard the foreign egg if it is discovered (probability = $prob_a$). The cuckoo search (CS) algorithm is expected to decrease the number of nests over time. Still, abandoned nests are believed to be replaced by new nests built in different locations, thus maintaining the same number of nests over time and introducing diversity to the algorithm [23,24]. The CS algorithm requires a well-defined objective function, single or multi-objective, and constrained or unconstrained. The algorithm optimizes the objective function, starting with a random population for the nest location at $itr = 0$. Javaid et al. [23] applied the CS algorithm to design a digital filter for medical image denoising. The iteration of the CS algorithm starts at $itr = 0$ by selecting a random population for the nest location. Then, updation of the nest location is performed with regard to time, and mathematically, it is represented as:

$$nest_{itr} = nest_{itr-1} + \alpha * Step_{itr} \quad (4)$$

where $nest_{itr}$ and $Step_{itr}$ represent the nest location and step size for the current iteration, respectively. The scaling factor is expressed as α , whose value is greater than 0 and generally lies between 0.001 and 0.01. This value depends on the search space's largest value. For designing digital filters, the CS algorithm searches the system coefficients having the following objective function:

$$objective_{function} = \min \left\{ \int_0^\pi (\omega - |F_D(e^{j\omega})|)^2 d\omega \right\} \quad (5)$$

The optimization problem dimension (represented as Dim_M) is also represented as the number of system coefficients, such as $m_i, n_i, 0 \leq i \leq O$. Here, system order is represented as O . Mathematically, it is represented as

$$Dim_M = 2O + 2 \quad (6)$$

Each nest location in the Dim_M is considered a solution for the filter response.

Algorithm 2. Cuckoo Search Optimization

Input: Minimization criteria function $f(X)$
Output: $nest_{best}$
 Generalize the initial population of n host nest $nest_i$ ($i = 1, 2, 3, \dots, n$)
 While $itr < max_itr$ do
 Get a cuckoo randomly by levy flights
 Evaluate $f(X)$
 Chose $nest_{itr}$ randomly at $itr = 0$
 If $nest_i > nest_{i-1}$ then
 replace $nest_{i-1}$ with a new solution.
 End if
 Worst nests are removed.
 Return best $nest_i$
 Arrange the solutions in order of preference and determine the most optimal $nest_i$
 End While

2.3. Firefly Optimization

Three main ideals make up the firefly algorithm [25,26]:

- There is no such thing as a male or female firefly; all fireflies can attract mates.
- Fireflies are attracted to bright objects, and this attraction weakens with increasing distance. If you have a pair of fireflies, the brightest one will attract the other.
- A firefly's brilliance is based on how well it does in an objective function.

Mathematically, brightness B_{nm} , and attraction A_{nm} are calculated as follows:

$$B_{nm} = B_0 * e^{-\gamma * \alpha_{nm}^2} \quad (7)$$

$$A_{nm} = A_0 * e^{-\gamma * \alpha_{nm}^2} \quad (8)$$

Here, B_0 and A_0 are the initial brightness and attraction, respectively. γ represents the coefficient for light absorption, and α represents the distance between m_{th} and n_{th} fireflies.

In this, fireflies with high brightness (ff_n) attract fireflies with low brightness (ff_m). Mathematically, this is represented as:

$$loc_n = loc_n + B_{nm}(loc_m - loc_n) + \vartheta(rand - 0.5) \quad (9)$$

Here, ϑ is represented as the step size. loc_n and loc_m represent the location of the n_{th} firefly and the m_{th} firefly. Algorithm 3 describes the firefly (FF) algorithm.

Algorithm 3. Firefly Optimization

Input: Firefly Particle
Output : loc_n
 For iteration $itr = 1, 2, \dots$ Do
 Create a sample of particles as, $q(x_m^n | x_{m-1}^n, Y_n)$
 Update the weight as $wt_m^n = wt_{m-1}^n * p * (y_m | x_m^n)$
 Choose q with maximum wt_m^n as the global optimal particle q_m^{best} .
 Update loc of the particle as Equation (9).
 Calculate weight as wt_m^n of updated particle
 Estimate the state $st_m = \sum_{m=1}^N W_m^N x_m^n$
 End for

2.4. Noise Characteristics

Noise in medical images can have a detrimental effect on diagnostic accuracy and clinical decisions. The noise characteristics depend on several factors, including the imaging modality, parameters, and anatomical region being imaged. Understanding the noise characteristics in medical images is essential for improving image quality and ensuring accurate diagnoses. Some common types of noise in medical images are:

Gaussian noise: Gaussian noise is a type of statistical noise that can be artificially added to an image to simulate real-world noise. Gaussian noise typically affects the gray level z in digital images, characterized by its probability density function or normalized histogram to the gray level z . It follows a bell-shaped curve around the mean value μ and can significantly impact the quality of images, especially in regions with low contrast or subtle features. The probability density function ρ is represented as

$$\rho(z) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(z-\mu)^2}{2\sigma^2}} \quad (10)$$

Poisson noise: Poisson noise is a type of statistical noise that occurs in digital images as random variations in the intensity of pixels due to the counting of discrete events, such as photons or particles. This noise can significantly impact the quality of medical images and affect the accuracy of diagnosis, especially in low-light or low-contrast images. It is important to consider the specific characteristics of Poisson noise when selecting and optimizing noise reduction methods to preserve image detail and sharp edges. The Poisson noise variance $\eta^2(x)$ is characterized as

$$\eta^2(x) = \alpha x \quad (11)$$

Here, the Poisson noise parameter is α with respect to the original image x .

Salt and pepper Noise: Salt and pepper noise is a common image distortion in digital images, caused by errors during image acquisition or transmission. It is characterized by noisy pixels alternating between the minimum and maximum intensity values. It can be expressed mathematically as

$$f(x) = \begin{cases} i_{min} & \text{with probability } p \\ i_{max} & \text{with probability } q \\ u(x) & \text{with probability } 1 - p - q \end{cases} \quad (12)$$

Speckle Noise: Speckle noise is another image distortion that is commonly found in digital images. It is caused by random interference, resulting in random variations in brightness or darkness across the image. Noisy image $I(x)$ is represented as

$$I(x) = \emptyset x \quad (13)$$

Here, the speckle noise parameter is $\emptyset$ with respect to the original image x .

3. Proposed Methodology

Hybrid Optimization Based Image Denoising Filter

In this work, we propose a filter for medical images. The model is designed with hybrid bio-inspired algorithms with a digital filter for coefficient estimation. The block diagram of the designed medical image filter is shown in Figure 2.

The basic step of the proposed algorithm is dependent on a guided decimation box filter using a hybrid cuckoo particle swarm optimization model for medical image filters. In the first step, the input image (noisy) is taken, and its red, green, and blue sub-components are extracted. Further, each sub-band is passed through a low-pass filter. Here, the Butterworth low pass filter is used to filter noisy images by removing high-frequency noise from a digital image and preserving low-frequency components. The transfer function of LPF of order n is mathematically represented as

$$H(u, v) = \frac{1}{1 + \left[\sqrt[2]{(u^2 + v^2)} / D_o \right]^{2n}} \quad (14)$$

Here, $\sqrt[2]{(u^2 + v^2)}$ is the Euclidean distance between the origin and any point (u, v) in the input image. D_o is the cutoff frequency. After LPF, a two-level discrete wavelet transform (2-DWT) is applied over all sub-components. Then, desired coefficients are selected among each sub-band correspondingly and passed through a decimation box filter of $n \times n$ size having n factor; for this, padding is performed on each sub-band. Then, noisy

coefficients are extracted by using the designed hybrid cuckoo particle swarm optimization (HCPSO) algorithm. Then, thresholding functions are applied to find the Optimized Filter Coefficients (OFC) to obtain R_{coeff} , G_{coeff} and B_{coeff} to remove noise from each component, respectively. The fitness function of the optimized solution is evaluated, and then the best solution or coefficient is evaluated. Later, coefficients respective to zero-padding locations are removed and passed through inverse discrete wavelet transform (IDWT) to generate a filtered image [27]. The entire proposed algorithm is presented in Algorithm 4.

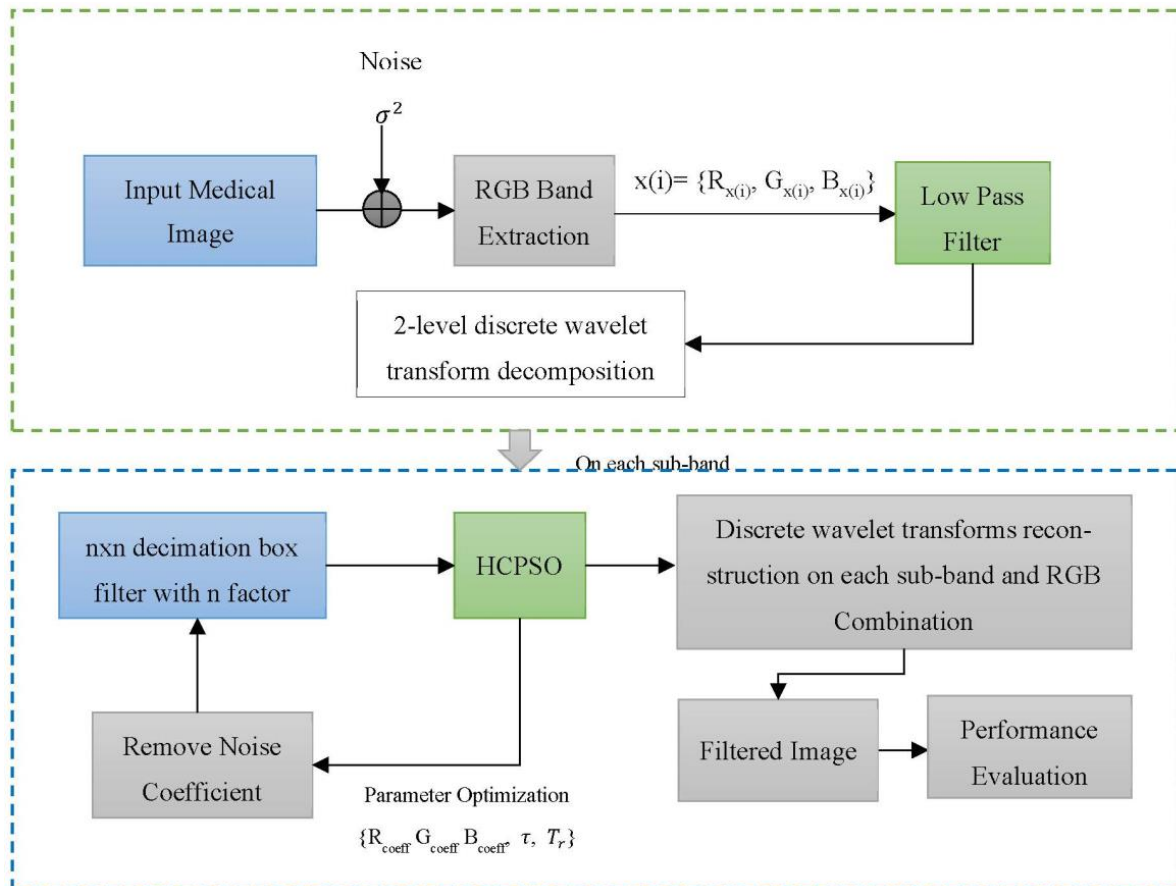


Figure 2. Flowchart of medical image filtering using proposed novel guided decimation box filter.

Algorithm 4. Proposed Hybrid-Optimization-based Image Filter

Input : $I_{x,y}$ input noisy image

Output : $O_{x,y}$ output filtered image

Begin

1. $I_{x,y} \xrightarrow{\text{RGB Extraction}} \{I_R, I_G, I_B\}$
 2. For $I = 1:3$
 3. Initialize decimation box of $n \times n$ size with n decimation factor
 4. $I_i \xrightarrow{2\text{-DWT}} I_{coeff}$ {here, I_{coeff} is the DWT coefficient}
 5. $I_{coeff} \xrightarrow{n \times n} D_I$ {here, D_I is the decimation box coefficient}
 6. $D_I \xrightarrow{\text{HCPSO}} D_{Iopt}$ {here, D_I is the optimized filter coefficient}
 7. $D_{Iopt} \xrightarrow{2\text{-IDWT}} \{O_i\}$
 8. End
 9. $O_R, O_G, O_B \xrightarrow{\text{RGB Combine}} \{O_{x,y}\}$
 10. Return $O_{x,y}$
- End
-

First, an input image $I_{x,y}$ is considered and corrupted by introducing random noise with a noise factor $N_{x,y}$. Then, the corrupted image $I_{c(x,y)}$ is represented as

$$I_{c(x,y)} = I_{(x,y)} + N_{(x,y)} \quad (15)$$

Different levels of noise are introduced by the variance in the noise. These filters are designed to remove this noise. Generally, bilateral filters are used for image denoising, but it shows computational complexity and sometimes introduce unwanted radiant reversal artifacts that cause image distortion. Therefore, these guided filters are used as digital image filters to denoise the image, $\hat{I}_{(x,y)}$, but these filters are linear filters [28], which are represented as

$$\hat{I}_{(x,y)} = \sum w_{t(x,y)} * G * I_{c(x,y)} \quad (16)$$

Here, $w_{t(x,y)}$ represents the kernel weight value for the decimation box used, and G is represented as guidance image G .

In terms of coefficients, the denoised images are represented as

$$\hat{I}_{(x,y)} = i_k * G_x * j_k \quad (17)$$

Here, i_k and j_k are linear coefficients at pixel k concerning guidance image G_x . Filter aims to minimize the cost function (i.e., the difference between the original image and the denoised image) by regularizing parameters. The cost function, $\varphi_{(i_k,j_k)}$, is represented as

$$\varphi_{(i_k,j_k)} = \sum_{x \in w_k} i_k * G_x + j_k - \hat{I}_{(x,y)}^2 + \varepsilon i_k^2 \quad (18)$$

Here,

$$\begin{aligned} i_k &= \frac{\frac{1}{w} \sum_{x \in w_k} (G_x * \hat{I}_{(x,y)} - \mu_k \hat{I}_{(x,y)})}{\sigma^2 + \varepsilon} \\ j_k &= \hat{I}_{(x,y)} - i_k \mu_k \end{aligned} \quad (19)$$

Here, the cost function is assumed as constant linear coefficients in the decimation box. The smoothness degree is represented as ε and w represents the decimation box. σ and μ_k represent the variance and mean value of the decimation box, respectively.

In each decimation box, the denoised image is different for different pixels. Therefore, the average of these is taken. Like edge preservation, guided filtering is a feature. Additionally, it acts as a filter to make things more even. It labels as “flat” or “high variance” the areas of an image contaminated by noise. Pixels found to be in the exact center of flat patches have their values averaged out and replaced with new ones that have those average values. A pixel’s value does not change if it is found to be in the middle of a region with a lot of variation. The degree of smoothing, also called the regularisation parameter, is used to categorize areas into low-variance “flat patch” regions and high-variance “high variance” regions. If the variance of a given patch is larger than the regularization parameter’s value, then the patch is smoothed; otherwise, the variance is retained. Pixels on the far side of an image’s edge are given no importance by the guided filter kernel. The gradient filter is effective in eliminating the gradient reversal artifacts. Complexity increases as the kernel size grows. The output of a box filter can be obtained using the integral image method, and each summing operation is identical to a box filter.

To filter the noise-corrupted image most effectively, the appropriate smoothing degree is picked in the specified neighborhood. The degree of smoothing indicates a somewhat lenient limit on the neighborhood’s standard deviation. As depicted in Figure 3, some pixels are filtered as output. Let us assume an image of size $P \times Q$. The input image is divided into $n \times n$ kernels, and the mean value of each kernel is the output of the decimation box. In this paper, the hybrid bio-inspired optimization approach is used to determine the filter coefficients for the image based on the amount of noise contained in the image. The guided filter is sized $n \times n$ based on decimation boxes with n downsampling ratio, which could be further optimized using HCPSO, as illustrated in Figure 3. When calculating the size of a decimation box filter, the time complexity is $O(m * N)$, where m is the size of the filter, and N is the total number of pixels. For filters with big kernels, this can lead to a significant

increase in the amount of time required to calculate the filter's output. If we utilize an integral image, we can compute box filters in $O(N)$ time.

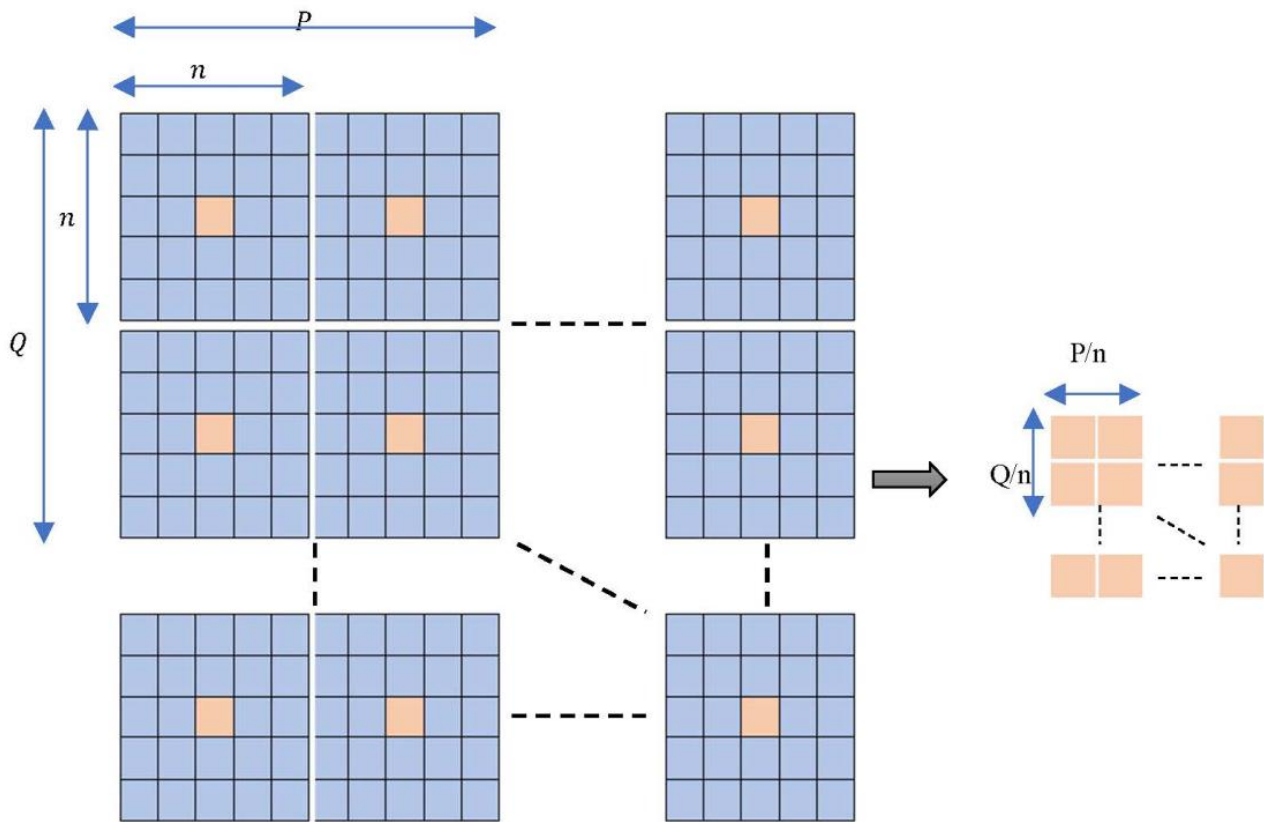


Figure 3. Guided decimation filter.

In this paper, the HCPSO algorithm is applied to optimize the coefficients of the decimation filter. The HCPSO algorithm is designed by combining the cuckoo search algorithm and particle swarm optimization algorithm that are capable of solving the nonlinear problems related to denoising constraints. The main idea for designing a hybrid model is to improve the exploration search for obtaining optimal solutions by resolving the limitations of the CS and PSO algorithm. As PSO is the most popular optimization algorithm among researchers. It still has some limitations and easily falls into local optimal value under high-dimensional space. At the same time, the CS algorithm increases the cost during the iterative process. To overcome these drawbacks, the designed algorithm improves the PSO particles that are improved or optimized using the building nest of the CS algorithm. The designed flowchart is presented in Figure 4. In the initialization step, the number of particles, swarms, acceleration coefficients, weights, etc., and then lower and upper bounds for each particle are specified. The first generation is randomly initialized as a position $POS_i = \{pos_1, pos_2, \dots, pos_n\}$. The fitness function $f(POS_i = f_i)$ is evaluated to obtain P_{best} and G_{best} , which are represented as

$$P_{besti}(t+1) = \begin{cases} pos_i(t+1) & \text{if } f(pos_i(t+1)) < f(pos_i(t)) \\ P_{besti}(t) & \text{otherwise} \end{cases} \quad (20)$$

$$G_{best}(t+1) = \operatorname{argmin} (P_{best1}, P_{best2}, \dots, P_{bestn}) \quad (21)$$

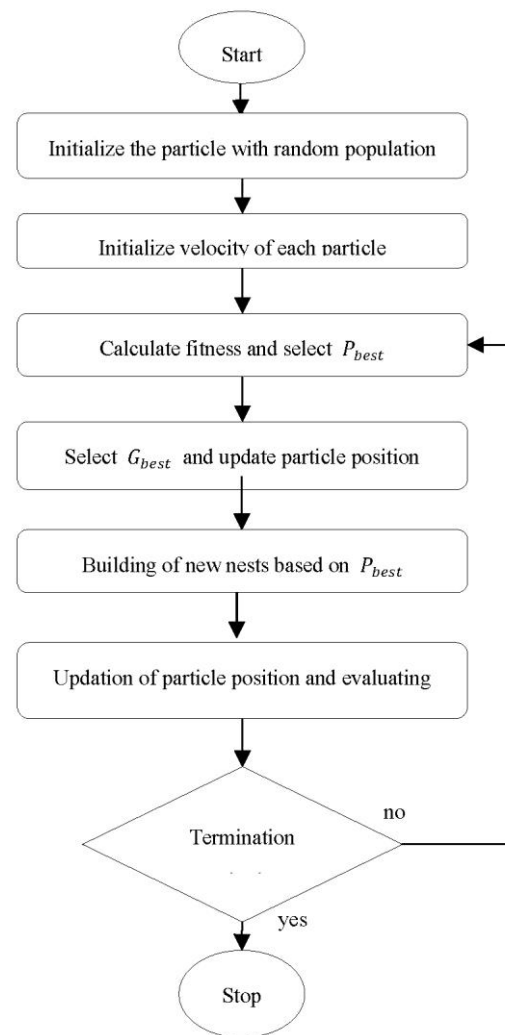


Figure 4. Flowchart of hybrid cuckoo particle swarm optimization.

In the HCPSO algorithm, Lévy flight is not included for building the nest population. This is achieved by P_{best} obtained from the PSO algorithm. By applying this, some fraction of the worst nests W_{nest} are left abandoned, and new good nests are selected for further use, as presented in Algorithm 5. In HCPSO, a new adaptive thresholding function is applied to update selection criteria. This is mathematically represented as

$$\tau(P_{best}, T_r) = \begin{cases} P_{best} - \frac{T_r^2}{2 * P_{best}} & P_{best} > T_r \\ 0.5 * \frac{P_{best}^3}{T_r^2} & P_{best} \leq T_r \end{cases} \quad (22)$$

Here, P_{best} is the best-selected nest value or the filter coefficient, and T_r is the adaptive threshold value, which is updated in each iteration as the threshold is set to the minimum swarm parameter in all populations created.

Finally, velocity and positions are updated as follows:

$$vel_n(t+1) = \omega * vel_n(t) + C_1 \oplus Levy(\lambda) * (p_{bestn}(t) - pos_n(t)) + C_2 \oplus Levy(\lambda) * (g_{best}(t) - pos_n(t)) \quad (23)$$

$$pos_n(t+1) = pos_n(t) + vel_n(t+1) \quad (24)$$

To achieve the best Tr for the adaptive thresholding function, optimization techniques are used. The objective function, in this case, is to minimize the mean squared error (MSE). By employing optimization techniques, the goal is to find the values of the Tr that result in the lowest MSE.

Algorithm 5. HCPSO Optimization

Input
 N_p = Number of Particles (filter coefficients)
 N_v = Number of variables
 Itr_{tmax} = Maximum iterations
 Domain
 Output:
 $nest_{best}$ = best optimal solution
 Initialize : $pos_0 \leftarrow$ random points in domain of Δ & δ
 Initialize : $vel_0 \leftarrow$ random velocity
 $P_{best} \leftarrow pos_0$
 $G_{best} \leftarrow pos_{best}[\text{argmin}(f(P_{best}))]$
 Update the hybrid parameter using adaptive thresholding function (Equation (22))
 While $itr < Itr_{tmax}$ do
 Get the best cuckoo by P_{best}
 Evaluate $f(X)$
 Choose $nest_{itr}$ randomly at $itr = 0$
 If $nest_i > nest_{i-1}$ then
 replace $nest_{i-1}$ with a new solution;
 End if
 Worst nests are removed.
 Return best $nest_i$
 Arrange the solutions in order of preference and determine the most optimal $nest_i$
 End While

4. Results and Discussion

This section discusses the validation of simulation experiments for a proposed model. The experiments were conducted using MATLAB (R2020a) on an Intel(R) Core (TM) i5 with CPU 1.60 and 2.11 GHz with 2 GB graphics. Input images of size 192×192 were degraded with Gaussian noise of varying variance $\sigma^2 \in [0.01-0.09]$, Poisson with a noise density of 0.05, salt and pepper with a noise density of 0.05, and speckle noise with a noise variance of 0.05, and then the proposed hybrid-optimization-based decimation box filters were used to remove the noise. The filters were trained for 100 epochs and performance metrics were used to evaluate the results. PSO, FF, CS, and proposed HCPSO optimization methods were compared in the experiments. For result analysis, medical image datasets are used that are described in the below sub-section.

4.1. Dataset Description

In this paper, three medical image datasets are used for result analysis: CHASEDB1 [29], MRI [30], and Ultrasound [31]. CHASEDB1 was collected from multi-ethnic schoolchildren [29]. This image library contains annotated blood vessel ground truths together with retinal images. The collection contains images with considerable variations in the amount of retinal pigmentation in the foreground. MRI consists of several brain MRI datasets, including simulated and actual images of healthy and diseased people [30]. The ultrasound contains images of 10 volunteers' common carotid arteries (CCAs) with a range of weights (mean weight: 76.5 kg). The image database includes 84 longitudinal B-mode ultrasound images of CCA [31].

4.2. Performance Parameters

Performance parameters used in this research are discussed below:

Peak signal-to-noise ratio (PSNR): PSNR stands for the peak signal-to-noise ratio and is used to evaluate the image quality.

$$PSNR = 10 \log_{10} \frac{(L-1)^2}{MSE} \quad (25)$$

Thus, L is an image's maximum number of intensity levels that can exist.

$$MSE = \frac{1}{mn} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} (O(i, j) - D(i, j))^2 \quad (26)$$

Here, $O(i, j)$ refers to the original image's matrix data. $D(i, j)$ refers to the filtered image's matrix data, m , which is the number of pixel rows, and i denotes the row's index within the image. Meanwhile, n denotes the number of pixel columns, and j denotes the index of that column inside the images.

Structural Similarity Index (SSIM): The Structural Similarity Index (SSIM) is a perceptual metric used to evaluate the degradation of image quality that may occur due to various image processing steps. Mathematically, SSIM is represented as

$$SSIM(x, y) = l(x, y)^\alpha \cdot c(x, y)^\beta \cdot s(x, y)^\gamma \quad (27)$$

Here, setting the weights $\{\alpha, \beta, \gamma\}$ to 1, the formula can be reduced to the form shown above. For three comparison measurements between the samples of x and y , luminance is given by l , contrast by c , and structure by s .

Feature Similarity Index (FSIM): The low-resolution features or low-level features of the image are measured by another variable known as the Feature Similarity Index (FSIM). These features are assessed and prove how effective the human visual system is. Phase congruency (Ph_c), a local feature or major feature for FSIM, is used to assess it. The measurement has no dimensions. Next, a different variable is assessed using gradient magnitude (Gr_m). Ph_c and Gr_m work together in a complimentary manner to enhance the local image quality.

For Ph_c and Gr_m , low-resolution (LR) features $f_1(x)$ and high-resolution (HR) features $f_2(x)$ are computed between them to determine how comparable the features are. The similarity is assessed as follows:

$$S_{phc}(x) = \frac{2Ph_{c1}(x) * Ph_{c2}(x) + E}{Ph_{c1}^2(x) + Ph_{c2}^2(x) + E} \quad (28)$$

Here, Ph_{c1} and Ph_{c2} are the phase congruencies for the LR and HR images, respectively, and S_{phc} is the phase congruency similarity. E is a constant that improves S_{phc} effectiveness.

Additionally, the evaluation of the similarity measures $Gr_{m1}(x)$ and $Gr_{m2}(x)$ between LR and HR, respectively, is as follows:

$$S_{GM}(x) = \frac{2Gr_{m1}(x) * Gr_{m2}(x) + E}{Gr_{m1}^2(x) + Gr_{m2}^2(x) + E} \quad (29)$$

Here, Gr_{m1} and Gr_{m2} are the gradient magnitudes of the LR and HR images, respectively, and E is the variable used to increase the stability of the model.

4.3. Result Analysis

In this section, first, a comparison is provided for the ablation study of the designed hybrid approach with other bio-inspired optimization approaches. This analysis emphasizes the behavior of hybrid cuckoo particle swarm optimization with decimation box filters concerning medical images. The learning parameters for each bio-inspired optimization algorithm are listed in Table 1.

Figure 5 shows the convergence analysis of optimization-based filters with different algorithms, such as PSO, firefly, cuckoo, and the proposed HCPSO model. The number of iterations taken is 100 epochs, and it shows the fitness value vs. the number of iteration curves. The hybrid model fitness value curve shows a better convergence curve. The graph of the designed hybrid approach shows retrieval of the best cost function.

Table 1. Parameters for bio-inspired optimization algorithms.

Algorithm	Parameter
Particle swarm optimization	Size of particle = 20
	No. of iterations = 100
	Max inertia wt. = 0.95
	Min inertia wt. = 0.4
Firefly algorithm	Size of fireflies = 15
	No. of iterations = 100
	Absorption coefficient = 1
	Light absorption coefficient = 1
Cuckoo search	Mutation value = 0.2
	Size of nests = 15
	No. of iterations = 100
	Mutation probability = 0.1
Hybrid cuckoo particle swarm optimization	Scaling factor = 1.5
	Size of particle = 15
	Size of nests = 10
	Max inertia wt. = 0.9
	Min inertia wt. = 0.4
	No. of iterations = 100
	Mutation probability = 0.1
	Scaling factor = 1.5

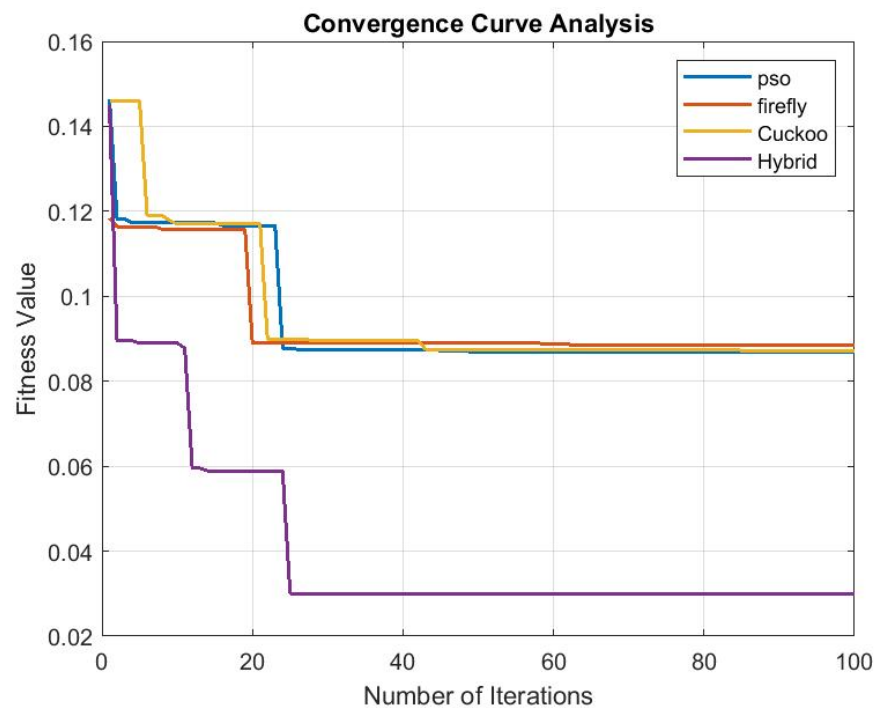
**Figure 5.** Convergence analysis of optimization-based filters.

Table 2 shows the optimal parameter values for GDBF + HCPSO with different algorithm parameters. The first set of parameters is related to the filter order, which determines the complexity of the filter. The values tested in this case are 20, 25, 30, and 35. The best value is obtained at order 30. The next set of parameters is the population size, such as 5, 10, 15, and 20. The corresponding PSNR values for these population sizes are 35.75, 35.79, 35.72, and 35.63, respectively. In this optimal population size was 10. Finally, the table includes the initial training parameter (Initial Tr) with values of 0.01, 0.02, and 0.03. The associated PSNR values are 35.79, 35.49, and 35.62, respectively. The optimal initial Tr was 0.01.

Table 2. Optimal parameters for HCPSO algorithm.

GDBF + HCPSO	Parameter Values	PSNR
Filter Order	20	35.16
	25	35.30
	30	35.72
	35	35.16
Population Size	5	35.75
	10	35.79
	15	35.72
	20	35.63
Initial T_r	0.01	35.79
	0.02	35.49
	0.03	35.62

Figure 6 shows the visual representation after denoising. Hereafter, RGB decomposition, LPF is applied to each component individually. Its outcome with a varying cutoff frequency D_o is represented in Figure 6. Here, $D_o = 192$ shows the best outcome. Then, it is decomposed using 2DWT, and coefficient optimization is performed using HCPSO. After optimization and noise coefficient removal, 2DWT reconstruction is performed, whose outcome is represented below. Finally, all DWT components are combined to visualize the final image. Below, Figure 6 represents stepwise image reconstruction.

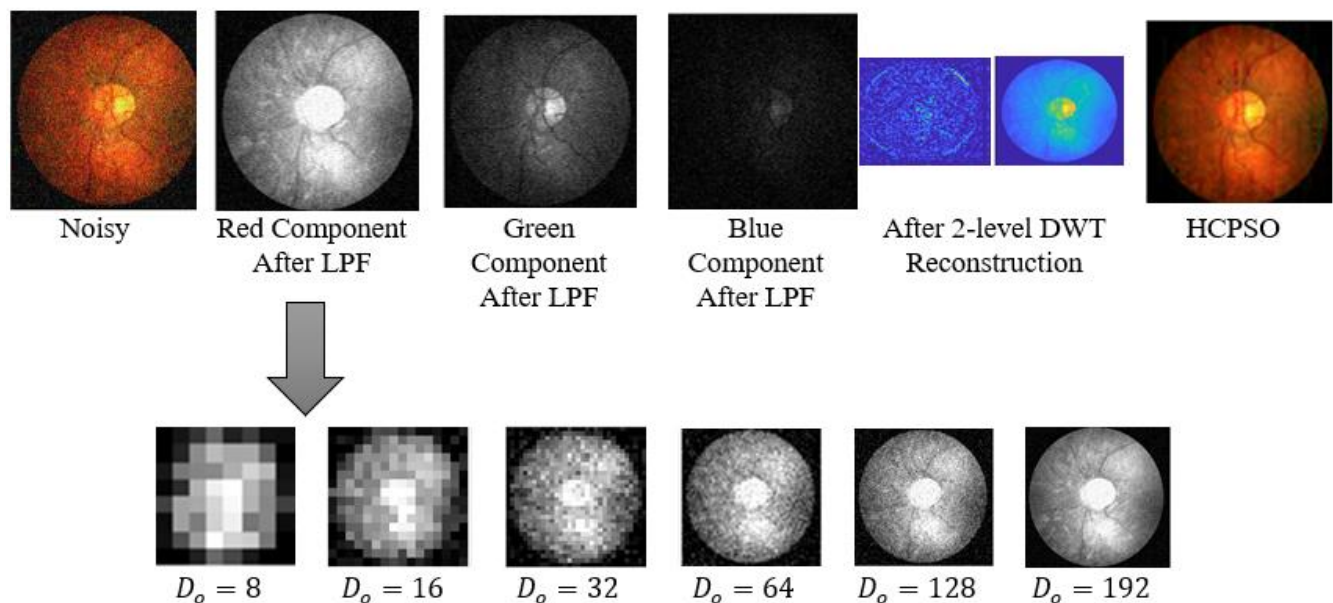
**Figure 6.** Visual representation of denoising using HCPSO.

Table 3 shows the performance analysis of conventional filters, such as the bilateral filter and FIR filters, with the proposed bio-inspired optimization algorithms, i.e., the HCPSO model. The number of images taken for testing was 25. Table 3 shows the performance analysis by considering PSNR, SSIM, and FSIM. The results analysis was performed on an input medical image of size 192×192 . The input image is corrupted with noise, having variable variance ranging from 0.01 to 0.09. In Table 3, it is observed that the proposed HCPSO has achieved the highest PSNR, SSIM, and FSIM values. Therefore, from this analysis, it is observed that the designed hybrid HCPSO model shows fast and best convergence towards the best solution compared to conventional approaches.

Table 3. Comparative analysis of conventional filters with proposed bio-optimized filter with respect to noise variance.

	Variance	Bilateral Filter	FIR	HCP SO
PSNR	0.01	23.80	29.14	35.704
	0.03	17.41	25.46	33.981
	0.05	14.94	23.62	33.229
	0.07	13.50	22.22	32.967
	0.09	12.64	21.22	32.664
	Variance	Bilateral Filter	LPF	HCP SO
SSIM	0.01	0.26	0.56	0.916
	0.03	0.09	0.47	0.872
	0.05	0.06	0.41	0.843
	0.07	0.05	0.38	0.822
	0.09	0.04	0.35	0.798
	Variance	Bilateral Filter	LPF	HCP SO
FSIM	0.01	0.67	0.84	0.886
	0.03	0.43	0.78	0.842
	0.05	0.34	0.72	0.819
	0.07	0.30	0.69	0.802
	0.09	0.27	0.66	0.781

Table 4 shows the performance analysis of bio-inspired optimization algorithms, i.e., PSO, firefly, cuckoo, and the proposed HCP SO model. The number of images taken for testing was 25. Table 4 shows the performance analysis by considering the PSNR, SSIM, and FSIM of the bio-inspired optimization algorithms. The results analysis was performed on an input medical image with a size of 192×192 . The input image is corrupted with noise with variable variance ranging from 0.01 to 0.09. In Table 4, it is observed that the proposed HCP SO has achieved the highest PSNR, SSIM, and FSIM values. Therefore, from this analysis, it is observed that the designed proposed HCP SO model shows fast and best convergence towards the best solution compared to other bio-inspired algorithms. In contrast, the HPSO model also presented better edge preservation compared to others.

Table 4. Performance analysis of bio-inspired optimization algorithms with respect to noise variance.

	Variance	PSO	FF	CS	HCP SO
PSNR	0.01	34.529	32.931	34.571	35.704
	0.03	31.966	31.997	32.763	33.981
	0.05	32.010	31.743	32.687	33.229
	0.07	30.407	30.699	31.326	32.967
	0.09	30.866	30.435	31.274	32.664
	Variance	PSO	FF	CS	HCP SO
SSIM	0.01	0.496	0.498	0.555	0.916
	0.03	0.514	0.428	0.519	0.872
	0.05	0.483	0.429	0.494	0.843
	0.07	0.453	0.365	0.463	0.822
	0.09	0.378	0.381	0.434	0.798
	Variance	PSO	FF	CS	HCP SO
FSIM	0.01	0.691	0.644	0.670	0.886
	0.03	0.683	0.611	0.645	0.842
	0.05	0.641	0.596	0.629	0.819
	0.07	0.604	0.574	0.618	0.802
	0.09	0.608	0.565	0.598	0.781

Table 5 shows the performance analysis of bio-inspired optimization algorithms, i.e., PSO, firefly, cuckoo, and the proposed HCP SO model in terms of the varying low-pass filter orders used. Table 5 shows the performance analysis by considering PSNR, SSIM, and FSIM of the bio-inspired optimization algorithms. The results analysis was performed on an input medical image with a size of 192×192 . The input image is corrupted with noise with a variable variance of 0.01. Here, HCP SO optimization with a filter order of

30 achieved better results, i.e., PSNR = 35.727, SSIM = 0.929, and FSIM = 0.887. Therefore, in this analysis, it was observed that the best filter order was 30, in which the HCPSO algorithm achieved better performance compared to others. Overall, the HCPSO algorithm performed consistently well across all three image quality metrics and all filter orders, making it a promising bio-inspired optimization algorithm for image-filtering applications.

Table 5. Performance analysis of bio-inspired optimization algorithms with respect to filter order.

	Filter Order	PSO	FF	CS	HCPSO
PSNR	20	33.509	33.094	34.342	35.162
	25	34.239	33.091	34.370	35.300
	30	33.758	33.100	34.868	35.727
	35	32.730	31.777	34.394	35.167
	Filter Order	PSO	FF	CS	HCPSO
SSIM	20	0.696	0.647	0.693	0.924
	25	0.720	0.637	0.684	0.924
	30	0.639	0.655	0.678	0.929
	35	0.711	0.644	0.688	0.921
	Filter Order	PSO	FF	CS	HCPSO
FSIM	20	0.502	0.494	0.571	0.882
	25	0.531	0.487	0.583	0.882
	30	0.495	0.477	0.558	0.887
	35	0.533	0.472	0.586	0.878

In Figure 7, the paper presents a visual comparison of bio-inspired algorithms, i.e., particle swarm optimization (PSO), firefly (FF) algorithm, cuckoo search (CS) optimization, and hybrid cuckoo particle swarm optimization (HCPSO) on all three datasets, as described above. For this, σ^2 is kept at 0.01.

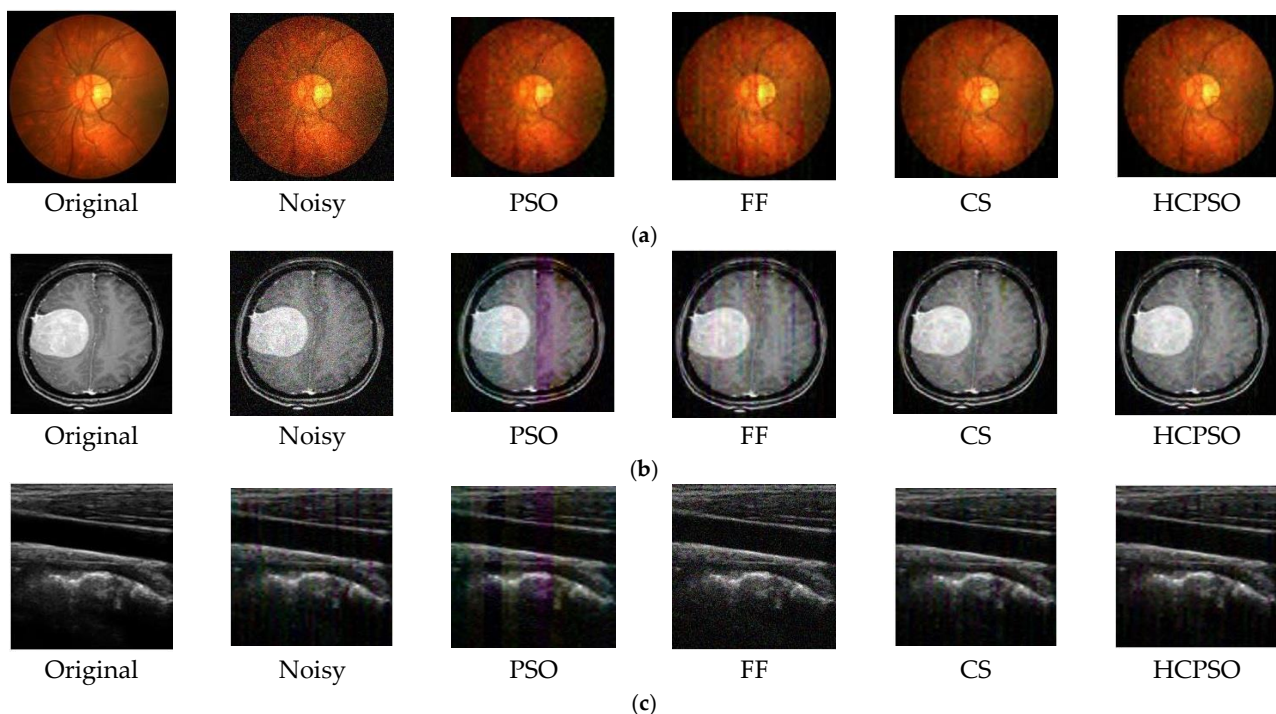


Figure 7. Visual comparison of different bio-inspired-optimization-based filters on (a) CHSEDB1 dataset, (b) MRI dataset, and (c) ultrasound dataset.

Similarly, in Figure 8, the paper presents a visual comparison with the variable σ^2 . In both diagrams, it is seen that edges are preserved more in the designed HCPSO-based guided decimation box filter.

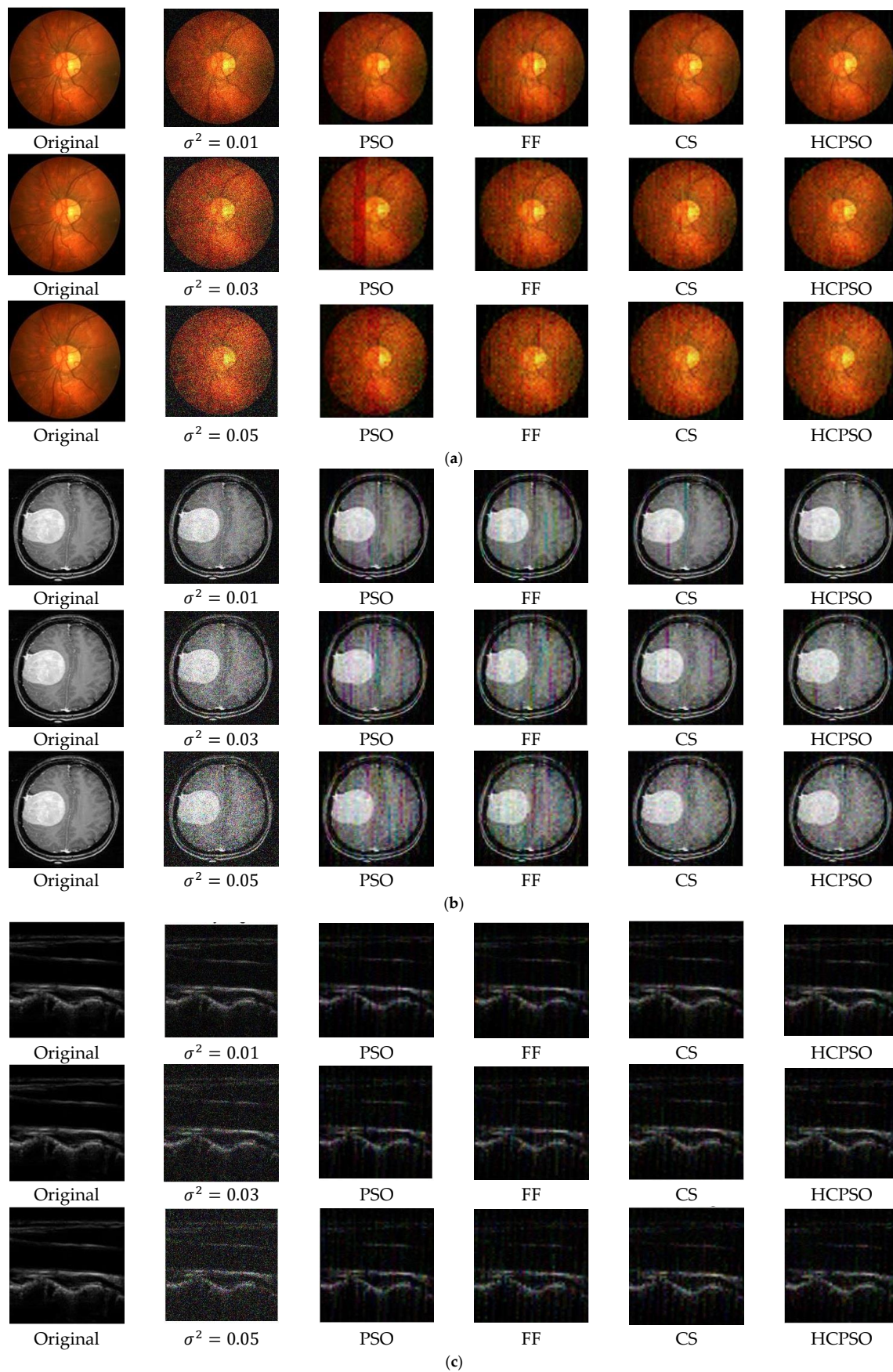


Figure 8. Visual comparison of different bio-inspired optimization-based filters of variable σ^2 on (a) CHSEDB1 dataset, (b) MRI dataset, and (c) ultrasound dataset.

Figure 9 shows the performance of the HCPSO-based GDB filter on varying noise variance with the datasets CHASEDB1, MRI, and ultrasound. The variance varied from $\sigma^2 = 0.01$ to $\sigma^2 = 0.09$. PSNR, SSIM, and FSIM are the maximum for $\sigma^2 = 0.01$, i.e., 35.77, 0.926, and 0.899, respectively, for the CHASEDB1 dataset. PSNR, SSIM, and FSIM are the maximum for $\sigma^2 = 0.01$, i.e., 33.33, 0.925, and 0.915, respectively, for the MRI dataset. PSNR, SSIM, and FSIM are the maximum for $\sigma^2 = 0.01$, i.e., 35.63, 0.928, and 0.904, respectively, for the ultrasound dataset.

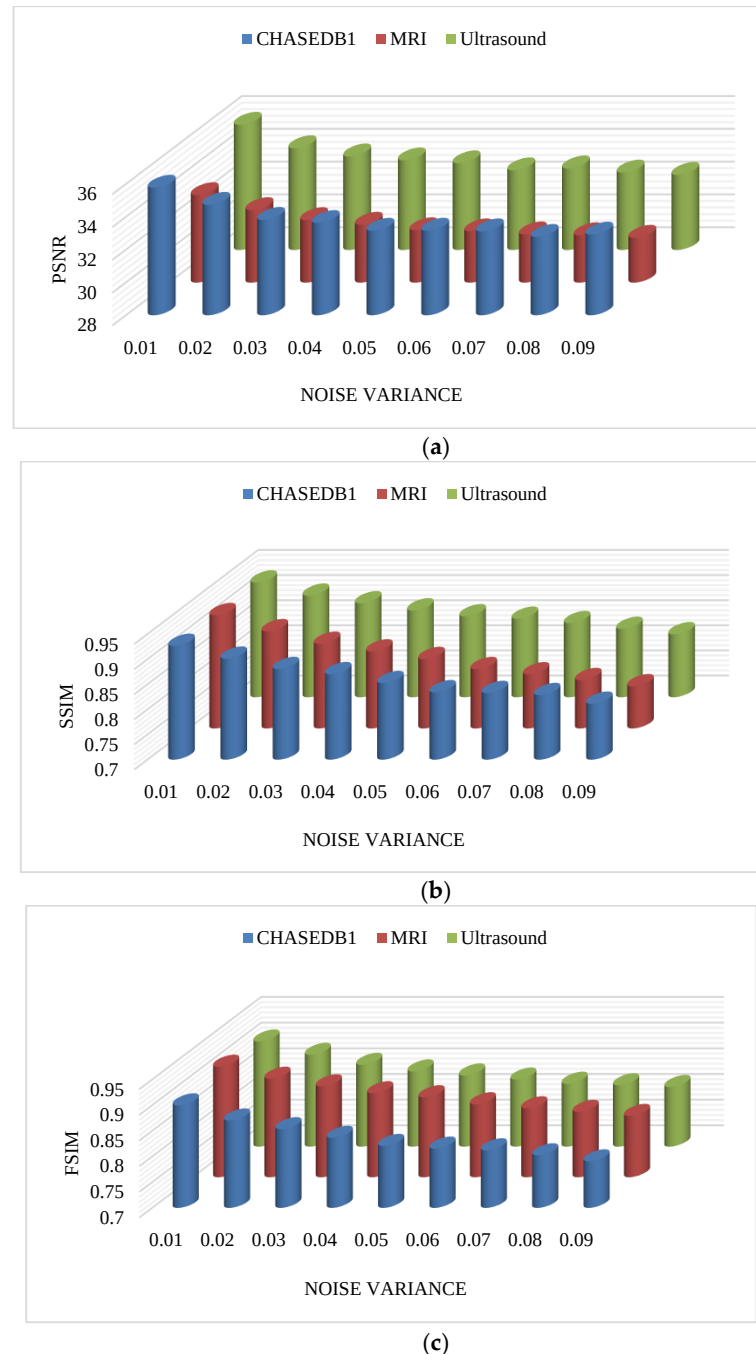


Figure 9. Performance of proposed HCPSO-based novel GDB filter for varying noise variance in terms of (a) PSNR, (b) SSIM, and (c) FSIM.

Similarly, Figure 10 shows the performance of the proposed HCPSO-based GDB filter on varying decimation sizes. For the CHASEDB1 dataset, PSNR, SSIM, and FSIM are the maximum for the decimation 2×2 , i.e., 37.34, 0.951, and 0.9241, respectively. For the MRI

dataset, PSNR, SSIM, and FSIM are the maximum for the decimation 2×2 , i.e., 34.608, 0.946, and 0.9355, respectively. For the ultrasound dataset, PSNR, SSIM, and FSIM are maximum for the decimation 2×2 , i.e., 37.26, 0.957, and 0.9335, respectively. Given these results, the best result was obtained at a smaller size of the decimation box filter. For reliable and robust comparison among bio-inspired optimization-based digital filters, all input images were taken same on the same execution platform.

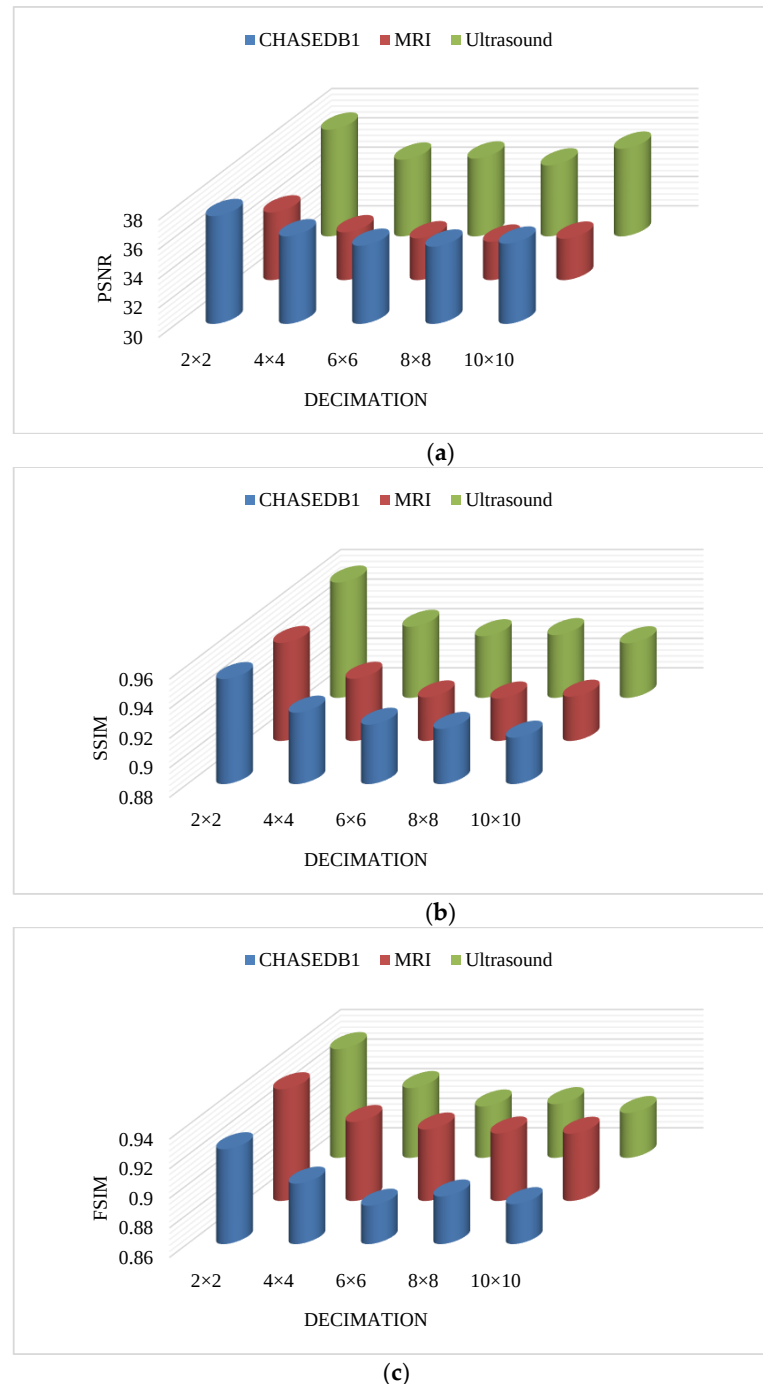


Figure 10. Performance of proposed HCPSO-based GDB filter for varying decimation in terms of (a) PSNR, (b) SSIM, and (c) FSIM.

Figure 11 shows the performance of the proposed HCPSO-based GDB filter on varying input image sizes with different datasets, CHASEDB1, MRI, and ultrasound. The image size varied from 128×128 , 192×192 , 256×256 , and 512×512 . PSNR, SSIM, and FSIM are

the maximum for the 512×512 image size, i.e., 37.135, 0.940, and 0.906, respectively, for the CHASEDB1 dataset. PSNR, SSIM, and FSIM are the maximum for the 512×512 image size, i.e., 35.964, 0.950, and 0.943, respectively, for the MRI dataset. PSNR, SSIM, and FSIM are the maximum for the 512×512 image size, i.e., 37.306, 0.952, and 0.924, respectively, for the ultrasound dataset.



Figure 11. Performance of proposed HCPSO-based GDB filter for varying input image sizes in terms of (a) PSNR, (b) SSIM, and (c) FSIM.

Figure 12 shows the performance of the proposed HCPSO-based GDB filter on varying types of noise, such as Gaussian, Poisson, salt and pepper, and speckle with different datasets, including CHSEDB1, MRI, and ultrasound. The image size is taken as 192×192 . PSNR, SSIM, and FSIM are the maximum for Poisson noise.

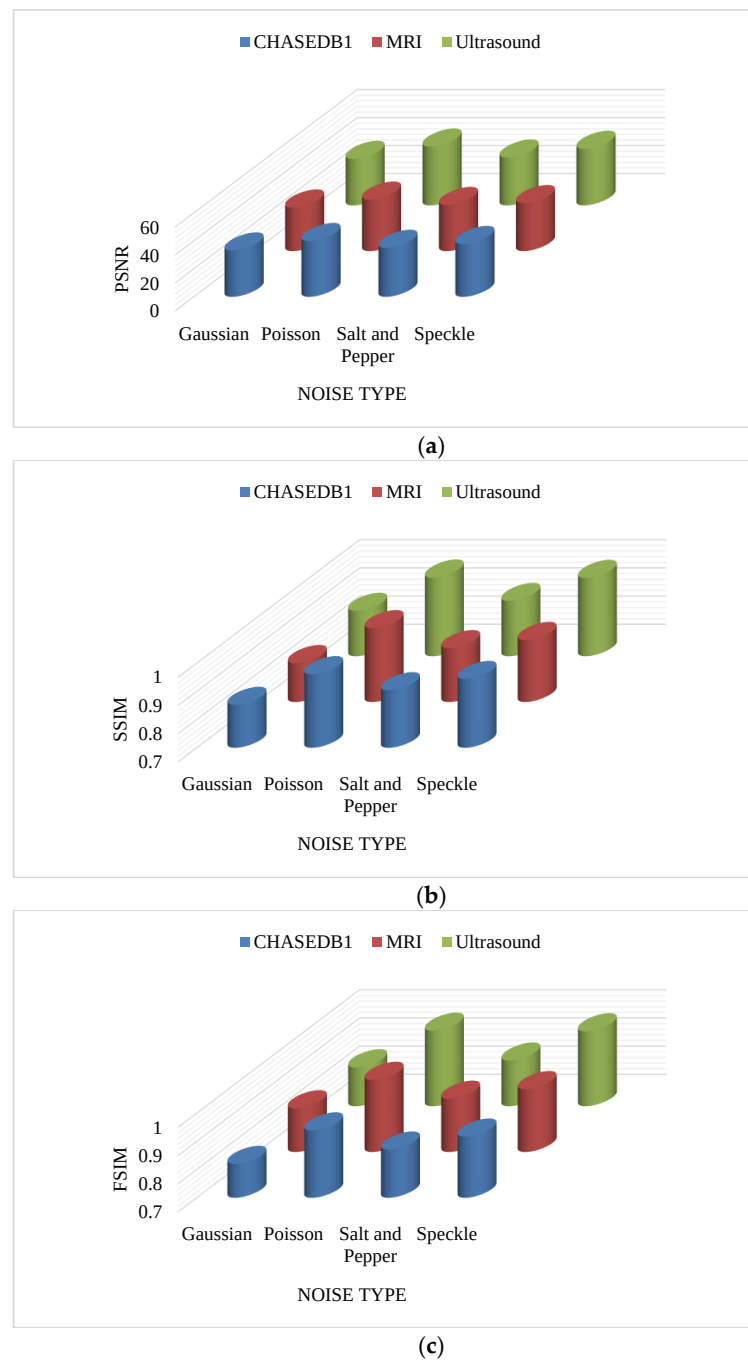


Figure 12. Performance of proposed HCPSO-based GDB filter on different noises in terms of (a) PSNR, (b) SSIM, and (c) FSIM.

Figure 13 presents the time complexity analysis of the proposed HCPSO model for different noises. The average computational complexity of the model is ~ 1 s, which is quite diminished. Figure 14 presents the performance analysis of digital filters designed for spatial domain filters for images. In terms of the comparative state-of-the-art, the most popular models are considered, such as the Deep Convolutional Neural Network method (DNCNN) [32], adaptive cuckoo search optimization (AD-CSO) [33], adaptive modified cuckoo search optimization (AD-MCSO) [33], bilateral filter optimization using cuckoo search optimization (BF-CSO) [34], deep image prior combined with regularization by denoising (DeepRED) [35], enhanced GWO optimization [13], unsupervised deep learning (DNN) [36], ant colony optimization (ACO) [37], Bi-dimensional Empirical Mode Decomposition (BEMD) [38], a bilateral filter with a genetic algorithm (BF-GA) [39], the linear

minimum mean square error method for principal component analysis (LMMSE-PCA) [40]. These existing state-of-the-art models are compared with the proposed HCPSO on approximate PSNR and SSIM values. The comparative graphs are also presented in Figure 14. Given the above graphs, it is clear that the proposed HCPSO provides better results in terms of PSNR and SSIM compared to the existing state-of-the-art models, as the PSNR is the quantitative performance evaluation parameter, while SSIM is the qualitative performance evaluation parameter. Therefore, it can be concluded that the designed HCPSO preserves the quality of the image after denoising. Table 6 presents the comparative state of the art for the noise-handling capability of algorithms. In the table, it is clear that the proposed HCPSO is more adaptive to all possible types of noise that may occur in medical images. Therefore, it proves that the proposed HCPSO is adaptable to existing artifacts and can handle future artifacts.

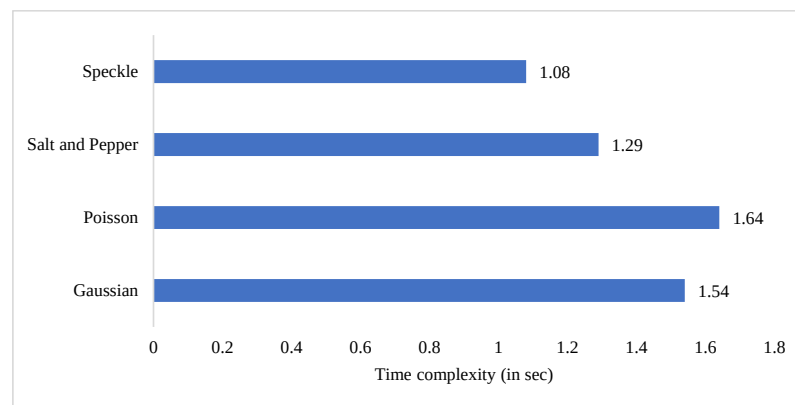


Figure 13. Computational time complexity during denoising.

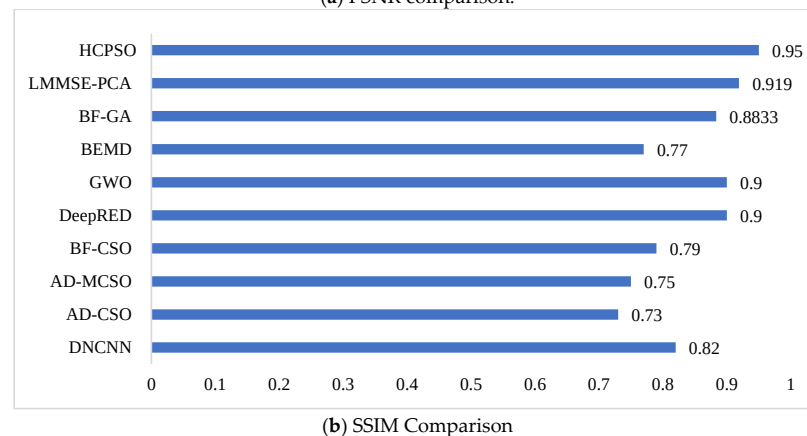
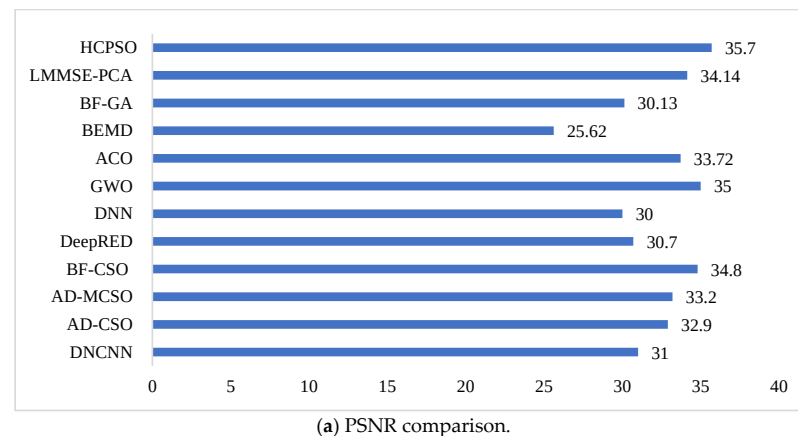


Figure 14. Comparative state-of-the-art.

Table 6. Comparative state of the art for noise-handling adaptation.

Ref	Algorithm	Application Area	Image Type	Gaussian	Poisson	Salt and Pepper	Speckle
[12]	Backtracking Optimized Search Algorithm	Medical	CT	×	×	×	×
[13]	Enhanced Grasshopper optimization	Medical	CT	✓	×	×	×
[14]	Firefly	Medical	CT, X-ray, MRI	✓	×	×	×
[15]	Dragonfly (DF) and Modified Firefly	Medical	MRI and CT	×	×	✓	×
[16]	Domain Translation	Medical	PET	✓	×	×	×
[32]	DNCNN	General	-	✓	×	×	×
[33]	Modified Cuckoo Search Algorithm	General	-	✓	×	×	×
[35]	DeepRED	Medical	PET	✓	×	×	×
	Proposed HCPSO	Medical	CT, X-ray, MRI, Ultrasound	✓	✓	✓	✓

5. Conclusions

The presence of noise in a medical image makes it difficult to identify and analyze diseases. The traditional approach experiences losses and causes over-smoothing, demanding greater computational requirements. Therefore, there is a requirement for optimization approaches for medical image denoising, and medical image denoising is essential as a pre-processing step for any further diagnosis process. In this paper, a novel digital filter for medical image denoising is proposed using hybrid cuckoo particle search optimization with a decimation box filter for restoration from noisy images. This paper presents the resulting ablation study on different optimization algorithms. For the evaluation of results, the input medical images were corrupted with different noises and then filtered through a designed hybrid-optimization-based guided decimation box filter. The optimal coefficients and degree of smoothing were obtained. The result was observed with a variance in the noise, input image size, and decimation box. Apart from this, to validate the designed filter, its comparison was performed on some existing approaches for image denoising. The results prove that the developed model exhibits better performance in terms of quantitative measures. In the future, this work will be extended to some real-time applications.

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