

Comparative Analysis of Particle Swarm Optimization and Whale Optimization Algorithm for Medical Image Enhancement

Oloyede, M. O.¹, Hameed-Ibidokun, T. K.², Olawoyin L. A.³, and Omotosho, K.¹

¹Department of Information Technology, University of Ilorin, Nigeria.

²NHS Business Service Authority, Newcastle, United Kingdom.

³Department of Telecommunication Science, University of Ilorin, Nigeria.

Corresponding email: oloyede.om@unilorin.edu.ng

Abstract

Medical images play a critical role in diagnosing and treating various diseases, making their quality a crucial factor in clinical decision-making. However, raw medical images often suffer from issues such as low contrast, noise, blurring, and poor illumination, which can erase important anatomical details and reduce diagnostic accuracy. Histogram equalization and unsharp masking are the classic methods of enhancing images, which can be effective, although they frequently do not effectively trade-off between contrast enhancement and noise reduction. Therefore, advanced and intelligent image enhancement methods are crucial for ensuring more precise visualization of critical features, such as tumours, blood vessels, and tissue structures. Metaheuristic optimization methods (MOAs) are frequently applied for image optimization task, especially, in the circumstance of medical image enhancement (MIE). Nevertheless, as the rate of newer MOAs proposed in the literature continues to escalate, a question arises and whether there are any meaningful differences between these various MOAs and specifically in terms of MIE. This paper will compare two metaheuristic algorithms, particle swarm optimization (PSO) and whale optimization algorithm (WOA) in the process of medical image enhancement. In the study, we utilize a practical evaluation function and transformation function on both MOAs. Medical images were then taken from the Medpix dataset where the representative samples were taken across the various parts of the body to carry out MIE evaluation. Results show that WOA algorithm performed slightly better than PSO in the selected performance metrics, for example for number of edges WOA produced 4724 while PSO produced 4623. Findings further show that both metaheuristic algorithms enhance medical images, which will improve medical diagnosis and decision-making, thereby saving more lives.

Keywords: Medical image enhancement, Metaheuristic optimization, Particle swarm optimization, Whale optimization algorithm, Diagnostic accuracy.

1. Introduction

Medical imaging, such as Magnetic Resonance Imaging (MRI), Computed Tomography (CT) scans, X-rays, and Ultrasound are essential to the current healthcare. (Zhang et al., 2024). They provide non-invasive means for clinicians to visualize internal anatomical structures, monitor disease progression, and plan surgical interventions. The diagnostic accuracy derived from these images is directly proportional to their visual quality (Abhisheka et al., 2024). Unfortunately, images captured from these modalities are frequently compromised by various inherent and acquired degradations, such as poor illumination, low contrast, and random noise, which can lead to misdiagnosis and delayed treatment (Thaku et al., 2024).

Histogram equalization (HE) and its variations have

been used widely as a traditional method of improving contrast. Nevertheless, they can be characterized by some serious disadvantages (Archana et al., 2024). For instance, global HE can over-enhance background noise and suppress subtle details, while adaptive HE methods can be computationally intensive and may introduce artifacts. Similarly, simple spatial filtering techniques for noise reduction often lead to blurring of important edges (Rivera-Aguila et al. 2024 & Oloyode et al., 2022). The trade-off between enhancing contrast and suppressing noise remains a significant challenge that requires a more sophisticated approach (Archana et al., 2024).

Over the past few years, image processing has seen a rise in the use of Metaheuristic Optimization Algorithms (MOAs) in order to meet this challenge (Toma et al., 2024). The MOAs are motivated by natural processes and social behaviour, and provide a strong and versatile framework to solve complex, non-linear optimization problems in which conventional methods can be ineffective (Yaqoob et al., 2024). In the perspective of medical image enhancement (MIE),

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the minimization of a problem can be formulated as an optimization challenge i.e. the task to find the best set of parameters of a transformation function that optimizes the image based on some specified objective function (Dehghani et al., 2023).

Among the vast number of MOAs proposed in the literature, Particle Swarm Optimisation (PSO) and the more recent Whale Optimisation Algorithm (WOA) have gained significant attention due to their effectiveness and computational efficiency (Almufti et al., 2023). A simple flocking-based method that has proven to converge quickly, PSO, is based on the collective behaviour of flocks of birds and fish schools (Gad et al., 2022). WOA, based on the unique hunting strategy of humpback whales, is celebrated for its balance between exploration and exploitation (Amiribrahimabadi et al., 2024). Despite their individual successes in various optimization tasks, a fair and unbiased comparison of their performance, specifically for MIE remains a critical research question. Many comparative studies rely on the number of generations, which can be misleading due to varying computational costs per iteration across different algorithms (Wang et al., 2024). Also, identifying which algorithms perform more effectively in MIE remains unclear. This paper addresses this gap by conducting a comparative analysis of PSO and WOA for medical image enhancement. Major contributions of this research include:

1. Implementing both MOAs with a standard, practical objective functions that balances contrast enhancement with noise reduction.
2. Confirming if there is any clear benefit of using either of the MOAs for MIE. For this, the two MOAs, including WOA and PSO, were considered.
3. The timing performance for the two MOAs was measured, and it was observed that there was no significant difference to show.

The other sections of this article are organised as thus: Section 2 discusses related work. Section 3 describes the intended methodology, including the purpose of the function and particular execution of PSO and WOA. The results and detailed discussion appear in section 4. Lastly, Section 5 gives a conclusion to the paper and provides future research directions.

2. Related Work

Image enhancement has been a subject of extensive research for decades. Traditional approaches can be broadly classified into spatial and frequency domain methods (Rivera-Aguilar et al., 2024). Histogram equalization (HE), a spatial domain technique, is a fundamental method that spreads the intensity values to cover the entire dynamic range, thereby improving contrast. Nevertheless, it is prone to overly contrast-enhancing the image, and noise amplification and it is especially unwanted in sensitive medical imaging

(Rivera-Aguilar et al., 2024). Alternatives such as Adaptive Histogram Equalization (AHE) and Contrast Limited AHE (CLAHE) were created to overcome these problems by processing HE to local areas. While effective, they can be computationally expensive and may introduce blocky artifacts (Härtinger et al., 2024). Recently, researchers have turned to nature-inspired optimization algorithms to overcome the limitations of traditional methods. Genetic Algorithms (GA), inspired by biological evolution, has been successfully applied to optimize image enhancement parameters (Mazoukh et al., 2024). However, their high computational cost due to the selection, crossover, and mutation operations can be a limiting factor. Ant Colony Optimization (ACO) has also been used, but its performance can be highly dependent on parameter tuning (Mazoukh et al., 2024).

Particle Swarm Optimisation (PSO) is one of the most popular MOAs due to its simplicity and fast convergence (Gad et al., 2022). It has been widely applied in various image processing tasks, including image segmentation and enhancement. For MIE, PSO has been utilized to optimize parameters of enhancement functions, demonstrating superiority over traditional methods (Saifullah et al., 2024). The Whale Optimization Algorithm (WOA), a relatively recent metaheuristic, has yielded promising results in a wide range of optimization problems. Inspired by the hunting behaviour of humpback whales, it mimics the unique "bubble-net" feeding method (Fan, et al., 2024). WOA has a strong balance between searching for new solutions and refining existing solutions. This has made WOA a powerful contender in the MOA landscape (Amiribrahimabadi et al., 2024). Its application in image enhancement, while less extensive than PSO, has already shown great promise (Yang et al., 2024).

Despite the individual successes of these algorithms, a direct and fair comparison for MIE is rare in the literature. Most comparative studies use the number of generations as a termination criterion, which can be misleading. For instance, one iteration of GA or ACO may take significantly longer to compute than one iteration of PSO or WOA, thus a fixed number of generations does not equate to the same amount of computational effort (Islam et al., 2024).

3. Methodology

The methodology will make a just comparison between PSO and WOA on medical image enhancement. A transformation function is typically followed by the purpose of transforming the number of intensity values of the original image to obtain a more refined image of the medical output (Oloyede et al., 2022). This transform functionality is usually defined in terms of parameters, the value of which requires optimal computation to maximize the performance. The metaheuristic methods are therefore often implemented to obtain the optimistic combination of these parameters in the transformation function by an

objective function (Oloyede et al., 2019). In this way, we first define the transformation function used in this analysis. The assessment role applied to the two MOAs is thereafter discussed. The performance evaluation measures employed in this research, and the database where medical images are picked at are discussed.

3.1 Transformation function

In (Munteanu et al., 2004), a transformation function was proposed and has been widely used in related studies, confirming its effectiveness. Hence, this transformation function has been used in this study, and the function is thus:

$$g(i, j) = T(f(i, j)) = k \left(\frac{M}{\sigma(i, j) + b} \right) \bullet [f(i, j) - c \bullet m(i, j)] + m(i, j)^a \quad (1)$$

In equation (1), parameters a, b, c and k: The functions of a, b, c, and k are as follows: Parameter a adds a bias of brightening to the output image depending on the preceding term $m(i, j)$. This gives the ability to regulate the degree of smoothening effect desired in the output picture. The parameter b has the effect of certifying that a zero-standard deviation value at local neighbourhood pixels does not play a significant part in whitening of the final output image. The parameter c enables a fraction of the means, $m(i, j)$ to be removed off the original pixels of the input image, but also the degree of darkening introduced in the output image. The parameter k establishes an objective balance of the pixels being present in the middle range limits of the grey scale. This prevents the pixels being either too dark or too bright in the process of enhancement. The following parameters were identified to be effective after a parameter tuning exercise undertaken in our work: $2 \leq a \leq 2.5$; $0.3 \leq b \leq 0.5$; $0 \leq c \leq 3$; and $3 \leq k \leq 4$. The values determined the boundaries of the constraints adopted in the optimization of our approach. The average of the original image, M, is calculated in the world as expressed in equation (2):

$$M = \sum_{i=0}^{H_{SIZE}-1} \sum_{j=0}^{V_{SIZE}-1} f(i, j) \quad (2)$$

3.2 Evaluation function

This is applied to verify the quality of an improved image $g(i, j)$ but without human judgment. It is applied to examine the optimal parameter values of T the transformation function that gives the best enhanced image. Therefore, the assessment role as suggested by the (Oloyede et al., 2019) is used for investigation. According to some parameters the evaluation function is developed as indicated in equation (3):

$$E = 1 - \exp\left(\frac{\rho_g}{100}\right) + \frac{N_g + \phi_g}{H \times V} + \frac{\beta_g}{8} \quad (3)$$

3.3 Particle swarm optimization

The particle swarm optimization technique resembles the behaviour of particles within a search space with the goal of approaching a useful optimal solution. The local best position of each solution in the populations determines its evolution and the velocity parameter

directs it to a more effective solution. In the literature, the algorithm to be used in the PSO is described (Oloyede et al., 2022).

3.4 Whale optimization algorithm

It is a more recent optimization algorithm which imitates the natural foraging behaviour of humpback whales. Such whales are able to perceive the presence of prey and surround it (Yang et al., 2024). Because the optimum designs location in the search space is unknown in advance, the WOA algorithm supposes that the current effective candidate solution is the target prey. The algorithm of WOA is found in literature (Oloyede et al., 2022). Once the optimal search agent has been identified the remaining search agents will endeavor to optimize their position relative to the optimal search agent.

4. Dataset

Images used in this work have been chosen in the MedPix database. It is a free web based database of medical imagery, clinical topics, teaching cases and external metadata. It contains more than 10, 000 patient case scenarios, 9000 topics, and approximately 59,000 images. The pictures in the database have been classified as cardiovascular, chest, pulmonary, and abdomen (Lau et al., 2018). In this work, two images were taken at random as samples to represent the human body under two use cases namely use case 1 and use case 2.

4.1 Performance Metrics

The following measures were applied to ascertain the performance of the two MOAs in this study. These are the number of edges, number of pixels in the foreground, entropic measure, peak signal to noise ratio, and the absolute mean error value of brightness as indicated in equations (4) to (8).

Number of edges

$$N_g = \sum_{i=1}^H \sum_{j=1}^V E_g(i, j) \quad (4)$$

Number of pixels

$$\phi_g = \sum_{i=1}^H \sum_{j=1}^V D_g(i, j) \quad (6)$$

Then, the entropic measure, b_g , of $g(i, j)$ is computed as

$$\beta_g = \begin{cases} -\sum_m \Omega_m \log(\Omega_m) & \text{for } \Omega_m \neq 0 \\ 0 & \text{for } \Omega_m = 0 \end{cases} \quad (6)$$

where Ω_m is the frequency of pixels having gray levels in the histogram bin $m = 1, \dots, 256$. The PSNR, ρ_g , of $g(i, j)$ is obtained as

$$\rho_g = 10 \log_{10} \left[\frac{(L-1)^2}{MSE} \right] \quad (7)$$

where L is the maximum pixel intensity value in $g(i, j)$ and MSE is given as

$$MSE = \frac{1}{H \times V} \sum_{i=1}^H \sum_{j=1}^V |f(i, j) - g(i, j)|^2 \quad (8)$$

Absolute mean brightness error

$$\varepsilon = |\delta(f(i, j)) - \delta(g(i, j))| \quad (9)$$

5. Results and Discussion

5.1 Qualitative analysis

Use case 1: This image shows axial and coronal sections of abdominal and chest CT, significant for the absence of IVC below the liver. Enlarged azygous/hemiazygous systems are present as shown in Figure 1a. The picture was retrieved at no cost in MedPix database. The PSO and WOA-enhanced picture are presented in Figure 1b and Figure 1c, respectively.

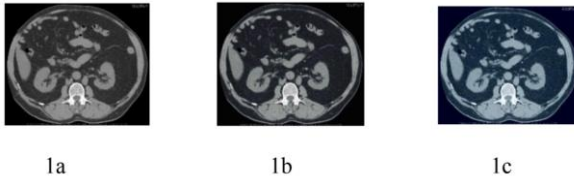


Figure 1: Axial and coronal sections of abdominal and chest CT.

Use case 2: This image comprises a low attenuating lesion in the left brachipontine region with mass effect on the fourth ventricle, as shown in Figure 2. The image was acquired freely from the MedPix database. The enhanced image by PSO and WOA is shown in Figure 2b and Figure 2c, respectively.

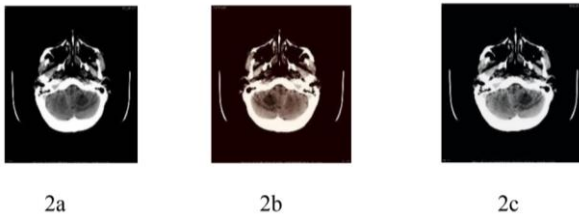


Figure 2: low attenuating lesion in the left brachipontine region with mass effect.

From the above, it is evident that the two MOAs significantly enhance the original medical images as shown in Figures 1(b) -1(c) and 2(b) -2(c).

5.2 Quantitative analysis

The two MOAs experimented with in this paper are compared with the help of image enhancement measures and the outcome is presented in the Tables 1 and 2. Table 1 indicates that WOA contained more edges than PSO. Whereas Peak SNR, the ratio of the largest possible power of a signal to the power of

corrupted noise, WOA was smaller than PSO, which shows that the PSO is of superior quality. In the case of the entropy value, indicating that an increase in information has been inserted in the improved image, WOA had a higher value than PSO. Whereas WOA took the AMBE into account, which measures the extent of brightness of an enhanced image, it exhibited a bigger value.

Table 1: Use case 1: Image improvement enactment metrics

	PSO	WOA
Number of edges	4623	4724
Peak SNR	18.632	17.264
Entropy	4.7354	4.8765
AMBE	0.0013	0.0134

In Table 2, there was a similar performance of the MOAs on use case 2. This indicates that regardless of the images, the performance of the MOAs remains the same.

Table 2: Use case 2: Image improvement enactment metrics

	PSO	WOA
Number of edges	6784	6839
Peak SNR	6.7435	6.4276
Entropy	6.864	6.923
AMBE	0.3115	0.3254

Qualitative analysis (visual inspection) further supported these findings. Images enhanced by WOA exhibited slightly more precise fine details, such as enlarged azygous/hemiazygous, which were slightly blurred in the PSO-enhanced images. This suggests that WOA's unique search behaviour, which mimics the bubble-net strategy, is particularly effective at avoiding local minima in the complex landscape of image enhancement, leading to more optimal parameter sets.

5.3 Timing Performance

The timing performance of the two MOAs was observed and presented by use case as shown in Table 3. Experiments were conducted using a PC equipped with a Core i7 CPU processor at 3.40GHz and 16 GB of installed memory. The two algorithms were coded and simulated in MATLAB 2020b.

Table 3: Processing time (seconds) for the use cases.

	Use case 1	Use case 2
PSO	4.3092	4.6458
WOA	4.1795	4.3581

Regarding the runtime of the two MOAs, it is observed that the WOA converged quickly than PSO in both use cases. However, the difference in time is not too significant. This finding is crucial as it demonstrates that while WOA offers a slight advantage in terms of image quality, this improvement does not come at the cost of significantly higher processing time, making it a viable alternative for real-time diagnostic systems.

6. Conclusion

Medical image optimization is an essential stage of up-to-date diagnostics, and metaheuristic optimization algorithms provide a potent response to the insufficiency of conventional approaches. This paper has made a comparative study of PSO and the WOA in medical image enhancement. Our findings demonstrate that both PSO and WOA are effective in enhancing medical images, leading to improved diagnostic quality. Nevertheless, the WOA algorithm was a little bit better in the majority of quantitative image quality measures, which indicates that the algorithm is better at estimating optimal enhancement parameters. It is interesting to note that at the timing analysis, there was no statistically significant difference in the real time processing speed of the two methods. This suggests that WOA offers a marginal but meaningful improvement in image quality without a corresponding increase in computational cost. Both algorithms are highly viable for clinical applications, and their deployment will undoubtedly improve medical diagnosis and decision-making, thereby saving more lives. From a clinical perspective, both MOAs have produced more precise visualizations of critical features, which can directly improve diagnostic accuracy and clinical decision-making. A physician's ability to detect subtle abnormalities promptly can lead to earlier intervention and ultimately save lives. Future work will explore hybrid algorithms that combine the strengths of different MOAs, such as using WOA for global search and PSO for local refinement. These methods can also be applied to a wider range of medical imaging modalities and to a larger dataset to validate our findings further.

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