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A Robust Digital Image Watermarking Using Gorilla Troop Optimization Algorithm in Hybrid Frequency Domain

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Abstract: Because of the nature of the Internet and the growing number of people using digital media, copyright protection is becoming more important. One of the most common ways to protect this is by implementing digital image watermarking. This protection method safeguards the image from unauthorized access. The Gorilla Troop Optimization Algorithm (GTO), a new evolutionary algorithm, is what we propose to be a powerful watermarking technique. Initially, we applied Discrete Wavelet Transform (DWT) to the cover image, followed by Singular Value Decomposition (SVD) for enhanced security, and finally, we applied SVD to the Watermark image for its embedding into the cover image. In this process, we aim to optimize the multiple scaling factors (MSFs) by applying the GTO algorithm and testing the proposed algorithm in the MATLAB environment using some standard images. We then evaluated the experiment using performance metrics such as Normalized Cross-Correlation (NCC), the Structural Similarity Index (SSIM), and the Peak Signal-to-Noise Ratio (PSNR). These metrics proved the imperceptibility of different attacks and the proposed algorithm's performance.

Index Terms: Digital Watermarking, Gorilla Troop Optimization Algorithm, Discrete Wavelet Transform, Singular Value Decomposition, Multiple Scaling Factors

1. Introduction

Nowadays, users can easily transfer various types of digital files, such as videos and audio files, from one gadget to another. Technological advancements have intensified the challenge of protecting digital information's intellectual property and piracy rights. The nature of data transmission leaves it vulnerable to a variety of attacks and operations. Digital watermarking can help protect intellectual property rights by controlling the flow of information [1]. Its usage is evident in multiple applications such as copyright protection, ownership authentication, hidden communications, IoT, 3D imaging, fingerprinting, and e-government. Embedding and extracting the watermark is crucial to watermarking. This step considers the temporal and spatial features of the image. Because the embedded images have high spectral coefficients, digital watermarking has an advantage in the frequency domain over the spatial domain in that it can produce unique patterns [2].

Many approaches based on the spatial domain, the transform domain, or both have been introduced in recent years. Through the modification of pixel values in the host image, the spatial domain method incorporates the watermark. However, the transform domain alters the coefficients of the transformation. Exemplary transformations are Discrete Cosine Transform (DCT), Discrete Fourier Transform (DFT), and Discrete Wavelet Transform (DWT) [2]. The hybrid method balances imperceptibility, robustness, capacity, and security to combine any arbitrary two or three modifications. However, because of their extraordinary performance, transformation domain algorithms have recently gained more recognition and are in principle replacing spatial domain algorithms. Prominent and contemporary applications of digital picture watermarking include monitoring of broadcasts, identification of ownership, fingerprinting, authentication of material, verification of integrity, and security in telemedicine. When improving the efficiency of a specific watermarking algorithm, the scaling factor's ideal strength is a critical aspect to consider. A small scale factor may make the image less noticeable, but it also weakens the algorithm's robustness. However, larger scale factor values may affect the visibility and quality of the host image.

The imperceptibility and robustness of digital image watermarking techniques primarily determine their efficiency. As we increase one attribute, the effects of the other decrease. There is a trade-off between these qualities. Therefore, each of these factors has to be balanced against each other to develop an efficient watermarking algorithm The meta-heuristic method [3, 4, 5] is the optimal choice which emerges. These optimization techniques provide the best possible solution within a limited range of constraints, increasing efficiency. The selection of the optimal set of variables to address the problem is part of the optimization process [6].

To ensure robustness and imperceptibility, it is necessary to optimize the algorithm's performance by selecting the right scaling factor. Given the complexity of watermarking techniques, it can be difficult to select the best scaling factor for a particular one. Optimization is a popular way to solve this problem. Using multiple scaling factors is better than single scaling factors since altering the original image's pixel values is not ideal [6]. Optimizing numerous scaling factors is a complex problem, especially since it involves determining the optimal values. To achieve this, researchers have used a wide range of optimization techniques, including artificial bee colonies (ABC), particle swarm optimization (PSO), genetic algorithms (GA), firefly optimization (FFA), whale optimization (WOA), etc. To prevent early convergence and sustain a balanced interaction between exploitation and exploration, it is essential to update these optimization methods [7].

Here, we present a novel watermarking technique that combines a hybrid DWT-SVD approach with the GTO algorithm [8] for optimizing multiple scaling factors (MSFs). The novel aspect of our approach is the unique fitness function we created to strike a balance between robustness and imperceptibility, as well as the particular use of GTO to optimize the scaling factors at every stage of the DWT decomposition. When compared to other watermarking schemes, this particular combination of GTO and a multi-level DWT-SVD framework provides better performance. Because of its distinct exploration phase, which helps it avoid local optima, and its exploitation mechanisms, which allow it to converge quickly, the GTO algorithm is especially well-suited for this task (see [8]). Compared to algorithms like PSO [9–10,12], GA [11,12] with its known drawbacks, and FA [12], GTO offers a better balance between exploration and exploitation, which leads to a more successful optimization of the scaling factors in our watermarking scheme.

Our current study primarily focused on demonstrating the effectiveness of the GTO algorithm for optimizing watermarking parameters with standard gray-scale images. The proposed method has the potential to be used in copyright protection for digital libraries or online image repositories, where robust watermarking is essential to deter unauthorized use.

2. Previous Works

Many researchers have proposed digital watermarking schemes in the frequency domain using various optimization algorithms.

Loukhaoukha, K. et al., [13] explained the concept of optimizing the performance of the SSIM and the PSNR when it comes to creating image-based security threats. The proposed method is to improve the scaling factor using the Firefly algorithm. They show that the simulation results can perform well in various image-processing attacks.

Mishra et al. [14] proposed a combination of the advantages of the DWT-SVD transformations in an extraction and embedding algorithm. Multiple scaling factors (MSFs) alter the singular value of LL3 coefficients for the cover image. The Firefly algorithm (FA) optimizes the MSFs. The proposed algorithm focuses on determining the optimal scaling factors with the FA method. The test produced high levels of PSNR values and was robust against various image processing attacks.

Anurag Mishra et al., [15] proposed a new watermarking scheme using Harmony Search Algorithm (HSA) for grayscale images. This algorithm achieves excellent visual quality and high robustness values by optimizing the Multiple Scaling Factors (MSFs) of the signed image.

Xinchun Cui, et al., [16] proposed a method using a Differential Evolution optimization algorithm in the wavelets domain for selecting scaling factors of color watermark adaptively. The information can be embedded in the image using these values. They also randomized the image with Arnold's transformation.

S. Sharma et al. [17] presented a watermarking algorithm for digital images that was biologically inspired, such as the Grasshopper optimization algorithm. For best results, it considers a scaling factor. The method is guaranteed to be efficient and to have a good scaling factor in the case of the use of GOA. Analysis of experiment performance is compared using two different modern techniques.

Maloo, S., [18] presented a robust, reliable, and imperceptible image watermarking scheme based on 3 Level DWT and SVD hybridization with MWOA. The algorithm provides a global solution and is evaluated for various attacks, comparing it to other recently published schemes like CSO, FA, MOACOW, and PSO-based DIW.

3. Materials and Methods

The concepts used such as the hybrid DT-SVD scheme, algorithm for embedding and extraction methods and Gorilla Troop Optimization algorithm are explained in this section.

3.1. Hybrid DWT and SVD Scheme

The Discrete Wavelet Transform (DWT) is a frequency-domain transformation that offers advantages for watermarking due to its ability to handle non-stationary signals and separate image frequencies. DWT decomposes an image into different frequency sub-bands (LL, LH, HL, and HH), where the LL sub-band contains the most significant image information. Watermarking in the lower-frequency sub-bands enhances robustness, while embedding in higher-frequency sub-bands (HH) can improve imperceptibility.

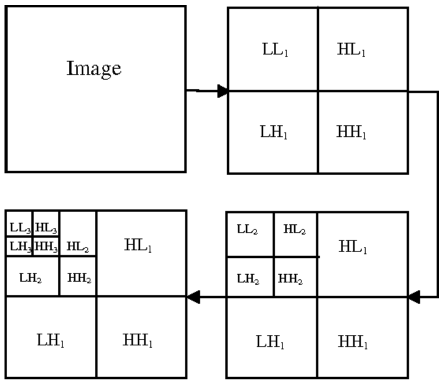


Fig. 1.Three-level DWT

Singular Value Decomposition (SVD) is a matrix factorization technique that decomposes a matrix into three matrices: U, S, and V. The singular values in the diagonal matrix S represent the importance of different image features, making SVD useful for watermarking. By modifying these singular values, a watermark can be embedded.

$$A = USV^T \tag{1}$$

The hybrid DWT-SVD method combines the advantages of transforms, offering a balance between robustness the embedding and extraction process of image ability. The next sections explain how to use this hybrid DWT-SVD-based approach [19, 20, 21, 22, 24] to embed and extract data.

3.2 Algorithm for Embedding a Watermark

The procedure for using the hybrid DWT-SVD method to embed an image into a watermark is as follows.

1. The cover image H of size M × M is subjected to a DWT transform at three levels using the HAAR filter to produce an LL3 sub-band of size p × p.
2. The singular value matrix S is obtained by applying equation (2) to the cover image, which transforms the LL_3 coefficients.

$$[U^1, S^1, V^1] = SVD(LL_3) \tag{2}$$

Where, U^I represents the left singular matrix, S^I represents a singular value matrix whose diagonal elements are singular values and the non-diagonal elements are zeros. and V^I represents a right singular matrix of SVD decomposition of LL_3 sub band matrix respectively.

3. Apply SVD to the watermark W of size $p \times p$ using Equation (3) and obtain the singular values (S_w^I).

$$[U_w^I, S_w^I, V_w^I] = SVD(W) \tag{3}$$

U_w^I, S_w^I, V_w^I represents the left singular matrix, the singular value matrix and the right singular matrix of the SVD decomposition of the watermark image W respectively.

4. Embed the singular values S_w^I obtained in step 3 using the following Equation (4) into S^I

$$S^1 = S^I + \delta_s \times S_w^I \tag{4}$$

Where, δ_s is a single scaling factor (SSF) that controls a proposed watermarking system's robustness and imperceptibility.

5. Calculate the adjusted coefficients using the Equation (5)

$${LL_3}^1 = U^I \times S^1 \times (V^I)^T \tag{5}$$

6. Determine the signed image I^1 by applying Inverse DWT

The above-detailed procedure for embedding a watermark, as shown in Figure 2

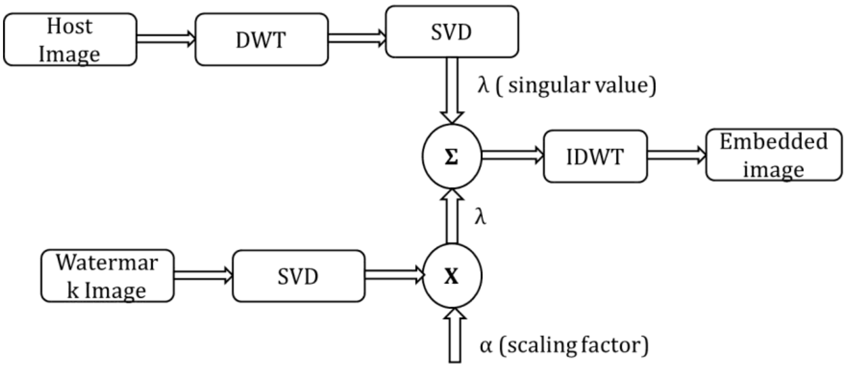


Fig. 2. Block Diagram of embedding an image using Hybrid DWT– SVD

3.3 Algorithm for Extracting a Watermark

One can remove the watermarks that are embedded in a signed image by using the extraction process performed by combining DWT-SVD with the actual hosted image and the watermark then received by the original hosted image and its corresponding one. W^1 represents the watermark extracted by the following procedure.

1. Apply a three-level DWT transform to the hosted image H and the embedded image H^1 using the HAAR filter to obtain the coefficients of LL_3 and the ${LL_3}^1$ sub-bands for both images, which are of size p by p.
2. Using Equations (6) and (7), SVD may be used on the coefficients of LL3 and ${LL_3}^1$ subbands to get the singular values S^I and S_1^I respectively.

$$[U^I, S^I, V^I] = SVD(LL_3) \tag{6}$$

$$[U_1^I, S_1^I, V_1^I] = SVD\left({LL_3}^1\right) \tag{7}$$

Where, U^I and U_1^I represents the left singular matrices by SVD decomposition of LL_3 and ${LL_3}^1$ subband matrices respectively. S^I and S_1^I represents singular matrices whose diagonal elements are singular values and the non-diagonal elements are zeros. V^I and V_1^I represents right singular matrices respectively.

3. Determine watermark singular values (S'_{1w}) using the formula given by Equation (8)

$$S'_{1w} = (S_1^I - S^I) \tag{8}$$

4. Using the formula given by Equation (9), the extracted watermark can be recovered.

$$W' = U_{1w} \, S'_{1w} \, V_{1w} \tag{9}$$

The above process of watermark extraction depicted in Figure 3.

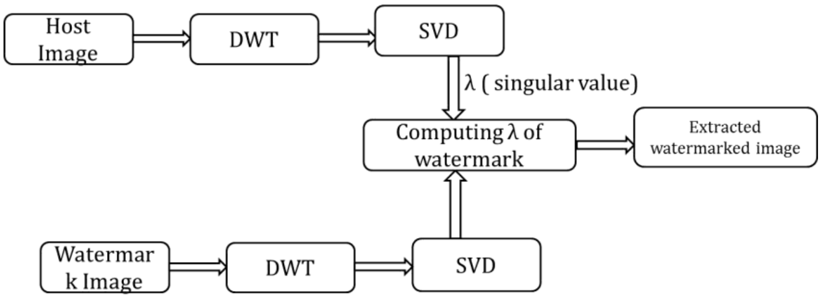


Fig. 3. Block Diagram of extracting an image using Hybrid DWT– SVD

3.4 Gorilla Troop Optimization (GTO) Algorithm:

Here we propose a new evolutionary algorithm, the GTO algorithm [8], shown in algorithm 1. It uses a collective behavior inspired by the gorillas' collective actions. The GTO algorithm simulates five operators performing different optimization tasks on gorilla behavior. It's used here to determine the optimal scaling factor values in our watermarking technique. Essentially, we have a group of "gorillas," and each gorilla represents a possible set of scaling factor values. The algorithm then simulates how these gorillas move and interact to discover better and better sets of scaling factors.

The GTO algorithm operates in two main phases depicted in Figure 4.

- Exploration: This is where the gorillas search for new areas that might have good solutions.
- Exploitation: This is where the gorillas refine the solutions they've already found to make them even better.

Here's a breakdown of the core behaviors in each phase:

3.4.1 Exploration Phase:

During exploration, gorillas move to different locations in the search space using three behaviors:

- **Travel to an unknown location**: A gorilla moves to a completely random position. This helps the algorithm discover new possibilities it hasn't explored before.
- **Travel to another gorilla's location**: A gorilla moves toward the position of another, randomly selected gorilla. This allows gorillas to share information and learn from each other's discoveries.
- **Travel to a known location**: A gorilla moves toward a position that was found to be good in the past. This encourages the algorithm to focus its search on promising areas.

The mathematical formulation of these three mechanisms are given in Equation (10)

$$GR_X(t+1) = \begin{cases} (ub-lb)s_1 + lb & ran < p \\ (s_2 - C)X_r(t) + L \times H & ran \geq 0.5 \\ X(i) + L[L(X(t) - GRX_r(t)) + s_3(X(t) - GRX_r(t))] & ran < 0.5 \end{cases} \tag{10}$$

Where,

The gorilla candidate position vector in the next iteration is represented by the vector $GR_X(t+1)$,

$X(t)$ is the value of the current vector for the gorilla position.

The random values of the various elements s_1, s_2, s_3 and *ran* in the algorithm are updated for each iteration,

Before performing optimization, the value of p should be given, and it has a range of 0 to 1,

lb: lower bound and ub: upper bound

X_r, represents the gorilla that was chosen at random from the population.

The gorilla position vectors represent the random selection process and have updated positions in each stage denoted by $GRX_r(t)$.

The calculated positions of gorillas for C, H, and L are shown in the equations (11), (13), and (14) respectively.

$$C = F\left(1 - \frac{Itr}{MaxItr}\right) \tag{11}$$

$$F = \cos(2r_4) + 1 \tag{12}$$

$$L = C \times l \tag{13}$$

$$H = Z \times X(t) \tag{14}$$

Where,
Itr is the current iteration value.
$MaxItr$ is the max no. of iterations
The updated random value in each iteration is r_4,
1 is a randomly selected value in [−1, 1] ,
Z is a randomly selected value in the [−C, C].

3.4.2 Exploitation Phase:

During exploitation, gorillas refine their search based on the following behaviors:

- **Follow the silverback**: Gorillas move toward the position of the "silverback," which represents the best solution found so far. This helps to improve the quality of good solutions.
- **Compete for females**: Gorillas compete with each other, leading to more significant changes in their positions. This helps the algorithm to avoid getting stuck in poor solutions and encourages further exploration.

The selection of the competition for adult females or the following silverback behaviour can be made using the C value. The two behaviours during the exploitation phase are simulated by using Equations (15) and (18).

1) Follow the silverback

$$GR_X(t+1) = L \times M \times (X(t) - X_{silverback}) + X(t) \qquad C \geq W \tag{15}$$

where

$$M = \left(\left|\frac{\sum_{i=1}^{n} GX_i(t)}{N}\right|^g\right)^{\frac{1}{2}} \tag{16}$$

and

$$g = 2^L \tag{17}$$

2) Competition for adult females

$$GR_X(i) = X_{silverback} - ([X_{silverback} - X(t)] \times Q) \times A \qquad C < W \tag{18}$$

Where

$$Q = 2r_5 - 1 \tag{19}$$

$$A = \beta \times T \tag{20}$$

$$T = \begin{cases} M_1 & ran \geq 0.5 \\ M_2 & ran < 0.5 \end{cases} \tag{21}$$

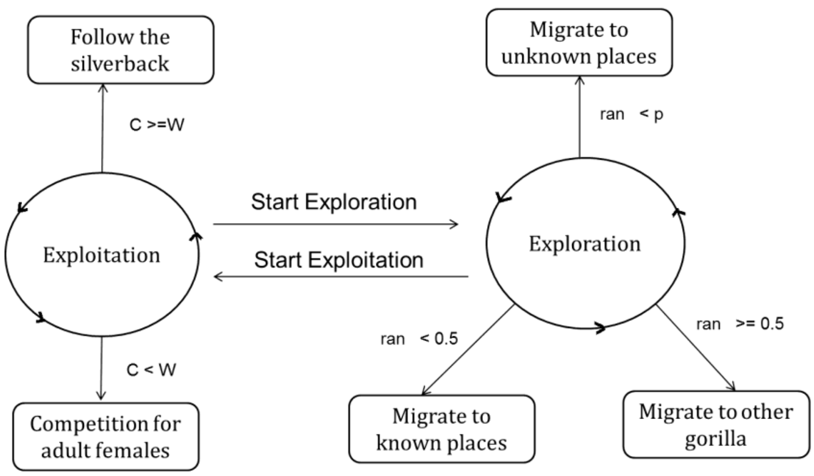


Fig. 4. A Gorilla Troop Optimization algorithm phases

Algorithm 1: Gorilla Troop Optimization algorithm (GTO)

INPUT: The size of the population is N, max no.of iterations are T and β and p as parameters
OUTPUT: Gorilla's best location and fitness value
The population of Gorilla's chosen at random and initialized to the value of Xi, i = (1, 2, . . . , N)
Determine Gorilla fitness values
while (The condition to stop is not satisfied) do
    Usng Equation (11) Update C value
    Using Equation (13) Update L value
    for all Gorilla Xi do
        Updated Equation (10) for location of Gorilla
    end for
    Calculate Gorilla fitness values
    Replace GRX by X, If GRX is better than X
        Set $X_{silverback}$ as the best location of silver-back
    for all Gorilla Xi do
        if (|C| ≥ 1) **then**
            Update equation (15) for location of Gorilla
        else
            Update equation (18) for location of Gorilla
        end if
        end for
    Determine Gorilla fitness values
    New solutions should be replaced if they are better than the ones used before
    Set best location as $X_{silverback}$ of silver-back
end while
Return $X_{BestGorilla}$, best-Fitness

4. Gto-Based Watermarking Scheme

Since the scaling factor establishes the ideal degree of embeddedness, it is a crucial element of image watermarking. Watermarking's success is determined by its robustness and imperceptibility. These ideas are incompatible. For example, the imperceptibility of a watermarking system decreases with its reliability, or vice versa. Keeping these two factors in balance is the goal of this research. Figure 5 shows a thorough procedure for applying the GTO algorithm to optimize MSFs.

Algorithm 2: GTO-based watermarking Scheme

1. Randomly initialize n gorillas. Group them all into a vector of size p × p, which is the watermark's size.
2. For each gorilla, do the following
(a) Perform the algorithm specified in Section B of III by using following Equation (22) instead of Equation (4)

$$S^1 = S^I + \delta_{msf} \times S_w^I \tag{22}$$

Where, multiple scaling factors (MSF) are given by δ_{msf} that controls a proposed watermarking system's robustness and imperceptibility.
(b) We applied seven attacks (t=7) to create different types of signed images using different processing attacks.
(c) From the attacked image, the watermark needs to be extracted by using the procedure in Section B of III
(d) The imperceptibility between I (the original cover image) and I' (the signed image) was determined using the PSNR value. The NC(W,W') value was used to determine the robustness of the attacked images..
(e) Use the fitness function provided by Equation (23), to determine the GTO's fitness value.

$$F = PSNR + \emptyset * [NC(W, W') + \sum_{i=1}^{t} NC(W, W_i')] \tag{23}$$

Where,$NC(W, W')$ is the normalized cross-correlation between the original watermark and extracted watermark from signed image.
$NC(W, W_i')$ is the normalized cross correlation between the original watermark and extracted watermark for all different seven attacks, $\emptyset$ is the weighting factor $NC(W, W')$ for values
3. Use the procedure specified in Algorithm 1 to update these n gorillas.
4. Repeat steps 2 and 3 until maximum number of generations.

The robustness can be improved by a single scaling factor, but this may be less apparent. People have chosen multiple scaling factors (MSF) over single scaling factors (SSF) to achieve the desired imperceptibility and robustness. Various optimization algorithms have accomplished MSF-based optimization in previous works, meeting all the requirements for a good image watermarking scheme. These various techniques can fulfill the requirements for effective image watermarking. Unfortunately, they are computationally demanding, and the range of values that are suitable for such applications is limited. This is why it is important to use the right algorithm for the process. We used a new evolutionary GTO algorithm for each component to optimize each block's scaling factor based on its standard deviation Different threshold values are derived for each population from the algorithm offered by the proposed system, which act as scaling factors in the process of embedding. The following Figure 5 gives the flow chart of the above discussed algorithm 2

4.1 Parameter Selection for the GTO algorithm:

The parameters for the GTO algorithm were chosen based on a combination of recommendations from the original GTO paper [20] and preliminary experimentation. The number of gorillas (30) and the maximum number of iterations were set to balance computational cost and optimization performance. We conducted a sensitivity analysis by varying these parameters and observing the resulting PSNR and NCC values. The values shown in Table 1., provided a good trade-off between convergence speed and solution quality. The parameters p, β, and W were set to the values suggested in [8] as they were found to provide effective exploration and exploitation of the search space in various optimization problems. Table 1 provides the parameters of GTO for the implementation phase.

4.2 Computational Complexity Analysis:

The proposed watermarking scheme has a high computational complexity due to the DWT, SVD, and GTO algorithms.

The DWT has a complexity of O (N log N) for an N-pixel image.

The SVD has a complexity of O(n^3) for an n x n matrix.

The GTO algorithm's complexity is O (iterations * population_size * evaluation_complexity).

The overall complexity of our scheme is influenced most significantly by the SVD, due to the repeated SVD computations within the GTO optimization loop. However, the optimization is performed on the LL3 sub-band, which is much smaller than the original image, reducing the computational burden. Compared to other optimization-based watermarking schemes, the complexity of our method is comparable, but the improved performance justifies the computational cost. Future work could explore techniques to further optimize the SVD computations to improve efficiency for real-time applications.

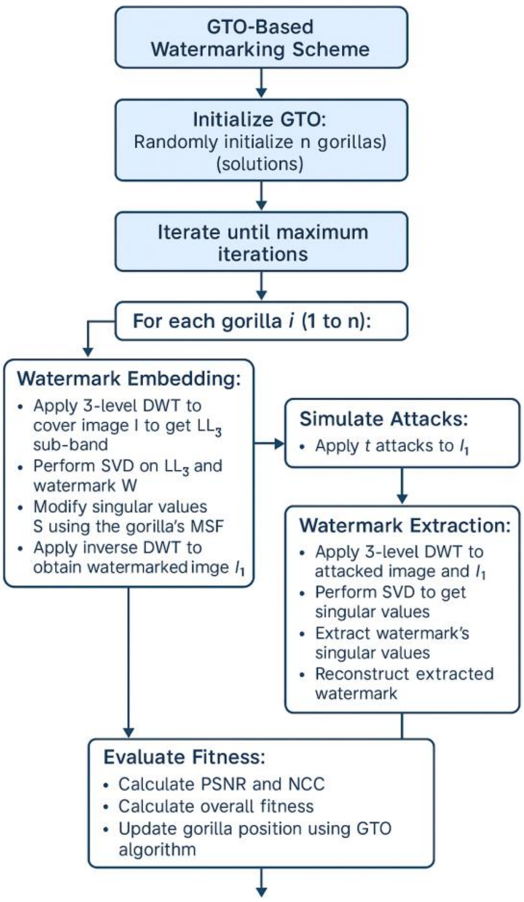


Fig. 5. GTO Based digital watermarking in hybrid DWT-SVD frequency domain

Table 1. Parameters used in the GTO algorithm

Gorilla Troop Optimization Parameters	**Value**
Number of gorillas	30
Maximum number of iterations	20
r1, r2, r3, r4, r5 and rand is random values	Range of 0 to 1
l is a random value	range of −1 and 1
Solution Space	
lb: lower bound	0.005
ub: upper bound	0.5
Controlling parameters	
p: Used to select the mechanism of migration to an unknown location.	0.03
B	3
W	0.8

5 Experimental Results

We used a variety of test images to evaluate the performance of the proposed method which incdes

- **Grayscale images**: Barbara.jpg, Boat.png, Lena.tif, Mandrill.jpg, Cameraman.tif, and Peppers.jpg (512x512)
- **Color images**: A standard color image (e.g., 'Parrot.png') and a real-world image (e.g., arial view.jpg) (512x512)
- **Watermark image**: A 256x256 grayscale image (logo.tif)

This expanded test set allows for a more comprehensive assessment of the algorithm's robustness and imperceptibility across different image types as shown in Figure 6.

5.1 Performance Metrics:

The term “robustness” refers to the ability to accurately detect embedded watermarks even if watermarked image changes due to image processing attacks. The following equations (24) to (27) are used to study the watermarking scheme’s imperceptibility and robustness using the PSNR and NCC tests respectively. To assess the quality of an image, PSNR is used and it is measured in decibels (dB) [25].

$$PSNR = 10 \log_{10} \left[\frac{max(I(r,s))}{MSE}\right] \tag{24}$$

Where,

$$MSE = \frac{1}{M*N} \sum_{r=1}^{M} \sum_{s=1}^{N} [I(r,s) - I'(r,s)]^2 \tag{25}$$

Here $I(r,s)$ is the original cover image and $I'(r,s)$ is the extracted cover image. Mean Squared Error (MSE) serves as a measure to evaluate the disparity between the original image and its watermarked counterpart. A value of zero is widely recognized as the accepted standard for MSE [23-25].

Simple Similarity Index (SSIM) is utilized to assess the level of similarity between the original picture and the watermarked image [26].

$$SSIM = \frac{(2\delta_r\delta_s + C_1)(2\sigma_{rs} + C_2)}{({\delta_r}^2 + {\delta_s}^2 + C_1)({\sigma_r}^2 + {\sigma_s}^2 + C_2)} \tag{26}$$

Let C1 and C2 represent the constants for regularization pertaining tor brightness and contrast, respectively, for each image r and s. The variables δ_r, δ_s, σ_r, σ_s, and σ_{rs} represent the local means, standard deviations, and cross-covariance.

The Normalized cross correlation [27] can be obtain by the following equation (27)

$$NC = \frac{\sum_{r=1}^{M} \sum_{s=1}^{N} [W(r,s) - W'(r,s)]}{\sqrt{\sum_{r=1}^{M} \sum_{s=1}^{N} [W(r,s)]^2} \sqrt{\sum_{r=1}^{M} \sum_{s=1}^{N} [W'(r,s)]^2}} \tag{27}$$

Where, $W(r,s)$ represents the original watermark and $W'(r,s)$ represents the extracted watermark. The size of the watermark is given by M x N.

Fig. 6. Host Images: (a) Barbara (b) Boat (c) Lena (d) Mandrill (e) Cameraman (f) Peppers (g) parrot (h) Arial view Watermark image: (i) logo

Performance Metrics and Thresholds: We evaluated the performance of our watermarking scheme using three standard metrics:

- **PSNR (Peak Signal-to-Noise Ratio):** A PSNR value above 50 dB is generally considered to indicate excellent image quality, meaning the watermark is nearly invisible to the human eye [25].

PSNR value		**Imperceptibility**
(a) >= 50	-	Excellent
(b) Between 40 and 49	-	High and
(c) Between 30 and 39	-	medium respectively.

- **SSIM (Structural Similarity Index):** It provides a more perceptually relevant measure of image quality than PSNR. SSIM values range from -1 to 1, with 1 indicating perfect similarity. An SSIM value above 0.95 is generally considered to represent high structural similarity [26].
- **NCC (Normalized Cross-Correlation):** NCC measures the similarity between the original and extracted watermarks. It quantifies the robustness of the watermarking scheme against attacks. NCC values range from -1 to 1, with 1 indicating perfect correlation. An NCC value above 0.8 generally indicates good robustness, meaning the watermark can be reliably detected even after significant image distortions [cite NCC reference].

NCC value		**Robustness**
(a) Between 0.9 and 1	-	perfect
(b) between 0.8 and 0.89	-	good

The selection of these metrics is crucial because they provide a comprehensive evaluation of the watermarking scheme's imperceptibility and robustness. High PSNR and SSIM values ensure that the watermark does not degrade the visual quality of the host image, while high NCC values guarantee the reliable extraction of the watermark even under various attacks. As mentioned in the GTO-based watermarking scheme in Algorithm 2, the objective of the GTO is determined in step 5 to analyze the watermarking scheme's imperceptibility and robustness. The experimental results for the GTO algorithm are shown in Tables 2 and 3 below.

Table 2. Performance metrics of the Proposed GTO based Watermarking algorithm

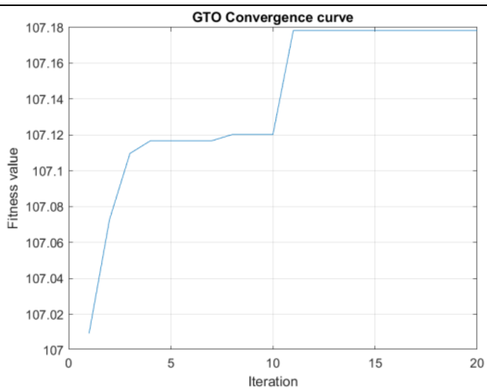
Cover Image	PSNR	SSIM	NC
Barbara	80.61	0.9996	1
Boat	71.79	0.9998	1
Lena	70.88	0.9997	1
Mandrill	61.51	0.9985	1
Cameraman	65.33	0.9987	1
Peppers	53.32	0.9716	1
Parrot	71.92	0.9997	1
Arial View	51.76	0.9492	1

Table 3. Best silver back and silverback scores of each cover image using GTO algorithm

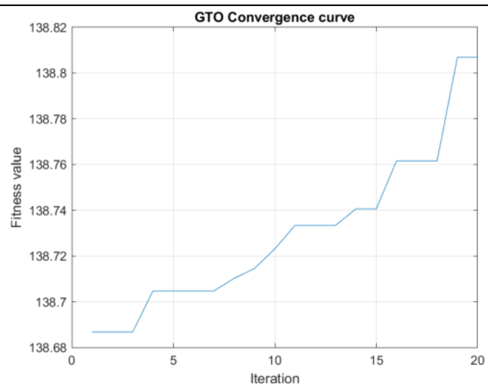
	Cover Images							
	Barbara	**Boat**	**Lena**	**Mandrill**	**Cameraman**	**Peppers**	**Parrot**	**Arial View**
Best silverback	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
Best Silverback score	107.19	138.80	152.71	104.46	146.24	150.31	148.28	110.57

Table 2 shows the PSNR, SSIM, and NC (W, W^1) values for the watermarked images. The high PSNR values (ranging from 51.76 dB to 80.61 dB) indicate that the watermark embedding process introduces minimal distortion to the cover images, thus ensuring good imperceptibility. A PSNR above 50 dB is generally considered to represent excellent image quality, and all our results exceed this threshold. The SSIM values, all very close to 1 (ranging from 0.9716 to 0.9998), further confirm this, demonstrating a high degree of structural similarity between the original and watermarked images. The efficacy of the embedding and extraction process is demonstrated by NCC values of 1 for each image, which show a perfect correlation in the absence of attacks between the original and extracted watermarks. The best silver back and best fitness score (silverback score) of each image by GTO algorithm are also displayed in Table 3. Table 4 gives the convergence curve of fitness function F to the global optimum when performing GTO-based watermarking.

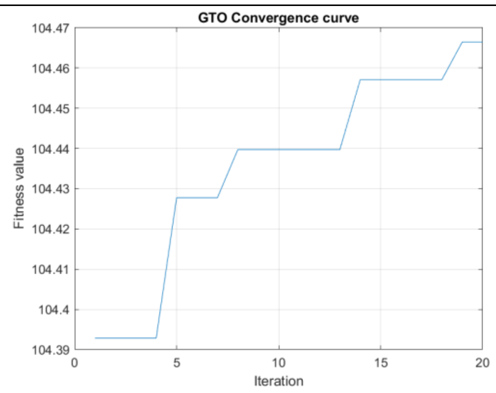
Table 4. Convergence Curve of Fitness Function Using GTO Algorithm



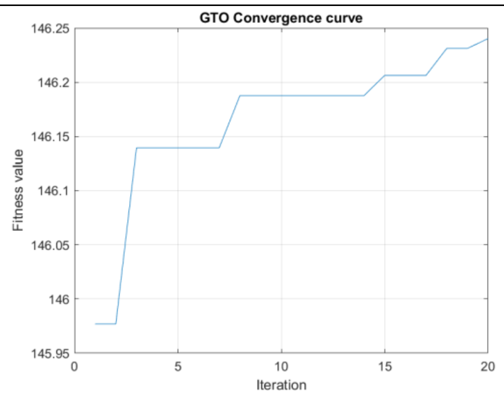
Barbara Image



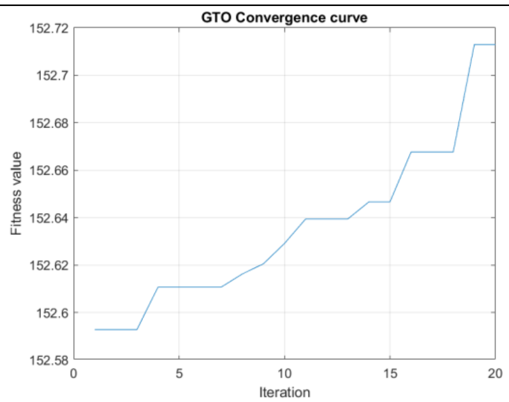
Boat Image



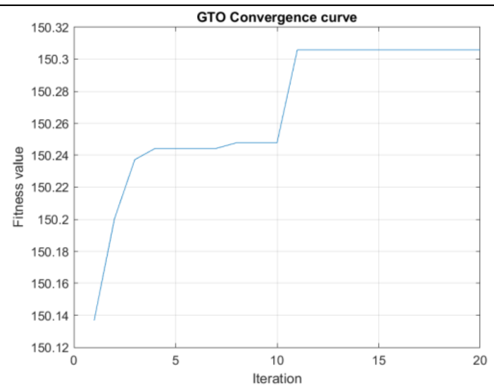
Mandrill Image



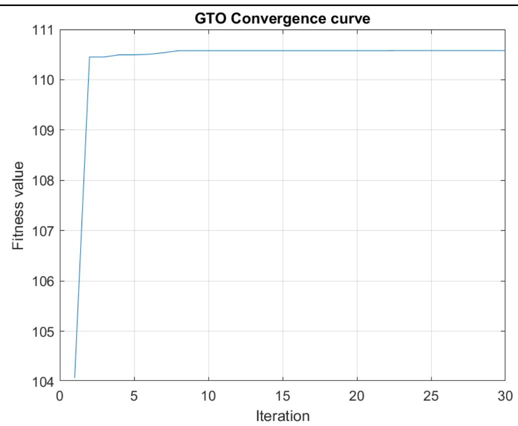
Cameran Image



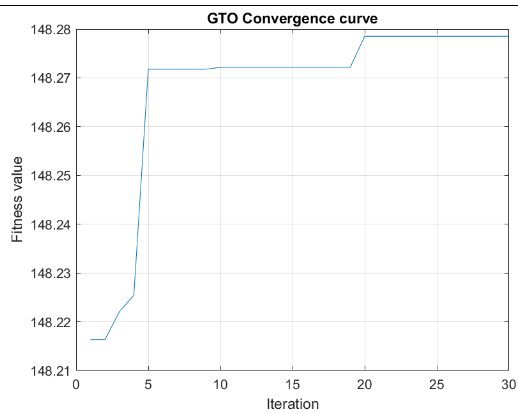
Lena Image



Peppers Image



Arial View image



Parrot image

5.2 Security Analysis:

This section assesses the security, robustness, and visual quality of the proposed encryption technique and its overall performance. A comprehensive image quality analysis was performed using gray-scale images. Table 5 presents the NCC values of the extracted watermarks under various seven attacks, assessing the robustness of the proposed method. High NCC values indicate strong robustness, meaning the watermark can be reliably extracted even after the watermarked image undergoes distortions. For example, the NCC values for Gaussian Filtering are consistently above 0.99, demonstrating excellent robustness to this type of noise. However, the Histogram Equalization attack shows slightly lower NCC values (e.g., 0.8959 for Peppers), indicating that this attack introduces more significant distortions to the watermark. Nevertheless, most NCC values remain above 0.9, suggesting an overall high degree of robustness. The values for the attacks were obtained from the fitness function F. These attacks are Salt & Pepper , Gaussian Filtering , Sharpening **,** Histogram , Scaling , Quantization **,** and Cropping. The specific parameters for each attack are as follows:

- **Salt & Pepper (SP)**: Noise density = 0.02
- **Gaussian Filtering (GF)**: Kernel size = 3x3, standard deviation = 0.5
- **Sharpening (SH)**: intensity is 0.2 (relatively mild sharpening)
- **Histogram Equalization (HG):** (No parameters needed)
- **Scaling (SC):** Scaling factor = 0.5 and 2.0

- **Quantization (QU):** Quantization levels = 8
- **Cropping (CR):** Cropping percentage = 3% from each side"

Figure 7 gives the NC values comparison graph of different cover images with 7 attacks shown in Table 5. Figure 8 shows the attacked images of each cover image using different attacks as mentioned above.

Table 5. NC Values of Reconstructed Image with Different Attacks

Cover Image	SP	GF	SH	HG	SC	QU	CR
Barbara	0.9382	0.9965	0.9991	0.9947	1.0000	0.9885	0.9845
Boat	0.9921	0.9979	0.9994	0.9261	1.0000	0.9824	0.9561
Lena	0.9925	0.9984	0.9995	0.9907	1.0000	0.9885	0.9652
Mandrill	0.9903	0.9880	0.9979	0.9888	1.0000	0.9828	0.9583
Cameraman	0.9947	0.9997	0.9999	0.9385	1.0000	0.9810	0.9749
Peppers	0.9901	0.9994	0.9998	0.8959	1.0000	0.9790	0.9616
Parrot	0.9545	0.9992	0.9998	0.9924	1.0000	0.9899	0.9541
Arial View	0.9396	0.9957	0.9989	0.9895	1.0000	0.9872	0.9702

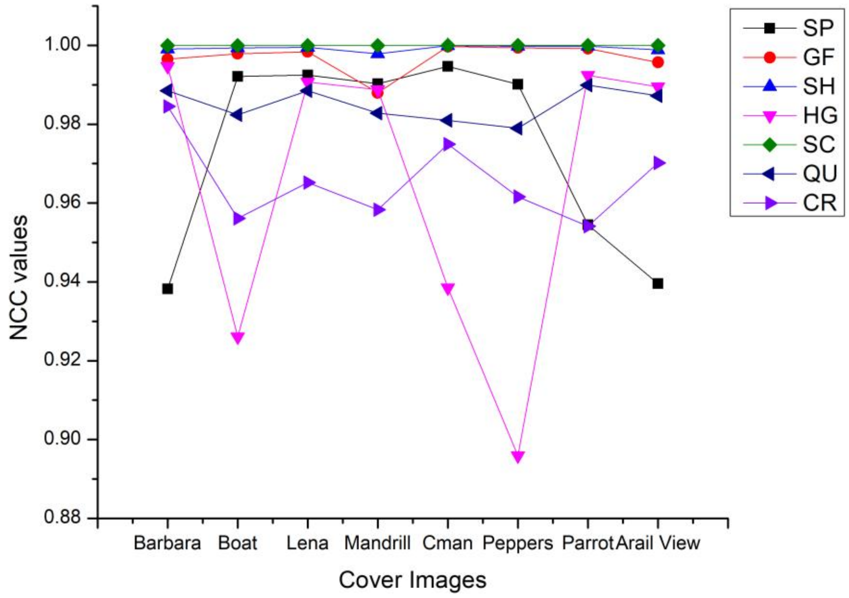


Fig. 7. NC values comparison of cover images with different attacks

Attacked Images

SP (0.02) | **GF** | **SH (0.2)** | **HG**

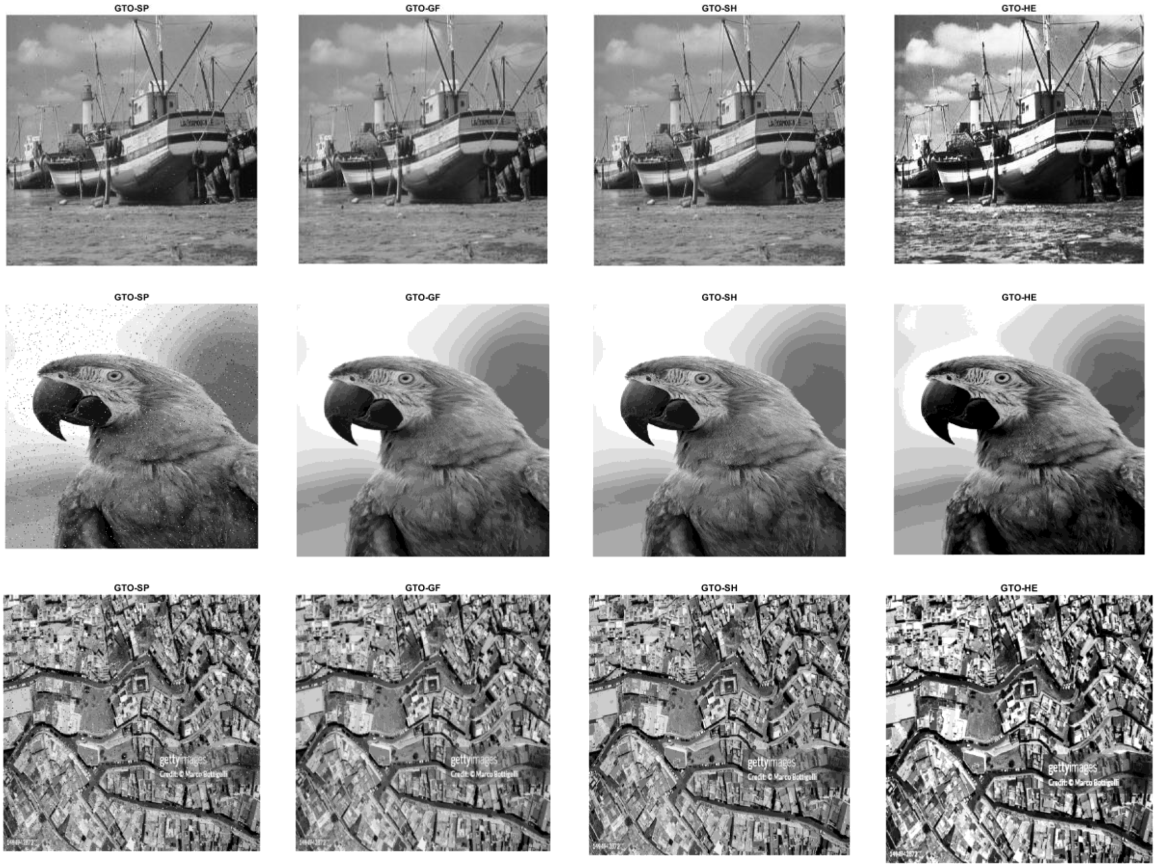


Fig. 8. Attacked Images of the 3 gay scale and 2 color cover image using different attacks

5.3 Comparative Analysis

The proposed scheme demonstrates superior performance compared to existing techniques, as evidenced by the high NCC values (close to 1) shown in Table 5. This indicates that the watermarked images retain their visual integrity after the watermark embedding, preserving both aesthetic attributes and structural features. This is crucial for practical watermarking applications where maintaining image quality is essential. Furthermore, the robustness of the proposed scheme, as shown by the high NCC values under various attacks, confirms its suitability for protecting digital content against common image processing manipulations.

Furthermore, GTO demonstrates competitive performance compared to other optimization algorithms [cite GTO paper]. As shown in Table 6 and Fig. 9, GTO achieves higher PSNR values than Multi-Objective Particle Swarm Optimization (MOPSO), Harmony Search Algorithm (HSA), Grass Hopper Optimization Algorithm (GOA), Self-adaptive Step Firefly Algorithm (SAFSA), Artificial Bee Colony Algorithm (ABC), and Coyote Optimization Algorithm (COA), indicating better imperceptibility. This is attributed to GTO's efficient exploration of the search space and its ability to avoid premature convergence, a common problem in algorithms like PSO and GA [9,10,11,12]. While COA shows comparable results, GTO offers a simpler implementation and faster convergence [8,32], making it a more efficient choice for optimizing the watermarking process.

Table 6. Comparison of PSNR Values with Existing Methods

Reference NO	**Optimization algorithm used**	**Frequency Domain used**	**Cover Images**				
			Boat	**Mandrill**	**Camera man**	**Lena**	**Peppers**
[13]	MOPSO	DWT-SVD	54.91	52.86	49.7	49.51	NR
[15]	HSA	DWT-SVD	53.1	55.31	54.98	55.92	NR
[17]	GOA	DWT-DCT	NR	80.87	81.47	49.89	NR
[18]	MWOA	DWT-SVD	55.46	53.45	56.13	54.61	55.57
[24]	ABC	DWT-SVD	NR	45.48	NR	47.63	44.65
[31]	SASFA	DWT-SVD	41.1	42.64	44.14	45.55	45.42
[32]	COA	DWT-SVD-EVD	NR	66.49	67.66	69.14	76.21
[33]	HSV-PSO	DWT-SVD	40.29	40.03	NR	43.32	40
Proposed Algorithm	**GTO**	**DWT-SVD**	**71.79**	**61.51**	**65.33**	**70.88**	**53.32**

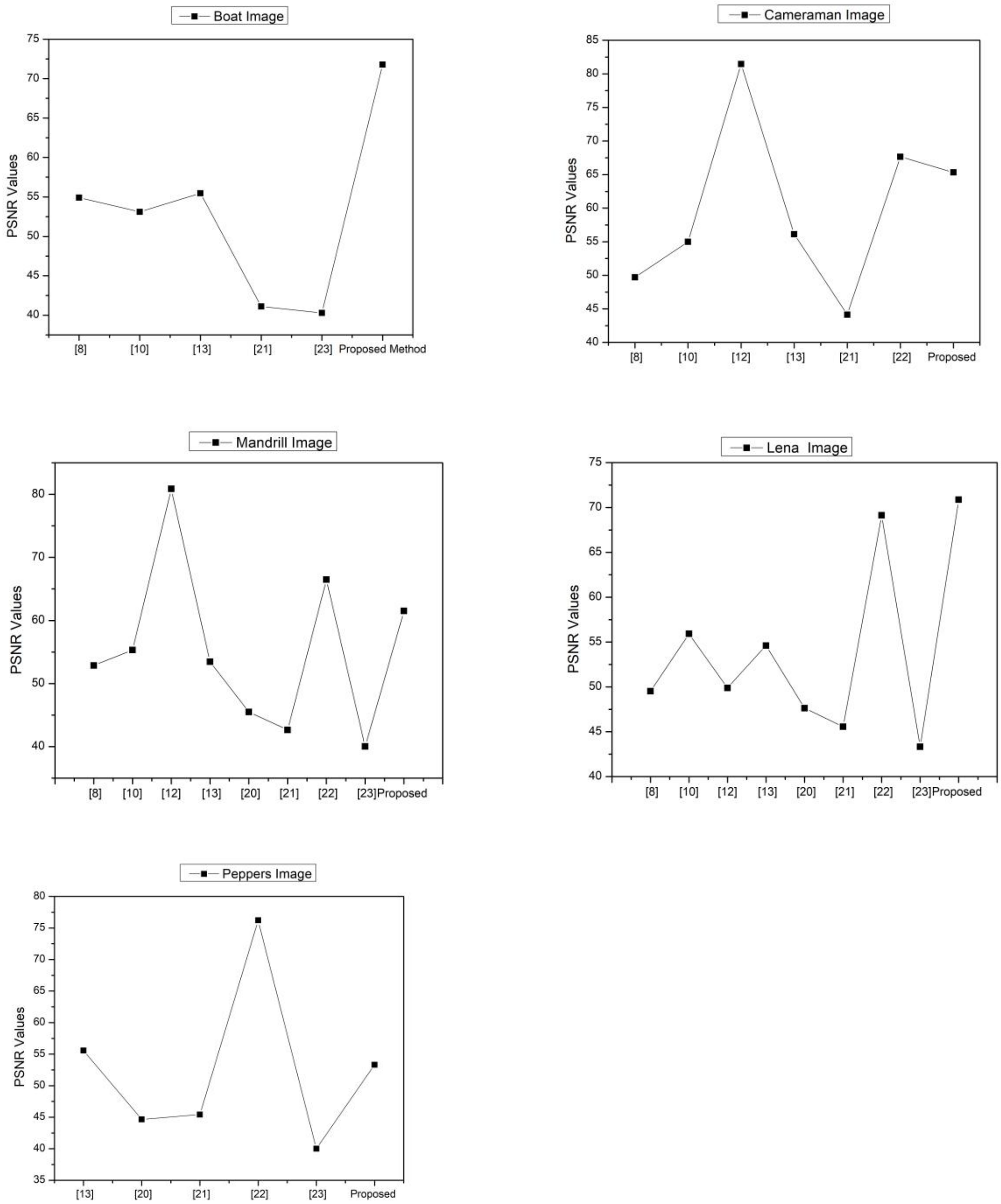


Fig. 9. PSNR comparative graphs of each cover image with the existing works

6. Conclusions

We propose a novel watermarking method using the Gorilla Troop Optimization (GTO) algorithm to optimally select multiple scaling factors in a hybrid DWT-SVD watermarking scheme. The unique contribution of this work is the application of GTO to fine-tune scaling factors at each DWT level, enhancing imperceptibility and the robustness of the watermark. We carried out the embedding and extraction process of this digital watermarking technique using a hybrid DWT and SVD approach and presented the experimental results of the proposed work, which include PSNR values and NC values for various images under seven different attacks. Using an alternative process, the GTO algorithm modifies the exploration and exploitation phases. Additionally, this algorithm has proven its exceptional performance and can serve as a robust metaheuristic algorithm, utilizing a variety of mechanisms to solve a wide range of problems. The GTO test performance demonstrates the need for proper exploration and exploitation operations to yield excellent results on some of the standard features under experimentation.

Despite GTO's promising performance, it, like other metaheuristic algorithms, can suffer from premature convergence and becoming trapped in local optima, especially with highly complex optimization problems. To mitigate these limitations, future work could explore several strategies:

- Parameter Tuning: Investigating the impact of different GTO parameters (e.g., p, β) and developing adaptive parameter control mechanisms.
- Hybridization: Combining GTO with other optimization algorithms (e.g., GA) to leverage their complementary strengths. For instance, GA's global search capabilities could help GTO escape local optima.
- Restart Mechanisms: Implementing strategies to restart the GTO algorithm with different initial populations if convergence stagnates.
- Chaotic Maps: Integrating chaotic maps into the GTO algorithm to enhance its exploration capabilities and promote diversity in the population.

While our current work focuses on images, the underlying principles of GTO-based optimization could be extended to video watermarking for applications such as protecting ownership of video content distributed online. Extending the method to large image datasets introduces challenges related to computational complexity, which we plan to investigate in future research by exploring parallelization techniques or more efficient implementations of the GTO algorithm. Future work will involve adapting the algorithm to handle video's specific characteristics and evaluating its performance on standard video datasets. Real-world scenarios often involve diverse image and video formats and varying levels of noise. We will evaluate the method's robustness under a wider range of conditions and explore adaptive parameter selection strategies. Our initial focus on grayscale images allowed us to isolate and thoroughly evaluate the GTO algorithm's optimization performance. We are currently working on extending the method to color images and more complex real-world datasets.

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