PCA -RDWT-SVD based Robust Digital Watermarking Optimization Technique using Gray Wolf Method

DRajani[1], PRajesh Kumar[2]

[1]Research Scholar, [2]Professor, Department of ECE
[1,2]Andhra University, Vishakhapatnam, Andhra Pradesh, India

Abstract

Today's generation is witness of developments of digital media. An example of Digital media is text, audio, video etc. We know an internet is the fastest medium of transferring data to any place in a world. As this technology grown up the threat of piracy and copyright obvious thoughts are in owners mind. So Watermarking is a process of secure data from these threats, in which owner identification (watermark) is merged with the digital media at the sender end and at the receiver end this owner identification is used to recognize the authentication of data. Challenges include design considerations, requirements analysis, and choice of watermarking techniques, speed, robustness, and the trade-offs involved. We describe common attributes of watermarking systems and discuss the challenges in developing real world applications. The choice of a wavelet filter bank for a digital watermarking scheme can have a significant influence on the scheme's performance in terms of image quality and robustness. The traditional watermarking algorithms prove the rightful ownership via embedding of independent watermarks like copyright logos, random noise sequences, text etc into the cover images. Coupling biometrics with watermarking evolved as new and secure approach as it embeds user specific biometric traits and thus, narrows down the vulnerability to impostor attacks. In this paper PCA-RDWT-SVD with Gray Wolf optimisation is applied in to Two biometric traits of the user i.e. the iris and facial features are embedded independently into the sub-bands of the RDWT of cover image taking advantage of its translation invariant property and sufficient embedding capacity. The robustness of the scheme has been tested against various attacks and the verification accuracy evaluated based on false acceptance rate, false rejection rate, area under curve and equal error rate to validate the efficacy of the proposed scheme.

Keywords: Digital watermarking, principle component analysis, redundant discrete wavelet transform, singular value decomposition, gray wolf optimizer.

1. INTRODUCTION

Robust digital watermarking (e.g.,for copyright protection) has gained increasing importance with the availability and popularity of Internet and e-Commerce applications. Digital object formats do not restrict copying or further distribution of image files. Watermarking is used to assert rightful ownership or track down pirate copies by previous invisible embedding of a logo or a serial number into the file. The performance of watermarking schemes is measured in terms of two rather contradicting requirements: imperceptibility (i.e., optimally minimum image degradation) and robustness (i.e., withstanding various attacks that aim to remove the watermark or render it undetectable). Benchmarking tools,] combine most attacks and show that most existing watermarking schemes are vulnerable. The advantages of PCA-RDWT-SVD-based watermarking are well accepted; we looks at the effect of matching the domain of marking to the domain for lossy compression, yet existed methods do not discuss the effect of a chosen domain's individual parameters. Besides the choice of a filter bank, a RDWT marking scheme's performance depends on features, like subband depth and the decomposition scheme used. Characteristics shared with non-wavelet-based schemes are the embedding technique and embedding intensity. RDWT-SVD is constructed based on Gray Wolf spatial support, variation in texture, details, and gray scale/color are likely to have some impact too. Recent watermarking schemes use a variety of different measures to achieve robustness. Most such schemes have a number of things in common: significant wavelet coefficients are chosen for embedding, information is embedded in single coefficients (normally through additive/multiplicative embedding), are possible, resulting in different levels of robustness. Different marking schemes may differ in the exact choice of coefficients for embedding, the algorithm that locates embedded mark, the intensity of embedding, the nature of the watermark (statistically undetectable, kind of message, etc.), and the detection device and decision process. Some schemes are designed to perform specific measures against certain attacks. In this paper, we extend the work reported in [2], and compare the performance of some well-known filters and methods in terms of image degradation resulting from embedding and the watermark quality after attacks. Locating previously marked coefficients does not really depend on the chosen filter bank; we thus focus on how particular filters cope with changes to marked coefficients.

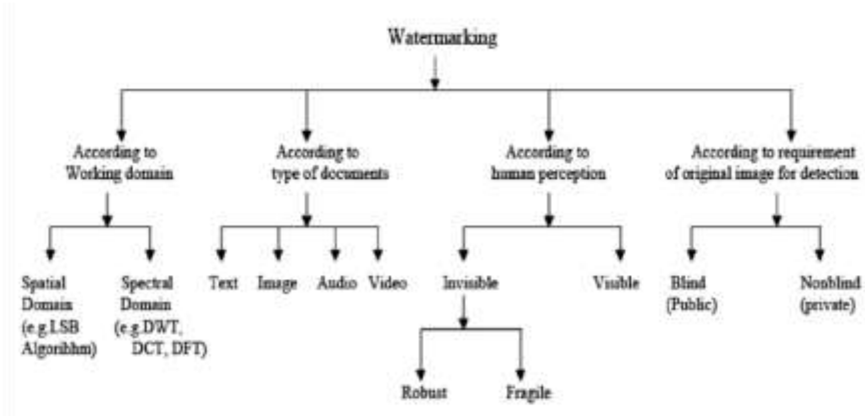


Fig. 1: classification of watermarking.

For our experiments, we implemented a very simple watermarking scheme based on the common features listed above, which also allows to choose from two alternative embedding algorithms. We use 6 quality levels of JPEG compression and, to test for dependencies between the results and the kind of compression, a RDWT-based compression at 4 different ratios as an attack on 8 different images. We then compare the results achieved with different filters to obtain general rankings. Our results indicate that though there is optimal filter bank, good compromise choices can be found that can even be further optimized through additional measures. Also, one of the used embedding algorithms clearly outperforms the other more popular one. The rest of the paper is organized as follows: in Section 2 we describe the watermarking system, the test course, and the tested filters and images. We then present and discuss our existed system and proposed system in Sections 3 and 4 respectively. In sec-5 discuss the results; at last sec-6 concluded the proposed method.

2. EXISTED METHOD

The Discrete wavelet transform emerged as one of the very powerful tools for varied applications of image processing but it proved not vey optimal choice for other applications involving analysis of signals, filtering, detection, de-convolution etc. The reconstructed image from the altered wavelet coefficients contained many visual artifacts. This mainly arose owing to lack of the translation invariant property in wavelet transform. The Discrete wavelet transform (DWT) evolved as a discrete estimation of the continuous wavelet transform. Although, history has roots that DWT was existed independently via different names like the overcomplete WT (OWT) [18], discrete wavelet frames (DWFs)[20], the shift-invariant WT (SIWT) [19], the undecimated WT (UWT)[17], and algorithm a trous [16]. These names were given since the down sampling was removed which resulted in shift invariance property of DWT and remaining with a fixed spatial sampling rate across the whole scale. Thus, resulting in size of the sub-bands same as the size of the input signal. Mathematically, DWT can be defined in terms of scaling h_l2(Z) and wavefilters g_l2(Z) of an underlying orthonormal wavelet transform. To maintain the multiresolution property at each scale, these filters should be adjusted accordingly. The up sampling can be defined as follows:

$$x[k] \uparrow 2 = \begin{cases} x[k/2], & \text{if } k \text{ is even} \\ 0, & \text{otherwise} \end{cases} \quad \text{----- (1)}$$

Existed method has two schemes of the watermarking technologies: DWT and PCA, to perform the embedding process.

2.1. Discrete Wavelet Transform (DWT)

Wavelets are functions defined over a finite interval and having an average value of zero. The basic idea of the wavelet transform is to represent any arbitrary occupation as a superposition of a set of such wavelets or basis functions. The 2-D (DWT) decompose the image in to sub-images, 3 detail and 1 approximation sub-image that resembles the original on ¼ scale of the original. The 2-D DWT is an application of the 1-D DWT in both the horizontal and also the vertical directions. The DWT mould an image into a lower resolution approximation image (LL) as well as horizontal (HL), vertical (LH) and diagonal (HH) detail. Frequency information and spatial information of the transformed data is exploited by wavelet based watermarking methods in multiple resolutions to gain robustness [9]. Due to its excellent spatial-frequency localization properties DWT is very suitable to identify areas in the frames where a watermark can be embedded imperceptibly. The discrete wavelet transform stipulates great form of the human visual system [7]. Since the HVS is less sensitive to high frequencies, embedding the watermark in high frequency sub-bands makes the watermark more imperceptible while embedding in low frequencies makes it more robust against a variety of attacks. In Discrete Wavelet Transform Human Visual System (HVS) is more realistic than in Discrete Cosine Transform and Discrete Fourier Transform. DWT even has better multi resolution approach. DCT and DFT are full frame transform whereas DWT has spatial frequency localization. DWT provides both frequency and spatial description for an image. Here we have used Haar Wavelet Transform (DWT), which is in general a simple form of compression which involves averaging and differencing terms, storing detail coefficients, eliminating data, and reconstructing the matrix such that the resulting matrix is similar to the initial matrix [6-7].

2.2. Principle Component Analysis (PCA)

Principal component analysis (PCA) is a mathematical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of uncorrelated variables called principal components. The number of principal Components is less than or equal to the number of original variables. PCA is a method of identifying patterns in data and expressing the data in such a way so as to highlight their similarities and differences. Since patterns in data can be hard to find in data of high dimension, where the advantage of graphical representation is not available, PCA is a powerful tool for analysing data. The other main advantage of PCA is that once these patterns in the data have been identified, the data can be compressed by reducing the number of dimensions, without much loss of information. It plots the data into a new coordinate system where the data with maximum covariance are plotted together and is known as the first principal component. Similarly, there are the second and third principal components and so on. The maximum energy concentration lies in the first principal component. The key ingredient is combined data set normally distributed, therefore guaranteed to be independent. PCA is an analogue of the principal axis's theorem in mechanics. Principal component analysis can be achieved by disintegration of eigenvalues of an image correlation matrix or single value disintegration of an image matrix, basically after mean centring the image matrix for every variable [12]. Principal component analysis is the easiest form of the true eigenvector that works on multivariate synthesis. combination of above two techniques are not much efficient compared to proposed system.

Algorithm for embedding

Step 1: Click a picture through a webcam or from database known as webcam image or input image for watermarking.

Step2: Calculate the intensities of watermark image and input image watermark.

Step 3: Ever intensity is greater will be embedded in the original image.

Step 4: Convert the $n \times n$ binary watermark logo into a vector $W = \{ w1, w2, \ldots\ldots, wn \times n \}$ of ‗0‘s and ‗1‘s.

Step 5: Transform image from RGB to YUV color format and apply the PCA components on selected image

Step 6: Apply 1-level DWT to the luminance (Y component) of image to obtain four sub-bands LL, LH, HL and HH of size N x N.

Step 7: Fragment the LL sub-band into k non-overlapping sub-blocks each of dimension n × n (of the same size as the watermark logo).

Step 8: Algorithm 2 is used for embedding with strength α into each sub-block by first obtaining the principal component scores for watermark bits.

The general form for embedding is carried out as equation.

$$Score_i = Score_i + W \text{ ………… } (2)$$

Where, $Score_i$ represents the principal component matrix of the ith sub-block.

Step 9: Obtain inverse PCA is applied on the modified PCA components of the sub-block of the frequency district of the LL sub-band to achieve the desired wavelet coefficient variables.

Step10: Inverse DWT is applied to obtain the watermarked luminance component of the image. Then convert the image back to its RGB components.

Algorithm for extraction

Step 1: Divide the watermarked (and possibly attacked) image into distinct frames and convert them from RGB to YUV format.

Step 2: Choose the luminance (Y) component of an image and DWT is applied to disintegrate the Y component into the four sub-bands LL, HL, LH, and HH of size N×N.

Step 3: Divide the LL sub-band into n × n non overlapping sub-blocks

Step 4: Put PCA to every block that is selected in sub-band LL by using Algorithm PCA

Step 5: Provided from the LL sub-band of image, the watermark bits are drawn out from the principal components of every sub-block as in equation 2.

$$W_{i'} = (Score_{i'} – Score_i) /alpha \text{ -------(3)}$$

Where, $W_{i'}$ is the watermark drawn out from the ith' sub-block. Existed system face problems at salt andpepper noise, rotation horizontal, flipping, contrast adjustment, gaussian blur and histogram equalization. So, our research area is simplifying the above parameters and perform the analysis on attacks.

3. PROPOSED METHOD

Grey wolf optimizer (GWO) is a recently proposed intelligent optimization method inspired by hunting behaviour of grey wolves. In GWO algorithm, the parameter of a is decreased from 2 to 0 balance exploitation and exploration, respectively. A novel time-varying parameter of a decreasing linearly is used to enhance the performance of GWO algorithm. In order to enhance the global convergence, when generating the initial population, the good-point-set method is employed. The simulation results tested on 10 standard unconstrained functions demonstrate that the proposed method has fine solution quality and convergence performance comparing to standard GWO method and performs superior to the other intelligent optimization method in most functions.

3.1 Gary Wolf Pseudo code Algorithm

Initialize the grey wolf population Xi (i = 1, 2, ..., n)

Initialize a, A, and C

Calculate the fitness of each search agent

X α{\displaystyle X_{\alpha }}=the best search agent

{\displaystyle X_{\beta }}X β=the second best search agent

X γ{\displaystyle X_{\delta }} =the third best search agent

While ({\displaystyle t}t < Max number of iterations)

For each search agent

Update the position of the current search agent by above equations

end for

Update a, A, c, C {\displaystyle a}

{\displaystyle A}Calculate the fitness of all search agents

Update {\displaystyle X_{\alpha }} X α, X β, X γ{\displaystyle X_{\delta }} t=t+1

End while

Return

Process

The GWO mimics the hunting behavior and the social hierarchy of grey wolves. In addition to the social hierarchy of grey wolves, pack hunting is another appealing societal action of grey wolves. The main segments of GWO are encircling, hunting and attacking the prey. The algorithmic steps of GWO are presented in this section.The GWO algorithm is described briefly with the following steps:

Step 1: Initialize the GWO parameters such as search agents (Gs), design variable size (Gd), vectors a, A, C and maximum number of iteration (itermax).

$$\vec{A}. = 2\vec{a}.rand_1 - \vec{a}$$

$$\vec{C}. = 2.\,rand_2$$

The values of a → are linearly decreased from 2 to 0 over the course of iterations.

Step 2: Generate wolves randomly based on size of the pack. Mathematically, these wolves can be expressed as,

$$Wolves = \begin{bmatrix} G_1^1 & G_2^1 & G_3^1 & \cdots & G_{Gd-1}^1 & G_{Gd}^1 \\ G_1^2 & G_2^2 & G_3^2 & \cdots & G_{Gd-1}^2 & G_{Gd}^2 \\ \cdot & \cdot & \cdot & \cdots & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdots & \cdot & \cdot \\ G_1^{Gs} & G_2^{Gs} & G_3^{Gs} & \cdots & G_{Gd-1}^{Gs} & G_{Gd}^{Gs} \end{bmatrix}$$

Where, G i j is the initial value of the j th pack of the ith wolves.

Step 3: Estimate the fitness value of each hunt agent using above two steps

$$\vec{D} = \left| \vec{C}.\ \vec{G}_p(t) - \vec{G}(t) \right|$$

$$\vec{G}(t+1) = \vec{G}_p(t) - \vec{A}.\ \vec{D}$$

Step 4: Identify the best hunt agent (G), the second best hunt agent (G) and the third best hunt agent (Ga)

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

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

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

$$\vec{G}_1 = \vec{G}_{\alpha} - \vec{A}_1 .(\vec{D}_{\alpha})$$

$$\vec{G}_2 = \vec{G}_{\beta} - \vec{A}_2 .(\vec{D}_{\beta})$$

$$\vec{G}_3 = \vec{G}_{\delta} - \vec{A}_3 .(\vec{D}_{\delta})$$

Step 5: Renew the location of the current hunt agent using

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

Step 6: Estimate the fitness value of all hunts.

Step 7: Update the value of G_1,G_2 and G_3.

Step 8: Check for stopping condition i.e., whether the Iter reaches Itermax, if yes, print the best value of solution otherwise go to step 5

3.2 GWO-PCA-RDWT-SVD Method

The proposed hierarchy assists GWO to save the best solutions obtained so far over the iteration. This encircling mechanism defines a circle-shaped neighbourhood around the solutions which can be extended to higher dimensions as a hyper-sphere. The random parameters A and C assist candidate solutions to have hyper-spheres with different random radii so hunting method allows candidate solutions to locate the probable position of the prey Exploration and exploitation are guaranteed by the adaptive values of a and A. The adaptive values of parameters a and A allow GWO to smoothly transition between exploration and exploitation With decreasing A, half of the iterations are devoted to exploration ($|A|\geq 1$) and the other half are dedicated to exploitation ($|A|<1$) The GWO has only two main parameters to be adjusted (a and C). The behavior under additive noise of the redundant discrete wavelet transform (RDWT), which is a frame expansion that is essentially an undecimated discrete wavelet transform, is studied. Known prior results in the form of inequalities bound distortion energy in the original signal domain from additive noise in frame-expansion coefficients. a precise relationship between RDWT-domain and original-signal-domain distortion for additive white noise in the RDWT domain is derived. The RDWT scaling filter at scale j+1 is recursively

$$h_{j+1}[k] = h_j[k] \uparrow 2 = \begin{cases} h_j\left[\frac{k}{2}\right], & k \text{ even} \\ 0, & k \text{ odd} \end{cases}$$

Where h0 [K] =h [K]

This is implemented recursively with the filter-bank operations

$$c_{j+1}[k] = h_j[-k] * c_j[k]$$
$$d_{j+1}[k] = g_j[-k] * c_j[k]$$

RDWT domain, one recursively performs the synthesis operation

$$c_j[k] = \frac{1}{2}\left(h_j[k] * c_{j+1}[k] + g_j[k] * d_{j+1}[k]\right)$$

In the frequency domain, we have

$$\widehat{c}_j(\omega) = \left[\prod_{\lambda=0}^{j-1} \widehat{h}_0^*(2^\lambda \omega)\right] \widehat{x}(\omega)$$

$$\widehat{d}_j(\omega) = \widehat{g}_0^*\left(2^{j-1}\omega\right) \left[\prod_{\lambda=0}^{j-2} \widehat{h}_0^*(2^\lambda \omega)\right] \widehat{x}(\omega)$$

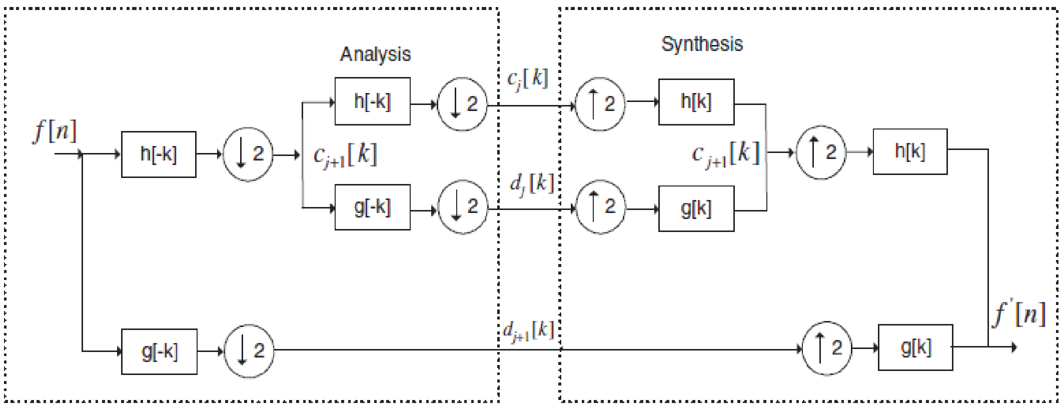


Fig. 2: DWT analysis and synthesis filter banks

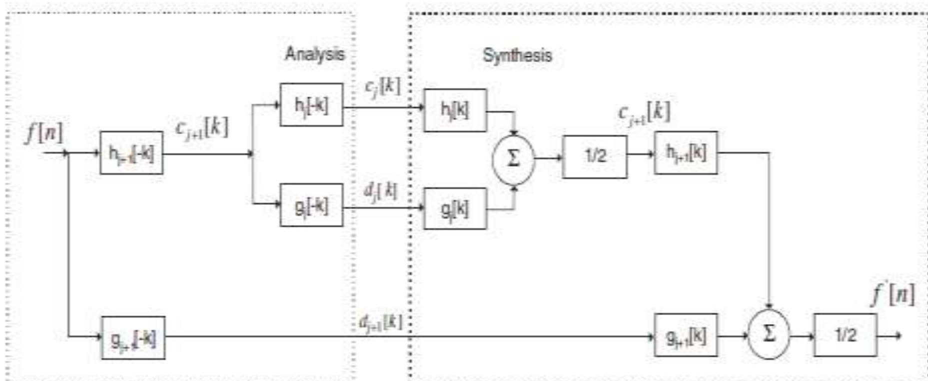


Fig. 3: RDWT analysis and synthesis filter banks.

For marking, the image is first decomposed into the DWT domain by a given number of steps using the Pyramid decomposition and a given filter bank. Assuming that the watermark is of size n, the n most significant coefficients are picked from appropriate chosen marking subbands. For simplicity we store the marked coefficients' positions as part of the key needed for extracting the mark since the significant coefficients are likely to change position after marking. after that A PCA is used on a block by block basis to de-correlate the image pixel, watermarks areadded in the Principle Components of an image. Simulation shows the performance of the method to be robust for image cropping and some attacks such as additive noise, low pass filtering, median filtering, and jpeg compression. Finally, we apply the SVD.

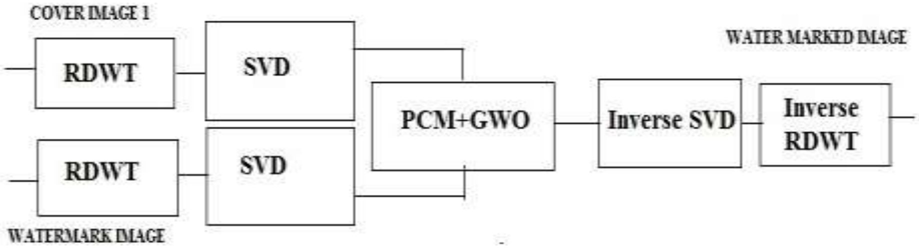


Fig. 4:Proposed watermark embedding algorithm.

The steps of watermark embedding algorithm are as follows:

1. Apply RDWT to the cover image to decompose it into LL, HL, LH, and HH subbands.

2. Apply SVD to the low frequency subband LL of the cover image: $U^l S^l V^l$

3. Apply RDWT to the visual watermark.

$$S^{*1} := S^1 + \alpha S^w$$

4. Apply SVD to the low frequency sub-band of watermark:

5. Modify the singular values of the cover image with the singular values of watermark image where α is

scaling factor, S^l and S^w are the diagonal matrices of singular values of the cover and watermark images, respectively.

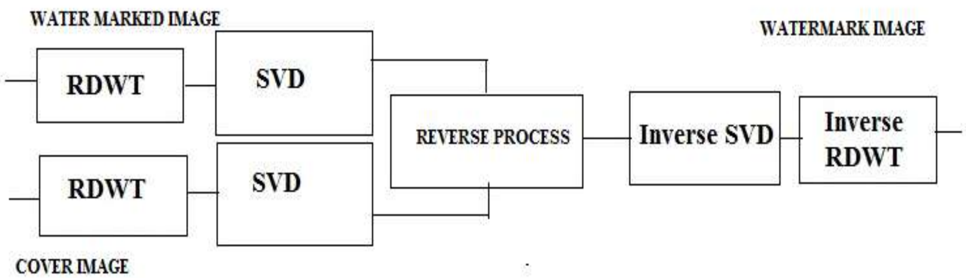


Fig. 5:Proposed watermark extracting algorithm.

The steps of watermark extraction algorithm are as follows:

1. Using RDWT, decompose the watermarked image I* into 4 sub-bands: HH, HL, LH and LL.

2. Apply SVD to low frequency sub-band LL: I^{*l}, $U^{*l} S^{*l} V^{*l}$.

3. Extract the singular values from low frequency sub-band of watermarked and cover image:

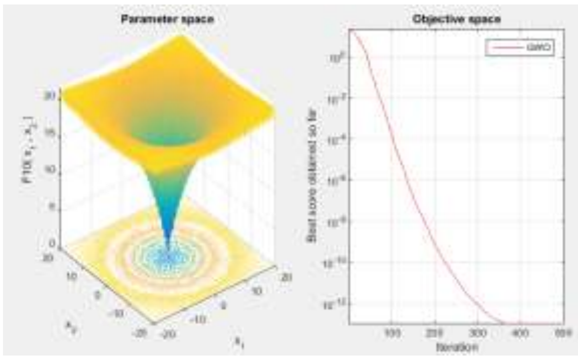
$$S^w=S^{*l}-1/\alpha*S^l$$

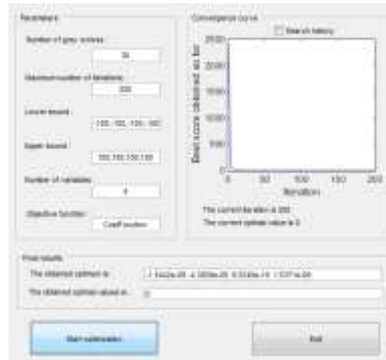
where S^l contains the singulars of the cover image.

4. Apply inverse SVD to obtain low frequency coefficients of the transformed watermark image.

5. Apply inverse RDWT using the coefficients of the low frequency subband to obtain the watermark image.At final we get good enhancement method after that applying the gray wolf algorithm.

4. RESULTS





(a) (b)

Fig. 6: (a) Parameter space and objective space (b) iterations.

(a) (b)

(c) (d)

Fig. 7: (a) cover image. (b) watermark image. (c) watermarked image. (d) extracted image.

Table 1.Without attack

Quality metrics	DWT + GWO	IRDWT + PSO	PROPOSED
PSNR (in dB)	50.02	48.898	88.12
MSE	1.391	0.838	0.0176
NCC	0.988	0.9812	0.915

Table 2. Obtained quality metrics in attack scenario.

Attacked image	Extracted message	MSE	PSNR in dB	NCC
 Noise		0.20	63	0.990
 Rotation		0.19	62	0.97
 Scaling		0.009	89	1
 Compression		0.72	51.50	0.98
 Resizing		0.18	63	0.990

 Histogram equalization		0.7341	51.5	0.989
 Median filtering		0.17	63	0.97
 Sharpening		0.71	51	0.9899
 Flipping		0.70	52	0.92
 Cropping		0.65	54	0.978
 Salt and pepper noise		0.631	59	0.988

Table3. Comparison table for existing and proposed approaches.

PARAMETER	EXISTED METHOD			PROPOSED METHOD		
	MSE	PSNR	NCC	MSE	PSNR	NCC
Noise	0.21	61.30	0.9901	0.20	63	0.990
Compression	0.73	0.73	0.99	0.72	51.50	0.98
Histogram equalization	0.7344	50.81	0.991	0.7341	51.5	0.989
Flipping	0.73	50.80	0.99	0.70	52	0.92
Cropping	0.74	50.90	0.99	0.65	54	0.978
Salt and papper noise	0.732	50.70	0.99	0.631	59	0.988

5. CONCLUSION

We displayed a novel and vigorous picture watermarking plan which depends on (PCA)+SVD+GWO in excess discrete wavelet (R-DW) area. Likewise executed novel inserting and extraction calculations for acquiring the watermarked and removed watermark pictures with higher intangibility and power by using different quality measurements over traditional BW approaches. Moreover, enhanced dark wolf streamlining agent is used to advance the execution of proposed BW. Near investigation additionally gave R-DWT to uncover the adequacy of our proposed structure. Proposed approach got 80% of subtlety and 1.0% vigor contrasted with R-DWT based visually impaired picture watermarking. In future, this WATERMARKED grayscale picture can be stretched out to RGB or genuine nature applications with the usage of novel implanting and extraction calculations for visually impaired RGB watermarking by adjusting improved enhancement strategies.

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