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A Hybrid Digital Image Watermarking based on Discrete Wavelet Transform, Discrete Cosine Transform and General Regression Neural Network

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ABSTRACT: In this paper, a new hybrid digital watermarking technique for gray image based on combination of discrete wavelet transform (DWT), discrete cosine transform (DCT), and general regression neural network (GRNN) is proposed. The watermarking signal is embedded in higher DCT frequency, which is in the lower and middle frequencies of original image by DWT joined with DCT. The ability of attracting is improved by pretreatment and re-treatment of image scrambling and GRNN. Features of lower and middle frequencies sub-band of wavelet coefficient limit the positions for watermarking embedding. The positions are taken as indexes of points for embedding watermarking and map these positions to low and medium frequency spaces to carry watermarking. Detection of watermarking is free of original image and the balance between transparency and robustness are realized. The implementation results show that the watermarking algorithm has very good robustness to all kind of attacks.

KEYWORDS: Hybrid Digital Image Watermarking, Discrete Wavelet Transform, Discrete Cosine Transform, General Regression Neural Network.

1. INTRODUCTION

Digital watermarking plays a significant role to handle the problems of copyright protection, owner's identification and information security. Digital watermarking [1] is the process of embedding the watermark bits into the digital protected media such as image, audio and video. Imperceptibility, robustness, capacity and security are the main features of any watermarking algorithm [2]-[4]. The watermarking can be done either in spatial domain [2] or in frequency domain [4], [6]-[8]. The study of watermarking schemes either in spatial domain or in frequency domain have shown that transform domain techniques are more imperceptible and more robust to common image processing operations like addition of noise, JPEG compression, blurring in spatial domain , sharpening and geometric operations such as scaling, translation and rotation as comparison to spatial domain schemes.

Neural network technology in the application of digital watermarking is proposed only in recent years. The literature [23]-[26],[9] designed different watermarking algorithm, using neural networks to classify or generating adaptive watermark on the image when watermarking embedded, its purpose is to improve the strength of watermark embedded and fidelity of the image. The literature [11] is the watermark detection by neural network. Through training to learn and adjust the weights of neural networks approximate the relationship of the original signal and the watermark signal, the watermark is extracted by using the trained neural network in the receiver, which aims to improve the accuracy of watermark detection rate, and realize the blind watermark detection. Given a network architecture, a set of training input and the expected output, the network can learn from the training set and then can be used to classify or predict the unseen data [10], [5], and [21].

In the field of signal and image processing, efforts have been made to take the advantage of transform algorithms like fast Fourier transform (FFT) [27], discreet cosine transform [12],[13], wavelet transform [14] are used in watermark embedding and extracting procedure. The problems associated with conventional. Another kind of algorithm realizes watermarking positioning by means of recording the positions in a secret table during watermarking embedding [15]. This makes the position of watermarking very precise and not affected by watermarking embedding, image processing and compression, even malicious attacks. The disadvantage of this kind of algorithm is that the owner of digital images must pay more attentions to storing the position tables one by one. Using secret keys and special algorithms to create positions of watermarking [16], [17] is a good choice by which the cost on storage is decreased. In fact, the positions produced by the secret keys and special algorithms do not take the transparency of watermarking into

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account which will result obvious trace of watermarking embedding. The tradeoff between transparency and robustness cannot be realized.

2. Scheme Design

Scheme design is organized as follows; Scrambling Watermark is given in section A. DWT coefficients and embedding positions are discussed in section B. Discrete cosine transform (DCT) after DWT is presented in section C. The training of GRNN is described in section D. The Watermark embedding, and extracting processes are shown in section E, and F.

A. Watermark Scrambling

Original watermark is the logo of company or institute where is a black-white image with size 64×64; the entries of this image are zero and one values. Scrambling process can be implemented in both spatial domain such as color space, position space, and frequency domain of a digital image, which is regarded as a cryptographic method to an image, allows rightful users to choose proper algorithm and parameters easily. As a result, the illegal decryption becomes more difficult, and security of the watermark more strengthened. Scrambling image in spatial domain is to change correlation between pixels, leading to the image beyond recognition, but maintain the same histogram. In a practical application, the scrambling algorithm with small computation and high scrambling degree is needed. This paper applies the famous toral Automorphism mapping, Arnold transformation [20], which was put forward by V. I. Arnold when he was researching ring endomorphism, a special case of toral Automorphism. Arnold transformation is described as the following formula:

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} 1 & 1 \\ 1 & 2 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} \bmod 64 \qquad (1)$$

Where *x,y* is the coordinates of a point in the plane, and *x'*,*y'* is the ones after being transformed. The constant, 64 is relevant to original watermark image size. Arnold transformation changes the layout of an image by changing the coordinates of the image, so as to scramble the image. Furthermore, the transformation with a periodicity like T, the watermark image goes back to its original state after T transformations. In the recovering process, the transformation can scatter damaged pixel bits to reduce the visual impact and improve the visual effect, which is often used to scramble the watermark image. In this paper, the periodicity T is for 24, scrambling process is displayed as the following **Error! Reference source not found.**(a) ~ (d), which are original watermark image, 6, 12, and 24 Arnold transforming effect. For T, here is for 24, the 24 transforming is equivalent to the recovering effect. Let $T=k_1+k_2$, Scrambling the watermark image k_1 times before embedding it, then after extracting scrambled watermark form watermark image, k_2 times of transformation can recover the original extracted watermark, where k_1, and k_2 are secret keys. After scrambling watermark image, it is arranged to one dimensional array W (k), where k=1, 2… 64×64.

Figure 1: Image effect after being Arnold transformed

B. DWT coefficients and embedding positions

The wavelet transform is based on small waves. It was in 1987 when the wavelets became the base of the multi-resolution analysis. In two-dimensional DWT, each level of decomposition produces four bands of data, one corresponding to the low pass band (LL), and three other corresponding to horizontal (HL), and vertical (LH) middle pass bands, and diagonal (HH) high pass band. The decomposed image shows an approximation image in the lowest resolution low pass band, and three detail images in higher bands. The low pass band can further be decomposed to obtain another level of decomposition. **Error! Reference source not found.**, shows three level decompositions of

DWT coefficients.

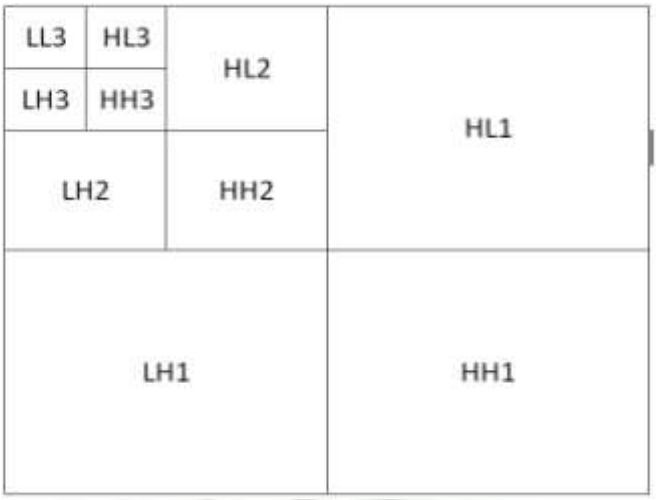

Figure 2: Three level decomposition of 2-D DWT coefficients

Watermarking positioning is a critical technique for watermarking. For detecting watermarking precisely, the embedding points must be stable in variety of conditions. It requires the embedding points have following features:

- The embedding position shall have ideal position features;
- Watermarking embedding shall have insignificant affection to embedding positions;
- The embedding positions shall have good noise proof properties;
- The embedding positions shall be stable after image processing or deformation.

To avoid the disadvantages in algorithm [14]-[18], the watermarking algorithm based on two-dimensional Discrete Wavelet Transform (2D-DWT) and 2D-DCT, for watermarking positioning is proposed in this paper. The algorithm utilizes the good local spatial properties of DWT and establishes wavelet coefficient tree to index the positions for watermarking. Experimental results show that the positions are stable against interferences and image compression. Determination of embedding positions consists of two steps. The first step is multi-resolution decomposition of image and the second step is the algorithm for determining the root node of wavelet tree. In the first step, 512×512 original image will subject to 3-level multiple resolution decomposition by using 2D-DWT to form 10 sub-bands with different resolutions in different directions.

Among these sub-bands, the one in lower frequency labeled LL3 with size of 64×64 concentrates 95 percent of energy of original image and has property of anti-reference. For establish the relationship between coefficients in different sub-bands and different directions. A wavelet tree is created by taken any point in sub-band LL3 as root node combining with points in horizontal, vertical and diagonal directions in different resolutions according to multi-resolution features of wavelet transform. An established 3-level wavelet tree is shown in Figure 3. In the wavelet coefficient tree shown in figure 3, the route in any direction pointed by arrows consists of several coefficient blocks, for example the route LL3→HH3→HH2. It can be shown that if the root node is determined, the whole wavelet coefficient tree is uniquely determined. The second step is to determine the root node. As index of watermarking position, the root node must be stable in any conditions. So, it shall satisfy the conditions mentioned above.

The steps for determining the root node are as follows:

(1) Carry out 3-level wavelet decomposition to the original image and extract sub bands LL3, HL3, HL2, HL1, LH3,LH2,LH1,HH3, and HH2,; the sub band HH1 is not considered, because of high frequency features.

(2) Carry out image filter to the mentioned sub bands order sequentially, and the output image is local variance of each point in 3×3 neighborhood. The calculation formula is below:

$$\sigma^2(x,y)=\sum_{i=-1}^{i=1}\sum_{j=-1}^{j=1}\frac{(f(x,y)-f(x+i,y+j))^2}{8} \qquad (2)$$

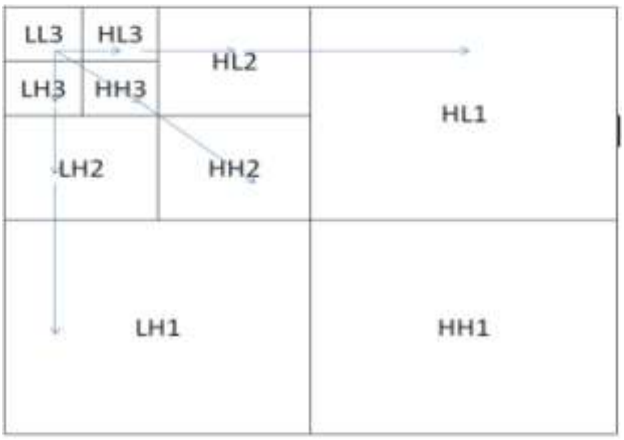

Figure 1: 3-level wavelet coefficient tree

Where f(x,y) is the DWT coefficient, $L \leq x, y \leq H$, and L, and H are the low, and high DWT sub band coordinates, for example: L (LL3) =0, H (LL3) =63.

(3) Divide the matrix constructed by local variances in to several data blocks with size of 8×8 and calculate the average of each data block:

$$E_k = \frac{1}{64}\sum_x \sum_y \sigma_k^2(x,y) \qquad (3)$$

Where E_k is the average value of kth block, $\sigma_k^2(x,y)$ is the variance entry in the kth block.

(4) Set threshold Th=$\frac{1}{2}$ ×max {E_k}. Select the data blocks that the average values are less than Th as reference blocks. The reference blocks in variance matrix have the relative blocks in mentioned DWT sub bands, because the size of variance matrix is with the same size as the mentioned sub bands. The selected data blocks in 3-level DWT coefficient with size 8×8 are considered as input matrixes for DCT and GRNN processes that are described in watermark embedding and extracting algorithms. The positions of selected blocks are saved in the *key matrix K* for future use in watermark embedding and extracting processes.

C. Discrete cosine transform (DCT) after DWT

The image transformed by wavelet, most of its energy is concentrated in low-frequency sub-band, if watermark is embedded directly in low frequency sub-band, and the transparency of image containing watermark will decline. If watermark is embedded directly in high frequency sub-band, a lot of high frequency information is lossed when containing watermark image after filtering, and the algorithm robustness will decline. The correlation between every coefficient is larger in low frequency sub-band, and then it separated further by discrete cosine transform (DCT). After DCT, most of the energy in low frequency sub-band focused on few low frequency coefficients, so most of the energy is concentrated about the whole image. The image changed bigger if these coefficients amended arbitrary; therefore, it should guarantee that these coefficients did not amend. Because the high coefficients is not sensitive in the eye, the high frequency DCT components in low and middle DWT frequency sub- bands are the ideal regionals of embedded watermark [18], the contradictions about watermarking robustness and transparency can be solved.

After a selected 8×8 DWT coefficients block is transformed with DCT, the coefficients in low-frequency domain contain very low energy of the image. If the watermark is embedded in this range, the robustness of the watermark will not be guaranteed while the nonvisibility of the watermark will be poor, and also authentication to the carrier content. On the contrary, the coefficients in middle frequency domain contain less energy of the image, which usually stand for the edge and texture part of the image, if the watermark is embedded in this range, where the nonvisibility of the watermark will be ensured while the ability to resist against normal processes like data compression and format conversion, all kinds of attacks weakens greatly ,which makes the watermark disappear and being destroyed easily .So

we select 36 high-frequency coefficients in each 8 by 8 block as the destination area where the watermark is embedded, which are labeled as the following
Figure 2.

							1
						1	1
					1	1	1
				1	1	1	1
			1	1	1	1	1
		1	1	1	1	1	1
	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1

Figure 2: DCT higher frequency coefficients

As a result, each watermark bit is embedded into the 36 given locations, which implements redundant watermark embedding, being equivalent to an application of spread spectrum technology, improves the robustness and security of digital watermark [17].

D. General regression neural network

The GRNN, proposed by Donald F. Specht in [10], is special network in the category of probabilistic neural networks (PNN). GRNN is a one-pass learning algorithm with a highly parallel structure. This makes GRNN a powerful tool to do predictions and comparisons of large data sets. A block diagram of GRNN is illustrated in Figure 3.

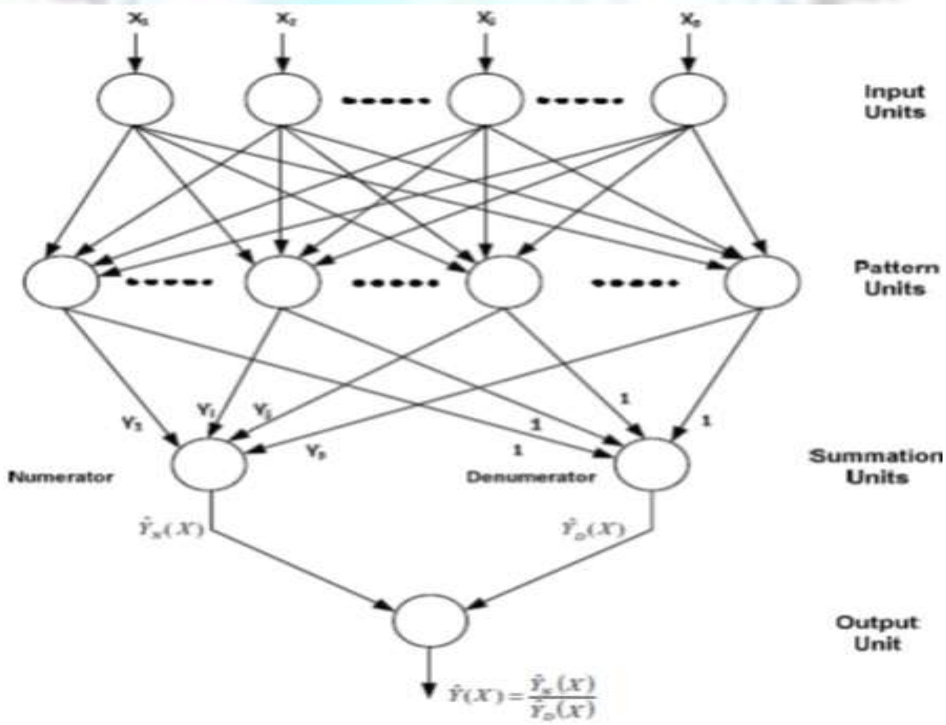

Figure 3: GRNN structure

The input units are the distribution units. There is no calculation at this layer. It just distributes the entire measurement variable X to all of the neurons in the pattern units' layer. The pattern units first calculate the cluster center of the input vector, X_i. When a new vector X is entered the network, it is subtracted from the corresponding stored cluster center. The square differences D_i^2 are summed and fed into the activation function f(x), and are given by.

$$D_i^2 = (X - X_i)^T . (X - X_i) \tag{4}$$

$$f_i(X) = \exp\left(\frac{-D_i^2}{\sigma^2}\right) \tag{5}$$

The signal of the pattern neuron i going to the numerator neuron is weighted with the corresponding values of the observed values (target values), Yi, to obtain the output value of the numerator neuron $\overline{Y_N}(X)$. The weights on the signals going to the denumerator neuron are one, and the output value of the denumerator neuron is $\overline{Y}_D(X)$

The output of the GRNN is given by relation (8).

$$\overline{Y_N}(X) = \sum_{i=1}^{p} Y_i f_i(X) \tag{6}$$

$$\overline{Y}_D(X) = \sum_{i=1}^{p} f_i(X) \tag{7}$$

$$Y(X) = \frac{\overline{Y_N}}{\overline{Y_D}} \tag{8}$$

In GRNN, only the standard deviation or smooth parameter, σ, the kernel width of Gaussian function is subject for a search [10]. In our work, we have two GRNN structures; each GRNN has 17 input neurons, 17 pattern neurons, 2 summation neurons for a numerator neuron and a denumerator neuron, and 1 output neuron. The detail how this GRNN works is described in the next section.

E. Watermark embedding process

Each high frequency coefficient of 8×8 DCT block is scanned in a zigzag manner, and arranged as shown in Figure 4. Let $Y_{i1} = HF(k), Y_{i2} = HF(k+1)$ be the desired outputs for two GRNN structures, which are the central values of input high frequency coefficients and input vectors are:

$$X_1 = \{HF(k-17), HF(k-16), ..., HF(k-1)\},$$
$$X_2 = \{HF(k+2), HF(k+3), ..., HF(k+18)\}$$

Then the watermark bits are embedded into output obtained by trained GRNNs, the central coefficients are replaced by the insertion of watermark bits according to the following rules:

$$HF(k) = HF^{'}(k) + (2W(2k) - 1) \times \alpha,$$
$$HF(k+1) = HF^{'}(k+1) + (2W(2k+1) - 1) \times \alpha \tag{9}$$

Where, $HF^{'}(k), HF^{'}(k+1)$ are the outputs obtained by two GRNNs. The constant α is the watermarking strength and W (2k), and W (2k+1) are the even, and odd bits of watermark, in other words, in each DCT block two watermark bits are inserted, it is possible to have desired watermarking capacity, if only at least half of DWT data blocks select for embedding, that the value of threshold Th guaranteed it.

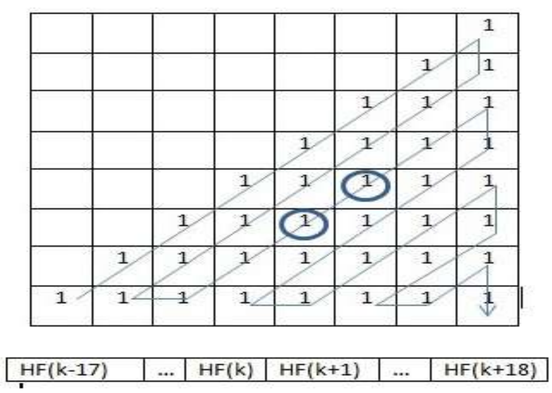

Figure 4: Coefficient selection from 8×8 DCT block using zigzag scanning and arrangement of high frequency DCT coefficients of each block for training values for two GRNNs.

After embedding all of the watermark bits, getting IDCT for each DCT block, performing IDWT, and making the watermarked image finally. The total embedding process is shown in

Figure 5.

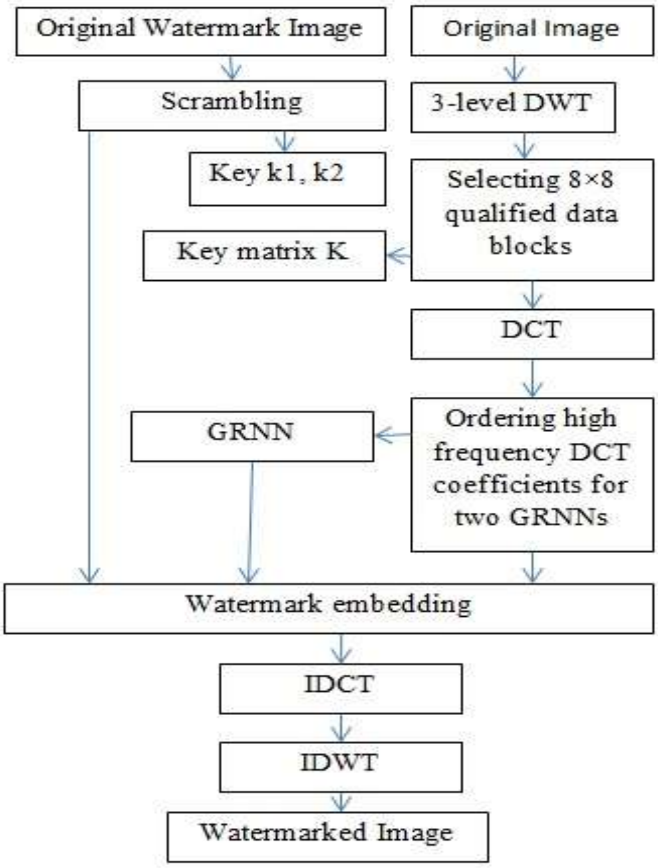

Figure 5: Watermark embedding diagram

F. Watermark extracting process

Extracting he watermark from the watermarked image is the reverse process of watermark embedding which includes the following steps: Perform 3-level DWT for watermarked image and select positions of watermark insertion data blocks based on key matrix K as described in section B. Transform each data block using DCT. Scan each selected DCT block in a zigzag order as shown in Figure 4, organize input vectors, and desired outputs for two GRNN structures similar to embedding process, then the watermark bits are extracted to the following rules:

$$W^{'}(2k) = \begin{cases} 1 & HF(k) > HF^{'}(k) \\ 0 & otherwise \end{cases},$$

$$W^{'}(2k+1) = \begin{cases} 1 & HF(k+1) > HF^{'}(k+1) \\ 0 & otherwise \end{cases}$$

(10).

Where, $HF^{'}(k), HF^{'}(k+1)$ are the outputs obtained by two GRNNs for watermarked image. After obtaining all of the watermark bits, the descrambling is performed for watermark sequence and extracted watermark image can be

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obtained. The diagram of extracting algorithm is shown in Figure 6.

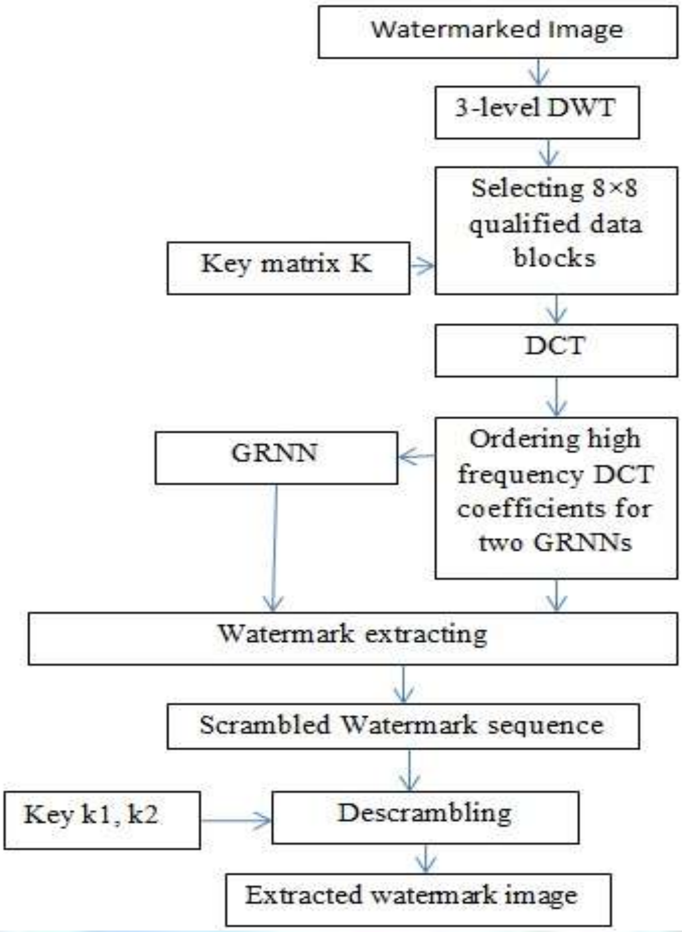

Figure 6: Watermark extracting diagram

3. IMPLEMENTATION RESULTS

Two original and watermarked images with size 512×512 have been shown in Figure 7, Figure 8, Figure 9, and Figure 10, Barbara, and Baboon images have been used to implement the watermarking algorithm. Original Watermark is a binary image and its size is 64 × 64. The original watermark image is shown in Figure 11. Extracted watermarks after some kind of attack on mentioned watermarked images for Barbara and Baboon have been shown in Figure 12, and Figure 13. The performed attacks on the watermarked images are as follows: Gaussian noise; median filtering 3*3; low pass filtering; and resizing 1/5 the image; jpeg compression with quality factors of 10, 25, 50, 75 and finally jpeg 2000 compression with bit rate 3 .

The estimate of similarity between the extracted watermark image and the original watermark image according to relation (11), along the peak signal to noise ratio (PSNR) of watermarked image and Original image, to relation (12), were calculated having performed each one of the mentioned attacks on the watermarked image of Barbara and Baboon, and results have been integrated in table 1, and table 2.

In relation (11) W is the original watermark and W' is the Extracted logo watermark image. Dot operation in this relation is explanatory sum of product of respective entries between matrix W and W'. Square operation is explanatory sum of product of each entry of matrix W with itself.

$$SIM(W,W') = \frac{W.W'}{W.W} \qquad (11)$$

$$PSNR = 10\log\left(\frac{255}{\sum_{i,j} I(i,j) - I_w\ (i,j)}\right)^2 \qquad (12)$$

Figure 7: Original Barbara image

Figure 8: Watermarked Barbara image.

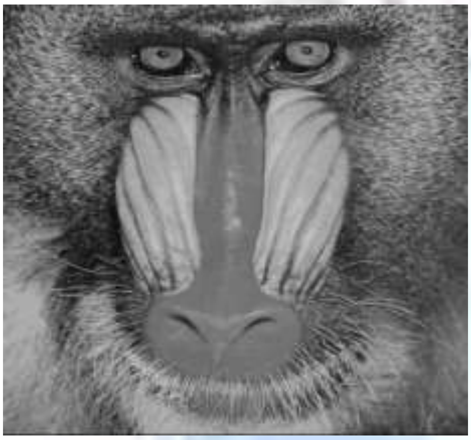

Figure 9: Original Baboon image

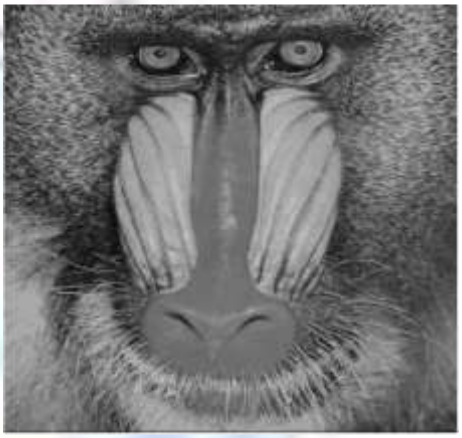

Figure 10 Watermarked Baboon image

Figure 11: Original watermark image

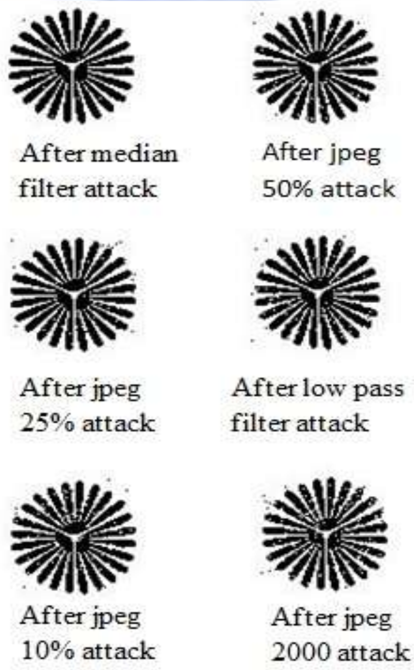

Figure 12: Extracted watermark image after some kinds of watermarking attacks for Barbara image

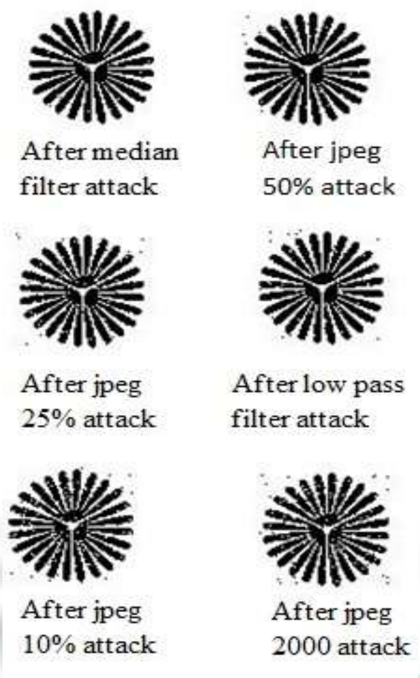

Figure 13: Extracted watermark image after some kinds of watermarking attacks for Baboon image

Table 1: Implementation Results and Comparisons for Barbara Image

Kind of attack	Our method		Method in [22]	
	SIM	PSNR	SIM	PSNR
Gaussian Noise	98.3	27.0	93.5	31.44
Low Pass Filter	92.8	25.8	-	-
Median Pass Filter	95.7	27.4	85.95	32.7
Scaling 1/5	86.3	20.0	88.1	28.5
JPEG 75%	98.9	37.4	91.2	37.7
JPEG 50%	98.1	35.8	89.4	33.5
JPEG 25%	94.5	34.7	86.3	29.8
JPEG 10%	91.2	28.2	81.2	24.1
JPEG 2000 with bit rate 3	88.1	19.4	-	-

Table 2: Implementation Results and Comparisons for Baboon Image

Kind of attack	Our method		Method in [19]	
	SIM	PSNR	SIM	PSNR
Gaussian Noise	93.7	27.5	-	-
Low Pass Filter	89.0	25.0	78.26	24.9
Median Pass Filter	95.2	28.8	86.74	32.7
Scaling 1/5	83.0	18.4	76.69	28.5
JPEG 75%	97.9	37.2	93.51	37.7
JPEG 50%	96.8	34.5	88.79	33.5
JPEG 25%	91.7	32.1	75.17	29.8
JPEG 10%	88.3	26.1	69.87	24.1
JPEG 2000 with bit rate 3	85.1	19.2	-	-

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