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Hybrid and Adaptive Block Based Watermarking Algorithm Using DWT-DCT and Artificial Neural Network

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ABSTRACT

In this paper we propose the use of artificial neural networks (ANN) to predict the most suitable areas of an image for embedding. This ANN is trained based on the human visual system (HVS) model. Only blocks which produce least amount of perceivable changes are selected by this method. A joint DWT and DCT based watermarking technique with low frequency watermarking with weighted correction is proposed. DWT has excellent spatial localization, frequency spread and multi-resolution characteristics, which are similar to the theoretical models of the human visual system (HVS). In the proposed method watermark bits are embedded in the low frequency band of each DCT block of selected DWT sub-band. Compared with the similar approach by DCT based approach and DWT based approach, the experimental results show that the proposed algorithm apparently preserves superior image quality and robustness under various attacks such as JPEG compression, scaling, filtering, and so on.

Keywords: Digital Image Watermarking, Discrete Wavelet Transform (DWT), Discrete Cosine Transform (DCT), Artificial Neural Network (ANN), Human Visual System (HVS).

INTRODUCTION

In the recent years, it becomes a daily need to create copy, transmit and distribute digital data as a part of wide spread multimedia technology by means of the World Wide Web. Hence copyright protection has become essential to avoid unauthorized replication problem. Digital image watermarking provides the essential mechanism for the ownership authentication. Image watermarking is the process of inserting hidden information in an image by introducing modifications of minimum perceptual disturbance. Robustness, perceptual transparency, capacity and blind watermarking are four essential factors to determine quality of watermarking scheme [1]. Image watermarking techniques proposed so far can be divided into two group's accordingly processing domain of host image. Commonly used frequency-domain transforms include the Discrete Wavelet Transform (DWT) and the Discrete Cosine Transform (DCT). However, DWT has been used in digital image watermarking more frequently due to its excellent spatial localization and multi-resolution characteristics, which are similar to the theoretical models of the human visual system and DWT gives perfect reconstruction of decomposed image. The DCT has special property that most of the visually significant information of the image is concentrated in just a few coefficient of the DCT. Moreover DCT based watermarking techniques offer compression while DWT based watermarking technique offer scalability. Further performance improvements in DWT based digital image watermarking algorithms and DCT-based watermarking algorithms could be obtained by combining DWT with DCT [2-4]. The idea of applying two transform is based on the fact that combined transforms could compensate for the drawbacks of each other, resulting in effective watermarking.

To implement the adaptive algorithms many methods have been proposed. Due to need for enhancing the invisibility, we require a system to imitate human model. The adaptiveness in Human Visual System (HVS) is produced by the nature of neural structure of the human eye. Therefore, using Artificial Neural Network (ANN) may be a good choice to achieve imperceptibility in the watermarking process. Embedding the ownership information will inevitably change some of pixels in the image. But our eyes are not sensitive to all parts of an image and all levels of brightness change. Thus the embedding process can be done in locations where eyes are least attracted to this areas. Some researches tried to model this biological system and invented some watermarking methods based on HVS [5, 6]. Since the human eye sensitivity is relatively complex, ANN can learn the process and helps watermarking methods to develop their results on the basis of modeling human neural system.

In this paper a novel use of ANN is introduced. We tried to minimize the degradation of watermarked images such that less obvious differences could be perceived between the original and watermarked one. This approach attempts to define an adaptive watermark scheme based on Multi-Layer Feed-forward (MLF) neural networks. We use MLF to pick original image blocks which are less detectable by human eye after embedding. These blocks will be introduced as the most appropriate places for embedding. Then, to compare our proposed method with similar works in this domain, random blocks have been used for embedding and have shown that the watermarked image quality degrades while preserving the robustness comparing to our approach. The rest of this paper is organized as follows. After a brief review of the human visual system and its characteristics in section 2, our proposed method is presented in section 3. Experimental results are described in section 4, followed by a conclusion in section 5.

HUMAN VISUAL SYSTEM

The human eye can not completely distinguish between minor differences of brightness and this weakness can be exploited to embed the watermark image bits [7]. However the study of human perception ability is not simple, a lot of watermarking methods attempted to identify some of HVS properties to improve imperceptibility of watermarked images. Contrast sensitivity, texture sensitivity and entropy sensitivity are some of these properties modeled in HVS [8].Also, the human eye sensibility depends on the average brightness of the background. Brightness sensitivity is a measure of this property in HVS and it obtains the average block intensity of an image as an estimation of the block saliency function of eye [5]. The contrast sensitivity refers to the ability of detecting a signal in the presence of another signal. Its major contribution occurs when both signals are of the same spatial frequency, orientation and location [9, 10]. Human eye sensitivity to image distortion decreases from smooth blocks to texture and edge blocks.

This is another property called texture sensitivity. Most of the works in perceptual watermarking use these characteristics of human visual system to determine Just Noticeable Difference (JND) thresholds on these criteria. Although these methods try to formulize specific functionalities in human eye using JND, the operation of this biological system completely depends on the situation and the viewed scene. This adaptiveness makes these metrics inefficient to a biological system which takes advantage of dynamic thresholds. Therefore we would prefer a more dynamic model which can be adaptable to the visual model of the eye. There has been much work to realize the vision system for media application systems. While statistical modeling techniques try to examine the image quality, it is ultimately the viewer who can decide how the modified image has maintained its previous quality. Perceptual models take advantage of characteristics of the human visual system in order to qualify image processing applications. As we said, the complexity of human visual system cannot exactly be formulized; therefore, using the visual system itself to monitor an artificial neural network after embedding and back propagating the errors to the network would have better approximation of this dynamic system.

WEBER RATIO

The image formation in the human eye is not a simple phenomenon and only some of the visual properties are measurable. Weber ratio is one of nonlinear characteristics of this system. Let us consider a spot of intensity $I + dI$ in a background having intensity I . dI is increasing from 0 until it becomes noticeable. The ratio dI/I, is called Weber Ratio [11]. It is obvious that brightness discrimination is low at low illumination levels and it improves at high levels of illumination. Figure1. demonstrates the Weber ratio diagram for a wide range of brightness values and states more sensibility of human eye to changes for bright regions of image. This fact will be helpful to introduce the amount of tolerable extensive changes in each block as the target value for training ANN.

To maintain invisibility while embedding, we have proposed a method to find proper blocks. As mentioned above, we have designed a Multi-Layer Perceptron (MLP) neural network which can predict blocks that will not make major changes in quality of image after watermarking. The input patterns of our neural network are the block features effective in perceptual quality of image. The targets are the number of pixels in each watermarked block that intolerably changed on the basis of Weber ratio. Output of this network is a set of corrected weights and biases. After this phase, our trained network can be used for targeting in other images. The block diagram of our proposed method for training neural network is shown in Figure 2.

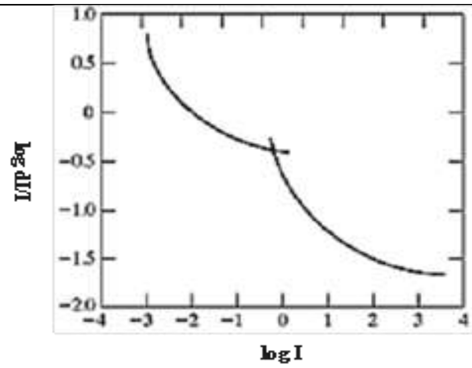

Figure 1. Weber ratio for different levels of brightness

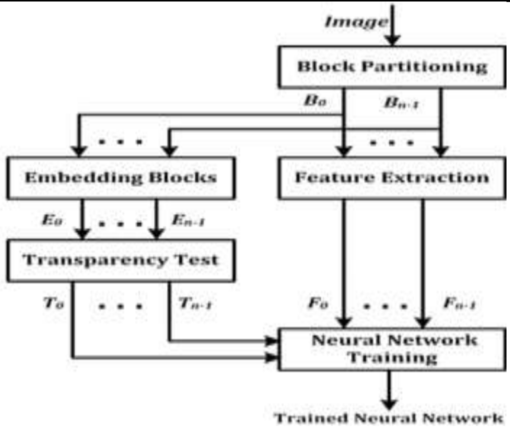

Figure 2. Block diagram of ANN training

PROPOSED METHOD

The proposed method consists of image feature extraction by ANN, working on DWT, working on DCT, watermark embedding process, and watermark extraction process.

IMAGE BLOCK IDENTIFICATION BY ANN

Based on the description of human visual system in section two, brightness sensitivity, contrast sensitivity, texture sensitivity, and entropy sensitivity are effective issues in an imperceptible watermarking. These features should provide a suitable description of human visual system based on these issues. Simplicity of these descriptors is another necessity which causes to decrease the computational load in calculation of input values and also number of neurons in input layer of our network. Other HVS based algorithms use intricate formulas that impose high computational load and they are time consuming. In addition, these formulas are not so accurate according to such a dynamic system of human eye. Thus we devolve this complexity to the training phase of ANN and we select only the simple features that their combination will provide a thorough description of visual system. Given a pixel point (x, y) with the pixel value $g(x, y)$ in any 8×8 image block k, its visual features are calculated using its pixel values as the following [8];

(1) Brightness sensitivity

$$B_k = \frac{1}{64} \sum_{x,y=(1,1)}^{x,y=(8,8)} g(x, y) \tag{1}$$

(2) Texture sensitivity

$$T_k = \sum_{x,y=(1,1)}^{x,y(8,8)} |g\,(x, y) - B_k| \tag{2}$$

(3) Contrast sensitivity

$$C_k = \max_{x,y=(1,1)}^{x,y=(8,8)}\left(g(x,y)\right) - \min_{x,y=(1,1)}^{x,y=(8,8)}\left(g(x,y)\right) \tag{3}$$

(4) Entropy sensitivity

$$E_k = -\sum_{x,y=(1,1)}^{x,y=(8,8)} p_k(x,y).\log p_k(x,y) \tag{4}$$

Where

$$p_k(x,y) = \frac{g(x,y)}{64 \times B_k} \tag{5}$$

The entropy values of image blocks represent the amount of the information in a block. The entropy values of smoother blocks are smaller than those of edge and textured blocks [5]. According to the relationships we have selected these four special domain features as the input pattern vectors, which are simple but sufficient descriptors to meet the needs of imperceptible watermarking. After the training phase this network is expected to find proper blocks for watermarking. Extensive HVS researches indicate that the sensitivity of information distortion to human eye diminishes from edge block to smooth block and texture.

Contrast sensitivity provides a set of features of an object that are not affected by many of the complications experienced in other methods, such as object scaling and rotation. . Contrast sensitivity features are local and based on the appearance of the object at particular interest points, and are invariant to image scale and rotation. These features are also robust to changes in illumination and noise. The last feature, variance measures the value of distribution in image blocks.

Perceptual transparency is one of the most important requirements of a proper watermarking method. HVS model results in scoring the blocks of cover images on the basis of their brightness changes after embedding. Human eye is tolerant to changes less than a specific threshold for each brightness level. So the best blocks for embedding logo pixels are the ones make less perceptible difference comparatively to others. Artificial neural networks are well known in approximating adaptive nonlinear decision. Therefore theses networks are able to easily learn the intricacies of the biological neuron-system. The selected ANN in this paper is a two-layer feed-forward ANN including 5 neurons in the hidden layer. Figure 3, shows the network architecture.

The four feature components of a feature vector $F = [f_1 = B_k, f_2 = T_k, f_3 = C_k, f_4 = E_k]$ include brightness, texture, contrast, and entropy in respective blocks for the explained reasons above. Different numbers for neurons in the hidden layer have been experimented and the best test results obtained for 5 neurons. The desired outputs are the number of pixels in each block which are changed tangibly by human eye on the basis of Weber ratio. The activation function in the hidden layer is a sigmoid function, but the output neuron uses the purelin activation function. We have selected Levenberg-Marquardt as the network training function which is often one of the fastest back propagation algorithms and it won't get into local minima during training process.

It is highly recommended as a first choice supervised algorithm and although it does require more memory than other algorithms. During training operation, information is propagated back to the network and used to update connection weights. It repeats learning experiment many times for every pattern vector in the training set until achieving acceptable values for output errors. This neural network provides an automatic system in order to locate the best host blocks for embedding. Now we have a trained ANN which can get the same features of image blocks as utilized in the training phase.. As the human visual system is too complicated to be completely formulized, training the neural network helps finding the host blocks which will be less modified after embedding.

The block identification process is completely independent form embedding and extracting process. Image is partitioned into 8×8 blocks and each block is sent to the trained ANN. The network selects the most appropriate blocks for embedding. In ANN, complex block is determined and used for embedding. After embedding step, complex blocks that contain watermark bit and non-complex blocks retile in appropriate place and will form watermarked image.

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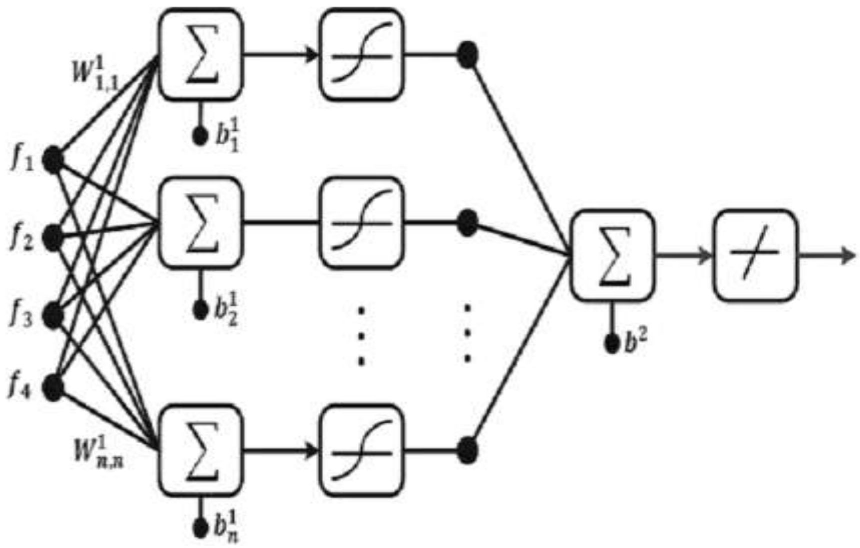


Figure 3: The structure of used Artificial Neural Network

3.2. WORKING ON DWT

Discrete wavelets transform consist of discrete sample of wavelet. It has ability to hold both location information and frequency. With the help of this property, the filter is used to divide the image in four non-overlapping sub bands like LL, LH, HL, and HH.LL sub-band is low pass band and remaining three sub-bands are high pass band: HL denotes horizontal sub-band, LH denotes vertical sub-band and HH denotes diagonal sub-band as shown in Figure 4.

LL: Approximate Subband	HL: Horizontal Subband
LH: Vertical Subband	HH : Diagonal Subband

Figure 4: DWT Sub-bands in General Watermarking Method

The coarse scale of DWT coefficient is represented by LLI sub-band and the finite scale DWT coefficient is represented by LH1, HL1, and HHI sub-bands. The sub-band LLl is processed further and divides into four non-overlapping sub-bands like LL2, LH2, HL2, and HH2 to obtain the next coarse scale of DWT coefficient t. This process continues until some final coarse scale of wavelet coefficient. Energy of image is concentrated at lower frequency sub-band LLx and therefore embedding watermark in such sub-band may degrade the quality of image. However, embedding the watermark in these low frequency sub-bands may increase robustness. The edges and texture of image is included in high frequency sub-band HHx and human vision is not generally sensitive to change in such sub-band. This property allows the watermark to embed without being perceived by the human vision. Many DWT algorithm used for digital watermarking is to embed the watermark in the middle frequency sub-bands LHx and HLx from where robustness, imperceptibility performance can be achieved.

WORKING ON DCT

A discrete cosine transform (DCT) can also be expresses as a sum of cosine functions oscillating at different frequencies which has a sequence of finitely many data points[12-15]. The definition of DCT Regions is shown in Figure 5.

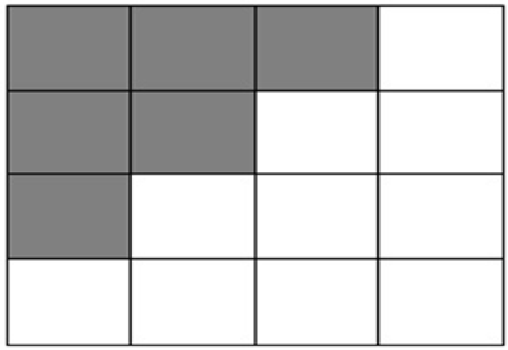


Figure 5: Definition of Low frequency coefficients of 4×4 DCT Block

Equation of discrete cosine transform and its inverse are calculated as follows:

$$\mathrm{DCT}(u,v) = \propto(u) \propto(v) \sum_{x,y=0}^{N-1} f(x,y) \cos\left[\frac{(2x+1)u\pi}{2N}\right] \cos\left[\frac{(2y+1)v\pi}{2N}\right].$$
$$\text{for } u,v = 0,1,\dots,N-1$$
$$\text{for } x,y = 0,1,\dots,N-1$$
$$\text{Where}$$
$$\propto(u) = \propto(v) = \frac{1}{\sqrt{2}} \text{ for } u,v = 0$$
$$\propto(u) = \propto(v) = 1 \text{ for } u,v = 1,\dots,N-1 \tag{6}$$

$$f(x,y) = \sum_{u,v=0}^{N-1} \propto(u) \propto(v) \mathrm{DCT}(u,v) \cos\left[\frac{(2x+1)x\pi}{2N}\right] \cos\left[\frac{(2y+1)y\pi}{2N}\right]. \tag{7}$$

Watermark scrambling

Original watermark is the logo of company or institute where is a black-white image with size 32×32; 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 [16], 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:

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} 1 & 1 \\ 1 & 2 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} \bmod 32 \tag{8}$$

Where x, y is the coordinates of a point in the plane, and x', y' is the ones after being transformed. The constant, 32 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 Figure 6. (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 $T = k1 + k2$, Scrambling the watermark image k1 times before embedding it, then after extracting scrambled watermark form watermark image, k2 times of transformation can recover the original extracted watermark, where k1, and k2 are secret keys.

After scrambling watermark image, it is arranged to one dimensional array W (k), where $k = 1, 2 \ldots\ 32 \times 32$.

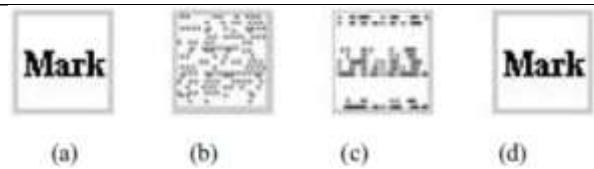


Figure 6. Image effect after being Arnold transformed

Watermark embedding process

Step1: Apply single level of DWT on the most appropriate 8×8 image block which was determined previously, to decompose it to four non-overlapping multiresolution sub-division bands like LL1, LH1, HL1, and HH1. Save the coordinates of selected image block as a matrix key K for extracting watermark process.
Step2: Select the sub band HL1 for embedding the watermark bit, which is 4×4 coefficient block. Apply DCT on sub band HL1, and gain 4×4 DCT coefficient block.
Step3: Convert the scrambled watermark into binary one dimensional array format W (k), and select the low frequency DCT coefficients in the coordinates (1, 2), and (2, 1) for the 4×4 DCT coefficient block.
Step4: Embed the watermark bit base on the following equations:

$\mathrm{DCT}(1,2) = \begin{cases} \mathrm{DCT}(2,1) - \propto & \text{if } W(k) = 1 \text{ and } \mathrm{DCT}(1,2) > \mathrm{DCT}(2,1) \\ \mathrm{DCT}(1,2) + \propto & \text{if } W(k) = 0 \text{ and } \mathrm{DCT}(1,2) > \mathrm{DCT}(2,1) \end{cases}$	(9)
$\mathrm{DCT}(1,2) = \begin{cases} \mathrm{DCT}(2,1) + \propto & \text{if } W(k) = 0 \text{ and } \mathrm{DCT}(1,2) < \mathrm{DCT}(2,1) \\ \mathrm{DCT}(1,2) - \propto & \text{if } W(k) = 1 \text{ and } \mathrm{DCT}(1,2) < \mathrm{DCT}(2,1) \end{cases}$	(10)

The gain factor (α) is used for embedding watermark bit, the bigger α, the more accurate the extracted watermark and the less transparent the output block will be.
Step5: Perform the inverse DCT on each block after its middle-band coefficient has been modified on embed the watermark bit as described in the previous step.
Step6: Perform the inverse DWT on the DWT transformed image, including the modified coefficient, to produce the watermarked image. The flowchart of watermark embedding process is shown in Figure 7.

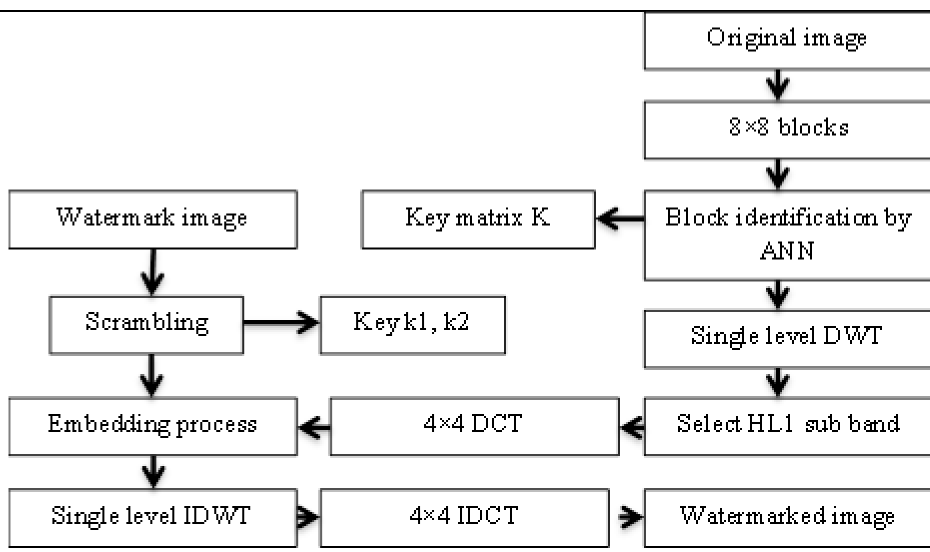


Figure 7. Flowchart of watermark embedding process

Watermark extracting process

Step1: Partition the watermarked image into the 8×8 blocks, and base on matrix Key K select the most appropriate image blocks.
Step2: Apply single level of DWT on image block, and gain the HL1 sub band frequency
Step3: Perform DCT on HL1 sub band and select two DCT coefficients in coordinates (1, 2), and (2, 1).
Step4: Extract the scrambled watermark bit base on the following equation:

$$W'(k) = \begin{cases} 0 & DCT(1,2) > DCT(2,1) \\ 1 & DCT(1,2) < DCT(2,1) \end{cases} \quad (11)$$

Step5: Convert the extracted scrambled watermark sequence $W'(k)$ into watermark image and descramble the watermark image, considering key k1, k2, and obtain the extracted watermark image respectively. The flowchart of watermark extracting process is shown in Figure 8.

IMPLEMENTATION RESULTS AND COMPARISON

To evaluate the performance of watermarking algorithm, some kinds of watermarking attack are performed on watermarked image. We test the algorithm with different attacks such as JPEG compression, JPEG2000 compression, amplitude scaling, low pass filter, median pass filter, salt and pepper, and Gaussian noises. It is necessary to explain briefly these attacks for more clarity of implementation results of watermarking algorithm. After reviewing the watermarking attacks, the experimental results and comparisons will be considered.

Watermarking attacks

- JPEG compression attack

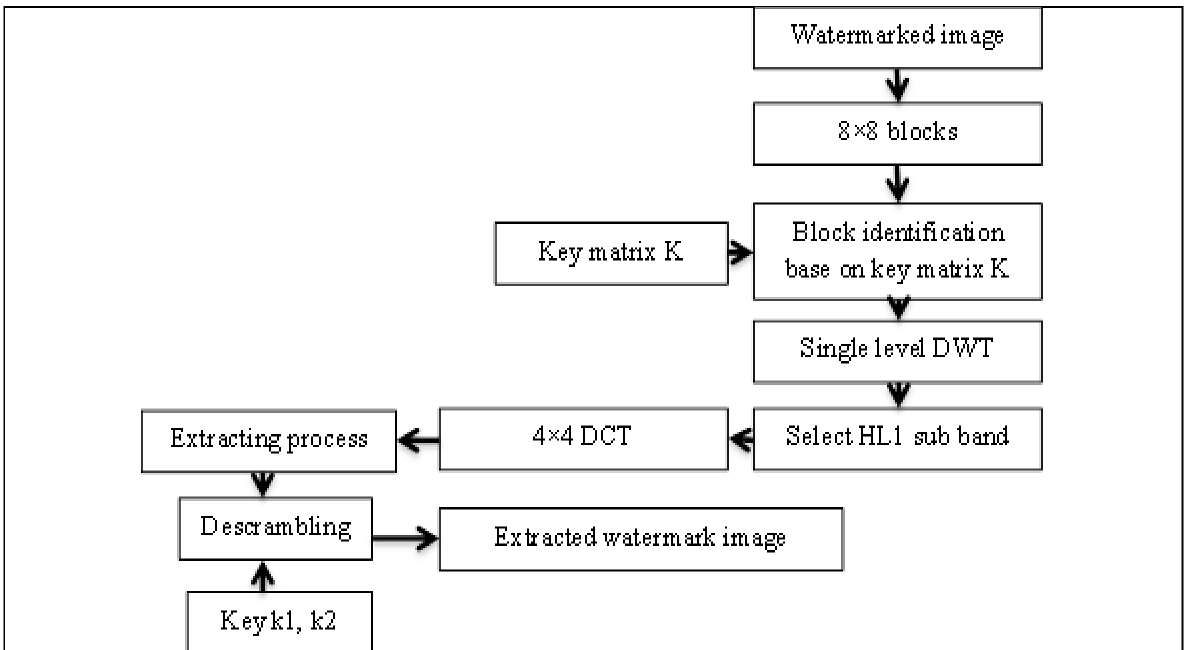


Figure 8. Flowchart of watermark extracting process

The algorithm behind JPEG is relatively straightforward and can be explained through the following steps [17]:

1. Take an image and divide it up into 8×8 pixel blocks. If the image cannot be divided into 8×8 blocks, then you can add in empty pixels around the edges, essentially zero-padding the image.
2. For each 8×8 block, get image data such that you have values to represent the color at each pixel.
3. Take the Discrete Cosine Transform (DCT) of each 8×8 block.
4. After taking the DCT of a block, matrix multiply the block by a mask that will zero out certain values from the DCT matrix base on mentioned quality factor.

5. Finally, to get the data for the compressed image, take the inverse DCT of each block. All these blocks are combined back into an image of the same size as the original.

- JPEG2000 compression attack

We not decide to explain the JPEG2000 completely, it is available in [18], but the brief operation flow of a typical JPEG 2000 compression can be shown in Figure 7. After the wavelet transform, all wavelet coefficients are uniformly quantized according to the rule:

$$Q(m,n) = \mathrm{sign}(DWT(m,n)) \times \left\lfloor \frac{|DWT(m,n)|}{\partial} \right\rfloor \qquad (12)$$

Where $Q(m,n)$ is the quantization factor, and ∂ is the quantization step size.$\lfloor \quad \rfloor$, is the floor function. Following the quantizing, each sub band coefficient of DWT, is then independently encoded through a sub bit plane entropy coder, The embedded bit stream of the code-blocks are assembled by the bit stream assembler module to form the compressed bit stream of the image. The JPEG2000 compression is a complicated issue. More details about this kind of attack are available in [18].

- Amplitude scaling attack

Spatial size scaling of an image can be obtained by modifying the Cartesian coordinates of the source image according to the equation:

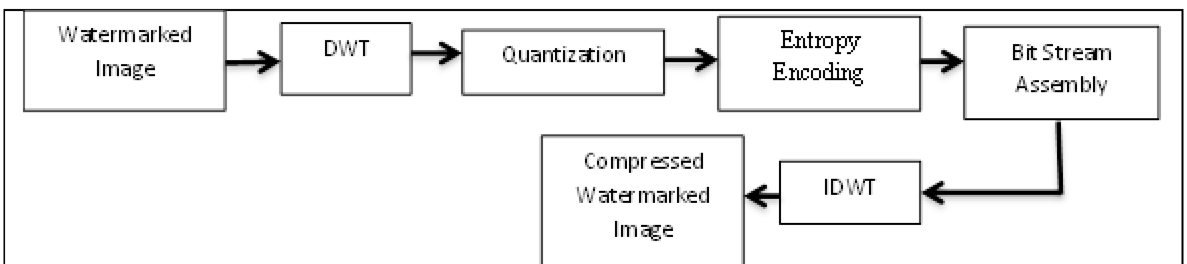


Figure 7. JPEG2000 compression flow chart attack

$$X = \beta . x \, , Y = \beta . y \qquad (13)$$

Where β is positive-valued scaling constant, but not necessarily integer valued. If X and Y are each greater than maximum coordinate of watermarked image, the address computation will lead to magnification.

- Low pass filter attack

A low pass filter is the basis for most smoothing methods. An image is smoothed by decreasing the disparity between pixel values by averaging nearby pixels. Using a low pass filter tends to retain the low frequency information within an image while reducing the high frequency information, by the matrix multiplication with the following 3 by 3 matrix:

$$\text{Low Pass filter matrix: } \begin{bmatrix} 1/9 & 1/9 & 1/9 \\ 1/9 & 1/9 & 1/9 \\ 1/9 & 1/9 & 1/9 \end{bmatrix} \qquad (14)$$

- Median pass filter attack

The median filter considers each pixel in the image in turn and looks at its nearby neighbors to decide whether or not it is representative of its surroundings, it replaces pixel with the median of those values. The median is calculated by first sorting all the pixel values from the surrounding neighborhood into numerical order and then replacing the pixel being considered with the middle pixel value. (If the neighborhood under consideration contains an even number of pixels, the average of the two middle pixel values is used.)

- Gaussian noise attack

The Gaussian noise, changes the pixel value of image in the coordinate (x, y) base on the following equation:

$$G(x,y) = \frac{1}{2\pi\lambda\sigma^2}\exp\left\{-\frac{(\frac{x}{\lambda})^2 + (\frac{y}{\lambda})^2}{2\sigma^2}\right\} \quad (15)$$

Where σ is the Gaussian spread factor and λ is the aspect ratio between the x and y coordinates.

- Salt and pepper noise attack

Salt and pepper noise is a bipolar impulse like noise i.e. the noise impulses can take very high positive (or negative) values. Since scaling is a part of image digitizing process, the corrupted intensity values (very high positive and negative) are digitized as extreme values i.e. either 255 (pure white salt) or zero (pure black - pepper) in the 8-bit gray image

EXPERIMENTAL RESULTS AND COMPARISONS

The original watermark image is shown in Figure 9. Three original and watermarked images with size 512×512 have been shown in Figures 10-12, Barbara, Cameraman, and Baboon images have been used to implement the watermarking algorithm. Original Watermark is a binary image and its size is 32 × 32. Extracted watermarks after some kinds of attack on mentioned watermarked images for Barbara, Cameraman, and Baboon have been shown in Figures 13-15. The performed attacks on the watermarked images are as follows: JPEG compression with quality factors 10%, 25%, 50%, 75%, JPEG2000 compression, amplitude scaling, low pass filter, median pass filter, salt and pepper, and Gaussian noises. The estimate of similarity between the extracted watermark image and the original watermark image according to equation (16), along the peak signal to noise ratio (PSNR) of watermarked image and Original image, to equation (17), were calculated having performed each one of the mentioned attacks on the watermarked image of Barbara, Cameraman, , and Baboon, the results have been integrated in tables 1-3.

$$SIM(W, W') = \frac{W.W'}{W.W} \quad (16)$$

$$PSNR = 10\log\left(\frac{255}{\sum_{i,j} I(i,j) - I_w(i,j)}\right)^2 \quad (17)$$

In equation (16) 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.

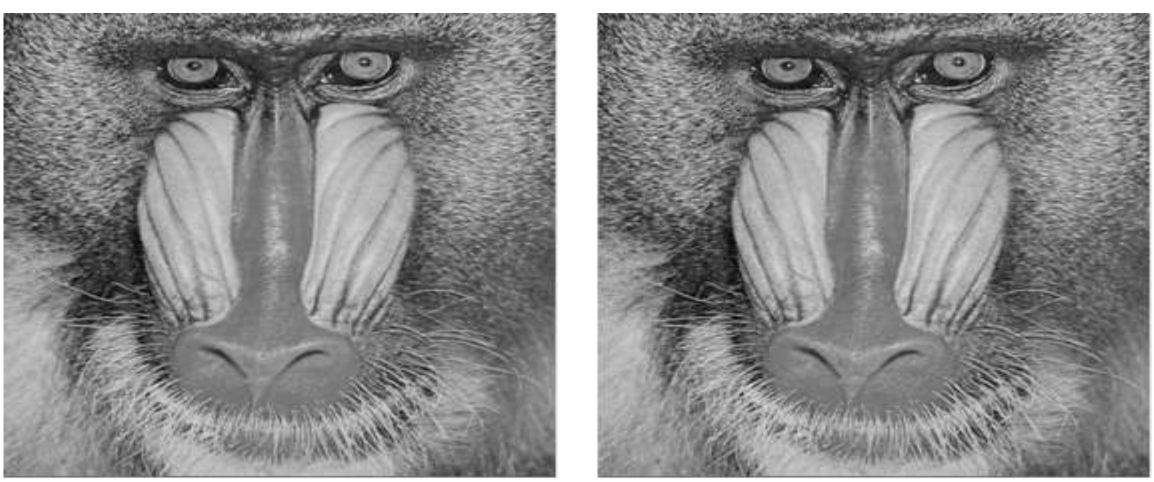
Figure 9. Watermark image

Original Barbara Image　　Watermarked Barbara Image

Figure 10: Original and watermarked Barbara images

Original Cameraman Image　　Watermarked Cameraman Image

Figure 11: Original and watermarked Cameraman images



Original Baboon Image　　Watermarked Baboon Image

Figure 12: Original and watermarked Baboon images

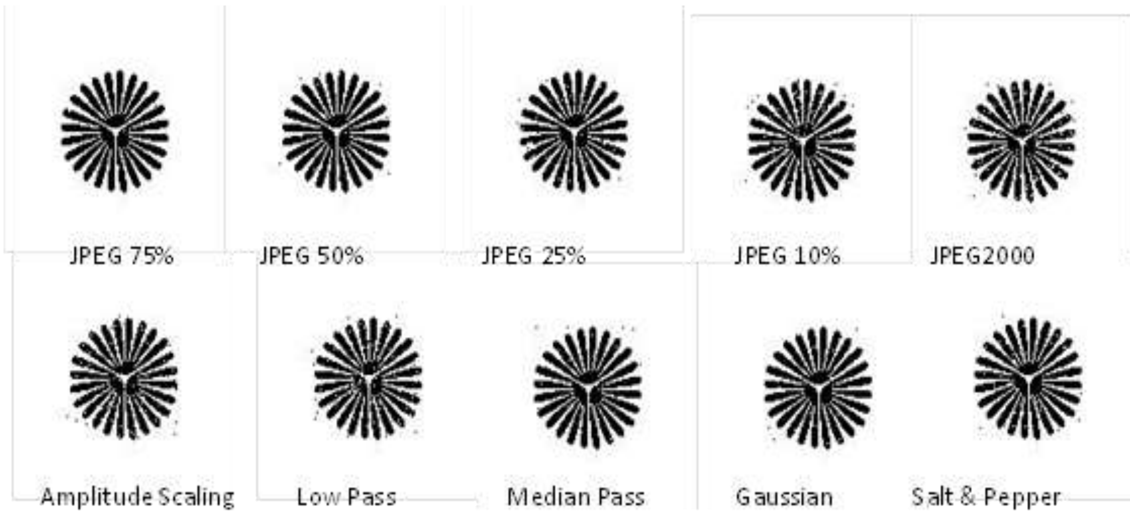


Figure 13: Separated Extracted Watermark images versus some kinds of watermarking attacks for watermarked Barbara image

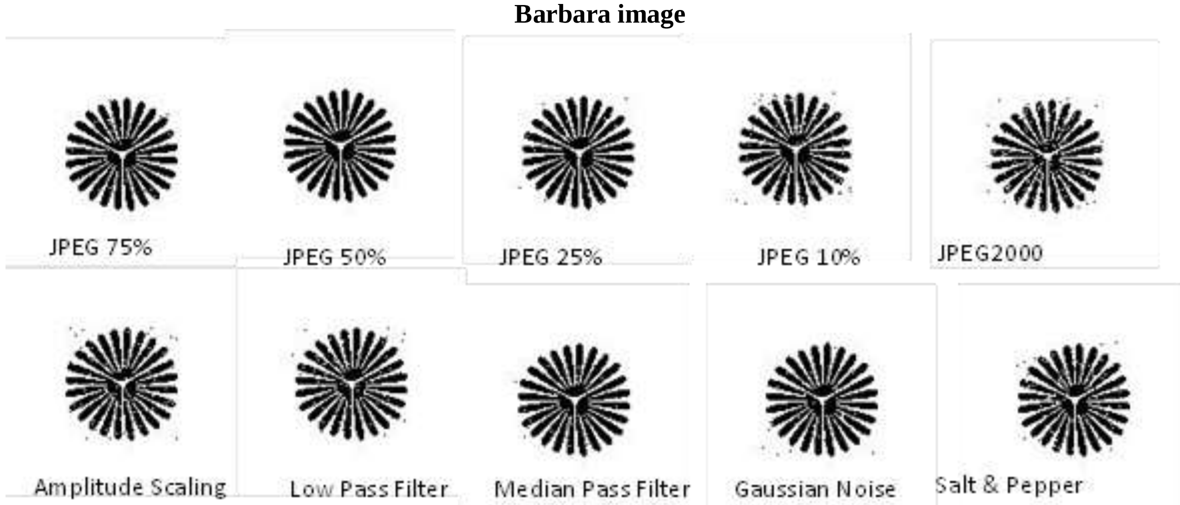


Figure 14: Separated Extracted Watermark images versus some kinds of watermarking attacks for watermarked Cameraman image

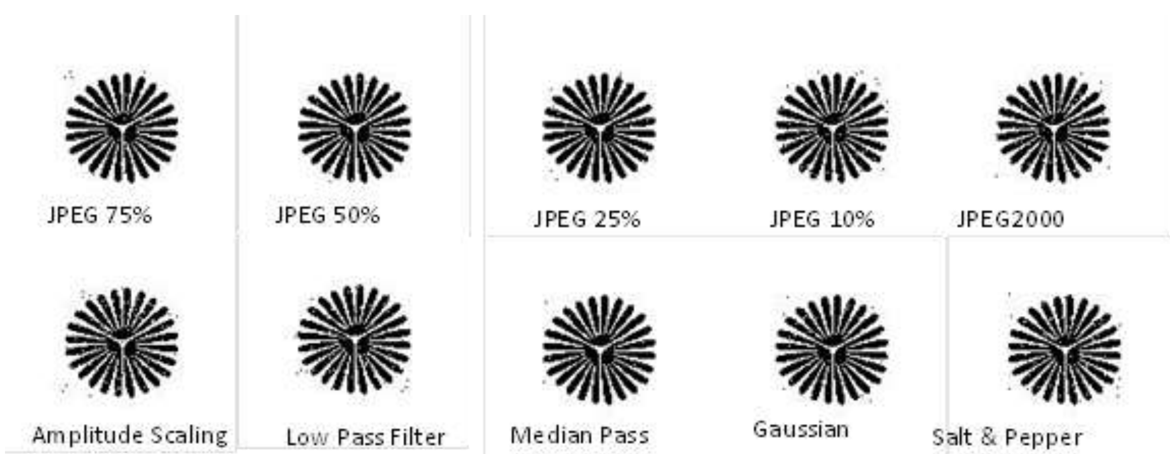


Figure 15: Separated Extracted Watermark images versus some kinds of watermarking attacks for watermarked Baboon image

Table 1: Implementation results and comparison for Barbara image

Kind of attack	Proposed method		Method in [19]	
	SIM	PSNR	SIM	PSNR
JPEG 75%	97.5	39.0	98.9	37.4
JPEG 50%	95.8	38.2	98.1	35.8
JPEG 25%	93.8	36.9	94.5	34.7
JPEG 10%	89.9	32.6	91.2	28.2
JPEG2000	88.7	25.1	88.1	19.4
Amplitude Scaling ($\boldsymbol{\beta} = \mathbf{5}$)	81.0	17.5	86.3	20
Low Pass Filter	88.8	29.0	92.8	25.3
Median Pass Filter	97.6	34.7	95.7	27.4
Gaussian Noise	92.3	31.3	98.3	27.0
Salt And Pepper Noise	89.0	22.8	-	-

Table 2: Implementation results and comparison for Cameraman image

Kind of attack	Proposed method		Method in [20]	
	SIM	PSNR	SIM	PSNR
JPEG 75%	97.7	39.3	-	-
JPEG 50%	95.6	39.0	93.7	37.2
JPEG 25%	92.2	36.4	90.0	33.0
JPEG 10%	90.0	35.4	87.2	24.2
JPEG2000	87.1	29.0	83.7	22.0
Amplitude Scaling ($\boldsymbol{\beta} = \mathbf{5}$)	82.1	26.8	84.5	27.3
Low Pass Filter	89.5	30.0	92.5	31.0
Median Pass Filter	94.2	36.2	88.1	30.7
Gaussian Noise	93.7	31.5	94.4	32.15
Salt And Pepper Noise	88.5	27.5	-	-

Table 3: Implementation results and comparison for Baboon image

Kind of attack	Proposed method		Method in [19]	
	SIM	PSNR	SIM	PSNR
JPEG 75%	97.0	40.5	97.9	37.2
JPEG 50%	97.0	39.8	96.8	34.5
JPEG 25%	94.5	38.8	91.7	32.1
JPEG 10%	91.7	33.4	88.3	26.1
JPEG2000	89.6	27.1	85.1	19.2
Amplitude Scaling ($\boldsymbol{\beta} = \mathbf{5}$)	82.4	20.7	83.0	18.4
Low Pass Filter	93.9	35.3	89.0	25.0
Median Pass Filter	97.5	32.9	95.2	28.8
Gaussian Noise	94.0	35.3	93.7	27.5
Salt And Pepper Noise	90.1	32.5	-	-

CONCLUSION

Watermarking is a popular method in order to protect the copyright while permitting to access the media content. To save the transparency and robustness, much work has been done. In this paper we intended to propose a method to find places of an image which are more suitable for watermarking. This was done by exploiting the visual properties of human eye to train an ANN. This multi-layer network gets some related features and predicts the proper blocks for embedding watermark. Using the trained ANN, the publisher can chose non perceptual blocks with minor preprocessing. Thus working of Combined DCT-DWT Digital Watermarking Technique is explained in this paper. The DCT and DWT provide high robustness and imperceptibility to the image. This watermarking algorithm provides security, copyright protection and data authenticity to image. In this paper, it also describes a digital image watermarking algorithm based on combining two transforms; DWT and DCT. Watermarking is done by altering the wavelets coefficients of carefully selected DWT sub-bands, followed by the application of the DCT transform on the selected sub-bands.

REFERENCES

[1]. Ming-Shing Hsieh (2010), Perceptual Copyright Protection using multiresolution Wavelet Based Watermarking and Fuzzy Logic, International Journal of Artificial Intelligence & Applications, 1(3).
[2]. Ali Al-Haj (2007), Combined DWT-DCT Digital Image Watermarking, Journal of Computer Science 3 (9): 740-746.
[3]. Shital Gupta, Dr Sanjeev Jain (2010), A Robust Algorithm of Digital Image Watermarking Based on Discrete Wavelet Transform, Special Issue of IJCCT1(2,3,4) for International Conference.
[4]. Saeed K, Ahmad R. Naghsh-Nilchi (2009), Digital Image Watermarking Based on Joint DWT-DCT, Internationl Journal of Digital Content Technology and its Applications, 3(2).
[5]. S.Oueslati, A. Cherif, (2011), Adaptive Image Watermarking Scheme based on Neural Network", International Journal of Engineering Science and Technology, Tech3: 748-756.
[6]. P. T. Yu, H. H. Tsai, and J. S. Lin (2001), Digital watermarking based on neural networks for color images, Signal Processing, 81: 663-671.
[7]. S. Oueslati, A. Cherif, and B. Solaiman (2011), A Fuzzy Watermarking Approach Based on the Human Visual System, International Journal Of Image Processing, Proc4: 218-231.
[8]. N. Sakr , Copyright protection of learning using wavelet objects using wavelet-based watermarking and fuzzy logic, in Proc. 2006. annual e-learning conference on Intelligent Interactive learning.
[9]. P. Meerwald and A. Uhl (2001), A survey of wavelet domain watermarking algorithms, in Electronic Imaging, Security and Watermarking of Multimedia Contents, 43(14).
[10]. M. Jayalakshmi, S. N. Merchant and U. B. Desai, Digital Watermarking in Contour let Domain, International Conference on Pattern Recognition, pp. 861-864, 2006.
[11]. K. H.Thung, P. Raveendran, A Survay of Image Quality Measures," Technical Postgraduates Conference, pp.1-4, 2009.
[12]. Mahasweta JJoshil, Prof Zankhana H.Shah2(2011), Watermarking in DCT¬ DWT Domain, Interntional Journl of Computer Science and Inonnation Technologies, 2 (2):717-720 .
[13]. Ben Wangl, Jinkou Ding2, Qiaoyan Wenl, Xin Liaol, Cuixiang Liul , An Image Watennarking Algorithm Based on DWT DCT and SVD, Proceedings of IC-NIDC 2009 Conference.
[14]. Ruiling Zhu, Xin Wang. Effient Digital Watennarking in DCT Domain, School of Infonnation Science and Engineering, ShandongUniversity, Jinan, Shandong, 250062, China 2009 Inerntional Forum on Inonnation Technology and Applications.
[15]. Liwei Chen, Mingf Li. A Effective Blind Watennark Algorithm Based on DCT, Proceedings of the 7th World Congress on Inelligent Control and Automation June 25 - 27,2008,Chongqing,China.
[16]. Edi. Pearson, D.K. Arrowsmith, and C.M.Place (1999), An Introduction to Dynamical systems, Cambridge Univ. Press, p. 823
[17]. Matt Marcuss ,"Jpeg Image compression", http:// www.cs.darmouth.edu/mgm/finalreport.pdf, June 2014. M. W. Marcellin, M. Gormish, A. Bilgin, M. P. Boliek, An Overview of JPEG2000, Proc. of the Data Compression Conference, Snowbird, Utah, March 2000, pp. 523-544.
[18]. M. W. Marcellin, M. Gormish, A. Bilgin, M. P. Boliek, An Overview of JPEG2000, Proc. of the Data Compression Conference, Snowbird, Utah, March 2000, pp. 523-544.
[19]. A. Taheri(2014), A Hybrid Digital Image Watermarking based on Discrete Wavelet Transform, Discrete Cosine Transform and General Regression Neural Network, International Journal of Enhanced Research in Science Technology & Engineering, 3(11): 18-28.
[20]. A. Taheri(2014), A New Robust Digital Image Watermarking Based on Statistical Information of Wavelet Coefficients Transform and Back-Propagation Neural Network, International Journal of Enhanced Research in Science Technology & Engineering, 3(10): 145-154.