Enhancements in Digital Image Watermarking using Neural Networks

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Abstract: The proliferation of digitized media due to the rapid growth of networked multimedia systems has created an urgent need for copyright enforcement technologies that can protect copyright. In this paper implementation of three different watermarking algorithms in the frequency domain presents a digital image watermarking based on two dimensional discrete wavelet transform (DWT2), two dimensional discrete cosines transform (DCT2) and two dimensional Discrete tchebichef transform (DTT) and Back propagation Neural Network signal to noise ratio (SNR) and similarity ratio (SR) are computed to measure image quality for each transform. All schemes are tested using images and the simulation results are compared and the comparison shows the best scheme.

Keywords: DCT, DWT, DTT, Back propagation Neural Network, Image watermarking

I. INTRODUCTION

We are living in the era of information where billions of bits of data is created in every fraction of a second and with the advent of internet, creation and delivery of digital data (images, video and audio files, digital repositories and libraries, web publishing) has grown many fold. Since copying a digital data is very easy and fast too so, issues like, protection of rights of the content and proving ownership, arises. Digital watermarking came as a technique and a tool to overcome shortcomings of current copyright laws for digital data. The specialty of watermark is that it remains intact to the cover work even if it is copied. So to prove ownership or copyrights of data watermark is extracted and tested.

A.Watermarking Issues

There are essential factors which make watermarking alogrithm are: (i)Transparency: The most fundamental requirement for any Watermarking method shall be such that it is transparent to the end user. The watermarked content should be consumable at the intended user device without giving annoyance to the user. Watermark only shows up at the watermark-detector device. (ii)Security: Watermark information shall only be accessible to the authorized parties. Only authorized parties shall be able to alter the Watermark content. Encryption can be used to prevent unauthorized access of the watermarked data ii)Ease of embedding and retrieval: Ideally, Watermarking on digital media should be possible to be performed “on the fly”. The computation need for the selected algorithm should be minimum. (iv)Robustness: Watermarking must be robust enough to withstand all kinds for signal processing operations, “attacks” or unauthorized access. Any attempt, whether intentional or not, that has a potential to alter the data content is considered as an attack. Robustness against attack is a key requirement for Watermarking and the success of this technology for copyright protection depends on this. (v)Effect on bandwidth: Watermarking should be done in such a way that it doesn’t increase the bandwidth required for transmission. If Watermarking becomes a burden for the available bandwidth, the method will be rejected. (vi)Interoperability: Digitally watermarked content shall still be interoperable so that it can be seamlessly accessed through heterogeneous networks and can be played on various plays out devices that may be watermark aware or unaware.

B. Classifications of digital watermarking techniques

There are many watermark techniques in terms of their application areas and purposes. And they have different insertion and extraction techniques

II. FRAME WORK AND PARAMETERS

A. Amount of embedded information

This is an important parameter since it directly influences the watermark robustness. The more information one wants to embed; the lower is the watermark robustness. The information to be hidden depends on the application. (i)Watermark embedding strength,(ii) Size and nature of the image (iii)Secret information

B. Distortions and attacks

The harsh term "attack" can be easily justified: an efficient image compression has to suppress or discard perceptually irrelevant information the invisible watermark. A wide range of attacks has been described in the literature . The following four large categories of attacks can be invoked to penetrate a watermarking system (i) Removal attacks (ii) Geometrical attacks (iii) Cryptographic attacks (iv)Protocol attacks

CLASSIFICATION		CONTENT
Inserted media category		Text, image, audio, video
Perceptivity of watermark		Visible, invisible
Robustness of watermark		Robust, semi-fragile, fragile
Inserting watermark type		Noise, Image format
Processing method	Spatial domain	LSB, Random function
	Transform domain	Look-up table, spread spectrum
Necessary data for extraction		Private, semi-private, public

Table 1: Classification of Watermarking according to several viewpoints

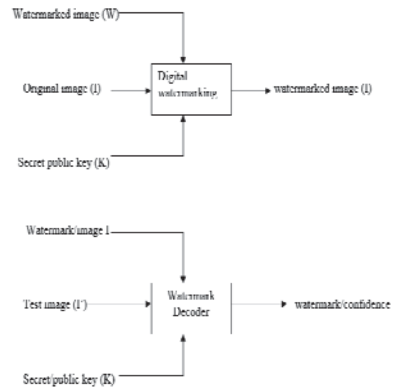

Figure 1. Variables and parameters

III. IMPLEMENTED ALGORITHMS

A. Discrete cosine transform (DCT)

This technique embeds the watermark in the DCT domain to increase the robustness of the watermarking scheme against JPEG compression. The watermark bits are embedded in each n x n DCT block of the image. The embedding algorithm needs to carefully choose where to embed the watermark bits in the n x n block. It is not wise to embed the watermark bits in the low frequency components of the DCT block, because these coefficients are subject to heavy quantization during JPEG compression. Hence, it is better to embed the watermark in mid or high frequency DCT components. If the embedding factor M is chosen small, embedding the watermark in lowest frequency components will be more desirable, because these components are the ones that are least likely to be quantized in JPEG compression.

(a)watermark embedding process

Step 1:Load the image to be watermarked (original image). The size of the original image is 512 × 512.

Step 2: Load the watermark image. The size of the watermark is 64×64.

Step 3: The host image is divided into a number of blocks, the size of each block is 4×4

Step 4:Guarantee that the number of host image blocks is equal to or greater than the number of watermark pixels.

Step 5: Calculate the variance of each block in host image in spatial domain.

Step 6: For each host image block compute the DCT transform coefficients.

Step 7: Select the DC component of blocks which has highest variance, and each watermark pixel Wq(0 or 1) is embedded in the DC component Xdc in order as follow:

$$X'_{dc} = X_{dc} + M \quad \text{if} \quad W_q = 1 \qquad (1)$$

$$X'_{dc} = X_{dc} - M \quad \text{if} \quad W_q = 0 \qquad (2)$$

Where q=1,2,3,………..rc,

Where: rc= size of the watermarked image ,

M is the embedding watermark strength.

Step 8: After embedding the watermark, IDCT transform is applied for each block and then the watermarked image is reconstructed

(b)Watermark extraction process

To obtain the extracted watermark from watermarked image, the following procedure was performed:

Step 1: Original image is used for watermark retrieval, as in the embedding process, original image and watermarked image are divided into a number of 4×4 blocks.

Step 2: Calculate the DCT transform coefficients for each block in both original image and watermarked image.

Step 3: Watermark extraction process is done by comparing the DC coefficient of each two corresponding blocks with the same embedding order (of maximum block variance) as follow:

$$\begin{array}{lll} W'q = 1 & \text{If} & Xw - Xo \geq 0 \\ W'q = 0 & \text{if} & Xw - Xo \leq 0 \end{array} \quad (3)$$

Where Xw is the DC coefficient of the watermarked image, Xo is the DC coefficient of the original image and W'q is the extracted watermark pixel. After extracting the watermark, the normalized cross-correlation (NCC) is calculated to evaluate the effectiveness of our scheme. The normalized cross-correlation is calculated between the original watermark W(i,j), and the extracted one W'(i,j) from this relation :

$$NCC = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}\left[W(i,j).W'(i,j)\right]}{\sum_{i=1}^{M}\sum_{j=1}^{N}\left[W(i,j)\right]^2} \quad (4)$$

As NCC can take values from 0 to 1, and as long as NCC more closed to 1, this means that the extracted watermark is more similar to the original watermark.

B.wavelet transform

As a mathematical tool, wavelets can be used to extract information from many different kinds of data, including – but certainly not limited to – audio signals and images. Sets of wavelets are generally needed to analyze data fully. A set of "complementary" wavelets will deconstruct data without gaps or overlap so that the deconstruction process is mathematically reversible. Thus, sets of complementary wavelets are useful in wavelet based compression/decompression algorithms where it is desirable to recover the original information with minimal loss. The Wavelet analysis is performed using a prototype function called a wavelet, which has the effect of a band pass filter. Wavelets are functions defined over a finite interval and having an average value of zero.

(a)discrete wavelets transform

The discrete wavelet transform can be applied to either 1D and 2D .Based on the wavelet transform is of two types they are

(i)1D Discrete Wavelet Transform (ii) 2D Discrete Wavelet Transform. The wavelet transform describes a multi-resolution decomposition process in terms of expansion of an Image onto a set of wavelet basis functions. Discrete Wavelet Transformation has its own excellent space frequency localization properly. Applying DWT in 2D images corresponds to 2D filter image processing in each dimension. The input image is divided into 4 non-overlapping multi- resolution sub-bands by the filters, namely (LL1), (LH1), (HL1) and (HH1). The sub-band (LL1) is processed further to obtain the next coarser scale of wavelet coefficients, until some final scale “N” is reached. When “N” is reached, we will have 3N+1 sub-bands consisting of the multi-resolution sub-bands (LLN) and (LHX), (HLX) and (HHX) where “X” ranges from 1 until “N”. Generally most of the Image energy is stored in these sub-bands. The Forward Discrete Wavelet Transform is very suitable to identify the areas in the Host image where a stego image can be embedded effectively due to its excellent space- frequency localization properties. In particular, this property allows the exploitation of the masking effect of the human visual system such that if a DWT co-efficient is modified, it modifies only the region corresponding to that coefficient. The embedding secret image in the lower frequency sub-bands (LLX) may degrade the image significantly, as generally most of the Image energy is stored in these sub- bands. Embedding in the low-frequency sub-bands, however, could increase robustness significantly

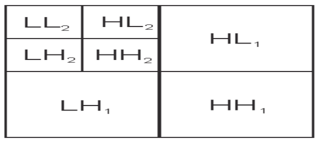

Figure 2: sub-bands of DWT

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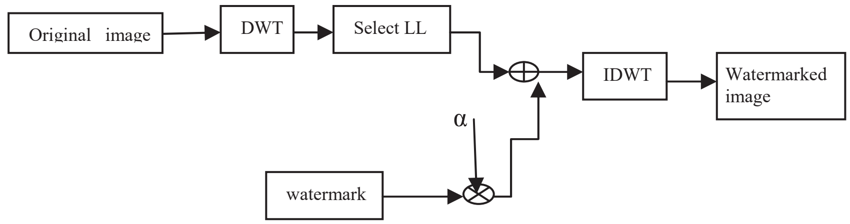


Figure 3: embedding process

In contrast, the edges and textures of the image and the human eye are not generally sensitive to changes in the high frequency sub-bands (HHX). This allows the stego-image to be embedded without being perceived by the human eye. The compromise adopted by many DWT based algorithms, to achieve acceptable performance of imperceptibility and robustness, is to embed the secret image in the middle frequency sub-bands (LHX) or (HLX) and (HHX). The Haar wavelet is also the simplest possible wavelet. Haar wavelet is not continuous, and therefore not differentiable. This property can, however, be an advantage for analysis of signals with sudden transitions.

©embedding process

Step 1:DWT is applied to host image (I_{MXN}) to obtain LL low frequency and three LH, HL and HH high frequency sub bands.

Step 2:The gray values of watermark image to be hidden are obtained into the matrix W_{mxn}.The watermark is scaled with the scaling factor 'k'.

Step 3:The intensity values of scaled watermark are placed into the Mid frequency sub band of the Host image i.e. HL sub band of host image is replaced with W_{mxn}.

Step 4:Inverse DWT is applied to these sub bands LL, LH, W_{mxn} and HH to obtain the Watermarked image(**d)** *(d)extraction process*

Step 1:The DWT decomposes image into single Low and three High frequency sub bands where in the watermark intensity values are the one of the LH, HL and HH sub band of the watermarked image.

Step 2:The sub band where the watermark is embedded is to be divided with the scaling factor 'k' to obtain the watermark.

C.Discrete tchebichef transform (DTT)

Discrete Tchebichef transform is based on a polynomial kernel derived from discrete Tchebichef polynomials. By performing DTT on an image, we transform the pixel intensity values in the spatial domain to the frequency domain. From theandpoint of digital signal processing applications, the importance of DTT is evident. DTT and DCT share many common characteristics such as high energy compaction, near optimal decorrelation and computational tractability. Due to these properties, DTT is useful for transform operations in image and video processing applications like feature extraction, image compression and video coding. The basis function of the 1-DTT is defined as the following recurrence relation in polynomials tp(X) of degree p on a discrete domain X=0,1…..N-1

$$tp(X)=(\alpha_1 X+\alpha_2)t_{p-1}(X)+\alpha_3 t_{p-2}(X) p=2,N-1 \quad (5)$$

$$\text{Where } \alpha_1= (2/p)*(4p2-1/N^2-P^2)^{1/2} \quad (6)$$

$$\alpha_2=(1-N/p)*(4p2-1/N^2-P^2)^{1/2} \quad (7)$$

$$\alpha_3= (p-1/p)*(2p+1/2P-3)^{1/2}*(N^2-(P-1)^2 /N^2-P^2)^{1/2} \quad (8)$$

The starting valves of t0(X) and t1(x) are obtained from following equation to

$$(X)=N^{(-1/2)} t1(X)=(2X+1-N)*(3/N(N^2-1))^{1/2} \quad (9)$$

The 2-D DTT transformation equation can be expressed as

$$T_{pq}=\Sigma_{x=0}^{3}\Sigma_{y=0}^{3} tp(X)tq(y)fi(x,y) \quad (10)$$

$$p,q,x,y=0,1,2,3 \quad (11)$$

The first transformation coefficient is the average valve of the sample sequence. This valve is referred to as the DC coefficient. All other transformation coefficients are called the AC coefficients .DTT can be expressed using a series representation involving matrices as follows

$$f(i,j)= \Sigma_{p=0}{}^{3}\Sigma_{q=0}{}^{3} Tpq\ G\ pq\ (i,j)\ p,q=0,1,2,3 \qquad (12)$$

Where G_{pq} is an 4x4 matrix called a basis images and is defined as p,q=0,1,2,3 Where G_{pq} is an 4x4 matrix called a basis images and is defined as

$$\begin{pmatrix} tp(0)tq(0\ ) & tp(0)tq(1) & tp(0)tq(2) & tp(0)tq(3) \\ tp(1)tq(0) & tp(1)tq(1) & tp(1)tq(2 & tp(1)tq(3) \\ tp(2)tq(0) & tp(2)tq(1) & tp(2)tq(2) & tp(2)tq(3) \\ tp(3)tq(0) & tp(3)tq(1) & tp(3tq(2) & tp(3)tq(3) \end{pmatrix} \qquad (13)$$

IV.BACK PROPAGATION NEURAL NETWORK

A neural network represents a highly parallelized dynamic system with a directed graph topology that can receive the output information by means of reaction of its state on the input nodes. The ensembles of interconnected artificial neurons generally organized into layers of fields include neural networks. The behavior of such ensembles varies greatly with changes in architectures as well as neuron signal functions [2].. Neural networks are classified as feed forward and feedback networks. Back propagation network is of feed forward type. In BPNN the errors are back propagated to the input level.The back propagation network with input, hidden and output layers is shown in figure Bias is applied to both the hidden units and output units. The bias is always set to 1. The aim of this network is to train the net to achieve the balance between the ability to respond correctly to the input pattern that are used for training and the ability to provide good response to the input that are similar.

The weight updating formula for BPNN is

$$Wjk(t+1) = Wjk(t) + \alpha\delta k\ yj + \mu\ [Wjk(t) - Wjk(t-1)] \qquad (14)$$

$$Vij(t+1) = Vij(t) + \alpha\delta j\ xi + \mu\ [Vij(t) - Vij(t-1)] \qquad (15)$$

where Wjk are weights between hidden layer and output layer,Vij are weights between input layer and hidden layer,α is the learning rate parameter , μ is the momentum factor

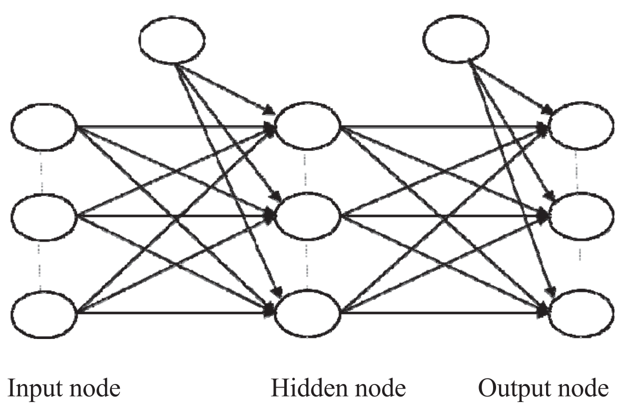


Figure 4 :Back propagation neural network

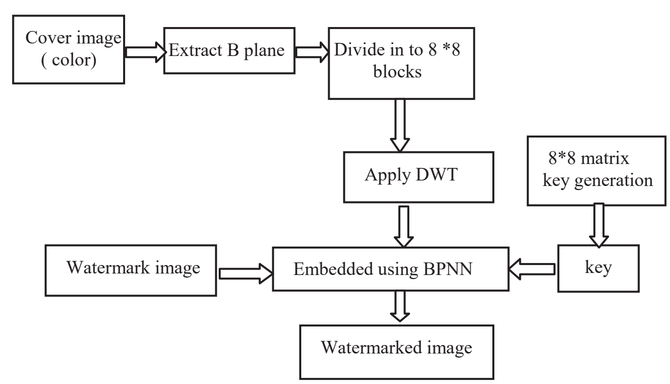


Figure 5 : BPNN Embedding

Back Propagation Neural Network has good nonlinear approximation ability. It can establish the relationship between original wavelet coefficients and watermarked wavelet coefficients by adjusting the network weights and bias before and after embedding watermark. Owning to the use of neural network, we can extract watermark without the original signal and thus reduce the limit in practical applications. Using the neural network based on BPNN algorithm willmeet the problem: how to determine the optimal structure of BPNN namely how to choose the network layers and the number of neurons. If we can't select an appropriate network, it is difficult to significantly improve network performance, even if a large number of improvements have been made to the training algorithm.. The common method of selection is the trial and error method, generally based on experience to select the hidden layer of nodes, is very random. The empirical formula for determining the number of hidden nodes is

$$n = (om + cm + d)^{1/2} \quad (16)$$

Where n is the hidden nodes; 'm' is the number of input nodes; 'o' is the number of output nodes; 'c' & 'd' are the parameters to be determined. In general, the following posterior formula is used.

$$n = (o\,m + 1.6799m + 0.9298)^{1/2} \quad (17)$$

In this project, m = 8, o = 1, n ≈ 4.8 ,taking n = 5 ,The neural network has three layers, there are 8 nodes in input layer, 5 nodes in hidden layer, 1 node in output layer.

A.watermark embedding

The cover image is resized with 512x512 pixels, the R, G and B planes are separated and blue (B) plane is selected to embed watermark. The bitmap is selected as watermark and is resized to 64x64 pixels. The DWT is applied to blue plane of cover image and watermark is embedded in high and middle frequency components. The quantization levels selected as Q1=16 and Q2=6. The back propagation neural network is used to embed and extract watermark. The training process is completed before embedding. After getting the coefficients from the watermark image, the relationship between the high frequency wavelet coefficients and the watermark can be established. The extra information is used to train the neural network to make it sure it must have the capability of memorizing the characteristics of relations between the watermarked image and the watermark. Sigmoid activation function is used in the hidden layer and linear activation function is used in the output layer.

(a)watermark embedding algorithm

Step 1. Read the color image of size NxN.
Step 2. Resize the color image to 512x512 pixels and use it as a cover image. Step 3. Select the Blue (B) plane to embed the watermark.
Step 4. Read the image of size 64x64 as the watermark.
Step5. The frequency subcomponents {HH1, HL1, LH1, {HH2, HL2, LH2},{HH3, LH3, LL3}}} are obtained by computing the third level DWT of the Blue plane of RGB cover image.
Step 6. Select the beginning position of watermark using the secret key.
Step 7. Quantize the DWT coefficient T(j+key) by Q as the input to the BPNN, then get the output of BPNN.
Step 8. Embed the watermark using the following equation
T'(j+key) = BPNN(round((T(j+key))/Q) + xj Where xj is the random watermark sequence.
Step 9. Perform IDWT on each coefficient to get watermarked image.

(b)Watermark extraction

The watermark extraction process is that anti- process of watermark embedding. The trained neural network is used in the extraction process, because neural networks have associative memory which can realize blind detection. The normalized correlation coefficient is used to detect the correlation between the original watermark and extracted watermark.

©Watermark extraction algorithm

Step1. Transform the watermarked image by the DWT.
Step 2. Quantize the DWT coefficient T''(j) by Q, as the input of BPNN, then get the output of BPNN as round[T''(j)/Q].
Step 3. Extract the watermark x' using the equation x'i=T''(j) – BPNN(round(T''(j)/Q)) where j=1 to8.
Step 4. Measure the NC of the extracted watermark x' and the original watermark x.

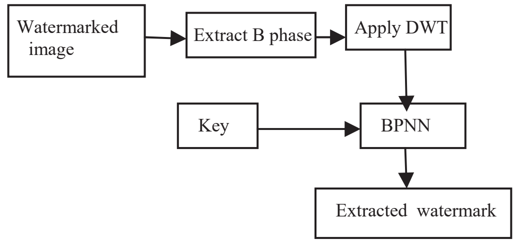


Figure 6:BPNN extraction

V. EVALUATION STANDARDS

In this work the results are evaluated based on Correlation and PSNR for the resultant images. Correlation is watermark image. PSNR and Correlation are the measurements between host image and watermarked image.

A.Correlation

$$NC = \frac{\sum_i \sum_j \left(x_{ij} - \bar{x}\right)\left(x_{ij}' - \bar{x}'\right)}{\sqrt{\left[\sum_i \sum_j \left(x_{ij} - \bar{x}\right)^2\right]\left[\sum_i \sum_j \left(x_{ij}' - \bar{x}'\right)^2\right]}} \quad (18)$$

Correlation (CORR) is defined as the degree through which two image relate to each other. It is calculated between used water mark and the extracted watermark. The normalized Correlation is given by the equation (18)

B.Peak Signal to Noise Ratio (PSNR)

Signal to noise ratio (SNR) effectively measures the quality of the watermarked image as compared to the original image. This difference is represented as an error function that shows how close the watermarked image is to the original image and it is written as shown in equation 4.2.

$$e(x,y) = I(x,y) - Iw(x,y) \quad (19)$$

The larger the value of e (x, y) the greater is the distortion caused by the watermark and the attacks. One of the simplest distortion measures is the mean square error (MSE) function which is given by the formula as shown in equation

PSNR is given by

$$PSNR(Iorg, Iw) = 10 * \log\left(\frac{255^2}{MSE(Iorg, Iw)}\right) \quad (20)$$

Where MSE is mean square error between the original image (I_{org}) and the watermarked one (I_w). The MSE is defined as:Where N is image dimensions. (21)

$$MSE(Iorg, Iw) = \frac{1}{N * N}\sum_{i=0}^{N-1}\sum_{j=0}^{N-1}\left(Iorg(i,j) - Iw(i,j)\right)^2 \quad (21)$$

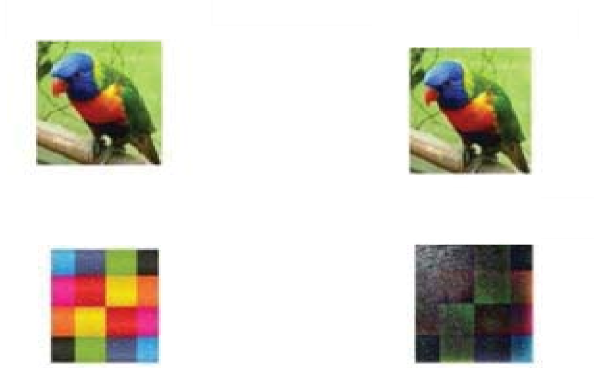
CORR is the two-dimensional Correlation coefficient

VI. RESULTS

A. Discrete Cosine Transform

B. Discrete wavelet transform

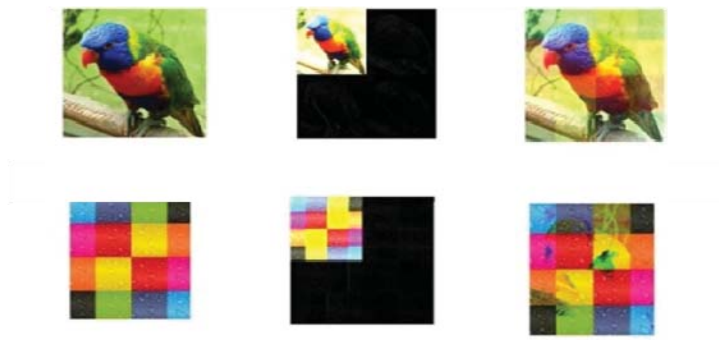
Original Image Watermarked Image



watermark for embedding watermark extracted

Figure 7:Result of Discrete Cosine Transform

Original Image Watermarked Image

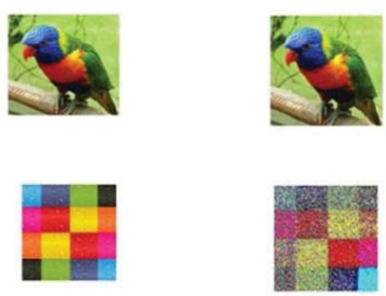


watermark for embedding watermark extracted

Figure 8: Result of Discrete wavelet transform

C. Discrete Tchebichef Transform

Original Image Watermarked Image

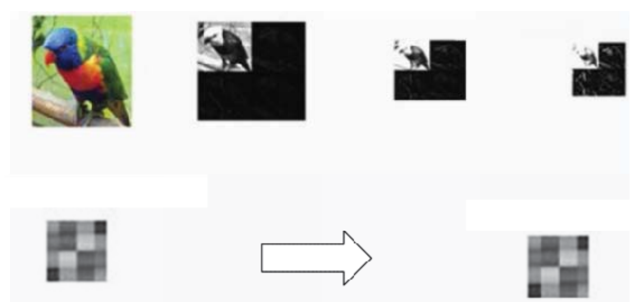


watermark for embedding watermark extracted

Figur91: Result of Discrete Tchebichef Transform

D. BackPropagation Neural Network

Original Image Watermarked Image



watermark for embedding watermark extracted

Figure 10: Result of backpropagation neural network

E.comparision table

Algorithm	PSNR values
Discrete Cosine Transform	38.12
Discrete Wavelet Transform	41.68
Discrete Tchebichef Transform	43.02
Back Propagation Neural Network	48.23

Table 2: Comparison of PSNR values

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