Robust Digital Image Watermarking Technique in DWT domain based on HVS and BPNN

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Abstract

Most of the data distribution or redistribution occurs on the internet either by means of images, documents, videos, etc. But to claim the ownership and copy right protection, some extra information which cannot be removed by intruders is necessary to provide security. Such a security is provided by Watermarking. In this paper, a robust Digital Image watermarking algorithm is projected in Discrete Wavelet Transform domain using back propagation neural networks and Human Visual System Parameters like Luminous sensitivity and Texture sensitivity. Neural Networks are used in embedding and extracting the watermark. The proposed method is more protected and robust to several attacks like: Resizing, Median filtering, Row-Column copying, Low pass filtering, JPEG Compression, Rotation, Salt and Pepper Noise, Cropping, Bit Plane Removal, Blurring, Row-Column blanking, Intensity Transformation, etc. Outstanding experimental outcomes were perceived with the suggested method over a method proposed by Qiao Baoming et al. in terms of Peak Signal to Noise Ratio (PSNR) and Normalized Cross Correlation (NCC).

Keywords: Image Watermarking, Discrete Wavelet Transform, Human Visual System, Back Propagation Neural Networks, Imperceptible, Robust.

1. INTRODUCTION

With the greatest advancement in technology and usage of internet, lossless copying and powerful tools for editing have been emerged. In such a scenario, it is quite necessary to claim the ownership. Digital Image Watermarking is one of the best methods for copyright protection [1,2]. It is a technique in which some secret information called watermark data is embedded in the original image or host image. Then, the watermarked image is detected for watermark for illegal copying, ownership protection etc. [3]. Digital Watermarking provides two basic requirements as robustness and perceptual transparency [4]. The term robustness indicates flexibility of inserted watermark in contrast to distortions and attacks that try to remove the embedded watermark. Perceptual transparency indicates that watermark embedding must not lower the quality of watermarked data [5]. According to watermarking domain, watermarking methods can be classified into spatial domain methods [6] & transform domain methods [7-10].

In order to increase imperceptibility of watermarked image and robustness of watermark, many scholars have made various research based on Neural Network Techniques [11-20].

Asmaa Qasim Shareef et al. [11] suggested a watermarking algorithm based on back propagation based learning algorithm and feed-forward multi-layered neural network. Back-propagation centered learning algorithm is used to get the weights and these weights are inserted within the original cover image, which was processed from noise by the Gaussian filter. Maryam Karimi et al. [12] described a transparent image signal watermarking method centered on psychovisual properties using Multi-Layer Feed-forward (MLF) neural networks. The blocks which are less detectable by human eye are identified by using MLF neural networks and they are used for embedding the watermark. Mohamad Vafaei et al. [13] projected a method based on wavelet coefficient quantization using artificial neural networks. A digital watermarking algorithm based on feed-forward neural networks was presented. Sameh Oueslati et al. [14] suggested an adaptive image signal watermarking method centered on the Human Visual System (HVS) model and neural network method. This method uses Back Propagation Neural Network for embedding the watermark are fed to neural network as input and target vectors.

N. Mohananthini et al. [15] presented a digital image signal watermarking method centered on Back-Propagation Neural Networks (BPNN) & Human Visual System. Using improved BPNN, watermark image is embedded into Discrete Wavelet Transform (DWT), which can reduce the error and improve the rate of the learning; trained neural networks are used to rebuild the watermark image signal from the watermarked image. Qiao Baoming et al. [16] projected a watermarking method centered on Back Propagation Neural Network (BPNN) and Discrete Wavelet Transform (DWT). 2-level DWT is applied to host cover image. Blocks are selected based on standard deviation values. Block values are fed to network as input and target vectors.

Yonghong Chen et al. [17] proposed an image watermarking scheme combining backpropagation neural network, error correction coding and chaotic sequence in wavelet transform domain. The wavelet transform domain of cover image is first divided into set of blocks, and later different back propagation neural network simulations for every selected block are exercised to remember relationship between samples and equivalent sub sequence is separated from a processed disordered sequence. The watermark image is embedded by varying a small number of wavelet transform coefficients. Song Huang et al. [18] projected an image watermarking scheme based on Image features, fractional dimension technique to form the watermark and back propagation neural networks. The watermark used is fusion of a binary image and image feature label and obtained by investigating the image fractal dimension. This watermark is scrambled by using Arnold transform and inserted into the multi wavelet transformed cover image. Back propagation neural network was applied to increase the transparency and robustness.

This paper is a modified watermarking method using Human Visual System parameters for inserting the watermark image established on scheme projected by Qiao Baoming et al. [16] in which, coefficients of 3x3 non overlapping blocks are chosen as inputs to neural networks. But the Proposed method makes use of HVS parameters like Luminous and Texture sensitivity values as inputs which gives better imperceptibility and robustness.

The rest of the document is planned as follows: Section 2 illustrates Preliminaries about Discrete Wavelet Transform & Back Propagation Neural Network. Section 3 describes the suggested watermarking scheme. Experimental results are presented in section 4. Conclusions are specified in section 5.

2. PRELIMINARIES

2.1 Discrete Wavelet Transformation (DWT)

DWT is most suitable for transient, time varying signals because the wavelets obtained after DWT have their energy focused in time and most of the real life signals vary with time; hence DWT is presently applied in wide range of signal processing usages such as in video & audio

compression, elimination of noise in audio etc. The elementary thought of Discrete Wavelet Transform in image processing is to decay the image into sub image of dissimilar spatial domains & independent frequencies. After DWT transformation, four wavelets as (LL, LH, HL, HH) bands are obtained. This is single level or 1-level DWT. The low-frequency wavelet data can be again decayed into sublevel frequency wavelet data of LL2, HL2, LH2 and HH2 respectively. Similarly any wavelet can be further decomposed. In this paper, HH band is further decomposed into three sub levels as shown in Figure 1. So, the host image can be disintegrated for n level wavelet conversion.



FIGURE 1: DWT Wavelets after Transformation.

2.2 Back Propagation Neural Network (BPNN)

BPNN is one of the artificial neural network. The Artificial Neural Network is a data handling system with features called neurons to process the information content. The signals are spread by ways of the connection links with accompanying weight that is multiplied with arriving signal to obtain the net input for any typical neural network. The output signal is acquired by employing activation to the net input. Back Propagation provides an efficient method for changing weights by back propagation of errors in a feed forward network. Figure 2 shows back propagation neural network.



FIGURE 2: Back Propagation Neural Network.

In this network the total squared error of output is reduced by gradient descent method acknowledged as back propagation or generalized delta rule. The increase in number of hidden layers result in the computational difficulty of network and hence time taken to reduce the error may be very high.

The back propagation training algorithm has four stages:

- 1. Initializing the weights
- 2. Feed forwarding
- 3. Back propagating the errors
- 4. Updating the biases and weights

The bias acts like weights on the linking from units whose output is always 1. During initialization of weights, some arbitrary values are given initially to give some output by feed forwarding through the layers. So, the difference between the obtained and actual values is calculated as error and back propagated. High initial weight will result in fast learning rate. But weights may oscillate. If initial weights are too small, then learning rate will be slow. For best results, initial weights may be considered between -0.5 to 0.5 or -1 to 1.

3. THE PROPOSED METHOD

The proposed scheme involves watermark insertion & extraction schemes which are given below:

3.1 Watermark Embedding

1. The host image is a gray level image of dimension 512x512 pixels.

2. The binary image of dimension 32x32 pixels is chosen as watermark.

3. One level DWT is employed on host image and cD1 is split into 3x3 non-overlapping blocks.

4. 1024 blocks are selected based on their standard deviation values (in ascending order).

5. The selected block numbers is provided as secret key1 that is used for extraction of watermark.

6. HVS parameters like Luminance and Texture sensitivity are calculated for the selected 1024 blocks.

7. These are fed as input to neural network and centre element of each block as target vector.

8. Centre element from each block is chosen for embedding watermark.

9. Embedding formula is as follows

$$C'=C + (2^{*} \alpha) + 1)^{*}(2^{*}(wok)-1)$$
(1)

Where α is adaptive weight of watermark (BPNN output), C is center coefficient and wok is watermark bit.

10. One level IDWT is employed to obtain the watermarked image.

3.2 Watermark Extraction

1. 1-level DWT is applied to watermarked image and cD1 is divided into 3x3 non-overlapping blocks.

2. Based on the key1, 1024 blocks are selected.

3. For the selected blocks, Centre value in each block is provided to BPNN as target vector, and HVS parameters like Luminance and Texture sensitivity of selected 1024 blocks are fed as input vector.

4. By using some additional information and BPNN output, watermark can be extracted by using reverse embedding equation.

Extracted watermark= (emb-obt)/
$$(4*y1+2) + 0.5$$
 (2)

Where 'emb' is matrix of 1024 elements after embedding, 'obt' is obtained 1024 elements matrix during extraction and y1 is output from neural network.

The Peak Signal to Noise Ratio (PSNR) and Normalized Cross correlation (NCC) are exploited to test the working of the proposed algorithm. Let us consider the cover image signal of size MxM be denoted as g(i,j) and let the watermarked signal equivalent be G(i,j). Then the PSNR is known by

$$\mathsf{PSNR} = 10 \log_{10} \left(\frac{\sum_{i=1}^{M} \sum_{j=1}^{M} (g(i,j))^2}{\sum_{i=1}^{M} \sum_{j=1}^{M} (g(i,j) - g(i,j))^2} \right)$$
(3)

Watermark signal is symbolized by wm(i,j) & let recovered watermark signal be symbolized by w'm(i,j), then the NCC is given as

$$NCC = \frac{\sum_{i=1}^{M} \sum_{j=1}^{M} (wm(i,j) - wmean) (w'm(i,j) - wmean)}{\sqrt{\sum_{i=1}^{M} \sum_{j=1}^{M} (wm(i,j) - wmean)^2 \sum_{i=1}^{M} \sum_{j=1}^{M} (w'm(i,j) - wmean)^2}}$$
(4)

In Eq. (4), Wmean & W'mean specify the average of the unique watermark and removed watermark signals correspondingly.

4. EXPERIMENTAL RESULTS

Experimentations are conducted to assess the performing of the algorithm using cover gray-scale images 'LENA', 'PEPPERS' and 'MANDRILL' which are shown in Figure 3.





FIGURE 3: 512x512 (a) Lena, (b) Peppers and (c) Mandrill (Host Images).

The host images are of sizes 512×512 pixels. The size of watermark image signal of 32×32 pixels is a logo represented with the letters 'ECE' as shown in figure 4.

ECE

FIGURE 4: Watermark Image.

In Figure 5 Watermarked Lena, Peppers and Mandrill are shown.



FIGURE 5: 512x512 Watermarked (a) Lena (47.69dB), (b) Peppers (45.78dB) and Mandrill (37.25dB).

Different attacks that are exploited to assess the robustness of the watermarked image signal are Low pass filtering, Resizing, Row-Column copying, Rotation, JPEG Compression, Salt and Pepper Noise, Cropping, Median filtering, Gamma correction, Bit Plane Removal, Blurring, Row-Column blanking, Histogram equalization, Intensity Transformation. All these attacks were experimented using MATLAB 7.8.0. Peak Signal to Noise Ratio (PSNR) and Normalized Cross correlation (NCC) are exploited as the performance metric to evaluate the transparency and robustness and are synopsized in Tables 1, 2 and 3. Extracted watermark images from the watermarked images are shown in Table 4.

Type of Attack	Qiao Baoming et al. [16] method		Proposed method	
	PSNR in dB	NCC	PSNR in dB	NCC
No attack	47.73	0.9742	47.69	0.9995
Median Filtering	41.04	0.4998	41.16	0.8884
Resize (512-256-512)	40.07	0.5206	40.12	0.9239
Row-Column blanking	31.47	0.0524	31.47	0.9453
Row-Column copying	38.10	0.1744	38.10	0.8426
Rotation	37.15	0.5579	28.01	0.9017
JPEG Compression (QF:90)	44.27	0.6350	45.08	0.8821
Low pass Filtering (3x3 Kernel)	37.87	0.1248	37.95	0.9244
Salt & Pepper Noise(0.001)	40.96	0.3554	40.46	0.9846
Cropping	18.48	0.0070	18.48	0.9661
Gamma Correction(0.9)	19.27	0.8167	19.28	0.9492
Bit plane removal	46.09	0.7258	46.17	0.8971
Histogram Equalization	25.14	0.4388	25.12	0.8436
Blurring	41.16	0.6299	41.37	0.9222
Intensity Transformation	28.05	0.7404	28.06	0.9466

TABLE 1: Comparison of PSNR and NCC values for Lena image with Qiao Baoming et al. [16] scheme and the proposed method.

Type of Attack	Qiao Baoming et al.[16] method		Proposed method	
	PSNR in dB	NCC	PSNR in dB	NCC
No attack	43.13	0.9822	45.78	0.9984
Median Filtering	39.96	0.3930	40.90	0.8657
Resize (512-256-512)	37.92	0.4308	38.01	0.9113
Row-Column blanking	32.28	0.0998	32.44	0.5953
Row-Column copying	36.71	0.1998	37.15	0.5579
Rotation	27.69	0.1559	27.73	0.8919
JPEG Compression (QF:90)	41.08	0.6007	43.54	0.8002
Low pass Filtering (3x3 Kernel)	37.38	0.1759	37.62	0.9096
Salt & Pepper Noise(0.001)	39.23	0.2636	39.53	0.9775
Cropping	17.81	0.0960	17.81	0.9579
Gamma Correction(0.9)	19.94	0.6274	19.97	0.9242
Bit plane removal	42.57	0.7474	44.76	0.8718
Histogram Equalization	24.59	0.3889	24.60	0.7370
Blurring	39.21	0.5043	39.91	0.8751

Intensity Transformation	27 37	0 8178	27 38	0 9539
interienty manererination	2.101		1.100	0.0000

TABLE 2: Comparison of PSNR and NCC values for Peppers image with Qiao Baoming et al. [16] scheme
and the proposed method.

Type of Attack	Qiao Baoming et al. [16] method Pro		Proposed	Proposed method	
	PSNR in dB	NCC	PSNR in dB	NCC	
No attack	34.39	0.9714	37.25	0.9928	
Median Filtering	29.34	0.0968	29.77	0.8512	
Resize (512-256-512)	29.59	0.0527	29.67	0.8360	
Row-Column blanking	28.96	0.0274	29.59	0.3334	
Row-Column copying	32.81	0.4406	34.56	0.9424	
Rotation	26.99	0.1472	27.26	0.8845	
JPEG Compression (QF:90)	33.86	0.5242	36.37	0.6996	
Low pass Filtering (3x3 Kernel)	29.06	0.0750	29.30	0.7753	
Salt & Pepper Noise(0.001)	33.68	0.3421	36.02	0.9905	
Cropping	17.79	0.1499	17.81	0.9634	
Gamma Correction(0.9)	18.89	0.2963	18.95	0.9467	
Bit plane removal	34.32	0.7733	37.08	0.9269	
Histogram Equalization	23.11	0.1582	23.35	0.8069	
Blurring	30.42	0.1066	31.02	0.8502	
Intensity Transformation	25.21	0.2377	25.58	0.9300	

TABLE 3: Comparison of PSNR and NCC values for Mandrill image with Qiao Baoming et al. [16] scheme and the proposed method.

Type of attack	Watermarked image Type			
	Lena	Peppers	Mandrill	
No attack	ECE	ECE	ECE	
	NCC: 0.9995	NCC:0.9984	NCC:0.9928	
Median Filtering	ECE	ECE	ECE	
Modian i intering	NCC: 0.8884	NCC: 0.8657	NCC: 0.8512	
Resize (512-256-512)	ECE	ECE	ECE	
	NCC: 0.9239	NCC: 0.9113	NCC: 0.8360	
Row-Column blanking	ECE	ECE	ECE	
	NCC: 0.9453	NCC: 0.5953	NCC: 0.3334	
Row-Column copying	ECE	ECE	ECE	
	NCC: 0.8426	NCC: 0.5579	NCC: 0.9424	

Rotation	ECE	ECE	ECE
	NCC: 0.9017	NCC: 0.8919	NCC: 0.8845
JPEG Compression (QF:90)	ECE	ECE	ECE
	NCC: 0.8821	NCC: 0.8002	NCC: 0.6996
Low pass Filtering	ECE	ECE	ECE
	NCC: 0.9244	NCC: 0.9096	NCC: 0.7753
Salt & Pepper Noise(0.001)	ECE	ECE	ECE
	NCC: 0.9846	NCC: 0.9775	NCC: 0.9905
Cropping	ECE	ECE	ECE
	NCC: 0.9661	NCC: 0.9579	NCC: 0.9634
Gamma Correction(0.9)	ECE	ECE	ECE
	NCC: 0.9492	NCC: 0.9242	NCC: 0.9467
Bit plane removal	ECE	ECE	ECE
	NCC: 0.8971	NCC: 0.8718	NCC: 0.9269
Histogram Equalization	ECE	ECE	ECE
	NCC: 0.8436	NCC: 0.7370	NCC: 0.8069
Blurring	ECE	ECE	ECE
	NCC: 0.9222	NCC: 0.8751	NCC: 0.8502
Intensity Transformation	ECE	ECE	ECE
	NCC: 0.9466	NCC: 0.9539	NCC: 0.9300

TABLE 4: Extracted Watermarks from the watermarked image.

The bar plot in Figure 6 shows the PSNR values for proposed method and Qiao Baoming et al. [16] algorithm.



FIGURE 6: PSNR Values of watermarked test images.

The plots in Figures 7, 8 and 9 displays the NCC values for the extracted watermark from test images when image processing attacks are applied to it along with the NCC values from Qiao Baoming et al. [16].



FIGURE 7: NCC values of the extracted watermark under various attacks from the watermarked Lena image.



FIGURE 8: NCC values of the extracted watermark under various attacks from the watermarked Peppers image.



FIGURE 9: NCC values of the extracted watermark under various attacks from the watermarked Mandrill image.

5. CONCLUSIONS

In this paper, an algorithm centered on Discrete Wavelet Transform and Back Propagation Neural Network using Human Visual System parameters like Luminous sensitivity and Texture sensitivity has been presented. HVS parameters usage as inputs to the neural network and DWT gives better performance as compared to neighboring coefficients as inputs as in Qiao Baoming et al. [16] method. The projected algorithm is extremely robust and sustained many image processing attacks. Using other Artificial Intelligence techniques like Fuzzy and Hybrid Intelligence Techniques, robustness and imperceptibility can be improved.

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