International Journal of Enhanced Research in Science Technology & Engineering, ISSN: 2319-7463
Vol. 3 Issue 10, October-2014, pp: (184-191), Impact Factor: 1.252, Available online at: www.erpublications.com

An Adaptive Digital Image Watermarking Based on Image Features in Discrete Wavelet Transform Domain and General Regression Neural Network

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ABSTRACT: In this paper, a new intelligent, robust and adaptive digital watermarking technique for gray image based on combination of discrete wavelet transform (DWT), human visual system (HVS) model and general regression neural network (GRNN) is proposed. Wavelet coefficients are analyzed by a HVS model to select suitable coefficients for embedding the watermark. The watermark bits are extracted from the watermarked image by training a GRNN. Some statistical characteristics of wavelet coefficients are used in extracting process for better performance and accuracy of watermarking algorithm. The implementation results show that the watermarking algorithm has very good robustness to all kind of attacks.

KEYWORDS: Digital Image Watermarking, Discrete Wavelet Transform, General Regression Neural Network, Human Visual System.

1. INTRODUCTION

Digital watermarking is the technique of embedding information (watermark) into a carrier signal (video, image, audio, text) such that the watermark can be extracted or detected later for copyright protection, content authentication, identity, fingerprinting, copy control and broadcast monitoring [1]. The important requirements for the watermarking systems are robustness, transparency, capacity, and security [2], [11]. These requirements can vary under different applications. Digital watermarking can be categorized into two classes, depending on the domain of embedding watermark, (i) spatial domain watermarking, and (ii) transformed domain watermarking [1]. The implementation of spatial domain watermarking is easy and fast, and it usually requires no original image for watermark extraction. However, it is susceptible to tampering and signal processing attacks such as compression, adding noise, and filtering. Transformed domain watermarking offers more robustness under most of the casual signal processing attacks. Transformed watermarking algorithms usually require the original image for watermark detection. Suhail et al. [3] have proposed a robust method of embedding watermark coefficients in DCT domain of JPEG compression process. The watermark is extracted by the comparison of the watermarked image with the original image. Discrete wavelet transform (DWT) has been introduced by Hsu et al. [4] for digital image watermarking. In their work, both the host image and watermark are performed wavelet transform then combined together. This method also strictly requires the original image to detect the watermark. These methods are not feasible for applications with a large image database or communications applications. Recently, some researchers have applied neural networks to design transparent and robust watermarking systems which can detect the watermark without requiring the original image. 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 [12].

It is widely accepted that robust image watermarking systems should largely exploit the characteristics of the HVS, for more effectively hiding a robust watermark [6], [7]. Lewis and Knowles [8] proposed a mathematical model of the HVS that can be constructed to allow the estimation of noise sensitivity for any part of the transformed image. The study showed that wavelet decomposition closely mimics the HVS that is very helpful to create a visual mask for highly-perceptual compression applications [8]. The HVS has also been studied extensively by Jayant et al. [9] for signal compression applications. In this work, Just-Noticeable Difference (JND) profile is introduced as a visual masking based on HVS characteristics for perceptual coding of signals.

2. SCHEME DESIGN

Scheme design is organized as follows; Scrambling Watermark is given in section A. HVS weighting function relative to DWT techniques are discussed in section B. The Watermark embedding process is presented in section C. The training of GRNN is described in section D. The Watermark extracting process is shown in section E.

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 [13], 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 Figure 1(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… 64×64

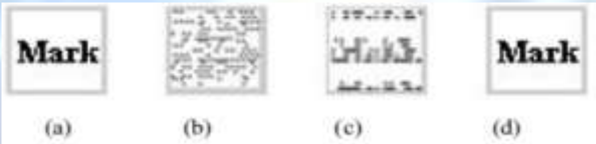

Figure 1: Image effect after being Arnold transformed

B. DWT coefficients and HVS model

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), vertical (LH), and diagonal (HH) high pass bands. 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. The proposed method uses the wavelet domain in frequency domain techniques. Because, compared to DCT and DFT the wavelet transform is performed a multi resolution analysis is good localization in frequency domain and DWT is higher flexibility. Figure 2 shows three levels of decomposition. Studies in [7]-[9] have shown that the human eye is: less sensitive to noise in high resolution bands, less sensitive to noise in those areas of the image where brightness is high or low, less sensitive to noise in highly texture areas but, among these, more sensitive near the edges.

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

In the proposed method of this paper, the image is subdivided into non-overlapped blocks with 8x8 size, each block is transformed by 3-level DWT, and the 8x8 DWT coefficients block are gained. For each transformed image block, the sub band LL1 is select for watermark embedding. In three decomposition level DWT, the sub band LL1 is decomposed to sub bands LL3, HL3, LH3, HH3, HL2, LH2, and HH2. This sub band has 4×4 size, which is divided to four overlapped 3×3 sub blocks of coefficients. Figure 3 shows the organization of sub blocks in the DWT coefficients block, the circles shows the center coefficient of each sub blocks. Each sub block denoted as B (i,j), (i=0,1,j=0,1) and the coordinates of each coefficient in it, denoted as B (i,j,x,y), (x=0,1,2,y=0,1,2) The watermark bit insert in center coefficient of each sub block B (i,j), that has the desired HVS weighting function value.

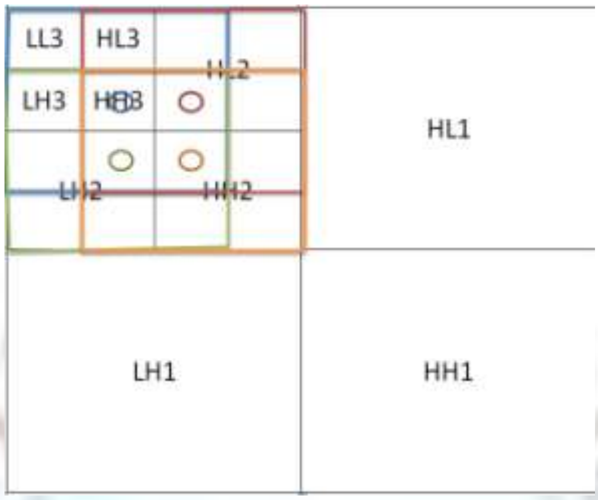

Figure 3: Organization of four 3×3 coefficients sub blocks in LL1 sub band, the circles shows the center coefficient in each sub block.

To adapt the watermarking system to the local properties of the image, we use the quantization model based on HVS in [8], [7] to calculate the weighting function for each sub block, Wf(i,j). [11].

$$Wf(i,j) = \frac{1}{256}\left\{ \sum_{x=0,\,y=0}^{x=2,\,y=2} B(i,j,x,y)^2 \right\} \times Var\{B(i,j,x,y)\}_{\substack{x=0,1,2\\ y=0,1,2}} \qquad (2).$$

The suitable sub blocks B*(i,j) for embedding are chosen by comparing the center coefficient value B(i,j,1,1) with its corresponding weighting function value Wf(i,j) given by

$$B^*(i,j) = \{B(i,j) : B(i,j,1,1) > \frac{1}{4} Wf(i,j)\} \qquad (3)$$

C. Watermark embedding algorithm

The scrambled watermark bit W (k) is embedded in center coefficient of selected sub block B* (i,j) as the following relation:

$$B^*(i,j,1,1) = B^*(i,j,1,1) + (2 \times W(k) - 1) \times \frac{Wf(i,j)}{B^*(i,j,1,1)} \times \alpha) \qquad (4).$$

Where B*(i, j, 1, 1) is the center coefficient of selected sub block, W (k) is the scrambled watermark bit, and Wf(i,j) is the corresponding HVS weighting function value for this sub block. The constant α is the watermarking factor, relative to robustness and transparency of algorithm. The suitable value for α is gained by practical implementation and experience. There is no need to save the positions of watermark embedding, if the watermarked image in extracting process has the acceptable PSNR (Peak Signal to Noise ratio), the HVS weighting function values recover victoriously [11], and it is the other positive point for algorithm. After embedding all of watermark bit in image blocks, IDWT is performed for each image block, and the watermarked image is obtained. Figure 4 shows the diagram of embedding algorithm.

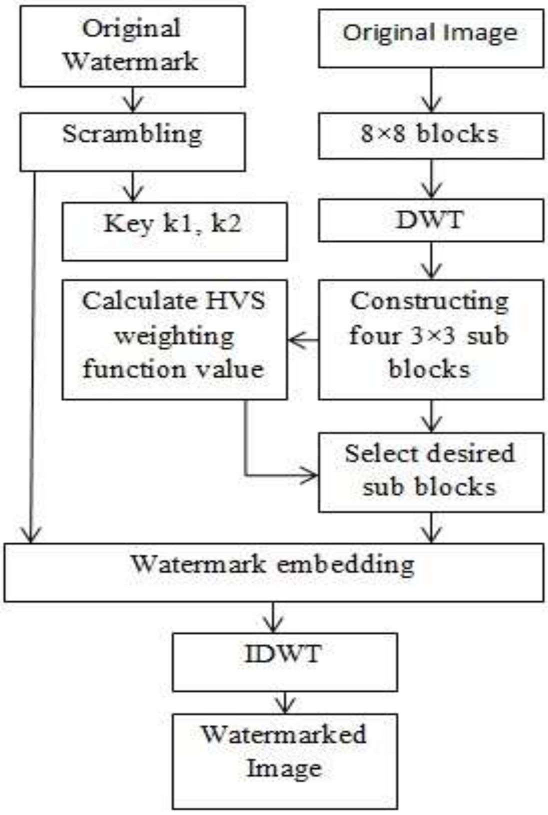

Figure 4: Watermark embedding diagram

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 5

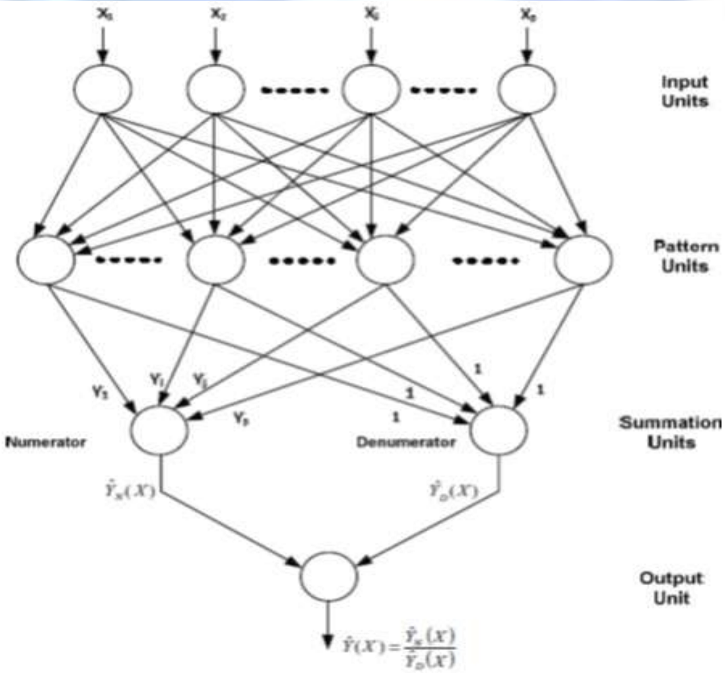

Figure 5: GRNN structure

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, Xi. When a new vector X is entered the network, it is subtracted from the corresponding stored cluster center. The square differences are summed and fed into the activation function f(x), and are given by

$$D_i^2 = (X - X_i)^T.(X - X_i) \qquad (5)$$

$$f_i(X) = \exp\left(\frac{-D_i^2}{\sigma^2}\right) \qquad (6)$$

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 (9).

$$\overline{Y_N}(X) = \sum_{i=1}^{p} Y_i f_i(X) \qquad (7)$$

$$\overline{Y}_D(X) = \sum_{i=1}^{p} f_i(X) \qquad (8)$$

$$Y(X) = \frac{\overline{Y_N}}{\overline{Y_D}} \qquad (9)$$

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, the GRNN has 9 input neurons, 9 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 Extracting Process

The diagram of process is shown in Figure 6. The point of extracting procedure is the feature extraction of the relationship among the neighbor wavelet coefficients. The relationships among wavelet coefficients within selected 3x3 sub blocks in watermarking embedded position are treated as the training sets. Similar to embedding algorithm, the watermarked image is divided to 8×8 non overlapping blocks; three-level DWT is performed for each image block, in each DWT coefficient block, four overlapping 3×3 sub blocks are reorganized, based on the HVS weighting function value, the sub blocks have special features, are detected. The reason for using GRNN is the training speed of it, because of block by block watermarked image processing, the speed of algorithm can be improved.

The input vector of GRNN can be constructing as follows:

$$X_p = \{\partial^*(i, j, x, y), x = 0,1,2, y = 0,1,2\} \quad (10).$$
$$, p = 1,2,\ldots,9$$

Where

$$\partial^*(i, j,1,1) = B^*(i, j,1,1) - Avg_{B^*(i,j)} \qquad (11)$$

$$\partial^*(i, j, x, y) = B^*(i, j,1,1) - B^*(i, j, x, y) \quad (12).$$
$$, (x, y) \neq (1,1)$$

$$Avg_{B^*(i,j)} = \frac{1}{8} \sum_{x=0}^{x=2} \sum_{y=0}^{y=2} B^*(i, j, x, y) - B^*(i, j,1,1) \qquad (13)$$

The desired output for GRNN is

$$Y_p = \begin{Bmatrix} (B^*(i, j,1,1) - \partial^*(i, j,1,1) & if \quad W(k) = 1 \\ -(B^*(i, j,1,1) - \partial^*(i, j,1,1) & if \quad W(k) = 0 \end{Bmatrix}, \qquad (14)$$

$$W'(k) = \begin{Bmatrix} 1 & Y_k' > 0 \\ 0 & otherwise \end{Bmatrix} \qquad (15)$$

In relation (14), W (k) is the original scrambled watermark bit, in the other words, for gaining watermark bit in extraction process need to have original scrambled watermark. The extracted watermark bit is calculated based on relation (15).In this relation, $Y_k^{'}$ is the final GRNN output for detected DWT coefficients sub block $B^*(i,j)$. After recovering entire watermark bits, $W^{'}$ is the extracted watermark sequence, which is descrambled by Arnold transform and key k_2, and the extracted watermark logo image can be obtained.

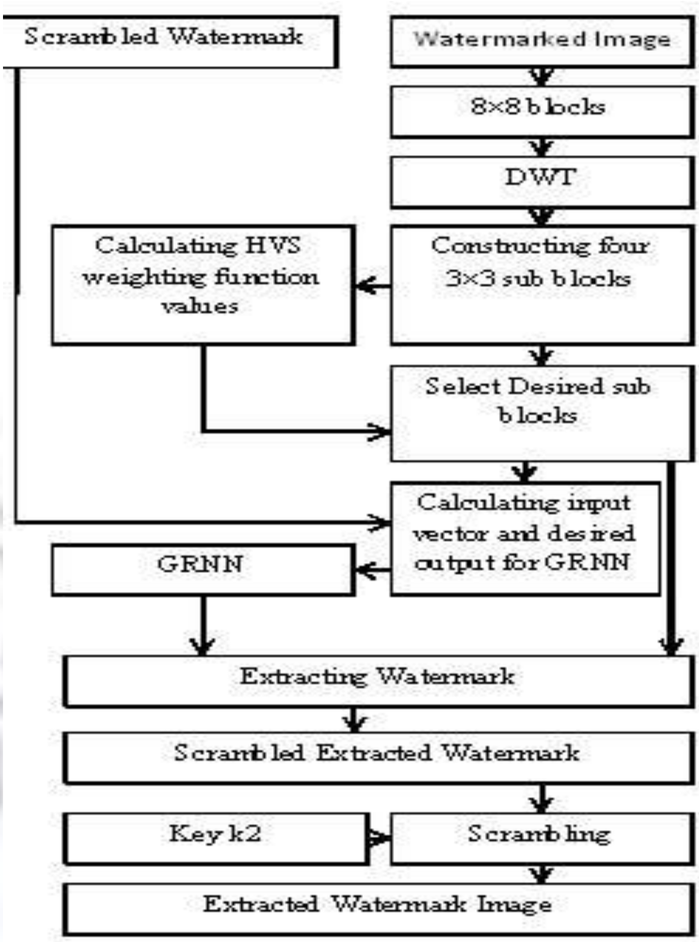

Figure 6: Watermark extracting diagram

3. IMPLEMENTATION RESULTS

The original and watermarked images with size 512×512 have been shown in Figure 7 and Figure 8. Gold Hill, image has 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 9. Extracted watermarks after some kind of attack on mentioned watermarked images have been shown in Figure 10. 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, and 90 and finally jpeg 2000 compression with bit rate 3 .

Figure 7: Original Gold Hill image.

Figure 8: Watermarked Gold Hill image.

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The estimate of similarity between the extracted watermark image and the original watermark image according to relation (16), along the peak signal to noise ratio (PSNR) of watermarked image and Original image, to relation (17), were calculated having performed each

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

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

one of the mentioned attacks on the watermarked image, and results have been integrated in table (1). In relation (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: Original Watermark

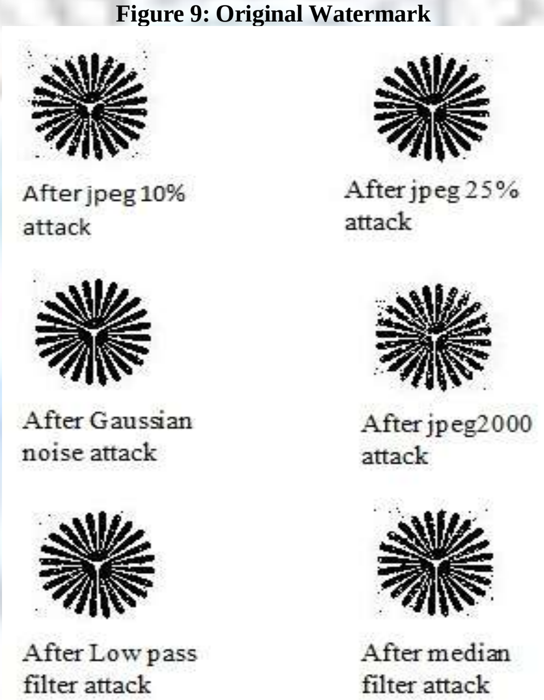

Figure 10: Extracted logo watermarks after some kinds of watermarking attack on the watermarked image.

TABLE 1: IMPLEMENTATION RESULTS AND COMPARISONS

Kind of attack	Our method		Method in [14]	
	SIM	PSNR	SIM	PSNR
Gaussian Noise	97.1	31.0	93.5	31.44
Low Pass Filter	95.0	29.5	-	-
Median Pass Filter	90.5	31.5	85.95	32.7
Scaling 1/5	83.6	24.2	88.1	28.5
JPEG 90%	98.5	42.7	91.2	37.7
JPEG 50%	96.7	41.3	89.4	33.5
JPEG 25%	92.4	36.1	86.3	29.8
JPEG 10%	89.3	30.0	81.2	24.1
JPEG 2000 with bit rate 3	84.2	23.9	-	-

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