A New Digital Image Watermarking Approach Based on DWT-SVD and CPPN-NEAT

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Abstract* — Digital watermarking has been proposed as a way to claim ownership. In this paper, a new approach in digital image watermarking based on discrete wavelet transform (DWT) and singular value decomposition (SVD) is presented. We use compositional pattern producing networks (CPPNs) to make a very compact representation of watermark. Using Neuro Evolution of Augmenting Topologies (NEAT) will evolve the CPPN structure to produce a suitable watermark image. In the embedding phase, at first we perform decomposing of the host image with 2D-DWT transform at 5-level, then the SVD is applied to LH3-LH5 sub-bands of transformed image, and embed the watermark by modifying the singular values. In watermark extraction phase, the embedded coefficients of CPPN neat are extracted from the watermarked image. Then the watermark image is rendered by CPPN. The experiments indicate that the watermark is robust against the different attacks, such as average filter, Jpeg compression and etc.

***Keywords-* Discrete wavlete transform; Singular value decomposition; Compositional pattern producing networks; Neuro evolution of augmenting topologies.**

I. INTRODUCTION

In recent years the rapid development of Internet introduces a new set of challenging problems concerning security. One of the most important problems is to discourage unauthorized duplication of digital data. Digital watermarking has been proposed as an effective technique for protecting, authenticating, and tracking the copyrighted contents.

In general, a watermarking scheme shall satisfy two properties. First, the watermark should not affect the quality of the host media and be imperceptible to human eyes. Second, if the watermark is used for Internet applications such as transmitting data through a noisy channel or compressing data, the watermark must survive under those situations.

A large batch watermarking algorithms in the transform domain, are based on DWT and SVD Transforms. The major advantage of transform domain methods is their superior robustness to common image distortions [1]. While many of these algorithms claim that they have proposed a blind watermarking method, in fact they are completely non blind algorithms. In watermark extraction procedure of these algorithms, u and v matrices of SVD transform of watermark image are used. On the other hand, u and v matrices have a lot of information from image, particularly from image's texture. However these matrices are not embedded in the host image.

In this study, based on the image rendering by CPPN network, a novel semi-blind watermarking method for digital image watermarking with high quality of transparency and robustness is presented.

In this work, the images produced by CPPN networks are indirectly watermarked. CPPNs are similar to artificial neural networks (ANNs), they differ in their set of activation functions and how they are applied [2, 8]. CPPNs produce spatial patterns by composing basic functions. ANNs often applies sigmoid functions (and sometime Gaussian functions), however, CPPNs can include both types and many other functions. The choice of functions for the canonical set creates a bias toward specific types of patterns and regularities. Thus, the structure of a CPPN-based system can bias the types of patterns it generates by deciding the set of canonical functions to include. In this network, input can be a conventional image such as a constant white image. The image rendered from CPPN network is obtained by running the network with its activation functions. The structure of the CPPN networks restricts the images produced by these networks to images which include properties such as symmetry, imperfect symmetry, repetition, repetition with variation exist [2].

The main idea of this work is based on compact representation of watermark image by coefficients of related CPPN network. Unlike conventional watermarking algorithms, instead of storing the image as watermark, we embedded the CPPN network weight matrix in embedding stage. In the reconstruction phase, the coefficients embedded in the host image, are extracted. Then the network with the extracted weight matrix is run, and the final watermark image is obtained.

Experimental results show that the proposed watermarking scheme not only has significant superior visual quality compare to the other methods but also is robust to common attacks such as rotation, average filtering, noise addition, scaling, Jpeg compression and cropping.

The rest of this paper is organized as follows. DWT and SVD transform are describe in sections 2 respectively. Section 3 describes CPPNs and then NEAT algorithm is explained in the next section. The proposed scheme is explained in details in section 5. The experimental results *to demonstrate the performance of this scheme is described in section 6. The conclusion is drawn in section 7.*

II. DWT AND SVD TRANSFORMS

A. Discrete Wavlete Transform

Wavelet transform decomposes an image into a set of band limited components which can be reassembled to reconstruct the original image without error. Since the bandwidth of the resulting coefficient sets is smaller than that of the original image, the coefficient sets can be down sampled without loss of information. Reconstruction of the original signal is accomplished by up sampling, filtering and summing the individual sub bands. For 2-D images, applying DWT corresponds to processing the image by 2-D filters in each dimension. The filters divide the input image into four non-overlapping multi-resolution coefficient sets (LL, LH, HL and HH) [3].

DWT is very suitable to identify the areas in the host image where a watermark can be embedded effectively. In particular, this property allows the exploitation of the masking effect of the human visual system such that if a DWT coefficient is modified, only the region corresponding to that coefficient will be modified [4]. In general most of the image energy is concentrated at the lower frequency coefficient sets LLx and therefore embedding watermarks in these coefficient sets may degrade the image significantly. However, embedding in the low frequency coefficient sets, could increase robustness significantly. On the other hand, the high frequency coefficient sets HHx include the edges and textures of the image and the human eye is not generally sensitive to changes in such coefficient sets. This allows the watermark to be embedded without being perceived by the human eye. The agreement adopted by many DWT-based watermarking methods, is to embed the watermark in the middle frequency coefficient sets HLx and LHx which is better in perspective of imperceptibility and robustness [4,6].

B. Singular Value Decomposition

Let A be a general real (complex) matrix of order m×n. The singular value decomposition is the factorization

$$A = U \times S \times V^T \quad (1)$$

Where U and V are orthogonal (unitary) and S =diag (σ1, σ2, ..., σr), where σi, i = 1,..., r are the singular values of the matrix A with r = min (m, n) and satisfying

$$\sigma_1 \geq \sigma_2 \geq \ldots \geq \sigma_r \quad (2)$$

Use of SVD in digital image processing has some advantages. First, the size of the matrices from SVD transformation is not necessarily square and can be a rectangle. Secondly, singular values in a digital image are less affected if general image processing is performed. Finally, singular values contain intrinsic algebraic image properties, where singular values correspond to the brightness of the image and singular vectors reflect geometry characteristics of the image. [5].

SVD can effectively reveal essential property of image matrices, so it has been used in a variety of image processing applications such as noise estimation and digital watermarking [7]. In recent years application of SVD transform in watermarking domains is increased, but in most of these works embedding of u and v matrices at the watermarking stage are ignored.

The following example shows the importance of the u and v matrices in the SVD transform. For our test we use two images (i.e. Lena and Cameraman). First, SVD transform separately is applied to both images. Then, S matrices of these two images are exchanged together. In continue, reverse SVD is applied to reconstruct the images. We see that although the two S matrices have been exchanged, but resulted in terms of light, is slightly different with the original image (Figure 1). Therefore, a lot of image information is in U and V matrices and algorithms which use them at the reconstruction phase without embedding them do not represent a blind algorithm, although many of them claim[11,12].

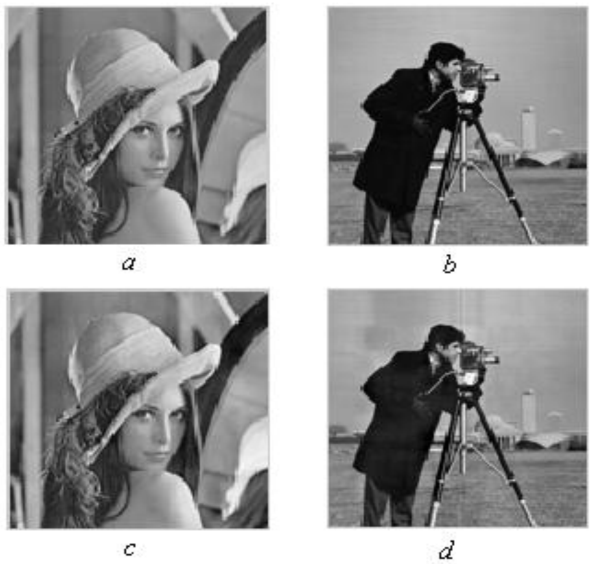

Figure 1: Importance of U, V matrices. a, b are original images. c, d are reconstructed images with exchanged S matrices.

III. COMPOSITIONAL PATTERN PRODUCING NETWORKS

Such networks are called Compositional Pattern Producing Networks because they produce spatial patterns by composing basic functions [2]. The idea behind CPPNs is that geometric patterns can be encoded by a composition of functions that are chosen to represent common regularities. Internally, a CPPN is represented as a connected-graph (i.e. a network) of functions chosen from a canonical set (i.e. sine, cosine, Gaussian and etc.). The structure of the graph represents how the functions are composed to process each coordinate. For example, any function of the output of a Gaussian alone will output a symmetric pattern because the Gaussian is symmetric. The internal structure of a

CPPN is represented as a weighted network, similar to an artificial neural network (ANN) that denotes which functions are composed. Images are rendered from CPPNs in this paper by querying the network as the function CPPN(x; y; d) to obtain the grayscale value of the pixel located at (x; y) in the image (Figure 2). The extra input d is the distance from the center to the (x; y) location being queried, which gives the CPPN a sense of radial symmetry that provides a bias towards appealing images. Since CPPNs are a composition of continuous functions in a geometric space, they provide a compact representation of the image at any resolution [8, 9]. Firstly; images that rendered from CPPNs are not comprehensible, so for solve this problem we used NEAT method for evolving CPPNs to create intelligible images. The next section describes the NEAT method.

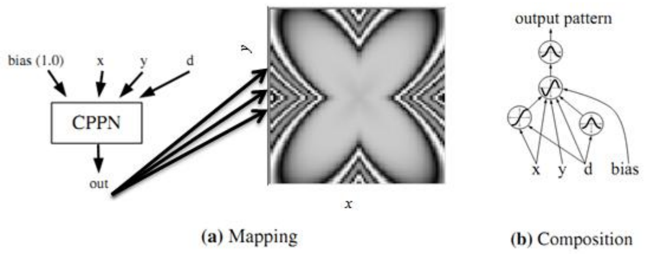

Figure 2: CPPN Encoding. (a) The CPPN takes arguments x, y, d and bias; then are mapped to watermark image. Internally, the CPPN (b) is a graph that determines which functions are connected. As in an ANN, the connections are weighted such that the output of a function is multiplied by the weight of its outgoing connection. The CPPN in (b) actually produces the pattern in (a).

IV. NEUROEVOLUTION OF AUGMENTING TOPOLOGIES

NEAT stands for NeuroEvolution of Augmenting Topologies. It is a method for evolving artificial neural networks with a genetic algorithm. NEAT implements the idea that it is most effective to start evolution with small, simple networks and allow them to become increasingly complex over generations. This process of continual elaboration allows finding highly sophisticated and complex neural networks. By evolving networks in this way, the topology of the network does not need to be known a priori; NEAT searches through increasingly complex networks to find a suitable level of complexity. More specifically, the NEAT algorithm starts with a population of simple CPPNs and complexifies them over generations by adding new nodes and connections through structural mutations [10].

V. PROPOSED ALGORITHM

In this section first briefly aim of the research and key point of innovation of the proposed method. Second we have been discussed a scheme for embedding and extraction watermark.

- Aim of research and innovation: As regards in recent years, in the semi-blind and blind proposed algorithms a set of basic requirements for watermarking schemes(i.e. Capacity, Transparency, Robustness) are satisfying restricted. In this research using compact representation of the watermark image (by CPPN-NEAT), the capacity measure and so on transparency and robustness are very good satisfied.

- Proposed algorithm: We have used DWT and SVD for developing an algorithm. In this paper work, watermark construction is presented in Figure 3. Structure of a typical CPPN network is represented in Figure 4 and weight matrix of connections between this CPPN's nodes is represented in Table (1).

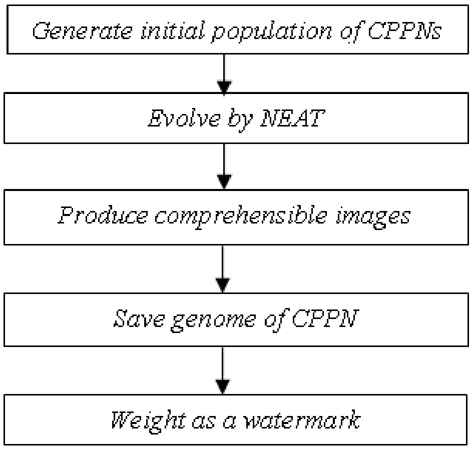

Figure 3: Watermark construction diagram

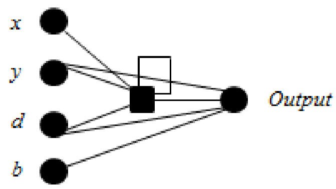

Figure 4: CPPN's structure.

Table 1: Weights of connection between nodes in CPPN,

d to h = -0.39	y to h = -0.49	x to h = 0.51
d to output =0.54	y to output = 0.01	x to output = 0.095
h to h = -0.69	h to output =0.03	bias to output = 0.41

We used Gaussian function as activation function in the typical CPPN. CPPN genome is including weight matrix, activation function and how edges are connected together. Watermark is 9 coefficients in table 2. In this table h means hidden node.

A. Embedding Algorithm

The watermark embedding procedure is represented in Figure 5, followed by a detailed explanation:

1. Perform 5-level 2D-DWT on the host image to provide multi-resolution sub bands: LL5, LH5, HL5 and HH5.
2. Apply SVD transform to sub bands LH3, LH4 and LH5 to get U, V and S matrices.

$$I \Rightarrow USV^T \tag{3}$$

3. *Modify singular values of the host image in LH_x sub-band according to those of the watermark (coefficients importance). Thus, which coefficients are significant, insert in deep. In the CPPN structure, Coefficients of 3 connections such as from d to hidden, x to hidden and y to hidden are very important, because empirically these connections construct image texture.*
4. *Perform inverse SVD with updated S matrix.*
5. *Apply 5-level 2D-IDWT to obtain watermarked image.*

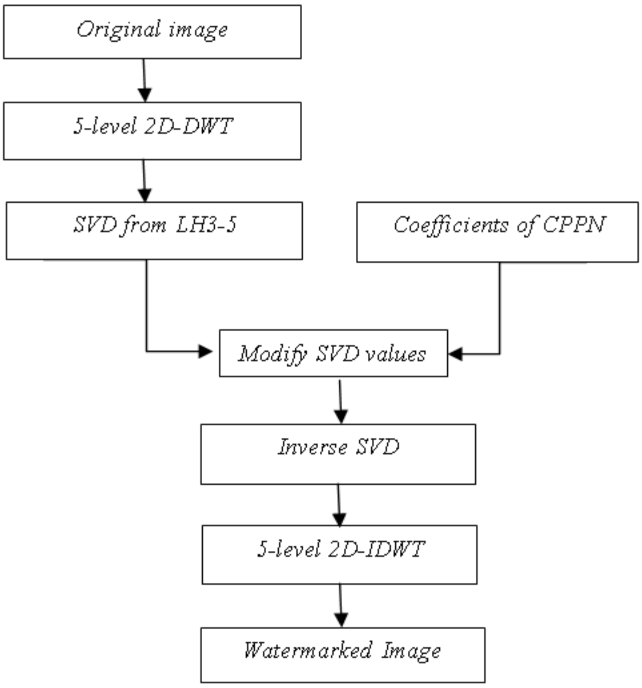

Figure 5: Embedding algorithm

B. Extraction Algorithm

Our aim of watermark extraction is to obtain embedded coefficients. Then in the next stage, to reconstruct the watermark image, the CPPN network is run with the extracted coefficients. To extract the coefficients from the watermarked image, only S matrix from applied SVD transform in the embedding stage is need. The extraction procedure is explained as follows.

1. *Perform 5-level 2D-DWT on the Watermarked image to provide multi-resolution sub bands: LL5, LH5, HL5 and HH5.*
2. *Apply SVD transform to sub bands LH3, LH4 and LH5 to get U, V and S matrices.*

$$\hat{I} \Rightarrow \hat{U}\hat{S}\hat{V}^T \tag{4}$$

3. *Extract coefficients from $\hat{S}$ (3) matrices by the following equation:*

$$Cofficient \Leftarrow \frac{\hat{S} - S}{\alpha} \tag{5}$$

Where α represent the scaling factor (in this paper α=0.1).

VI. Exprimental Result

Each watermarking application has its own specific requirements. Since in our algorithm, we used coefficients as watermark many of these requirements such as transparency, capacity, robustness and extraction key are well satisfied.

Several experiments were carried out to verify the validity of the proposed watermarking scheme. The image Lena with size 256×256 and 9 coefficients of CPPN network are used as the cover image and the watermark (rendered image), respectively. These images are illustrated in Figures 6(a) and (b). Figures 7(a) and (b) represent the watermarked image and watermark after running the CPPN network with extracted coefficients. In order to evaluate the Transparency of watermarked image, we use parameter peak value signal-to-noise ratio (PSNR). PSNR is used efficiently measure of visual fidelity between the host image and the watermarked image and PSNR in decibels is given below in equation 6:

$$PSNR = 10\log_{10}\frac{255^2}{MSE} \tag{6}$$

With

$$MSE = \frac{\sum_{i=1}^{N_1}\sum_{j=1}^{N_2}\left[I\ (i,j) - I^{'}\ (i,j)\right]^2}{N_1 \times N_2} \tag{7}$$

Where $N_1 \times N_2$ is the size of image, I, I' is the pixel gray value of host image and the watermarked image respectively. Since the higher value of PSNR presents better transparency, it is desired. PSNR value between the original and the watermarked image is 66dB.

In order to evaluate the robustness of watermarking algorithm, the watermarked image is attacked by several type of attacks (table 2) and then correlation coefficients between original watermark w and detected watermark $w^{'}$ is calculated (table3). After applying any attack to the watermarked image and extraction the coefficients, CPPN network running with these coefficients to rendering the watermark image. Rendered images are show in Figure 8.

Figure 6: (a) Host image. (b) Watermark used in the experiments.

Figure 7: (a) Watermarked image. (b) Reconstruct watermark after running CPPN.

Table2: *Weight matrices extracted after apply attacks.*

No	Attacks	Extracted weight matrix								
1	No attack	0.4100	0.0300	-0.6900	0.0950	0.0100	0.5400	0.5100	-0.4900	-0.3900
2	Average filter 9*9	0.4128	0.0302	-0.6947	0.0957	0.0101	0.5437	0.5135	-0.4934	-0.3927
3	Median filter 9*9	0.3150	0.0230	-0.5301	0.0730	0.0077	0.4149	0.3918	-0.3765	-0.2996
4	Histogram equalization	0.3954	0.0289	-0.6654	0.0916	0.0096	0.5208	0.4918	-0.4726	-0.3761
5	Gaussian noise 75%	0.4212	0.0308	-0.7089	0.0976	0.0103	0.5548	0.5240	-0.5034	-0.4007
6	Contrast adjustment	0.4396	0.0322	-0.7399	0.1019	0.0107	0.5790	0.5469	-0.5254	-0.4182
7	Cropping 50%	0.3959	0.0290	-0.6663	0.0917	0.0097	0.5214	0.4925	-0.4732	-0.3766
8	Jpeg compression with QF=20	0.4012	0.0294	-0.6752	0.0930	0.0098	0.5284	0.4991	-0.4795	-0.3817
9	Resizing	0.4215	0.0308	-0.7093	0.0977	0.0103	0.5551	0.5243	-0.5037	-0.4009
10	Rotation 50 degree	0.3628	0.0265	-0.6105	0.0841	0.0088	0.4778	0.4513	-0.4336	-0.3451

Table3: *Correlation coefficients.*

No	Attacks	Proposed Algorithm
1	No attack	0.9999
2	Average filter 9*9	0.9269
3	Median filter 9*9	0.3396
4	Histogram equalization	0.5989
5	Gaussian noise 75%	0.8221
6	Contrast adjustment	0.4707
7	Cropping 50%	0.6050
8	Jpeg compression with QF=20	0.7952
9	Resizing	0.8175
10	Rotation 50 °	-0.5759

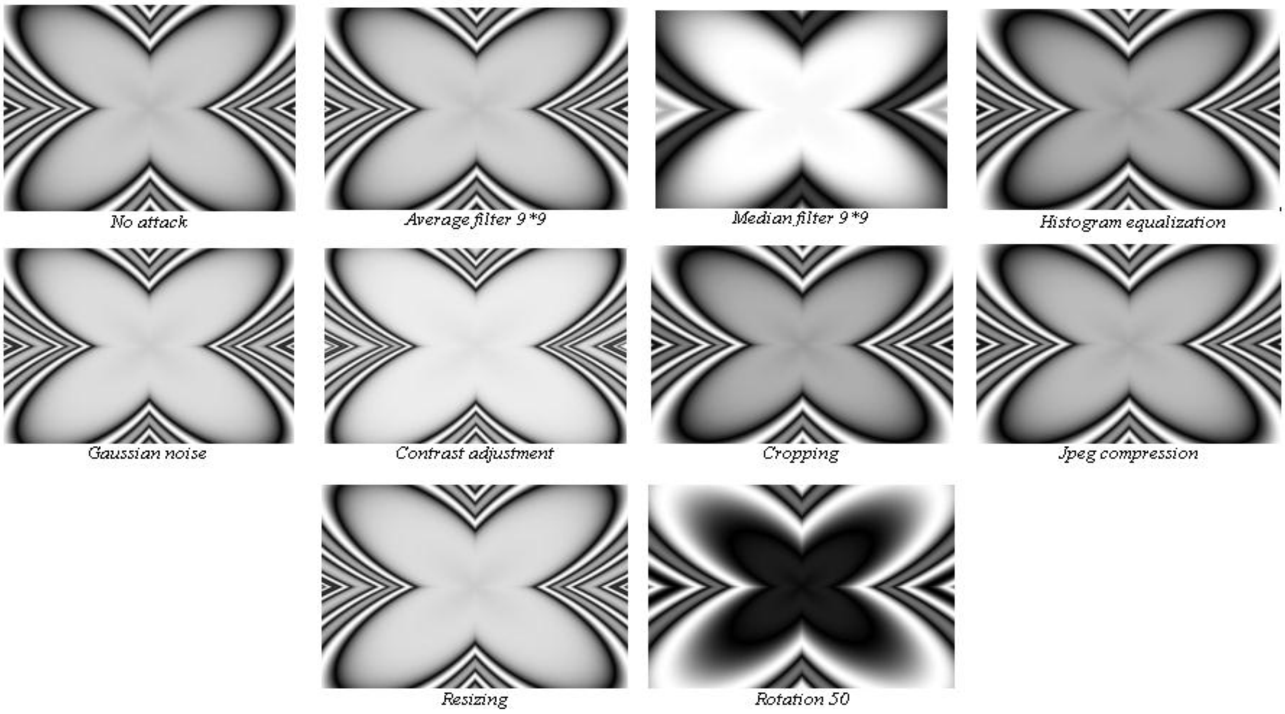

Figure 8. Rendering images by CPPN after applied attacks.

VII. CONCLUSION

In this paper, a novel approach for digital image watermarking has been proposed. In our algorithm, after applying 5-level 2D-DWT to host image; the singular values of the sub-bands LH3 to LH5 are modified to embed the watermark which is created by CPPN network. In this way, using CPPN coefficients and Gaussian function, watermark image is rendered from CPPN. Our algorithm is robust against various attacks including average filter, median filter, Contrast adjustment, Jpeg compression, rotation, noise addition, scaling, resizing and cropping. Since, proposed algorithm used small data payload, many of watermarking requirements such as transparency, capacity, robustness and extraction key are well satisfied.

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