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A new approach for digital image watermarking to predict optimal blocks using artificial neural networks

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Abstract: In this paper, we propose a novel nonblind digital image watermarking based on discrete wavelet transform and singular value decomposition. This robust scheme takes advantage of artificial neural networks for selecting suitable image blocks in which the watermark signal can be embedded. Local characteristics of the blocks such as luminance and texture sensitivity are the main criteria that the selections are based on. Generally, selection is based on a prediction of the results with the objective of transparency and watermark resilience. In other words, before embedding the water mark signal, it is estimated which blocks would be the best for embedding the signals to achieve the desired robustness and quality. Simulation results confirm the superiority of the proposed scheme in terms of the transparency of the images as well as robustness under various kinds of attacks.

Key words: Digital image watermarking, discrete wavelet transforms, singular value decomposition, artificial neural networks, human visual system

1. Introduction

Digital watermarking, typically, is embedding specific information in a host signal such as an image, a video, a sound, or even a data file. Digital watermarking is mainly used to verify the authenticity and copyright protection of digital signals. In other words, a secret logo, namely a watermark signal (WS), is hidden in the data source. A magnificent digital image watermarking scheme must guarantee high quality for the watermarked image (WI) as well as error resilience for the WS. On the other hand, the watermarking system should cause the least amount of distortion on the cover signal after embedding the watermark logo. Furthermore, it should offer high robustness against passive and active attacks [1].

Large numbers of methods and schemes have been proposed in the literature for authenticity verification of digital images, which can be generally categorized into two groups. The first group is called blind watermarking. It only requires WIs for the extraction step. In contrast, nonblind watermarking methods also need the original host image (HI) (also known as a cover image) in order to extract the WS. Although nonblind watermarking methods require more information in the detector to extract the WS, they are more robust against intentional attacks than the blind watermarking methods [2].

In a watermarking system there are two possible approaches in the decomposition process. The decomposition is performed either in the spatial domain or the frequency domain. The advantage of spatial domain decompositions is that they require less complexity and consequently less computational costs than frequency

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domain decompositions. However, the penalty is their poor robustness and fragility under attacks. In contrast, using frequency domain decomposition, though it needs more complex algorithms, it gives the opportunity of choosing components that are more error-resilient while being less sensitive for the human visual system (HVS) [3].

Different transforms can be used in order to decompose images in the frequency domain, such as discrete Fourier transform (DFT) [4], discrete cosine transform (DCT) [5], or discrete wavelet transform (DWT) [6]. DWT transform has more benefits compared to the other aforementioned transforms. The fact that it is closer to the human vision model in comparison with DFT and DCT is one of its very important advantages [7].

Moreover, in digital signal processing, singular value decomposition (SVD) is very applicable due to its helpful advantages for inserting the WS in the HI. This technique results in a minor perceptual difference under data embedding. In addition, the largest singular values are changed slightly during the common attacks and invasions. There are also other reasons why SVD is very useful for data insertion. For instance, it reduces the size of the watermark signal, which is helpful to eliminate redundant information. Singular values of the WI are also less influenced by attacks [7].

2. Related works

In this study, after selecting the optimum block for inserting a watermark by artificial neural network (ANN), we combine DWT and SVD for the embedding process. Therefore, previous studies in the literature are reviewed in the following text. Lagzian et al. [8] presented a new watermarking method based on redundant discrete wavelet transform (RDWT) combined with SVD to embed watermark images that can be as large as the cover image. They considered nonblind image watermarking that is robust against regular attacks and ordinary image manipulation. After applying RDWT to both cover and watermark images, SVD is performed to the low-low (LL) subbands of them and then singular values of the cover image are modified by using singular values of the WS. They found that RDWT-based signal processing tends to be more robust than DWT-based techniques for the same size of cover and watermark image.

Jane and Elbaşı [9] investigated a nonblind watermarking method based on a DWT-LU-SVD scheme. They found that lower and upper decomposition (LU) improved robustness and transparency via filtering, scaling, and rotation attacks in comparison with a DWT-SVD scheme.

It is obvious that embedding a WS into the HI can be treated as adding weak noise into a strong background. The HVS cannot detect changes as long as the strength of noise is below the “just noticeable difference” (JND) threshold of the HVS [10]. Thus, massive research has been done on the watermarking method and schemes based on the HVS. Radouane et al. [11] proposed a robust method, which first selects the optimal blocks with the maximum entropy to insert the WS in the HI by modifying the SVD in DWT combined with DCT.

ANNs also could be used for HVS simulation. There are many characteristics to study while modeling the HVS. In [12], entropy, frequency, luminance, and texture sensitivity were taken into considerations. The authors of [13] focused on angular second moment, contrast, correlation, and entropy to simulate the HVS and watermark strength coefficients were adaptively determined. Huang et al. [14] took HVS characteristics into consideration during the watermark embedding process, and then a backpropagation neural network was used to learn the characteristics of the watermark image. Then the trained neural network can exactly recover the watermark from the watermarked image.

An overview of the previous works in this area shows that each has its own positive and negative sides. Some of them are immune against different attacks but could not preserve perceptual quality with high performance. On the other hand, others cause the least amount of distortion on the cover signal but are fragile against intentional and unintentional attacks. This led us to present a method with high perceptual quality and robustness against a couple of different attacks.

In this paper, we propose a nonblind watermarking method. We use DWT as the transform domain because it prepares an appropriate domain for watermarking in both perceptual and robustness aspects. We also take advantage of SVD to remove redundancies in data. Furthermore, singular values have high resistance against attacks. Hence, by combining these two methods we can propose a system that boosts both robustness and perceptual quality. In addition, we improve the performance of our system further by using an intelligent approach during embedding. For this purpose, the original cover image is separated into nonoverlapping subblocks. An objective function for optimizing is defined on them. It is a combination of transparency and robustness features. Only blocks with the best performance are selected for final data embedding. A self-trained ANN is used for selection of the optimum blocks for inserting the WS. The ANN is designed to extract specific characteristics of the HI so that the algorithm can guarantee high quality and transparent output while being robust under different kinds of attacks. Simulation results illustrate the superiority of the proposed method in robustness of the watermark and quality and transparency of the WI simultaneously.

3. Proposed algorithm

In this section our robust watermarking scheme is introduced. We show how the embedding and extraction steps should follow, and why this method could outperform the other methods. Since HVS sensitivity depends on the luminance and texture of the image, it is more reasonable to place the distortion made by inserting the WS in special locations of the image such as bright or dark areas, around edges and dense textures [10]. Hence, we would take advantage of this characteristic in the proposed method to improve the quality of the cover signal after embedding.

The key point in the proposed scheme is that first the HI is divided into distinct blocks. Then a vector of specification is drawn. Based on this vector, a positive number is assigned to each block, which shows the estimation of the transparency and robustness of the watermarking process for the block. The estimation is done by an ANN. Finally, the blocks with the highest values for transparency and robustness are selected as keys for the watermarking process. Using an ANN as a smart way for estimation helps us to select the best blocks for each image based on its own characteristic. In other words, unlike the conventional methods, which just a specific area selected for watermarking, the proposed algorithm selects blocks with the highest level of robustness as well as the lowest level of distortion. In the next section, we clarify how to select optimum blocks for data insertion. Then the embedding algorithm is introduced and, finally, the extraction phase is presented.

3.1. Selection of optimum blocks

First of all, we are going to select the proper blocks of the image for watermark embedding. These blocks are selected based on their characteristics. Our proposed scheme takes advantage of four substantial features, i.e. luminance, variance, entropy, and contrast. The luminance of each block is calculated by averaging the value of all pixels. The other specifications (variance, entropy, and contrast) are used to determine the texture of the block. After decomposing the host image into 16×16 blocks, 3-level wavelet transform is applied to each block. Then, from the 12 obtained subbands of each block, the four desired features are extracted. Consequently, 48 features are obtained from each block ($4 \times 12 = 48$). This vector of features is then used for estimation of robustness and transparency of the block after being watermarked. This estimation is made by an ANN.

Due to the aspects of the problem a multilayer perceptron (MLP)-based ANN is used, which is trained by an error backpropagation algorithm. Since the extracted features of each block are categorized into four groups, four neurons in the hidden layer are supposed to perform properly. Therefore, the ANN includes 48 inputs, one hidden layer with four neurons, and one output. The inputs are equal in number to the extracted features of one block and the only output is the estimation of the system about the suitableness of that block for watermarking. A supervised learning process is used to train the ANN. The dataset of STANDARD 512×512 GRAYSCALE TEST IMAGES is used for training the ANN. This dataset contains 50 standard images of all kinds. The aptly selected blocks could optimize the transparency and robustness of the watermarking algorithm. Under these circumstances, we propose a simple objective function that addresses transparency and robustness issues simultaneously. Here we are dealing with an optimization problem. To solve it, just minimizing the following objective function is needed to achieve the goal:

$$J = \frac{1 - mean\,(NC)}{PSNR}, \tag{1}$$

where NC is the normalized cross-correlation vector between the original and extracted watermarked signal [11]. $PSNR$ (peak signal-to-noise ratio) is the signal power-to-noise ratio [11]. Hence, by considering the objective function as Eq. (1), while there is more similarity between the inserted and extracted watermarks under predefined attacks, the NC will be more close to 1, which results in decreasing the J value to zero. On the other hand, more similarity between the HI and WI also results in a larger value of $PSNR$ and consequently in decreasing the J value to zero. Therefore, any optimization technique or algorithm can be used to find the minimum value of J.

A genetic algorithm (GA) commonly is used to optimize the problem with the objective of achieving maximum robustness without sacrificing the transparency as mentioned in [15–17]. We also use a GA with a population of 100 and 200 generations to optimize the same problem in order to train the ANN. After extracting a specification vector of 50 images and assigning 1 to suitable blocks and −1 to unsuitable ones for watermarking, we have a perfect dataset for estimation. Eventually, after training the ANN, it is obvious that it could properly select the suitable blocks not only for watermarking but also for any other image.

3.2. Watermark embedding algorithm

The HI and the WS are first divided into 16×16 and 8×8 blocks, respectively. Then the trained ANN according to the specification vectors determines the proper blocks for embedding the WS. The process of WS insertion is as follows:

1. DWT is applied to selected blocks of the HI to decompose it into 4 subbands: a lower resolution image (low-low) LL_{HI}, horizontal (high-low) HL_{HI}, vertical (low-high) LH_{HI}, and diagonal (high-high) HH_{HI} detail components.

2. The LL_{HI} subband is decomposed into three matrices $[U_{HI}, S_{HI}, V_{HI}]$ using SVD: $LL_{HI} = (U_{HI}) \times (S_{HI}) \times \left(V_{HI}^T\right)$.

3. SVD is performed on the block of the WS: $WS = (U_{WS}) \times (S_{WS}) \times \left(V_{WS}^T\right)$.

4. The WS singular values matrix (S_{WS}) is inserted into the S_{HI} with α as an embedding strength coefficient of the watermark: $S_{WI} = S_{HI} + \alpha \times S_{WS}$, where S_{WI} indicates the singular values of the LL subband of watermarked image.

5. Using the obtained singular values matrix, the LL wavelet subband of the WI is constructed: $LL_{WI} = (U_{HI}) \times (S_{WI}) \times \left(V_{HI}^{T}\right)$.

6. The new LL subband (LL_{WI}) substitutes for the old one (LL_{HI}) and then the inverse DWT (IDWT) first is computed to obtain watermarked blocks. Deblocking is implemented to obtain the watermarked image respectively:

$$[LL_{WI}, HL_{HI}, LH_{HI}, HH_{HI}]\ \underline{IDWT}\ watermarked\ blocks\ \underline{de-blocking}\ WI.$$

7. The index of the selected blocks is needed to be stored or sent in order to be used as a key for watermark extraction.

A flow diagram of the watermark embedding algorithm is shown in detail in Figure 1.

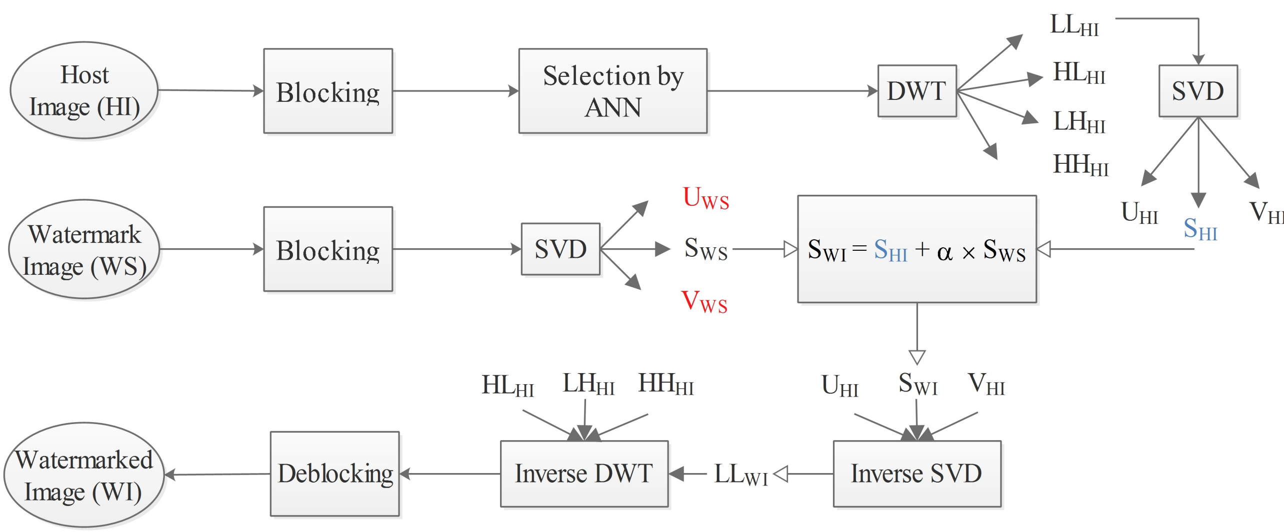

Figure 1. Flow diagram of the watermark embedding algorithm.

4. Watermark extraction algorithm

For watermark extraction, in addition to the WI, the key and the original HI are needed. With the following steps we can easily extract the WS:

1. According to the key, the blocks in which the WS is inserted are selected.

2. DWT is performed to the specified blocks of WI in order to calculate the LL subbands: $WI\ \underline{DWT}\ [LL_{WI}, HL_{WI}, LH_{WI}, HH_{WI}]$.

3. The LL subband is then decomposed into $[U_{WI}, S_{WI}, V_{WI}]$ using SVD: $LL_{WI} = (U_{WI}) \times (S_{WI}) \times \left(V_{WI}^{T}\right)$.

4. Steps 1 to 3 of the embedding process are performed on the HI and WS to obtain the singular values of the HI and WS.

5. In order to extract the singular values of the extracted watermark (W*) we use: $S_{W*} = \frac{(S_{WI} - S_{HI})}{\alpha}$.

6. Finally, after extracting all the singular values of the W*, inverse SVD and deblocking are performed to construct the estimation of the WS:

$$Blocks\ of\ W^* : (U_{WS}) \times (S_{W*}) \times \left(V_{WS}^T\right)\ \underline{de-locking}\ W^*.$$

A flow diagram of the watermark extraction algorithm is shown in detail in Figure 2.

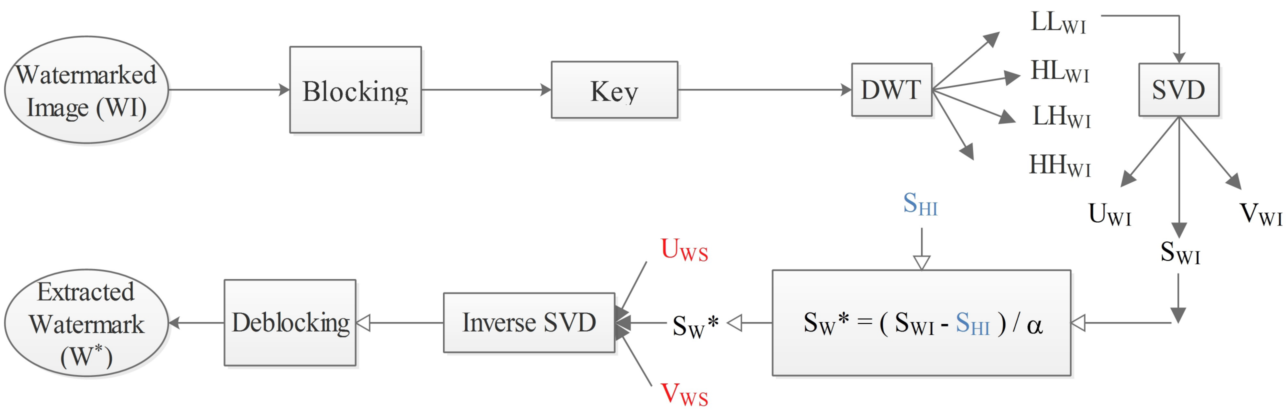

Figure 2. Flow diagram of the watermark extraction algorithm.

5. Experimental results

In this section simulation results of our scheme are presented to illustrate the superiority of the proposed algorithm both in robustness under attacks and transparency of the output images. In order to have a fair comparison between the proposed algorithm in this study with RDWT-SVD in [8] and DWT-SVD in [9], which are used as the bench mark to show the outperformance, first simulations are performed in the absence of attacks, and then under several attacks such as JPEG compression, additive noises (Gaussian, salt and pepper), and cropping. It is worth mentioning that in this paper we used binary images as the WS. To comply with the aforementioned methods in [8,9], three well-known test images (HIs), i.e. "Lena", "Baboon", and "cameraman", are considered in grayscale with the size of 512 $\times$ 512 and the WS is chosen to be a 32 $\times$ 32 binary image for simulation as shown in Figure 3.

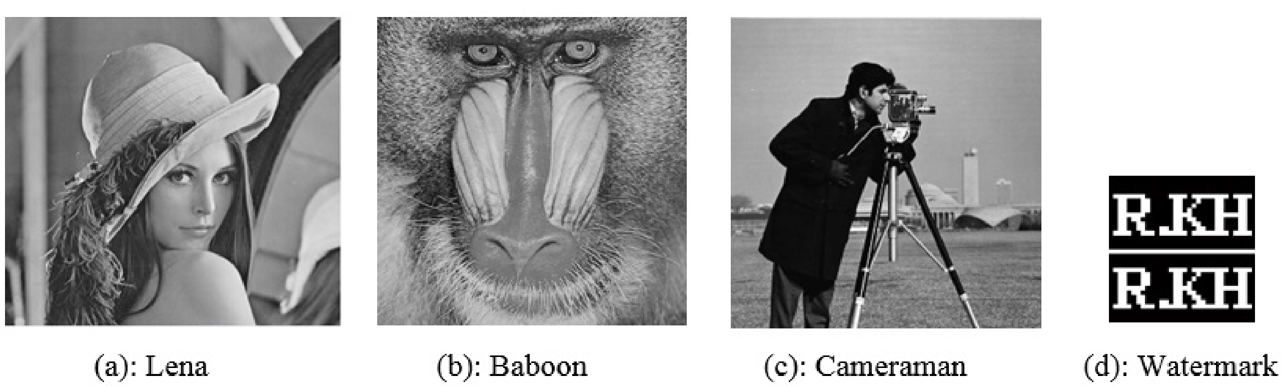

Figure 3. (a, b, c): Host images and (d): watermark image.

Since in [8,9] it was not mentioned where the suitable location is for embedding the WS with the same input data, inserting of the WS in singular coefficients on the diagonal matrix are considered in the beginning, middle, and end of the S. It is worth mentioning that since the results depend on the location of inserting the WS in coefficients of the S, simulations are performed for all possible conditions.

In order to obtain good visual quality of watermarked images, choosing the embedding strength coefficient, α, plays an important role in watermark embedding procedures. If the value of α is chosen close to 0, the watermarked image is less distorted and a maximum PSNR can be obtained. However, for lower α values, watermarked images are less robust to attacks, which means a lower NC [9]. Therefore, we select a value of α equal to 0.05 in a heuristic procedure. In this paper, we used the PSNR for measurement of the similarity of the HI and WI [18], and NC is utilized to measure the correlation of the original and extracted watermark image.

In order to have a qualitative comparison, the results of watermark embedding and watermark extraction of the methods in [8,9] and the proposed algorithm are illustrated in Figure 4 for Lena as the host image. Results show that since the proposed algorithm selects suitable locations for data embedding, it leads to relatively complete extraction in comparison with random selection of the methods in [8,9]. The improvement of the performance of the presented algorithm is shown in Figure 4.

Tables 1 and 2 represent the quantitative simulation results using the RDWT-SVD method of reference [8] and the DWT-SVD method of reference [9], respectively, by supposing the input data of this study (as illustrated in Figure 3) and by inserting the WS in the 32nd coefficient of the beginning, middle, and end of the S. As is shown in Table 1, correlations of extracted watermarks from the ending coefficients of matrix S of the three HIs are almost the same. This specifies the similarity of the HIs' texture, small length of the S vector of the WS, and small value of these coefficients, besides the fact that choosing a low value for α plays an effective role. However, the similarity of the textures is the main reason for the resemblance of the coefficients of S. Since the values of these coefficients are relatively small, the process of embedding and extracting the watermark and attacking watermarked images for the mentioned HIs cause almost the same effects.

Table 1. Simulation results of the RDWT-SVD method.

Attacks	Host images	S: 1–32		S: 245–276		S: 481–512	
		PSNR	NC	PSNR	NC	PSNR	NC
Without attack	Lena	56.9179	1	59.7720	0.1052	56.9281	0.1052
	Baboon	56.9197	1	59.7426	0.1217	56.9177	0.1050
	Cameraman	56.9180	1	59.4742	0.1085	56.9180	0.1054
JPEG compression QF = 70	Lena	38.6257	0.2269	38.6810	0.0625	38.6200	0.1052
	Baboon	30.4600	0.2960	30.4678	0.0986	30.4617	0.1052
	Cameraman	41.1899	0.0493	41.2452	0.0986	41.1485	0.1032
Gaussian noise (Var 0.001)	Lena	29.9912	0.8983	29.9925	0.1131	29.9904	0.1048
	Baboon	29.9873	0.8858	29.9859	0.0259	30.0022	0.1043
	Cameraman	30.1055	0.8434	30.1202	0.2174	30.0991	0.1051
Salt & pepper noise (0.01 d)	Lena	25.4523	0.8243	25.2017	0.2838	25.4349	0.1052
	Baboon	25.4521	0.4424	25.4235	0.1065	25.7427	0.1030
	Cameraman	24.9575	0.4039	25.2018	0.3743	24.8837	0.1044
Cropping (25%)	Lena	13.0050	0.1611	13.0050	0.0559	13.0050	0.1027
	Baboon	11.2517	0.1578	11.2517	0.0197	11.2517	0.1035
	Cameraman	10.2509	0.1184	10.2510	0.0986	10.2509	0.1035

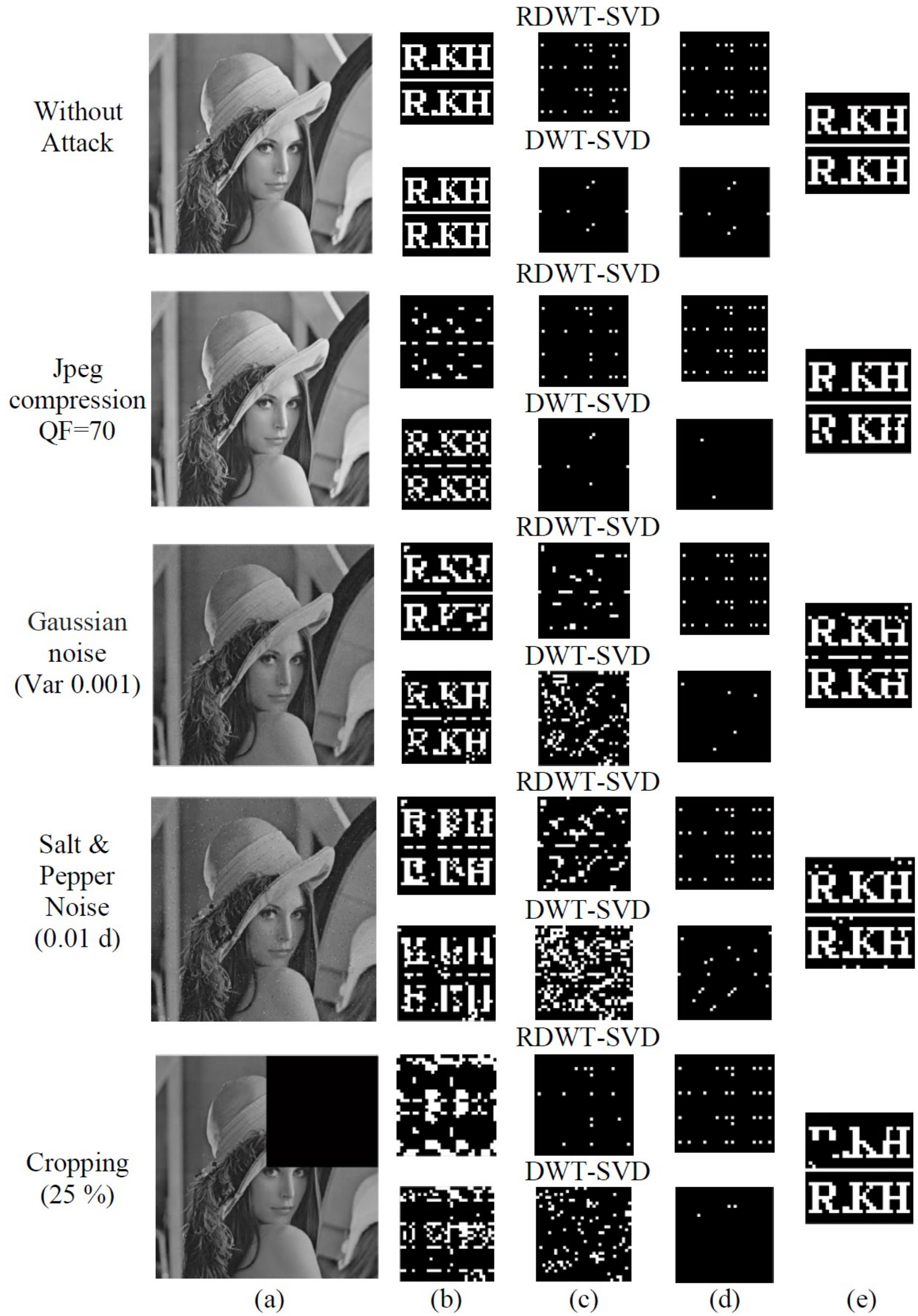

Figure 4. Lena host image: (a) the watermarked image against various attacks; (b) beginning, (c) middle and (d) end coefficients of matrix S for watermark extraction process for the RDWT-SVD and DWT-SVD methods; e) extracted watermark by the ANN-DWT-SVD method.

Table 2. Simulation results of the DWT-SVD method.

Attacks	Host images	S: 1–32		S: 113–144		S: 225–256	
		PSNR	NC	PSNR	NC	PSNR	NC
Without attack	Lena	55.3773	1	55.3773	0.0230	55.3773	0.0230
	Baboon	55.3773	1	55.3773	0.0098	55.3773	0.0164
	Cameraman	55.3773	1	55.3773	0.0098	55.3773	0.0164
JPEG compression QF = 70	Lena	38.5542	0.7401	38.6146	0.0263	38.6353	0.0065
	Baboon	30.4478	0.8256	30.4573	0.0032	30.4587	0.0164
	Cameraman	41.0122	0.7894	41.1252	0.0197	41.1720	0.0032
Gaussian noise (Var 0.001)	Lena	29.9672	0.9105	29.9870	0.2717	29.9721	0.0069
	Baboon	29.9792	0.8825	29.9881	0.0529	29.9795	0.0095
	Cameraman	30.1059	0.7559	30.1036	0.2447	30.1018	0.0069
Salt & pepper noise (0.01 d)	Lena	25.5114	0.7345	25.4694	0.6065	25.6582	0.0585
	Baboon	25.5287	0.2891	25.6062	0.2503	25.5215	0.0088
	Cameraman	25.1269	0.2276	24.9481	0.5960	25.1738	0.0947
Cropping (25%)	Lena	13.0049	0.1875	13.0049	0.0065	13.0049	0
	Baboon	11.2517	0.2302	11.2517	0.0263	11.2516	0
	Cameraman	10.2509	0.1940	10.2509	0	10.2509	0

Because of larger values of the first coefficients of matrix S to the middle and end coefficient, higher NC and consequently higher robustness could be achieved by inserting the watermark in the first coefficient. Therefore, as can be seen from Tables 1 and 2, NCs obtained from inserting the watermark in the first coefficients of the singular value diagonal matrix (S: 1–32) are larger compared to other coefficients. Thus, it is obvious that in this case the correlation between the WS and W* is increased.

Table 3 represents the simulation results of the ANN-DWT-SVD of the proposed method.

Table 3. Simulation results of the ANN-DWT-SVD method.

Attacks	Host images	PSNR	NC
Without attack	Lena	55.3773	1
	Baboon	55.3773	1
	Cameraman	55.3773	1
JPEG compression QF = 70	Lena	38.5980	0.927632
	Baboon	30.4572	0.950658
	Cameraman	41.0985	0.898026
Gaussian noise (Var 0.001)	Lena	29.9754	0.863487
	Baboon	29.9824	0.817763
	Cameraman	30.1151	0.859868
Salt & pepper noise (0.01 d)	Lena	25.4912	0.906373
	Baboon	25.5500	0.849013
	Cameraman	25.1846	0.847039
Cropping (25%)	Lena	13.0049	0.881579
	Baboon	11.2517	0.641447
	Cameraman	10.2509	0.572368

Generally, the human perceptual system cannot sense the distortion when the PSNR of a watermarked image is more than 30 dB [9]. Comparing the results presented in Tables 1, 2, and 3, all three methods have proper transparency because of high PSNR values. Furthermore, the obtained values of the NC for the RDWT-SVD and DWT-SVD methods under predefined attacks are less than the obtained corresponding NC of the proposed method (ANN-DWT-SVD), for all three different modes of S coefficients. Moreover, the obtained NC for this study is close to 1, which means high similarity of the original and extracted watermark and consequently more robustness against attacks.

6. Conclusion

In this paper, a nonblind ANN-DWT-SVD watermarking method was proposed. An ANN algorithm was used to estimate which blocks are suitable for watermark embedding and could better hide the WS as long as transparency and robustness under attacks are guaranteed. By comparing the results of all three aforementioned methods, as can be seen in Figure 5, the robustness of the proposed method is considerably improved because of selecting a suitable location for watermark insertion in comparison with random selection in the RDWT-SVD and DWT-SVD methods. Qualitative comparisons based on visual results presented in this study confirm the superiority of the proposed method, which could promise high quality as well as strong robustness under attacks.

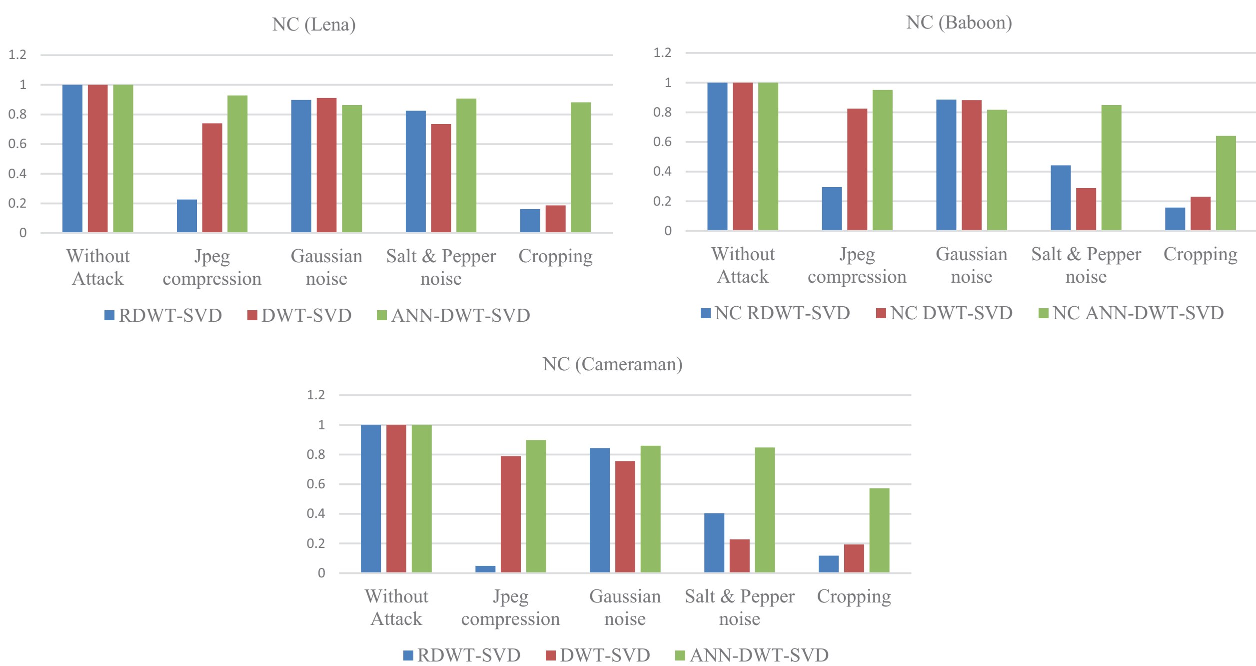

Figure 5. Comparative study of the NC after attacks for different watermarking algorithms for Lena, Baboon, and Cameraman host images. For the RDWT-SVD and DWT-SVD methods data embedding is done in the first 32 SVD coefficients, which provides the best results for them.

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