Hidden Logo Watermarks by Redundant Transform and Independent Component Analysis

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***Abstract* - This paper presents adaptive image watermarking using redundant wavelet transform (RDWT) and independent component analysis (ICA). To embed logo watermarks, the original image is decomposed into 2 levels using RDWT, and watermarks are embedded into LH2 and HL2 frequency sub-bands. The perceptual model is applied with a stochastic multi-resolution model for adaptive watermark embedding. This is based on computation of a noise visibility function (NVF) which has local image properties. For watermark security, embedded logo watermarks are encrypted to random noise signal. By RDWT, less image distortion is obtained when watermarking with fixed watermark energy than orthogonal basis. We also propose an intelligent ICA based detector that directly extracts watermarks in spatial domain. A novel characteristic of this detection is that it does not require the transformation process to extract the watermark. The experimental results show that logo watermarks are perfectly extracted, and demonstrate the robustness against image processing and compression.**

1. INTRODUCTION

Recently, the explosive growth of the Internet has increased multimedia services, such as electronic commerce, pay-per-view, video-on-demand, electronic newspapers, and peer-to-peer media-sharing. As a result, multimedia data can be obtained quickly over high-speed network connections. However, authors, publishers, owner and providers of multimedia data are reluctant to grant the distribution of their documents in a networked environment because the ease of intercepting, copying and redistributing electrical data in their exact original form encourages copyright violation. Therefore, it is crucial for the future development of networked multimedia systems that robust methods are developed to protect the intellectual property right of data owners against unauthorized copying and redistribution of the material made available on the network. Classical encryption systems do not completely solve the problem of unauthorized copying because once encryption is removed from a document, there is no more control of its dissemination.

A possible solution consists of marking multimedia work to allow their spreading to be tracked: Digital watermarking presents a viable solution to the above problem, since it is possible to identify the source, author, creator, owner, distributor or authorized consumer of a document, by means of the identification code. The watermark is permanently embedded into digital data for copyright protection and for checking if the data has been corrupted. One of the important requirements of watermark is to compromise between the invisibility and the robustness. First, the watermark should be embedded in an invisible way to avoid degrading of perceptual quality. Second, the watermark should be robust against watermark attacks which are applied to image content. These attacks include but not limit to lossy image compression, filtering, noise-adding, geometrical modification, etc.

Many watermarking techniques for still images and video contents have been proposed [1-5] in which transformation based on an orthogonal basis is widely used to embed watermark signal as random noise to a small subset of frequency coefficients. Usually, this subset belongs to the medium range of frequency spectrum to grant a trade-off between perceptual invisibility and robustness.

Moreover, the conventional watermark detection uses transform techniques to decompose the corrupted image, of which the ownership is determined, and from which the watermark is recovered. In general, toward the aim of watermark recovery, some detection systems require the previous knowledge of the watermark such as its location, the strength, the threshold or the original image. Also in some cases, the watermark system requires embedding multi-information such as sources, authors, creators, owners, distributors or authorized consumers of a document. Therefore, a watermarking algorithm must be able to embed multi watermarks to satisfy those requirements.

In this paper, a new technique to add multi-logo watermarks into digital images is presented. The proposed algorithm operates by using redundant discrete wavelet transform (RDWT). By RDWT, logo watermarks are added to transform coefficients, and it gives results with less signal distortion for RDWT than for orthogonal basis. The perceptual model is applied with stochastic approach for watermark embedding. This is based on computation of a NVF that has local image properties. A new intelligent detection technique based on ICA is introduced for extraction to ensure blind watermark. We directly extract the logo watermarks from a corrupted image in spatial domain.

The paper is organized as follows: in Section 2, watermark embedding algorithm is described, and the detection system is shown in Section 3; in Section 4 experimental results are presented; finally conclusions are drawn in Section 5.

2. A NEW WATERMARK EMBEDDING SYSTEM

2.1. RDWT

RDWT gives an over complete representation of the input sequence which functions to a certain extent as an approximation to the continuous wavelet transform. The RDWT is shift invariant, and its redundancy introduces an over complete frame expansion. It is known that frame expansion increases the robustness to additive noise [1],[7],[8]; that is, addition of noise to transform coefficient results in less signal distortion for frame expansions than for orthogonal expansion. RDWT has been proposed for signal detection and enhancement [7], [8], since the RDWT maintains uniform sampling rate in time domain and in some respects, is a discrete approximation to the continuous wavelet transform. Instead of down-sampling, the low-pass signal during each filter-bank iteration is done in the usual DWT, the filters themselves are up-sampled before performing filter convolution at each scale.

RDWT removes the decimation operators from DWT filter banks. To retain the multi-resolution characteristic, the wavelet filters must be adjusted accordingly at each scale. Specifically, $h_{j_1}[k] = h[k]$ where J_1 is starting scale, $h_{j_1}[k]$ is the RDWT scaling filter at scale J_1, and $h[k]$ is a normal DWT scaling filter.

Filter at later scales are up sampled versions from the filter coefficients at the upper state,

$$h_j[k] = h_{J+1}[k] \uparrow 2$$

and similar definitions are applied to $g_j[k]$, the wavelet filter of the orthogonal DWT.

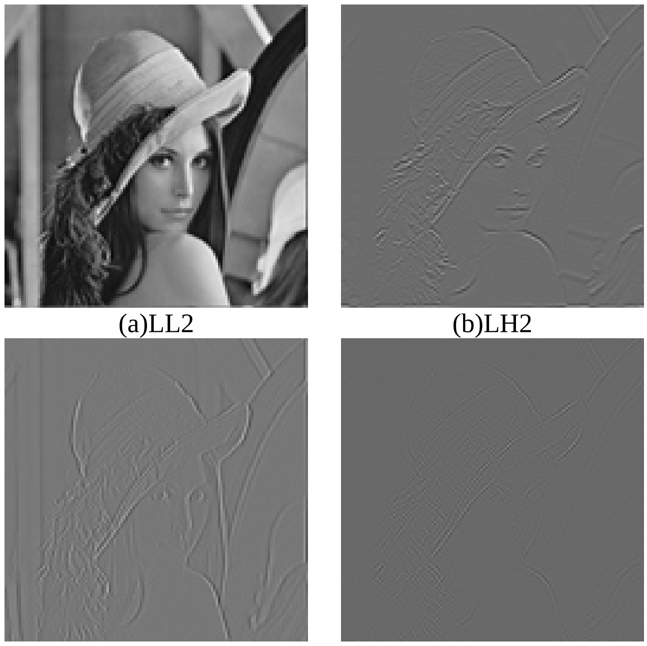
The RDWT multi-resolution analysis can be implemented via the filter bank equation:

Analysis:
$$c_j[k] = h_{J+1}[-k] * c_{J+1}[k]$$
$$d_j[k] = g_{J+1}[-k] * d_{J+1}[k]$$

Synthesis:
$$c_{j+1}[k] = \frac{1}{2}\left[h_{j+1}[k] * c_j[k] + g_{j+1}[k] * d_j[k]\right]$$

Lack of down-sampling in the RDWT analysis yields a redundant representation of the input sequence. Specifically, two valid descriptions of the coefficients exist after one stage of RDWT analysis.

Fig.1 shows redundant discrete wavelets transform of 512x512 "Lena" at two levels: LL2 is the approximation of the input image, LH2 is the detailed image containing information in the vertical, HL2 is the detailed image containing information in the horizontal, and HH2 is the detailed image containing information in diagonal. LL2 band at the highest level can be classified as most important, and the other 'detailed' bands can be classified as less important. The LL2 band can be decomposed once again in the same manner, thereby producing even more sub-bands. This can be done up to any levels.



(a)LL2 (b)LH2

(c)HL2 (d)HH2

Fig.1 Redundant transform of 512x512 "Lena" at two levels.

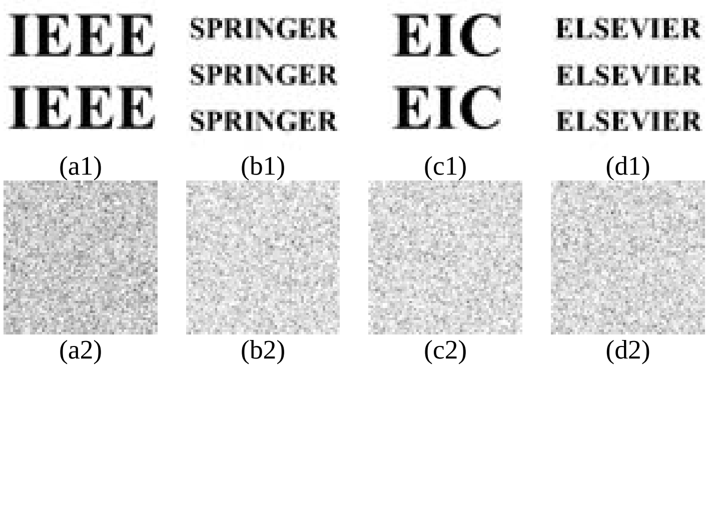
2.2. Watermarks

Our watermarks are four digital text images $\{+1,-1\}$. It is beneficial to preprocess watermarks before embedding to enhance security of the watermark. We randomly encrypted watermarks by scrambling; the pixels of the watermark are pseudo-randomly permuted to form a new watermark image. Let W and W_k be the original and permuted watermark, that is

$$W_k = \left\{ W_k(i,j) = w(i', j') \middle| 0 < i, i' < M \text{ and } 0 < j, j' < N \right\}$$

which pixel at (i', j') is mapped to pixel at (i, j) in a pseudorandom order, M and N are watermark sizes. In this proposal, four watermarks are used to embed.

Fig.2 shows four images used for watermarks and its corresponding permutation.



(a1) (b1) (c1) (d1)

(a2) (b2) (c2) (d2)

Fig.2 (a1), (b1), (c1), and (d1) Watermarks, (a2), (b2), (c2), and (d2) Random encryption of watermarks.

2.3. Stochastic perceptual model

A stochastic model of the cover image is applied to an adaptive watermark by computing NVF with non-stationary Gaussian model. In this case, NVF can be written as:

$$NVF(i,j) = \frac{1}{1+\sigma_x^2(i,j)} \tag{1}$$

where $\sigma_x^2(i,j)$ denotes the local variance of the host image in a window centered on the pixel with coordinates (i,j) [4]. By applying NVF, the watermark in texture and edges is stronger than in flat areas and the proposed embedding algorithm is adaptive.

2.4. Embedding watermark

The watermark is embedded in RDWT domain. N x N RDWT sub-bands of the N x N gray scale image I is computed by two levels RDWT.

The watermarks are embedded through the following steps:

Step 1: The original image is decomposed into 2 levels using RDWT. The approximation components at LL2 sub-bands are not chosen to embed because they will seriously degrade image quality.

Step 2: Watermark embedding process. Select the middle frequency sub-bands at $I_{LH2}(i,j)$ and $I_{HL2}(i,j)$ to embed four logo watermarks of size $(N/2)x(N/2)$

Watermark embeds at *LH* sub-band:

$$I'_{LH2}(i,j) = I_{LH2}(i,j) + E\{LH_2\}.\alpha_1.(1-NVF(i,j)).W(i,j) + \frac{E\{LH_2\}}{10}.\alpha_2.NVF(i,j).W \tag{2}$$

Watermark embeds at *HL* sub-band:

$$I'_{HL2}(i,j) = I_{HL2}(i,j) + E\{HL_2\}.\alpha_1.(1-NVF(i,j)).W(i,j) + \frac{E\{HL_2\}}{10}.\alpha_2.NVF(i,j).W(i,j) \tag{3}$$

where $I'_{LH2}(i,j)$ $I'_{HL2}(i,j)$ are watermarked transform coefficients, $E\{LH_2\}\alpha_1$, $\frac{E\{LH_2\}}{10}\alpha_2$ denote the watermark strengths of texture and edge regions and flat regions at $I_{LH2}(i,j)$ sub-band and $E\{HL_2\}\alpha_1$, $\frac{E\{HL_2\}}{10}\alpha_2$ denote the watermark strengths of texture and edge regions and flat regions at $I_{HL2}(i,j)$ sub-band, α_1, α_2 are smoothing factors at the texture regions and flat regions; E denotes the mean. $W(i,j)$ are the watermarks:

$$\{W(i,j);(0<i,j\le N)\} = \{W_k(m,n)|(k=1,2,3,4);(0<m,n\le N/2)\}.$$

Logo watermarks are embedded in order $k = 1,2,3,4$ as follows:

$$
\begin{array}{l}
for\ m = 1\ to\ N/2 \\
\quad for\ n = 1\ to\ N/2 \\
\quad \begin{cases} W(m,n) = W_1(m,n) \\ W(m+N/2,n) = W_2(m,n) \\ W(m,n+N/2) = W_3(m,n) \\ W(m+N/2,n+N/2) = W_4(m,n) \end{cases} \\
\quad end \\
end
\end{array}
$$

where W of size $N\ x\ N$ is considered as the watermark to embed at whole LH2 and HL2 bands.

Step 3: Perform the inverse RDWT to retrieve the watermarked image.

Step 4: In order to apply ICA to blind watermark detection, the embedding process needs to create a key for extraction. The key is encrypted by key K and the original media.

3. WATERMARK DETECTION

In this section, we will describe how the intelligent watermark detector works based on ICA.

3.1. Independent component analysis

ICA linearly transforms data so that outputs are as statistically independent of each other as possible. The general model can be described as follows:

We start with the assumption that data vector $x = (x_1,..,x_M)$ can be represented in term of linear superposition of basis functions,

$$x = As = a_1 s_1 + ... + a_N s_N$$

where $s = (s_1,..,s_N)$ are the coefficients, A is an *MxN* matrix and the columns $a_1,...a_N$ are called basis functions. Basis functions are consistent while coefficients vary with data. The goal of the efficient coding is to find a set of a_i which results in coefficient values being statistically as independent as possible over a set of data. Thus, the linear analysis process is to find a matrix W such that

$$y = Wx$$

and to recover independent components s, possibly permuted and rescaled. Rows of *W* correspond to columns of *A*. Aapo Hyvärinen and Erkki Oja proposed FastICA algorithm. The approach first processes the data for centering and whitening [6]. The observer variable x is centered by subtracting the mean vector $m = E\{x\}$ from the observed variable, which makes *x* a zero-mean variable. This processing is designed to simplify the ICA algorithms. After estimating the mixing matrix A with centered data, we can complete the estimation by adding the mean vector of the original source signal back to the centered estimation of the source data. Another processing is to whiten the observed variables. Whitening mean transforms the variable x linearly so that the new variable x is white, i.e., its components are uncorrelated, and their variances equal unity [6]. Perform the FastICA to the signal that has been centered and whitened to find the separate matrix *W*.

3.2. Watermarks detection

ICA was introduced for extracting the watermark [5] in which watermarked image can be considered as a mixture and required the transform process to get middle frequency sub-bands. This proposal introduces a new intelligent ICA detector which does not require the transform process to separate LH and HL bands for watermark extraction. ICA is applied directly on the watermarked image with the help of the private key. One can extract successfully the watermark to claim the ownership.

Mixtures are created by the following equations:

$$\begin{aligned} X_1(i,j) &= I'(i,j) + K_p(i,j) \\ X_2(i,j) &= K(i,j) + K_p(i,j) \\ X_3(i,j) &= I'(i,j) \end{aligned} \tag{4}$$

where X_1, X_2 X_3 are mixtures, I' is the watermarked image, and K_p is a key in watermark embedding process. Those mixtures can be modeled as:

$$\begin{aligned} X_1 &= a_{11}I + a_{12}W + a_{13}k \\ X_2 &= a_{21}I + a_{22}W + a_{23}k \\ X_3 &= a_{31}I + a_{32}W + a_{33}k \end{aligned} \tag{5}$$

where $A = \begin{bmatrix} a_{11}a_{12}a_{13} \\ a_{21}a_{22}a_{23} \\ a_{31}a_{32}a_{33} \end{bmatrix}$ is the mixing matrix, and W is the watermark. Applying the ICA algorithm for those mixtures, watermarks W is extracted. From watermark W, we can separate $W_k = \{W_k(m,n) | (k = 1,2,3,4); (0 < m,n \le N/2)\}$.

When watermarks are extracted, users compare the extracted and reference watermark subjectively. A similarity measurement of the extracted, $W_k'(m,n)$ and the reference watermarks, $W_k(m,n)$ can be defined by the normalized correlation (NC):

$$NC = \frac{\sum_{m=1}^{N/2}\sum_{n=1}^{N/2}\left[W_k(m,n)W_k'(m,n)\right]}{\sum_{m=1}^{N/2}\sum_{n=1}^{N/2}\left[W_k(m,n)\right]^2} \tag{6}$$

The value of NC lies in the unit range $[0,1]$, and if we acquire higher NC values, the embedded watermark is more similar to the extracted one.

4. EXPERIMENTAL RESULTS

The proposed watermarking scheme was tested on a 512x512 standard images. We used Daubechies filters for computing RDWT with 2 levels. Highest middle frequency sub-bands $I_{LH2}(i,j)$ and $I_{HL2}(i,j)$ are selected to embed watermarks. Four 256x256 binary images, “IEEE”, “SPRINGER”, “EIC” and “ELSEVIER” were used as watermarks, and α_1 and α_2 were set to 0.2 to ensure the invisibility.

Fig. 3(a) and Fig. 3(b) show the original and the watermarked “Lena” image, respectively. The two images are evidently indistinguishable. The effect of NVF on the watermarked image is shown in Fig. 3(c). It can be confirmed that the watermark in texture and edges is stronger than in flat areas and the proposed embedding algorithm is adaptive embedding.

Table 1. PSNR/MSE and NC values of standard images

Image	PSNR(dB)/ MSE	NC1	NC2	NC3	NC4
Lena	51.90/0.41	0.9970	0.9976	0.9964	0.9978
Man	44.37/2.37	0.9258	0.9682	0.9557	0.9706
Elaine	53.15/0.31	0.9993	0.9998	0.9998	0.9999

Table 1 shows PSNR, MSE and NC values of standard images. From the results, we find that the visual quality of watermarked image increased compared to other methods [1-5]. By the proposed RDWT based embedding, the watermark is distributed over the entire image, and produces less image distortion and with more watermark energy than conventional DWT.

To identify the ownership of watermarked image, proposed watermarking detection was performed. Fig. 4 shows four 256x256 extracted and decrypted watermarks of watermarked image “Lena”. The proposed detection can perfectly extract logo watermarks (NC1 = 0.9970, NC2 = 0.9976, NC3 = 0.9964, NC4 =0.9978).

(a)

(b)

(c)

Fig.3 (a) The original “Lena” image, (b) Watermarked “Lena” (c) Difference between the original “Lena” and the watermarked “Lena”

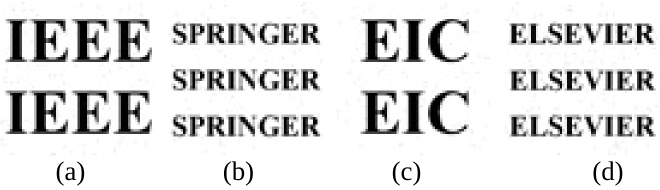


Fig.4 Extracted watermarks

To evaluate the robustness of the proposed watermarking scheme, several attacks were considered including the random, salt & pepper noise adding process, the cropping process, the filtering process, the Jpeg compression process, the Jpeg2000 coding and compression process, and SPIHT (set-partitioning in hierarchical trees) coding and compression process.

Lossy compression is an operation that usually eliminates perceptually non-salient components of an image. Most processing of this sort takes place in the frequency domain. In fact, data loss usually occurs among the high frequency components. The watermarked image is compressed by Jpeg compression, Jpeg 2000 compression, and wavelet-SPIHT (set-partitioning in hierarchical trees) compression with different compression ratios. Fig.5 shows the extracted results from Jpeg compression with a quality factor of 10, JPEG-2000 compression with 0.400 bits/pixel, wavelet-SPIHT coding and compression with 0.400 bits/pixel. The proposed method embeds watermark in the perceptual components, therefore the detection system shows reliable extraction of the watermark when the watermarked image is compressed.

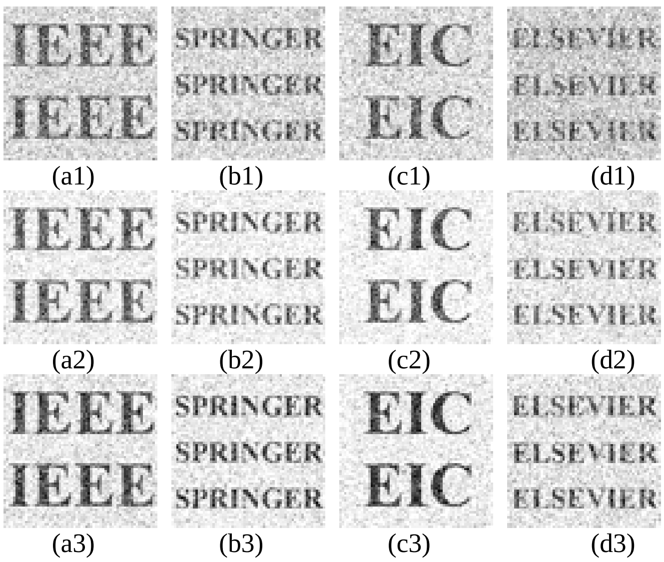


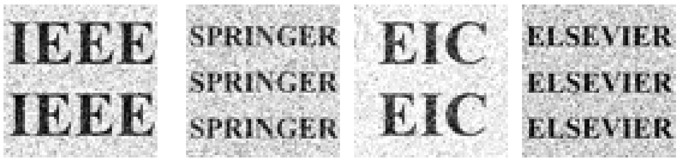
Fig.5 (a1), (b1), (c1), (d1) the extracted watermarks from jpeg (quality factor = 10%), (a2), (b2), (c2), (d2) jpeg 2000 (rate = 0.400), and (a3), (b3), (c3), (d3) SPITH (rate = 0.400).

Lowpass filtering of an image will result in a blurred image. Fig. 6(a1) shows lowpass filtered version of watermarked image with window size of 5x5. Fig. 6(a2), Fig. 6(a3), Fig. 6(a4), and Fig. 6(a5) show corresponding extracted watermarks.

Fig. 6(b1) shows the median filtered version of watermarked “Lena” with window size of 5x5. Fig. 6(b2), Fig. 6(b3), Fig. 6(b4), and Fig. 6(b5) show corresponding extracted watermarks.

Fig.6. (a1), (b1) Watermarked image “Lena” low-pass and median filtered 5x5, and (a2), (a3), (a4), (a5), (b2), (b3), (b4), (b5) the corresponding ICA watermarks extracted.

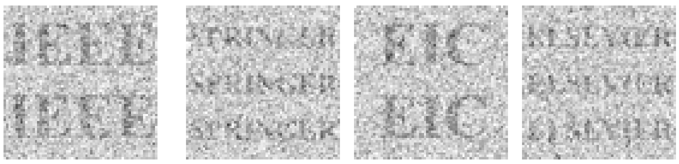
Fig.7 shows the cropping attacked “Lena” in experiments. Fig. (7a1) cropped 15% centered; Fig. (7b1) cropped 45% of the surroundings and replaced with pepper image, and Fig. (7a2), Fig. (7a3), Fig. (7a4), Fig. (7a5), Fig. (7b2), Fig. (7b3), Fig. (7b4), and Fig. (7b5) the corresponding ICA watermarks extracted.



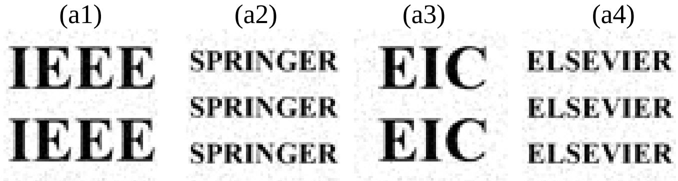
(b2) (b3) (b4) (b5)

Fig.7. The cropped versions "Lena" in experiment and detector output

Watermarked image is added of random noise with power =200, and Salt & Pepper noise with noise density = 0.05. Fig.8 shows extracted watermarks from adding noise.



(a1) (a2) (a3) (a4)



(b1) (b2) (b3) (b4)

Fig.8. (a1), (a2), (a3), (a4) watermarks extracted from adding random noise and (b1), (b2), (b3), (b4) watermarks extracted from adding Salt & Pepper noise

Table 2. PSNR/MSE, NC values of Jpeg, Jpeg 2000, SPITH compression, adding noise, cropping and filtering attacks. The higher NC values indicates the greater robustness

Attacks	PSNR(dB)/ MSE	NC1	NC2	NC3	NC4
Center crop (15%)	20.4853/ 581.4953	0.9142	0.9322	0.9220	0.9360
Surrounding crop (45%)	17.4376/ 1173.0536	0.7547	0.8239	0.6776	0.6920
Jpeg (Quality = 10)	32.4395/ 37.0793	0.5966	0.6553	0.5558	0.6392
Jpeg2000 (Rate=0.400 bpp)	36.2700/ 15.3489	0.7162	0.8003	0.7205	0.7774
Spiht (Rate=0.400 bpp)	36.7956/ 13.5994	0.7184	0.8021	0.7258	0.7780
Random noise (Power = 200)	25.1394/ 199.1297	0.4350	0.4923	0.4874	0.4826
Salt&Pepper (Noise density =0.05)	22.3997/ 374.2093	0.9785	0.9806	0.9777	0.9786
Lowpass filter (Window 5x5)	29.1766/ 78.6001/	0.6711	0.7499	0.5611	0.7191
Median filter (Window 5x5)	32.1267/ 39.8487	0.7993	0.8829	0.8136	0.8662

Table 2 shows PSNR, MSE and NC values of Jpeg, Jpeg 2000, and SPITH, compression at different compression ratios, adding of random noise, adding Salt&Pepper noise, cropping and filtering.

5. CONCLUSION

A new image watermarking scheme based on redundant wavelet transform and independent component analysis is proposed. The proposed watermark embedding algorithm is an adaptive algorithm, and offers increasing invisibility of the watermarked image. The advantage of the method is the possibility to embed multi-information into image, and have less distortion when watermarking with fixed watermark energy than orthogonal basis. Besides, the proposed intelligent ICA based detector can extract the watermark directly and correctly without using any information about the original image and embedded watermark parameters. Experimental results have demonstrated that the proposed watermark is robust with respect to some important attacks such as cropping, filtering, adding noise, and image compression.

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