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Research Article

A Robust Image Watermarking in the Joint Time-Frequency Domain

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With the rapid development of computers and internet applications, copyright protection of multimedia data has become an important problem. Watermarking techniques are proposed as a solution to copyright protection of digital media files. In this paper, a new, robust, and high-capacity watermarking method that is based on spatiofrequency (SF) representation is presented. We use the discrete evolutionary transform (DET) calculated by the Gabor expansion to represent an image in the joint SF domain. The watermark is embedded onto selected coefficients in the joint SF domain. Hence, by combining the advantages of spatial and spectral domain watermarking methods, a robust, invisible, secure, and high-capacity watermarking method is presented. A correlation-based detector is also proposed to detect and extract any possible watermarks on an image. The proposed watermarking method was tested on some commonly used test images under different signal processing attacks like additive noise, Wiener and Median filtering, JPEG compression, rotation, and cropping. Simulation results show that our method is robust against all of the attacks.

1. Introduction

Recently, the production, distribution, and use of digital media has become very popular. Although these products have the advantages of high quality, ease of modification, and quality duplication, they introduce the problems of copyright protection issues because they can be easily copied and altered. Watermarking techniques are proposed as a solution to copyright protection problems of digital media files. The basic idea in watermarking is embedding a secret data into a multimedia file. In recent research, new methods are proposed to watermark audio, image, and video files.

In digital watermarking, a specific information called watermark is embedded in a multimedia file in such a way that it can be detected or extracted when necessary. The watermark may contain information about the digital object as well as information about the user or owner. As for image and video files, the watermark can be another image or signature logo. The watermark may be embedded so that it is either visible or invisible.

The principle of watermarking is to embed a digital code (watermark) within the host multimedia document, and to use such a code to prove ownership, to prevent illegal copying, to give some indications about the watermarked data or to enable the access to enhanced versions of the content or to additional services. The watermark code is embedded by making imperceptible modifications to the original data.

A watermarking algorithm in general consists of three basic components: (i) watermark, (ii) encoder (watermarking algorithm), and (iii) decoder (detection or extraction algorithm). To be useful a digital watermarking system must satisfy some basic requirements. First of all, the embedded watermark should be perceptually invisible. In other words, its presence should not affect the image quality. Moreover, the embedded watermark should be robust against the common signal processing manipulations like additive or multiplicative noise (Gaussian or salt and pepper (SP) noise), filtering, JPEG Compression, and rotation.

Image watermarking algorithms are mainly concentrated on spatial or spectral domains. Although successful methods have been presented using both approaches, they also have limitations and weaknesses. In the spatial domain, the image area where watermark is embedded is chosen based on the texture of the original image [1, 2]. In the spectral approach, watermark is embedded in a transform domain using discrete cosine transform, discrete wavelet transform, and so forth. For an invisible and robust watermarking, the watermark is embedded into middle frequencies range [3–5]. Watermarking in the frequency domain has advantages in terms of robustness, but there are limitations like invisible embedding may be difficult. Some new techniques are introduced by combining the advantages of both spatial and spectral domains for robust and invisible watermarking. This can be done using joint SF representations of images [6, 7]. Watermarking in the joint SF domain provides flexibility in terms of how much watermark will be embedded in which image region, and in what frequency band.

A new spatiofrequency- (SF-) based image watermarking algorithm which uses Discrete Evolutionary Transform (DET) has been presented in our past works [8]. In this paper, a new approach is presented for embedding watermark into SF representation of the image. By using this approach, more robust, invisible, secure and high capacity watermarking algorithm is obtained.

The rest of the paper is organized as follows: In Section 2, we give a brief introduction to DET calculated by a multiwindow Gabor expansion as a linear time-frequency representation method. Then we present our SF domain image watermarking technique based on DET in Section 3. Watermark extraction algorithm with correlation detector is given in Section 4. Embedding and extraction performance tests are given in Section 5, followed by conclusions and discussion of the results in Section 6.

2. Time-Frequency Analysis by DET

In the following, we briefly explain the Discrete Evolutionary Transform (DET) as a tool for the time-frequency representation of image sequences.

Wold-Cramer representation [9], of a nonstationary random sequence $y(n)$ can be expressed as an infinite sum of sinusoids with random and time-dependent amplitudes and phases, or

$$y(n) = \int_{-\pi}^{\pi} \Gamma(n,\omega) e^{j\omega n} dZ(\omega), \tag{1}$$

where $Z(\omega)$ is considered a random process with orthogonal increments. This is a generalization of the spectral representation of stationary processes. Priestley's evolutionary spectrum [9, 10] of $y(n)$ is given as the magnitude square of the evolutionary kernel $\Gamma(n,\omega)$. Analogous to the above Wold-Cramer representation, a discrete, time-frequency representation for a sequence $x(n)$ with a time-dependent spectrum is possible [11, 12]:

$$x(n) = \sum_{k=0}^{K-1} X(n,\omega_k) e^{j\omega_k n}, \quad 0 \le n \le N-1, \tag{2}$$

where $\omega_k = 2\pi k/K$, K is the number of frequency samples, and $X(n,\omega_k)$ is a time-frequency evolutionary kernel. A similar representation can be given in terms of the corresponding bifrequency kernel $X(\Omega_s,\omega_k)$:

$$x(n) = \sum_{k=0}^{K-1} \sum_{s=0}^{K-1} X(\Omega_s,\omega_k) e^{j(\omega_k+\Omega_s)n}, \tag{3}$$

where ω_k and Ω_s are discrete frequencies. Discrete evolutionary transformation (DET) is obtained by expressing the kernels $X(n,\omega_k)$ or $X(\Omega_s,\omega_k)$ in terms of the signal. This is done by using conventional signal representations [11]. Thus, for the representation in (2) the DET that provides the evolutionary kernel $X(n,\omega_k)$, $0 \le k \le K-1$, is given by

$$X(n,\omega_k) = \sum_{\ell=0}^{N-1} x(\ell) W_k(n,\ell) e^{-j\omega_k \ell}, \tag{4}$$

where $W_k(n,\ell)$ is, in general, a time and frequency dependent window.The DET can be seen as a generalization of the short-time Fourier transform, where the windows are constant. The windows $W_k(n,\ell)$ can be obtained from either the Gabor representation that uses nonorthogonal frames, or the Malvar wavelet representation that uses orthogonal bases. Details of how the windows can be obtained for the Gabor and Malvar representations are given in [11]. Here, for the representation of image pixel sequences in spatiofrequency domain, we consider DET calculated by multiwindow Gabor frames.

The multiwindow Gabor expansion is given by [12]

$$x(n) = \frac{1}{I} \sum_{i=0}^{I-1} \sum_{m=0}^{M-1} \sum_{k=0}^{K-1} a_{i,m,k} h_i(n-mL) e^{j\omega_k n}, \tag{5}$$

where $\{a_{i,m,k}\}$ are the Gabor coefficients, and $\{h_{i,m,k}\}$ are the Gabor basis functions defined as

$$h_{i,m,k}(n) = h_i(n-mL) e^{j\omega_k n}, \tag{6}$$

and the synthesis window $h_i(n)$ is obtained by scaling a unit-energy mother window $g(n)$ as

$$h_i(n) = 2^{i/2} g\left(2^i n\right), \quad i = 0,1,\ldots,I-1. \tag{7}$$

The multiwindow Gabor coefficients are evaluated by

$$a_{i,m,k} = \sum_{n=0}^{N-1} x(n) \gamma_i^*(n-mL) e^{-j\omega_k n}, \tag{8}$$

where the analysis window $\gamma_i(n)$ is solved from the biorthogonality condition between $h_i(n)$ and $\gamma_i(n)$ [11]. Hence by comparing the representations of the signal in (5) and (2) we obtain the DET kernel as

$$X(n,\omega_k) = \frac{1}{I} \sum_{i=0}^{I-1} \sum_{m=0}^{M-1} a_{i,m,k} h_i(n-mL). \tag{9}$$

Substituting for the coefficients $\{a_{i,m,k}\}$, we obtain that

$$X(n,\omega_k) = \sum_{\ell=0}^{N-1} x(\ell) W(n,\ell) e^{-j\omega_k \ell}, \tag{10}$$

where we defined a time-varying window as

$$W(n,\ell) = \frac{1}{I}\sum_{i=0}^{I-1}\sum_{m=0}^{M-1}\gamma_i^*(\ell - mL)h_i(n - mL). \tag{11}$$

Then the evolutionary spectrum of $x(n)$ is given by

$$S(n,\omega_k) = \frac{1}{K}|X(n,\omega_k)|^2. \tag{12}$$

We should mention that above evolutionary spectral estimate is always nonnegative, and normalizing $W(n,\ell)$ to unit energy, the total energy of the signal is preserved, thus justifying the use of $S(n,\omega_k)$ as a TF energy density for $x(n)$. Furthermore, DET provides a linear signal representation where the sequence may be obtained from the TF representation much easier than it is with the bilinear TF representations such as Wigner distribution [13]. Hence DET is appropriate for watermarking applications in the SF domain where embedding and extracting a watermark will be easily implemented using linear operations.

3. Watermark Embedding in the Joint SF Domain

In our SF-based watermarking approach, the rows of the image to be watermarked are considered as one dimensional sequences and transformed into the joint SF domain. Watermark is embedded onto coefficients which are selected from these SF representation matrices. Therefore, it is possible to increase the length of the watermark to high values. Thus, we can embed more information to image.

Although it is possible to embed the watermark to all rows of the image, it is embedded only to chosen rows because of the security reasons. Also the watermark is embedded to chosen coefficients of the DET matrices. So, two different keys have to be used. One of them is used for the chosen rows, and the other one is for the chosen coefficients. Therefore, a more secure watermarking method is obtained.

There are methods to represent two dimensional images in the SF domain, but computational complexity and the dimensionality problems make them difficult to use in watermarking applications [6]. Recently new methods are presented where TF distributions (TFDs), usually the Wigner distribution, of each row of an image is used for embedding a watermark in the joint TF domain [7, 14]. However, synthesis of a sequence from its modified bilinear TFD is generally a difficult problem. Hence, we propose a new SF domain watermarking where we use the linear DET explained above to embed the watermark into any row of the image. Then the watermarked rows are easily obtained by the inverse transformation. We used multiwindow Gabor expansion based DET in our approach. However, other linear time-frequency representations may be used instead. For instance, the short-time Fourier transform (STFT) may be employed as well which is a special case of the DET where the window function is constant. Multiwindow Gabor-based DET is compared and shown to perform better than the STFT in many applications in previous studies [8, 12].

Let $I(x,y)$, $0 \le x,\ y \le N-1$, be the original image. The DET of row x of the image,

$$X_I(y,\omega_k) = \sum_{\ell=0}^{N-1} I(x,\ell)W(y,\ell)e^{-j\omega_k\ell} \tag{13}$$

$0 \le y,\ k \le N-1$, is obtained. The window $W(y,\ell)$ is obtained by using Gabor representation. Watermark sequence, $w(n)$, $0 \le n \le M-1$ is the copyright or some other necessary information. M is the length of the watermark sequence. In this paper, normally distributed random sequences that have zero mean and unity variance are used. The lengths of the sequences are chosen as 512.

For the watermark embedding process, the number of M coefficients are chosen from the DET matrix of image's xth row, in chosen space and frequency band. Then, the watermark is embedded to these coefficients as follows [15]:

$$\hat{c}(n) = c(n)[1 + w(n)]. \tag{14}$$

Here, $c(n)$, $0 \le n \le M-1$, represents the chosen DET coefficients. $w(n)$ is the watermark sequence. If it is needed to decrease the power of the watermark, a weighting constant can be used.

The places of the watermarked coefficients are saved as a key, because they are necessary at watermark extraction. Therefore, the unauthorized persons who does not have the key, cannot detect the embedded coefficients, and the safety of the watermark is guaranteed. After the watermark embedding process in SF domain finished, watermarked image rows are obtained by using inverse DET (IDET) as follows:

$$\hat{I}(x,y) = \sum_{k=0}^{K-1}\hat{X}_I(y,\omega_k)e^{j\omega_k y}. \tag{15}$$

Here, $\hat{X}_I(y,\omega_k)$ is the watermark embedded DET matrix, and $\hat{I}(x,y)$ is the watermarked image matrix.

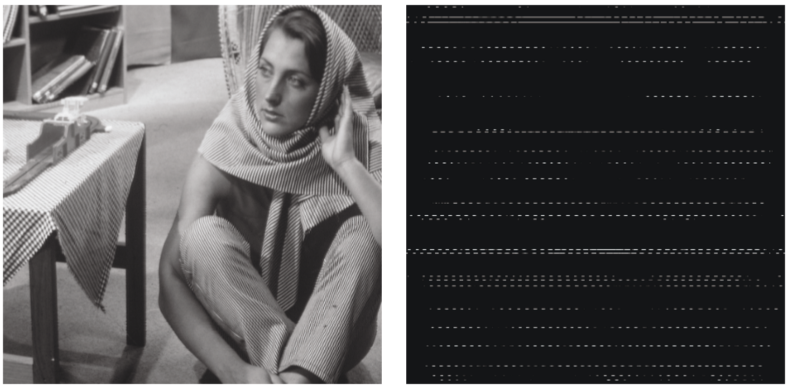
4. Watermark Extraction

In digital watermarking studies, methods have been presented for detection and extraction of the watermark by assuming that some information used in the embedding is known to the detector [14]. However, there are many works where blind detection is achieved without using any extra information. In practical applications such as copyright protection, the most important goal is the detection of watermark existence even after the watermarked image is attacked. In our study, we assume that we have the original and the watermarked images and try to extract the watermark.

In this paper, a correlation based detection method is used. First of all, the DET of the watermarked image row is calculated by using the key which shows the watermarked rows of the image. With the help of the second key, watermarked coefficients are chosen from the DET matrix, and they are saved as a sequence, $\hat{c}(n)$. $\hat{c}(n)$ contains watermarked and probably attacked coefficients. After that,

(a) (b)

Figure 1: (a) Watermarked Boats Image, (b) 1000 times magnified difference between the original and the watermarked Boats images.



(a) (b)

Figure 2: (a) Watermarked Barbara Image, (b) 1000 times magnified difference between the original and the watermarked Barbara images.

the DET of the original image's same row is calculated and $c(n)$ sequence is obtained again.

Then, $\hat{w}(n)$ extracted watermark sequence is obtained as follows:

$$\hat{w}(n) = \frac{\hat{c}(n) - c(n)}{c(n)}. \tag{16}$$

The extracted watermark sequence is probably corrupted because of the attacks. So, it is different from the original watermark. By using a correlation based detector, the similarity between the extracted watermark, $\hat{w}(n)$ and the series of the possible watermarks, $w(n)$, can be calculated to determine the embedded watermark. The correlation $t = \langle \hat{w}(n), w(n) \rangle$ is calculated and then a correlation based detector is given by

$$\begin{aligned} t > \eta &\Longrightarrow \text{true watermark}, \\ t < \eta &\Longrightarrow \text{wrong watermark}, \end{aligned} \tag{17}$$

where η is a threshold which may be derived by using the Neyman-Pearson criterion

$$P_F = \int_{\eta}^{\infty} f_T(t)dt, \tag{18}$$

and $f_T(t)$ is the probability density of t. Assuming all watermarks are zero mean and Gaussian distributed, we have that

$$P_F = Q\left(\frac{\eta - \mu_t}{\sigma_t}\right), \tag{19}$$

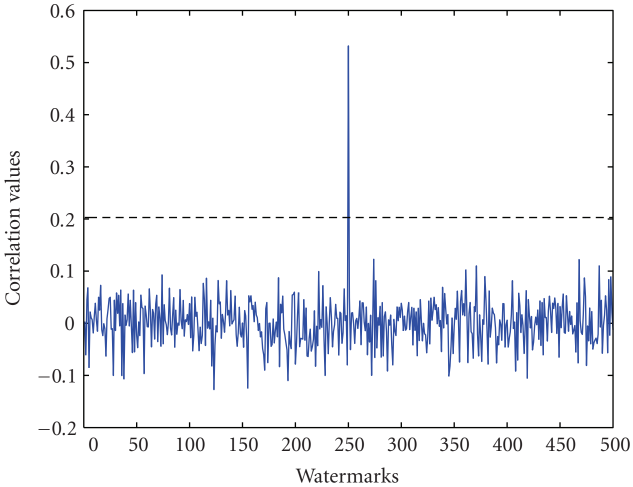
where $Q(\cdot)$ is the standard error function and μ_t and σ_t are the mean and standard deviation of t, respectively. From above we can obtain that

$$\eta = \sigma_t Q^{-1}(P_F). \tag{20}$$

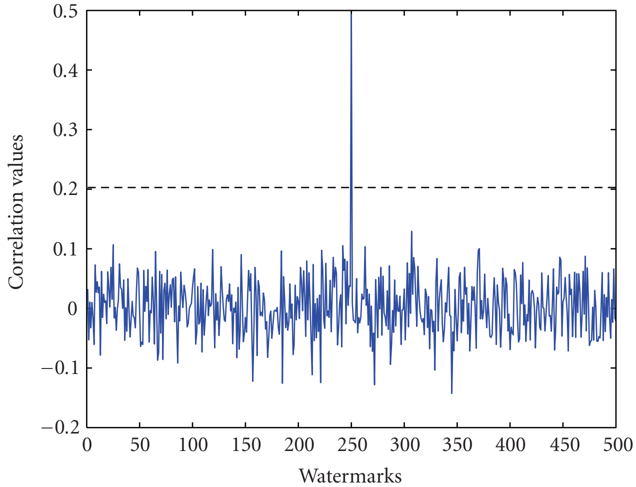
In our simulations, we take $\sigma_t^2 = 524$, $P_F = 0.01$, and $\eta = 0.2029$. t takes the highest value when the original and the extracted watermarks are same. So, we take the variance of the original watermark as variance of t.

5. Simulations

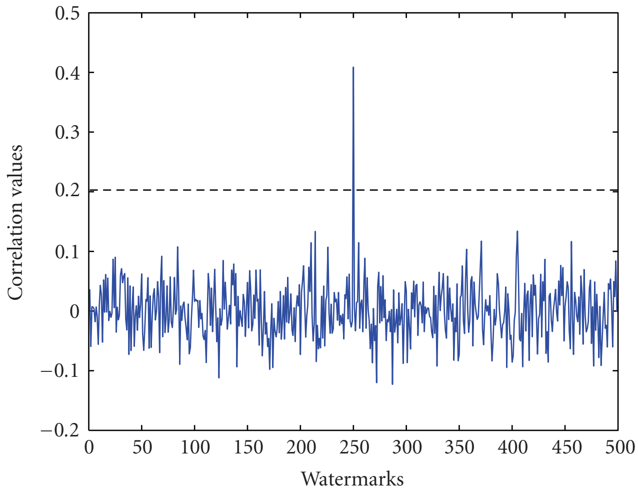
The proposed watermarking method was tested on some commonly used test images (Lena, Baboon, Boats, and Barbara) and the detection performance was investigated. The sizes of images are 512×512. Watermark is chosen as a zero mean and normal distributed random sequence. We



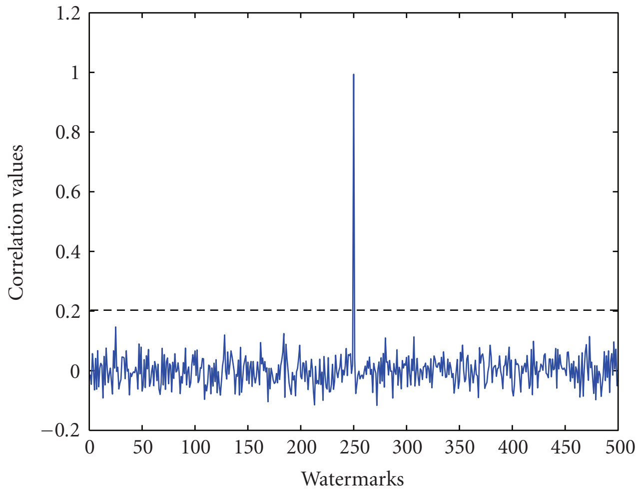
(a)



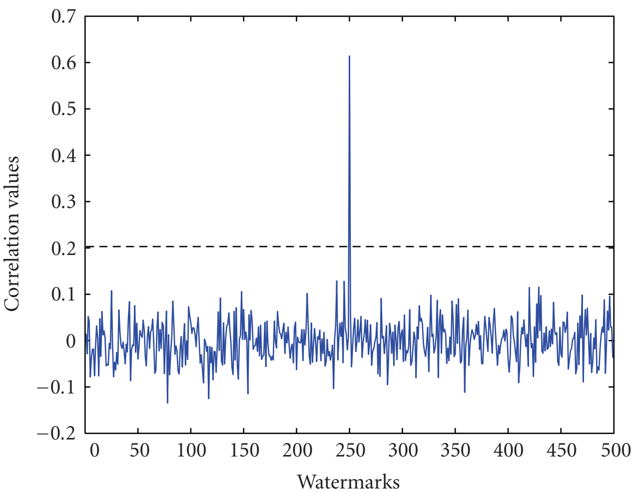
(b)



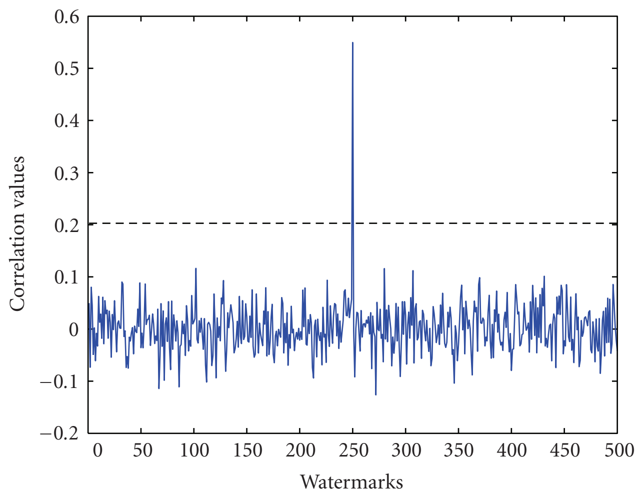
(c)



(d)



(e)



(f)

Figure 3: Continued.

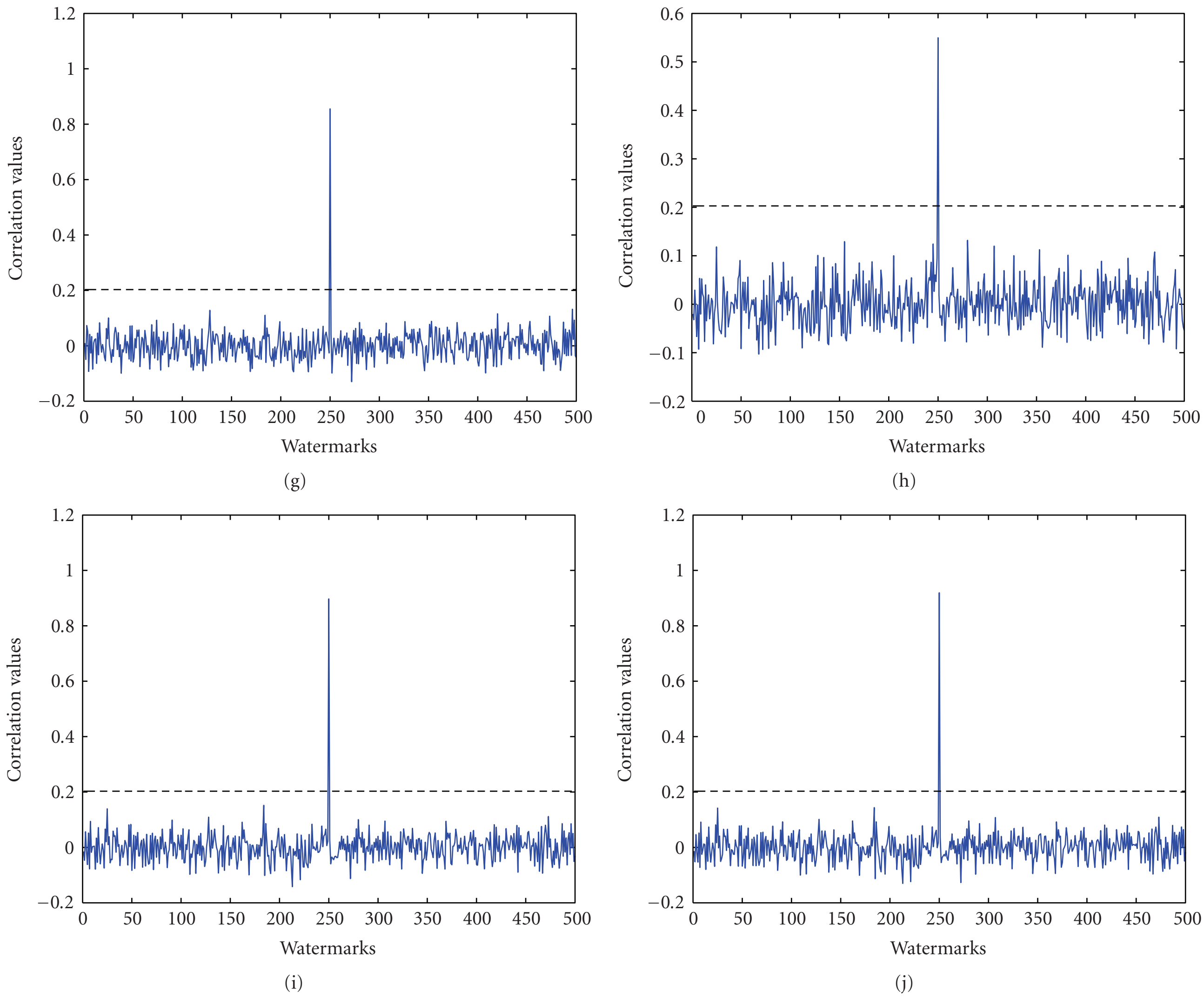


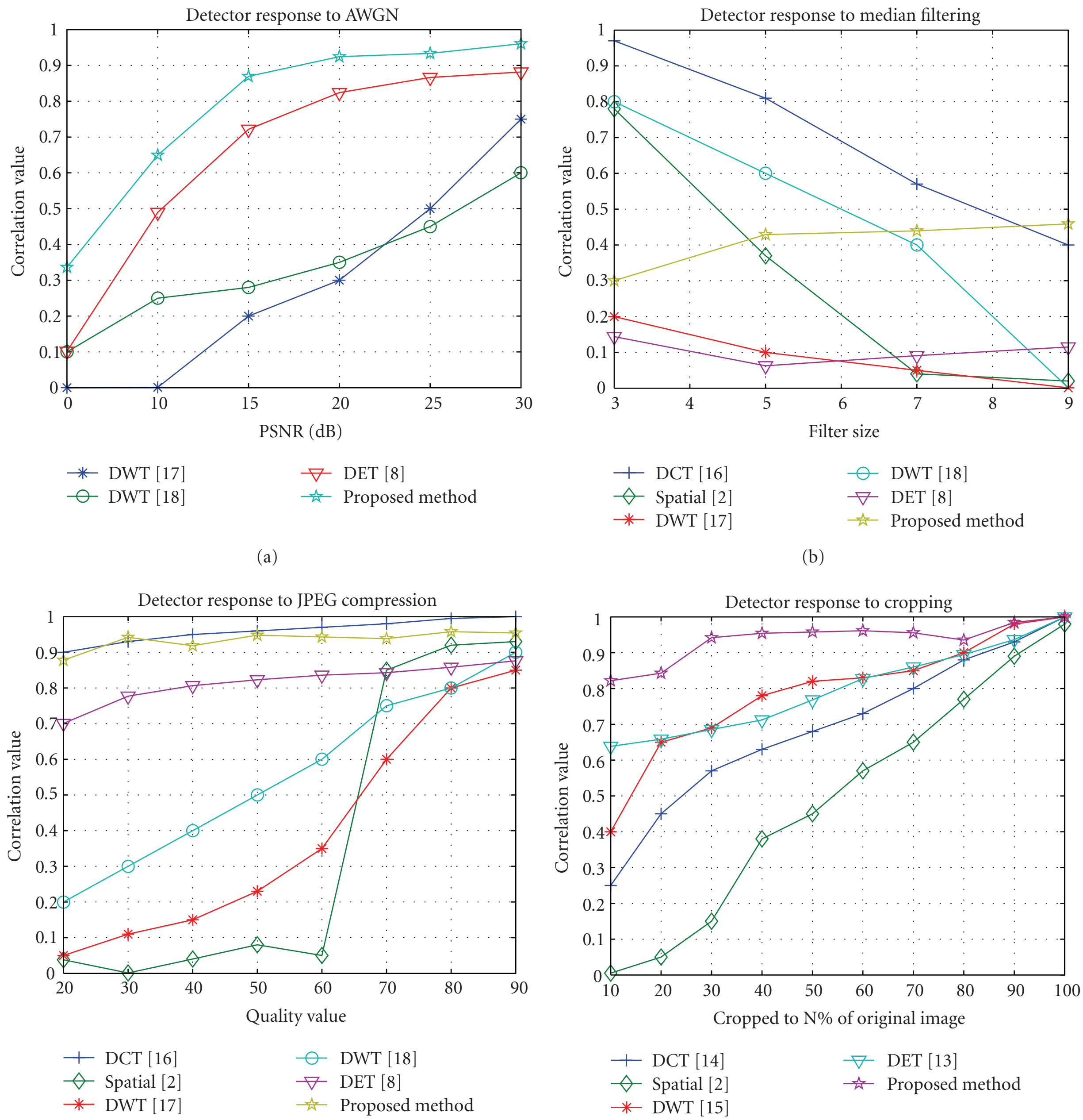
Figure 3: Correlation detector response under (a) AWGN ($\sigma^2 = 0.025$), (b) AWGN ($\sigma^2 = 0.85$), (c) Salt and Pepper noise, (d) Wiener Filtering, (e) Median Filtering, (f) JPEG Compression ($Q = 10\%$), (g) JPEG Compression ($Q = 50\%$), (h) Rotation (5°), (i) Cropping (50 column), (j) Cropping (100 column) attacks.

Table 1: PSNR Values of the watermarked images.

Image	Lena	Baboon	Boats	Barbara
PSNR (dB) (25 rows watermarked)	63.0542	59.0494	62.4428	63.0009
PSNR (dB) (All rows watermarked)	49.2935	46.5275	48.4713	49.9196

generate 500 possible watermarks and embed the 250th of them onto each test image. The watermarked Boats image and the difference between the watermarked and the original images can be seen in Figure 1. The difference, shown in Figure 1, is obtained by magnifying the real difference image by 1000, so we can see the effects of the embedding algorithm. Notice that the watermark embedding algorithm does not cause any visible changes on the image. Peak signal to noise ratio (PSNR) values are given in Table 1 for all test images. First column shows the PSNR values for partial watermarking. In this case, we chose 25 rows of the image randomly and embedded the watermark in each of them. Also, second column shows PSNR values for fully watermarked images. In this case, watermark was embedded in all image rows.

The watermarked Barbara image and the difference between the watermarked and the original images can be seen in Figure 2, where the difference image is also obtained by multiplying the real difference by 1000. The performance of the method was also tested under different attacks for the above images. Additive white Gaussian noise (AWGN), SP noise, Wiener filtering (WF), Median filtering (MF), JPEG



(a) (b) (c) (d)

Figure 4: The comparison of the proposed method and the methods in [2, 8, 16–18] under (a) AWGN, (b) Median Filtering, (c) JPEG Compression, (d) Cropping attacks.

Compression, rotation, and cropping attacks are applied. When we test our method against the cropping attack, we only eliminated some columns of the image (hence it is a vertical cropping). This is because the row (or horizontal) cropping has no effect on our algorithm since we embed the same watermark into many predetermined rows. The normalized correlations between the extracted and the original watermarks are calculated and presented for all images in Tables 2 and 3. In our simulations, correlations are calculated for all 25 watermarked rows of the images separately, then the best result is chosen and shown in tables.

We also tested our watermark detection algorithm using a test set composed of 500 possible watermarks which are again zero mean, Gauss distributed random sequences. The watermark that is in the middle of the set (number 250) is embedded into the Lena image. Figure 3 shows the correlations between the extracted watermark and all 500 possible watermarks in the test set. It is shown in figures that, when the original watermark is tested with the extracted one, the correlation takes its maximum value. In above simulations, the worst correlation value is shown among the 25 rows. We can observe from the

Table 2: Correlations between the original and the extracted watermarks under Noise and Filtering attacks.

Attack	Lena	Baboon	Boats	Barbara
AWGN ($\sigma^2 = 0.005$)	0.9126	0.8592	0.9443	0.9045
AWGN ($\sigma^2 = 0.010$)	0.9070	0.8705	0.9383	0.8740
AWGN ($\sigma^2 = 0.015$)	0.9251	0.9053	0.9165	0.8772
AWGN ($\sigma^2 = 0.020$)	0.8981	0.9040	0.8372	0.9219
AWGN ($\sigma^2 = 0.025$)	0.8655	0.8183	0.8875	0.8796
SP Noise (Density = 0.02)	0.9325	0.9354	0.9907	0.9689
SP Noise (Density = 0.04)	0.9189	0.9221	0.9063	0.9291
SP Noise (Density = 0.06)	0.8633	0.8721	0.8849	0.9139
SP Noise (Density = 0.08)	0.8834	0.8712	0.8295	0.8936
SP Noise (Density = 0.10)	0.8777	0.8616	0.8470	0.8737
WF (3×3)	0.9834	0.9109	0.9923	0.9730
WF (4×4)	0.9686	0.8851	0.9805	0.9532
WF (5×5)	0.9687	0.8890	0.9815	0.9565
WF (6×6)	0.9602	0.8168	0.9701	0.9154
WF (7×7)	0.9813	0.8011	0.9940	0.9163
MF (3×3)	0.3004	0.6862	0.3818	0.6111
MF (6×6)	0.2580	0.3820	0.1761	0.5817
MF (9×9)	0.4588	0.4429	0.3489	0.5800
MF (12×12)	0.3975	0.4467	0.3215	0.5643
MF (15×15)	0.4396	0.4498	0.3368	0.5773

Table 3: Correlations between the original and the extracted watermarks under different attacks.

Attack	Lena	Baboon	Boats	Barbara
JPEG (Q = 10%)	0.8909	0.8392	0.8414	0.8763
JPEG (Q = 30%)	0.9422	0.8783	0.9148	0.8798
JPEG (Q = 50%)	0.9480	0.8902	0.9133	0.9126
JPEG (Q = 70%)	0.9384	0.8579	0.9132	0.9356
JPEG (Q = 90%)	0.9543	0.8937	0.9114	0.9516
Rotation (5°)	0.5481	0.4119	0.7071	0.5505
Rotation (10°)	0.5041	0.7318	0.5672	0.6447
Rotation (15°)	0.5184	0.6140	0.5045	0.5467
Rotation (20°)	0.4918	0.3878	0.4159	0.6098
Rotation (25°)	0.3894	0.4957	0.4903	0.5161
Cropping (10 column)	0.9873	0.9488	0.9726	0.9612
Cropping (25 column)	0.9845	0.9351	0.9698	0.9550
Cropping (50 column)	0.9354	0.9215	0.9655	0.9293
Cropping (75 column)	0.9556	0.9000	0.9622	0.9423
Cropping (100 column)	0.9614	0.8787	0.9688	0.9382

correlation detector responses that we achieve outstanding performance for AWGN, SP noise, Wiener filtering, JPEG compression, and cropping attacks. And also we achieve satisfactory performance for Median filtering and rotation attacks.

We finally present the comparison of our proposed method with some other well-known methods with Spatial domain [2], Discrete Cosine Transform (DCT) [16], and Discrete Wavelet Transform (DWT) [17, 18] based embedding algorithms. We also compare the proposed method with another DET based method presented earlier in [8]. Simulations are carried out under AWGN, Median Filtering, JPEG Compression, and Cropping attacks and results are shown in Figures 4(a)–4(d), respectively. The proposed method is compared with only published and accessible results. It is clear from the figures that the proposed TF based method outperforms other watermark embedding algorithms under additive noise and cropping attacks.

As we mention before, there are methods using TF techniques for watermark embedding in the literature. A two-dimensional (2D) SF based watermarking approach is presented in [6] where a special 2D chirp-type watermark is presented. The method differs from the watermarking technique we present in this paper in that the original image is added this 2D chirp signal, and 2D Radon-Wigner distribution is used for watermark extraction. Increased dimensions of the data makes this approach computationally demanding. Another method for embedding a one-dimensional watermark sequence into the rows of an image in the joint SF domain by using Wigner-Ville distribution is presented in [7]. We adopt this idea here, and use a linear SF representation which is efficiently implemented to embed and extract any type of watermark sequence into images.

6. Conclusions

In this work, a new watermarking algorithm that is based on a spatiofrequency transform is proposed. Discrete evolutionary transform is used for the SF representation of the rows of an image. Watermark embedding algorithm is developed to combine the advantages of both spatial and spectral domain watermarking techniques. Thus, a more successful method is proposed than methods that use only spatial or spectral domain embedding. At the detection end, the watermark can be extracted by using the original image. The performance of the method is tested under several attacks and observed that it is very successful against additive white Gaussian noise, salt and pepper noise, Wiener filtering, JPEG compression, and cropping. Furthermore, the proposed algorithm which is based on a linear representation is computationally simpler than other bilinear TFD-based methods [7, 14].

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