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Using Curvelet Transform for Watermarking Based on Amplitude Modulation

Mohammad Reza Akbarzadeh Lari [1], *Sedigheh Ghofrani [1] and Des McLernon [2]

[1] Electronic and Electrical Engineering Department, Islamic Azad University, South Tehran Branch, Tehran, Iran.

[2] School of Electronic and Electrical Engineering, University of Leeds, Leeds, UK.

E-mail: st_m_akbarzadeh@azad.ac.ir, s_ghofrani@azad.ac.ir, d.c.mclernon@leeds.ac.uk

*Corresponding author

E-mail: s_ghofrani@azad.ac.ir

Tel: +98-21-88731446

Fax: +98-21-88532683

Mail address: No. 9, 14th Street, Pakistan Street, Shahid Beheshti Street, Pars Gostareh, 15317-64611), Tehran, Iran.

ABSTRACT

In this paper we propose a precise and robust watermarking scheme based on the technique called amplitude modulation. A watermark is embedded in a color image by modifying the pixel values in the blue channel. At the receiver, the watermark bits are retrieved using a prediction system, by a linear combination of nearby pixel values around the embedded pixels, and without having the original image. Because amplitude modulation is a spatial-domain watermarking method, it may not be robust enough, i.e. incapable of exact watermark retrieval. In order to enhance the bit retrieval, we apply a Gaussian mask to equalize the luminance intensity; we employ the pixel value replacing technique to enhance the prediction performance; and we use two additional bits as a geometrical reference. In addition, we demonstrate that choosing an improper location (like singularities) for watermarking will lead the prediction system to malfunction. In order to increase the robustness, we propose using the Curvelet transform to detect singularities such as lines and curves and prevent the system from using these locations in an image for embedding the watermark bits. The experimental results indicate that our proposed method has a better performance in comparison with two other similar approaches and in addition it is robust against various geometrical and non-geometrical attacks as well as having a good imperceptibility.

Keyword: Curvelet transform, amplitude modulation, digital image watermarking, copyright protection.

1. INTRODUCTION

In general, digital watermarking refers to embedding information in an image for different purposes like broadcast monitoring, authentication, tracking and owner identification [1]. A digital watermark should have two main properties, i.e. robustness and imperceptibility. Robustness means that the watermark can withstand different image processing attacks and imperceptibility means that the watermark should not introduce any perceptible artefacts [2]. In general, watermarking approaches are divided into two main categories: the spatial and the transform domain techniques. Transform domain techniques perform the watermarking by changing the coefficients in the transformed domain of a host image. For example, the methods of watermarking obtained by modifying the discrete wavelet transform (DWT) coefficients and the discrete cosine transform (DCT) coefficients were proposed in [3]-[4]. However many researchers demonstrated that watermarking in the transform domain is not robust to geometrical attacks, e.g. cropping and rotation.

Being robust against geometrical distortion is an important property for digital image watermarking. This is because minor geometrical manipulation can disable the watermarking system's ability to extract the correct watermark. Among the image watermarking approaches, feature point-based schemes can resist geometrical distortion like rotation, scaling and translation. A geometric invariant image watermarking approach was proposed in [5] by using the Harris-Laplace detector to extract the feature points. Later, the state of the art feature-based method by feature selection (affine covariant feature regions extraction), the image normalization and the orientation alignment, proposed by the same authors [6]. Their scheme is robust against the geometric attacks including cropping, non-isotropic scaling, random bending and affine transformations, as well as common image processing operations. Recently, the robust Curvelet-domain image watermarking (by matching the feature point [7]) was proposed which it is robust against these various distortions.

However, watermarking in the spatial domain may naturally be robust to geometrical attacks and there are different approaches for watermarking in the spatial domain- among them watermarking based on amplitude modulation for copyright protection was proposed in [8]. In this method, a watermark is embedded in a color image by modifying the pixel values in the blue channel. It was shown that watermarking based on amplitude modulation is robust to some attacks like blurring, JPEG compression, and rotation. Later Puertpan et.al enhanced the robustness of this method by using the Gaussian mask to localize the luminance values [9]. In [10], in addition to using the Guassian mask, all watermark bits are XORed with a psedu-random bit stream and a pixel value that most differs from the watermarked pixel is excluded in the prediction process, in order to improve the watermarking performance. More details on this are given in Section 2.

Finding suitable locations to embed the desired data or the watermark is the main problem for some watermarking methods. In general, all these aforementioned watermarking methods based on amplitude modulation perform watermarking without finding the suitable location or selecting the suitable pixels belonging to the host image.

In this paper, we show that embedding a watermark in locations where there is singularity such as a line or a curve affects the performance of the prediction system. It means that an error may occur during the bit retrieval process. So, we use the Curvelet transform to localize the singularities and find the suitable locations in a color host image for embedding the watermark.

This paper is organized as follows: watermarking based on amplitude modulation is explained in Section 2. The Curvelet transform is briefly reviewed in Section 3. In Section 4, we discuss suitable locations for embedding the watermark bits. We look at the prediction system performance and then we present our proposed method. Simulation results and discussions are given in Section 5 and finally concluding remarks are presented in Section 6.

2. WATERMARKING BASED ON AMPLITUDE MODULATION

The RGB model is an additive color model which contains three channels (i.e. red, green and blue). Let w denotes a single bit that is to be embedded in a color image by modifying the pixel value in the blue channel. The blue channel is preferred because of the human visual system's reduced sensitivity and it also guarantees virtual imperceptibility. The modifications are either additive or subtractive (depending on the watermark bit $w \in \{0,1\}$) and are proportional to the luminance component $L(i, j)$ at a position (i, j) in an image. The watermarked pixel is,

$$\hat{B}(i, j) = B(i, j) + (2w-1)L(i, j)s \tag{1}$$

where $B(i, j)$ is the original pixel value of the blue channel and the luminance value of the pixel is obtained from $L(i, j) = 0.299R + 0.587G + 0.114B$. Here '$s$' is the scaling parameter. The parameter 's' must be chosen carefully because it controls the trade-off between imperceptibility and robustness [8], [10]. A prediction of the original pixel value is needed for retrieving the watermark signal. The prediction pixel value, $p(i, j)$, is determined from the nearby (over a range of $\pm c$) pixel values around (i, j) as

$$p(i, j) = \frac{1}{4c}\left(\sum_{k=-c}^{c}\hat{B}(i+k, j) + \sum_{k=-c}^{c}\hat{B}(i, j+k) - 2\hat{B}(i, j)\right). \tag{2}$$

Fig. 1 shows a sample of nearby pixels around (i, j) which are used to predict the original pixel value according to (2). The watermark bit (w) can be retrieved from the blue channel by subtracting the predicted pixel value, $p(i, j)$, from the watermarked pixel value, $\hat{B}(i, j)$, as follows:

$$\Delta = \hat{B}(i, j) - p(i, j). \tag{3}$$

We notice that the sign of Δ determines the embedded watermark bit if the following conditions are satisfied:

(i) The scaling parameter 's' is sufficiently large. As it controls the difference between the watermarked pixel value, $\hat{B}(i, j)$, and the original pixel value, $B(i, j)$, we notice that the bit retrieval will be more accurate when the absolute value of Δ is large.

(ii) The luminance of the image is smooth. Under this circumstance, the adding or subtracting an amount of each pixel in the embedding process (the second part of (1)) is approximately equal and therefore the bit retrieval process based on the sign of Δ should be more precise.

(iii) The prediction system according to (2) accurately determines the original pixel value, i.e. $p(i, j) \approx B(i, j)$.

If the blue channel is smooth, ideally all pixels around (i, j) will have the same value and the prediction system can exactly predict the original value, $B(i, j)$, independent of the watermarked centre pixel, $\hat{B}(i, j)$. In [8], two extra bits (in addition to the watermark bits) were used to embed in the original image. These two bits were used to obtain a threshold value that may improve the retrieval process and define a geometrical reference. This reference can compensate geometrical attacks like rotation. Later, this method was developed in [9] to improve the bit retrieval rate. The authors used a Gaussian weighting mask (with parameter, σ) for averaging the luminance of an image and therefore equalizing the luminance intensity at every pixel around position (i, j). The Gaussian mask is:

$$\frac{1}{2\pi\sigma^2}\begin{bmatrix} e^{-\frac{1}{\sigma^2}} & e^{-\frac{1}{2\sigma^2}} & e^{-\frac{1}{\sigma^2}} \\ e^{-\frac{1}{2\sigma^2}} & 1 & e^{-\frac{1}{2\sigma^2}} \\ e^{-\frac{1}{\sigma^2}} & e^{-\frac{1}{2\sigma^2}} & e^{-\frac{1}{\sigma^2}} \end{bmatrix} \tag{4}$$

The performance of this method is not appropriate whenever the host image is not smooth (it means that the image has many singularities). As smoothing the luminance has no effect on smoothing the blue channel, the condition (ii) is approximately satisfied, but condition (iii) is not. Furthermore, when the image contains a large amount of the same pixel value (e.g., the logo of a company) the performance of the prediction system is considerably suppressed. Clearly embedding a bit in a pixel belonging to the host image increases or decreases the pixel value according to (1). Hence if the number of 1s and 0s around position (i, j) are not equal, the prediction system (according to (2)) does not work properly. Assume that $\Delta y > 0$ is the amount of increase in pixel values around (i, j) due to embedding ones and $\Delta x < 0$ is the amount of decrease in pixels values around (i, j) due to embedding zeros. Then we can predict approximately the original pixel value with (2) if the bias is zero, i.e.

$$\Delta x + \Delta y = 0\,. \tag{5}$$

That is, for the prediction system described by (2):

$$\frac{1}{4c}\Big(\sum_{k=-c}^{c} wsL(i+k,j) + \sum_{k=-c}^{c} wsL(i,j+k) - 2wsL(i,j)\Big) = 0\,. \tag{6}$$

To overcome this drawback, a new method was proposed in [10]. It works by balancing the watermark bits around the embedding pixels in the watermark preparation process. For this purpose, all watermark bits, w, are

XORed with another pseudo-random bit-stream. This approach is based on an assumption that an equal number of 1s and 0s are generated and XORed with w around (i, j) and the number of 1s and 0s around (i, j) are approximately equal. Also, at the receiver, the retrieved bits must be XORed with the same pseudo-random bit-stream to obtain the correct watermark bit, w. Moreover, they suggested that one neighbouring pixel around (i, j) that most differs from $\hat{B}(i, j)$, is excluded from the prediction system. In other words, instead of computing $p(i, j)$ from the eight pixel values around (i, j), they used only seven. This technique is called pixel value replacing. But the two main drawbacks of this method are requiring the pseudo-random bit-stream at the receiver in order to retrieve the watermark and affecting the balance of w around (i, j) because of pixel value replacing. The authors also used a pre-processing Gaussian weighting mask for averaging the luminance of a host image as was previously explained. To satisfy the condition (iii) (see earlier list) the same mask for averaging the blue channel of the host image showed is not used because it will impact strongly on image perceptibility. But in Section 4, we will show how the proper locations (i.e. non singularities) for embedding watermark bits are determined based on use of the Curvelet transform.

In general, all these methods embed the watermark bits in pixels belonging to the host image irrespective of their positions [8]-[10]-i.e. whether the pixel is located on a singularity or not. Recently, Bei et al. [11] explained a new watermarking method based on amplitude modulation. The locations of where to embed the watermark bits are chosen based on the human visual system and issues of perceptibility. In this work, we follow a similar strategy in order to decide the best locations for embedding the watermark bits and achieving bit precision when extracting the watermark. We divide an original image into non-overlapping blocks of size 5×5. Pixels at the centre of each block may be chosen for embedding a watermark bit (in order to satisfy (5); $\Delta y = \Delta x = 0$) if the pixel is far from line or curve singularities. We use the Curvelet transform to detect such singularities in an image. The Curvelet transform was developed in order to represent edges along curves much more efficiently than any traditional transform and it is explained briefly in the section 3.

3. THE CURVELET TRANSFORM

The Curvelet transform was first introduced by Candes and Donoho [12]. The procedure at first was decomposing an image into a set of wavelet bands, and then analysing each band by a local Ridgelet transform. Later, the second-generation Curvelet transform based on a frequency partition technique was proposed by the same authors [13]-[15]. The continuous Curvelet transform (CCT) of $f(x)$ is,

$$\Gamma_f(a,b,\theta) = \langle f(x), \gamma_{a,b,\theta}(x) \rangle \qquad (7)$$

where a, b and θ denote respectively the scale, location and direction. The analysing element, $\gamma_{a,b,\theta}(x)$ is named "Curvelet" and it obeys the paramount parabolic scaling principle, i.e. width=(length)^2. The Curvelets are smooth and of rapid decay away from an $a \times \sqrt{a}$ rectangle with minor axis pointing in direction θ. This anisotropic behaviour allows tracking the behaviour of singularities along curves. By applying examples which included point/line/polygonal and curve singularities, they showed that for a constant pair (b_0, θ_0), the Curvelet transform $\Gamma_f(a, b_0, \theta_0)$ decays rapidly as $a \to 0$, if f is smooth near b_0, or if the singularity of f at b_0 is oriented in a different direction than θ_0 [13]. The discrete tight frame by sampling the CCT at dyadic intervals, with scale $a_j = 2^{\frac{j}{2}}$, equi-spaced direction, $\theta_{j,l} = 2\pi\, 2^{-[\frac{j}{2}]} l$, and equi-spaced sampling on a rotated anisotropic grid in space, $b^{j,l}_{k1,k2} = R_{\theta_{j,l}}(k_1 2^{-j}, k_2 2^{-\frac{j}{2}})$, was derived in [13]. Assume that r and θ are polar coordinates in the frequency domain. The window functions $W(r)$ and $V(t)$ were introduced where $W(r)$ is called the radial window supported on $r \in (1/2, 2)$ and $V(t)$ is called the angular window supported on $t \in (-1, 1)$. They obey the admissibility conditions

$$\sum_{j=-\infty}^{\infty} W^2(2^j r) = 1 \quad r \in (1/2, 2) \tag{8}$$

$$\sum_{j=-\infty}^{\infty} V^2(t-l) = 1 \quad t \in (-1, 1). \tag{9}$$

The mother Curvelet $\varphi_j(x)$ is defined in the frequency domain (i.e. Fourier transform) as $\hat{\varphi}_j(\omega) = U_j(\omega)$ [15]. The support of U_j is a polar "wedge" defined by the support of W and V, see Fig. 2:

$$U_j(r,\theta) = W(2^j r) V\left(\frac{2^{[j/2]}\theta}{2\pi}\right) 2^{-3j/2}. \tag{10}$$

The Curvelet coefficient is obtained as:

$$\begin{aligned} c(j,l,k) &= \langle f(x), \gamma_{j,l,k}(x) \rangle \\ &= \frac{1}{(2\pi)^2} \int \hat{f}(\omega) U_j(R_{\theta l}) e^{\langle j(b_k^{j,l}, \omega\rangle} d\omega. \end{aligned} \tag{11}$$

With the Cartesian array input of the form $f[n_1, n_2]$ a collection of Curvelet coefficients $C^D(j,l,k)$ is obtained by:

$$C^D(j,l,k) = \sum_{n_1, n_2} f[n_1, n_2]\, \gamma^D_{j,l,k}[n_1, n_2]. \tag{12}$$

Defining the Cartesian windows, $\tilde{W}_j(\omega) = W(2^{-j}\omega)$ and $V_j(\omega) = V(2^{[\frac{j}{2}]} \frac{\omega 2}{\omega 1})$, the following equation was derived [15]:

$$\tilde{U}_{j,l}(\omega) = W_j(\omega) V_j(S_{\theta l}\omega) \tag{13}$$

where $S_{\theta l} = \begin{pmatrix} 1 & 0 \\ -\tan(\theta) & 1 \end{pmatrix}$, and $\tilde{U}_{j,l}$ is the Cartesian equivalent of the polar window of (10), and it isolates frequencies near the trapezoid wedge. Fig. 3 shows the digital frequency tilling of the Curvelet.

The above discrete Curvelet transform can be implemented through either wrapping or USFFT algorithms which have been described in detail in [14]. In this work, we use the wrapping algorithm because it is easier and faster.

4. PROPOSED METHOD

Before explaining our proposed method, we show that embedding a watermark in locations where there is singularity such as line or curve suppresses the performance of the prediction system and thus during the bit retrieval process an error may occur. Suppose, the content shown in Fig. 4 is a part of the watermarked image. The centre pixel at a block is decreased to 45 (the original value was 50) due to embedding a bit equal to 0. Simply, using (2)-(3), then the output of prediction system is $p(i, j) = 32.5$ and $\Delta = 12.5 > 0$ and so obviously an error has occurred. Thus, in this paper, we localize the singularities by using the Curvelet transform and we do not embed the watermark bits at these specific positions.

In one dimension the only type of discontinuity is a point, which can be represented by wavelets. However, images in two dimensions also have discontinuities along lines and curves. As wavelets ignore the geometric properties of objects with edges and do not exploit the regularity of the edge curves [16]-[17], they exhibit large wavelet coefficients in all scales for edges in the image. So, the edges of an image are seen repeatedly at different scales [18]. Although it is possible to indicate line and curve singularities by using the wavelet transform [19], the procedure includes finding the corresponding wavelet coefficients in all scales. This is not efficient and it may be complicated and time consuming. The Curvelet transform can represent edges and singularities along curves much more efficiently than the traditional wavelet transform.

In this work, we detect the image edges similar to [20] for the blue channel. The rule for partitioning the scale level is: $\text{scale} = \log_2(n) - 3$ where the parameter n for any square size image refers to the number of rows. Fig. 5 shows the five scale levels corresponding to an image with size 256×256. As shown in Fig. 5(b) the coefficients of the coarse level include general information about the original image. Detail levels mostly embody the edge information of the original image, see Fig. 5(c-f). It was shown in [20]-[22] that the Curvelet coefficients belonging to the finest decomposition level contain information about singularities in general (point, line and curve, see Fig. 5(f)). So, in this work, the host image is decomposed and all Curvelet coefficients are set to zero except those belonging to the 5th decomposition level and then the inverse Curvelet transform is performed. If the pixel value of the reconstructed image is greater than the predefined threshold value 'T', this pixel is considered as a singularity. After determining the positions of the singularities, the host image is partitioned into non-overlapping blocks each with size 5×5. The centre pixel of each block is chosen to embed a watermark bit if it is not lying on singularity.

Maximum embedding capacity (MEC) means the maximum number of bits that can be hidden in the host image. MEC is achieved whenever all the center pixels at each block are not lying on singularities:

$$\text{MEC} = \frac{M \times N}{B_s} \tag{14}$$

where $M \times N$ is the host image size and B_s is the block size. In this paper, the size of test images and blocks are 256×256 and 5×5 respectively, so MEC is equal to 2621 pixels. In general, embedding capacity (EC) depends on the number of the center pixels those are not located on singularities. Therefore, EC depends on the considered threshold value chosen. As all pixels of the reconstructed image are equal to or greater than zero, theoretically 'T' can get any value greater than or equal to zero. In order to find the smoothest regions in the host image, the convenient value is T=0. In the special case, when the computed EC is less than the size of the watermark image, either the watermark size has to be reduced or the threshold value has to be increased.

At the receiver, we obtain the blue channel and extract the watermark bits according to (3). We now summarize our proposed algorithm for both embedding and extracting a watermark.

Embedding Procedure

1. Use the Gaussian weighting mask (see (4)) for averaging the luminance of an image.
2. Compute the Curvelet transform via wrapping for the blue channel of the host image and obtain the Curvelet coefficients.
3. Obtain the 5-th level reconstructed image by keeping only the finest level Curvelet coefficients ($C^D(j=5,l,k)$) and setting all other Curvelet coefficients to zero.
4. Partition the blue channel into non-overlapping blocks of size 5×5.
5. Select those centre pixels of each block where the corresponding values of the 5-th level reconstructed image are less than the predefined threshold value 'T', and embed the watermark bits along with two extra bits for saving a geometrical reference. We note that the locations of these additional bits are to be known.

Extracting Procedure

1. Extract the two additional reference bits based on (3) and compensate for geometrical attacks like rotation, if appropriate.
2. Extract the watermak bits based on (3).

Notice, in this method like [8], the embedding bit locations are known at the receiver.

5. EXPERIMENTAL RESULT

In this paper, we use eleven different color images as the test images. As shown in Figs. 6 (a-k), they are 'Lena', 'Tower', 'Bird', 'Fish', 'Peppers', 'House', 'Girl', 'Baboon', 'Airplane', 'Barbara', and 'Boat' - all with dimensions 256×256. In addition, the black and white binary logo 'CPE 2011' with size 32×32 is synthesized as a watermark, shown in Fig. 6 (m). In order to evaluate our proposed method, two criteria are used. They are "peak-signal-to-noise-ratio (PSNR)" and "normalized correlation (NC)". The PSNR is computed to measure the quality of the watermarked image whereas the NC is used to measure the quality of the extracted watermark. These two parameters are defined as follows:

$$\mathrm{PSNR} = 10\log_{10}\left(\frac{L^2}{\frac{1}{N\times M}\sum_{i=1}^{N}\sum_{j=1}^{M}\left|x_{ij}-y_{ij}\right|^2}\right) \qquad (15)$$

$$\mathrm{NC} = \frac{\sum_{i=1}^{N}\sum_{j=1}^{M} w(i,\ j)\hat{w}(i,\ j)}{\sqrt{\sum_{i=1}^{N}\sum_{j=1}^{M} w^2(i,\ j)}\sqrt{\sum_{i=1}^{N}\sum_{j=1}^{M} \hat{w}^2(i,\ j)}} \qquad (16)$$

where L is the dynamic range of the pixel intensity; $N\times M$ is the image size; x_{ij} and y_{ij} are the pixel values of the original and the watermarked images; and $w(i,\ j)$ and $\hat{w}(i,\ j)$ are respectively the original and the retrieved watermark. In the following, we compare the performance of our proposed algorithm based on using the Curvelet transform for detecting the positions of singularities with publications [8] and [10]. The procedures of these two methods and our proposed algorithm are explained briefly in Table 1.

At first, to compare performance with [8] and [10] under the same circumstances, we use the well-known color test image 'Lena' with size 256×256. The best values for 's' is in the range [0.1 0.5] according to the tradeoff between robustness and imperceptibility [8]-[11]. So in this work, we also use the same interval values to obtain 's'. The determined EC for all test images based on using the different threshold values is shown in Fig. 7. In this paper, we consider the threshold value T=0, then the EC obtained for all test images is about 1400 pixels. So, a watermark image with size $32\times 32 = 1024$ can be embedded. In addition, two bits are used to save as a geometrical reference.

The number of errors for different values for the scaling parameter 's' for our proposed method and [8], are given in Table 2. The extracted watermarks are also shown in Fig. 8. The PSNR and NC of these three methods are shown in Fig. 9 and Fig. 10. Although the PSNR of our proposed method is comparable with [8], the achieved NC is better than [8] and [10]. Now, we also compare the performances of these three methods when the Gaussian weighting mask (see (4)) for averaging the luminance of an image is used and 'Lena' is considered as the host image. The achieved PSNR and NC based on using a different variance parameter (σ^2) for the Gaussian mask are shown in Fig. 11 and Fig. 12. As all the pixels in the watermarked image are to be changed in [10], and in addition (5) is not completely satisfied in this method, they achieved lower values for both PSNR and NC in comparison with our proposed method.

The watermarked images for Lena, Tower, Bird and Fish are shown in Fig. 13 where the scaling parameter is s=0.4 and the variance of Gaussian mask is $\sigma^2 = 0.5$. We also compute the NC measure for all eleven images and compare with [8], and show the results in Fig. 14 where the scaling factor is s=0.4. As regards, the robustness of our proposed method to geometrical and non-geometrical attacks, we consider 'Lena' and show the watermarked image and the extracted watermark under different situations in Fig. 15.

6. CONCLUSION

An improved retrieval method for watermarking based on amplitude modulation has been proposed in this paper. Using the Curvelet transform to detect singularities prevents embedding the watermark bits at singular points, lines, and polygons. The experimental results show that by using our proposed method, the performance of the watermark retrieval process has been improved in terms of PSNR and normalized correlation when compared with two other similar methods.

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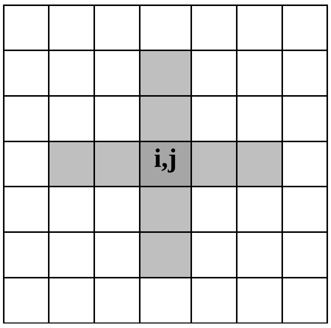


Fig. 1: The neighboring pixels around (i, j) which are used to predict the original pixel, for c=2 in (2).

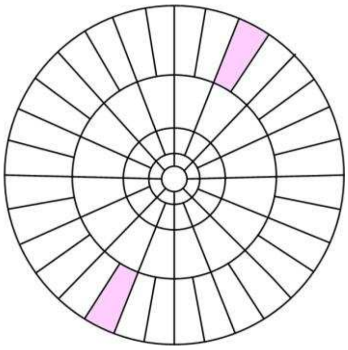
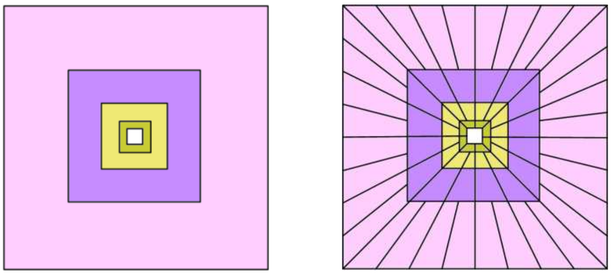


Fig. 2: Continuous Curvelet tiling of frequency.



(a) (b)

Fig. 3: The basic digital Curvelet tiling by using, (a) W segmentation and (b) V direction segmentation.

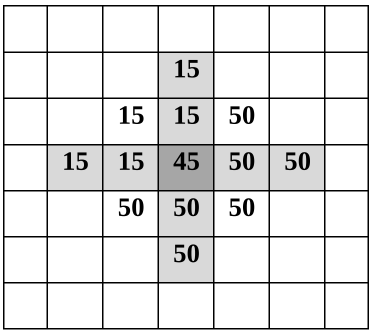
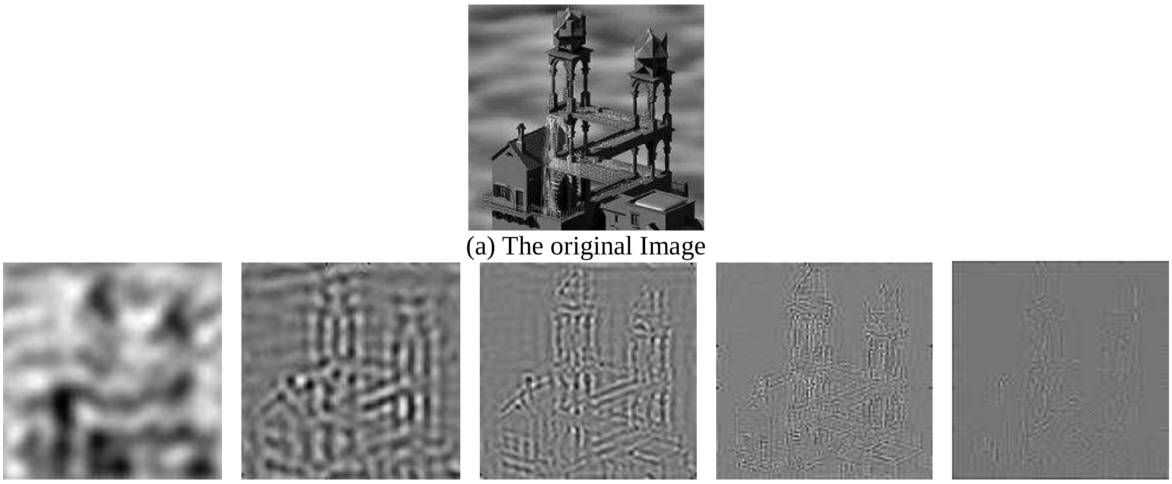


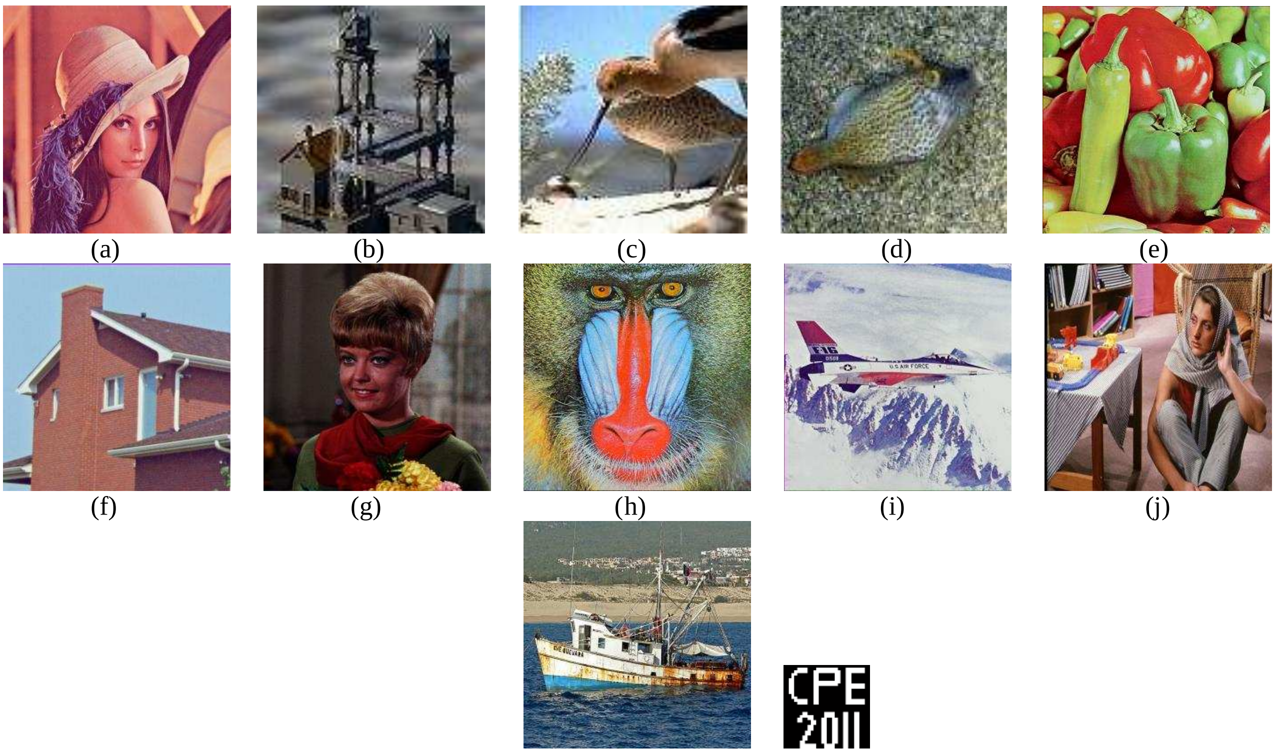
Fig. 4: An example of error in bit retrieval when the watermark bit is embedded in the line singularity.



(a) The original Image

(b) level 1 (c) level 2 (d) level 3 (e) level 4 (f) level 5

Fig. 5: The reconstructed image by using the inverse Curvelet transform for each scale level.



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

(f) (g) (h) (i) (j)

(k) (m)

Fig. 6: Eleven original images, (a) Lena, (b) Tower, (c) Bird, (d) Fish, (e) Peppers, (f) House, (g) Girl, (h) Baboon, (i) Airplane, (j) Barbara, (k) Boat and (m) the binary watermark with size 32×32.

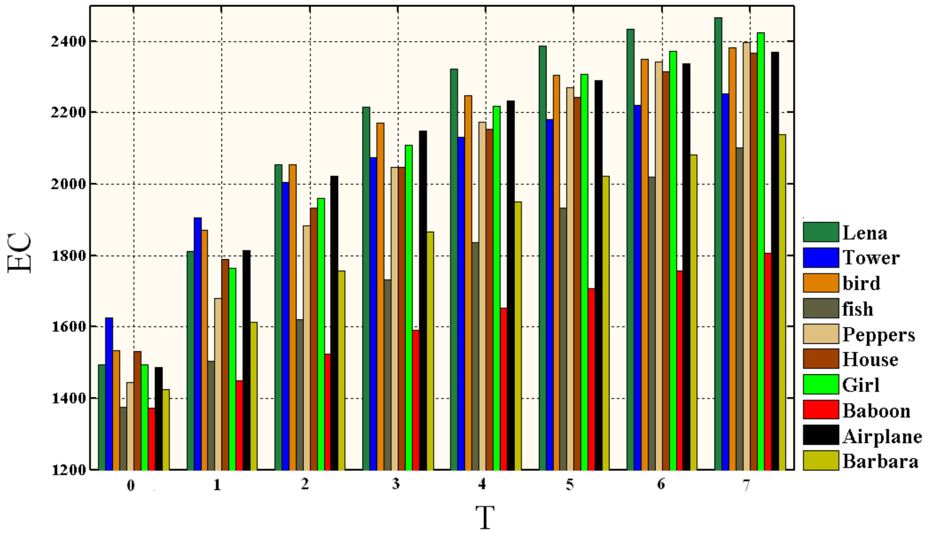


Fig. 7: the computed EC for eleven test images based on different threshold values.

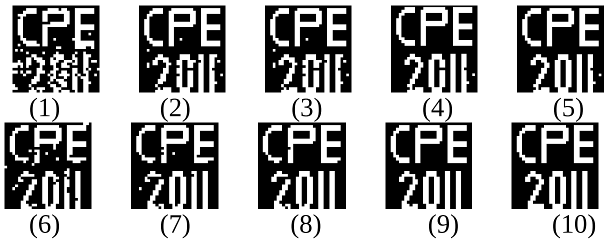


Fig. 8: Extracted watermark via different scaling parameters s=[0.1 0.5] from left to right, where ‘Lena’ is used as the host image. The first row belongs to [8] and the second row belongs to our proposed method without using the Gaussian mask.

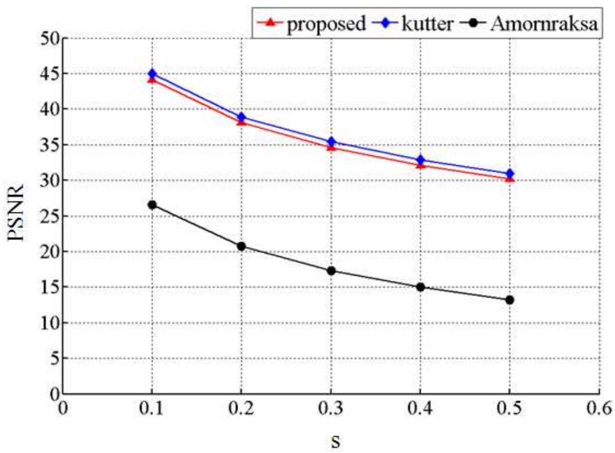


Fig. 9: PSNRs for different values of the scaling parameter (s) where ‘Lena’ is used as the host image.

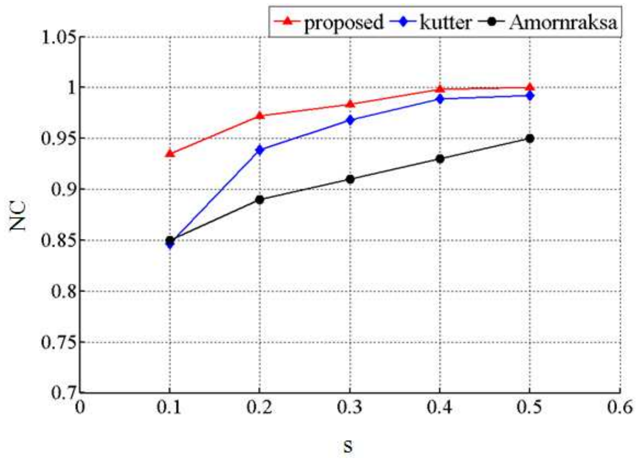


Fig. 10: NCs for different values of the scaling parameter (s) where 'Lena' is used as the host image.

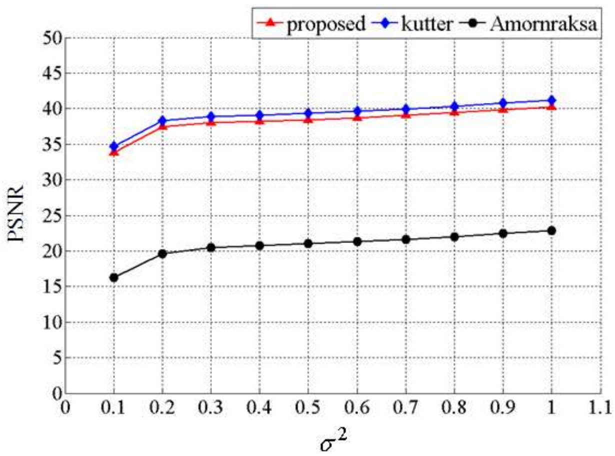


Fig. 11: PSNRs for different variances of the Gaussian mask. The scaling parameter is s=0.2.

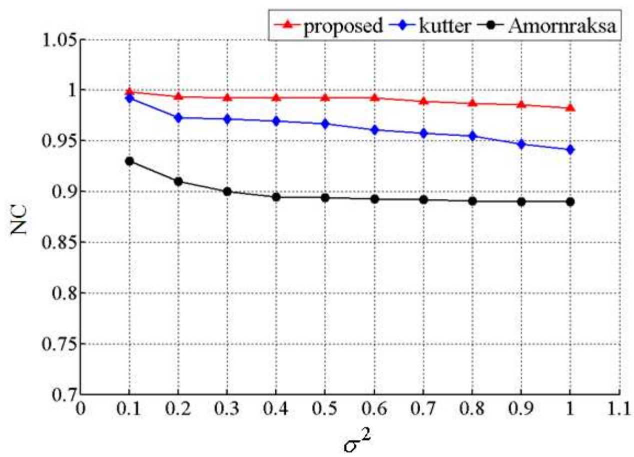


Fig. 12: NCs for different variances of the Gaussian mask. The scaling parameter is s=0.2.

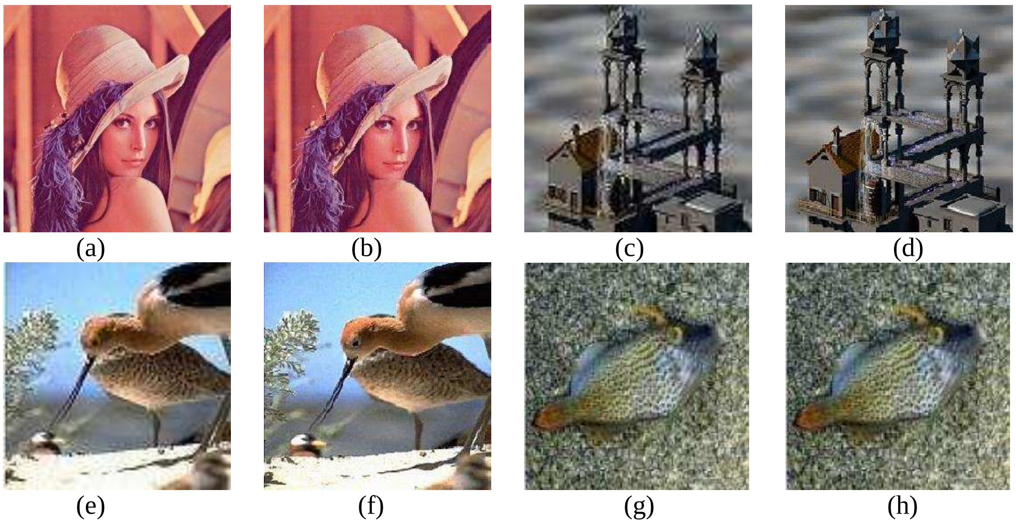


Fig. 13: Vision comparison between the original images (a, c, e, and g) and the watermarked images (b, d, f, and h) where s=0.4 and σ^2 =0.5. The computed PSNRs are in order [32.40, 33.75, 29.77, 30.23].

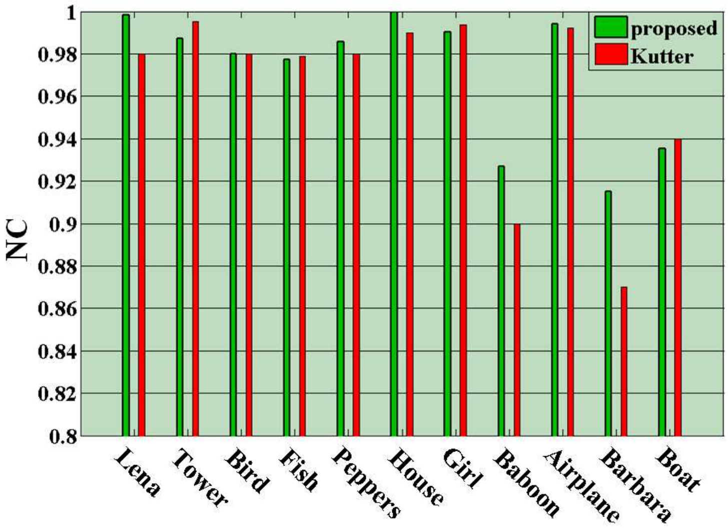


Fig. 14: Computed NC for s=0.4 and where the variance of Gaussian mask is $\sigma^2 = 0.5$.

Fig. 15: (a) The original image, 'Lena', (b)-(m) the watermarked image and the extracted watermark under different attacks and different situations.

Table 1: The procedure of the three watermarking methods.

Method	Watermark Embedding Position	Watermark Embedding Procedure	Watermark Retrieval
[8]	random position	using two additional bits	cross shape with 8 pixels
[10]	all pixels	1. balancing the watermark bits 2. Gaussian pixel weighing mask 3. pixel value replacing	surrounding 8 neighbors
Our Proposed Algorithm	no singularities	1. using Curvelet transform 2. Gaussian pixel weighing mask 3. pixel value replacing 4. using two additional bits	cross shape with 8 pixels (Fig. 1)

Table 2: Number of errors for different values of ‘s’.

Scaling Parameter	[8]	Our Proposed Algorithm
s= 0.1	101	40
s=0.2	39	17
s=0.3	20	10
s=0.4	7	1
s=0.5	5	0