PERCEPTUAL WATERMARKS IN THE WAVELET DOMAIN

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ABSTRACT

In a watermarking system, robustness evaluation should be made if invisibility criteria are satisfied. For this purpose, perceptual watermarks are being used to overcome the issue of robustness against invisibility. In the literature, there was proposed a blind spread spectrum technique that uses a perceptual mask in the wavelet domain, taking into account the noise sensitivity, texture and the luminance content of all image subbands. In this paper, we describe new techniques proposed by the authors, based on the modifications of this perceptual mask, in order to increase robustness, while still maintaining imperceptibility. Moreover, using the new mask, information is successfully hidden in the lower frequency levels, thus increasing the capacity and making the mark more robust to common attacks that affect both high frequencies and low frequencies of the image. A good balance between robustness and invisibility of the watermark is achieved when embedding is made in all detail subbands for all resolution levels, except the coarsest level. We also present three types of detectors that take advantage of the hierarchical wavelet decomposition. The effectiveness of the new perceptual mask is appreciated by comparison with the former watermarking system. Simulation results show the superiority of the proposed methods.

1. INTRODUCTION

Because of the unrestricted transmission of multimedia data over the Internet, content providers are seeking technologies for protection of copyrighted multimedia content. Watermarking has been proposed as a means of identifying the owner, by secretly embedding an imperceptible signal into the host signal [1]. Important properties of an image watermarking system include perceptual transparency, robustness, security, and data hiding capacity [2].

There are some ways to assure imperceptibility. One way is to embed the watermark in coefficients of known robustness (which are usually large coefficients) or perceptually significant regions [1], i.e. contours and textures of an image. This can be done empirically, selecting larger coefficients [2] or using a thresholding scheme in the transform domain [3,4]. Another approach is to insert the watermark in all coefficients of a transform, using a variable strength for each coefficient [5]. Hybrid techniques, based on compression schemes, embed the watermark using a thresholding scheme and variable strength [3].

We study a blind watermarking system that operates in the wavelet domain. The watermark is masked according to the characteristics of the human visual system (HVS), taking into account the texture and the luminance content of all the image subbands [5]. For coefficients corresponding to contours of the image a higher strength is used, for textures a medium strength is used and for regions with high regularity a lower strength is used, in accordance with the analogy water-filling and watermarking proposed in [6]. Barni’s method [5] is quite robust against common signal processing techniques like filtering, compression, cropping etc. However, because embedding is made only in the last resolution level, the watermark information can be easily erased by a potential attacker. We present some results using a new pixel-wise mask proposed by the authors [7,8] that models the HVS behavior in a better way. This allows embedding the watermark in resolution levels with lower frequency as well [10].

The texture content is appreciated with the aid of the local standard deviation of the original image, which is further compressed in the wavelet domain. For data hiding in lower frequency levels, the luminance mask is also computed using a high resolution approximation image. At the detection side, since the threshold is image dependent, we suggest using the correlation vs. threshold ratio; hence the detection function becomes nonlinear with a fixed detection threshold [11]. In [10], the insertion is made in three resolution levels, while the quality of the images is still preserved. For detection accuracy, we proposed to use three types of detectors, to take advantage of the wavelet hierarchical decomposition. The watermark presence is detected from 1) all resolution levels, 2) separately from each resolution level, considering the maximum detector response per level and 3) separately from each subband, considering the maximum detector response per subband. Evaluating correlations separately per resolution level or subband is sometimes advantageous. For cropping, the watermark will be damaged more likely in the lower frequency than in the higher frequency, while lowpass filtering affects higher frequency than lower ones. We discard layers or subbands with lower detector responses, similarly to the approach used in [3]. This type of embedding combined with new detectors is
more attack resilient to a possible erasure of the three subbands. The paper is organized as follows. Section 2 presents the system proposed by Barni, Bartolini and Piva [5]; the new masking technique and the improved detection are presented in sections 3 and 4; simulation results are discussed in section 5; finally conclusions are drawn in section 6.

2. THE SYSTEM PROPOSED BY BARNI, BARTOLINI AND PIVA

2.1 Embedding

The image I, of size 2M×2N, is decomposed into 4 levels using Daubechies-6 wavelet mother, where \( T^l \) is the subband from level \( l \in \{0,1,2,3\} \), and orientation \( \theta \in \{0,1,2,3\} \) (corresponding to horizontal, diagonal and vertical detail subbands, and approximation subband). A pseudorandom binary (±1) sequence is casted into 2D binary watermarks, each of size MN/4×MN/2. In [5], the watermark is embedded in all coefficients from level \( l=0 \) by addition:

\[
\tilde{T}_l^\theta (i,j) = T_l^\theta (i,j) + \alpha w_i^\theta (i,j) x_i^\theta (i,j) \tag{1}
\]

where \( \alpha \) is the embedding strength and \( w_i^\theta (i,j) \) is a weighing function, which is a half of the quantization step \( q_i^\theta (i,j) \). The quantization step of each coefficient is computed in [5] as the weighted product of three factors:

\[
q_i^\theta (i,j) = \Theta (l,\theta) \Lambda (l,i,j) \Xi (l,i,j) \tag{2}
\]

and the embedding takes place only in the first level of decomposition, for \( l=0 \).

The first factor is the sensitivity to noise depending on the orientation and on the level of detail:

\[
\Theta (l,\theta) = \begin{cases} 
\sqrt{2}, & \theta = 1 \\
0.32, & l = 1 \\
0.16, & l = 2 \\
0.10, & l = 3 
\end{cases} \tag{3}
\]

The second factor takes into account the local brightness based on the gray level values of the low pass version of the image (the 4th level approximation image):

\[
\Lambda (l,i,j) = 1 + \text{L'}(l,i,j) \tag{4}
\]

where

\[
\text{L'}(l,i,j) = \begin{cases} 
1 - L(l,i,j), & L(l,i,j) < 0.5 \\
L(l,i,j), & \text{otherwise}
\end{cases} \tag{5}
\]

and

\[
L(l,i,j) = i^l \left(1 + \left|\frac{i}{2^{2^{-l}}} \right|,1 + \left|\frac{j}{2^{2^{-l}}} \right|\right) / 256
\]

The third factor is computed as follows:

\[
\Xi (l,i,j) = \sum_{k=0}^{2^l-1} \sum_{x=0}^{2^l-1} \sum_{y=0}^{2^l-1} \left( T^\theta_{l,x,y} \left( y + i/2^l, x + j/2^l \right) \right)^2 \tag{6}
\]

\[
\text{Var} \left( T^\theta_{l,x,y} \left( y + i/2^l, x + j/2^l \right) \right)_{y=0,1} \]

\[
\text{Var} \left( T^\theta_{l,x,y} \left( y + i/2^l, x + j/2^l \right) \right)_{x=0,1}
\]

and it gives a measure of texture activity in the neighborhood of the pixel. In particular, this term is composed by the product of two contributions; the first is the local mean square value of the DWT coefficients in all detail subbands, while the second is the local variance of the low-pass subband (the 4th level approximation image). Both these contributions are computed in a small 2×2 neighborhood corresponding to the location \((i,j)\) of the pixel. The first contribution can represent the distance from the edges, whereas the second one the texture. This local variance estimation is not so precise, because it is computed with a low resolution. We have proposed another way of estimating the local standard deviation [7].

2.2 Detection

In [5], detection is made using the correlation between the marked DWT coefficients and the watermarking sequence to be tested for presence:

\[
\rho (i) = 4^l \sum_{\theta=0}^{3} \sum_{x=0}^{2^l-1} \sum_{y=0}^{2^l-1} \tilde{T}_l^\theta (i,j) x_i^\theta (i,j) / (3MN) \tag{7}
\]

The correlation is compared to a threshold \( T_{\rho(i)} \), computed to grant a given probability of false positive detection, using the Neyman-Pearson criterion. For example, if \( P_f \leq 10^{-6} \), the threshold is

\[
T_{\rho(i)} = 3.97 \sqrt{2 \sigma^2_{\rho(i)}}, \quad \text{with } \sigma_i^2, \quad \text{the variance of the wavelet coefficients, if the image was watermarked with a code Y other than } X:
\]

\[
\sigma_i^2 = \left( 4^l / (3MN) \right)^2 \sum_{\theta=0}^{3} \sum_{x=0}^{2^l-1} \sum_{y=0}^{2^l-1} \left( \tilde{T}_l^\theta (i,j) \right)^2 \tag{8}
\]

3. IMPROVED PERCEPTUAL MASK

Another way to generate the third factor of the texture is by segmenting the original image, finding its contours, textures and regions with high homogeneity. The criterion used for this segmentation can be the value of the local standard deviation of each pixel of the host image. In a rectangular moving window \( W(i,j) \) containing \( W_i \times W_j \) pixels, centered on each pixel \((i,j)\) of the host image, the local mean is computed with:

\[
\hat{\mu}(i,j) = W^{-2}_S \sum_{(m,n)\in W(i,j)} I(m,n) \tag{9}
\]

and the local variance is given by:

\[
\hat{\sigma}^2(i,j) = W^{-2}_S \sum_{(m,n)\in W(i,j)} \left( I(m,n) - \hat{\mu}(i,j) \right)^2 \tag{10}
\]

Its square root represents the local standard deviation. For example, the image Barbara is segmented in classes whose elements have a value of the normalized local standard deviation, belonging to one of six possible intervals \( I_p = (a_{p-1}, a_p) \), \( p=1,...,6 \), where \( a_0=0, a_0=0.025, a_0=0.05, a_0=0.075, a_0=0.1, a_0=0.25, a_0=1 \) (Fig.2). This image was selected for its rich content. It contains a lot of contours, textures and zones with high homogeneity. In Fig. 2, the class corresponding to the interval \( I_p \), \( p=1,...,6 \), is represented, the elements of the other classes being ignored (represented in white). These figures prove the good quality of the segmentation based on the local standard deviation values.
The texture for a considered DWT coefficient is given by a value proportional with the local standard deviation of the corresponding pixel from the host image, as we mentioned before. Let us denote this local standard deviation image with $S$, and the local mean image with $U$. Both these images have the same size as the original image, $I$, of $2\times 2$. Because embedding is made in the subband $s$, level $l$, the size of the texture must agree with the size of the subband, which is $M\times N/4^l$. The local standard deviation image $S$, must be compressed. The compression ratio required for the mask corresponding to the $l$th wavelet decomposition level is $4^{l+1}$, with $l\in\{0,1,2\}$. This compression can be realized exploiting the separation properties of the DWT. To generate the mask required for the embedding into the detail sub-images corresponding to the $l$th decomposition level, the DWT of the local standard deviation image is computed (making $l+1$ iterations). The required mask will be the approximation sub-image from level $l$, denoted $S_l^3$. Normalization is also required since the texture values obtained are too high. This is normalized to the local mean, also compressed in the wavelet domain, like described before, $U_l^3$. This type of compression is illustrated in Fig. 3. One difference between the watermarking method proposed in our paper [7] and the one presented in [5], is given by the computation of the local variance – the second term – in (6). To obtain the new values of the texture, the local variance of the image to be watermarked is computed, using the relations (9) and (10). The local standard deviation image is decomposed using one iteration wavelet transform, and only the approximation image is kept. Relation (7) is then replaced with:

$$z(i,j) = \sum_{k=0}^{L-1} \sum_{x=0}^{N/2^k-1} \sum_{y=0}^{M/2^k-1} \left[ I_{i,j,k}^o \cdot \left( y + j/2^k, x + j/2^k \right) \right]^2 \cdot S_l^3(i,j) / U_l^3(i,j)$$  

$$(11)$$
A scheme is provided in Fig. 4. The second difference [8] is that the luminance mask is computed on the approximation image from level \( l \), where the watermark is embedded. The DWT of the original image using \( l \) decomposition levels was computed and the approximation sub-image corresponding at level \( l \) was separated, obtaining the image \( S_0^l \). The luminance content is computed using relation (12):
\[
L(i, j) = \frac{L_1^0(i, j)}{256}
\] (12)
Since both factors already described are more dependent on the resolution level in the method proposed in [8], the noise sensitivity function is also replaced
\[
\theta(l, \theta) = \begin{cases} \sqrt{2}, & \theta = 1 \\ 1, & \text{otherwise} \end{cases} \quad \text{if } l \in \{0,1\}
\] (13)

### 4. IMPROVED DETECTION

Throughout the rest of this paper, we considered the ratio between the correlation \( \rho(l) \) in Eq. (16) and the image dependent threshold \( T_{d1} \), hence the detector was viewed as a nonlinear function with a fixed threshold. In [10], three types of detectors are used, to take advantage of the wavelet hierarchical decomposition. The watermark presence is detected

1) from all resolution levels,
2) separately from each resolution level, considering the maximum detector response from each level,
3) separately from each subband, considering the maximum detector response from each subband.
Evaluating the correlations separately per resolution level or subband can be sometimes advantageous. In the case of cropping, the watermark will be damaged more likely in the lower frequency than in the higher frequency, while lowpass filtering affects higher frequency than lower ones. We discard layers or subbands with lower detector response. This type of embedding combined with new detectors is more attack resilient to a possible erasure of the three subbands watermark. The first detector evaluates the watermark’s presence on all resolution levels:
\[
d_1 = \rho_{d1} L_{d1}
\] (14)
where the correlation \( \rho_{d1} \) is given by
\[
\rho_{d1} = \sum_{i=0}^{M-2} \sum_{j=0}^{N-2} \sum_{i=0}^{N-2} \sum_{j=0}^{M-2} \frac{\tilde{I}_l^i(i, j) x_l^0(i, j)}{3MN \sum_{i=0}^{M-2} \sum_{j=0}^{N-2} \tilde{I}_l^i(i, j)^2}
\] (15)
The threshold for \( P_t \leq 10^{-8} \) is \( T_{d1} = 3.97 \sqrt{\sigma_{\rho_{d1}}^2} \), with
\[
\sigma_{\rho_{d1}}^2 \approx \sum_{i=0}^{M-2} \sum_{j=0}^{N-2} \sum_{i=0}^{N-2} \sum_{j=0}^{M-2} \left( \tilde{I}_l^i(i, j) \right)^2 \left( 3MN \sum_{i=0}^{M-2} \sum_{j=0}^{N-2} \tilde{I}_l^i(i, j)^2 \right)^2
\] (16)
The second detector considers the responses from different levels, as \( d(l) = \rho(l) / T(l) \), with \( l \in \{0,1,2\} \), and discards the detector responses with lower values:
\[
d_2 = \max_l \left\{ d(l) \right\}
\] (17)
The third detector considers the responses from different subbands and levels, as \( d(l,\theta) \) the ratio \( \rho(l,\theta)/T(l,\theta) \), with \( l,\theta \in \{0,1,2\} \), and discards the detector responses with lower values
\[
d_i = \max_{l,\theta} \{ d(l,\theta) \}
\] (18)

The correlation and threshold are computed with the same rationale on one subband, indicated by its orientation and level.

5. EVALUATION OF THE METHODS

In a first set of experiments, we have modified the system proposed by Barni et al., using the texture mask as given in relation (11) [7]. The image Barbara is watermarked with various embedding strengths \( \alpha \). The binary watermark is embedded in all the detail wavelet coefficients of the first resolution level using eq. (1) to (5) and (11). The watermarked Barbara for \( \alpha=1.5 \) is shown in Fig. 5.

![Fig. 5 Watermarked Barbara image with \( \alpha = 1.5 \).](image)

To assess the validity of our algorithm, we give in Fig. 6 the results for JPEG compression. Each watermarked image is compressed using the JPEG standard, for six different quality factors: 5, 10, 15, 20, 25, 50. We choose to show in Fig. 6 only the ratio \( \rho/T \), as a function of the peak signal-to-noise ratio (PSNR) between the marked (un-attacked) image and the original one, and respectively as a function of \( \alpha \). For each PSNR and each compression quality factor \( Q \), the correlation \( \rho \) and the threshold \( T \) are computed. The probability of false positive detection is set to \( 10^{-8} \). The effectiveness of the proposed watermarking system can be measured using the ratio \( \rho/T \). If this ratio is greater than 1 then the watermark can be extracted. Analyzing Fig. 6(left), it can be observed that the watermark can be extracted for a large PSNR interval and for a large interval of compression quality factors. For PSNR values higher than 30 dB, the watermarking is invisible. For compression quality factors higher or equal than 25 the distortion introduced by JPEG compression is tolerable. For all values of the PSNR from 30 dB to 35 dB, of practical interest, the watermark can be extracted for all the significant compression quality factors (higher or equal than 25). So, the proposed watermarking method is of high practical interest.

Fig. 6 (right) shows the dependency of the ratio \( \rho/T \) on the embedding strength \( \alpha \) in case of JPEG compression. Increasing the embedding strength, the PSNR of the watermarked image decreases, and the ratio \( \rho/T \) increases. The ratio \( \rho/T \) decreases for higher embedding strengths and for higher compression ratios (Fig. 6 left) or lower embedding strengths (Fig. 6 right). The watermark is still detectable even for very small values of \( \alpha \). For the quality factor \( Q=5 \) (or a compression ratio \( CR=32 \)), the watermark is still detectable even for \( \alpha=0.5 \).

Fig. 7 shows the detection of a true watermark for various quality factors, in the case of \( \alpha=1.5 \); the threshold is well beyond the detector response. In Table 1 we give a comparison between our method and Barni’s method [5]. This time, the algorithm was tested on the Lena image, for \( \alpha=1.5 \) and a JPEG compression with a quality factor of 5, which yields into a compression ratio of 46. \( P_f \) was set to \( 10^{-8} \). We give the detector response for the original embedded watermark \( \rho \), the detection threshold \( T \), and the second highest detector response \( \rho_2 \). \( P_f \) was set to \( 10^{-8} \) and 1000 marks were tested. The detector response is higher than in Barni’s case in [5].

Fig. 6 Left: The ratio \( \rho/T \) as a function of the PSNR between the marked and the original images, for different quality factors, JPEG compression. \( P_f \) is set to \( 10^{-8} \). Right: Ratio \( \rho/T \) as a function of embedding strength, for different quality factors, JPEG compression. \( P_f \) is set to \( 10^{-8} \) [7].
In a second sets of experiments, we have modified the system proposed by Barni et al., using the texture mask as given in relation (11), as well as the luminance factor using relation (12) [8]. The masks obtained using our method and using the method in [5] are shown in Fig. 8. The improvement is clearly visible around edges and contours. We applied the method in two cases, one when the watermark is inserted in level 0 only and the second one when it’s inserted in level 1 only. To evaluate the method’s performance, we consider the attack by JPEG compression. The image Lena is watermarked at level $l=0$ and respectively at level $l=1$ with various embedding strengths, starting from 1.5 to 5. The binary watermark is embedded in all the detail wavelet coefficients of the resolution level, as previously described. For $\alpha=1.5$, the watermarked images, in level 0 and level 1, as well as the image watermarked using the mask in [5], are shown in Fig. 9. Obviously the quality of the watermarked images are preserved using the new pixel-wise mask. Their peak signal-to-noise ratios (PSNR) are 38 dB (level 0) and 43 dB (level 1), compared to the one in [5], with a PSNR of 20 dB.

Tab. 1 A comparison between the proposed method [7] and Barni et al. method.

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<tr>
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<tbody>
<tr>
<td>$\rho$</td>
<td>0.3199</td>
<td>0.038</td>
</tr>
<tr>
<td>$T$</td>
<td>0.0844</td>
<td>0.036</td>
</tr>
<tr>
<td>$\rho_2$</td>
<td>0.0516</td>
<td>0.010</td>
</tr>
</tbody>
</table>

Fig. 8 Original image Lena; new mask and the mask from [5] for level $l=0$. The masks are the complementary of the real ones.

Fig. 9 Watermarked images, $\alpha=1.5$, level 0 (PSNR = 38 dB); level 1 (43 dB); using the mask in [5], level 0 (20 dB).
The PSNR values are shown in Fig. 10(left) as a function of the embedding strength. The mark is still invisible, even for high values of $\alpha$. We give in Fig. 11 the results for JPEG compression. Each watermarked image is compressed using the JPEG standard, for six different quality factors, $Q \in \{5,10,15,20,25,50\}$. For each attacked image, the correlation $\rho$ and the threshold $T$ are computed. In all experiments, the probability of false positive detection is set to $10^{-8}$. The effectiveness of the proposed watermarking system can be measured using the ratio $\rho/T$. If this ratio is greater than 1 then the watermark is detected. Hence, we show in Fig. 11 only the ratio $\rho/T$, as a function of $\alpha$. It can be observed that the watermark is successfully detected for a large interval of compression quality factors. For PSNR values higher than 30 dB, the watermarking is invisible. For quality factors $Q \geq 10$, the distortion introduced by JPEG compression is tolerable. For all values of $\alpha$, the watermark is detected for all the significant quality factors ($Q \geq 10$). Increasing the embedding strength, the PSNR of the watermarked image decreases, and $\rho/T$ increases. For the quality factor $Q = 10$ (or a compression ratio CR = 32), the watermark is still detectable even for low values of $\alpha$.

Fig. 10 (right) shows the detection of a true watermark from level 0 for various quality factors, for $\alpha=1.5$; the threshold is below the detector response. The selectivity of the watermark detector is also illustrated, when a number of 999 fake watermarks were tested: the second highest detector response is shown, for each quality factor. We can see that false positives are rejected.

In Table 2 we give a comparison between our method [8] and the method in [5], for JPEG compression with $Q=10$, equivalent to a compression ratio of 32. We give the detector response for the original watermark $\rho$, the detection threshold $T$, and the second highest detector response $\rho_2$, when the watermark was inserted in level 0. The detector response is higher than in the case of the method in [5].

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**Fig. 10 Left:** PSNR as a function of $\alpha$. Embedding is made either in level 0 or in level 1. Right: Detector response $\rho$, threshold $T$, highest detector response, $\rho_2$, corresponding to a fake watermark, as a function of different quality factors (JPEG compression). The watermark is successfully detected. $P_f$ is set to $10^{-8}$. Embedding was made in level 0 [8].

**Fig. 11** Logarithm of ratio $\rho/T$ as a function of the embedding strength $\alpha$. The watermarked image is JPEG compressed with different quality factors $Q$. $P_f$ is set to $10^{-8}$. Embedding was made in level 0 (left), and in level 1 (right) [8].
Tab. 2 A comparison between the proposed method [8] and Barni et al. method [5].

<table>
<thead>
<tr>
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<tbody>
<tr>
<td>ρ</td>
<td>0.0750</td>
<td>0.062</td>
</tr>
<tr>
<td>T</td>
<td>0.0636</td>
<td>0.036</td>
</tr>
<tr>
<td>p2</td>
<td>0.0461</td>
<td>0.011</td>
</tr>
</tbody>
</table>

The third set of experiments allowed embedding of the watermark in all resolution levels, except the last one [10]. Three types of detectors are being used, to take advantage of the wavelet hierarchical decomposition. The watermark presence is detected 1) from all resolution levels, 2) separately from each level, considering the maximum detector response from each level and 3) separately from each subband, considering the maximum detector response from each subband. Various images, all of size 512x512, have been watermarked at levels \( l \in \{0,1,2\} \) using the new mask. The embedding strength \( \alpha \) was set to 1.5 in all experiments. Based on human observation and the peak-signal-to-noise ratio, PSNR, the images are indistinguishable from the original ones. For the method in [5] a watermark is embedded in all the detail wavelet coefficients of the first resolution level, \( l=0 \), for \( \alpha=0.2 \), that results in a similar image quality (see Fig.12). This has been concluded in [9], where by limiting the watermark strength such that the PSNR is 35 dB and in average the percentage of affected pixels is less than 25%, the quality of the images is greatly improved. We have used Girod’s model for determining the location and number of affected pixels [12]. For instance, in Barni’s case, the watermarked image with \( \alpha=0.2 \) has a PSNR of 36.39 dB, 11.84% affected pixels, compared to the one watermarked with \( \alpha=1.5 \) has a PSNR of 20 dB, and all pixels are affected. What is kept constant for comparison are the 2D watermarks embedded in the first level, and the image quality. We do not compare our method with the one in [5] when the watermark is embedded in all resolution levels, simply because their mask isn’t suited for embedding in other levels than the highest resolution level. We present results for some of the standard images from the USC SIPI Image Database [13]. We show in Table 3 the PSNR values for the two cases. For the first detector, we will show estimate of the false positive probability for the image Lena, before and after JPEG compression attack, with quality factor \( Q=10 \), as a function of the detection thresholds, \( T_{\rho_1} \). The threshold values have been computed using as estimate the variance of the \( \rho_1 \) obtained from experiments. The mean PSNR for the twelve images is 34.16 dB for the proposed method and 34.06 dB for Barni’s method.

Fig. 12 (left) Original image Lena, Watermarked images for (middle) our method, \( \alpha=1.5 \), PSNR=36.86 dB, (right) method in [5], \( \alpha=0.2 \), PSNR=36.39 dB

Tests were made for JPEG compression, median filtering, cropping, resizing, gamma correction and blurring. For each attacked image, and for each detector type, the detector responses, \( d_i \) for \( i \in \{1,2,3\} \), are computed as the ratio between correlation and image dependent thresholding. The probability of false positive detection is set to \( 10^{-8} \). Table 3 shows the mean values of the detector responses for each attack. We chose a particular attack parameter where the watermark is still detectable by at least one detector. For compression, our method successfully detects the watermark at quality factor 10. The 1\textsuperscript{st} detector is better in all cases. Our method has better results than Barni’s technique [5]. The watermark of both methods survived in all images for median filtering with kernel sizes up to 3. For kernel size 5, watermark of our method using the first and third detector is detectable; Barni’s method fails to detect the watermark. In the case of scaling to 50%, the watermark was successfully detectable in both cases, with better results for our method. The third detector has the best performance in detecting the mark. Watermark of our method was successfully detected in the cropped image of 32\times32, only with the third detector, which proves its efficiency. Barni’s method detects the watermark with similar detector responses as in the case of the third detector. As expected for normalized correlation detection, both methods are practically insensitive to gamma correction adjustment [1]. For the motion blur attack, both methods have successfully detected the watermark in all cases. Detector 3 has slightly better results than the others. For the first detector, we have estimated the probability of false positive by searching many different watermarks into
one watermarked image, Lena. Each threshold $T_{\rho_1}$ was set in such a way to grant a given value of $P_f$. The trial was repeated for values of $P_f$ ranging from $10^{-1}$ through $10^{-4}$. In total we have tested $5 \times 10^4$ watermarks per image. The estimation has been done before any type of manipulation and after JPEG compression, with quality factor 10. The estimated $P_f$ is plotted in Fig. 13 versus the ratio $T_{\rho_1}/\sigma_{\rho_1}$ between the detection thresholds and standard deviations of correlations for the case corresponding to certain estimates of this probability of false positive. This case corresponds to the situation where the image is watermarked with a code $Y$ other than $X$.

Surprisingly, the estimated false alarm $P_f$, came out to be lower in the case of compression than in the case of no attack, for the same detection threshold. This can be explained by the fact that before compression, the empirical pdf of the correlations in the case for an incorrect watermark is embedded, was not Gaussian. Although the two empirical pdf’s are closer after the attack, they are still very good separated and the empirical pdf for an incorrect watermark has the mean below zero, compared to the equivalent one before – which is centered on zero. Thus setting a particular threshold can indeed result in a lower false alarm after attack. Similar results were obtained for Barbara, and for the same attack.

For the first detector, the obtained probability of false positive is close to the expected one. We can thus conclude that the assumption that the wavelet coefficients from different levels and subbands are i.i.d. is a reasonable one and the detector has a good performance.

**Tab. 3 Resistance to different attacks, for the proposed method. The detector response is a mean value of different responses**

<table>
<thead>
<tr>
<th>Detector response vs. attack</th>
<th>Proposed method [10]</th>
<th>Barni’s method</th>
</tr>
</thead>
<tbody>
<tr>
<td>JPEG compression, Q=10</td>
<td>2.38</td>
<td>1.75</td>
</tr>
<tr>
<td>Median filtering, M=5</td>
<td>1.32</td>
<td>0.25</td>
</tr>
<tr>
<td>Scaling, 50%</td>
<td>4.06</td>
<td>1.85</td>
</tr>
<tr>
<td>Cropping, 512x512 -&gt; 32x32</td>
<td>0.68</td>
<td>1.32</td>
</tr>
<tr>
<td>Gamma correction, $\gamma=2$</td>
<td>20.32</td>
<td>32.54</td>
</tr>
<tr>
<td>Motion blur, $L=31, \theta=11$</td>
<td>1.98</td>
<td>6.14</td>
</tr>
</tbody>
</table>

**Fig. 13** Experimentally evaluated probability of false positive $P_f$ vs. $T_{\rho_1}/\sigma_{\rho_1}$, the ratio between the detection threshold and standard deviation of the correlations in the case where an incorrect watermark was embedded. The theoretical trend is also shown (‘o’ marker). Tests were made on Lena, before and after JPEG compression with quality factor 10, using $5 \times 10^4$ different watermarks.
6. CONCLUSION

In a watermarking system, robustness evaluation should be made if invisibility criteria are satisfied. For this purpose, perceptual watermarks are being used to overcome the issue of robustness against invisibility. In the literature, there was proposed a blind spread spectrum technique that uses a perceptual mask in the wavelet domain, taking into account the noise sensitivity, texture and the luminance content of all image subbands. In this paper, we describe new techniques proposed by the authors, based on the modifications of this perceptual mask, in order to increase robustness, while still maintaining imperceptibility. Moreover, using the new mask, information is successfully hidden in the lower frequency levels, thus increasing the capacity and making the mark more robust to common attacks that affect both high frequencies and low frequencies of the image. A good balance between robustness and invisibility of the watermark is achieved when embedding is made in all detail subbands for all resolution levels, except the coarsest level; this can be particularly useful against erasure of high frequency subbands containing the mark in Barni’s system.

A nonlinear detector with fixed threshold – as ratio between correlation and the image dependent ratio – has been used; we also present three types of detectors that take advantage of the hierarchical wavelet decomposition: 1) from all resolution levels, 2) separately from each level, considering the maximum detector response for each level and 3) separately from each subband, considering the maximum detector response for each subband. This has been advantageous for cropping, scaling and median filtering where the 3rd detector shows improved performance. We tested our methods against different attacks, and found out that it is better than the method described in [5]. The behavior of our methods can be explained by the fact that we have used a better estimate of the mask and we took advantage of the diversity of the wavelet decomposition. The effectiveness of the new perceptual mask is appreciated by comparison with the former watermarking system. Simulation results show the superiority of the proposed methods.

REFERENCES