Significant Pixel Watermarking Using Human Visual System Model in Wavelet Domain

Jayalakshmi M., S.N. Merchant, and U.B. Desai

SPANN Lab, Electrical Engineering Department
Indian Institute of Technology, Bombay, Powai, Mumbai-76
{jlakshmi, merchant, ubdesai}@ee.iitb.ac.in

Abstract. In this paper, we propose a novel algorithm for robust image watermarking by inserting a single copy of the watermark. Usually, robustness is achieved by embedding multiple copies of the watermark.The proposed method locates and watermarks 'significant pixels' of the image in the wavelet domain. Here, the amount of distortion at every pixel is kept within the threshold of perception by adopting ideas from Human Visual System (HVS) model. The robustness of the proposed method was verified under six different attacks. To verify the advantage of selecting the significant pixels over the highest absolute coefficients, simulations were performed under both cases with quantization of pixels as per HVS model. Simulation results show the advantage of selecting the 'significant pixels' for watermarking gray images as well as color images.

1 Introduction

Recent years have witnessed an outgrowth in the volume of digital data which can be easily manipulated and reproduced. Digital watermarking has been proposed as a means for owner verification, content authentication, broadcast monitoring etc. A number of watermarking algorithms in spatial domain [1], [2] as well as transform domain have been proposed. A major disadvantage of spatial domain techniques is the low robustness of the watermark. The robustness of the watermark could be improved if the properties of the cover image could be exploited. The most commonly used transforms for digital watermarking are Discrete Fourier Transform (DFT), Discrete Cosine Transform (DCT) and Discrete Wavelet Transform (DWT) [3], [4], [5], [6], [7], [8].

Given its suitability to model the HVS behavior, the DWT has gained interest among watermarking researchers. In [9] a blind watermarking algorithm which embeds the watermark in the DWT domain by exploiting the characteristics of the HVS is presented. Here, watermark strength modulation is accomplished through a mask giving a pixel by pixel measure of the sensibility of the human eye to local image perturbations. Mask construction relies on a work by Lewis and Knowles [10]. Some modifications to the method by Lewis and Knowles are proposed in [9] to make it suitable to the computation of the maximum visibly tolerable watermark energy that can be used for each DWT coefficient.

We propose a wavelet based non-blind watermarking scheme for images with a comparatively larger size than the watermark. Usually robustness is achieved

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by inserting multiple copies of the watermark, whereas we have inserted a single copy of the watermark and still robustness is maintained by selecting the coefficients with respect to their interband dependencies [11]. Wavelet transform allows us to study the image at different space-frequency resolutions and making use of this property, we locate some important feature points in images. These pixels are referred as 'significant pixels'. Generally watermarking schemes embed information only in the high frequency components or in a selected subclass of them. But in our proposed scheme the pixels are so chosen that they have significant magnitude in high frequency as well as low frequency regions. This should in turn provide better robustness.

Transparency is one of the important criteria in digital watermarking. Since the significant pixels bear a very important role in the perceptual quality of the image, the distortion at these pixels are kept below the threshold of perception as per HVS model [9].

To test the resilience of the proposed method to different signal processing operations, we have selected mainly six different attacks in the case of gray images and color images. The attacks considered are salt-pepper noise with median filtering, Gaussian noise addition, mean filtering, quantization of watermarked pixels, JPEG compression and cropping. On color images, color palette filtering using Adobe Photoshop software was also experimented. The simulation results show the added advantage of selecting significant pixels compared to high absolute coefficients.

The rest of the paper is organized as follows. Section 2 illustrates the proposed algorithm. Section 3 and Section 4 give the experimental results and conclusion respectively.

2 Proposed Algorithm

Wavelet representation of any data gives information about the variations of the data at different scales. Wavelet detail image is obtained as the convolution of the image with the wavelet function dilated at different scales. We know from which signal points each wavelet coefficient at a particular scale is computed. We can further study the wavelet coefficients for the same points at a finer scale. These coefficients are called children coefficients.

We have used three level wavelet decomposition using Haar wavelet to locate significant pixels [12]. The three level wavelet decomposition is shown in Fig. 1. In the proposed algorithm watermark is embedded only in the significant pixels in bands V_2, D_2 and H_2. But for calculating the significance factor 'S' we have considered all the bands except L_2.

2.1 Watermark Embedding

Let us denote the bands by ${B_i}^{\theta}$ where 'B' can be replaced by V, H or D as 'θ' varies. The suffix 'i' denotes the level of wavelet decomposition in which that particular band is present. To locate the significant pixels, choose every pixel in third level, say ${B_2}^{\theta}$ and its corresponding children coefficients at all finer

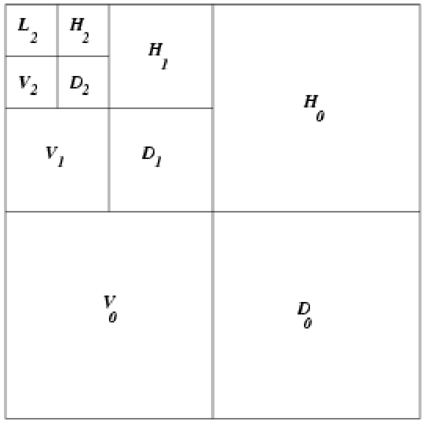


Fig. 1. Three level wavelet decomposition with different bands

resolutions namely ${B_1}^\theta$ and ${B_0}^\theta$. The significance factor (S) of every pixel in band ${B_2}^\theta$ is defined as follows.

$$S(i,j) = |{B_2}^\theta(i,j)| + \max_{l,k=0,1} |{B_1}^\theta(2i-k, 2j-l)| + \max_{m,n=0,1,2,3} |{B_0}^\theta(4i-n, 4j-m)|, \quad \forall\ (i,j) \in B_2 \tag{1}$$

After calculating significance factor(S) at every pixel in bands V_2, H_2 and D_2, these values are sorted. In our method only the highest significant pixels will be watermarked. Let the watermark be represented by a column vector w of size $K \times 1$, obtained after randomizing. The watermark is embedded at every significant pixel in band $B_2(i,j)$ as follows.

$$B_2'^{\theta}(i,j) = {B_2}^\theta(i,j) + \alpha w_k q_2^\theta(i,j) \qquad k = 1, 2, ...K \tag{2}$$

Here $B_2'^{\theta}$ is the watermarked pixel and α is the multiplication factor to keep the watermark below the level of perception. The value of α is unity if the watermark is binary. The value of q, which is the maximum quantization at every pixel below the level of perception, is calculated using HVS model as given in [9].

The model presented in this paper is with reference to the four level decomposed image, where band L_2 in Fig. 1 is further decomposed into V_3, H_3, D_3 and L_3. According to this model maximum allowable distortion at every pixel is estimated as the weighted product of three different parameters.

$$q_l^\theta(i,j) = \hat{q}_l^\theta(i,j)/2 \tag{3}$$

$$\hat{q}_l^\theta(i,j) = \Theta(l,\theta)\Lambda(l,i,j)\Xi(l,i,j)^{0.2} \tag{4}$$

Each term in the above equation is explained below. Here $'l'$ and $'\theta'$ denote the level of decomposition and the orientation of the selected band respectively. The first term $\Theta(l,\theta)$ takes into account the sensitivity to noise depending on the band. Eyes are less sensitive to noise in high resolution bands and bands having orientation of 45^o.

$$\Theta(l,\theta) = \begin{Bmatrix} \sqrt{2}, & if\theta = 1 \\ 1, & \text{otherwise} \end{Bmatrix} \cdot \begin{Bmatrix} \text{1.00, if l=0} \\ \text{0.32, if l=1} \\ \text{0.16, if l=2} \\ \text{0.10, if l=3} \end{Bmatrix}$$

The second term takes into account the local brightness based on the gray-level values of the low pass version of the image. Also it considers the fact that eyes are less sensitive to very dark and very bright regions of the image. In [10], this factor is computed in the following way.

$$\Lambda(l,i,j) = 1 + L(l,i,j) \tag{5}$$

where

$$L(l,i,j) = \frac{L_3}{256}(1 + \lfloor\frac{i}{2^{3-l}}\rfloor, 1 + \lfloor\frac{j}{2^{3-l}}\rfloor) \tag{6}$$

Since eye is less sensitive to very dark regions as in the case of bright regions, in [9], this factor is modified as in the following equation.

$$\begin{aligned} \hat{L}'(l,i,j) = 1 - L(l,i,j), \qquad & ifL(i,j) \leq 0.5 \\ L(l,i,j), \qquad & otherwise \end{aligned} \tag{7}$$

The third term takes care of the fact that eye is less sensitive to noise in highly textured areas but more sensitive near edges.

$$\begin{aligned} \Xi(l,i,j) = \sum_{k=0}^{3-l} \frac{1}{16^k} \sum_{\theta=0}^{2} \sum_{x=0}^{1} \sum_{y=0}^{1} [B_{k+l}^{\theta}(y + \frac{i}{2^k}, x + \frac{j}{2^k})]^2 \\ .Var\{L_3(1 + y + \frac{i}{2^{3-l}}, 1 + x + \frac{j}{2^{3-l}})\} \end{aligned} \tag{8}$$

where the first term gives the local mean square value and Var gives the variance around the 2x2 neighborhood of each pixel. After embedding the watermark, inverse transformation is performed to get the watermarked image.

2.2 Watermark Detection and Evaluation

For extracting the watermark from a possibly tampered image we need to use the original image and hence our algorithm is non-blind. Since watermark bits are embedded only at the significant pixels, we need to locate these pixels on the possibly attacked image and then get the quantization at those pixels. We have used Peak Signal-to-Noise Ratio (*PSNR*) as measure of perceptual quality of the watermarked image. Normalized correlation coefficient(γ) is defined as a measure of similarity between the original watermark (w) and retrieved watermark (w').

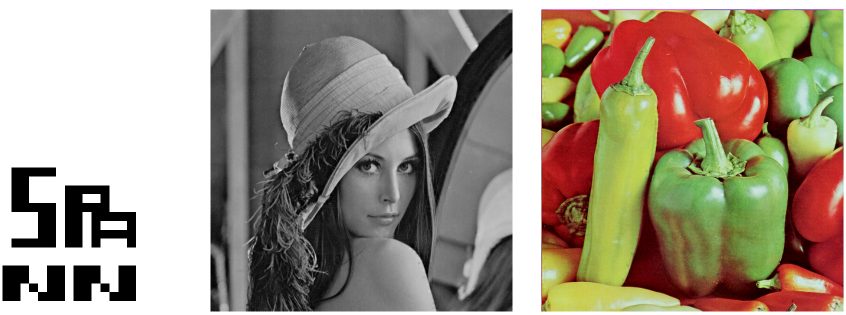
Suppose there are K pixels in the watermark, then normalized correlation coefficient is defined as follows.

$$\gamma = \frac{\sum_{i=1}^{K} w_i w_i'}{\sqrt{\sum_{i=1}^{K} w_i^2 \sum_{i=1}^{K} {w'}_i^2}}. \tag{9}$$

3 Experimental Results

The proposed algorithm was tested on both gray and color images of size 512×512. The binary watermark of size 16×16, shown in Fig. 2a, is embedded only once in the image. We have proposed to use the third decomposed level for embedding. But for the purpose of comparison, results of embedding and retrieval with second and fourth level decompositions are also included. Since the watermark is embedded only once and the quantization to each coefficient is as per HVS model, as a fair means of comparison, simulations were performed with highest absolute coefficients in second, third and fourth level decomposition, quantized as per HVS model given in [9].

The significant pixels of color images were located by considering the luminance component of the images in YCbCR representation. We have chosen four gray level images and two color images for experimentation. The watermarked images of Lena and Peppers are shown in Fig. 2b and 2c. We have not included all the test images in the paper due to space limitations. The PSNR of the watermarked images under all the considered cases are tabulated in Table 1.



(a) Watermark (b) Watermarked Lena (c)Watermarked Peppers

Fig. 2. Original watermark and watermarked images

3.1 Resilience to Attacks

Any watermarking scheme should be able to withstand both intentional and non-intentional signal processing operations. We have considered six different attacks, namely, salt-pepper noise with median filter, Gaussian noise addition, mean filter, quantization of the watermarked pixels, JPEG compression and

Table 1. PSNR(dB) of watermarked images

Images	Lena	Barbara	Baboon	Airplane	Peppers(color)	Airplane(color)
Significant pixels{2-level}	49.56	51.37	50.43	47.84	50.30	49.45
Significant pixels{3-level}	47.46	47.93	48.83	45.21	47.95	46.39
Significant pixels{4-level}	42.25	43.05	44.02	39.10	42.06	40.32
High absolute coeff{2-level}	50.04	50.76	51.63	47.43	49.98	48.50
High absolute coeff{3-level}	47.38	47.28	49.50	44.77	47.81	45.87
High absolute coeff{4-level}	42.30	42.14	44.29	39.27	41.87	40.40

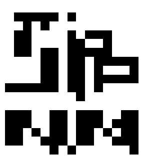
cropping. The results discussed below are of third decomposed level unless otherwise specified. Also, only a few results are included in the paper due to lack of space. Nevertheless, simulations were carried out on all images and results were tabulated.

Salt- pepper noise with zero mean and 0.01 variance was added to the watermarked images and were then median filtered to get an output image that closely matched the original. Fig. 3a and Fig. 3b show the attacked images by salt-pepper noise and median filter and Fig. 3c and Fig. 3d show the retrieved watermarks from them. The correlation coefficient and visual similarity of the retrieved watermarks emphasize the advantage of selecting significant pixels for watermarking over highest absolute pixels. It can be seen from the results that the significant pixels in third decomposed level gave better performance than the highest absolute coefficients with salt pepper noise addition with median filtering.

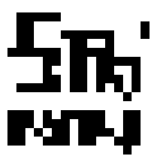
Digital images may be corrupted due to Gaussian noise while transmission. Therefore, we have considered Gaussian noise addition as another attack. The

(a) Significant pixels

(b) High absolute pixels

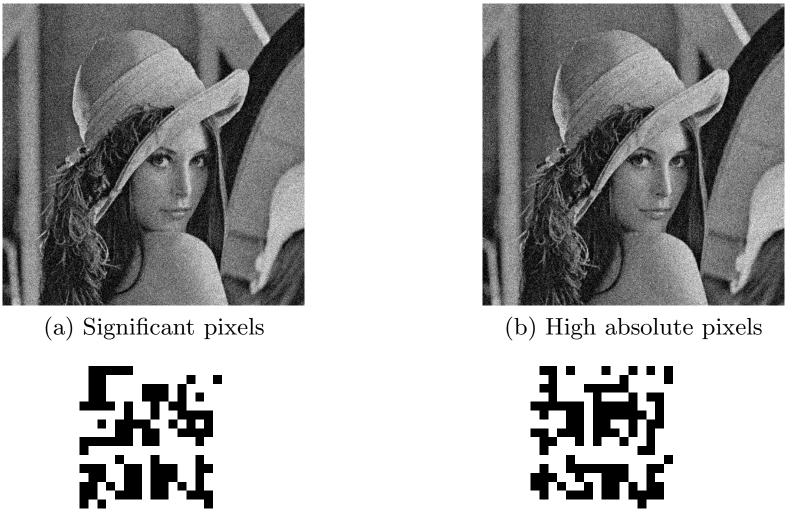


(c) From a, $\gamma = 0.9063$



(d) From b, $\gamma = 0.8828$

Fig. 3. Salt-pepper noise with median filtered images and retrieved watermarks



(a) Significant pixels

(b) High absolute pixels

(c) From a, $\gamma = 0.7578$

(d) From b, $\gamma = 0.6094$

Fig. 4. Gaussian noise added images and retrieved watermarks

noise considered has mean zero and variance 0.001. The attacked images of Lena and the retrieved watermarks from them are shown in Fig. 4. The results for all the cases were considered and the significant pixels outperformed the highest absolute coefficients. The results with noise were averaged over 100 sample runs.

Mean filtering was performed with a 3×3 mask and the averaged image had very good visual similarity with the original image. The mean filtered images and the retrieved watermarks are shown in Fig 5. The advantage of selecting significant pixels instead of highest absolute coefficients is obvious in case of averaging.

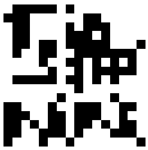
Quantization of the watermarked images were performed by quantizing the watermarked pixels to multiples of 10, 20 and 40. Fig. 6 shows the quantized images to multiples of 40 and the retrieved watermarks from them.

JPEG compression is one of the attacks to which all image watermarking methods should be resistant to. We have tabulated the correlation coefficients for all the test images for quality factors varying from 10 to 100. The correlation coefficients obtained were very close to unity in most cases, the lowest being 0.8594 and 0.7812, with quality factor 10, for Lena watermarked using significant pixels and high absolute coefficients respectively.

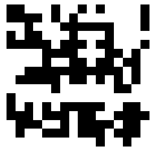
We have also tried to retrieve the watermark after cropping the watermarked image. The simulation results show that the method proposed works satisfactorily, provided cropping does not remove any significant part of the image. For example, cropped baboon image along with the retrieved watermark is shown in Fig. 8. The coefficients watermarked are the significant pixels from third and fourth levels of decomposition. Here 62.5% of the watermarked image is retained after cropping. The correlation coefficient obtained is 0.8906 and 0.8672 from the

(a) Significant pixels

(b) High absolute pixels

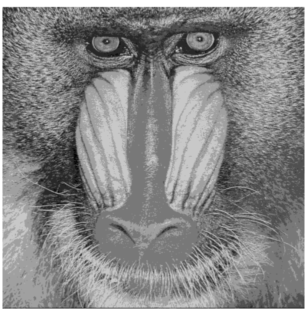


(c) From a, $\gamma = 0.7813$

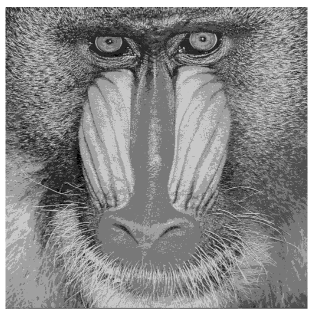


(d) From b, $\gamma = 0.5547$

Fig. 5. Mean filtered images and retrieved watermarks

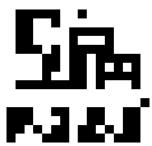


(a) Significant pixels



(b) High absolute pixels

(c) From a, $\gamma = 0.9453$

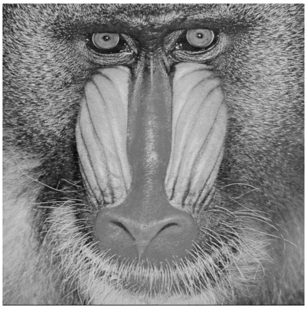


(d) From b, $\gamma = 0.8984$

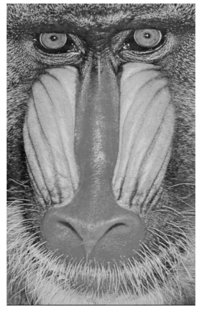
Fig. 6. Quantized images to multiples of 40 and retrieved watermarks

fourth and third levels respectively. For the purpose of comparison the retrieved watermark from the highest absolute coefficients of fourth and third levels of decomposition are also shown.

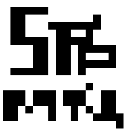
Another attack that was specifically performed on color images was color palette filter using Adobe Photoshop software. The selected filter had stroke size 2, stroke detail 3 and softness 5 so that the attacked image was not perceptually



(a) Watermarked Image

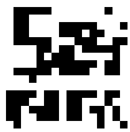


(b) Cropped Image

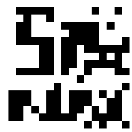


(c) 4th Sig.Pixels
$\gamma = 0.8906$

(d)3rd Sig.Pixels
$\gamma = 0.8672$



(e)4th High abs.
$\gamma = 0.7812$



(f)3rd High abs.
$\gamma = 0.8047$

Fig. 7. Retrieved Watermarks from cropped image

much distorted. Table 2 shows the correlation coefficients of the retrieved watermarks from three different color images, with the original watermark and the values show the superior performance of the significant pixels over highest absolute pixels.

Table 2. Color palette filtering

Images	Sailboat	Peppers	Airplane
Significant pixels{2-level}	0.3984	0.4688	0.5859
Significant pixels{3-level}	0.5703	0.6250	0.5703
Significant pixels{4-level}	0.7188	0.8594	0.8594
High absolute coeff{2-level}	0.2188	0.2500	0.2891
High absolute coeff{3-level}	0.4375	0.5469	0.3906
High absolute coeff{4-level}	0.6641	0.7656	0.8125

4 Conclusion

We have introduced significant pixels in wavelet domain for robust watermarking. Moreover, every selected pixel was quantized to the maximum using HVS model. The scheme worked well without losing robustness and transparency. The simulation results show that the significant pixel would be a better choice for watermarking compared to high absolute coefficients. Also the simulation results prove that, higher the level of decomposition better the robustness. But the transparency may be crucial and difficult to maintain as higher bands are selected. Obviously, as we move from one band to the next higher band, larger number of pixels are distorted in the original image and the number of available pixels for watermarking becomes comparable with the number of watermark bits.

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