A JND Model Using a Texture-Edge Selector Based on Faber-Schauder Wavelet Lifting Scheme

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Abstract. Modeling the human visual system has become an important issue in image processing such as compression, evaluation of image quality and digital watermarking. In this paper we present a spatial JND (Just Noticeable-Difference-) model that uses a texture selector based on Faber-Schauder wavelets lifting scheme. This texture selector identify non-uniform and uniform areas. That allows to choose between JNDs models developed by Chou and Qi. The chosen JND will determine the value of the embedding strength in each pixel, related to the identified region. Results show that by this process, we can generally ameliorate the visual quality with the same robustness.

Keywords: Perceptual models · Human Visual System · Digital watermarking · Wavelet · Lifting schemes · JND

1 Introduction

Digital watermarking is an efficient alternative to guarantee safety of multimedia document [1]. The most important in a digital watermark is to solve the trade-off between invisibility, robustness and the capacity for insertion of the watermark [2,3]. To improve the robustness we can increase the embedding strength but this degrade the invisibility of the mark, and vise-versa. If we ameliorate the image quality after watermarking we may lose the robustness of the mark.

To ameliorate at the same time image quality and robustness we can take into account the properties of the Human Visual System (HVS) [4] by developing perceptual models; HVS modeling has become an important issue in the image processing [5,6]. Models based on the HVS determine the maximum quantity that can be added to each pixel without affecting the visual quality of the image. Barni [7] summarized the observations and experiments on the HVS into the following three rules: First degradation are much less visible in highly textured

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areas than in uniform ones. Second contours are more sensitive to noise addition than textured regions but less sensitive than the uniform regions. Finally degradation are less visible in dark areas than in bright ones.

Digital watermarking is composed of two steps: insertion of the mark in a digital document and detection of the presence of the watermark or its extraction [1,8]. In psychophysical studies, a level of distortion that can be just seen in experimental tests is called JND (just noticeable difference) [1] and is used to determine the invisibility threshold [9]. This allows to adjust the embedding strength, optimally and adaptively with respect to areas of the image. The principle of digital watermarking using JND in spatial domain can be described by the following expression:

$$I_w(x, y) = I_o(x, y) + JND(x, y) * W(x, y) \tag{1}$$

where I_w is the watermarked image, I_o original image, W is a pseudo-random sequence represented the insertion watermark and JND is the parameter strength of the mark that controls the trade-off between visibility and robustness of the watermark.

In the literature, several JND models have been proposed for images [4,10,14]. Here we quote some important models that are designed in different domains, namely the spatial domain and transform domain.

In [10] Chou and Li proposed a spatial domain JND model for compression. This model takes into account the luminance adaptation and texture masking. The JND is defined as the dominant effect between the texture masking and luminance adaptation. In [11] Yang et al. and in [4] Qi et al. ameliorate the texture masking of Chou and Lis JND. One of the first JND model in Discrete Cosine Transform (DCT) domain was developed by Watson et al. [12] for compression. This model estimates the perceptibility changes in each image DCT block. Finally Nguyen et al. [13] proposed JND models in Discreet Wavelet Transform (DWT) domain.

In this paper we propose a JND that combines both JNDs introduced by Qi and Chou and we introduce a texture selector between non-uniform and uniform area. In the case of no textured area we will use luminance masking developed by Chou and Li. Otherwise we use texture masking developed by Qi et al.

The texture selector is based on Faber-Schauder wavelet coefficient. The wavelet coefficient are represented in a mixed scales way. The density of blocs of dominant wavelet coefficient gives an efficient method to select textural region in image [14]. We test the proposed method on several images and we show that the use of texture selector ameliorate the image quality with the same robustness of the watermark compared to method developed by Chou et al. and Qi et al.

This paper is organized as follows. Section 2 presents the JND of Chou and Li and Qi et al. In Sect. 3 we present our watermarking method with JND using Faber-Schauder lifting schemes. In Sect. 4 we present the results obtained for the evaluation of visual quality and robustness on several natural images. Finally in Sect. 5, we end with conclusion and perspectives.

2 Perceptual Models Proposed by Chou and Li and Qi et al.

2.1 Luminance Masking of Chou and Li

A luminance masking has been proposed by Chou and Li [10] wherein the luminance threshold due to the luminance of the background is given by the luminance masking JNDL (x, y). The relationship between noise sensitivity and background luminance is controlled by a subjective test. Thus JNDL (x, y) can be determined by modeling the curve obtained by experiments (Fig. 1-a). Figure 1-b shows an example of luminance masking.

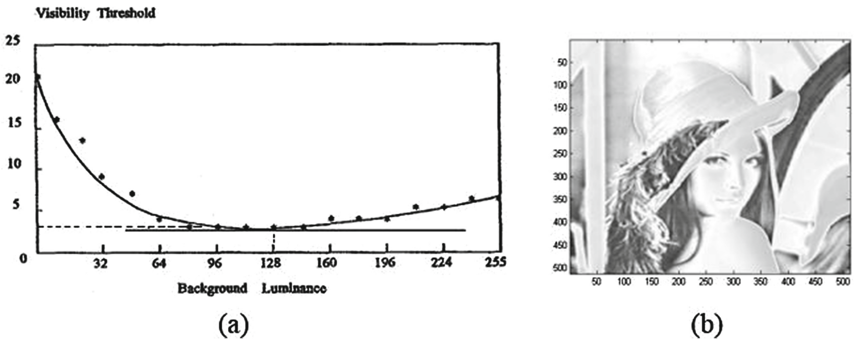

Fig. 1. (a) Visibility threshold relatively to background luminance modeled by Chou [10]. (b) Luminance masking JNDL(x,y) (with inversed color) obtained for Lena image. Black parts in the masking correspond to high watermark embedding strength.

Computing the luminance masking is the following for 8-bits gray scale images.

$$JND_L(x,y) = \begin{cases} 17\left(1 - \left(\frac{b_g(x,y)}{127}\right)^{\frac{1}{2}}\right) + 3 & \text{for } b_g \leq 127 \\ \frac{3}{128}(b_g(x,y) - 127) + 3 & \text{for } b_g \geq 127 \end{cases} \quad (2)$$

$$b_g(x,y) = \frac{1}{32}\sum_{i=1}^{5}\sum_{j=1}^{5} I_o(x-3+i, y-3+j).B(x,y), \quad B(i,j) = \begin{bmatrix} 1\,1\,1\,1\,1 \\ 1\,2\,2\,2\,1 \\ 1\,2\,0\,2\,1 \\ 1\,2\,2\,2\,1 \\ 1\,1\,1\,1\,1 \end{bmatrix}$$

where $0 \leq x < H, 0 \leq y < W$. H and W denote respectively the height and width of the image I_o. $b_g(x,y)$ is the average luminance of the background calculated using an averaging filter B.

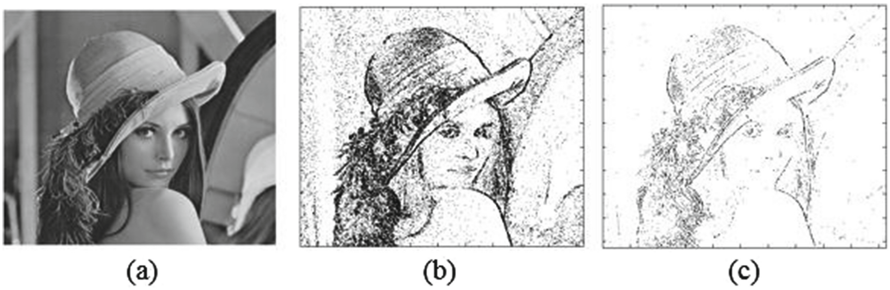

Fig. 2. (a) Lena image. (b) Texture masking $JND_T(I_o)$ with sliding windows 3 × 3. (c) Edge masking $JND_L(I_o)$

2.2 Texture and Edge Masking of Qi et al.

For texture masking we use the one proposed by Qi et al. [4]. The texture masking (Fig. 2-b) uses the absolute value of the distance between each pixel and local average value of the pixels within a sliding window LxL, Eq. (4)

$$JND_T(I_o) = |I_o(i,j) - \bar{I}_o(i,j)| \tag{3}$$

$$\bar{I}_o(i,j) = \frac{1}{(2L+1)^2} \sum_{k=-L}^{L} \sum_{l=-L}^{L} I_o(i+k, j+l)$$

where JND_T is the texture masking, $I_o(i,j)$ is the pixel at the position (i,j), $(2L+1)^2$ represents the number of pixels in the sliding window.

We also consider the edge masking proposed by Qi et al. [4] Fig. 3-c which is a Laplacien filter.

$$JND_E = L(I_o) \tag{4}$$

3 Proposed Method Based on Lifting Schemes and Using Chou-Qi JND

In order to take advantage of the perceptual models developed by Chou et al. and Qi et al. we propose to introduce an additional performant texture selector which distinguishes between uniform area, textured area and edge area. The fact that the texture selector is based on Faber-Schauder wavelet lifting scheme and the use of an original mixed scale representation of the wavelets coefficients, make the selection between JNDs more efficient. The next scheme represent the proposed perceptual mask (Fig. 3):

3.1 Texture Selector Based on Faber-Schauder Lifting Schemes

The Faber-Schauder wavelet transform (FSWT) and inverse transform (IFSWT) can be giving by the lifting scheme [15]:

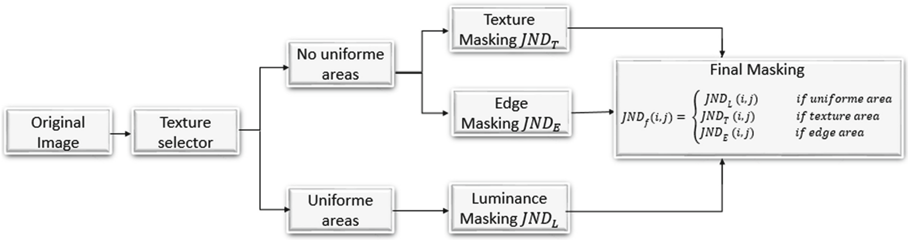

Fig. 3. Final masking, the texture selector uses Faber-Schauder wavelet lifting scheme.

$$FSDWT = \begin{cases} f_{ij}^0 = f_{ij} \text{ for } i,j \in Z \\ \qquad\qquad \text{for } 1 \leq k \leq N \\ f_{ij} = f_{2i,2j}^{k-1} \\ g_{ij}^k = (g_{ij}^{k1}, g_{ij}^{k2}, g_{ij}^{k3}) \\ g_{ij}^{k1} = f_{2i+1,2j}^{k-1} - \frac{1}{2}(f_{2i,2j}^{k-1} + f_{2i+2,2j}^{k-1}) \\ g_{ij}^{k2} = f_{2i,2j+1}^{k-1} - \frac{1}{2}(f_{2i,2j}^{k-1} + f_{2i+2,2j+2}^{k-1}) \\ g_{ij}^{k3} = f_{2i+1,2j+1}^{k-1} - \frac{1}{4}(f_{2i,2j}^{k-1} + f_{2i,2j+2}^{k-1} + f_{2i+2,2j}^{k-1} + f_{2i+2,2j+2}^{k-1}) \end{cases}$$

$$IFSDWT = \begin{cases} \qquad\qquad \text{for } 0 \leq k \leq N-1\, i,j \in Z \\ f_{2i,2j}^k = f_{ij}^k \\ f_{2i+1,2j}^k = g_{ij}^{k+1,1} + \frac{1}{2}(f_{i,j}^{k+11} + f_{i+1,j}^{k+1}) \\ f_{2i,2j+1}^k = g_{ij}^{k+1,2} + \frac{1}{2}(f_{i,j}^{k+1} + f_{i,j+1}^{k+1}) \\ f_{2i+1,2j+1}^k = g_{ij}^{k+1,3} + \frac{1}{4}(f_{i,j}^{k+1} + f_{i+1,j}^{k+1} + f_{i,j+1}^{k+1} + f_{i+1,j+1}^{k+1}) \end{cases}$$

where (f_{ij}^0) represent the image to transform, (f_{ij}^k) and (g_{ij}^k) represents approximation and details wavelet coefficient at scale k.

Usually a pyramidal representation is used to show the result of transformation, but here we privilege a mixed scale representation. In this representation each wavelet coefficient is at the place where its associated wavelet function is localized, so we have one transformed image (instead of pyramidal images) which can be considered as a good description of textural and edge areas in the image [14,15] (Fig. 4). Indeed we can distinguish areas that include edges and textured areas. These high activity regions correspond to a high density of absolute value wavelet coefficients.

The proposed approach is as follows: firstly we transform the image using Faber-Schauder wavelet transform. Then we select significant coefficient with absolute value exceeding a threshold Sc. Finally sliding windows centered on each pixel determine the density of such significant coefficient. The choice of parameter Sc as well as the sliding windows dimension can be adjusted manually or automatically [14]. As explained in [14] for low density we consider that the pixel belong to a uniform region, for medium density the pixel belong to a non-uniform region and maybe considered as an edge-region and for high density the pixel belong to a textured region (Fig. 5).

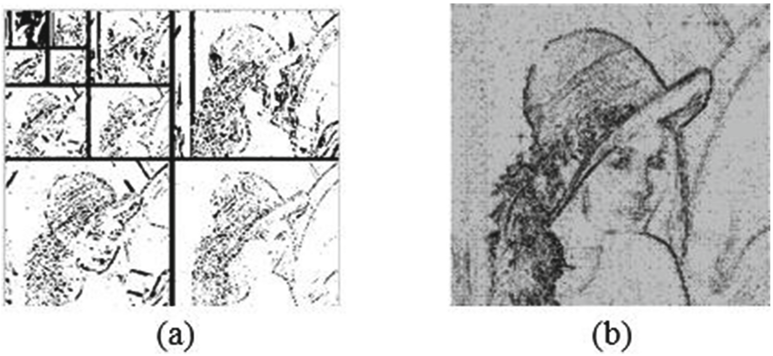

Fig. 4. (a) Pyramidal wavelet scale representation. (b) FSWT mixed-scale representation

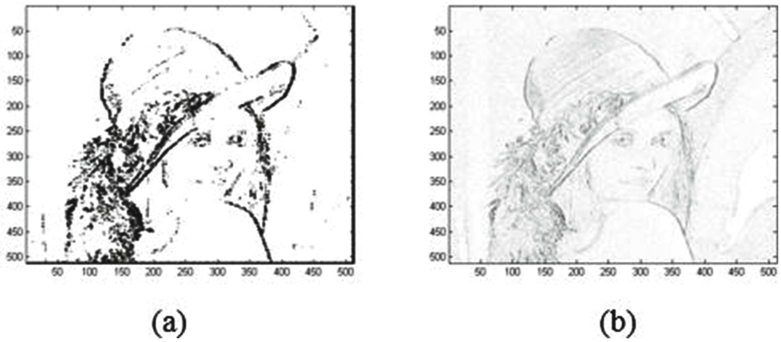

Fig. 5. (a) Texture selector using density of significant wavelet coefficient. (b) Inverted final masking using Chou and Qi models and the FSWT texture selector.

4 Watermarking Proposed Algorithm and Results

We evaluate the performances of the proposed JND model with mixed scale wavelet texture selector and we compare to those developed by Chou and Qi. We use a set of 22 natural images of variable textures and edges, for evaluation.

The watermarking system consists of three steps (Fig. 6): Firstly watermark embedding using perceptual models, second simulated attack are performed to test robustness of watermark and finally detection or extraction of watermark. In our method the watermark is inserted in spatial domain and coded according to a pseudo-random sequence of binary elements as in [16]. The image is divided into 8×8 [1] block and the watermark is embedded into each block. For the extraction of the watermark we calculate the linear correlation between the watermarked image and the coded watermark. Finally we test the visual quality of watermarked image and the robustness of the extraction by calculating respectively the Weighted Peak Signal-to-Noise Ratio (WPSNR) and the Bit-Error-Rate (BER).

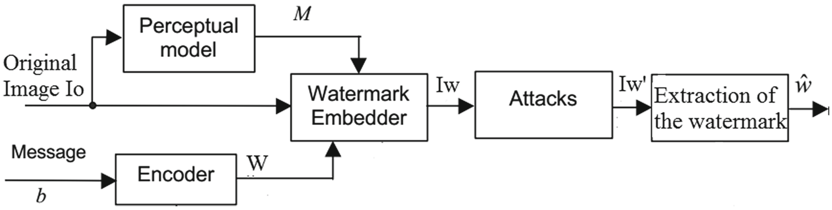

Fig. 6. Scheme of a watermarking system using perceptual models.

4.1 Visual Quality Evaluation

To measure the visual quality of watermarked images, we use the Weighted Peak Signal-to-Noise Ratio (WPSNR) proposed in [17]. For an 8-bit grayscale image, the WPSNR is as follows:

$$WPSNR = 10 \log_{10} \frac{\max(I_o)^2}{\| (I_w - I_o).NVF \|^2} \tag{5}$$

$$\text{with} \quad NVF = \frac{1}{1 + \theta\sigma^2_{I_o}(i,j)}$$

where $\sigma^2_x(i,j)$ denotes the local variance of the image in a window centered on the pixel with coordinates (i,j) and θ is a tuning parameter which plays the role of the contrast adjustment.

We calculate the WPSNR obtained after watermarking insertion by using either the proposed model or the Chou-Qi model. For the set of 22 images tested we find that the image quality obtained with the proposed method is always better than that of Chou-Qi model (Fig. 7).

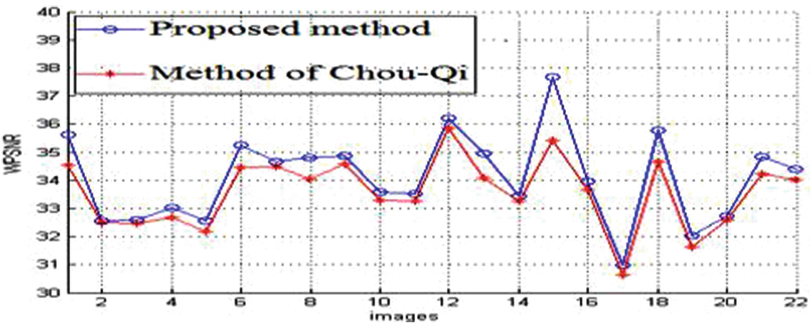

Fig. 7. Curve of WPSNR for 22 images

4.2 Robustness Evaluation

In order to test the robustness of the proposed method, we perform two type of simulated attacks, Pepper noise from 0.1 to 1, Jpeg compression from 80 % to

10 %. Figure 8 is the result for watermark detection. We use the BER to measure the rate of watermark extraction. For impulsive noise the proposed method is better. For Jpeg compression attack robustness of the other method is slightly better.

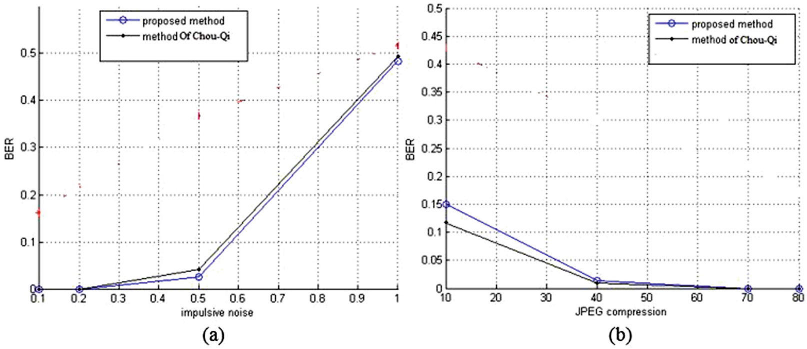

Fig. 8. BER curve of attacked watermarked image with different type of attack: (a) density of Impulsive noise. (b) Quality factor of JPEG compression

5 Conclusion and Perspectives

In this paper we propose a new spatial JND model that uses a texture selector based on Faber-Schauder wavelets lifting scheme. The choice of FSWT help us to distinguish very specific areas around the edges and around the textured areas of the image. We tested both the visual quality of our JND and the robustness of the watermark. We show that we can ameliorate the image quality. In order to ameliorate the robustness of the proposed method we project, for future works, to adapt our mixed scale wavelet transform to watermarking in DCT and DWT domain. We also Intend to improve our JND model by integrating other HVS mechanisms like the contrast sensitivity function (CSF). And also we project to do Psychophysical tests in our future work.

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