The Collaboration of Noise Reduction and Human Vision System Models for a Visible Watermarking Algorithm *

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ABSTRACT

A novel visible watermarking algorithm based on noise reduction and Human Visible System (HVS) model approach is presented in this study. In order to get the best tradeoff between the embedding energy of watermark and the perceptual translucence for visible watermark, the composite coefficients using global and local characteristics of the host image in the discrete wavelet transform (DWT) domain is considered. The application of the perceptual model of contrast-sensitive function (CSF) with the noise reduction of the visibility thresholds for HVS in DWT domain achieves the goal of fine tuning of the perceptual weights according to the basis function amplitudes for the best quality of perceptual translucence. Instead of three types of block classification- textures, edges and smooth areas, the computation of Noise Visibility Function (NVF) characterizes the local image properties to determine the optimal watermark locations and strength at the watermark embedding stage. The experimental results demonstrate that the proposed technique improves the PSNR values and visual quality than the CSF only based algorithms.

Index Terms—Visible watermarking, HVS, CSF, NVF.

1. INTRODUCTION

Because of the advantages of digital media and rapid development of digital signal processing, a variety of multimedia contents have been digitalized and easily distributed or duplicated without any reduction in quality through both authorized and unauthorized distribution channels. With the ease of editing and reproduction, protection of the intellectual rights and authentication of digital multimedia becomes an important topic in these years.

Digital watermarking [1] has been extensively studied and regarded as a potentially effective means for copyright protection recently. Among different categories of researches for digital watermarking, visible watermarking protect copyrights in a more active way since the approach not only prevents pirates but also visually recognizes the copyright of multimedia data.

Digital contents embedded with visible watermarks will overlay recognizable but unobtrusive copyright patterns identifying its ownership. Therefore, a visible watermarking technique should remain details of contents and ensure embedded patterns difficult or even impossible to be removed, and no one could use watermarked data illegally.

From the literature survey, visible watermarking has captured less attention than invisible one. Several visible watermarking schemes [2-4] have been proposed in transform domain such as DCT and DWT. Huang and Tang [2] presented a contrast sensitive visible watermarking scheme with the assistance of HVS. They first compute the CSF mask of the discrete wavelet transform domain. Secondary, they use square function to determine the mask weights for each subband. Third, they adjust the scaling and embedding factors based on the block classification with the texture sensitivity of the HVS. However, their scheme doesn't consider the following issues:

1. The application of CSF for the HVS in the wavelet transform domain
2. The embedding factors emphasize more weights in the low and high frequency domain instead of the medium-to-high frequency domain.
3. The interrelationship of block classification and the location characteristics

For the first issue, the direct application of CSF for the HVS in the wavelet transform domain needs to be further studied [4-6]. For the second issue, the watermark embedding in the low frequency components results high degradation of the image fidelity. In addition, the high frequency components of the watermarked image easily suffer common image signal processing attacks with low robustness. For the third issue, the block classification in [2] should be further considered for the local and global characteristics in DWT domain.

The goal of this paper is to present a novel visible watermarking algorithm based on noise reduction and HVS model approach. The collaboration of CSF and NVF for HVS models is leveraged with the noise reduction of the visibility thresholds for HVS in DWT domain. The perceptual weights is fine tuned for watermark embedding which results significant improvement over the watermarked images by CSF only algorithms regarding the image quality, translucence and robustness of the watermarking.

This paper will be organized as follows. The details of the algorithm will be explained in Section 2. Section 3 will show the experiments with discussion and conclusion is in Section 4.

2. THE APPROACH AND THE WATERMARKING ALGORITHM

HVS research offers the mathematical models about how humans see the world. Psychovisual studies have shown that human vision has different sensitivity from various spatial frequencies (frequency subbands). The HVS by using the contrast sensitive function (CSF) and noise visibility function (NVF) is integrated in this study and will be explained in brief as following:

* This work was supported by the National Science Council in Taiwan, Republic of China, under NSC94-2416-H009-018 and NSC95-2416-H009-027.

- CSF (Contrast Sensitive Function)

Mannos and Sakrison [3] originally presented a model of the CSF for luminance (or grayscale) images is given as follows: $H(f)=2.6*(0.0192+0.114*f)*e^{-(0.114*f)^{1.1}}$ where $f=\sqrt{f_x^{\,2}+f_y^{\,2}}$ is the spatial frequency in cycles/degree of visual angle (f_x and f_y are the spatial frequencies in the horizontal and vertical directions, respectively). The HVS is most sensitive to normalized spatial frequencies between 0.025 and 0.125 and less sensitive to low and high frequencies.

CSF masking [4-5] is one way to apply the CSF in the discrete wavelet domain. CSF masking refers to the method of weighting the wavelet coefficients relative to their perceptual importance. Some well-designed CSF masks which transforms the CSF curve into perceptual importance weight are presented in [5] and [2] uses the same method in [5] for 11-weight DWT CSF mask. For a 5 level pyramidal DWT decomposition, the HVS is most sensitive to the distortion in mid-frequency regions (level 3) and sensitivity falls off as the frequency value drifts on both sides (level 1, 2, 4 and 5). The square function in [2] is applied to approximate the effect of CSF masking. The adequate modulation rate β^k for each subband is determined by: $\beta^k=0.01+\frac{(7.20-r^k)^2}{7.20^2}$, r^k represents the wavelet coefficient CSF of the perceptual importance weight for each subband where k denotes the decomposition level.

- NVF (Noise Visibility Function)

S.Voloshynovskiy et al. [7] presented a stochastic approach based on the computation of a NVF (Noise Visibility Function) that characterizes the local image properties and identifies texture and edge regions. This allows us to determine the optimal watermark locations and strength for the watermark embedding stage. The adaptive scheme based on NVF calculated from stationary GG model is superior to other schemes, which is defined as follows:

$$NVF(x,y)=\frac{w(x,y)}{w(x,y)+\sigma_I^2} \qquad (1)$$

, $w(x,y)=\gamma[\eta(\gamma)]^{\gamma}\frac{1}{\|r(x,y)\|^{2-\gamma}}$ and σ_I^2 is the global variance of the cover image I, $\eta(\gamma)=\sqrt{\Gamma(3/\gamma)/\Gamma(1/\gamma)}$, $\Gamma(s)=\int_0^{\infty}e^{-u}u^{s-1}du$ (gamma function) and $r(x,y)=\frac{I(x,y)-\bar{I}(x,y)}{\sigma_I}$. γ is the shape parameter and $r(x,y)$ is determined by the local mean and the local variance. For most of real images, the shape parameter is in the range $0.3\le\gamma\le1$.

In order to further improve the HVS model for better image quality, the knowledge of detection thresholds for DWT coefficients should be also studied. A.B. Watson, et al. [6] proposed a mathematical model for DWT noise detection thresholds which is a function of level, orientation, and display visual resolution. The model is given by

$$\log Y=\log a+K(\log f-\log g_\theta f_0)^2$$

where a is the minimum threshold occurs at spatial frequency $g_\theta f_0$, f is the spatial frequency of decomposition level λ, and g_θ shifts the minimum by an amount that is a function of orientation. Table I shows the basis function amplitudes for a 5-level DWT. In this study, we use $A_{\lambda,\theta}$ indicating the basis function amplitudes, λ as DWT level, and θ as orientation.

From above discussion, we have implemented the CSF based visible watermarking and found the direct application of CSF square function in [2] emphasizes more weights in the low and high DWT frequency domain. Subsequently, the high frequency components of the watermarked image easily suffer common image signal processing attacks. In addition, this approach affects the quality of watermarked images and their PSNR values are often below 30dB for 512x512 color images. According to this observation, the concept of DWT noise detection threshold is adopted here to fine tune the perceptual weights by the basis function amplitudes $A_{\lambda,\theta}$ from [6]. Therefore, the perceptual weighting is modified as following:

$$\begin{cases}\beta_{\lambda,\theta}=\left[0.4+\frac{(7.20-r^{\lambda})^2}{7.20^2}\right]\times A_{\lambda,\theta} & if\ \beta_{\lambda,\theta}>0.2, \beta_{\lambda,\theta}=0.2\\ \alpha_{\lambda,\theta}=1-\beta_{\lambda,\theta} & \end{cases} \qquad (2)$$

Here, $\alpha_{\lambda,\theta}$ and $\beta_{\lambda,\theta}$ are scaling and embedding factors, λ is the DWT level, and θ is orientation where γ^{λ} is the wavelet coefficient CSF of the perceptual importance weight as shown in Fig. 1. Meanwhile, $\alpha_{\lambda,\theta}$ and $\beta_{\lambda,\theta}$ are the global characteristics of the host image, and they are independent to the digital images.

TABLE I
BASIS FUNCTION AMPLITUDES FOR A FIVE-LEVEL 9/7 DWT

Orien-tation	Level				
	1	2	3	4	5
LL	0.62171	0.34537	0.18004	0.09140	0.045943
HL	0.67234	0.41317	0.22726	0.11792	0.059758
LH	0.67234	0.41317	0.22726	0.11792	0.059758
HH	0.72709	0.49428	0.28688	0.15214	0.077727

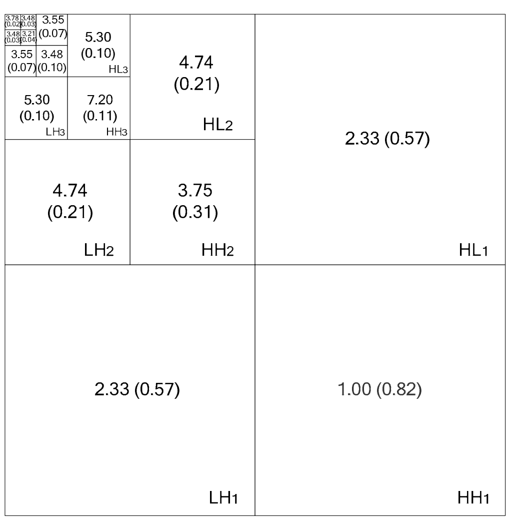


Fig. 1. A five-level wavelet pyramidal decomposition. $r^{\lambda}(\beta_{\lambda,\theta})$ values for each level λ are indicated at the center of each band.

To further improve the application of block classification by simply categorizing three type blocks in [2], the local and global characteristics in DWT domain is considered. In our content adaptive scheme, a stochastic image model for watermark embedding is adopted by using the NVF which characterizes the local image properties. In our scheme, we use the stationary GG model in the embedding stage, and the estimated shape parameter for $\gamma = 0.6$, and width of window is 1. In summary, the complete design of the proposed algorithm is summarized as following and the flow chart is shown in Fig. 2:

Watermarking embedding algorithm:

(1) The host color image is converted in the color space domain from RGB to YCrCb.

(2) By using Bi9/7 filter from [6], compute the wavelet coefficients of Y component from host color image and grayscale watermark image. If the width of watermark is not the same as the one of the host image, it should be proportionally scaled to the host image.

(3) Modify the DWT coefficients of the host image by using the following equation

$$Y_{i,j} = \alpha_{\lambda,\theta} \times X_{i,j} + (1 - NVF_{i,j}) \times \beta_{\lambda,\theta} \times S_{i,j}$$

Note: (i, j) indicates the spatial location. X and S are the decomposed wavelet coefficients of the original image and the watermark. NVF is defined in formula (1) and the relationship of $\alpha_{\lambda,\theta}$ and $\beta_{\lambda,\theta}$ is defined in (2).

(4) Inverse transform the DWT coefficients of the host image to obtain a watermarked image.

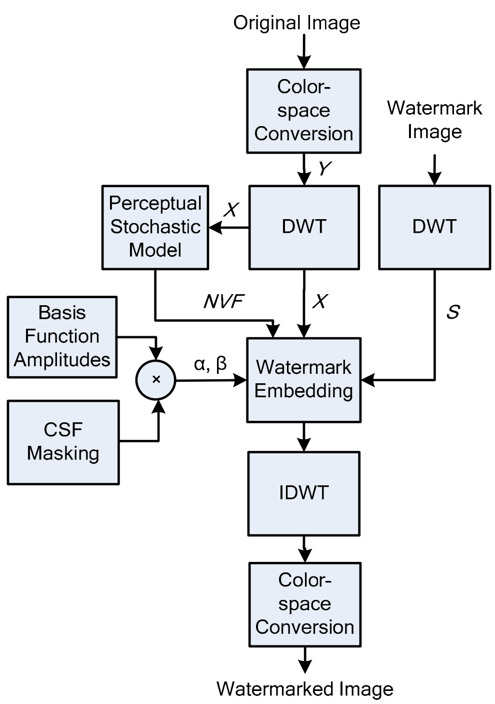


Fig. 2. The flow chart of the proposed visible watermarking approach

3. EXPERIMENTS AND DISCUSSION

The proposed visible watermarking algorithm has been implemented and intensively tested by using the commonly available color images from USC image database [8] and the performance of 512x512 color Lena, F16, Baboon, Peppers, Splash and Tiffany images are tabulated for comparison in Table II. The grayscale watermark of logo image adopted in the experiments is a NCTU school logo and shown in Fig. 3.

Fig. 4 (a) and 4 (d) illustrate the original cover images of Lena and F16 from [8], the results watermarked images from [2] are compared with the proposed approach and the results are in Fig. 4 (b)(c) and (e)(f). The performance analysis can be categorized as following:

A. Visual Quality

From Fig. 4 (b)(c) and (e)(f), the proposed method has the closest luminance maintenance compared with the original ones even the difference is sometimes identified subjectively. The watermarked images by using [2] have more bright effect in the unmarked areas. To further compare the details from the watermarked images, Fig. 5(a) and 5(d) are the close-up of the original image. Fig. 5(b) and 5(e) are the close-up of Fig. 4(b) and 4(e) by using [2]'s method. Fig. 5(c) and 5(f) are the close-up of Fig. 4(c) and 4(f) by using our proposed scheme. It is very clear that the watermark's edges and thin lines are blurred in Fig. 5(b) and 5(e) but the watermark patterns in Fig. 5(c) and 5(f) still has sharp edge and the logo watermark is evidently embedded.

B. PSNR (peak signal-to-noise ratios)

To make a fair comparison with the method from [2], it is better to embed the same watermark for the same cover image. However, the watermark used in [2] is not available currently, we embed the logo watermark from Fig. 3 to make the best effort for performance comparison. The tabulated results from TABLE II disclose that our watermarking scheme can achieve higher PSNR values than the method in [2] where the PSNRs are generally below 30dB for different images. The low PSNRs have positive correlation with the degradation in image quality. This denotes the fidelity of images from our method is better than the CSF only based method.

TABLE II
PSNR SUMMARY OF WATERMARKED COLOR IMAGES

Image	Method of [7]	Proposed method
Lena	27.1 dB	32.1 dB
Baboon	27.2 dB	30.5 dB
F16	28.9 dB	31.7 dB
Peppers	26.9 dB	31.8 dB
Splash	27.2 dB	31.6 dB
Tiffany	28.1 dB	32.4 dB

Fig. 3. Tested grayscale watermark : NCTU logo

C. Median Filtering

StirMark [9] software is adopted here for this attack. Fig. 6(a) is close-up of original Baboon image. Fig. 6(b) is close-up of 7x7 median filtering of watermarked image by the method of [2]. Fig. 6(c) is close-up of 7x7 median filtering of watermarked image by the proposed method. It is apparent that the logo pattern (i.e. the characters of E, S, A) is still evidently existed in Fig. 6 (c) but is blurred and hard to be recognized in Fig. 6 (b).

Other attacks from [9] are also preformed and the experimental results are consistent with the above findings which indicate our visible watermarking scheme has better visual effect and high PSNR values than other schemes like [2]. In summary, an intensive comparison for proposed technique has been illustrated above. Different attack and visual quality comparison is also illustrated. Therefore, we can conclude that the proposed method is more robust with better image quality than the algorithm in [2].

4. CONCLUSION

We propose a new visible watermarking technique where the intensity of the watermark in different regions of the image depends on the underlying content of the image and humans' sensitivity to spatial frequencies. The collaboration of CSF and NVF for HVS models is leveraged with the noise reduction of the visibility thresholds for HVS in DWT domain. The perceptual weights is fine tuned for watermark embedding which results significant improvement over the watermarked images by CSF only based algorithms regarding the image quality, translucence and robustness of the watermarking. The experimental results demonstrate the proposed visible watermarking scheme has achieved high PSNR values with better visual fidelity and robustness to attacks than other schemes.

REFERENCES

[1] I. J. Cox, J. Kilian, F. T. Leighton, and T. Shamoon,, "Secure spread spectrum watermarking for multimedia", IEEE Trans. on Image Proc., vol. 6, no. 12, pp. 1673-1687, Dec. 1997.

[2] B. B. Huang and S. X. Tang, "A contrast-sensitive visible watermarking scheme", IEEE Multimedia, vol. 13, no. 2, pp. 60-66, April-June 2006.

[3] J. L. Mannos and D. J. Sakrison, "The effects of a visual fidelity criterion on the encoding of images", IEEE Trans. on Info. Theory, vol. 20, no. 4, pp. 525-536, Jul. 1974.

[4] D. Levický and P. Foriˇs, "Human Visual System Models in Digital Image Watermarking," RADIOENGINEERING, vol.13, no. 4, pp. 38-43, 2004.

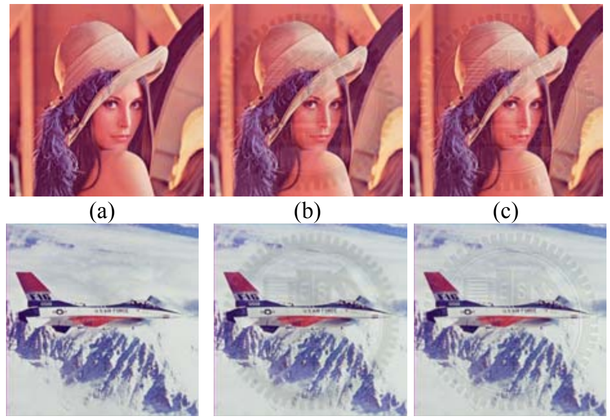
[5] A.P. Beegan, L.R. Iyer, and A.E. Bell, "Design and Evaluation of Perceptual Masks for Wavelet Image Compression", Proc. 10th IEEE Digital Signal Processing Workshop, IEEE CS Press, pp. 88-93, 2002.

[6] A.B. Watson, G.Y. Yang, J.A. Solomon, J. Villasenor," Visibility of wavelet quantization noise", Image Processing, IEEE Transactions on, vol.6, no.8, pp. 1164-1175, 1997.

[7] S. Voloshynovskiy, et al., "A stochastic approach to content adaptive digital image watermarking", in Proc. 3rd Int. Workshop Information Hiding, Dresden, Germany, pp. 211-236, Sep. 1999.

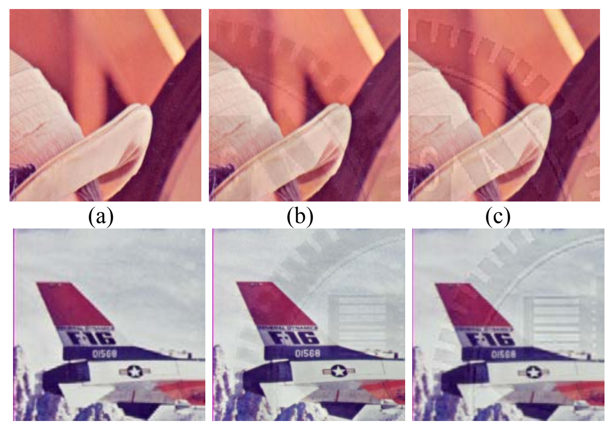
[8] USC SIPI–The USC-SIPI Image Database [Online]:http://sipi.usc.edu/services/database/Database.html

[9] StirMark,http://www.petitcolas.net/fabien/software/StirMarkBenchmark_4_0_129.zip



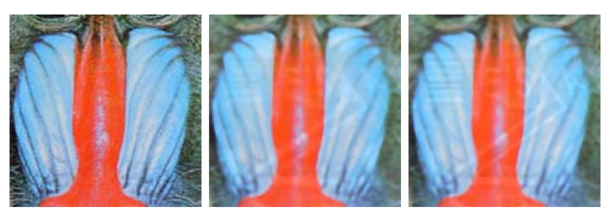
(a) (b) (c) (d) (e) (f)

Fig. 4. The visual quality comparison of original and watermarked images. (a) original Lena image. (b) watermarked Lena image by the method from [2] (c) watermarked Lena image by the proposed algorithm (d) original F16 image (e) watermarked F16 image by the method from [2] (f) watermarked F16 image by the proposed algorithm



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

Fig. 5. The visual quality comparison of close-ups for images in Fig. (4) (a) original Lena image. (b) watermarked Lena image by the method from [2] (c) watermarked Lena image by the proposed algorithm (d) original F16 image (e) watermarked F16 image by the method from [2] (f) watermarked F16 image by the proposed algorithm



(a) (b) (c)

Fig. 6. The visual quality comparison of close-ups for Baboon image (a) original Baboon image (b) watermarked Baboon image by the method from [2] (c) watermarked Baboon image by the proposed algorithm