Content Adaptive Watermarkding Using a Stochastic Visual Model Based on Multiwavelet Transform

Ki-Ryong Kwon*, Kyun-Ho Kang*, Seong-Geun Kwon**,
Kwang-Seok Moon***, Joon-Jae Lee****
*Division of Computer and Electronic Engineering, Pusan University of Foreign Studies
**School of Electrical Engineering and Computer Science, Kyungpook National University
***Division of Electronic and Telecommunication Engineering, Pukyung National University
****Division of Internet and Game, Dongseo University
*55-1 Uam-dong, Nam-gu, Pusan, KOREA, 608-738
Tel: +82-51-640-3176, Fax: +82-51-645-4525
E-mail : krkwon@taejo.pufs.ac.kr

Abstract: This paper presents content adaptive image watermark embedding using stochastic visual model based on multiwavelet transform. To embedding watermark, the original image is decomposed into 4 levels using a discrete multiwavelet transform, then a watermark is embedded into the JND(just noticeable differences) of the image each subband. The perceptual model is applied with a stochastic approach for watermark embedding. This is based on the computation of a NVF(noise visibility function) that have local image properties. The perceptual model with content adaptive watermarking algorithm embed at the texture and edge region for more strongly embedded watermark by the JND. This method uses stationary Generalized Gaussian model characteristic because watermark has noise properties. The experiment results of simulation of the proposed watermark embedding method using stochastic visual model based on multiwavelet transform techniques was found to be excellent invisibility and robustness.

1. Introduction

Digital contents and multimedia data can now be copied, stored, and distributed much easier and faster than the last few years. As a consequence, unauthorized copying and distribution has also become easier. A digital watermarking might be used to protect the copyright of multimedia data from illegal copying. It is an imperceptible signal embedded directly into the media content to detect from the host media data.

The design of data embedding systems is a compromise between the robustness and transparency of the embedded watermark [1]. First of all, the watermark must be robust against watermark attacks applied to the media content for the purposes of editing, storage or even circumvention of the watermark detection. These attacks include but are not limited to lossy compression, filtering, noise-adding, geometrical modification. Secondly, the watermark must be embedded in a transparent way to avoid degrading the perceptual quality of the host image. Users should not sense the existence of the watermark by viewing of the watermarked image.

Swanson *et al.* [2] was proposed to method using blocks in DCT domain using property of human perceptual system. It used in the context of image compression using *perceptually* based quantizers. Podilchuk *et al.* [3] were developed to a content adaptive scheme, where the watermark is adjusted for each DCT block and wavelet domain. Voloshynovskiy *et al.* [4] were proposed to adequate stochastic modeling for content adaptive digital image watermarking. Knowing stochastic models of the watermark and the host image, one can formulate the problem of watermark estimation/ detection according to the classical MAP (maximum a posteriori probability) and stochastic models and estimate the capacity issue of the image watermark scheme. Kwon and Tewfik [5] proposed adaptive watermark embedding algorithm using the successive subabnd quantization and perceptual model in the multiwavelet domain.

The conventional watermarking approach, based on global information about the image properties, the watermark is embedded by random noise with the same strength in the whole host image regardless of the local properties of the image. This embedding may lead to visible artifacts at regions that are characterized by small variability of reconstructed image. Stochastic watermark model is applied with an effective solution which embeds the watermark into the host image according to the local properties of the image. This approach has the advantage that it is applicable for very different types of images.

This paper presents content adaptive image watermark embedding using stochastic visual model based on multiwavelet transform. Multiwavelet using this paper is DGHM multiwavelet with approximation order 2 for the reduction of artifacts in the reconstructed image. To embedding watermark, the original image is decomposed into 4 levels using a discrete multiwavelet transform, then a watermark is embedded into the JND(just noticeable differences) of the image each subband. The perceptual model is applied with a stochastic approach for watermark embedding. This is based on the computation of a NVF that have local image properties. The perceptual model with content adaptive watermarking algorithm embed at the texture and edge region for more strongly embedded watermark by the JND. This method uses stationary Generalized Gaussian model characteristic because watermark has noise properties. The experiment results of simulation of the proposed watermark embedding method using stochastic visual model based on multiwavelet transform techniques was found to be excellent invisibility and robustness.

2. Multiwavelet Transform

Multiwavelet are a new addition to realize as vector-valued filter banks leading to wavelet theory [6]. Multiwavelet is an advantage, since it offers simultaneous compactly support, orthogonality, symmetry, and vanishing moments. Its system can simultaneously provide perfect reconstruction (orthogonality), good performance at the boundaries (linear-phase symmetry), and high order of approximation (vanishing moments).

One of the great challenges to successful watermark embedding of orthogonal multiwavelet is to construct the space spanned by the multiscaling function with a higher approximation order usually leads to better energy compaction than single wavelets. The prefilters are constructed for multiwavelet based matrix filter banks which preserve certain properties of the central filter bank. The prefilter must be compatible with the central matrix filter banks in order to fully exploit the underlying properties of the multiwavelet filter banks. The block diagram of orthogonal multiwavelet filter in this paper is shown Fig. 1. Multiwavelet has multiresolution (MRA) of the same concept as the scalar wavelets. $H_0(Z)$, $H_1(Z)$ are analysis filter banks, $G_0(Z)$, $G_1(Z)$ are synthesis filter banks. $P(Z)$ and $P^{-1}(z)$ are prefilter and postfilter banks. A basis for V_0 is generated by translates of vector form of N scaling functions $\phi_1(t-k), \phi_2(t-k), \cdots, \phi_N(t-k)$. The scaling vector $\Phi(t) = [\phi_1(t), \cdots, \phi_N(t)]^T$, will denote a compactly supported orthogonal scaling vector of length N with a matrix dilation equation.

$$\Phi(t) = \sqrt{2} \sum_{k \in Z} \mathbf{H}[k] \Phi(2t-k). \qquad (1)$$

Where, the multiwavelet coefficients $\mathbf{H}[k]$ are N by N real matrices.

An orthonormal basis of W_0 of where $W_0 = V_{-1} \oplus V_0$ is generated by N wavelets vector $\Psi(t) = [\varphi_1(t), \cdots, \varphi_N(t)]^T$, satisfying the matrix wavelet equation.

$$\Psi(t) = \sqrt{2} \sum_{k \in Z} \mathbf{G}[k] \Psi(2t-k). \qquad (2)$$

The $\mathbf{G}[k]$ are also N by N real matrices. The scaling vectors with $\boldsymbol{H}$ and $\boldsymbol{G}$ from matrix finite impulse response (FIR) filters have orthogonality, stability, smoothness, and good approximation property.

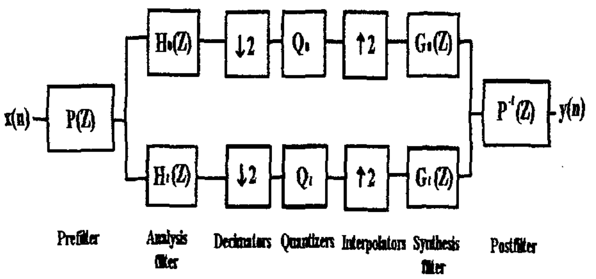


Fig. 1. Multiwavelet scheme with orthogonal filter bank.

3. Stochastic Visual Model for Watermarking

3.1 JND Paradigm

The JND thresholds determined by a model of human visual system and local image characteristics. JND threshold is dependent, as long as, the watermark values remain below JND threshold to achieve watermark transparency. Watermark embedding to perceptually siginificant coefficients is following.

$$X^*_{u,v,l,f} = \begin{cases} X_{u,v,l,f} + t^F_{l,f}\, w_{u,v,l,f}, & \text{if } X_{u,v,l,f} > t^F_{l,f} \\ X_{u,v,l,f} & \text{otherwise} \end{cases} \qquad (3)$$

where a weight $t^F_{l,f}$ is determined for each frequency band based on typical viewing condition. l denotes the resolution level where l=1,2,3,4 and f denotes the frequency orientation where f=1,2,3. The resulting weights in this paper use the Watson model [7]. $X_{u,v,l,f}$ refers to the wavelet coefficient at position (u,v) in resolution level l and frequency orientation f. The selected PSCs for Lena and Barbara imagse are represented in Fig. 1. The proposed watermark model is shown by block diagram of Fig. 2.

Fig. 1. Watermark embedding region by JND selection.

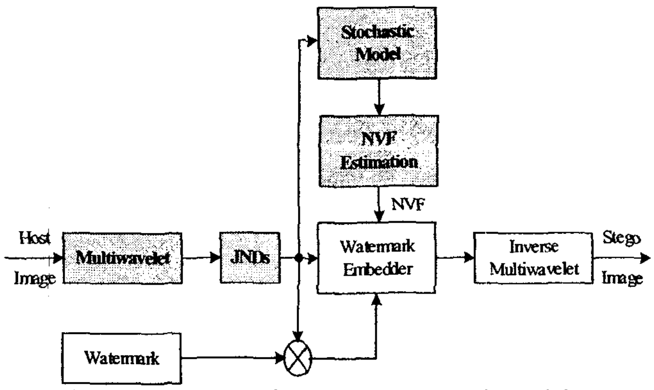


Fig. 2. The proposed adaptive watermark model.

3.2 NVF Function with Stationary GG Model

For optimal NVF decision, stationary GG model use shape parameter and variance of each subband in order to decrease visible artifact according to local properties of image. In the case of stationary Generized Gaussian model, NVF can be written in the eq. (4):

$$NVF(i,j) = \frac{w(i,j)}{w(i,j) + \sigma_x^2(i,j)} \qquad (4)$$

$$w(i,j) = \gamma[\eta(\gamma)]^{\gamma} \frac{1}{\|a(i,j)\|^{2-\gamma}} \qquad (5)$$

$$a(i,j)=\frac{x(i,j)-\bar{x}(i,j)}{\sigma_x},\quad \eta(\gamma)=\sqrt{\frac{\Gamma(\frac{3}{\gamma})}{\Gamma(\frac{1}{\gamma})}} \qquad (6)$$

where $\sigma_x^2(i,j)$ denotes the variance of image. $\bar{x}(i,j)$ is mean of image and γ is shape parameter. In this paper, the estimated shape parameter use the γ=0.67. $\Gamma(t)$ is Gamma function. The watermark embedding use use shape parameter and variance of each subband regions of multiwavelet domain, it is derived content adaptive criteria according to edge and texture.

The final equation with adaptive watermark embedding is following formulate:

$$x'=x+(1-NVF)wA+NVF\,wB \qquad (7)$$

where x', x, and w denote the watermarked image, original image, and watermark. A denotes the watermark strength of texture and edge regions. B denotes the watermark strength of flat region. The above rule embeds the watermark in highly textured areas and areas containing edges stronger than in the flat regions.

3.3 Watermark Detection

The watermark detection is the same Cox's as following.

$$w^*_{s,u,v,l,f}=X_{u,v,l,f}-\hat{X}^*_{u,v,l,f} \qquad (8)$$

$$w^*_{u,v,l,f}=\frac{w^*_{s,u,v,l,f}}{t^C_{u,v,l,f}} \qquad (9)$$

$$\rho_{\omega\omega^*}(l,f)=\frac{w^*_{l,f}\cdot w_{l,f}}{\sqrt{E_{w_{l,f}}E_{w_{l,f}}}},\quad \text{for } l=1,2,3,4 \text{ and } f=1,2,3 \qquad (10)$$

where $w^*_{s,u,v,l,f}$ is different value between original multiwavelet coefficients and watermarked and attacked multiwavelet coefficients.

3. Results of Computer Simulation

To illustrate the main features of the proposed content adaptive watermarking method using the stationarty GG model in the multiwavelet domain, we simulated our algorithm on several images of 512×512 size. The DGHM multiwavelet is decomposed the original image into 4 levels. The length of used watermark is variable to dependent image characteristics.

The PSNR of the visual quality of the stego images according to watermark strength variation are shown the Fig. 3. The length of watermark sequence using the proposed and Podilchuk algorithms is shown the Table 1. As the shown Table 1, we note the watermark length varies significantly depending on the particular image characteristics. Also, the watermark length of proposed method is more embedding than Podilchuk's method.

To establishment the robustness of the watermarked image under JPEG attack, we compressed it by JPEG with a Q factor varying 10% to 90%. The result knows the resilience of the watermarking scheme against the JPEG compression. As the PSNR comparison of JPEG in Fig. 4, proposed model is excellent PSNR than Podilchuk's, and correlation response of proposed model is better than Podilchuk's.

To evaluation the robustness of the watermarked image under cropping attack, we randomly cropped a region with size of a 10% to 90% from the watermarked image and then compressed it by JPEG with a quality factor varying 80%. The result knows the resilience of the watermarking scheme against the combination of cropping and JPEG compression as shown in Fig. 5. For the cropping attack, the proposed and Podilchuk methods are similar to PSNR and correlation response for the cropping ratio. As shown by he results in Table 2, the proposed algorithm remained robust against all these attacks when compare to Podilchuk's.

The correlation response for watermarked image, no attack, non-stationary and stationary GG models are shown in Fig. 6.

Stirmark benchmark test and extracted watermark for the Lena and Barbara images using the proposed models are shown in Fig. 7. The extracted watermark of proposed model is embedding the edge and textured regions as shown to Fig. 7(c).

4. Conclusion

In this paper, we have presented a new approach for content adaptive watermark embedding based on the multiwavelet domain. To embedd-ing watermark, the original image was decomposed into 4 levels using a discrete multiwavelet transform, then a watermark is embedded into the JND of the image each subband. The perceptual model is applied with a stochastic approach for watermark embedding. This is based on the computation of a NVF that have local image properties. The stochastic visual model with content adaptive watermarking algorithm embed at the texture and edge region for more strongly embedded watermark by the JND. This method uses stationary GG model because watermark has noise properties. The experiment results of the proposed watermark embedding based on multiwavelet transform techniques was found to be excellent invisibility and robustness.

References

[1] I.Cox, J.Kilian, T.Leighton, T.Shamoon," Secure Spread Spectrum Watermarking for Multimedia," *NEC Research Institute Tech Rep. 95-10*, 1995.

[2] M. Swanson, B. Zhu, and A. Twefik, "Transparent Robust Image Watermarking," *IEEE International Conference on Image Processing, ICIP96*, Vol.3, pp.211-214, 1996.

[3] C.Podilchuk, W.Zeng, "Image Adaptive Watermarking Using Visual Models," *IEEE Journal on Selected Areas in Communication*, Vol.16, No.4, pp.525-539, May 1998.

[4] S. Voloshynovskiy, A. Herrigel, N. Baumgaertner, and T. Pun, "A Stochastic Approach to Content Adaptive Digital Image Watermarking," *in proc. of Third Information Hiding Workshop*, 1999.

[5] K.R. Kwon and A.H. Tewfik, "Adaptive watermarking using successive Subband quantization and perceptual model based on multiwavelet transform," *Proc. of SPIE*, vol. 4675-37, Jan. 2002.

[6] D. P. Hardin and D. W. Roach, "Multiwavelet prefilters I: Orthogonal Prefilters Preserving Approximation order p≤ 2," *IEEE Trans. On Circuits and Systems II*, vol. 45, pp. 1106-1112, Aug. 1998.

[7] A. B. Watson, G. Y. Yang, J.A. Solomon, and J. Villasenor, "Visual Thresholds for Wavelet Quantization Error," *Proc. of SPIE*, vol. 2657-44, pp.1-11, 1996.

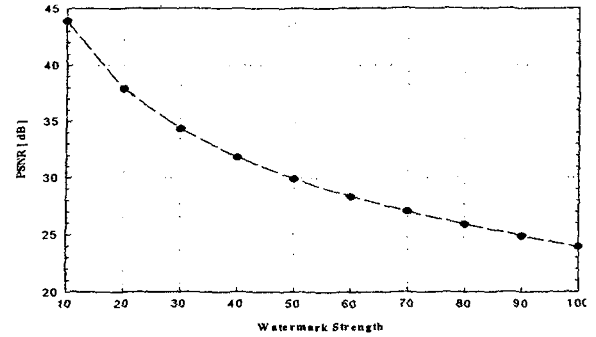
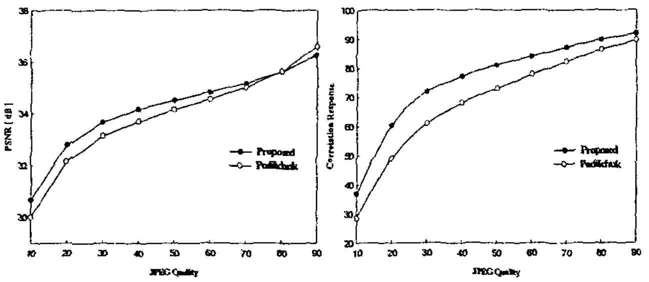


Fig. 3. The PSNR comparison according to watermark strength.

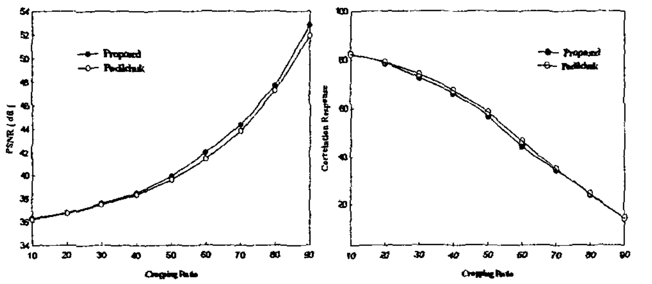
Table 1. Length of watermark sequence using the proposed and Podilchuk algorithms.

	Lema	Barbara	Baboon	Peppers	Airplane
Proposed	8,311	18,706	38,062	9,660	11,565
Podilchuk	7,973	17,749	37,655	7,458	10,318



(a) PSNR (b) correlation response

Fig. 4. The robustness test of JPEG attack.

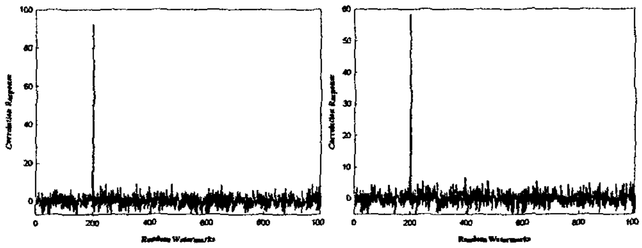


(a) PSNR (b) correlation response

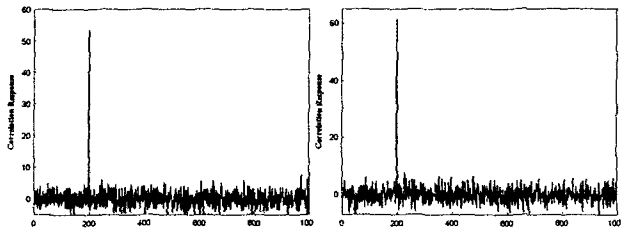
Fig. 5. The robustness test of cropping attack after JPEG compression Q=80%.

Table 2. Correlation response according to various attacks.

Image	Lena(512×512)			
Attack	PSNR[dB]		Correlation Response	
	Proposed	Podilchuk	Proposed	Podilchuk
JPEG Q=50%	34.52	34.16	81.22	73.14
Cropping 50%	41.94	42.12	58.39	61.57
3×3 Median	30.67	30.25	59.97	51.05
3×3 Gaussian	33.82	32.97	53.38	45.60
Sharpening	21.68	21.39	61.45	52.74
FMLR	32.65	31.93	45.76	36.02



(a) No attack(CR=92.63) (b) Cropping50%(CR=58.39)

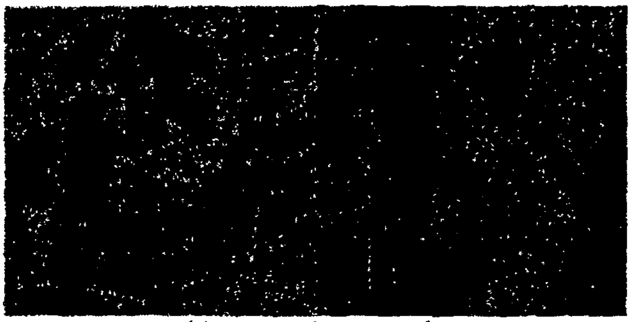


(c) Gaussian(CR=53.38) (b) Shapening(CR=61.45)

Fig. 6. Correlation response for attacks.

(a) watermarked images

(b) Stirmarked images



(c) extracted watermarks

Fig. 7. Stirmark benchmark test images.