Adaptive Image Watermarkimg Using a Stochastic Multiresolution Modeling

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Abstract: This paper presents perceptual model with a stochastic multiresolution characteristic that can be applied with watermark embedding in the biorthogonal wavelet domain. The perceptual model with adaptive watermarking algorithm embed at the texture and edge region for more strongly embedded watermark by the SSQ(successive subband quantization). The watermark embedding is based on the computation of a NVF(noise visibility function) that have local image properties. This method uses non-stationary Gaussian model stationary Generalized Gaussian model because watermark has noise properties. In order to determine the optimal NVF, we consider the watermark as noise. The particularities of embedding in the stationary GG model use shape parameter and variance of each subband regions in multiresolution.. To estimate the shape parameter, we use a moment matching method. Non-stationary Gaussian model use the local mean and variance of each subband. The experiment results of simulation were found to be excellent invisibility and robustness. Experiments of such distortion are executed by Stirmark benchmark test.

1. Introduction

There has been a lot of Internet in the digital watermarking research over the last few years, mostly due to the fact that digital watermarking might be used as a tool to protect the copyright of multimedia data. A digital watermark is an imperceptible signal embedded directly into the media content, and it can be detected from the host media for some applications. The insertion and detection of digital watermarks can help to identify the source or ownership of the media, the legitimacy of its usage, the type of the content or other accessory information in various applications. Specific operations related to the status of the watermark can then be applied to cope with different situations.

One of the important requirements of watermark embedding systems is to compromise between the invisibility and robustness of the embedding algorithm. First of all, the watermark must be embedded in invisible way to avoid degrading the perceptual quality of the host image. Users should not distinguish the existence of the watermark by viewing of the watermarked image[1]. Secondly, the watermark must be robust against watermark attacks in which applied to the image content for the purposes of editing, storage or even circumventing watermark detection. These attacks include but are not limited to lossy compression, filtering, noise-adding, geometrical modification. The HVS (human visual system) is less sensitive to changes in the neighborhood of the edges than in the smooth regions of the image. This is called the spatial masking effect, and can be exploited in data embedding by increasing the strength of the watermark around the edges and high textured areas of the image, and reducing the strength in smooth regions with low luminance.

Swanson *et al.*[2] was proposed to method using blocks in DCT (discrete cosine transform) domain using property of human perceptual system. It used in the context of image compression using perceptually based quantizers. Kutter[3] have developed content adaptive schemes on the basis of luminance sensitivity function of the human visual system. The masking function is based on the estimation of the image luminance for embedding is not efficient against wavelet compression or denoising attacks. Podilchuk and Zeng[4] were developed to a content adaptive scheme, where the watermark is adjusted for each DCT block and wavelet domain. This approach is very limited the practical applications since it can be shown that the usage of the cover image will results in watermark schemes which can be easily broken. Delaigle *et al.* [5] proposed a perceptual modulation function to overcome the problem of visibility of the watermark around edges. This method developed a content adaptive criterion that may easily be applied to any watermarking technique in coordinate, Fourier, DCT or wavelet domains. Voloshynovskiy *et al.*[6] were proposed to adequate stochastic modeling for content adaptive digital image watermarking. Knowing stochastic models of the watermark and the cover image, one can formulate the problem of watermark estimation/ detection according to the classical Bayessian and multiresolution paradigm and estimate the capacity issue of the image watermark.

The conventional watermarking approach, based on global information about the image characteristic, embed the watermarking signal as random noise in the whole cover image with the same watermark strength regardless of the local property of image. Therefore, this embedding method is leaded in practice to visible artifacts in the flat regions that are characterized by small variability. In order to decrease these artifacts, the given watermark strength has to be decreased. This reduces the robustness of the watermark against several attacks, since the image region which generate the most visible artifacts determine the final maximum strength of the watermark signal to be embedded.

This paper presents adaptive watermark embedding using a stochastic image modeling based on multiresolution techniques for the more strongly embedded watermarking. To embedding watermark, the original image is decomposed into 4 levels using a discrete wavelet transform of biorthogonal form, then a watermark is embedded into the PSCs of the image each subband. The PSCs in high frequency subband are selected by SSQ, that is, by setting the thresholds as the one half of the largest coefficient in each subband. After the PSCs in each subband are selected by SSQ, perceptual model is applied with a stochastic modeling for watermark embedding. This is based on the computation of a noise visibility function (NVF) that have local image properties. Stochastic watermark model with adaptive watermarking algorithm embed stationary Generalized Gaussian model and non-stationary Gaussian model at the texture and edge region for more strongly embedded watermark.

2. Adaptive Multiresolution Watermarking

2.1 Perceptual Property

The PSCs in other high frequency subband are selected by SSQ, that is, by the subband adaptive threshold [7]. It is selected by setting the thresholds as the one half of the largest coefficient in each subband. Then, for each selected coefficient in the high frequency subbands, the maximum amount of the watermark is embedded to the extent of satisfying the transparency according to the perceptual model of that coefficient. To select the PSCs, a subband adaptive threshold is used as follows

$$TH_i = 2^{\lfloor \log_2 D_i \rfloor} - 1. \quad (1)$$

where D_i represents the largest coefficients in each sub-band and $\lfloor I \rfloor$ represents the largest integer which is no greater than I. The watermark is embedded only to the PSCs greater than the subband adaptive threshold. As such, a constantly weighted watermark, which has the largest value without the introduction of a visual artifact, is embedded into the PSCs in the subband. Whereas, for the PSCs in the high frequency subbands, the watermark is embedded based on NVF so as to provide transparency and robustness. The selected PSCs for Lena image are represented in Fig. 1.

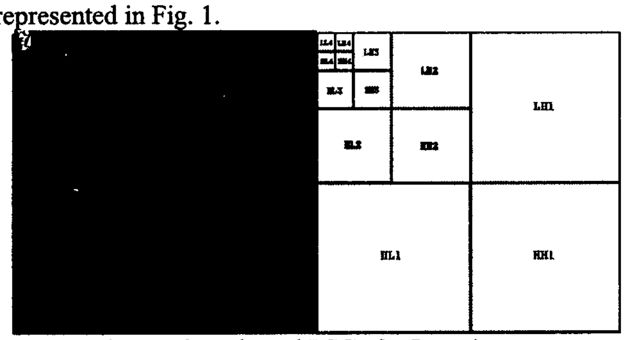


Fig. 1. The selected PSCs for Lena image.

2.2 Stochastic Multiresolution Model

This paper presents stationary GG model and non-stationary Gaussian model with a stochastic multiresolution which can be applied with watermark embedding in the biorthogonal DWT. This embedding method is based on the computation of a NVF that have local image properties based on [8]. Stochastic multiresolution model with adaptive watermarking algorithm embed at the texture and edge region for more strongly embedded watermark by the SSQ. This method uses NVF function because watermark has noise properties. In order to determine the optimal NVF, we consider the watermark as noise. The proposed watermark model is shown by block diagram of Fig. 2.

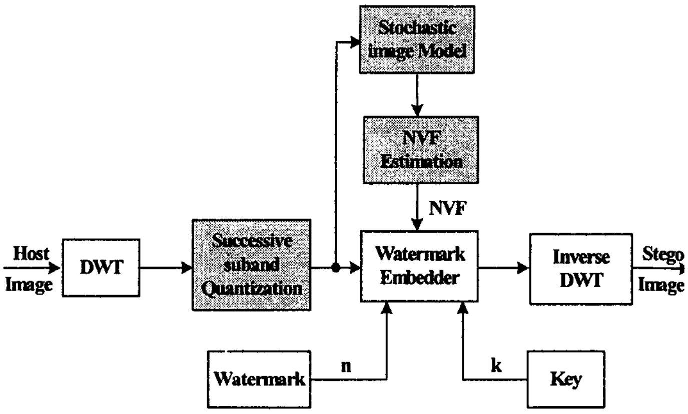


Fig. 2. The proposed adaptive watermark model.

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. In order to decrease these artifacts, the given watermark strength has to be decreased. However, this reduces remarkably the robustness of the watermark against various kinds of attacks, since the image regions which generate the most visible artifacts determine the final maximum strength of the watermark signal to be embedded. 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.

2.2.1 NVF Based on 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. (2):

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

$$w(i,j) = \gamma[\eta(\gamma)]^{\gamma} \frac{1}{\|a(i,j)\|^{2-\gamma}} \quad (3)$$

$$a(i,j) = \frac{x(i,j) - \bar{x}(i,j)}{\sigma_x}, \quad \eta(\gamma) = \sqrt{\frac{\Gamma(\frac{3}{\gamma})}{\Gamma(\frac{1}{\gamma})}} \quad (4)$$

where $\sigma_x^2(i,j)$ denotes the variance of image. $\bar{x}(i,j)$ is mean of image and γ is shape parameter. For estimation of shape parameter γ, it use the moment matching method. 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 in multiresolution of wavelet domain, it is derived content adaptive criteria according to edge and texture, flat region.

2.2.2 NVF Based on Non-Stationary Goussian Model

In the case of non-stationary Gaussian model, NVF can be written in the eq. (5):

$$NVF(i,j) = \frac{1}{1 + \sigma_x^2(i,j)} \quad (5)$$

where $\sigma_x^2(i,j)$ denotes the local variance of the image in a window centered on the pixel with coordinates $(i,j), 1 \le i,j \le M$. Assuming that the image is a locally i.i.d. Gaussian distributed random variable, the variance is given by:

$$\sigma_x^2(i,j) = \frac{1}{(2L+1)^2} \sum_{m=-L}^{L} \sum_{n=-L}^{L} (x(i+m,j+n) - x(i,j))^2 \quad (6)$$

with

$$x(i,j) = \frac{1}{(2L+1)^2} \sum_{m=-L}^{L} \sum_{n=-L}^{L} x(i+m,j+n) \quad (7)$$

where $(2L+1)\times(2L+1)$ is a window of size.

2.2.3 Adaptive Watermark Embedding

The final equation with adaptive watermark embedding is following formulate:

$$v' = v + (1 - NVF)wA + NVF\,wB \quad (8)$$

where v', v, 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.

The proposed adaptive watermark embedding can be required into these methods to achieve the trade-off between the goals of increasing the robustness by increasing the watermark strength and at the same time, decreasing the visual artifacts introduced by the watermarking process.

3. Results of Computer Simulation

To illustrate the main features of the proposed content adaptive watermark embedding method using the stationarty GG model in the wavelet domain, we simulated our algorithm on several images of 512×512 size. The (9/7) biorthgonal wavelet is decomposed the original image into 4 levels. The length of used watermark is 1000 i.i.d. (independent identically distributed) Gaussian random sequence with unit variance, $N(0,1)$. The highest frequency subband is thrown up watermark embedding step.

The first step of experiments, PSCs have to be selected by SSQ. It is selected by setting the thresholds as the one half of the largest coefficient in each subband. The second step, NVF has to do calculation according to the stochastic models of the host image. The NVF is the output of the perceptual model to a noise $N(0, 1)$. The next step of experiment is the PSNR comparison of the visual quality of the stego images generated using NVFs with the different watermark strength.

The PSNR comparison of the visual quality for stationary and non-stationary stochastic perceptual model of the stego images generated using NVF with the different watermark strength are shown the Fig. 3. The experiments of various attack for stationary and non-stationary model with respect to Lena iamge is shown the Table 1. As the shown Table 1, stationary GG model is excellent PSNR than non-stationary model, but correlation response of non-stationary model is better than stationary GG model.

To establishment the robustness of the watermarked image under JPEG attack, we compressed it by JPEG with a quality 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, stationary GG model is excellent PSNR than non-stationary model by larger Q, but correlation response of non-stationary model is better than stationary GG model between 10% and 50% of Q.

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, stationary GG model is more excellent PSNR than non-stationary model, but correlation response is the for cropping ratio.

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

Stirmark benchmark test for the Lena and Barbara images using the non-statinary and stationary GG models are shown in Fig. 7. The NVF based on the non-stationary Gaussian model is smoother and the intensity for the edges is about the same order as that of textured regions.

4. Conclusion

This paper proposed content adaptive watermarking using a stochastic multiresolution image modeling based on 9/7 biorthogonal wavelet transform techniques. A watermark was embedded into the PSCs of the image each subband. After the PSCs in each subband were selected by SSQ, perceptual model was applied with stationary GG and non-stationary model for watermark embedding. This was based on the computation of a noise visibility function (NVF) that have local image properties. The experiment results of simulation were found to be excellent invisibility and robustness for stationary GG and non-stationary model. Experiments of such distortion are executed by Stirmark benchmark test.

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] M. Kutter, "Watermarking Resisting to Translation, Rotation and Scaling," in *Proc. of SPIE*, Boston, USA, November 1998.

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

[5] J.F.Delaigle, C.De Vleeschouwer, B.Macq, "Watermarking Algorithm Based on a Human Visual Model," *Signal Processing*, Vol.66, pp.319-335, 1998.

[6] Sviatoslav 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.

[7] I.S. Ha, S.G. Kwon, S.J. Lee, K.R. Kwon, and K.I. Lee, "A New Wavelet-Based Digital Watermarking Using the Human Visual System and Subband Adaptive Threshold," in *IS&T's 2001 PICS conference Proceedings*, April 2001.

[8] 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.

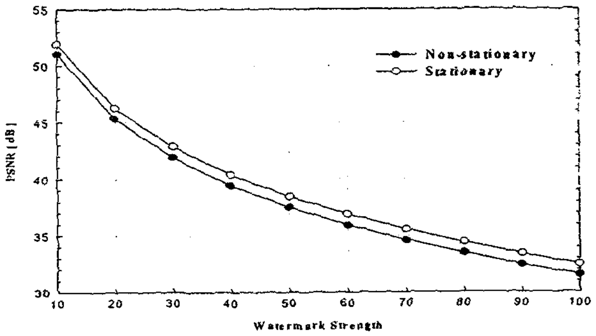
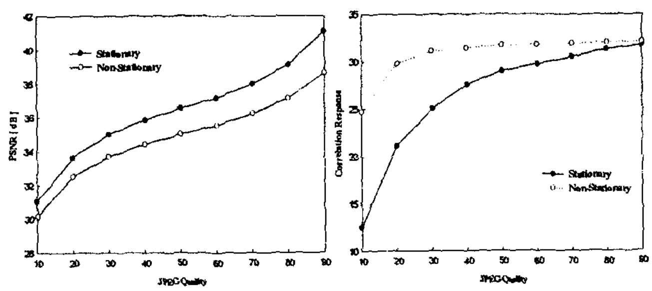


Fig. 3. The PSNR comparison according to watermark strength.

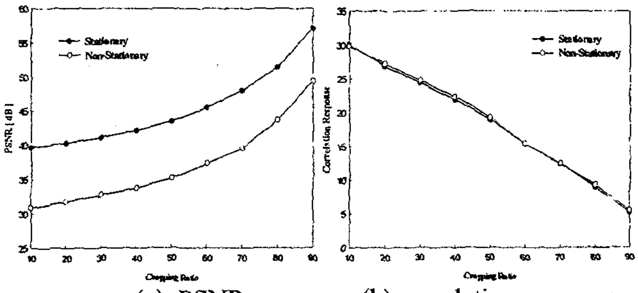
Table 1. The experiments of various attack for Lena image.

Lena 512*512				
	Stationary model		Non-stationary model	
	PSNR	CR	PSNR	CR
Shapening	22.50	6.61	21.74	16.75
Median	31.50	8.31	30.47	20.90
Gaussian	34.53	17.40	33.23	27.77
JPEG Q=50%	37.18	29.74	29.73	31.75
Cropping 50%	47.51	19.34	49.47	19.31



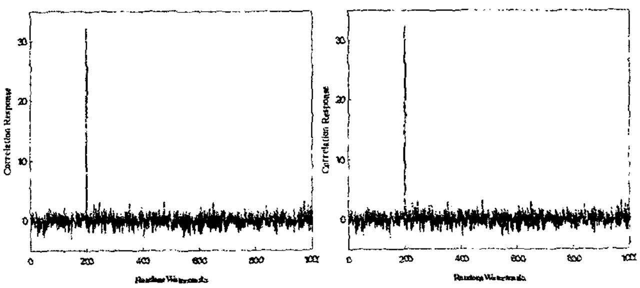
(a) PSNR (b) correlation response

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%.



(a) non-stationary(32.1761) (b) stationary(32.1785)

Fig. 6. Correlation response for Lena image.

(a) non-stationary

(b) stationary

Fig. 7. Stirmark benchmark test images.