Multiwavelet Image Watermarking Using Perceptually Tuned Model

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Summary
In this paper, we propose a novel watermarking method that has robust and transparent properties by perceptually tuned characteristics and stationary Generalized Gaussian model based on Multiwavelet transform domain. The proposed method embeds watermark signals at the texture and edge regions using the perceptual stochastic model with content adaptivenes. This method adopts stationary Generalized Gaussian model because watermark signal has noise properties. By the simulation results, we confirm that the proposed method is more robust and invisible for various attacks.

Key words:
digital watermarking, multiwavelet filter bank, perceptually tuned model

1. Introduction

There have been a lot of researches on digital watermarking over the last few years. 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. The most important requirements in the data embedding systems are the robustness and transparency, but unfortunately these are in the relation of trade-off.

Voloshynovskiy et al.[1] proposed a stochastic modeling method 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. *Podilchuk et al.*[2] have developed a content adaptive scheme, where the watermark is adjusted for each DCT block and wavelet domain. This approach can be restricted in practical applications since it can be shown that the usage of the cover image will results in watermark schemes which can be easily broken. In the conventional watermarking system, the watermark is embedded same strength regardless of local property of the cover images, and it leads to visible artifact at flat regions.

In this paper, we present an adaptive digital image watermarking with perceptually tuned characteristic based on wavelet transform. To embed a watermark signal, the original image is decomposed into 3 levels using a DWT(discrete wavelet transform)[3], then a watermark is embedded into the PCSs(perceptually significant coefficients) larger than the JND(just noticeable differences) threshold of the each subband. The perceptually tuned characteristic was used image coding for optimal quantization. *Kutter at al.*[4] 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, and thus embedding is not efficient against wavelet compression or denoising attacks. *Watson et al.*[5] used perceptual quantization to wavelet based image compression and used frequency sensitivity thresholding for perceptual bit assignment. *Kwon et al.*[6] proposed SSQ and perceptual characteristics in non-stationary model based on multiwavelet transform.

The proposed adaptive watermark embedding scheme can achieve two important requirements of watermarking, that is, increasing the robustness by increasing the watermark strength and at the same time, decreasing the visual artifacts introduced by the watermarking process.

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2. Adaptive Watermarking Using Perceptually Tuned Characteristic

2.1 Multiwavelet transform

Multiwavelet that is consisted of several scaling factors and wavelet functions shows special quality of image edge preserving. Also, with high level relationship approximation, perfection restoration of original image is possible. In this paper, we propose a new watermarking techniques, where the wavelet coefficients are disintegrated from 4-levels subbands in multiwavelet transform. This process is accomplished based on block degree that simplify multiwavelet filter banks relationship structure. Fig. 1 shows the structure of orthogonal multiwavelet filter bank.

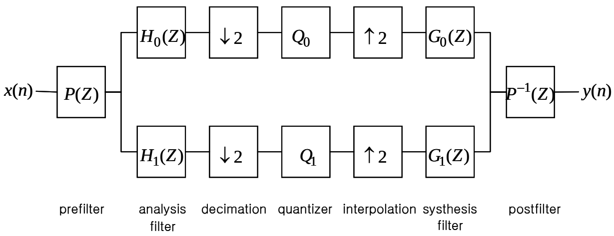


Fig. 1 Orthogonal multiwavelet filter bank.

Here, $H_0(Z)$ and $H_1(Z)$ are analysis filter banks, $G_0(Z)$ and $G_1(Z)$ are synthesis filter banks. P(Z) and $P^{-1}(Z)$ are prefilter and postfilter banks, respectively. Q_0 and Q_1 denote quantizers.

2.2 Watermark concealment using stationary state GG model

The proposed watermarking embedding method is based on the computation of an NVF(noise visibility function) that has local properties of image. Using this model, a watermark signal is inserted into the texture and edge region stronger than flat region. In the case of stationary generalized Gaussian model, NVF can be written in the Eq. (1).

$$NVF\ (i,j) = \frac{w(i,j)}{w(i,j)\ + \sigma^2(i,j)} \tag{1}$$

where $\sigma^2(i,j)$ denotes the variance of original image and $w(i,j)$ is a weight value represented by Eq. (2) – (5).

$$w(i,j) = \Gamma[\beta(\gamma)^{\gamma}]\frac{1}{\|a(i,j)\|^{2-\gamma}} \tag{2}$$

$$a(i,j) = \frac{I(i,j) - I(i,j)^*}{\sigma_x(i,j)}, \tag{3}$$

$$\beta(\gamma) = \sqrt{\Gamma(\frac{3}{\gamma}) \Big/ \Gamma(\frac{1}{\gamma})} \tag{4}$$

$$\Gamma(t) = \int_0^{\infty} e^{-u} u^{t-1} du \tag{5}$$

In eq. (3), $I(i,j)^*$ means local average of original image $I(i,j)$. The weight value $w(i,j)$ is used for adaptive watermark embedding using gamma function. The shape factor γ is calculated by conformity method. The shape factor for most real images is in the range of 0.3 ~ 1.0. The proposed watermark embedding scheme uses shape factor and variance of each subband regions of wavelet domain and they are adaptively derived from the properties of edge and texture region of original image[4]. The block diagram of proposed method is represented in Fig. 2.

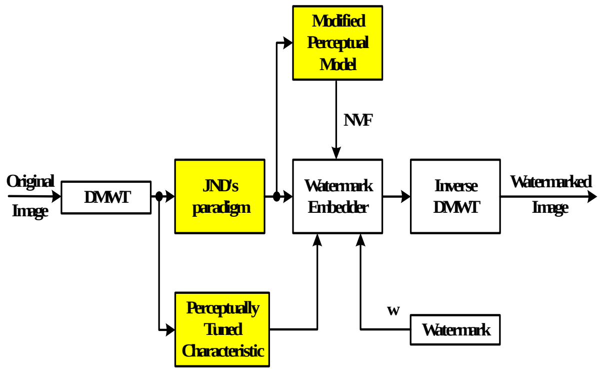


Fig. 2 Block diagram of proposed embedding method.

In the process of watermark insertion, multiwavelet transform is used in order to do in frequency domain. First, the original image is analyzed into 4-levels, and among analysis subbands, the baseband is excepted in insertion because it is weak in attack. And for the high frequency subband, threshold value is decided about each unit part using silence JND model, which is presented by Watson *et al.* for reflex compression treating. Because in general, watermark signals are weak in highest level subband attack, this level is excepted in insertion process. The threshold value is determined by visual importance of transform coefficient at each subband considering its level and direction. The watermark signal is inserted to multiwavelet coefficients of original image using Eq. (6).

$$v' = v + \{(1 - NVF) \cdot S_{ET} + NVF \cdot S_F\} w_i \qquad (6)$$

where x', x, and w_i denote the watermarked image, original image, and watermark signal, respectively. S_{ET} denotes the watermark strength at texture and edge regions. S_F denotes the watermark strength at flat region. In this paper, S_{ET} is used for perceptual quantization and bit allocation for image compression. S_F is determined according to the perceptual criteria employed in the perceptual subband image coder as used by R. J. Safranek and D. J. Jonson. The above rule embeds the watermark signal in highly textured areas and areas containing edges stronger than in the flat regions. The strength of watermark signal applied to each subband is described in Table 1 and 2. The original images and their PSCs using the proposed method are shown in Fig. 3.

Table 1: Watermark strength of edge or texture regions.

Level orientation	**2**	**3**	**4**
HL	14.685	12.707	14.156
LH	14.685	12.707	14.156
HH	28.408	19.54	17.864

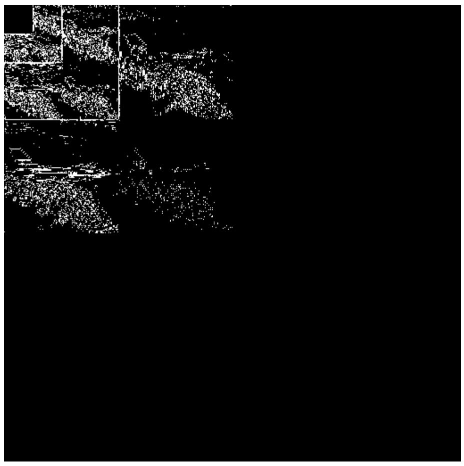
Table2: Watermark strength of flat regions.

Level orientation	**2**	**3**	**4**
HL	6.57	1.39	0.5
LH	8.33	1.24	0.2
HH	10.11	3.50	0.66

(a) Original LENA

(b) PSCs of LENA

(c) Original AIRPLANE



(d) PSCs of AIRPLANE

Fig. 3 Test images and their PSCs.

3. Results of Computer Simulation

To illustrate the main features of the proposed adaptive watermarking method, we simulated our algorithm on several test images of 512×512 size.

The original image is decomposed into 4-levels by Multiwavelet. We use unit variance cost of 1000 of Gaussian variance that have the 200th seed number at embedded watermark. As the threshold value must be determined adaptively at each subband, the PSCs of original images are first determined as in Table 1 by using JND paradigm. The first step of experiments, we selected PSCs larger than the predetermined threshold value in each subband. And in next step, the NVF is calculated in case of stationary Generalized Gaussian model as described in section 2.2. Finally, the watermark signal is embedded by using Eq. (6). We simulated the robustness of the watermark signal against the attack based on Stirmark benchmark test.

The watermark images of LENA and AIRPLANE are depicted in Figure 4, and the watermarked images after Stirmark random bend attack is presented in Fig. 5. To establish the robustness of the watermarked image against lossy compression, JPEG coding with various quality factors varying 10% to 90% was performed. The resulting correlation of PSNR vs. JPEG quality factor is shown in Fig. 6. The result shows the resilience of the proposed method against the JPEG compression. By the results, we know that the proposed method keeps good PSNR in higher compression ratio.

(a) Watermarked LENA

(b) Watermarked AIRPLANE

Fig. 4 Watermarked test images

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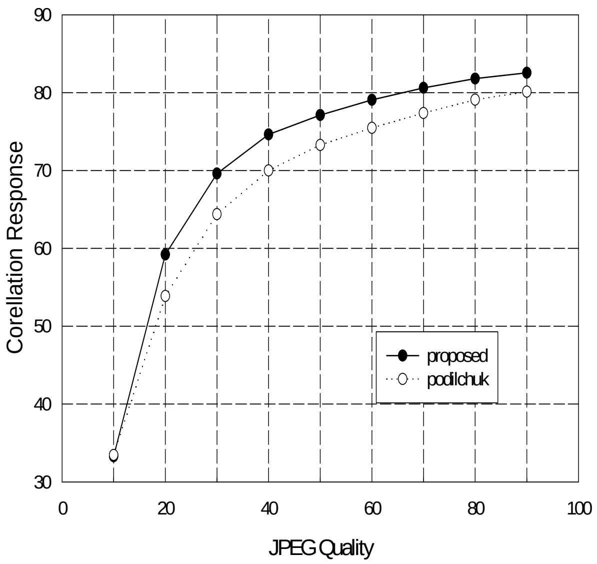
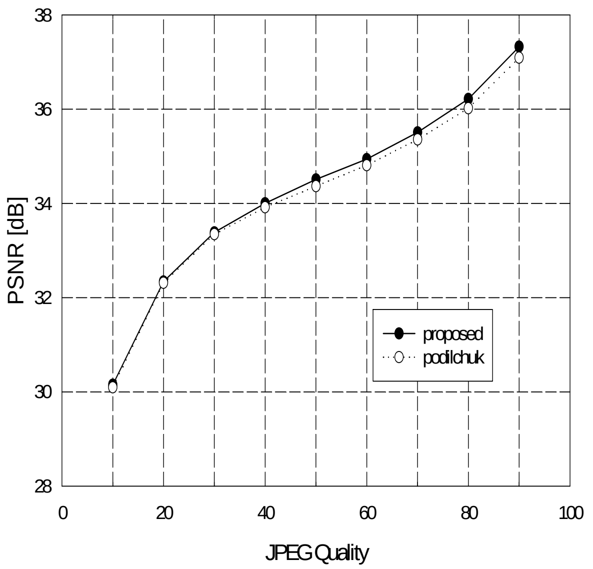
(a) LENA

(b) AIRPLANE

Fig. 5 Test images after Stirmark random bend attack.



(a) Correlation response



(b) PSNR

Fig. 6 Robustness and transparency test results according to various JPEG quality factor.

The correlation responses for various attacks including Gaussian filtering, sharpening, median filtering, and frequency mode Laplacian removal(FMLR) are shown in Table 3 and 4.

Table 3: Comparison of PSNR and CR after general image processing for LENA image.

Attack	Proposed		Podilchuk	
	PSNR [dB]	CR	PSNR [dB]	CR
Gaussian filtering	33.21	52.26	33.19	51.35
Sharpening	21.49	46.20	33.19	47.67
Median Filtering	30.15	51.46	30.29	51.08
FMLR	32.12	29.96	32.05	32.46

Table 4: Comparison of PSNR and CR after general image processing for AIRPLANE image.

Attack	Proposed		Podilchuk	
	PSNR [dB]	CR	PSNR [dB]	CR
Gaussian filtering	32.41	47.88	32.40	48.38
Sharpening	21.79	49.45	21.69	50.70
Median Filtering	28.82	44.66	29.04	53.60
FMLR	32.46	40.50	32.19	46.47

To evaluate the robustness of the watermarked image under cropping attack, we randomly cropped a region of JPEG compressed watermarked image with size of a 10% to 90%. In JPEG compression of watermarked image, the quality factor of 50% is used. The result is shown in Table 5. From Table 5, we can know that the resilience of the proposed scheme is outstanding compared to conventional approach in the case of the combination of cropping, geometrical alteration and JPEG lossy compression.

Table 5: Comparison of PSNR and CR to various cropping ratio with JPEG quality factor 50%

Cropping Ratio	**Proposed**		**Podilchuk**	
	PSNR [dB]	CR	PSNR [dB]	CR
10%	36.86	69.18	34.90	69.79
20%	37.39	65.26	35.39	65.96
30%	38.20	59.61	36.10	61.58
40%	39.16	53.82	36.95	56.46
50%	40.53	46.82	38.28	48.55
60%	42.42	37.95	40.38	37.78
70%	44.88	28.60	42.91	27.83
80%	48.10	19.10	46.24	19.04
90%	53.64	10.67	51.87	10.44

4. Conclusion

In this paper, we have presented adaptive watermarking with perceptually tuned characteristic based on 4-levels multiwavelet transform. The perceptual embedding strength is applied with a stochastic approach for adaptive watermark embedding. This is based on the computation of a NVF that has local and global image properties at the same time. The perceptual stochastic model with content adaptive watermarking algorithm embeds the watermark signal at the texture and edge regions for more strongly embedding. This method uses stationary generalized Gaussian model because in general, the watermark signal has noise properties. The experimental results of the proposed scheme show that the proposed method has better performance, especially in invisibility and robustness.

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