# An Adaptive Stochastic Perceptual Image Watermarking Based on Multiwavelet Transform

Ki-Ryong Kwon* · Dong-Kyue Kim** · Ji-Hwan Park***

## 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[1]. 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. 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 [2]. 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.*[3] 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[4] have developed

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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[5] 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.*[6] 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.*[7] 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[8]. 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 that generate the most visible artifacts determine the final maximum strength of the watermark signal to be embedded.

This paper presents highly reliable adaptive watermark embedding using a stochastic multiresolution 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 adaptive watermark embedding algorithm embed at the texture and edge region for more strongly embedded watermark by the JND. This methods use stationary GG model and non-stationary Gaussian characteristics because watermark has noise properties. The experiment results of simulation of the proposed watermark embedding method using stochastic perceptual model based on multiwavelet transform techniques was found to be excellent invisibility and robustness.

## 2. Stochastic Perceptual Model

### 2.1 Multiwavelet Transform

Multiwavelet are a new addition to realize as vector-valued filter banks leading to wavelet theory. Multiwavelet is an advantage, since it offers simultaneous compactly support, orthogonality, symmetry, and vanishing moments [9-11]. Its system can simultaneously provide perfect reconstruction (orthogonality), good performance at the boundaries (linear-phase symmetry), and high order of approximation (vanishing moments). But a single wavelet cannot possess all these properties at the same time.

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. And it contributes the reduction of checkboard artifacts in the reconstructed image. For a tree-structured vector filter bank in multiwavelet transforms, the lowpass and highpass properties for the two vector filters are not as clear as those for the two filters in single wavelet transforms.

The scaling vector $\Phi(t)=[\phi_1(t),\Lambda,\phi_N(t)]^T$, will denote a compactly supported orthogonal scaling vector of length N with a matrix dilation equation.

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

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 $\Psi(t)=[\varphi_1(t),\Lambda,\varphi_N(t)]^T$, satisfying the matrix wavelet equation

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

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.

### 2.2 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 significant coefficients is following.

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

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[12]. $X_{u,v,l,f}$ refers to the wavelet coefficient at position $(u,v)$ in resolution level $l$ and frequency orientation $f$. The selected PSCs (perceptually significant coefficients) for Lena and Barbara images are represented in Fig. 1.

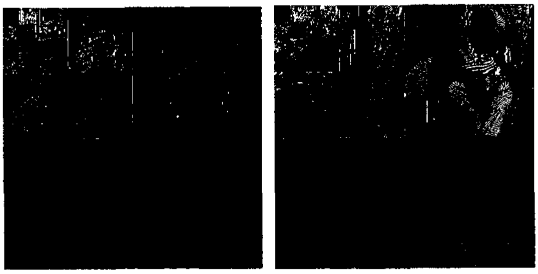


Fig. 1. Watermark embedded region by JND selection.

### 2.3 Stochastic Perceptual Model

The proposed watermark model is shown by block diagram of Fig. 2.

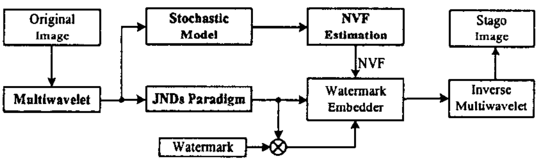



Fig. 2. The proposed adaptive watermark embedding model.

**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 GG model, NVF can be written in the (4):

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

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

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

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

**NVF with non-stationary Gaussian model.** In the case of non-stationary Gaussian model, NVF can be written in the (7):

$$NVF(i,j) = \frac{1}{1 + \sigma_x^2(i,j)} \tag{7}$$

Where $\sigma_x^2(i,j)$ denotes the local variance of the image in a window centered on the pixel with coordinates $(i,j), 1 \le i,j \le M$. The watermark is an *i.i.d.*(independent identically distributed) Gaussian process with unit variance, i.e. $N$(0, 1). The NVF is the output of the perceptual model to a noise $N$(0, 1). In order to estimate the local image variance the maximum likelihood (ML) estimate can be used. Assuming that image is a locally *i.i.d.* Gaussian distributed random variable, the ML estimate is given by:

$$\sigma_x^2(i,j) = \frac{1}{(2L+1)^2} \sum_{m=-L}^{L} \sum_{n=-L}^{L} (x(i+m, j+n) - x(i,j))^2 \tag{8}$$

with

$$x(i,j) = \frac{1}{(2L+1)^2} \sum_{m=-L}^{L} \sum_{n=-L}^{L} x(i+m, j+n) \tag{9}$$

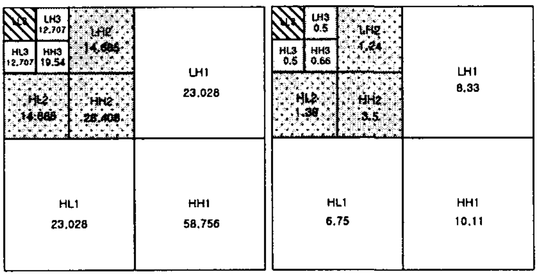
Where $(2L+1)\times(2L+1)$ is a window of size.

### 2.4 Adaptive Watermark Embedding

The final equation with adaptive watermark embedding is following:

$$X^*_{u,v,l,f} = X_{u,v,l,f} + \{(1-NVF)\cdot S_{ET} + NVF \cdot S_F\}w_{u,v,l,f} \tag{10}$$

Where $X^*_{u,v,l,f}$, $X_{u,v,l,f}$, and $w_{u,v,l,f}$ denote the watermarked image, original image, and watermark. $S_{ET}$ denotes the watermark strength of texture and edge regions. $S_F$ denotes the watermark strength of flat region. In this paper, $S_{ET}$ is used for perceptually quantization and bit allocation for image compression[12] from Fig. 3(a). $S_F$ is according to the perceptual criteria employed in the perceptual subband image coder by R. J. Safranek, *et al*,[13] by Fig. 3(b). The above rule embeds the watermark in highly textured areas and areas containing edges stronger than in the flat regions.




(a) (b)

Fig. 3. Watermark strength of (a) edge or texture regions, (b) flat regions.

### 2.5 Watermark Detection

The watermark detection is the following.

$$w^*_{s,u,v,l,f} = X_{u,v,l,f} - \hat{X}^*_{u,v,l,f} \tag{11}$$

$$w^*_{u,v,l,f} = \frac{w^*_{s,u,v,l,f}}{t^C_{u,v,l,f}} \tag{12}$$

$$\rho_{\omega\omega^*}(l,f) = \frac{w^*_{l,f}\cdot w_{l,f}}{\sqrt{E_{w_{l,f}} E_{w^*_{l,f}}}}, \text{ for } l=1,2,3,4 \text{ and } f=1,2,3 \tag{13}$$

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

## 3. Experimental Results

To illustrate the main features of the proposed adaptive watermarking method using the stochastic perceptual 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 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. The watermark lengths of stationary GG model and non-stationary Gaussian model are the same. Also, the watermark length of proposed method is more embedding than the Podilchuk's method. This is more robustness than the Podilchuk's. The PSNR of the visual quality of the stego images according to watermark strength variation for Lena and Peppers images are shown the Table 2. This means that quality of image is decided by embedding strength of watermark. At the Table 2, when heightened embedding strength more than 30, we could

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

| | | Lena | Barbara | Baboon | Peppers | Airplane |
|---|---|---|---|---|---|---|
| Proposed | Stationary<br>Non-stationary | 8,311 | 18,706 | 38,062 | 9,660 | 11,565 |
| Podilchuk | | 7,973 | 17,749 | 37,655 | 7,458 | 10,318 |

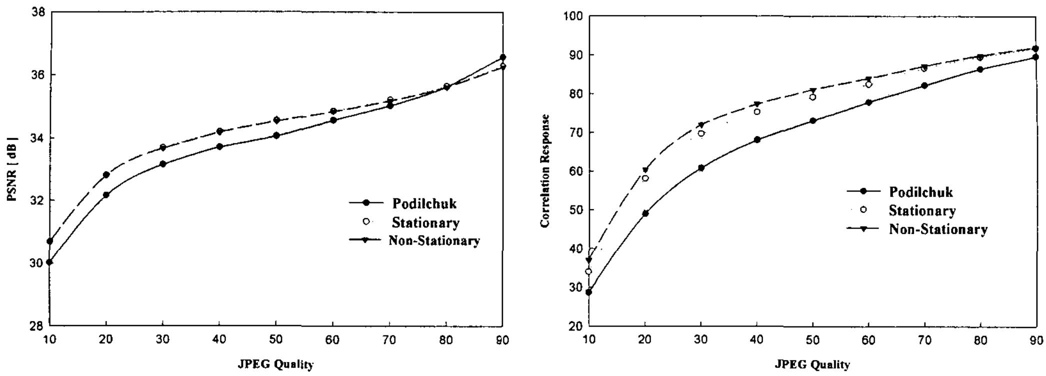
Table 2. The PSNR comparison according to watermarked strength

| Image | Lena (512×512) | | Peppers (512×512) | |
|---|---|---|---|---|
| Watermark Strength | Stationary | Non-stationary | Stationary | Non-stationary |
| | PSNR[dB] | PSNR[dB] | PSNR[dB] | PSNR[dB] |
| 10 | 43.97 | 43.93 | 43.32 | 43.26 |
| 20 | 37.95 | 37.91 | 37.30 | 37.25 |
| 30 | 34.43 | 34.39 | 33.78 | 33.73 |
| 40 | 31.93 | 31.89 | 31.28 | 31.23 |
| 50 | 30.00 | 29.96 | 29.34 | 29.29 |
| 60 | 28.41 | 28.37 | 27.76 | 27.71 |
| 70 | 27.08 | 27.03 | 26.42 | 26.37 |
| 80 | 25.92 | 25.87 | 25.26 | 25.21 |
| 90 | 24.92 | 24.85 | 24.23 | 24.18 |
| 100 | 23.98 | 23.94 | 23.32 | 23.27 |

know that quality of image fall off rapidly. Also, watermark is embedded in state that characteristics of low frequency bands and high frequency bands are ignored as fixed embedding strength. This method can derive higher PSNR as decision embedding strength of watermark as adaptively in each subband.

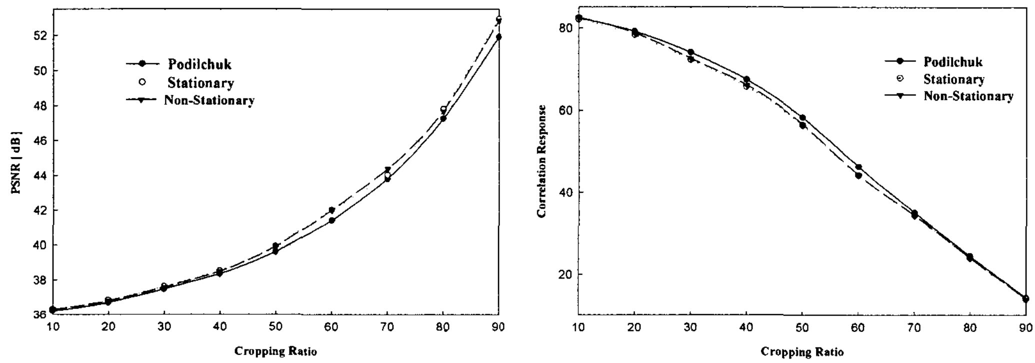
To establishment the robustness of the watermarked image under JPEG attack, we compressed it by JPEG with a Q factor varying 10% to 90%. We know that the result shows the resilience of the watermarking scheme against the JPEG compression. As the PSNR comparison of JPEG in Fig. 4, the Podilchuk's method showed higher PSNR in the 90% compression rate, but in different compression rates, the proposed method displayed higher PSNR. So we can say that proposed model is excellent PSNR than the Podilchuk's method, In the meantime, correlation response of proposed model shows that more superior than the Podilchuk's method in all compression rates.

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%. So, we could know that the result shows 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




(a) PSNR (b) correlation response

Fig. 4. The robustness test of JPEG attacks.




(a) PSNR (b) correlation response

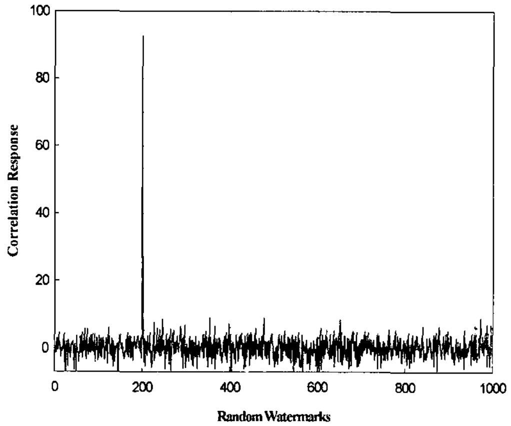
Fig. 5. The robustness test of cropping attack after JPEG compression Q=80%.

methods are similar to PSNR and correlation response for the cropping ratio. As shown by he results in Table 3, the proposed algorithm remained robust against all these attacks when compared to the Podilchuk's algorithm.

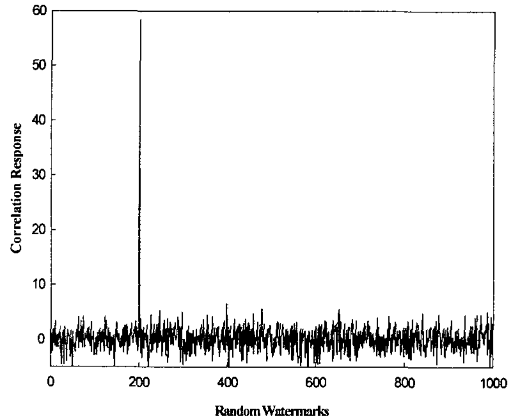
The correlation response for watermarked image, no attack, non-stationary and stationary GG models are shown in Fig. 6. We used the 200th watermark seed among 1000 watermark seed for experiments. As can know in Fig. 6,

Table 3. The correlation response according to attacks

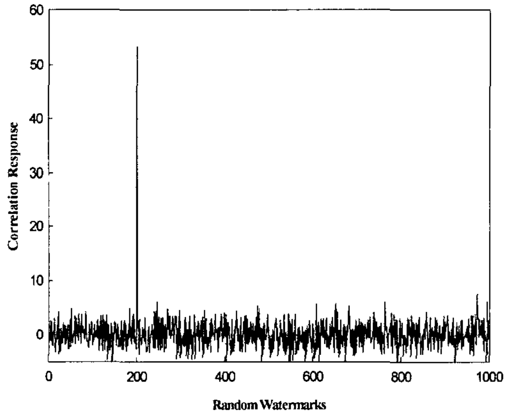
| | PSNR[dB] | | | Correlation Response | | |
|---|---|---|---|---|---|---|
| | Podilchuk | Non-stat. | Stationary | Podilchuk | Non-stat. | Stationary |
| No Attack | 38.67 | 37.91 | 37.95 | 90.87 | 92.63 | 92.62 |
| median | 30.25 | 30.67 | 30.66 | 51.05 | 59.97 | 59.59 |
| sharpening | 21.39 | 21.68 | 21.69 | 51.24 | 61.45 | 59.16 |
| gaussian | 32.97 | 33.82 | 33.83 | 45.60 | 53.38 | 51.76 |
| FMLR | 31.93 | 32.65 | 32.66 | 36.02 | 45.76 | 44.56 |
| crop50 | 42.12 | 41.94 | 41.99 | 61.57 | 58.39 | 58.36 |
| jpeg50 | 34.16 | 34.52 | 34.54 | 73.14 | 81.21 | 79.24 |



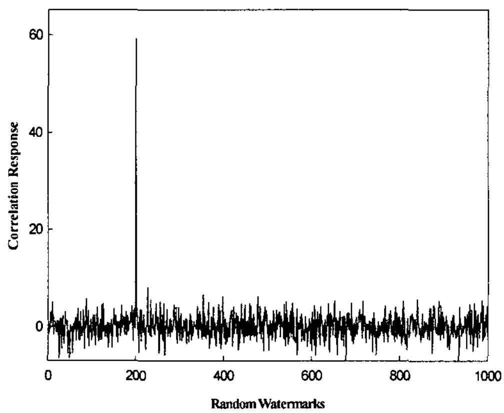

(a) No attack(CR=92.63)



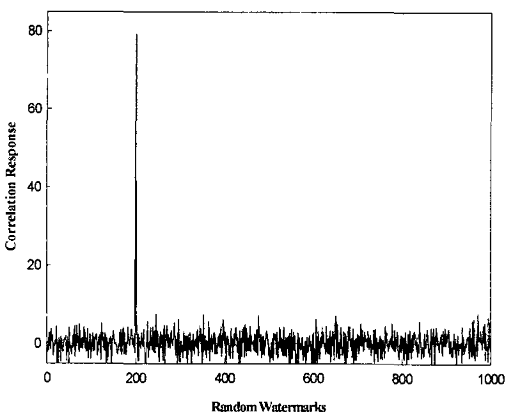

(b) Cropping50%(CR=58.39): Non-stat.



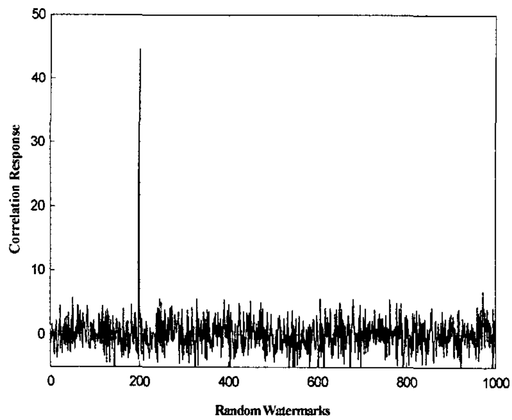

(c) Gaussian(CR=53.38): Non-stat.




(d) Shapening(CR=59.16): Stat.




(e) JPEG50%(CR=79.24): Stat.



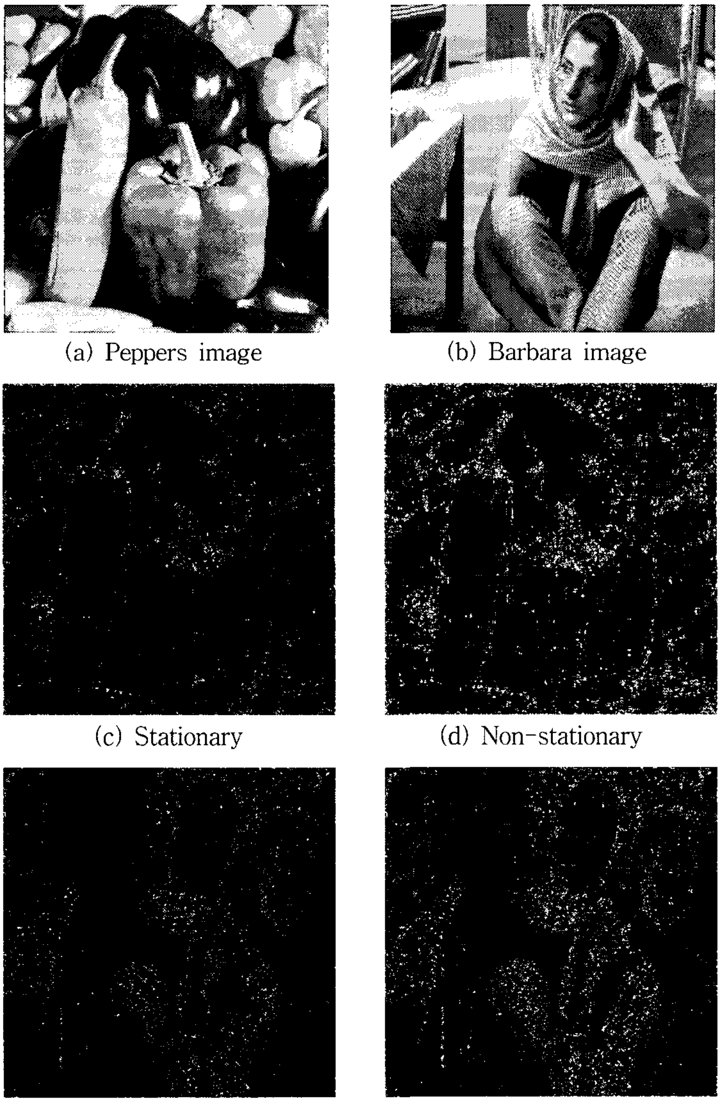

(f) FMLR (CR=44.56): Stat.

Fig. 6. The correlation response for attacks.

proposed method could detect correlation response of high numerical value to various image processing. This means that the proposed method is robustness in various attacks.

We displayed the result in Table 3 after we compare to non-stationary and stationary GG models and the Podilchuk methods about several attacks. We could know certainly that proposed method is superior more than the Podilchuk's method. And it showed that non-stationary model overmatches in equal PSNR.

The extracted watermark for the Peppers and Barbara images using the proposed model are shown in Fig. 7. The extracted watermark of proposed model is embedding the edge and



(a) Peppers image (b) Barbara image

(c) Stationary (d) Non-stationary

(e) Stationary (f) Non-stationary

Fig. 7. Extracted watermark images

textured regions as shown to Fig. 7(c)-(f).

## 4. Conclusions

In this paper, we have presented a new approach for highly reliable adaptive watermark embedding using stochastic perceptual model based on multiwavelet domain. To embedding watermark, the original image was decomposed into 4 levels using the DGHM multiwavelet transform, then a watermark is embedded into the JND of the image each subband. The perceptual model is applied with a stochastic approach of stationary GG model and non-stationary Gaussian model for watermark embedding. This is based on the computation of a NVF that have local image properties. The stochastic perceptual model with adaptive watermark embedding algorithm embed at the texture and edge region for more strongly embedded watermark by the JND. This method uses stationary GG model and nun-stationary Gaussian 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, and T.Shamoon.: Secure Spread Spectrum Watermarking for Multimedia. NEC Research Institute Tech Rep. 95-10, (1995).

[2] J.Huang and Y.Shi: Adaptive Image Watermarking Scheme Based on Visual Masking. Electronic Letters, Vol. 34, No. 8, (1998) 748-750.

[3] M. Swanson, B. Zhu, and A. Twefik.: Transparent Robust Image Watermarking. IEEE International Conference on Image Processing ICIP96, Vol. 3 (1996) 211-214.

[4] M. Kutter: Watermarking Resisting to Translation, Rotation and Scaling. Proc. of SPIE, Boston, USA (1998).

[5] C.Podilchuk and W.Zeng.: Image Adaptive Watermarking Using Visual Models. IEEE Journal on Selected Areas in Communication, Vol. 16, No. 4 (1998) 525-539.

[6] J.F.Delaigle, C.De Vleeschouwer, and B.Macq: Watermarking Algorithm Based on a Human Visual Model. Signal Processing, Vol.66, (1998) 319-335.

[7] Sviatoslav Voloshynovskiy, A. Herrigel, N. Baumgaertner, and T. Pun.: A Stochastic Approach to Content Adaptive Digital Image Watermarking. Proc. of Third Information Hiding Workshop (1999).

[8] Ki-Ryong Kwon and Ahmed H. Tewfik: Adaptive Watermarking Using Successive Subband Quantization and Perceptual Model Based on Multiwavelet Transform. Proc. of SPIE, 4675-32, (2002).

[9] V. Strela, P. N. Heller, G. Strang, P. Topiwala, and C. Heil: The Application of Multiwavelet Filterbank to Image Processing. IEEE Trans. On Image Processing, Vol. 8, No. 4, (1999) 548-563.

[10] X. G. Xia, J. S. Geronimo, D. P. Hardin, and B. W. Suter: Design of Prefilters for Discrete Multiwavelet Transforms. IEEE Trans. on Image Processing, Vol. 44, No. 1, (1996) 25-35.

[11] Douglas P. Hardin and David W. Roach: Multiwavelet Prefilters I: Orthogonal Prefilters Preserving Approxima-tion order p 2. IEEE Trans. On Circuits and Systems II, Vol. 45, (1998) 1106-1112.

[12] A. B. Watson, G. Y. Yang, J. A. Solomon, and J. Villasenor: Visual Thresholds for Wavelet Quantization Error, Proc. SPIE, Vol. 2657, (1996) 381-392.
[13] R. J. Safranek and J. D. Johnston: A Perceptually Tuned Subband Image Coder with Image Dependent Quantization and Post-quantization Data Compression. IEEE Intl. Conf. Acoustics, Speech and Signal Processing-ICASSP 89, (1989) 1945-1948.

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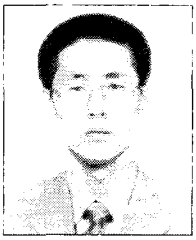

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