Implementations of HVS Models in Digital Image Watermarking

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Abstract. *In the paper two possible implementations of Human Visual System (HVS) models in digital watermarking of still images are presented. The first method performs watermark embedding in transform domain of Discrete Cosine Transform (DCT) and the second method is based on Discrete Wavelet Transform (DWT). Both methods use HVS models to select perceptually significant transform coefficients and at the same time to determine the bounds of modification of selected coefficients in watermark embedding process. The HVS models in DCT and DWT domains consist of three parts which exploit various properties of human eye. The first part is the HVS model in DCT (DWT) domain based on three basic properties of human vision: frequency sensitivity, luminance sensitivity and masking effects. The second part is the HVS model based on Region of Interest (ROI). It is composed of contrast thresholds as a function of spatial frequency and eye's eccentricity. The third part is the HVS model based on noise visibility in an image and is described by so called Noise Visibility Function (NVF). Watermark detection is performed without use of original image and watermarks have a form of real number sequences with normal distribution zero mean and unit variance. The robustness of presented perceptual watermarking methods against various types of attacks is also briefly discussed.*

Keywords

Digital image watermarking, human visual system models, discrete cosine transform, discrete wavelet transform, noise visibility function, watermark embedding, watermark detection.

1. Introduction

The massive spreading of broadband networks and new developments in digital technology has made ownership protection and authentication of digital multimedia a very important issue. The reason is the availability of powerful tools for editing, lossless copying and transmission of digital multimedia. A possible solution to this serious problem is digital watermarking. Digital watermarking is defined as a technique of embedding additional information called watermark into digital multimedia while preserving perceptual quality of watermarked data [1]. The watermark can be detected or extracted for purpose of legal owner or author identification and integrity verification of tested data. Digital watermarking can be used for various purposes like ownership protection, fingerprinting, copy control and integrity verification of digital multimedia. There are three basic requirements on digital watermarking: robustness, perceptual transparency and capacity. Robustness means the resilience of embedded watermark against distortions and attacks that try to destroy or remove the embedded watermark. Perceptual transparency means that the watermark embedding must not degrade the quality of watermarked data and the capacity expresses the number of different watermarks that can be embedded into digital media while preserving the perceptual quality requirement. These three requirements are in conflict which each other. If the embedded watermark shall be robust against attacks we have to increase the energy of watermark but on the other hand we get the problem with perceptual transparency requirement. Vice versa if we want a very good perceptual transparency of embedded watermark we have to decrease the watermark energy but at the same time a problem of watermark robustness arises. The proper selection of signal components or coefficients for watermark embedding and the allowed amount of modification of these signal components in watermark embedding process is therefore a very important issue. A very effective solution of this problem can be achieved by using of HVS models. HVS models in transform domain of DCT and DWT were originally developed for image compression based on DCT and DWT where there has been a need of a good quantization matrix that would provide better quality of compressed images with higher compression ratio. Common HVS models are composed of image dependent or independent Just Noticeable Difference (JND) thresholds, i. e. steps below which the signal is considered as insignificant or imperceptible. This paper presents two perceptual methods of invisible watermarking in transform domain for still images which do not require the presence of original data for watermark detection.

2. Perceptual Digital Image Watermarking

Perceptual digital image watermarking methods use knowledge of human visual system to fulfill conflicting requirements of digital watermarks. These methods incorporate HVS models used for two basic purposes:

- selection of perceptually significant image components for watermark embedding,
- scaling of watermark elements before embedding into original data.

In this paper we present two methods of perceptual watermarking of still grayscale images, where HVS models are used for both mentioned purposes. The first method operates in DCT domain and is denoted as M-DCT. The second method, denoted M-DWT, is based on DWT. The difference between these methods is the watermark embedding domain and the HVS model used in watermark embedding and detection processes.

2.1 Watermark Embedding Process

Watermark embedding into grayscale still images by using methods M-DCT and M-DWT can be described as follows (Fig. 1):

- transformation of original image,
- construction of HVS model,
- watermark generation,
- coefficients selection,
- watermark embedding,
- inverse transformation.

2.1.1 Transformation of Original Image

Method M-DCT uses 2D DCT with block size $M \times M$, which is applied on original gray scale image I. The DCT transform coefficients $I_{DCT}(u,v,k)$ of an $M \times M$ block k of pixels $I(i,j,k)$ are given by the following equation

$$I_{DCT}(u,v,k) = C(u).C(v)\sum_{i=0}^{M-1}\sum_{j=0}^{M-1} I(i,j,k).\cos\left(\frac{(2i+1).u\pi}{2M}\right).\cos\left(\frac{(2j+1).v\pi}{2M}\right), \quad (1)$$

where $C(u),C(v) = \sqrt{\frac{1}{M}}$ for $u,\ v = 0$,

$$= \sqrt{\frac{2}{M}} \quad \text{for } u,\ v = 1,2,3,\ldots,M-1.$$

Method M-DWT uses L_D levels 2D DWT based on 9/7 biorthogonal wavelets. The 2D DWT decomposes two dimensional signals such as images into subbands that vary in spatial frequency and orientation. On each decomposition level we can distinguish among approximation, horizontal, vertical and diagonal details. The result of this transformation are DWT coefficients $I_{DWT}(L,\Omega,m,n)$, where L is the decomposition level and Ω denotes orientation (1,2,3,4 for approximation, horizontal, diagonal and vertical details).

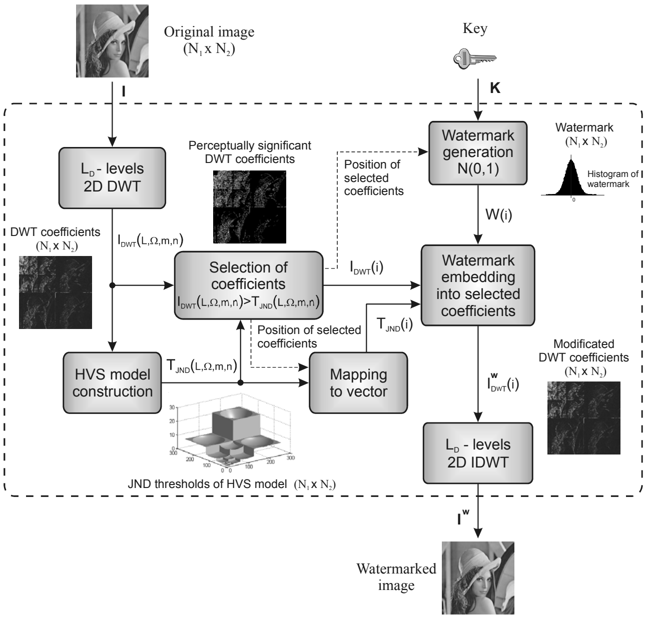

Fig. 1. Watermark embedding principle (M-DWT case).

2.1.2 Construction of HVS Model

Most HVS models in image processing use three basic properties of human vision: frequency sensitivity, luminance sensitivity and masking effects. Frequency sensitivity determines the human's eye sensitivity to various spatial frequencies. Luminance sensitivity measures the effect of the detectability threshold of noise on a constant background. It is the correction of frequency sensitivity according to the change of background luminance. Masking refers to the effect of decreasing visibility of one signal in the presence of another signal called masker. We can distinguish self masking and neighborhood masking. Self masking is when masking and masked signal have the same spatial frequencies, orientation and location in an image. Neighborhood masking refers to the masking where these signals have close spatial frequencies, orientation or location in an image.

2.1.2.1 HVS Model in DCT Domain

JND thresholds of frequency sensitivity $T(u,v)$ for individual basis functions in DCT domain were determined by psychological experiments and they can be approximated by the following equation

$$T(u,v) = \frac{T_{\min}\left(f_{u,0}^2 + f_{0,v}^2\right)^2}{C(u)C(v)\left(\left(f_{u,0}^2 + f_{0,v}^2\right)^2 - 4(1-\eta)f_{u,0}^2 f_{0,v}^2\right)} 10^{S\left(\log\sqrt{f_{u,0}^2+f_{0,v}^2} - \log f_{\min}\right)^2} \quad (2)$$

where $f_{0,v}$, $f_{u,0}$ are horizontal and vertical spatial frequency, respectively, $T_{\min}$ is the minimum threshold occurring at the spatial frequency $f_{\min}$, S determines the steepness of the parabola, and η is the model's parameter [2].

JND thresholds of frequency sensitivity are weighted by thresholds of HVS model based on Region of Interest (ROI) to incorporate nonuniform density of photoreceptors on a human's eye retina into the final HVS model. The eye is most sensitive at the point of fixation which is the center point of Region of Interest and its sensitivity decreases rapidly while the eccentricity gets larger. The contrast thresholds as a function of eccentricity $e(\vartheta,x)$ can be given by equation

$$T_{ROI}(\vartheta,f,x)=\begin{cases}\exp(0{,}0461.f.e(\vartheta,x)) & \text{for} \quad f\le f_m(x)\\ \exp(0{,}0461.f_m(x_{\max}).e(\vartheta,x_{\max})) & \text{for} \quad f>f_m(x)\end{cases} \tag{3}$$

where x is the pixel position in an image, $x_{\max}$ denotes a pixel position where T_{ROI} reaches its maximum and after that point remains constant, $f_m(x)$ is the cutoff frequency and ϑ is the viewing distance measured in image heights [4]. These thresholds of HVS model based on ROI are used as weights for JND thresholds of frequency sensitivity of HVS model in DCT domain according to the equation

$$T^f(u,v,k)=T(u,v).\left(1+\frac{\beta.T_{ROI}(\vartheta,f,x_k)}{100.\max(T_{ROI})}\right) \tag{4}$$

where $x_k = x$ from block k: $\min(\|x - x_{ROI}\|)$, x_{ROI} is the center point of ROI and β [%] controls the impact of HVS model based on ROI on final HVS model (Fig. 2).

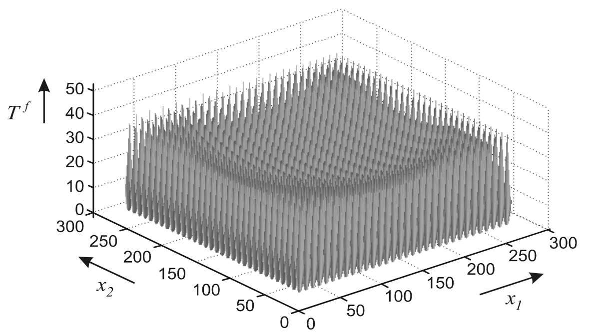

Fig. 2. Weighted frequency sensitivity thresholds of HVS model in DCT domain.

Thresholds of weighted frequency sensitivity $T^f(u,v,k)$ are further corrected by luminance sensitivity according to the following equation

$$T^l(u,v,k)=T^f(u,v,k).\left(\frac{I_{DCT}(0,0,k)}{\overline{Y}_{0,0}}\right)^{a_T} \tag{5}$$

where $I_{DCT}(0,0,k)$ is the DC coefficient for block k, $\overline{Y}_{0,0}$ is the DC coefficient corresponding to the mean luminance of the display, and a_T is a parameter which controls the degree of luminance sensitivity.

Further correction of luminance sensitivity thresholds by neighborhood masking effect can be evaluated as

$$T^c(u,v,k)=T^l(u,v,k).\max\left[1,\left(e^{\frac{-\pi\left((u-u_m)^2+(v-v_m)^2\right)}{\left(\varphi.\max\left(1,\sqrt{u^2+v^2}\right)\right)^2}}\frac{\left|I_{DCT}(u_m,v_m,k)\right|}{T^l(u,v,k)}\right)^{w_{u,v}(k)}\right] \tag{6}$$

where $I_{DCT}(u_m,v_m,k)$ is the value of the DCT coefficient in block k that acts as a mask of coefficient $I_{DCT}(u,v,k)$, φ is a model's parameter and $w_{u,v}(k)$ controls the degree of masking effect and it can take different values for different spatial frequencies and different image blocks [5]. It takes the values from the range of 0 to 1.

In the presented watermarking method we have determined the value of this parameter by using Noise Visibility Function (NVF) which describes noise visibility in an image. The most known form of NVF is given as

$$NVF(m,n)=\frac{1}{1+\mu\sigma_x^2(m,n)} \tag{7}$$

where σ_x^2 denotes the local variance of the image in a window centered on the pixel with coordinates (m,n), and μ is a tuning parameter corresponding to the particular image [3]. The NVF takes values between zero and one. Higher values of NVF indicate flat region and, vice versa, smaller values indicate textured regions or regions with edges. The model's parameter $w_{u,v}(k)$ used in the presented method is given by the following equation

$$w_{u,v}(k)=\begin{cases}\dfrac{\lambda}{3M^2}\sum_{u=1}^{M}\sum_{v=1}^{M}\left(1-NVF(u,v,k)\right) & \text{if} \sum_{u=1}^{M}\sum_{v=1}^{M}NVF_P(u,v,k)<M^2\\ \dfrac{\lambda}{M^2}\sum_{u=1}^{M}\sum_{v=1}^{M}\left(1-NVF(u,v,k)\right) & \text{if} \sum_{u=1}^{M}\sum_{v=1}^{M}NVF_P(u,v,k)=M^2\end{cases} \tag{8}$$

where λ determines the maximal value of this parameter according to the robustness requirements of embedded watermark, $NVF(u,v,k)$ are values of NVF in block k and $NVF_P(u,v,k)$ is the thresholded NVF which detects sharp edges in an image.

2.1.2.2 HVS Model in DWT Domain

Visibility thresholds of frequency sensitivity $T_{L,\Omega}$ in various subbands for 9/7 biorthogonal wavelets were determined via psychological experiments and can be expressed by the following equation

$$T_{L,\Omega}=\frac{T_{\min}}{A_{L,\Omega}}10^{S\left(\log\frac{r}{2^L f_0 g_\Omega}\right)^2} \tag{9}$$

where $A_{L,\Omega}$ are the basis function amplitudes, $T_{\min}$ is the minimum threshold occurs at spatial frequency $g_\Omega f_\Omega$, f_L is the spatial frequency of decomposition level L and g_Ω shifts the minimum thresholds by an amount that is a function of orientation [6].

Similarly as in the case of DCT domain, thresholds of frequency sensitivity are weighted by HVS model based on ROI according to the equation

$$T^f(L,\Omega,m,n) = T_{L,\Omega}\cdot\left(1+\frac{\beta.T_{ROI}^{L,\Omega}(m,n)}{100.\max\left(T_{ROI}^{L,\Omega}\right)}\right) \tag{10}$$

where $T_{ROI}^{L,\Omega}(m,n)$ are T_{ROI} thresholds in subband L,Ω. An example of HVS model based on weighted frequency sensitivity thresholds is shown in Fig. 3.

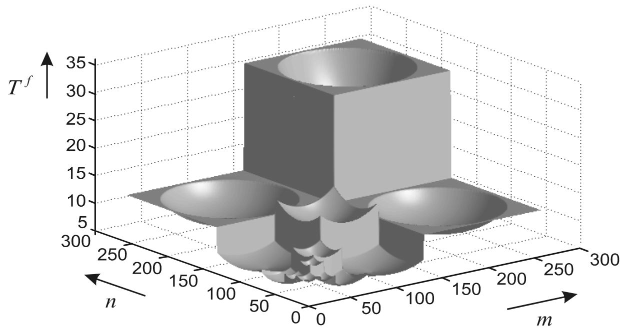

Fig. 3. Weighted frequency sensitivity thresholds of HVS model in DWT domain.

The correction of weighted frequency sensitivity thresholds by luminance sensitivity can be estimated as

$$T^l(L,\Omega,m,n) = T^f(L,\Omega,m,m).\left(\frac{I_{DWT}(L,1,m,n)}{\bar{I}_{DWT}(L,1,m,n)}\right)^{a_T} \tag{11}$$

where $I_{DWT}(L,1,m,n)$ is the DWT coefficient in approximation on decomposition level L of an image, $\bar{I}_{DWT}(L,1,m,n)$ is the DWT coefficient of an homogenous image with mean luminance in approximation on decomposition level L, and a_T is a parameter which controls the degree of luminance sensitivity.

JND thresholds of neighborhood masking for each DWT coefficient can be evaluated as

$$T^c(L,\Omega,m,n) = T^l(L,\Omega,m,n).\max\left[1,\left(\varphi(m_M,n_M).\frac{|I_{DWT}(L,\Omega,m_M,n_M)|}{T^l(L,\Omega,m,n)}\right)^{w_{L,\Omega,m,n}}\right] \tag{12}$$

where $I_{DWT}(L,\Omega,m_M,n_M)$ is the value of a DWT coefficient in subband L,Ω that acts as a mask of coefficient $I_{DWT}(L,\Omega,m,n)$, $\varphi(m_M,n_M)$ is a sensitivity function which describes the influence of masking coefficient to the masked one and $w_{L,\Omega,m,n}$ is evaluated by using of NVF according to the following equation

$$w_{L,\Omega,m,n} = \begin{cases} \frac{\lambda}{3\cdot 2^{L-1}}\left(1-NVF(L,\Omega,m,n)\right) & if\ NVF(L,1,m,n) < P_1 \\ \frac{\lambda}{2^{L-1}}\left(1-NVF(L,\Omega,m,n)\right) & if\ NVF(L,1,m,n) \geq P_1 \end{cases} \tag{13}$$

where $NVF(L,\Omega,m,n)$ is the NVF in subband L,Ω, λ determines the maximal value of this parameter according to the robustness requirements of embedded watermark and P_1 is the detection threshold of sharp edges.

2.1.3 Watermark Generation

Watermark has a form of real number sequence with normal distribution, zero mean and unit variance. It is generated by using of a Pseudo Random Number Generator (PRNG) initialized by the secrete key K. Watermark elements are formed in an array $W(m,n)$ with the size of an original image.

2.1.4 Coefficients Selection

Watermark embedding is performed only into perceptually significant coefficients, since perceptually unimportant components such as very small high frequency components are suppressed by lossy image compression and other lowpass operations. In M-DCT method the selection is performed among AC coefficients from each block and the selected coefficients are mapped to the vector $I_{DCT}(i)$ which expresses the following equation

$$I_{DCT}(i) = I_{DCT}(u,v,k)\ if\ I_{DCT}(u,v,k) > T_{JND}(u,v,k) \tag{14}$$

where $u,v \in$ zigzag sequence and $T_{JND}(u,v,k)$ are JND thresholds of HVS model. M-DWT method selects significant coefficients from detail subbands on each decomposition level and maps them to the vector $I_{DWT}(i)$

$$I_{DWT}(i) = I_{DWT}(L,\Omega,m,n)\ if\ I_{DWT}(L,\Omega,m,n) > T_{JND}(L,\Omega,m,n) \tag{15}$$

where $T_{JND}(L,\Omega,m,n)$ are thresholds of HVS model. The position of selected coefficients is used to select corresponding JND thresholds of HVS model and watermark elements which are mapped to vectors $T_{JND}(i)$ and $W(i)$ respectively.

2.1.5 Watermark Embedding

JND thresholds of HVS model are used to scale the watermark before embedding but according to the nature of watermark the modification of roughly 33 % of coefficients would be higher then corresponding JND threshold. Therefore the original image or each subband in the case of M-DWT method is segmented to three regions with a different amount of allowed modification. This segmentation is described by an image dependent mask denoted as $Mask(m,n)$

$$Mask(m,n) = \begin{cases} 0 & region\ inside\ of\ ROI\ without\ tetxures \\ 1 & region\ inside\ of\ ROI\ with\ textures \\ 2 & region\ outside\ of\ ROI \end{cases}. \tag{16}$$

Segmentation to inside and outside regions of ROI is done by T_{ROI} model thresholding and detection of textures is performed by local variance computation. Watermark embedding into selected transform coefficients describes the following equation

$$I_{DOT}^{W}(i)=\begin{cases} I_{DOT}(i)+sign(WT(i))\cdot\left(W(i)\left\lfloor\frac{T_{JND}(i)}{W(i)}\right\rfloor\right) & if \quad Mask(i)=0\wedge WT(i)>T_{JND}(i) \\ I_{DOT}(i)+sign(WT(i))\cdot\left(W(i)\left\lfloor\frac{2T_{JND}(i)}{W(i)}\right\rfloor\right) & if \quad Mask(i)=1\wedge WT(i)>2T_{JND}(i) \\ I_{DOT}(i)+W(i)T_{JND}(i) & otherwise \end{cases} \tag{17}$$

where $I_{DOT}(i)$ and $I^{W}_{DOT}(i)$ are DCT (DWT) coefficients of the original and watermarked image, respectively, *Mask*(i) are elements of *Mask*(m,n) corresponding to selected coefficients, *sign*(x) is the sign function, $\lfloor\ \rfloor$ is rounding towards zero and $WT(i) = W(i).T_{JND}(i)$.

2.1.6 Inverse Transformation

Modified and unmodified transform coefficients are transformed back to pixel domain by using of block 2D IDCT or L_D levels 2D IDWT. Finally the watermarked image I^W is obtained.

2.2 Watermark Detection Process

Watermark detection does not need the original image. The detection of watermark in a test image I^T can be described by following steps (Fig. 4):

- transformation of an original image,
- construction of HVS model,
- watermark generation,
- coefficients selection,
- watermark detection and decision.

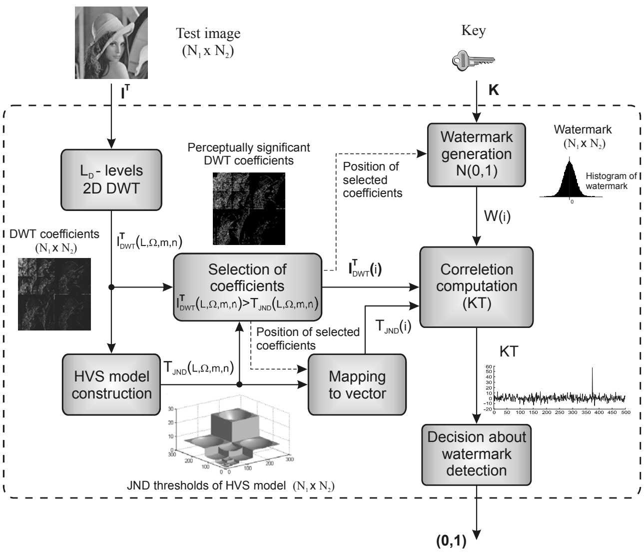

Fig. 4. Watermark detection principle (M-DWT case).

The first four steps are performed by applying the same procedures as in watermark embedding process except the fact that the computation of HVS model is based only on weighted frequency sensitivity evaluation. Watermark detection itself is performed by correlation *KT* between selected perceptually significant transform coefficients and the watermark scaled by visibility thresholds of HVS model which is given by equation

$$KT=\frac{1}{V_D}\sum_{i=1}^{V_D} I_{DOT}^{T}(i)T_{JND}(i)W(i) \tag{18}$$

where $I^{T}_{DOT}(i)$ are transform coefficients of a test image, $T_{JND}(i)$ are the thresholds of HVS model, $W(i)$ are the elements of watermark and V_D is the number of the selected significant transform coefficients.

In the end according to the correlation the decision about watermark presence in the test image is made. This decision can be based on a comparison between the computed correlation and a selected threshold.

3. Experimental Results

Verification of the proposed methods has been performed on a grayscale image “Lena” (256x256x8b). In both methods the impact of the viewing distance, the size of an image block (M-DCT) or the number of decomposition levels (M-DWT) and the impact of the HVS model based on ROI on the number of selected significant coefficients V_V, watermarked image quality and watermark robustness were tested. Experimental results are shown in Tab.1, Tab.2 and Tab.3.

ϑ	2	4	6	8	10
M-DCT					
V_V	7782	6333	4832	3748	2882
PSNR [dB]	45,275	44,15	42,875	41,709	40,65
KT	18,528	30,769	55,272	96,574	160,4
M-DWT					
V_V	12008	7102	5009	3686	2820
PSNR [dB]	47,369	43,88	41,694	39,968	38,771
KT	9,4032	36,507	88,111	176,57	317,5

Tab. 1. The impact of the viewing distance.

M-DCT					
MxM	2x2	4x4	8x8	16x16	32x32
V_V	1896	5332	4901	3693	2574
PSNR [dB]	52,666	45,155	42,246	39,883	37,261
KT	10,94	21,571	56,773	171,69	456,16
M-DWT					
L_D	1	2	3	4	5
V_V	2443	4501	5457	5790	5875
PSNR [dB]	45,924	43,838	42,701	42,253	42,069
KT	89,758	81,556	77,91	77,885	75,213

Tab. 2. The impact of the block size and the number of decomposition levels, respectively.

β [%]	0	20	40	60	80
M-DCT					
V_V	5402	5172	5005	4840	4696
PSNR [dB]	42,725	42,571	42,314	42,131	41,961
KT	47,036	50,242	55,145	59,238	64,426
M-DWT					
V_V	6359	6115	5895	5696	5535
PSNR [dB]	43,117	42,751	42,429	42,084	41,749
KT	57,726	65,738	73,453	82,054	91,901

Tab. 3. The impact of the HVS model based on ROI.

The watermarked image was also tested for robustness against various types of attacks and for quality of attacked images. Experimental results are shown in Tab. 4. After each attack the detection of 500 different watermarks from which only one was really used for embedding was evaluated. Among all detected watermarks only one should have given the largest correlation output. Embedding parameters were set to values which get the best image quality and watermark robustness. According to the experimental results the method based on DWT was more robust against attack then the method based on DCT. In M-DWT method watermark was reliably detected after all tested attacks except rotation 1°.

Attack	Attack's parameters	M-DCT		M-DWT	
		PSNR [dB]	KT	PSNR [dB]	KT
no attack	-	41,469	79,35476	41,364	111,1544
JPEG	Q = 70	34,633	76,84699	34,769	81,23402
	Q = 30	31,559	100,8347	31,636	56,26036
JPEG 2000	1.0 bpp	37,174	57,82904	36,803	101,1772
	0.5 bpp	33,171	34,86838	32,923	138,4197
Filtration	wiener 3x3	35,155	37,27961	35,060	83,23933
	median 3x3	31,552	25,04847	31,526	72,20963
Gaussian noise	μ=0,σ=0.001	29,748	40,73649	29,719	58,54053
	μ=0,σ=0.005	23,015	N	23,003	23,92239
Brightness change	+30	18,568	78,94217	18,567	111,2725
	-30	18,567	79,10172	18,566	110,7561
Contrast change	0.1	19,532	77,83728	19,613	111,0956
	0.5	20,455	79,69997	20,509	118,0618
Gamma correction	gamma=0.5	13,880	79,21807	13,882	106,8801
	gamma=1.5	17,719	70,08389	17,720	100,1048
Resize	1/2 of size	30,770	N	30,727	58,85016
	3/2 of size	39,344	62,95824	39,174	94,8573
Cropping	1/4 of image	11,198	80,29457	11,198	92,87105
	1/2 of image	7,858	88,59	7,859	90,18556
Rotation	0.5°	26,213	26,68238	26,206	46,40737
	1.0°	21,876	N	21,871	N

Tab. 4. Watermark robustness. N – detection failed.

4. Conclusions

In the paper two implementations of HVS models in digital image watermarking have been described. Experimental results showed that by modification of embedding parameters like viewing distance, size of image block, etc. the embedding methods can be accommodated to required image quality by maximized watermark robustness or to required watermark robustness by maximized image quality.

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References

[1] LEVICKÝ, D., FORIŠ, P., KLENOVIČOVÁ, Z., RIDZOŇ, R. Digital right management. In *Research in Telecommunication Technology 2005. 6th Int. Conf. RTT 2005*, 2005.

[2] PETERSON, H. A., AHUMADA, A. J., WATSON, A. B. An improved detection model for DCT coefficient quantization. In *Proc. SPIE Conf. Human Vision*, 1993, vol. 1913, p.191 - 201.

[3] VOLOSHYNOVSKIY, S., HERRIGEL, A., BAUMGARTNER, N., PUN, T. A stochastic approach to content adaptive digital image watermarking. In *Proceedings of the Third International Workshop on Information Hiding*, 1999, p.211-236.

[4] WANG, Z., BOVIK, A. C. Foveation scalable video coding with automatic fixation selection. *IEEE Transactions on Image Processing*, 2003, vol. 12, no. 2, p. 1 – 12.

[5] WATSON, A. B. DCT quantization matrices visually optimized for individual images. In *Proc. SPIE Conf. Human Vision*, 1993, vol. 1913, p. 202 - 216.

[6] WATSON, A. B., YANG, G. Y., SOLOMON, J. A., VILLASENOR, J. Visibility of wavelet quantization noise. *IEEE Trans. of Image Processing,* 1997, vol. 6, p. 1164 – 1175.

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