# Human Visual System Models in Digital Image Watermarking

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**Abstract.** *In this paper some Human Visual System (HVS) models used in digital image watermarking are presented. Four different HVS models, which exploit various properties of human eye, are described. Two of them operate in transform domain of Discrete Cosine Transform (DCT) and Discrete Wavelet Transform (DWT). HVS model in DCT domain consists of Just Noticeable Difference thresholds for corresponding DCT basis functions corrected by luminance sensitivity and self- or neighborhood contrast masking. HVS model in DWT domain is based on different HVS sensitivity in various DWT subbands. The third presented HVS model is composed of contrast thresholds as a function of spatial frequency and eye's eccentricity. We present also a way of combining these three basic models to get better tradeoff between conflicting requirements of digital watermarks. The fourth HVS model is based on noise visibility in an image and is described by so called Noise Visibility Function (NVF). The possible ways of exploiting of the described HVS models in digital image watermarking are also briefly discussed.*

## Keywords

Digital image watermarking, Human visual system models, Discrete cosine transform, Discrete wavelet transform, Just Noticeable Difference.

## 1. Introduction

The increasingly easy access to digital multimedia via more and more popular Internet, and the increasingly powerful tools available for editing digital media have made protection of the intellectual property rights and authentication of digital multimedia a very important issue. One way to solve this problem is the digital watermarking. Digital watermarking is defined as a technique of embedding additional information called watermark into digital multimedia by preserving perceptual quality of watermarked data. The watermark can latter be detected or extracted for purpose of owner or author identification and integrity verification of tested data. Watermarks and watermarking techniques can be divided into various categories and in various ways. The basic and most common used partitioning of watermarking is the spatial domain, transform domain, and parametric domain watermarking. Another way for categorization of watermarking methods is based on the condition whether or not they use the original data for extraction of watermarks from tested (watermarked) data. Besides that we can distinguish visible and invisible watermarks. There are three basic requirements of digital watermarks: perceptual transparency, robustness to intentional and unintentional attacks, and capacity [1]. These requirements are in conflict with each other. If we increase the energy of watermark to improve its robustness we get a problem with perceptual transparency and vice versa if we want to get very good perceptual transparency we have to decrease the energy of the watermark and so the embedded watermark will not be robust to attacks and signal processing. On the other hand, to satisfy the perceptual transparency of an embedded watermark, the watermark should be embedded in high frequency components of the original data. But such a watermark will not be robust. A problem with perceptual transparency of the embedded watermark arises by watermark embedding into low frequency components. In transform domain watermarking the selection of transform coefficients is one of the fundamental issues. The watermark should be embedded in perceptually significant components of original data to get good robustness. The amount of modifications that can be made by watermark embedding in these components is very important. This problem can be solved by using HVS models in digital watermarking as well as the problem with the best tradeoff between conflicting requirements of watermarks.

## 2. Human Visual System Models

A lot of work has been devoted to understanding the human visual system (HVS) and applying this knowledge to image processing applications. In image compression algorithms there has been a need of good metrics for image quality that incorporates properties of the HVS and of a good quantization matrix to provide better quality of compressed images with higher compression ratio. The design of a quantization matrix that provides an optimal quality for a given bit rate depends upon the visibility thresholds of visual signals, since the error caused by quantization will not be visible if this error is less than corresponding visibility thresholds of a visual signal. Extensive psycho-visual measurements have been performed to determine these thresholds. These measurements were performed on sinusoidal gratings with various spatial frequencies and orientations by given viewing conditions. The goal was to determine the contrast thresholds of gratings by the given frequency and orientation. Contrast as a measure of relative variation of luminance for periodic pattern such as a sinusoidal grating is given by the equation

$$C = \frac{L_{\max} - L_{\min}}{L_{\max} + L_{\min}} \tag{1}$$

where $L_{\max}$ and $L_{\min}$ are maximal and minimal luminance of a grating. Reciprocal values of contrast thresholds express the contrast sensitivity (CS), and the contrast sensitivity as a function of spatial frequency determines the Contrast Sensitivity Function (CSF) defined by the equation

$$CSF(f) = 2{,}6.(0{,}0192 + 0{,}114 f).e^{[-(0.114 f)^{1.1}]}, \tag{2}$$

where $f$ is the spatial frequency in cycles/degree of visual angle. The CSF curve in Fig. 1 indicates that HVS is most sensitive to spatial frequencies between 5 and 10 cycles per degree and less sensitive to very low and very high frequencies. This fact can be used to develop a simple image independent HVS model.

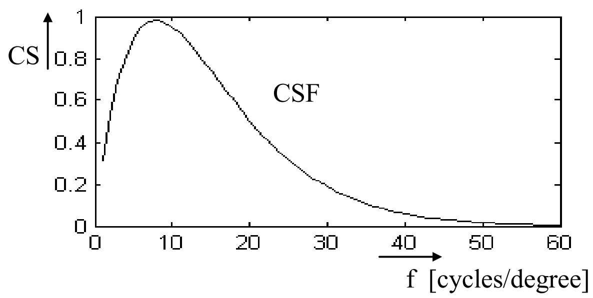


**Fig. 1.** Contrast Sensitivity Function.

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. Most of the models incorporate three basic properties of HVS: frequency sensitivity, luminance sensitivity and contrast masking.

## 2.1 HVS Model in DCT Domain

The discrete cosine transform is the basis of many compression standards. In image compression algorithms the image is divided into 8x8 pixel blocks that are transformed by using two-dimensional DCT into blocks of 64 coefficients. The DCT transform coefficients $y(u,v)$ of an $M$x$M$ block of pixels $x(i,j)$ are given by the following equation

$$y(u,v) = C(u).C(v) \sum_{i=0}^{M-1} \sum_{j=0}^{M-1} x(i,j).\cos\left(\frac{(2i+1)u\pi}{2M}\right).\cos\left(\frac{(2j+1)v\pi}{2M}\right), \tag{3}$$

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

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

In image compression algorithms based on DCT there has been a need of a good quantization matrix that would provide better quality of compressed images with higher compression ratio. The design of a quantization matrix that provides an optimal quality for a given bit rate depends on the visibility of DCT basis functions, since the error caused by quantization of a particular DCT coefficient will not be visible if its quantization error is less than corresponding JND threshold. HVS model in DCT domain can be obtained by approximation of experimentally measured detection thresholds for individual DCT basis functions. These JND thresholds $T(u,v)$ can be expressed in the following form

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

where $f_{0,v}$, $f_{u,0}$ are horizontal and vertical spatial frequency, respectively, the minimum threshold $T_{\min}$ occurs at spatial frequency $f_{\min}$, $K$ determines the steepness of the parabola, and $r$ is the model's parameter [2]. An example of this HVS model for an 8x8 block of DCT coefficients of a 256x256 image viewed from a viewing distance of 8 times image heights is depicted in Fig. 2.

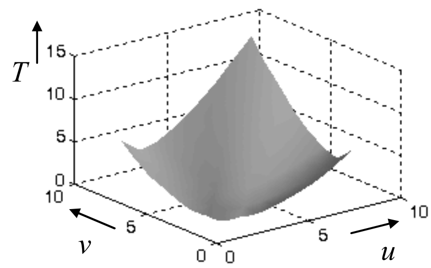


**Fig. 2.** HVS model in DCT domain for an 8x8 image block.

These thresholds determine frequency sensitivity of human visual system, which describes the human eye's sensitivity to sine wave gratings at various frequencies. The thresholds are image independent and represent the basic HVS model that depends only on viewing conditions. They are measured by a constant viewing distance and background (or mean) luminance. If the background luminance is changed then the thresholds change, too. A more complete perceptual model can be achieved by considering luminance sensitivity to finding the JND for each coefficient. Luminance sensitivity measures the effect of the detectability threshold of noise on a constant background. It is a nonlinear function of the local image characteristics and can be estimated as

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

where $y(0,0,k)$ 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 [3].

A much more precise perceptual model can be achieved by considering contrast masking by determining JND thresholds for each coefficient. Contrast masking refers to the effect of decreasing visibility of one signal in the presence of another signal called masker. The masking effect can be categorized as self-contrast masking and neighborhood masking. The self-contrast masking is a masking effect where the masking signal is of the same spatial frequency, orientation and location as the masked signal. JND thresholds of the contrast masking for each DCT coefficient by considering only the self-contrast masking can be evaluated as

$$T^C(u,v,k) = \max\left(T^L(u,v,k), \left|y(u,v,k)\right|^{w_{u,v}} (T^L(u,v,k))^{1-w_{u,v}}\right), \tag{6}$$

where $y(u,v,k)$ is the value of the DCT coefficient in block $k$, and $w_{u,v}$ is a number between zero and one. On the other hand the neighborhood masking arises when the masking signal is close in spatial frequency, orientation or location to masked signal. JND thresholds of contrast masking for each DCT coefficient by considering self-contrast masking and neighborhood masking can be evaluated as

$$T^C(u,v,k) =$$

$$= T^L(u,v,k).\max\left[1, \left( e^{\frac{-\pi\left((u-u_m)^2+(v-v_m)^2\right)}{\left(\varphi.\max\left(1,\sqrt{u^2+v^2}\right)\right)^2}} \frac{\left|y(u_m,v_m,k)\right|}{T^L(u,v,k)} \right)^{w_{u,v}}\right], \tag{7}$$

where $y(u_m,v_m,k)$ is the value of the DCT coefficient in block $k$ that acts as a mask of coefficient $y(u,v,k)$, $\varphi$ is a model's parameter, and $w_{u,v}$ is a number between zero and one [4]. There are some other masking effects, too. These include noise masking called activity masking, and entropy masking. By considering these masking effects one should obtain a very good model of human visual system.

## 2.2 HVS Model in DWT Domain

The discrete wavelet transform is widely used in signal processing applications such as signal analysis, denoising, compression etc. It is also the basis of image compression standard JPEG2000. The DWT decomposes a signal into a lowpass and a highpass signal by using a pair of QMF filters. The lowpass signal is called an approximation and the highpass signal is called a detail. This process of signal decomposition can be repeated by applying a second QMF filter pair on the just obtained approximation. The analyzed signal on the second level of decomposition is so expressed by one approximation and two detail signals. This process can be further repeated. Two-dimensional signals such as images are decomposed by DWT into subbands that vary in spatial frequency and orientation. Here we can distinguish between approximation, horizontal, vertical, and diagonal details.

In image compression based on DWT similarly to image compression based on DCT, a good quantization matrix is important. Such a quantization matrix should provide high compression ratio and at the same time a very good perceptual quality of a compressed image. For constructing that matrix, the knowledge of detection thresholds for DWT coefficients in various subbands and various levels of decomposition is needed. These visibility or detection thresholds $T_{L,O}$ in various subbands and on various decomposition levels for 9/7 biorthogonal wavelets were determined via psychological experiments and they can be expressed by the following equation

$$\log T_{L,O} = \log T_{\min} + K(\log f_L - \log f_0 g_O)^2, \tag{8}$$

where $L$ is the decomposition level, $O$ denotes orientation (1,2,3,4 for approximation, horizontal, diagonal, and vertical details), $T_{\min}$ is the minimum threshold occurs at spatial frequency $g_O f_O$, $f_L$ is the spatial frequency of level $L$, and $g_O$ shifts the minimum thresholds by an amount that is a function of orientation [5]. An example of visibility thresholds for DWT coefficients in a 256x256 image viewed form a viewing distance of 6 image heights and by using 4 level DWT is shown in Fig. 3.

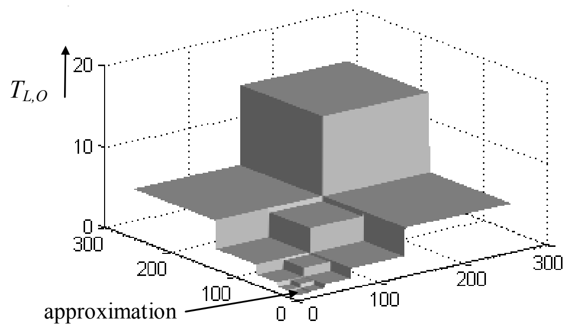


**Fig. 3.** HVS model in DWT domain by using 4 level image decomposition.

These visibility thresholds determine the basic image independent HVS model in DWT domain and express the frequency sensitivity of HVS in DWT domain. A more precise model would be achieved by considering other properties of HVS such as masking effect, to obtain an image dependent HVS model.

## 2.3 HVS Model Based on ROI

A man can see via photoreceptors on the retina. There are two kinds of photoreceptors – cones and rods. The density of these photoreceptors on the retina is nonuniform and thus determines the spatial resolution of HVS. The human's eye is most sensitive at the point of fixation that is the center point of Region of Interest (ROI) and its sensitivity decreases rapidly while the eccentricity (the distance to this point) gets larger. Based on psychological experiments that have been conducted to measure the contrast sensitivity as a function of eccentricity, the contrast thresholds CT that fit the experimental data can be given by the equation

$$CT(f,e) = CT_0 \exp\left(\gamma . f \frac{e+e_2}{e_2}\right), \tag{9}$$

where $f$ is the spatial frequency, $CT_0$ is the minimal contrast threshold, $e_2$ is the half-resolution eccentricity constant, $\gamma$ is the constant. and $e$ is the retinal eccentricity given by the equation

$$e(\vartheta, x) = \tan^{-1}\left(\frac{d(x)}{N.\vartheta}\right), \tag{10}$$

where $d(x)$ is the distance between the center point of ROI and the actual position in an image, $N$ is the horizontal image size and $\vartheta$ is a viewing distance measured in image widths [6].

An improvement of this model can be obtained by taking into account the cutoff frequency $f_m(x)$. The contrast thresholds $T_f$ are then defined as

$$T_f(\vartheta, f, x) = \begin{cases} \exp(0{,}0461.f.e(\vartheta,x)) & \text{for } f \le f_m(x) \\ \exp(0{,}0461.f_m(\bar{x}).e(\vartheta,\bar{x})) & \text{for } f > f_m(x) \end{cases} \tag{11}$$

where $x$ is a pixel position in an image, and $\bar{x}$ denotes a pixel position where $T_f$ reaches its maximum and after that point remains constant.

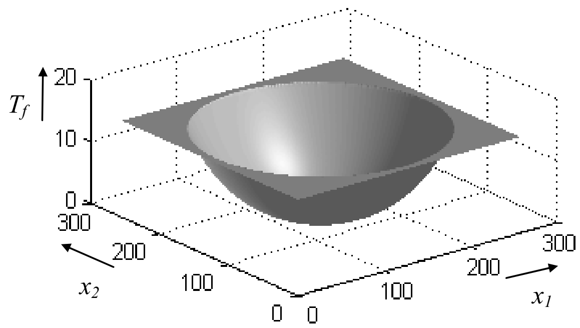


**Fig. 4.** HVS model based on ROI.

Thresholds $T_f$ represent the HVS model based on ROI and an example of that model for a 256x256 image viewed from a viewing distance of 6 image widths and with one ROI in the center of the image is shown in Fig. 4.

## 2.4 Combinations of Presented HVS Models

Contrast thresholds of HVS model based on ROI are used as weights for transform coefficients in compression algorithms. They can be used as weights for JND thresholds of frequency sensitivity of HVS model in DCT domain to incorporate the property of a nonuniform density of photoreceptors on the retina and to get a more complete HVS model. One possible combination of these two models is given by the following equation

$$T^F(\vartheta, f, u, v, k) = T(u,v).\left(1 + \frac{\beta . T_f(\vartheta, f, x_k)}{100.\max(T_f(\vartheta, f, x))}\right) \tag{12}$$

where, $x_k = x$ from block $k$: $\min(\|x - x_{ROI}\|_2)$, $x_{ROI}$ is the center point of ROI and $\beta$ [%] controls the impact of HVS model based on ROI on the final HVS model.

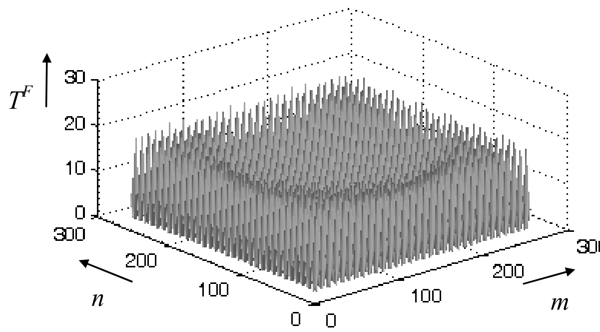


**Fig. 5.** Combination of HVS model in DCT domain and HVS model based of ROI.

An example of that model for a 256x256 image with 8x8 blocks decomposition viewed from a viewing distance of 6 image widths, with one ROI in the center of the image and $\beta$ = 100% is depicted in Fig. 5. These thresholds can be further corrected by luminance sensitivity and contrast masking as discussed in section 2.1.

HVS model based on ROI can be similarly used to weight visibility thresholds of HVS model in DWT domain. But it must be first expressed in DWT domain, that means the equivalent ROI and an equivalent distance between the actual position and the center point of ROI in each subband must be evaluated. This equivalent distance for a position $x$ in the subband $L,O$ is given by the equation

$$d_{L,O}(x) = 2^L \left\| x - x^f_{L,O} \right\|_2 \tag{13}$$

where $x^f_{L,O}$ is the equivalent center point of ROI in subband $L,O$. HVS model based on ROI in DWT domain is then given by the following equation

$$T_f(\vartheta, f, x) = T_f(\vartheta, f_L, d_{L,O}(x)). \tag{14}$$

One possible combination of the considered HVS models is given in the form

$$T_{f,L,O}(\vartheta, f, x) = T_{L,O}.\left(1 + \frac{\beta . T_f(\vartheta, f_L, d_{L,O}(x))}{100.\max(T_f(\vartheta, f_L, d_{L,O}(x)))}\right) \tag{15}$$

where $T_{f,L,O}$ are the JND thresholds of the final model and $\beta$[%] controls the impact of HVS model based on ROI on the final model. An example of this model for a 256x256 image, viewed from a viewing distance of 6 image widths with one ROI in the center of the image and $\beta$ = 50% is shown in Fig. 6.

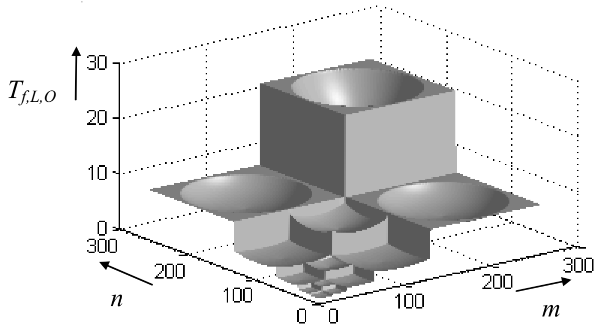


**Fig. 6.** HVS model in DWT domain by considering a combination with the HVS model based on ROI.

# 3. Applications of HVS Models

HVS models presented in the previous section were originally developed for image compression application. HVS model in DCT domain can be directly used to design a quantization matrix for a required compression ratio by providing optimal perceptual quality. A maximal quantization error is a half of a quantization step and therefore the straightforward way to get a quantization matrix is to set this quantization error equal to JND threshold of the corresponding DCT coefficient. Entries of the quantization matrix are then two times of the thresholds in HVS model. Another application is to use HVS model in an iterative process of optimization of the given quantization matrix to get the best image quality by required compression ratio. HVS model in DWT domain can be similarly used to find optimal quantization steps for DWT coefficients and to select perceptually important coefficients for coding. Thresholds of HVS model based on ROI are used as weights for transform coefficients in compression algorithms to select important coefficients and to sort these coefficients before coding.

The presented HVS models can be directly used in digital image watermarking, too. Here, we can distinguish three basic applications of HVS models:

- HVS models as image adaptive weights of watermarks,
- HVS models as filters of perceptually important image components,
- a combination of previous two applications.

In many watermarking algorithms the watermark is embedded by making a small modification of the original data. This modification is performed by adding or subtracting of watermark's elements. Before embedding the watermark is scaled by a weighting factor $\alpha$. The problem here is to find an optimal value of this weighting factor. A nice solution of this problem is the exploiting of HVS models. JND thresholds of a HVS model here determine the upper bounds of a modification of the original image by watermark embedding by preserving perceptual quality of the watermarked image. In this case watermark embedding can be described as

$$I^{w}(m,n) = I(m,n) + T(m,n).W(m,n) \quad (16)$$

where $I(m,n)$ and $I^{w}(m,n)$ are transform coefficients of the original and watermarked image, respectively, $T(m,n)$ is the corresponding JND threshold of HVS model, and $W(m,n)$ is an watermark element.

To get a robust watermark we need to embed it in perceptually significant components of an image, since perceptually unimportant components such as very small high frequency components are suppressed by a lossy image compression and other lowpass operations. To select these components (coefficients in transform domain) we can use HVS models as a filter of perceptually important image components. Watermark embedding is here expressed as

$$I^{W}(m,n) = \begin{cases} I(m,n) + \alpha.W(m,n) & \text{if } I(m,n) > T(m,n) \\ I(m,n) & \text{otherwise} \end{cases} . \quad (17)$$

The third application of the presented HVS models is the combination of previous two applications. Here HVS model is used as a filter of perceptually important image components and at the same time as image dependent weights for watermark scaling before its embedding [7]. Watermark embedding is expressed in this case by the following equation

$$I^{W}(m,n) = \begin{cases} I(m,n) + T(m,n).W(m,n) & \text{if } I(m,n) > T(m,n) \\ I(m,n) & \text{otherwise} \end{cases} . \quad (18)$$

Besides above presented HVS models that were developed originally for compression application there are other HVS models developed especially for image watermarking. One example is based on noise visibility in an image and is described by Noise Visibility Function (NVF). The original image is here considered as a random variable with non-stationary Gaussian or stationary Generalized Gaussian pdf. The best known form of NVF is given as

$$\mathrm{NVF(i,j)} = \frac{1}{1+\theta\sigma_{x}^{2}(\mathrm{i,j})} \quad (19)$$

where $\sigma_x^{2}(i,j)$ denotes the local variance of the image in a window centered on the pixel with coordinates $(i,j)$, $1 \le i, j \le M$ and $\theta$ is a tuning parameter corresponding to the particular image. Local variance is given by

$$\sigma_x^2(i,j) = \frac{1}{(2L+1)^2}\sum_{k=-L}^{L}\sum_{l=-L}^{L}(x(i+k,j+l)-\bar{x}(i,j))^2 , \quad (20)$$

with

$$\bar{x}(i,j) = \frac{1}{(2L+1)^2}\sum_{k=-L}^{L}\sum_{l=-L}^{L}x(i+k,j+l), \quad (21)$$

where a window of size (2$L$+1)x(2$L$+1) is considered. The image-dependent tuning parameter is given in the following form

$$\theta = \frac{D}{\sigma^2_{x\max}} \tag{22}$$

where $\sigma^2_{\max}$ is the maximum local variance for a given image and $D \in [50,100]$ is an experimentally determined parameter [8].


**Fig.7.** Noise Visibility Function of Lena image.

An example of NVF for image Lena is shown in Fig.7. NVF takes values between zero and one. Higher values of NVF (brighter regions in the image on Fig.7b) indicate flat region and vice versa smaller values of NVF (darker regions in the image on Fig.7b) indicate textured regions or regions with edges. Watermark embedding in a grayscale image in spatial domain by using NVF can be expressed in the following form

$$x^w(i,j) = x(i,j) + (1 - NVF(i,j)).w_{ij}.S + NVF.(i,j)w_{ij}.S_1 \tag{23}$$

where $x(i,j)$ and $x^w(i,j)$ are values of pixels for the original and watermarked image, respectively, $w_{ij}$ are watermark's elements, and $S$ and $S_1$ denote the watermark strength in busy and flat image regions. According to this equation the embedded watermark is content adaptive because the energy of the watermark is higher in textured and edges region than in the flat regions of the image. NVF can be also applied for watermark embedding in other domains such as DWT domain by evaluating NVF in particular subbands.

## 4. Conclusions

In this paper we have briefly described some HVS models used in image processing such as compression as well as digital image watermarking. Image compression algorithms such as JPEG use one quantization matrix for the whole image, since the amount of side information in a header of the compressed image data is limited. Therefore we cannot use different image dependent quantization matrix for each image block. However, in watermarking applications this limitation does not exist and we can take full advantage of HVS models and so get a very good tradeoff between perceptual transparency and robustness of embedded watermarks.

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