# ASYMMETRIC DCT-JND FOR LUMINANCE ADAPTATION EFFECTS: AN APPLICATION TO PERCEPTUAL VIDEO CODING IN MV-HEVC

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## ABSTRACT

Based on psychophysical experiments, we propose an asymmetric 3D just noticeable difference model (AJND) in the DCT domain taking into consideration the binocular properties of the human visual system (HVS), the background luminance and the spatial frequency of each DCT component. Subjective evaluations of the proposed AJND demonstrated that our proposed model offers good perceptual quality and could tolerate more distortion with PSNR reaching 24.19 dB. The proposed model has been used to perceptually optimize MV-HEVC by suppressing the residual transform coefficient that are lower than AJND values. Experimental results show that the proposed algorithm can achieve up to 14.62% bit-rate saving while preserving the perceived image quality.

*Index Terms*— Contrast sensitivity, Just Noticeable Difference, Stereoscopic, MV-HEVC

### 1. INTRODUCTION

Stereoscopic 3D video (S3D) is considered as the widely used image/video format due to its coding, transmission and display simplicity among other video formats. In the same vein, stereoscopic video can be easily adapted in communication applications with the support of existing technologies. However, for video coding applications the coding performance of a stereoscopic image/video could be further enhanced by reducing the perceptual redundancy in the scene. To address this problem, research efforts have been made to exploit the masking effect which is considered as one of the most complex properties of the human visual system (HVS) that refers to the perceptibility of one signal in the presence of another one in its spatial, temporal, or spectral vicinity [1]. The masking effect could be modelled by estimating an adaptive threshold known as the just noticeable difference (JND) referring to the maximum difference not perceived by the HVS.

Usually, JND models incorporate contrast sensitivity, luminance adaptation and contrast masking effects. Sophisticated JND computational models have been proposed in the literature and have been widely applied to perceptual image and video coding schemes [2,3], image/video quality assessment [4, 5] and watermarking/data hiding [6,7]. Typically, the state-of-the-art JND models can be classified regarding the applied domain into two categories : pixel-based domain [8-10] and subband-based domain [11-16] JND models. The thresholds for pixel-based (spatial) JND models are estimated directly form pixel luminance values. For subband-based domain, the thresholds are estimated over a transformed subband (DCT, DFT, Wavelets, etc). An early DCT-based JND model was proposed by Ahumada and Peterson [16], which estimates the threshold for each DCT component by using the contrast sensitivity function (CSF). Watson improved the threshold estimation proposed in [16] by incorporating the luminance adaptation (LA) and the contrast masking effects together with the CSF in the so-called DCTune [17]. Nevertheless, the vast majority of proposed DCT based JND models in the literature account only for cues related to 2D image and video contents and cannot accurately estimates the thresholds in the DCT domain when viewing 3D stereoscopic scenes.

To the best of our knowledge, there is no study of DCT based JND in the 3D stereoscopic images. So, in this paper, we propose a new asymmetric DCT based JND model allowing to estimate the thresholds in the presence of asymmetric distortion. We also propose a saliency modulation factor to be incorporated into the proposed JND model for coefficient suppression in the MV-HEVC.

The remainder of this paper is organized as follows. In Section 2, we introduce our proposed asymmetric JND for stereoscopic images. Perceptual validation of the proposed AJND model is presented in Section 3. The application of the proposed model on the MV-HEVC and the results are presented in Section 4. Finally, the contributions of this paper are summarized and the future work is outlined in section 5.

### 2. PROPOSED ASYMMETRIC 3D-JND MODEL

Our AJND (Asymmetric Just noticeable difference) model is expressed as the product of a basic threshold generated from the *CSF* and the luminance adaption factor. AJND is scaled by an adjustment factor according to the binocular disparity of the DCT block. The AJND model estimates the binocular distortion based on a generated DCT noise on the left view and is formulated as:

$$AJND(w,\psi,bg,D) = S \times N \times T_{basic}(w_{i,j},\psi) \times \alpha_{lum}(w,bg) \times T(D)(1)$$

where  $T_{basic}$  is the basic threshold generated by a spatial CSF and the  $\alpha_{lum}$  is the luminance adaptation effect modeled to enhance  $T_{basic}$  values accuracy based on the background luminance bg and the spatial frequency. S is the summation effect that compensates the (i, j) AJND values to estimate the AJND for all DCT coefficients (Sis set to 0.125 [12]). T(D) indicates the disparity adjustment factor defined in Eq.10 with D being the block disparity. In 1,  $w = w_{ij}$ stands for the spatial frequency of the (i, j) DCT coefficient, which is expressed in cycles per degree (cpd) and calculated using the following formula, where  $\theta_x$  and  $\theta_y$  are the horizontal and vertical visual angles respectively.

$$w_{ij} = \frac{1}{2N} \sqrt{\left(\frac{i}{\theta_x}\right)^2 + \left(\frac{j}{\theta_y}\right)^2} \tag{2}$$

For each (i, j) DCT coefficient,  $\psi$  is the directional angle between vertical and horizontal spatial frequency components  $(w_{i,0}$ and  $w_{0,j})$ .

$$\psi_{ij} = \arcsin\left(\frac{2.w_{i,0}.w_{0,j}}{w_{i,j}^2}\right) \tag{3}$$

### 2.1. Experimental setup

We conducted several perceptual experiments to measure the AJND thresholds regarding the binocular disparity and luminance adaption effect in the DCT domain. The experiment settings are presented in Table 1.(left). For the psychovisual experiments, the AJND values are measured for a zero disparity between both views of the test image (test image located at the screen plan). For each view, there is a test image of size  $256 \times 256$  that resides in the parafovea region with a central test patch of size  $32 \times 32$  (stimulus) corresponding to the foveal area. In this experiment, the DCT distortion is inserted only in the test patch of the left view as shown in Fig. 1.(right). To present each view to the appropriate eye, the subject has worn passive glasses.

Table 1: AJND psychophysical experiments description.

Experimenta	ITU-R comparison scales			
Display	Hyundai S465D	Score	Description	
Type and size	LCD 46"	-3	Much worse	
Resolution	$1920 \times 1080$ (Full HD)	-2	Worse	
Color Support	24-bit	-1	Slightly worse	
Number of subjects	13	0	The same	
Viewing distance	$2 \times H(\text{screen Height})$	1	Slightly better	
Ambient illumination	100 lux	2	Better	
Illumination behind the glasses	26 lux	3	Much better	

During the conducted experiment, the subject adjusts the injected noise in terms of amplitude of the DCT frequency component until the resulting distortion becomes binocularly visible. When more than 50% of the subjects detect the distortion, the injected noise is considered as above the AJND threshold. Furthermore, we assume that the DCT coefficients of the upper-right and down-left triangle of the  $8 \times 8$  DCT frequencies are nearly symmetric. By taking in consideration this property, we have selected 15 DCT coefficients for the psychophysical tests as described in Fig. 1.(left).



**Fig. 1**: (left): Selected subbands of the  $8 \times 8$  DCT (cell in red denotes the selected subbands). (right): Example of left view image distorted by injecting noise in the (0,5) DCT coefficient.

To avoid the effect of contrast masking, we have used ten test images with constant background luminance levels (bg). The set of bgs is defined from dark to bright gray levels as follows:

$$bg = \{13, 25, 51, 77, 102, 128, 153, 179, 204, 230\}$$
(4)

This experiment consists of 150 pairs of test images and DCT coefficients that are presented to the subject in a random way to avoid any kind of learning during the test. Each test took about 40 minutes with 5 minutes of rest after 20 minutes.

### 2.2. Basic AJND threshold

Fig. 2 illustrates the AJND values of all tested DCT coefficients according to the set of average background luminance bg. For most of the DCT coefficients used in the experiment, the AJND showed minimum values at the luminance background bg = 51. At this luminance level the effect of luminance masking would have a minor

effect on the basic thresholds. So, for modelling the generated CSF of this JND profile we have considered only the threshold values measured at the luminance background bg = 51. The oblique effect is one major factor that has to be considered when developing a basic DCT threshold [16]. This effect consists of the directionality of the HVS and considers a higher sensitivity for vertical and horizontal frequencies than diagonal ones. By taking advantage of the symmetry between DCT coefficients and the oblique effect, we need only to model the measured threshold values of diagonal and horizontal coefficients to obtain the  $T_{basic}$  threshold. As suggested by Fig.2.(left), the threshold of the horizontal and diagonal DCT coefficients could be modeled using a quadratic polynomial.



**Fig. 2**: Measured AJND threshold values: (left) JND threshold values from 0 to 13.33 (right) JND threshold values from 15.09 to 23.33.

The measured AJND values of DCT coefficients along diagonal and horizontal positions presented in Fig. 3, gradually increase along the spatial frequency axis. The least mean squared error method has been used to get the best fitted values of parameters D(w) and H(w)described previously. The obtained formulation is given in Eq.5.

$$\begin{cases}
D(w) = 0.0391.w^2 - 0.2167.w + 1.676 \\
H(w) = 0.0315.w^2 - 0.2914.w + 1.676
\end{cases}$$
(5)

Therefore, the basic threshold  $T_{basic}$  is expressed as:

$$T_{basic}(w,\psi) = D(w) + (H(w) - D(w)).cos(\psi)^2$$
(6)



Fig. 3: (a) Measured AJND values at bg=51 along the horizontal and diagonal DCT coefficients directions and their fitted curves. (b) Modeled  $T_{basic}$ . (c) LA values at bg = 13 and bg = 230 and their modeled curves  $\alpha_{13}$  and  $\alpha_{230}$ . (d) Modeled  $\alpha_{lum}$ .

#### 2.3. Luminance adaptation

According to the Weber-Fechner law [18], the minimum change in luminance  $\Delta I$  is a constant ratio of the original intensity I. Therefore, higher JND threshold values occur in brighter and darker regions knowing that the minimum thresholds has been found for bg = 51. Consequently, the luminance adaptation effect is shaped in V-shape curve according to bg. Since the proposed basic threshold  $T_{basic}(w)$  has been modeled only for background luminance intensity bg = 51, the rest of background levels have to be considered using the luminance adaptation effect  $\alpha_{lum}$ .  $\alpha_{lum}$  can be formulated as :

$$\alpha_{lum}(w, bg) = \frac{AJND}{AJND_{51}} \tag{7}$$

where  $AJND_{51}$  is the threshold values at bg = 51. We first model  $\alpha_{13}$  and  $\alpha_{230}$  that represent the  $\alpha_{luma}$  at bg = 13 and bg =230 respectively. Then, we extend to  $\alpha_{lum}$  in terms of w and bg.  $\alpha_{13}$  and  $\alpha_{230}$  are defined as:

$$\alpha_{13}(w) = -20.045 \times 10^{-4} \cdot w^2 + 9.612 \times 10^{-3} \cdot w + 1.746$$
  

$$\alpha_{230}(w) = 5.511 \times 10^{-3} \cdot w^2 - 0.2452 \cdot w + 5.226$$
(8)

Fig. 3.(c) and Fig. 3.(d) show the measured values of  $\alpha_{13}$ ,  $\alpha_{230}$  and their modeled curves respectively. Based on  $\alpha_{13}$  and  $\alpha_{230}$ , we define  $\alpha_{luma}$  for all values of bg as :

$$\alpha_{lum}(w, bg) = \begin{cases} 1 + (\alpha_{13}(w) - 1) \times \left(\frac{(51 - bg)}{38}\right)^5, & bg < 51\\ 1, & bg = 51 \ (9)\\ 1 + (\alpha_{230}(w) - 1) \times \left(\frac{(51 - bg)}{179}\right)^{1.8}, & bg > 51 \end{cases}$$

#### 2.4. Proposed disparity adjustment factor for AJND

It has been proven in [19] that the HVS is less sensitive to depth differences of objects at larger position from the fixation plane. In [20], authors assume that spatial distortion in objects with larger depth are less sensitive for the HVS. Based on empirical and geometrical studies, we defined T(D) as the adjustment factor of AJND to elevate the AJND value according to the disparity value of the block. Since, the AJND is estimated for a block of  $8 \times 8$  DCT, an average disparity value for each DCT block is calculated based on a pre-computed disparity map for each stereo-pair. T(D) is expressed as the ratio between the relative depth d and the depth Z to the observer:

$$T(D) = 1 - \frac{d}{Z} \tag{10}$$

The variation of the proposed adjustment factor values according to the depth z and the relative depth d is illustrated in Fig. 4.(a).

### 3. PERCEPTUAL VALIDATION OF THE AJND MODEL

To evaluate the effectiveness of the proposed DCT-based AJND, we performed a psychophysical validation based on the *Adjectival categorical judgment methods* as recommended by ITU-R BT.500-11 [21]. The experimental conditions remain the same as those given in Table 1 except for the viewing distance that has been set to four times the picture height. The observers are asked to evaluate the quality of the right stereoscopic image (distorted) in reference to the



**Fig. 4**: (a): Disparity adjustment factor relative to the depth and the relative depth of the object. (b): Principle of stereo-geometry. The angular disparity induced by point B  $\delta = \alpha_R - \alpha_L$ .

left stereoscopic image (original) and give quantitative scores as described in Table 1.(right). Nine  $512 \times 512$  uniform luminance images, for each image five levels of disparity have been applied. Furthermore, we computed the PSNR between the left and right views in the stereoscopic image in order to measure the amount of noise that the JND model can tolerate. The AJND noise is injected in all  $8 \times 8$  DCT coefficients as follows:

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$$C(k,i,j) = C(k,i,j) + S(k,i,j) \times AJND(k,i,j)$$
(11)

where C(k, i, j) is the (i, j)-th DCT coefficient in the (k)-th block and C'(k, i, j) is the noise-contaminated DCT coefficient with the AJND. S(k, i, j) is a bipolar random noise that takes a value of 1 or -1.

**Table 2**: Performance of the proposed AJND model in term of PSNR

 between the left and right images, and subjective scores (MOS).

		Crossed	Crossed disparity		No disparity		Uncrossed disparity			
Bg	2	20	1	0		0	2	20	1	10
	PSNR	MOS	PSNR	MOS	PSNR	MOS	PSNR	MOS	PSNR	MOS
13	31, 64	0,00	30, 83	0, 10	30,07	-0, 10	29, 38	-0,70	28,75	-0,70
25	33, 35	-0,60	32, 59	-0,60	31, 91	-0,70	31, 30	-1,00	30,75	-0,90
51	34,73	-0, 10	33, 91	-0,90	33, 16	-1, 10	32, 47	-1,20	31,84	-0,90
77	35,00	-0,40	34, 18	-0,60	33, 43	-1, 20	32,74	-1,20	32, 10	-1, 20
128	34, 56	-0, 10	33,74	-0, 20	33,00	-1,00	32, 31	-1, 10	31, 67	-1,00
153	32, 31	0,00	31, 49	-0, 40	30,75	-0,70	30,06	-1, 10	29, 42	-0,80
204	30,91	-0,30	30,09	0,00	29, 34	-0, 50	28,65	-1,00	28,02	-0,90
230	27,96	-0,30	27, 14	-0, 20	26, 39	-0, 40	25,70	-0,70	25,07	-1, 20
255	26,68	0,00	25,96	-0, 40	25, 31	-0, 10	24,72	-0,10	24, 19	-0,20
avg	31,90	-0,20	31,10	-0,36	30,37	-0,64	2 <b>9,70</b>	-0,90	2 <b>9,09</b>	-0,87

The PSNR and the mean opinion scores (MOS) for each image at different disparity levels are given in Table 2. It can be noticed that PSNR can reach lower values for brighter background luminance images that can reach 24.19 dB with less perceived distortion. This very significant tolerance to noise can be explained by the less sensitivity of the human eyes for distortion in lighter images. It is obvious from Table 2, that images at closer depth have higher values (less injected noise) than images at deeper depth. According to MOS values, the noise sensitivity decreases with depth position of the image.

### 4. AJND COEFFICIENT SUPPRESSION IN MV-HEVC

This section details the use of the proposed AJND model to perceptually optimize MV-HEVC based on the transform coefficient suppression. The later process suppresses every residual transform coefficient that does not exceed the AJND value. In order to effectively integrate the proposed model into MV-HEVC, we propose to incorporate the contrast masking as in [3]. Furthermore, we propose to control the intensity of the JND threshold values according to the visual attention generated by the saliency map from each frame in the left view video. Since HEVC uses variable block sizes for transform kernels from  $4 \times 4$  to  $32 \times 32$ , the AJND model designed for  $8 \times 8$  could not be effectively applied to such transform kernel. To fix this problem authors in [2] have proposed a new variable summation effect that consider the summation detection probability in TB. Based on the psychophysical experiment, authors in [2] propose a model for the summation effect that can handle the variation of TB sizes and is defined as  $S(N) = N^{-1}$ . The application of S(N)will cancel the effect of N in the AJND profile and AJND will be independent of TB size and is then defined as follows:

$$AJND(n, w, \psi, bg, D, R_S) = T(D) \times T_{basic}(w, \psi) \times \alpha_{lum}(w, bg) \times CM(n) \times \Delta S$$
(12)

where CM is the contrast masking effect which is calculated by dividing the DCT blocks into three categories. The masking factor can be derived based on inter- and intra-band masking.  $\Delta S$  is the saliency modulation factor which could enhance or reduce the visual sensitivity in a given scene.

#### 4.1. Saliency modulation factor

Visual saliency is one of the most important cognitive processes of the HVS, that can be used to modulate the visual sensitivity. The later one could be enhanced or reduced according to the visual saliency of the scene. Accordingly the JND model should be adjusted based on the saliency values of the given block. In the salient region the visual sensitivity is in it highest level, due to the high visibility of the region by HVS. In this work, we opted for the wellknown Itti-Koch saliency model [22], where saliency is derived from low-level visual features. The saliency modulation factor described by the following equation ranges between 0.53 and 1.85.

$$\Delta S(R_S) = 1.15 + 0.7 \times tanh\left(2 \times \left(\frac{1}{3.R_S + 0.1} - 1\right)\right) (13)$$

where  $R_S$  is the saliency level. As depicted in Fig. 5.(right) the saliency factor present a smooth transition between salient and no salient region in order to reduce the blocking artifact between neighbouring blocks.



Fig. 5: (left) Image from Balloons left view sequence and its predicted saliency map. (right) Saliency modulation factor

#### 4.2. AJND transform coefficient suppression in MV-HEVC

In HEVC, the transform basis functions are an approximation of the scaled DCT basis functions at the same size. HEVC explicitly inserts a right shift and clipping operation to ensure that intermediate values can be stored not exceeding 16-bit. The HEVC quantization process in the codec is defined as :

$$|D_{n,i,j}| = [|C_{n,i,j}| \times uiQ_{i,j} + O_f] \gg iQBits \qquad (14)$$

where iQBits indicates the number of bits for the right shift and is defined as  $iQBits = 14 + \frac{baseQp}{6} + iTransformShift$ , with iTransformShift representing the bits to be shifted for scale adjustment to approximate the DCT basis function and  $iTransformShift = 15 - 8 + log_2(N)$ .  $O_f$  is the rounding offset and uiQ refers to the quantization weighting multiplier for the transform coefficients.  $|C_{n,i,j}|$  and  $|D_{n,i,j}|$  denote the (i, j)output residual transform coefficient and the quantized one, respectively. Before, the suppression process, the AJND thresholds values have to be scaled as the transform coefficient. The scaled AJND is expressed as :

$$AJND_{n,i,j}^{s} = AJND_{n,i,j} \ll iTransformShift$$
 (15)

The coefficient suppression is implemented in the MV-HEVC quantization process. Here the quantization coefficient is equal to 0 for  $|C_{n,i,j}| \leq AJND_{n,i,j}^s$  and otherwise is calculated as :

$$\left(\left|C_{n,i,j}\right| - AJND_{n,i,j}^{s}\right) \times uiQ_{i,j} + O_f \gg iQBits \qquad (16)$$

#### 4.3. Performance evaluation

Comprehensive experiments were conducted in order to evaluate the performance of the proposed approach compared to the anchor MV-HEVC. Three well-known video sequences with two different resolutions ( $1024 \times 768$  and  $1920 \times 1088$ ) have been used in this experiment. Each sequence has been encoded using four quantization parameters 25, 30, 35 and 40. The coding performance are evaluated using the average bitrate saving over the four QP for each sequence ( $\Delta$ -BR) and the SSIM based metric which have been used in [23] to evaluate the stereoscopic image quality and is given by.  $SSIM_{disp1} = sqrt\left(\frac{SSIM(I_{lo}, I_{ld}) + SSIM(I_{ro}, I_{rd})}{2} \times SSIM(d_o, d_d)\right) (17)$  $(I_{lo}I_{ro})$  represents the original stereo-pair,  $(I_{ld}I_{rd})$  the distorted stereo-pair,  $(d_o, d_d)$ ) respectively original and distorted disparity maps. Table 3 illustrates the results obtained with the proposed AJND model in terms of bitrate-saving and  $MSSIM_{disp1}$  average. The proposed model provides significant bitrate savings depending on the used content and achieving up to 14.62% for the Kendo sequence. These saving comes with a negligible visual quality distortion that for all sequences (< 2%).

Table 3: Coding performance of the proposed model.

Sequences	$\Delta BR$	$\Delta SSIM_{disp1}$
Balloons	7.712%	1.188%
Kendo	14.62%	1.914%
UndoDancer	11.581%	1.298%

### 5. CONCLUSION

In this paper, we proposed a novel asymmetric JND (AJND) for stereoscopic images in the DCT domain. Based on psychophysical experiments, this model estimates the threshold of asymmetric noise in the DCT domain. The AJND incorporates the basic CSF and the luminance adaption effect and is modulated by a disparity adjustment factor. The subjective scores demonstrated that the proposed AJND can tolerate more noise at acceptable perceived quality. Objective and subjective results showed that the proposed method can provide significant bitrate saving without perceptible visual quality distortion. As a future work, the inclusion of effective contrast masking could be beneficial for the performance of the proposed model.

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