Curve-Based and Image-based JND Contrast Analysis for Inverse Tone Mapping Operators

Chih-Rung Chen and Ching-Te Chiu

***Abstract*—Recent studies on inverse tone mapping attempt to reproduce real-world images using low dynamic range (LDR) images. Evaluation metrics to qualify the performance of inverse tone mapping operators (iTMOs) are important. Just Noticeable Difference (JND) is widely used in image analysis as visual sensitivity measure for quality assessment. However, this measure does not provide insights into how the characteristics of iTMO curves affect the quality of high dynamic range (HDR) images. Therefore, based on the probability of various contrast changes, this study proposes a curve-based and an image-based JND quality assessment metric to detect visual distortion. The results of this curve-based and image-based quality metric match those of the visible difference predictor (VDP) method. This metric does not require complex calibration and involves only simple computation. In addition, this method reveals the effect of various iTMO curve parameters.**

***Index Terms*—Inverse tone mapping, Image quality assessment, Just noticeable difference**

I. Introduction

WITH the availability of high quality display devices, the acquisition of HDR images or videos is becoming more and more urgent. Though researchers have recently developed HDR video sensor technology, the cost of HDR acquisition devices remains high. HDR acquisition technologies that use a LDR detector have also been developed. Despite the increasing availability of HDR content, legacy LDR images and videos represent the majority content sources,. Other studies attempt to reproduce real-world images using LDR images. The problem of estimating HDR images from LDR photographs using inverse tone mapping operation (iTMO) has also received attention recently.

Rempel *et al*. [1] presented a linear scale curve in their real-time global iTMO algorithm. Akyüz *et al*. [2] evaluated several iTMO curves using two perceptual experiments and claimed that applying simple gamma curves to LDR images produces satisfactory results on HDR displays. Similar to Akyüzs experiments, Meylan *et al*. [3] introduced a piecewise tone scale function in which the shape of the scale function depends on the segmentation of the input images and its diffuse and specular components. Banterle *et al*. [5] proposed using an inverse photographic reproduction operator to extend the range of high luminance areas. Ke *et al*. [6] adopted inverse S-shaped curves to increase the contrast of brighter and darker area.

Most iTMO algorithms involve two types of quality assessment methods. One is based on perceptual experiments, the other type is quantitative analysis, which compares the difference of pixel intensity or contrast values between test and reference images. An HDR based visible difference predicator(HDR-VDP) presented by Mantiuk *et al* [7]. The VDP is a widely adopted evaluation metric that detects the difference between two images through a side-by-side comparison of individual image regions. The VDP simply indicates visual difference regions but is not suitable for identifying the exact types of differences. [8] presents a dynamic range independent quality assessment method capable of operating on an image pair with arbitrary dynamic ranges. They utilized a model of the human visual system, and defined visible distortion based on detection and classification of visible changes in the image structure.

One of the main purposes of these quality assessment metrics is to analyze the performance of various tone mapping operators. However, most approaches focus on the outcomes of the resulting images. The difference in the proposed quality assessment metric is that it measures image fidelity directly using an inverse tone mapping operator based on a model of the human visual system.

This study proposes an empirical inverse tone mapping evaluation framework and introduces a comparative analysis of contrast variation based on the concept of just noticeable difference (JND) [10]. This quality metric is suitable for inverse tone mapping curves directly or original input LDR images (LDRI) and output HDR images (HDRI). The proposed metric detects visual distortion based on the probability of various contrast changes using the JND model and the iTMO curves. Contrast changes include contrast loss, contrast retention, and contrast inversion. Using either curve-based or image-based JND evaluation methods, the results of this metric match those of VDP assessment methods. This metric does not require complex calibration and involves only simple computation. This method also helps reveal the effect of various parameters on the iTMO curves and analyzes which method is suitable for a given image. Compared with previous approaches, this evaluation metric provides valuable quality assessment results that are consistent with human perception while requiring relatively simple computation.

This paper is organized as follows. Section II describes the traditional and proposed evaluation framework for HDRI quality assessment. Section III presents curve-based and image-based JND contrast analyses, which define the contrast loss, retention, and inversion. This study uses global iTMO curves for evaluation. Section IV presents the assessment results of the proposed JND methods and HDR-VDP methods. Finally, section V provides a brief conclusion.

II. PROPOSED EVALUATION FRAMEWORK

Most assessment metrics require reference HDRIs to evaluate the image quality of a test HDRI generated from an iTMO. To obtain reference HDRIs, multi-exposure LDR photographs can be rendered to a high dynamic range image using synthesis tools. A reference HDRI can also be obtained by scaling from one input LDRI.

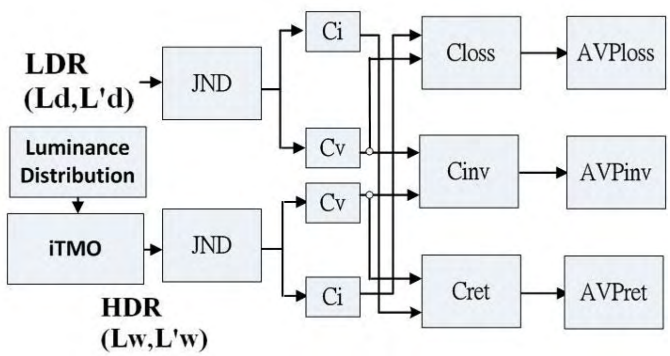


Fig. 1. Proposed JND-based iTMO evaluation frame work

Conventional HDR-VDP evaluation framework proposed by Mantiuk [7] compares visual differences in a pair of images, and the assessment results are closer to human perception system than traditional evaluation metrics like SNR. However, the HDR-VDP requires a reference HDR image for comparison.

JND is the smallest amount of luminance change for a luminance difference to be noticeable. JND has many applications in computer vision, image processing and multimedia technology, including video encoding, contrast enhancement, and distortion analysis, etc.

This study proposes a curve-based and image-based JND quality assessment metric to detect visual distortion based on various contrast change. Figure 1 shows the proposed JND-based iTMO evaluation framework. This JND-based evaluation metric compares the contrast variation of virtual HDRIs with original LDRIs using JND models. The contrast invisible (C_i) and contrast visible (C_v) are modelled in the LDR and HDR domains. Three types of contrast distortion, including contrast loss (C_{loss}), contrast retention (C_{ret}) and contrast inversion (C_{inv}) are evaluated after inverse tone mapping operations. In addition, the average contrast loss probability (AVP_{loss}), the average contrast inversion probability (AVP_{inv}), and the average contrast retention probability (AVP_{ret}) are calculated. The proposed framework consists of the curve-based and image-based JND analysis as Section III describes.

III. JND BASED CONTRAST EVALUATION

Sensing an observable difference in luminance requires a larger intensity difference for a bright background than a dark background. This study defines the contrast invisible $C_i(L, L')$ as Eq. (1) (a), where L is a reference luminance, and L' is a compared luminance. Taking JND into consideration, when the luminance difference $|L' - L|$ of L and L' is smaller than $\psi\cdot$ JND(L), the difference of the luminance or the contrast is invisible; otherwise the contrast can be perceived. The ψ is an adjustable constant for various just noticeable difference. The contrast invisible $C_i(L, L')$ and visible function $C_v(L, L')$ can be expressed as follows:

$$C_i(L,L')=\begin{cases}1, & |L-L'|<\psi\cdot JND(L)\\ 0, & |L-L'|\geq\psi\cdot JND(L)\end{cases} \tag{1a}$$

$$C_v(L,L')=1-C_i(L,L') \tag{1b}$$

Denote L_d as the display or LDR luminance and L_w as the world or HDR luminance. Then, consider three distortion cases. The first case is the loss of visible contrast C_{loss} that the original contrast is visible but contrast becomes invisible after inverse tone mapping. The second case is the retention of invisible contrast C_{ret} in which the original contrast is invisible and becomes visible after executing iTMO. The third case is the contrast inversion C_{inv} that the original visible contrast is still visible after inverse tone mapping but the polarity of the contrast becomes inverse. These three contrast distortions can be expressed as follows:

$$C_{loss}(L_d,L'_d) = C_i(L_w,L'_w)C_v(L_d,L'_d) \tag{2a}$$

$$C_{ret}(L_d,L'_d) = C_v(L_w,L'_w)C_i(L_d,L'_d) \tag{2b}$$

$$C_{inv}(L_d,L'_d) = C_v(L_w,L'_w)C_v(L_d,L'_d) \quad when \quad (L_w-L'_w)\cdot(L_d-L'_d)<0 \tag{2c}$$

where $L_w = iTMO(L_d)$ and $L'_w = iTMO(L'_d)$.

Following subsection analyze the curve-based and image-based JND evaluation metrics for contrast distortion.

A. Curve-based JND evaluation metric

This study adopts discrete analysis to find the contrast distortion probabilities. Assume that the input luminance levels can be discretized into N equally-spaced values which form a set S_L=$\{L_1, L_2, \ldots, L_N\}$, and the luminance distribution of the input image is $g(L)$. The $g(L)$ is a normalized luminance distribution in interval [0,1]. This study defines the contrast loss probability $P_{loss}(L)$, the contrast retention probability $P_{ret}(L)$, and the contrast inverse probability $P_{inv}(L)$ for a given luminance L in Eq. (3), where N_{ov} represents the number of luminance segments which are visible in the low dynamic range. N_{oi} is the number of invisible luminance segments in the low dynamic range.

$$\begin{aligned}
P_{loss}(L) &= \frac{1}{N_{ov}}\sum_{L'\in S_L} g(L')C_{loss}(L,L') && \forall L\in S_L\\
P_{ret}(L) &= \frac{1}{N_{oi}}\sum_{L'\in S_L} g(L')C_{ret}(L,L') && \forall L\in S_L\\
P_{inv}(L) &= \frac{1}{N_{ov}}\sum_{L'\in S_L} g(L')C_{inv}(L,L') && \forall L\in S_L\\
N_{ov} &= \sum_{L'\in S_L} g(L')C_v(L,L')\\
N_{oi} &= \sum_{L'\in S_L} g(L')C_i(L,L')
\end{aligned} \tag{3}$$

The average probability that the original visible contrast becomes invisible after iTMO is defined as the average of P_{loss} for all discrete luminance values (L_n). The N_L is the

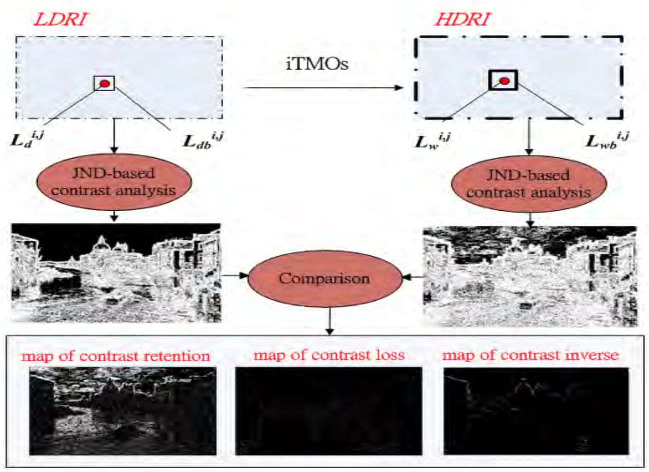


Fig. 2. Image-based JND contrast assessment flow

number of all discrete luminance values as Eq. (4) shows. When an iTMO curve has a high AVP_{loss}, the probability that contrast becomes lost after iTMO is high. The average probability that the original invisible contrast becomes visible after iTMO is AVP_{ret} as Eq. (4) shows. The higher the AVP_{ret}, the more likely it is that the imperceptible contrast between any two pixels will become visible after iTMO. A similar definition to the average probability of contrast inversion AVP_{inv}.

$$\begin{aligned} AVP_{loss} &= \tfrac{1}{N_L}\sum_{L\in L_n} P_{loss}(L) \\ AVP_{ret} &= \tfrac{1}{N_L}\sum_{L\in L_n} P_{ret}(L) \\ AVP_{inv} &= \tfrac{1}{N_L}\sum_{L\in L_n} P_{inv}(L) \end{aligned} \tag{4}$$

The contrast retention probability P_{ret} increases when the reference luminance L_d increases. Another observation is that when P_{loss} reduces to zero, P_{ret} begins to increase from zero. When an image histogram distribution is neglected for simplicity, the contrast inversion probability P_{inv} remains zero since the iPG iTMO curve is a strictly increasing function.

The distortion probabilities are defined under JND model for contrast variations of L_w and L_d after inverse tone mapping based on image histogram distributions. This definition is different from the detection probability in [8], which defined contrast distortion probability based on a detection function. For example, a contrast magnitude is visible with 50% probability if it can be detected by their predictor with 95% probability (about 2 JND) [8].

B. *Image-based JND assessment metric*

Figure 2 shows the image-based JND contrast assessment flow for a LDR image and the corresponding HDR image resulting from inverse tone mapping. For a pixel in position (i, j) with luminance $L^{i,j}$ in an image, the background luminance associated with this pixel denoted as $L_b^{i,j}$. The $L_b^{i,j}$ is obtained from the average luminance of an M by M block with (i, j) as the central pixel in this block. After obtaining the background luminance, JND value of this pixel at (i, j) is $JND(L_b^{i,j})$. When the difference between $L^{i,j}$ and $L_b^{i,j}$ exceeds the $\psi \cdot JND(L_b^{i,j})$, this pixel $L^{i,j}$ is visible compared to its background with a certain probability; otherwise, this pixel $L^{i,j}$ is invisible compared to its background with a certain probability. The luminance shown here could be either the display luminance or world luminance. The following discussion defines the contrast distortions under the image-based JND model.

$$C_{loss}^{i,j} = C_i(L_w^{i,j}, L_{wb}^{i,j})C_v(L_d^{i,j}, L_{db}^{i,j}) \tag{5a}$$

$$C_{ret}^{i,j} = C_v(L_w^{i,j}, L_{wb}^{i,j})C_i(L_d^{i,j}, L_{db}^{i,j}) \tag{5b}$$

$$C_{inv}^{i,j} = C_v(L_w^{i,j}, L_{wb}^{i,j})C_v(L_d^{i,j}, L_{db}^{i,j}), \quad when \quad C(L_w^{i,j} - L_{wb}^{i,j})C(L_d^{i,j} - L_{db}^{i,j}) < 0 \tag{5c}$$

Based on this concept, a visible contrast in the original LDR image but invisible contrast in the HDR images in the same position indicates a loss of original visible contrast. Conversely, if there is an invisible contrast in the original LDR image but the contrast becomes visible in the same pixel in an HDR image, this is contrast retention. Similar cases can be applied to contrast inversion distortion.

The default block size M for computing average luminance was set to 5 because experiment results show that differences of various contrast distortion under different block size M=5, 7, and 9 are slight.

Eq. (6) defines the AVP_{loss}, AVP_{ret}, and AVP_{inv} for image-based JND contrast assessment, which is similar as Eq. (4). The total number of pixels in an image is denoted as NP and L_n is the set of all pixels.

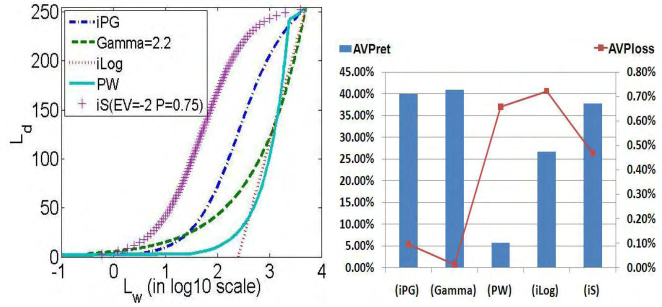
$$\begin{aligned} AVP_{loss} &= \tfrac{1}{NP}\sum_{i,j} P_{loss}(L) \\ AVP_{ret} &= \tfrac{1}{NP}\sum_{i,j} P_{ret}(L) \\ AVP_{inv} &= \tfrac{1}{NP}\sum_{i,j} P_{inv}(L) \end{aligned} \tag{6}$$

IV. EVALUATION RESULTS

A. *Curve-based JND analysis results*

HDR images generated from LDR images through inverse tone mapping are evaluated through the proposed curve-based and image-based JND quality assessment. This study considers five representative iTMO curves: inverse photographic curve(iPG)[5] , gamma expansion curve(Gamma) [2], inverse logarithmic curve(iLog)(an inverse tone mapping function from [9]), piecewise curve(PW) [3], and inverse S curve(iS)[6]. The following parameters are set for those curves: a maximum world luminance Lw_{max} =20 for the iPG, Gamma, iLog, and PW curves. Lw_{white} is set to 20 for iPG curve, while $\gamma = 2.2$ for the Gamma curve, and EV=0, P=1 for the iS curve. Figure 3(a) shows the mappings of LDR luminance to HDR luminance of those iTMO curves. Note that the output HDR luminance is scaled in log10 base.

There are several important ratiocinations in Fig. 3(a). First, the iLog curve becomes linear when the output is set as a log base, and the dynamic range expansion of iLOG is the smallest of the five iTMO curves. Although the iTMO curves except iLog significantly stretch contrast in bright and dark regions, the iS and PW curves enhance the bright regions more than



(a) (b)

Fig. 3. (a) The mapping curve of several iTMO curves (b) The probability distribution AVP_{loss} and AVP_{ret} of several iTMO curves

the others do. The iS curve achieves the largest dynamic range of output HDR luminance among these five curves.

This study uses the average contrast loss and retention probability AVP_{loss} and AVP_{ret} to analyze five iTMO curves, and Fig. 3 (b) shows the results. The iPG, Gamma, and iS curves have a higher average probability of contrast retention than the other two curves. The iPG and Gamma curves have a lower average probability of contrast loss than the other three curves.

Mapping the LDR luminance to HDR luminance through higher slope mapping curves stretches the luminance contrast more than applying smooth slope curves. This is why the AVP_{ret} values of iPG, Gamma=2.2, and iS iTMOs are higher than the other two curves. The iPG, Gamma, and iS curves have similar shapes. When the produced HDR luminance is brighter under a similar slope of mapping curves, it creates greater luminance contrast. This is why the iPG and Gamma curves have lower AVP_{loss} values than the iS curve.

B. Image-Based JND analysis results

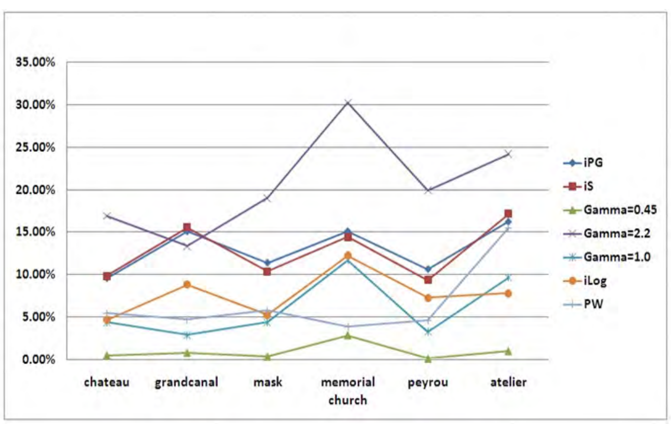


Fig. 4. Percentages of original invisible contrast retention area for 6 test images

Figure 4 shows the percentage of original invisible contrast retention area achieved by different iTMOs for these 6 test images. The parameter setting is the same as those in Table II. The percentages of iPG, iS and Gamma=2.2 iTMOs are higher than other iTMOs. Figure 5 shows the percentage of original visible contrast loss area of iTMOs for the 6 test images. The

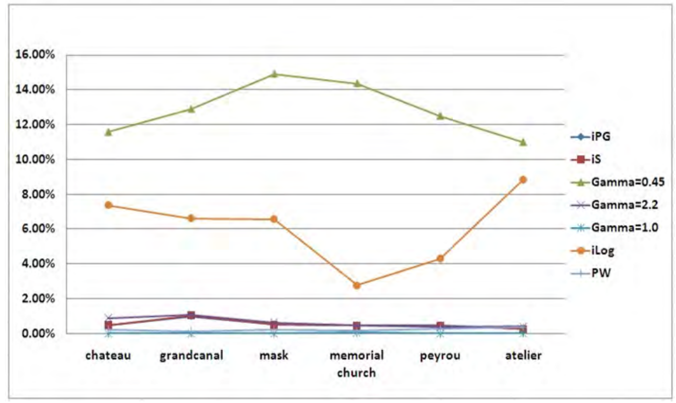


Fig. 5. Percentages of original visible contrast loss area for 6 test images

iLog and Gamma =0.45 curves have a larger contrast loss area, whereas the white areas of the other iTMO curves are lower than 2%.

V. CONCLUSION

This paper proposes a curve-based and image-based JND contrast analysis method for quality assessment for different iTMO operators. The results of this analysis match the characteristics of iTMO curves. A steep slope iTMO curve has a higher probability of contrast enhancement, whereas gentle slope means contrast loss. Inverse tone mapping curves such as iS, Gamma (2.2), and iPG have higher contrast retention than other iTMOs, while the Gamma (0.45) iTMO curve has the most contrast loss than others. The results of this curve-based and image-based quality metric matches with those of the HDR-VDP method. Compared with other evaluation methods, the proposed metric does not require complex calibration and involves relatively simple computation.

REFERENCES

[1] A. G. Rempel, M. Trentacoste, H. Seetzen, and H. D. Young, "Ldr2Hdr: On-the-fly Reverse Tone Mapping of Legacy Video and Photographs," *ACM Trans. Graph*, vol. 26, no. 3, pp. 267-276, 2007.
[2] A. O. Akyüz, R. Fleming, B. E. Riecke, E. Reinhard, and H. H. Blthoff, "Do HDR Displays Support LDR Content? A Psychophysical Evaluation," *ACM Trans. Graph*, vol. 26, no. 3, 2007.
[3] L. Meylan, S. Daly, and S. Ssstrunk, "Tone mapping for high dynamic range displays," *In Electronic Imaging*, 2007.
[4] B. Masia, S. Agustin, R. W. Fleming, O. Sorkine, and D. Gutierrez, "Evaluation of reverse tone mapping through varying exposure conditions," *ACM Trans. Graph*, vol. 28, no. 5, 2009
[5] F. Banterle, P. Ledda, K. Debattista, and A. Chalmers, "Inverse Tone Mapping," *In Proc. of GRAPHITE*, pp. 349-356, 2006.
[6] W. M. Ke, T. H. Wang, and C. T. Chiu, "Hardware-efficient virtual high dynamic range image reproduction," *IEEE ICIP*, 2009.
[7] R. Mantiuk, S. Daly, K. Myszkowski, and H. P. Seidel, "Predicting Visible Differences in High Dynamic Range Images - Model and its Calibration," *In: Proc. of Human Vision and Electronic Imaging X, IS&T/SPIE's 17th Annual Symposium on Electronic Imaging*, pp. 204-214, 2005.
[8] T. O. Aydin, R. Mantiuk, K. Myszkowski, and H. P. Seidel, "Dynamic range independent image quality assessment," *ACM Trans.Graph*, vol. 27, no. 3, 2008.
[9] F. Drago, K. Myszkowski, T. Annen, and N. Chiba, "Adaptive Logarithmic Mapping for Displaying high Contrast Scenes," *EUROGRAPHICS*, 2003.
[10] G. W. Larson, H. Rushmeier, and C. Piatko, "A Visibility Matching Tone Reproduction Operator for High Dynamic Range Scenes", *IEEE Trans. on Visualization and Computer Graphics*, vol. 3, no. 4, 1997.