Image Brightness Quantification for HDR

Stelios Ploumis
Electrical and Computer Engineering
University of British Columbia
Vancouver, Canada
sploumis@ece.ubc.ca

Ronan Boitard
Barco
Vancouver, Canada

Panos Nasiopoulos
Electrical and Computer Engineering
University of British Columbia
Vancouver, Canada

***Abstract*—Images' brightness quantification is challenging due to the perceptual nature of brightness. In Standard Dynamic Range (SDR), the most common brightness quantification metrics are the Average Picture Level (APL) and the Frame Average Luminance Level (FALL). These metrics rely on simple image statistics and they adequately quantify SDR images' brightness. However, they fail to sufficiently characterize the High Dynamic Range (HDR) broader luminance range and larger color volume. In this work, we propose a novel HDR image brightness quantification metric that weights each pixel contribution to overall brightness based on their color intensity and location. The proposed method is computationally inexpensive, thus suitable for real time applications. Results show that the proposed method outperforms the state-of-the-art HDR brightness quantification metrics.**

***Index Terms*—brightness quantification, brightness perception, high dynamic range**

I. Introduction

Brightness is the perception elicited by the light entering the human eye. [1]. In multimedia, "brightness" is described the perception of the light emitted by a display [2]. However, brightness is not linear to the absolute emitted luminance by a display [3]. Additional impact factors of brightness include the ambient illumination, the display's visual angle, the viewing distance as well as content characteristics. Given its complex nature, accurate images' brightness quantification is a challenging task.

In Standard Dynamic Range (SDR) the most common brightness quantification metrics are the Average Picture Level (APL) and the Frame Average Luminance Level (FALL). Both metrics are based on the arithmetic mean of an image's luminance channel and achieve to sufficiently quantify its brightness. However, they fail to characterize the impact on the Human Visual System (HVS) brightness mechanism of the High Dynamic Range's (HDR) broader luminance range and extended color volume.

There are a lot of applications for brightness quantification metrics in multimedia industry. First of all, content generation algorithms use such metrics to detect the brightest/dimmest frames of videos. Furthermore, tone mapping algorithms could also use them to preserve the brightness relationship of consecutive frames. Finally, brightness quantification metrics could also be used to avoid abrupt temporal brightness transitions that may lead to viewers' visual discomfort.

In this work, we propose a novel, real time, brightness quantification metric for HDR images. Our metric is based on the input images' luminance, color intensity, contrast and their pixels' spatial location to accurately quantify their brightness. More specifically, the proposed metric begins by converting the input images from perceptual to linear domain, which is more related to the adaptation level of the HVS. To acquire information about images' color (chromaticity and saturation) and the emitted light (when they are displayed), it computes the RGB_{max} matrix. The RGB_{max} is computed by preserving for each pixel only the maximum value of the RGB triplet. Then, the proposed metric weights each pixel's contribution to images' brightness based on their location with respect to the images' center. Pixels closer to the images' center are believed to contribute higher brightness than the ones closer to the edges [4]. Finally, the metric computes the Root Mean Square (RMS) of the weighted RGB_{max} matrix. The RMS is a statistic metric that combines the arithmetic mean with the standard deviation, making it ideal for brightness quantification metric. The arithmetic mean approximates the emitted light (when images are displayed) and color saturation while the standard deviation provides reliable information regarding contrast.

The rest of this paper is structured as follows. Section II provides an overview of brightness perception and presents the state-of-the-art image brightness quantification metrics. Section III describes our proposed HDR images' brightness quantification metric. Section IV presents and discusses results, while Section V concludes the paper.

II. Background

Human brightness perception mechanism has been extensively studied by computational neuroscientists [5], [6], [7] and psychologists [8], [9]. These studies mainly focus on characterizing how the HVS perceives and quantifies the luminance and color variations within an image. In contrast with these studies, in this work we focus on quantifying the overall perceived brightness of images. Previous studies have shown that overall images' brightness is determined by both the images' characteristics and the viewing conditions.

The main viewing conditions that impacts brightness perception of multimedia content is the ambient illumination level. The importance of ambient illumination comes from its key role to adaption level of HVS. In general, the human eye is able to detect luminance values ranging between 10^{-6} to 10^{8} cd/m^2, or in terms of dynamic range, 14 orders of magnitude [10]. However, the simultaneous dynamic range that the eye

can detect is limited to 5-6 orders of magnitude [11]. This limitation forces the HVS to constantly adapt to the ambient light conditions. Between the various adaptation levels spread throughout the entire dynamic range, the HVS perceives and interprets light and color differently. This results in images' brightness alteration between different adaptation levels [12].

In addition to the above, other viewing conditions factors that impact images' brightness are the display's visual angle and the viewing distance. Visual angle is the size of an object as seen by an observer and it is measured in degrees or arc. For a fixed physical set-up, the visual angle is getting greater as observers move closer to the display and vice versa. However, between different set-ups (i.e. living room and theater) the visual angle may be almost the same while the viewing distance is largely different. In [13] authors studied how these two factors impact images' brightness. The paper concludes that images' brightness increases when either the visual angle becomes larger or the viewing distance becomes lower or both.

Further to viewing conditions, brightness is also affected by images' characteristics, such as the total amount of light emitted by a display and its distribution. The total amount light emitted by a display contributes to the ambient illumination level, affecting the HVS adaptation light. On the other hand the distribution of the emitted light is highly correlated with the images' contrast. Higher contrast is assumed to lead in slightly brighter images even when the amount of emitted light remains fixed [14].

In addition to the emitted light,the colors depicted on images also affect their brightness. In [14] authors showed the independent impact of the primary colors (R,G,B) to an image's brightness. Specifically, they showed that the colors' brightness contribution is almost inversely proportional to their contribution to the luminosity function. In BT.709 [15], color gamut in SDR, the luminosity function is defined as:

$$Y = 0.2126 * R + 0.7152 * G + 0.0722 * B \tag{1}$$

while in BT.2020 [16], color gamut in HDR, is defined as:

$$Y = 0.2627 * R + 0.6779 * G + 0.0593 * B \tag{2}$$

For example, in the case of red, green and blue full frames of the same luminance, the blue frame is usually reported as brighter than the red one which in turn is reported as brighter than the green frame. Further to the colors' impact, the saturation of colors is also important for images' brightness. More saturated colors leads to higher brightness, even if the emitted light remains fixed [17].

Given the complexity of brightness, images' brightness quantification metrics are usually based only on content characteristics. Therefore, viewing conditions are assumed fixed. In SDR the main metrics (FALL and APL) are based on the arithmetic mean of the luminance channel (Y), differing only in the domain that they are computed. FALL is computed in the linear light domain (Y), while APL is computed in a perceptually linear domain (Y'). Perceptually linear domains are optimized to describe linearly the non-linear responses of HVS to light variations [18]. The most commonly used perceptually linear transform in SDR is the BT.1886 [19], while in HDR it is the Perceptual Quantizer (PQ) [18]. Regardless that both FALL and APL are based on simple image statistics (arithmetic mean), they both achieve to accurately quantify SDR images' brightness.

However, in HDR these metrics fail to characterize the impact on brightness perception of the broader luminance range and the extended color gamut [20], [4]. More specifically, the authors in [20] assessed the correlation of simple image statistic metrics with the images' brightness. The FALL, the APL, the 90 and 95th percentiles of the luminance intensities and the weighted mean of the luminance channel were some of the metrics used in this study. The authors concluded that the FALL provides the most accurate estimation for HDR images' brightness quantification over the rest evaluated metrics. This is explained by the FALL's impact on the HVS's adaptation level as it is equal to the average light emitted by a display. However, the small test set (13 images) is limiting the generality of this study.

In [4] authors proposed a new HDR brightness quantification metric. This method is based on the geometric mean (or logmean) and the variance of images' luminance channel in PQ domain (Y'). The metric is computed as follows:

$$Metric = \sqrt{0.65 \sqrt[n]{\prod_{i=1}^{n} Y'_i} + 0.35\sigma^2} \tag{3}$$

where, n is the total number of pixels and Y_n is the n-th pixel's Y' value. The use of the standard deviation (σ^2) provides to the metric information regarding the spread on the images' light distribution, or in other words of the contrast. Subjective evaluations indicating that this metric outperforms the FALL in predicting the brightest frame between two HDR frames. However, the overall accuracy of the method (60%) is considered relatively low.

The authors [4] further analyzed the cases where both of metrics failed to predict the brightest image. This analysis revealed a relationship between spatial location of specular highlights and images' brightness. Fig. 1 illustrates such an example with two HDR images. When the image with the large highlight on right was displayed on the right monitor (Fig. 1a) only 23% of the participants chose it as the brightest. However, this percentage was raised to 66%, when this image was displayed on the left monitor (Fig. 1b). Note that when showing sequentially those two images, only 8% of the participants voted as brightest the image with the large highlight. Driven by these results, we believe that images' brightness is also impacted by the relation of highlights' spatial location and observers' center of vision.

III. Proposed Method

In this work we propose an effective, computationally inexpensive HDR image brightness quantification method. The proposed method assumes fixed viewing conditions and it is based on images' light distribution, color and its pixels' spatial

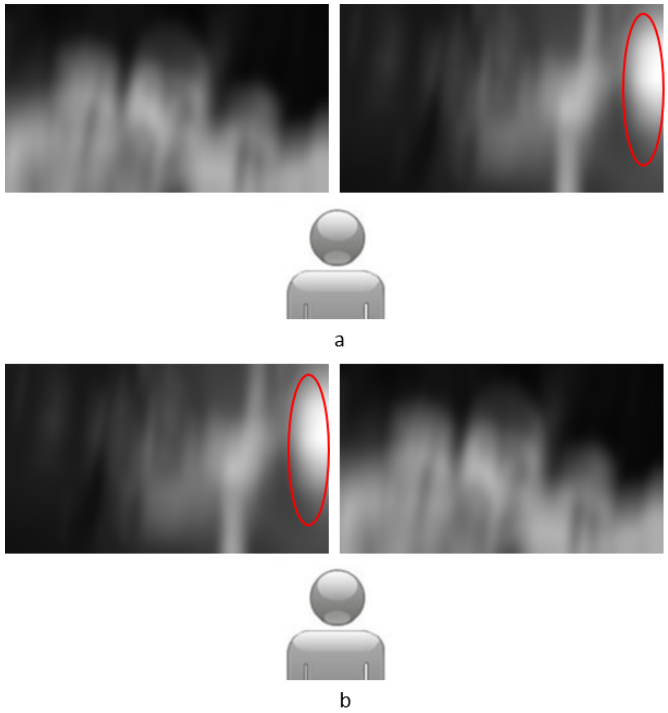

Fig. 1. Example of pixels on the edges' limited contribution to images' brightness.

location to quantify its brightness. The computational cost of the proposed metric is kept low to align with the applications that it is intended to be used.

Our method converts the input frames from perceptually linear domain (R'B'G') to absolute light linear values (RGB). As reported in [20], brightness quantification metrics perform better in the linear light domain. Perceptually linear domains tend to under-weight the high luminance values (Fig.2c,b), resulting in a less accurate approximation of emitted light's amount.

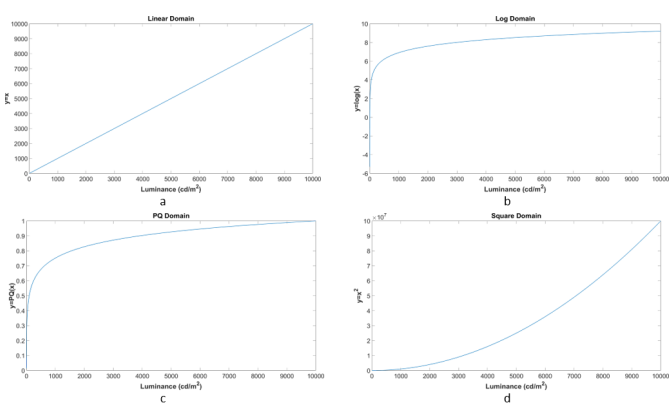

Fig. 2. Computational Domains (a)-Linear, (b)-Log, (c)-PQ, (d)-Square

The second step of the proposed method is to compute the RGB_{max} matrix from the input images' color channels (R,B and B). As it is stated by its name, the RGB_{max} matrix is calculated by keeping for each pixel only the maximum value of the RGB triplet (Fig.3b,c). The RGB_{max} matrix combines approximated information regarding images' luminance distribution and color. Fig. 3 shows the difference between the RGB_{max} matrix (Fig.3b,c) and the luminance channel (Fig.3d) as defined in (2). The pixels representing the blue sky are under-weighted on the luminance channel (Fig.3d), which comes in contrast with their contribution to image's brightness. On the other hand the RGB_{max} matrix (Fig.3c) emphasizes this area, achieving higher correlation with the image's brightness.

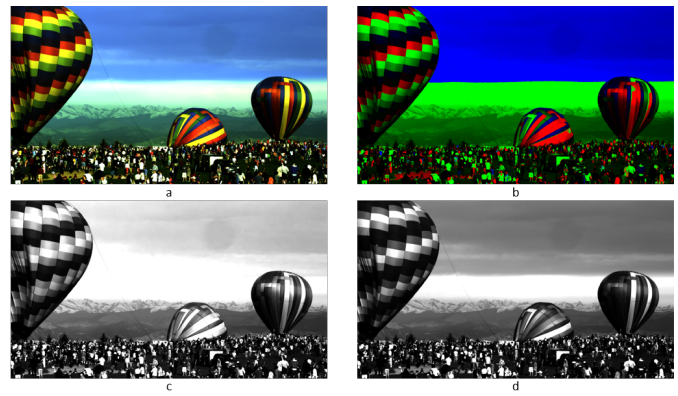

Fig. 3. Example of RGB_{max} matrix. (a)-Input frame, (b)-Color representation of RGB_{max} matrix. (c)-Actual RGB_{max} matrix. (d)-Luminance matrix

Our method continues by weighting the contribution of each pixel to image brightness according to their spatial location. The proposed weighting method (Fig. 4a,b) emphasizes the pixels located closer to the images' center over the pixels located closer to the edges. We compute the weighting filter by first calculating a 2D FIR filter (bandpass response [0,0.99]) followed by the application of a 2D Gaussian kernel ($\sigma = 2, H = 2$) and finally resizing the kernel to input image's size. Our method is based on previous studies [4], where authors reported the importance of images' center information their brightness. Furthermore, empirical evidence suggests that viewers' attention is mostly focused on images' center given its relationship with content action. Therefore, we believe that it is less likely for visual information on the edges to impact images' brightness. Fig. 4 shows the 3D (Fig.4a) and the 2D (Fig.4b) representations of the weighting filter while Figs.4 c and d illustrate its application.

To accurately quantify the HDR images' brightness using the filtered RGB_{max} matrix, we need to capture its mean and the degree of the distribution's spread. The mean provides information related to average emitted light and the average colors' saturation while the distribution's spread captures the images' contrast for both light and color.

The statistic metric that fulfills both requirements is Root Mean Square (RMS). The RMS is calculated as follows:

$$RMS = \sqrt{\frac{1}{n}\sum_{i=1}^{n} x_n^2} \tag{4}$$

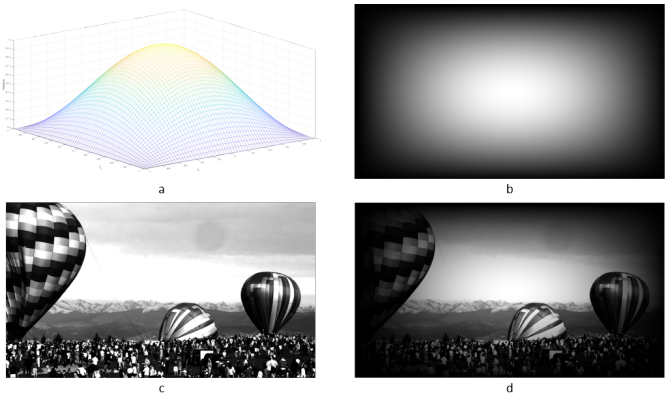

Fig. 4. The proposed weighting method and its application. (a)-3D representation, (b)-2D representation, (c)-Input RGB_{max} matrix, (d)-Resulting RGB_{max} matrix

where the n is the total amount of pixes and x_n is the n-th pixel's value on the RGB_{max} matrix. Due to fact that is calculated in the square domain, the RMS is highly correlated with the distribution's standard deviation (σ^2),as shown in:

$$RMS^2 = \overline{x}^2 + \sigma^2 \tag{5}$$

where, ($\overline{x}$) is the arithmetic mean ($\overline{x}$) and (σ^2) the standard deviation of a given set of n numbers. In other words, the RMS combines the arithmetic mean ($\overline{x}$) and (σ^2) the standard deviation.

IV. Results and Discussion

To assess the performance of the proposed method we used the dataset and the results of our previous subjective evaluation [4]. The dataset was composed of 100 professionally prepared (graded) HDR images (frames) at various average luminance levels. Specifically the FALL values of the dimmest and brightest images were 0.0895 cd/m^2 and 338.8536 cd/m^2 respectively while the peak luminance for this dataset was 1000 cd/m^2. These 100 images were organized in 50 pairs, where the FALL values of the two images of each pair were differing by 0.01 in the log domain.

In the first subjective study, each pair of images were displayed sequentially using one monitor, while in the second one each pair of images were displayed side-by-side using two monitors. For both studies, participants had to choose the brightest images of each pair. Two Sony BVM-X300 30" reference monitors were used for these studies.

In this work, we assess the performance of FALL, the method presented in [4] and our proposed metric. The metrics' performance evaluation is based on their accuracy to predict the brightest image for each pair, as it was picked by the participants of the experiments. Fig. 5 shows the results of the evaluation for both sequential and side-by-side experiments. On the y-axis is shown the percentage of pairs that the evaluated metrics' prediction was in agreement with the observers' choice regarding the brightest frame of each pair. As we observe, the proposed metric achieves the highest correlation with observers' choices for both experiments. Finally, regarding its processing speed, the Matlab implementation of the proposed metric process a FullHD image in 0.05 seconds on an Intel i7-7700k.

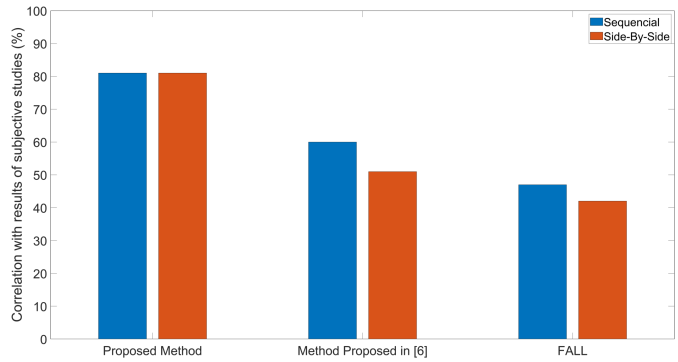

Fig. 5. Results of metrics evaluation. The proposed metric achieves higher correlation with observers' choices regarding the brightest image of each pair

At this point it is worth mentioning the weaknesses of the proposed method and to set the goals for future work. As shown in Fig. 5, the proposed metric outperformed by 35% the best state-of-the-art metric presented in [4]. However we believe that there is still room for improvement. The analysis of the pairs of images that our method failed, revealed that the images' content also impacts their brightness perception. For the majority of these pairs, the two member images were depicting scenes with different time in a day (i.e. afternoon and noon or morning and noon, etc). Therefore, we indent in future work to develop an HDR brightness quantification method that also considers images' semantic information such as time in day and indoor or outdoor.

V. Conclusion

In this paper, we proposed a novel brightness quantification metric for HDR images. Metrics used in SDR are not suitable for HDR due to the extended luminance range and larger color volume. The proposed method is based on pixels spatial location, luminance and color information to accurately quantify the images' brightness.

Performance evaluation results show that the proposed method achieves higher accuracy than other state-of-the-art methods in predicting the brightest of a pair of HDR images. More specifically, the proposed method outperformed the rest methods by at least 35%, achieving consensus with observers' picks of 81%. Furthermore, the low computational cost of the proposed metric makes it suitable for real time applications. In the future, we plan to further improve our method by utilizing information related to the context of an image. Preliminary analysis revealed that contextual features also impact images' brightness.

References

[1] Brian Wandell and Stephen Thomas, "Foundations of vision," *Psyccritiques*, vol. 42, no. 7, 1997.

[2] Robert William Gainer Hunt, *The reproduction of colour*, John Wiley & Sons, 2005.
[3] JC Stevens and Stanley S Stevens, "Brightness function: Effects of adaptation," *JOSA*, vol. 53, no. 3, pp. 375–385, 1963.
[4] Stelios Ploumis, Ronan Boitard, Jean-Philippe Jacquemin, Gerwin Damberg, Anders Ballestad, and Panos Nasiopoulos, "Quantitative evaluation and attribute of overall brightness in a high dynamic range world," *SMPTE Motion Imaging Journal*, vol. 128, no. 10, pp. 40–50, 2019.
[5] Stephen Grossberg and Dejan Todorovic, "Neural dynamics of 1-d and 2-d brightness perception: A unified model of classical and recent phenomena," *Perception & psychophysics*, vol. 43, no. 3, pp. 241–277, 1988.
[6] Thorsten Hansen and Heiko Neumann, "Neural mechanisms for representing surface and contour features," in *Emergent neural computational architectures based on neuroscience*, pp. 139–153. Springer, 2001.
[7] L Pessoa, E Mingolla, and H Neumann, "A contrast-and luminance-driven multiscale network model of brightness perception," *Ophthalmic Literature*, vol. 2, no. 49, pp. 120, 1996.
[8] Alan Gilchrist, Christos Kossyfidis, Frederick Bonato, Tiziano Agostini, Joseph Cataliotti, Xiaojun Li, Branka Spehar, Vidal Annan, and Elias Economou, "An anchoring theory of lightness perception.," *Psychological review*, vol. 106, no. 4, pp. 795, 1999.
[9] Sarah R Allred, Ana Radonjić, Alan L Gilchrist, and David H Brainard, "Lightness perception in high dynamic range images: Local and remote luminance effects," *Journal of vision*, vol. 12, no. 2, pp. 7, 2012.
[10] Ronan Boitard, Mahsa T Pourazad, Panos Nasiopoulos, and Jim Slevinsky, "Demystifying high-dynamic-range technology: A new evolution in digital media.," *IEEE Consumer Electronics Magazine*, vol. 4, no. 4, pp. 72–86, 2015.
[11] Erik Reinhard, Wolfgang Heidrich, Paul Debevec, Sumanta Pattanaik, Greg Ward, and Karol Myszkowski, *High dynamic range imaging: acquisition, display, and image-based lighting*, Morgan Kaufmann, 2010.
[12] Ali Iranli, Wonbok Lee, and Massoud Pedram, "Hvs-aware dynamic backlight scaling in tft-lcds," *IEEE Transactions on Very Large Scale Integration (VLSI) Systems*, vol. 14, no. 10, pp. 1103–1116, 2006.
[13] Alexandre Chapiro, Timo Kunkel, Robin Atkins, and Scott Daly, "Influence of screen size and field of view on perceived brightness," *ACM Transactions on Applied Perception (TAP)*, vol. 15, no. 3, pp. 18, 2018.
[14] Stelios Ploumis, Ronan Boitard, Gerwin Damberg, Anders Ballestad, and Panos Nasiopoulos, "Brightness in cinema: When is it too bright?," in *SMPTE 2019*. SMPTE, pp. 1–17.
[15] ITU BT.709 Recommendation, "Basic parameter values for the hdtv standard for the studio and for international programme exchange," *ITU-R BT*, 1990.
[16] ITU BT.2020 Recommendation, "Parameter values for ultra-high definition television systems for production and international programme exchange,," *ITU-R BT*, 2015.
[17] R Beau Lotto and Dale Purves, "The effects of color on brightness," *Nature neuroscience*, vol. 2, no. 11, pp. 1010–1014, 1999.
[18] Scott Miller, Mahdi Nezamabadi, and Scott Daly, "Perceptual signal coding for more efficient usage of bit codes," *SMPTE Motion Imaging Journal*, vol. 122, no. 4, pp. 52–59, 2013.
[19] Recommendation ITU-R BT. 2100-1, "Image parameter values for high dynamic range television for use in production and international programme exchange," 2017.
[20] Katy C Noland, Manish Pindoria, and Andrew Cotton, "Modelling brightness perception for high dynamic range television," in *2017 Ninth International Conference on Quality of Multimedia Experience (QoMEX)*. IEEE, 2017, pp. 1–6.