

PERCEPTION-BASED HIGH DYNAMIC RANGE COMPRESSION IN GRADIENT DOMAIN

Wen-Fu Lee, Tsung-Yi Lin, Mei-Lan Chu, Tai-Hsiang Huang, and Homer H. Chen

Graduate Institute of Communication Engineering, National Taiwan University

ABSTRACT

It is often required to map the radiances of a real scene to a smaller dynamic range so that the image can be properly displayed. However, most such algorithms suffer from the halo artifact or require manual parameter tweaking that is often a tedious process for the user. We propose an automatic algorithm for high dynamic range compression based on the properties of human visual system. The algorithm is performed in the gradient domain to avoid the halo artifact. It automates the parameter adjustment process while preserving the image details. Performance comparison is provided to illustrate the advantages of the proposed algorithm.

Index Terms—high dynamic range compression, human visual system, gradient domain, tone mapping, details compensation.

1. INTRODUCTION

The illumination in real world has vast dynamic range, normally from 10^{-3} to 10^5 . For example, the illumination of sunlight may be a million times stronger than that of shadows. However, the dynamic range we can perceive is usually between 0 and 10^4 because of the visual adaptation capability of human visual system (HVS). Conventional displays such as CRTs have an even more limited dynamic range, thus pixels with luminance value exceeding the dynamic range of the display are clipped.

In practice, since low dynamic range (LDR) images are unable to capture the wide range of illumination variation, high dynamic range (HDR) images are created. Techniques such as multiple exposure and image alignment [1] have been developed to produce HDR images with a dynamic range close to that of a real scene. However, how to display such images on a conventional display that only has a limited dynamic range (say, [0,255]) becomes a challenging problem. This is known as the tone mapping problem, for which a number of approaches have been proposed in recent years.

Existing tone mapping approaches can be classified into three categories: global operators, spatially variant operators, and gradient-domain operators. Reinhard et al. [1] give a thorough review of these operators. Global operators [6]-[8] treat each pixel independently and have the main

advantage of being computationally efficient. Since most displays accommodate no more than 256 levels of luminance value, all pixels must be quantized to fit within this range. Mathematically, global operators must be monotonically increasing functions to avoid contrast reversal [1]. Thus the use of a large quantization step size is inevitable, which makes it difficult for the global operators to preserve contrast and image details. Spatially variant operators [9]-[12] take local properties such as contrast and local average into account in the pixel mapping. Such local properties of images are extracted by a multi-scale scheme, which unfortunately produces halo artifact.

On the contrary, gradient-domain operators are almost free of the halo artifact. In the pioneering work by Fattal et al. [2], high gradients are attenuated more than low gradients, thereby achieving good compression. The perceptual framework proposed by Mantiuk et al. [3] also operates in the gradient domain. A transducer function is derived to transfer the luminance value of an image to the response of HVS to perceptual signal. The response is then compressed and inversely mapped to an LDR image. But the algorithm is more time consuming. Both algorithms require parameter tweaking.

We propose a gradient-domain algorithm that incorporates the properties of HVS in the high dynamic range compression process. A postprocessing technique for detail compensation is also developed to preserve the visual content. There is no parameter tweaking in the compression and the compensation processes.

We review the properties of HVS exploited in our work in Section 2. Then we describe the proposed algorithm in Section 3. The experimental results and discussion are given in Section 4, followed by the conclusion in Section 5.

2. PROPERTIES OF HUMAN VISUAL SYSTEM

This section describes the properties of HVS exploited in this work.

2.1. Contrast detection threshold

The contrast detection threshold is the smallest visible contrast of a stimulus presented on a uniform field. When the contrast is significantly above the detection threshold, human can detect it. This property is described by the Weber's law as follows [5]:

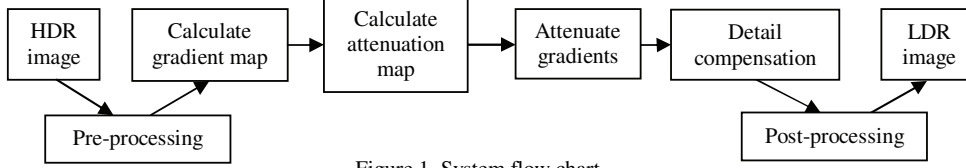


Figure 1. System flow chart.

$$W_{i,j} = \frac{L_i - L_j}{L_j} \approx 1\% \quad (1)$$

where $W_{i,j}$ is called the Weber Fraction that defines the contrast between pixels, and L_i and L_j are the luminance values of two neighboring pixels, $L_j \leq L_i$. According to the Weber's law, an image contrast smaller than 1% is not detectable by human eyes.

2.2. Suprathreshold contrast perception

A stimulus is considered a suprathreshold stimulus when its contrast is greater than the contrast detection threshold. The perception of contrast between pixels is affected by the luminance levels of the pixels. A reduction of contrast for pixels at low luminance level affects image perception more than the same reduction for pixels at high luminance level [4]. We apply this property in this work as well.

3. PROPOSED ALGORITHM

The algorithm described in [2] computes a gradient field of the image luminance and attenuates high gradients more than low gradients to achieve HDR compression. The resulting gradient field is converted to an image by a Poisson solver. Our algorithm is an extension of this gradient domain compression algorithm. However, our algorithm exploits the HVS properties described in Section 2 to enhance the visibility of image details while avoiding parameter tweaking. The system flow of our proposed algorithm is shown in Figure 1. The major steps of the algorithm are described in this section.

3.1. Preprocessing

The purpose of the preprocessing step is to compute the gradient map of an image. Among the various definitions of contrast, it is convenient to compute the contrast in the logarithm space [3]:

$$G_{i,j} = \log_{10} \left(\frac{L_i}{L_j} \right), \quad (2)$$

where L_i and L_j are the luminance values of two neighboring pixels, and $G_{i,j}$ is the contrast between pixels. Eq. (2) can be rewritten as:

$$G_{i,j} = \log_{10} \left(\frac{L_i}{L_j} \right) = \log_{10}(L_i) - \log_{10}(L_j) \triangleq x_i - x_j. \quad (3)$$

We use this equation to generate horizontal and vertical gradient maps.

3.2. Calculating the attenuation map

The visual adaptation properties of HVS are realized in the proposed system by computing the local contrast between a pixel and one of its neighbors and by applying Gaussian pyramid to get different levels of contrast as follows:

$$G_{i,j}^k = x_i^k - x_j^k, \quad (4)$$

where k denotes the level of Gaussian pyramid with G^0 as the full resolution image.

At each level k , an attenuation factor $\phi_{i,j}^k$ is computed:

$$\phi_{i,j}^k = \frac{\alpha}{\|G_{i,j}^k\|} \left(\frac{\|G_{i,j}^k\|}{\alpha} \right)^\beta, \quad (5)$$

where α determines which gradient magnitudes remain unchanged, and β controls the strength of gradient attenuation. The larger the gradient value is, the more the gradient value is attenuated. On the other hand, gradient values smaller than α are not attenuated such that the details of image are preserved. Then the attenuation function $\phi_{i,j}$ of the HDR image is computed from $\phi_{i,j}^k$ in a top-down fashion, similar to that described in [2]. Unlike the original method, where the parameters α and β are tuned manually for different HDR images, we propose an automatic approach based on the properties of HVS. More specifically, the fixed parameter β in Eq. (5) is replaced by $\beta_{i,j}^k$. For each pixel, we assign average contrast value of the HDR image to α as follows:

$$\alpha = G_{avg}^k \quad (6)$$

$$\beta_{i,j}^k = \begin{cases} 0.5 + \frac{0.25}{x_{max}^k - x_{avg}^k} (x_{max}^k - x_{i,j}^k), & \text{if } x_{i,j}^k > x_{avg}^k \\ 0.75 + \frac{0.25}{x_{avg}^k - x_{min}^k} (x_{avg}^k - x_{i,j}^k), & \text{otherwise} \end{cases}$$

where G_{avg}^k is the average contrast value of the HDR image at the k th level of the Gaussian pyramid, x_{max}^k ,

x_{min}^k and x_{avg}^k denote the maximum, minimum and average logarithm luminance values, respectively, at the k_{th} level of the Gaussian pyramid. We determine $\beta_{i,j}^k$ based on the suprathreshold contrast perception property of HVS described in Section 2.2. With $\beta_{i,j}^k$ and α , the gradients of high-luminance pixels are penalized more than those of low-luminance pixels. Besides, large gradients are attenuated more than small gradients. Finally, the attenuation function of the gradient map is determined by the gradient and luminance value at each level of the Gaussian pyramid.

3.3. Attenuating the gradient map

The Weber's law described in Section 2.1 should be converted to the logarithmic form so that it can be applied in the gradient domain. We modify Eqs. (1) and (2) as follow:

$$G_{i,j} = \log_{10}(W_{i,j} + 1) \approx 0.0043 \quad (7)$$

Pixels whose gradient magnitudes are smaller than 0.0043 are defined as the sub-threshold layer, and pixels whose gradient magnitudes are greater than 0.0043 are defined as suprathreshold layer. Since the contrast of sub-threshold layer is not detectable in an HDR image, we clip the gradient magnitudes of pixels in this layer to zero such that the limited dynamic range is not occupied with invisible contrast.

We only attenuate the gradients of pixels in the suprathreshold layer according to the attenuation map described in Section 3.2. For simplification, we use $G_{i,j}$ to represent the gradient of pixels in the suprathreshold layer in the rest of this paper. Attenuating $G_{i,j}$ by the attenuation function $\phi_{i,j}$ can be expressed as

$$G'_{i,j} = G_{i,j} \phi_{i,j}, \quad (8)$$

where $G'_{i,j}$ is the attenuated gradient map.

3.4. Detail compensation

Since one of the goals of tone mapping is to preserve the image details. We propose an algorithm to compensate the lost details due to compression.

By calculating the difference between $G_{i,j}$ and $G'_{i,j}$, we can get the lost gradients $D_{i,j}$ after tone mapping by

$$D_{i,j} = G_{i,j} - G'_{i,j}. \quad (9)$$

Then we perform the detail compensation

$$L_{i,j} = G'_{i,j} + \frac{D_{i,j}}{A|G_{i,j}| + \varepsilon} \quad (10)$$

where $L_{i,j}$ is the gradient map after detail compensation, ε is an offset used to avoid division by zero, and A is a constant. Here, $A|G_{i,j}|$ must be greater than one such that the gradient is not amplified in the compensation process.

Since high gradients in the HDR image are attenuated by a greater extent, the resulting $D_{i,j}$ for such gradients is relatively larger than that of the low gradient pixels. In Eq. (10), $D_{i,j}$ is divided by the corresponding original gradient magnitude multiplied by the constant A such that a smaller compensation is provided for pixels with large gradient magnitude in the HDR image, and vice versa. The constant A controls the extent of compensation. If it is too small, it may unnecessarily amplify every detail of the image, making the resulting image look unnatural and affecting the compression efficiency. In our work, we set A to 100 for all images. This value is determined empirically.

3.5. Post-processing

The resulting gradient map is converted to the image domain by a Poisson solver based on the multigrid algorithm, and then an exponentiation is applied to convert the image from the logarithm scale to the regular one.

Since our method operates on the luminance value of an HDR image, we employ the color-to-luminance ratio to recover a color image from its corresponding grayscale image [13],

$$C' = \left(\frac{C}{L}\right)^s L', \quad (11)$$

where C is the R, G or B value of the original HDR image, C' is the resulting R, G or B image after HDR compression, L and L' denote the luminance value before and after HDR compression, respectively, and s is a real-value parameter that controls the color saturation of the LDR images. In this work, we set $s = 0.7$.

4. EXPERIMENTAL RESULTS

We tested our proposed algorithm on a variety of HDR images. We compressed the dynamic range of HDR images exceeding $[1, 10^5]$ by the proposed algorithm and the algorithm described in [2]. The dynamic range of the resulting LDR images is limited to $[0, 255]$. The results are shown in Figure 2. The top row in Figure 2 is the LDR images produced by the competing algorithm and the bottom row by our algorithm. Since the parameters required by the competing algorithm needs manual adjustment to obtain visually pleasing results, we tuned those parameters to obtain results that look the best to us. We can find that the details of the image in Figure 2(a) are not as visible as those of the image in Figure 2(e). Likewise, the details of the sculpture in Figure 2(f) stand out better than those in Figure

2(b) and deliver a realistic impression, so are the remaining images in Figures 2(g)-(h).

5. CONCLUSIONS

We have proposed a gradient-domain algorithm based on the properties of HVS for high dynamic range compression. It performs better than existing algorithms and, more importantly, avoids the tedious parameter tweaking process required by most previous algorithms. We have also presented a compensation algorithm to preserve the details of the HDR image. Our algorithms work fairly well and demonstrate that automatic HDR compression is definitely feasible.

6. REFERENCES

- [1] E. Reinhard, G. Ward, and S. Pattanaik, P. Debevec, *High dynamic range imaging. Acquisition, display, and image-based lighting*, Morgan Kaufmann Publishers, San Francisco, 2005.
- [2] R. Fattal, D. Lischinski, and M. Werman, "Gradient domain high dynamic range compression," *Proc. SIGGRAPH*, pp. 249-256, 2002.
- [3] R. Mantiuk, K. Myszkowski, and H.P. Seidel, "A perceptual framework for contrast processing of high dynamic range images," *Proc. APGV*, pp. 87-94, 2005.
- [4] E. Peli, J. Yang, R. Goldstein, and A. Reeves, "Effect of luminance on suprathreshold contrast perception," *Journal of the Optical Society of America*, A8, pp. 1352-1359, 1991.
- [5] G. Wyszecki and W. Stiles, *Color Science*, John Wiley & Sons, New York, 2000.
- [6] J. Timblin and H. Rushmeier, "Tone reproduction for realistic images," *IEEE Computer Graphics and Applications*, pp. 42-48, 1993.
- [7] F. Durand and J. Dorsey, "Interactive tone mapping," *Eurographic Workshop on Rendering*, pp. 219-230, 2000.
- [8] S.N. Pattanaik, J. Tumblin, H. Yee, and D.P. Greenberg, "Timedependent visual adaptation for fast realistic display," *ACM Trans. Graph.*, pp. 47-54, 2000.
- [9] K. Chiu, M. Herf, P. Shirley, S. Swamy, C. Wang, and K. Zimmerman, "Spatially nonuniform scaling functions for high contrast images," *Proceedings of Graphics Interface*, pp. 245-253, 1993.
- [10] S.N. Pattanaik, J.A. Ferwerda, M.D. Fairchild, and D.P. Greenberg, "A multiscale model of adaptation and spatial vision for realistic image display," *Proc. SIGGRAPH*, pp. 287-298, 1998.
- [11] M. Ashikhmin, "A tone mapping algorithm for high contrast images," *Proc. 13th Eurographics Workshop on Rendering*, pp. 145-155, 2002.
- [12] E. Reinhard, M. Stark, P. Shirley, and J. Ferwerda, "Photographic tone reproduction for digital images," *Proc. SIGGRAPH*, pp. 267-276, 2002.
- [13] C. Schlick, "Quantization techniques for the visualization of high dynamic range pictures." *Proc. 5th Eurographic workshop on Rendering*, pp. 7-18, 1994

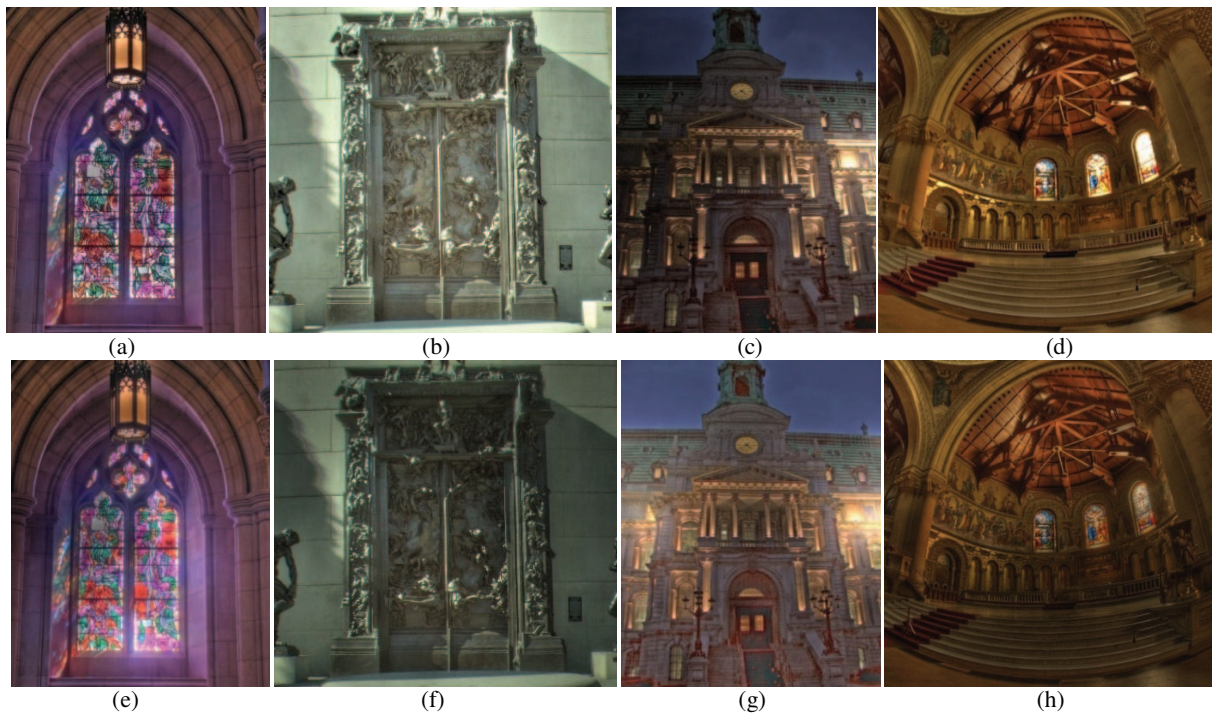


Figure 2. Images generated by Fattal *et al.* (top row) and our algorithm (bottom row).