

Gamut Mapping in a High-Dynamic-Range Color Space

Jens Preiss^a, Mark D. Fairchild^b, James A. Ferwerda^b, and Philipp Urban^c

^aTechnische Universität Darmstadt, Magdalenenstr. 2, 64289 Darmstadt, Germany;

^bRochester Institute of Technology, One Lomb Memorial Drive, Rochester, NY, 14623, USA;

^cFraunhofer Institute for Computer Graphics Research IGD, Fraunhoferstr. 5, 64283 Darmstadt, Germany

ABSTRACT

In this paper, we present a novel approach of tone mapping as gamut mapping in a high-dynamic-range (HDR) color space. High- and low-dynamic-range (LDR) images as well as device gamut boundaries can simultaneously be represented within such a color space. This enables a unified transformation of the HDR image into the gamut of an output device (in this paper called *HDR gamut mapping*).

An additional aim of this paper is to investigate the suitability of a specific HDR color space to serve as a working color space for the proposed HDR gamut mapping. For the HDR gamut mapping, we use a recent approach that iteratively minimizes an image-difference metric subject to in-gamut images.

A psychophysical experiment on an HDR display shows that the standard reproduction workflow of two subsequent transformations – tone mapping and then gamut mapping – may be improved by HDR gamut mapping.

Keywords: high dynamic range, tone mapping, gamut mapping, color space, image quality

1. INTRODUCTION

Natural scenes may have a dynamic range which is orders of magnitude higher than output devices (e.g., displays or printers) are able to reproduce. Furthermore, they may contain colors which considerably exceed the devices' color gamut. To account for such limitations, captured images must be distorted to fit into the reproducible color and dynamic range aiming to minimize the perceived difference to the original. Two subsequent transformations are usually applied for displaying high-dynamic-range (HDR) images on low-dynamic-range (LDR) output devices: 1. HDR tone mapping, and 2. color gamut mapping. Figure 1 (magenta box) illustrates the typical processing workflow. Such subsequent mappings may leave some room for improvement, particularly because most tone-mapping operators (TMOs) disregard color information and because gamut-mapping algorithms (GMAs) which operate on LDR color spaces may misinterpret the magnitude of perceived color contrasts within HDR scenes.

From the various TMOs proposed so far (for an overview see Reinhard et al.¹), only a few account for color. Disregarding color may result in tone-mapped images impaired by visually disturbing color shifts caused by luminance-induced appearance phenomena. The common practice in HDR tone mapping is color correction to obtain visually pleasant rather than perceptually accurate results.²⁻⁴ Another approach is to use color or image appearance models for tone mapping.⁵⁻⁷ Image appearance research is, however, in its infancy and existing models are combinations of multiple submodels empirically predicting individual mechanisms of the human visual system (HVS). It is questionable if this approach may accurately predict HVS responses for complex scenes or arbitrary viewing conditions. Furthermore, existing models require numerous viewing condition parameters which limit their applicability.

Further author information: (Send correspondence to Jens Preiss)

Jens Preiss: E-mail: preiss@idd.tu-darmstadt.de

Mark D. Fairchild: E-mail: jaf@cis.rit.edu

James A. Ferwerda: E-mail: mdf@cis.rit.edu

Philipp Urban: E-mail: philipp.urban@igd.fraunhofer.de

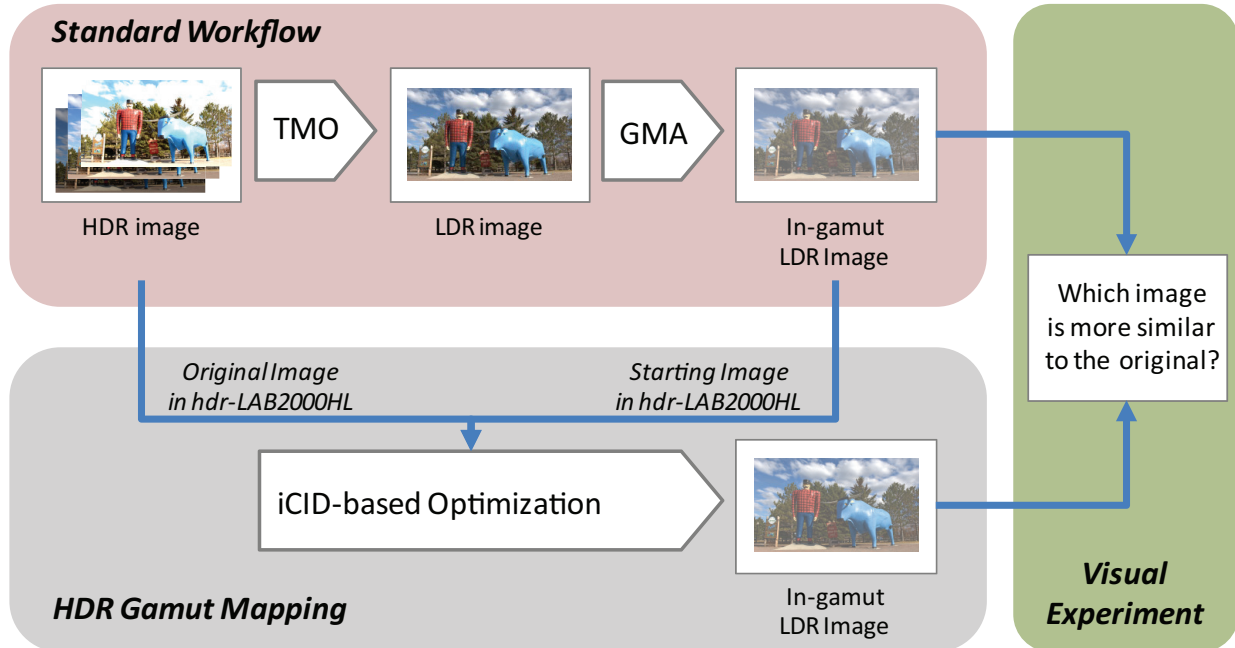


Figure 1. Illustration of 1. Standard Workflow, 2. HDR Gamut Mapping, and 3. Visual experiment.

The typical strategy of a subsequent color GMA (for an overview see Morović⁸) aiming to obtain a reproduction with a minimum perceptual distance to the original is to preserve the relationship between colors (contrast ratios). Since the original is the tone-mapped image represented in an LDR color space (usually hue corrected CIELAB or IPT⁹), the relation between colors may deviate from the one within the HDR image. Due to the aforementioned handling of colors by TMOs, it is unlikely that color contrast ratios of the original HDR image may be retained by the GMA.

In this paper, we present a novel approach of tone mapping as gamut mapping in an HDR color space. HDR and LDR images as well as device gamut boundaries can simultaneously be represented within such a color space. This enables a unified transformation of the HDR image into the gamut of an output device (in this paper called *HDR gamut mapping*).

We are not proposing a new GMA that operates within the HDR color space. In this work, we are particularly interested to what extent contrast ratios and structural information of the HDR image might be preserved by fully exploiting the LDR gamut. For this purpose, we minimize the perceptual disagreement between the original HDR image and a gamut-mapped image employing the iCID metric¹⁰ as the objective function in the HDR color space, i.e.,

$$Z = \operatorname{argmin}_{Y \in G} \mathbf{iCID}(X, Y), \quad (1)$$

where G is the device gamut, X is the HDR image, Z is the resulting LDR in-gamut image, and $Y \in G$ indicates that all pixels of Y are in G .

2. HIGH-DYNAMIC-RANGE COLOR SPACE

The recently introduced *hdr-CIELAB* and *hdr-IPT* color spaces¹¹ are HDR extensions of CIELAB and IPT. The modifications¹² consist mainly in a simple replacement of the spaces' non-linearities by an appropriately parametrized Michaelis-Menten function. We analogously adopt these modifications to the hue linear LAB2000HL color space¹³ designed to improve CIELAB with respect to perceptual uniformity. The resulting new HDR color space is denoted as *hdr-LAB2000HL*.

3. HIGH-DYNAMIC-RANGE GAMUT MAPPING

Since the concept of HDR color spaces is new, no experience within imaging applications has been gained so far. Therefore, an additional aim of this paper is to investigate the suitability of `hdr-LAB2000HL` to serve as a working color space for the proposed HDR gamut mapping. For the HDR gamut mapping, we used a recent approach that iteratively minimizes an image-difference metric subject to in-gamut images.¹⁴ The resulting image is within the LDR gamut and has a smaller difference to the original HDR image with respect to the metric. We used the *improved Color-Image-Difference* (iCID) metric¹⁰ as an objective function, which compares two images regarding local lightness, chroma, and hue differences as well as lightness-contrast, chroma-contrast, lightness-structure, and chroma-structure deviations. Visual experiments revealed that iCID-based gamut-mapping optimizations were judged to be perceptually more similar to the original image than results of state-of-the-art spatial GMAs.¹⁰

In this paper, we employed the same optimization algorithm but used an `hdr-LAB2000HL` representation of the images' pixels (see Figure 1 (gray box)). For transforming the HDR image to `hdr-LAB2000HL`, we computed the adapting luminance l_{adapt} by a geometric mean of the image pixels.¹⁵ The image's CIEXYZ values were then linearly scaled in order to map the adapting luminance l_{adapt} to the luminance of the middle gray value of `hdr-LAB2000HL`. An HDR image represented in `hdr-LAB2000HL` may contain pixels with significantly larger lightness values than the lightness of the perfectly reflecting white diffuser. Note that the `hdr-LAB2000HL` is optimized for CIE D65. In this work, no chromatic adaptation transform was applied to CIEXYZ values of the HDR image to account for different scene illuminants.

As starting image of the iterative optimization we used an in-gamut image that is derived from the original HDR image by applying a standard TMO and then a standard GMA. The iCID-based gamut mapping optimization is described in detail by Preiss et al.^{10,14} In each iteration the iCID distance between the actual in-gamut image and the reference HDR image decreases. In our experiments, the optimization was terminated after 20 iterations. Figure 2 shows the starting image (c) and the result of the optimization (d).

4. EXPERIMENT

In a psychophysical paired-comparison experiment (see Figure 1 (green box)), HDR gamut-mapped images obtained by minimizing the iCID metric were compared to the corresponding starting images (i.e., tone- and then gamut-mapped images). On an HDR display,¹⁶ one LDR representation was shown to the left and the other LDR representation was shown to the right of the original HDR image. The observers were asked to choose the LDR image which is perceptually more similar to the HDR image. Every image pair was shown twice but in reversed order. Tie decisions were not allowed.

Twelve natural images with indoor and outdoor scenes were used for the experiment. We applied three different TMOs: 1. Reinhard's bilateral TMO, 2. Drago's TMO (both from the HDR toolbox by Banterle¹⁷), and 3. tone mapping by iCAM06.⁶ For gamut mapping we used an existing gamut-mapping transformation incorporated in the `USNewsprintSNAP2007.icc` profile. We chose this small newspaper gamut to better illustrate the differences between results. A further gamut mapping which we applied was the color-space transformation from XYZ values to sRGB. The images were taken from Mark Fairchild's *HDR Photographic Survey*¹⁸ and from the DVD-ROM included in the book *High Dynamic Range Imaging* by Erik Reinhard et al.¹⁵

13 subjects attended the experiment. In total, 144 decisions were made by each subject (12 images \times 2 positions \times 3 TMOs \times 2 GMAs).

5. RESULTS

The fraction of all choices favoring the optimized image was computed for every image pair. The results are summarized in Table 1. We divided the image pairs into groups of gamuts (the `USNewsprintSNAP2007` newspaper gamut and the sRGB gamut, images (dominantly dark and others), and TMOs (Reinhard's bilateral TMO, Drago's TMO, and tone mapping by iCAM06).

For the small newspaper gamut (first row), about 95% of the subjects prefer the optimized to the reference LDR image for all images and TMOs (see first column). Thus, HDR gamut mapping might not only be an alternative to the standard HDR processing workflow but shows the potential for even significantly improving it.



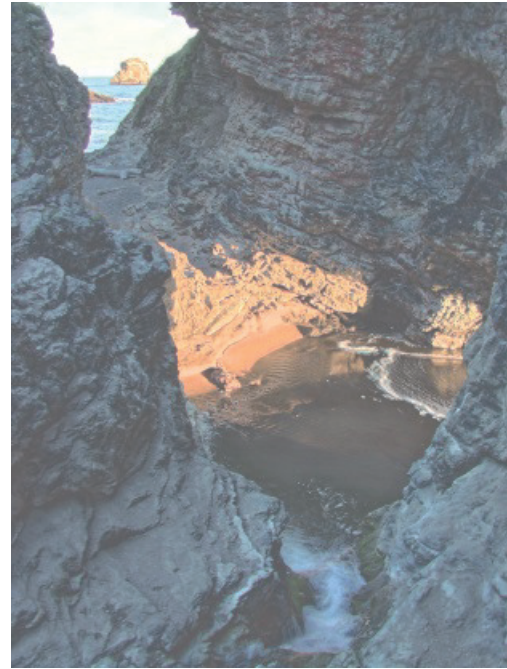
(a) HDR image



(b) Tone-mapped LDR image



(c) Tone- and gamut-mapped LDR image



(d) iCID-based optimized in-gamut LDR image

Figure 2. Steps of the proposed HDR gamut mapping: (a) HDR Reference, (b) Tone mapping, (c) Gamut mapping, (d) iCID-based optimization. Image (c) is used as starting image for the iCID-based optimization.

Table 1. Preference of the HDR gamut mapping to the standard HDR workflow.

		dominantly dark TMOs	all all	no all	yes all	Reinhard	all Drago	iCAM06
Gamut	Newspaper sRGB	0.95 0.52	0.98 0.63	0.90 0.35	0.93 0.51	0.95 0.53	0.96 0.51	



(a) Tone- and gamut-mapped LDR image



(b) iCID-based optimized in-gamut LDR image (20 iterations)



(c) Tone- and gamut-mapped LDR image



(d) iCID-based optimized in-gamut LDR image (20 iterations)

Figure 3. Example LDR image pairs of the experiment. Tone mapping by Drago and transformation to sRGB device gamut.

The results deviate noticeably for the sRGB device gamut (Table 1, second row). In total, only 52% of the observers preferred the iCID-based gamut-mapping optimization in this case (Table 1, first column). The optimization resulted sometimes in artificial looking images particularly if they are dominantly dark. In these cases, artifacts such as halos and over-sharpening were introduced and only 35% of the observer decisions favor the optimized results. For other images, 63% of all decisions preferred the optimized images. Examples for a dominantly bright and a dominantly dark image are shown in Figure 3.

For image scenes illuminated by daylight, color was improved compared to the standard workflow (e.g., see the sky and clouds in Figure 3(a–b)).

Further analysis reveals that for dark images used in the visual experiment 20 iterations of the iCID-based optimization were not enough. Figure 4 shows the decrease of iCID scores with increasing number of iterations for the dark image given in Figure 3(c–d). A noticeable improvement of iCID scores can be reached with 200

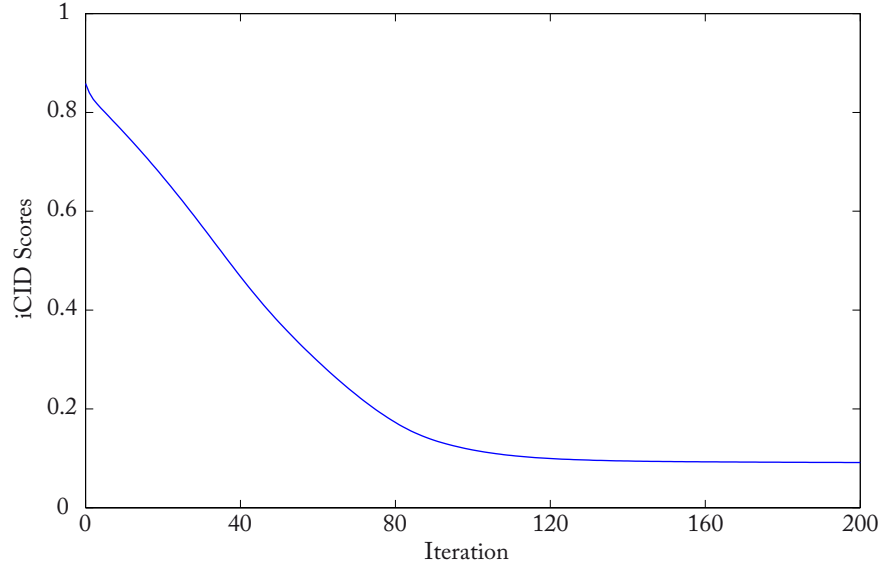


Figure 4. iCID scores vs. iteration number for the optimization of a dominantly dark image.



(a) iCID-based optimized in-gamut LDR image (200 iterations)

(b) iCID-based optimized in-gamut LDR image (200 iterations, chromatic adaptation)

Figure 5. Improvement of iCID-based HDR gamut-mapping optimization by applying 200 iterations (a) and CIECAM02 chromatic adaptation transform (b).

iterations. The corresponding image is illustrated in Figure 5(a). Halo artifact and over-sharpening artifacts were drastically reduced. The image looks natural. In future applications of the iCID-based HDR gamut-mapping optimization an appropriate number of iterations should be considered.

Note that we have not considered chromatic adaptation in the experiment and this image scene is dominantly illuminated by tungsten light. This is the reason for the hue shifts towards yellow. In Figure 5(b) this issue is handled by the CIECAM02¹⁹ chromatic adaptation transform (A to D65).

Even though only global luminance adaptation was considered in this work, details are visible in dark as well as in bright image regions. This is an interesting result indicating the suitability of the HDR color space for the purpose of HDR gamut mapping.

Finally, we analyzed the impact of different TMOs (used to compute the starting images) on the results of the HDR gamut mapping. The preference percentages in Table 1 (columns 4 – 6) are almost similar showing

that potential improvements by the iCID-based optimization are independent of the TMO used.

6. CONCLUSIONS

We have shown that tone mapping can be seen as a special case of gamut mapping if high-dynamic-range images are represented in a high-dynamic-range color space. Thus, tone and then gamut mapping can be replaced by one transformation. Further research shall consider local luminance adaptation for the hdr-LAB2000HL representation and an encoding within lookup tables similar as used by industrial color management systems for faster processing.

ACKNOWLEDGMENTS

This research is financed by the Deutsche Forschungsgemeinschaft (German Research Foundation).

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