Gamut Reduction Through Local Saturation Reduction

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Abstract

This work presents a local (spatially-variant) gamut reduction algorithm that operates only on the saturation channel of the image, keeping hue and value constant. Saturation is reduced by an iterative method that comes from inverting the sign in a 2D formulation of the Retinex algorithm of Land and McCann. This method outperforms the state-of-the-art both according to a quantitative metric and in terms of subjective visual appearance.

Introduction

Gamut reduction deals with the problem of modifying the color gamut of an input image to make it fit into a smaller destination gamut. Gamut reduction occurs both in the printing industry where images must be carefully mapped to those colors that are reproducible by the inks presented at a particular printer and in the cinema industry where cinema footage needs to be passed through a gamut reduction method in order to be displayed on a television screen [4], [10].

A thorough survey of gamut reduction methods can be found in the book of Morovič [18]. In general, we can group gamut reduction methods into two classes: global and local methods. Global methods [6, 9, 14, 15, 17, 20–22] treat pixels of the image independently from their surround by applying a point-to-point mapping from the colors present in the source gamut to those in the target gamut. While global methods are fast and quite effective in general, by construct they disregard the spatial distribution of colors which does cause some issues, like turning a smooth color gradient image region into a flat-color object by mapping several out-of-gamut colors onto the same in-gamut color, and ignoring the fact that in visual perception the appearance of colors is heavily influenced by their spatial context in the image. Local methods, like the ones presented in [2, 3, 8, 11, 16, 19, 23], are designed to cope with those problems.

The contribution of this paper is to present a novel, local gamut reduction algorithm that outperforms the state-of-the-art both according to a quantitative metric and in terms of subjective visual appearance. Our work builds on the assumption that, in order to perform gamut reduction in the HSV space, it is sufficient to decrease the saturation values while keeping the hue and value channels constant. We achieve this by applying, just to the saturation channel, an iterative method that reduces contrast, adapted from [5].

Proposed Gamut Reduction Algorithm

In their kernel-based Retinex (KBR) formulation, Bertalmío et al. [5] take all the essential elements of the Retinex theory (channel independence, the ratio reset mechanism, local averages, non-linear correction) and propose an implementation that is intrinsically 2D, and therefore free from the issues associated with implementations based on random paths. For each initial image channel intensity I_0, the KBR method iteratively computes the perceived value I with the equation

$$I^{k+1}(x) = \frac{I^k(x) + \Delta t \left(\beta I_0(x) + \frac{\gamma}{2} R_{I^k}(x)\right)}{1 + \beta \Delta t}, \tag{1}$$

where k is the iteration index, x is the pixel location, Δt is the time step, β and γ are constants, and $R_{I^k}(x)$ denotes a contrast-modification function:

$$\begin{aligned} R_{I^k}(x) = \sum_{y \in \Im} w(x,y) \bigg[& f\left(\frac{I^k(x)}{I^k(y)}\right) \mathrm{sign}^+(I^k(y) - I^k(x)) \\ & + \mathrm{sign}^-(I^k(y) - I^k(x)) \bigg], \end{aligned} \tag{2}$$

where $w(x,y)$ is a normalized Gaussian kernel of standard deviation σ, f is a monotonically increasing function, and the functions $\mathrm{sign}^+(\cdot)$ and $\mathrm{sign}^-(\cdot)$ are defined as:

$$\mathrm{sign}^+(a) = \begin{cases} 1, & \text{if } a > 0, \\ \frac{1}{2}, & \text{if } a = 0, \\ 0, & \text{if } a < 0, \end{cases} \tag{3}$$

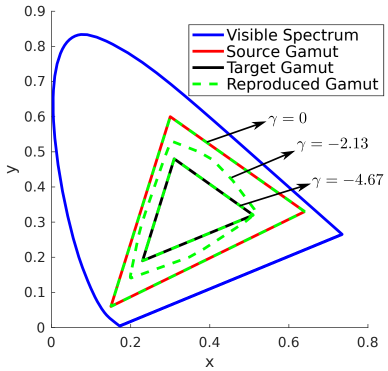
$$\mathrm{sign}^-(a) = 1 - \mathrm{sign}^+(a). \tag{4}$$

In [5] it is shown that, with $\gamma > 0$, running Eq. (1) to steady state produces a contrast-enhanced output I_{ss} where $I_{ss}(x) \geq I_0(x), \forall x$. But, if $\gamma < 0$, then the output I_{ss} has its values reduced with respect to the original, $I_{ss}(x) \leq I_0(x), \forall x$.

The human visual system is highly sensitive to hue changes, which is why one main aim while performing gamut mapping is to preserve hue. Therefore, we opt to work in the HSV color space and modify only the saturation component, keeping both hue and value constant: the gamut reduction goal can be formulated as decreasing the saturation. For this purpose, then, we first convert the RGB input image into the HSV color space, and then apply Eq. (1), with a negative value for γ, to the saturation component only.

Implementation

In the gamut mapping community, it is a very common and recommended practice to leave those colors of the input image unchanged that are already inside the destination gamut and apply gamut reduction operation to the out-of-gamut colors only. To follow this approach, the proposed GRA works iteratively. The general structure of our iterative GRA is as follows: at each iteration, we run Eq. (1) for some particular values of β and γ until we reach the steady state (in the first iteration the values are $\beta = 1$, and $\gamma = 0$). The steady state of each iteration will provide us with some pixels that we mark as "done" and we would not modify



(a)

(b)

Figure 1: Gamut reduction procedure. (a) Gamuts on chromaticity diagram. (b) Results of gamut reduction. Top left: input image. Top right: reduced gamut image (same as of input image) when $\gamma = 0$. Bottom left: reduced-gamut image with $\gamma = -2.13$. Bottom right: reduced-gamut image with $\gamma = -4.67$. Out-of-gamut colors are masked with magenta color; as we reduced γ value the number of out-of-gamut colors is also decreased.

Figure 2: sRGB test images. From left to right, top to bottom: first 2 images are from [1], image 3 and 4 are from [7], image 5 is from [8] and the last two images are from the photographer Ole Jakob Bøe Skattum.

Table 1: Primaries of gamuts.

Gamuts	Red Primaries		Green Primaries		Blue Primaries	
	x	y	x	y	x	y
sRGB	0.640	0.330	0.300	0.600	0.150	0.060
Toy	0.510	0.320	0.310	0.480	0.230	0.190

their values in subsequent iterations (i.e. these pixels are now part of the final output). We move to the next iteration where we make a small decrement in the γ value (for example, setting $\gamma = -0.05$) and run again Eq. (1) until steady state, and then check whether any of the pixels that were outside the gamut at the previous iteration are now inside the destination gamut: we select those pixels for the final image and leave them untouched for the following iterations. We keep repeating this process until all the out-of-gamut colors are mapped inside the destination gamut. An example of this iterative procedure is shown in Fig. 1b, where pixels in color magenta represent the out-of-gamut pixels remaining in that iteration. The corresponding evolution of the gamut is illustrated in Fig. 1a, showing that as γ decreases the gamut is gradually reduced.

Experiments and Results

In this section we compare, visually and by using a perceptual error metric [13], the performance of our GRA with other methods such as LCLIP [21], HPMINDE [20] and the algorithms of [22] and [2]. We apply the proposed GRA in HSV color space and the parameters values used in Eq. (1) are $\beta = 1$, $\Delta t = 0.10$. The non-linear scaling function that we use is $f(r) = A\log(r) + 1$, where $A = \frac{1}{\log(256)}$. The value for σ, the standard deviation for $w(x,y)$, is equal to the one-third of the number of rows or columns of the input image (whichever is greater). In order to map colors from a larger source gamut to a smaller destination gamut, we keep iterating the evolution equation (1) for each γ value until the difference between two consecutive steps falls below 0.5%.

Visual Quality Assessment

To evaluate the image reproduction quality, we map colors of sRGB images (Kodak dataset [12] and images of Fig. 2) to a challenging smaller 'Toy' gamut using the competing GRAs. The color primaries of sRGB and Toy gamuts are given in Table 1. The results presented in Fig. 3 show that the proposed GRA produces images that are perceptually more faithful to the original images than the other methods, preserving hues and retaining texture and color gradients. In the close-ups shown in Fig. 4 we can see that HPMINDE may introduce noticeable artifacts in the reproductions because it may project two nearby out-of-gamut colors to far-away points on the destination gamut. Also, the HPMINDE algorithm can produce images with loss of spatial detail, as it can be observed in rows 1 and 4 of Fig. 4. The methods of LCLIP and Schweiger et al. [22] may produce results with excessive desaturation in bright regions, as shown on the close-ups of the helmet and on the neck of the yellow parrot. The algorithm of Alsam et al. [2] can over-compensate the contrast, as shown in the example of the first row of 4. In the example of the second row of Fig. 4, all tested GRAs except the proposed one produce tonal discontinuities on the face of the woman.

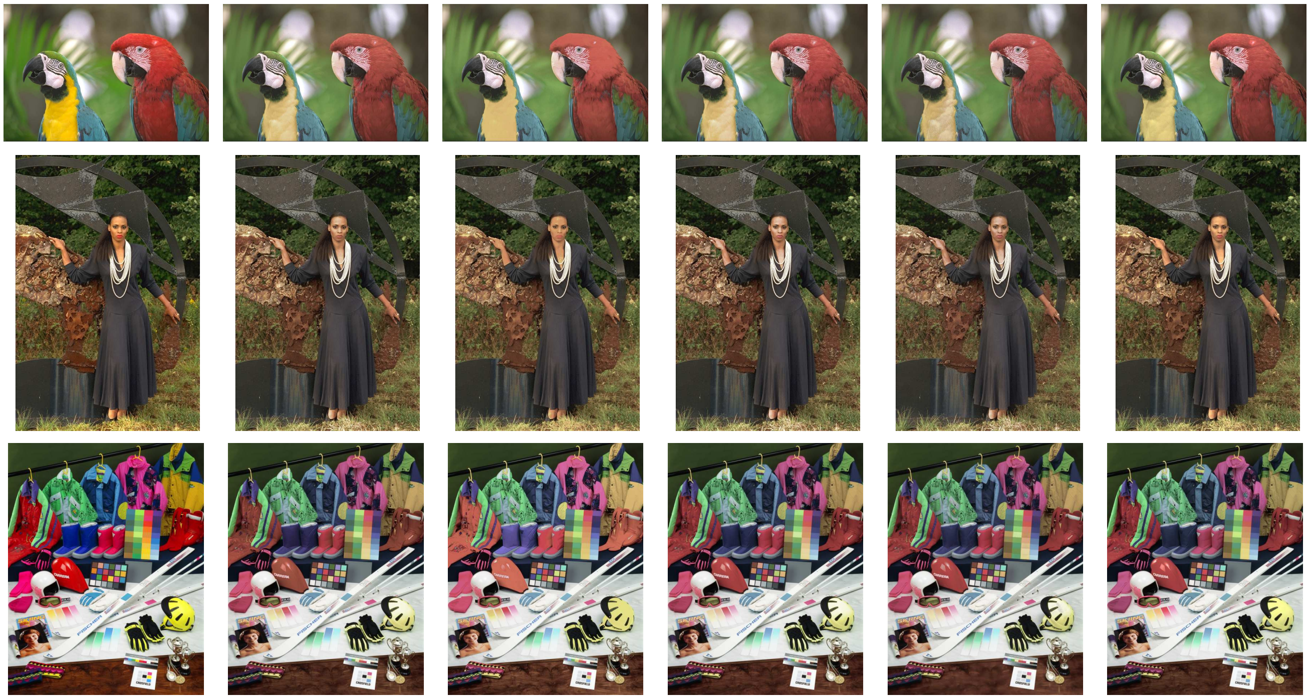


Figure 3: Reproductions of GRAs. Column 1: input images. Column 2: LCLIP [21]. Column 3: HPMINDE [20]. Column 4: Schweiger et al. [22]. Column 5: Alsam et al. [2]. Column 6: Our GRA. The original image in the last row is from [7], while rest of the input images are from Kodak dataset [12].

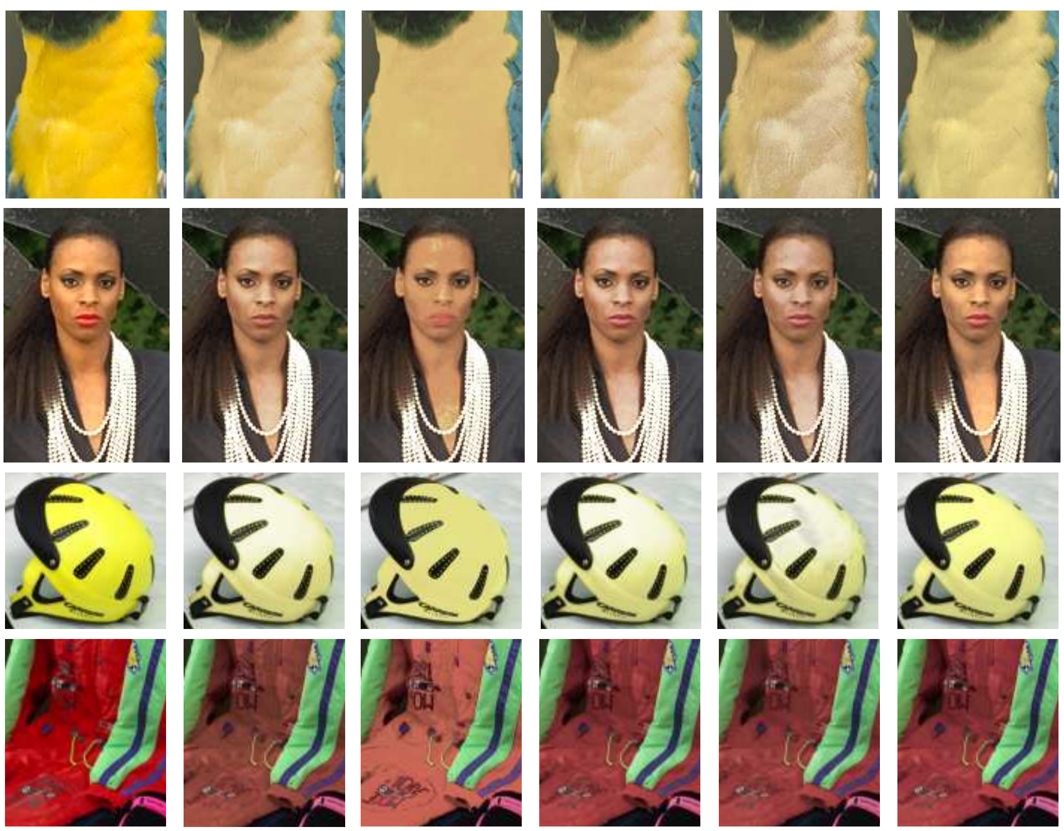


Figure 4: Comparison of GRAs: crops are from Fig. 3. Column 1: original cropped regions. Column 2: LCLIP [21]. Column 3: HPMINDE [20]. Column 4: Schweiger et al. [22]. Column 5: Alsam et al. [2]. Column 6: Our GRA.

Quantitative Assessment

This section is devoted to examining the quality of the compared GRAs using the perceptual color image difference (CID) metric [13], which is particularly tailored to assess the quality of gamut reduction results. The CID metric compares the gamut-mapped image with the reference (original) image and analyzes differences in several image features such as hue, lightness, structure, chroma and contrast.

We apply the competing GRAs on the Kodak dataset [12] and on seven other images (that are shown in Fig. 2). In Table 2 we summarize the results obtained using the CID measure. It can be seen that our GRA outperforms the other methods in 24 out of 31 test images. Furthermore, the statistical data (mean, median and root mean square) presented in Table 3 also underlines the good performance of the proposed algorithm over the other GRAs.

Conclusions

We have presented a gamut mapping method that efficiently maps colors of a large source gamut to a smaller destination gamut. We show that our GRA outperforms other gamut reduction methods in terms of visual quality and according to a perceptual error metric.

We are currently working on reducing the computational cost of our method aiming for real-time implementation

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Table 2: Quantitative assessment using CID metric [13]. The first 24 images are from Kodak dataset [12] and the rest of the images are sequentially shown from left to right in Fig. 2.

Image #	LCLIP [21]	HPMINDE [20]	Schweiger et al. [22]	Alsam et al. [2]	Our GRA
1	0.0046	0.0242	0.0059	0.0255	**0.0051**
2	**0.1098**	0.3238	0.1195	0.1668	0.1135
3	0.0397	0.0831	0.0405	0.0631	**0.0291**
4	0.0114	0.0766	0.0131	0.0398	**0.0101**
5	0.0158	0.0252	0.0188	0.0330	**0.0061**
6	0.0275	0.0155	0.0324	0.0792	**0.0002**
7	0.0123	0.0369	0.0121	0.0504	**0.0109**
8	0.0067	0.0061	0.0157	0.0326	**0.0001**
9	**0.0037**	0.0097	0.0047	0.0525	0.0047
10	0.0010	0.0019	0.0012	0.0216	**0.0004**
11	0.0014	0.0055	0.0022	0.0277	**0.0010**
12	0.0077	0.0114	0.0082	0.0453	**0.0008**
13	0.0038	0.0060	0.0049	0.0231	**0.0012**
14	0.0238	0.0635	0.0252	0.0473	**0.0224**
15	0.0278	0.0452	0.0275	0.0716	**0.0157**
16	0.0014	0.0032	0.0018	0.0214	**0.0003**
17	0.0018	0.0012	0.0030	0.0116	**0.0003**
18	0.0082	0.0175	0.0134	0.0325	**0.0056**
19	0.0042	0.0096	0.0086	0.0428	**0.0013**
20	0.0478	0.0358	0.0517	0.0945	**0.0041**
21	0.0071	0.0037	0.0095	0.0293	**0.0001**
22	0.0080	0.0157	0.0121	0.0327	**0.0009**
23	0.0309	0.1480	0.0336	0.0668	**0.0308**
24	0.0028	0.0017	0.0057	0.0175	**0.0001**
25	0.0040	0.0175	**0.0038**	0.0284	0.0045
26	**0.0142**	0.0413	0.0145	0.0467	0.0156
27	**0.0087**	0.0443	0.0094	0.0321	0.0100
28	0.0752	0.1503	**0.0741**	0.1067	0.0832
29	0.1476	0.2081	0.1333	0.1324	**0.1148**
30	0.0299	0.0769	0.0372	0.0830	**0.0289**
31	**0.0083**	0.0130	0.0102	0.0230	0.0098

Table 3: Quantitative assessment: statistical data

	LCLIP [21]	HPMINDE [20]	Schweiger et al. [22]	Alsam et al. [2]	Our GRA
Mean	0.0225	0.0491	0.0243	0.0510	**0.0171**
Median	0.0083	0.0175	0.0121	0.0398	**0.0051**
RMS	0.0396	0.0855	0.0397	0.0618	**0.0346**