Spatial and Color Adaptive Gamut Mapping: A Mathematical Framework and Two New Algorithms

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Abstract

A general framework for adaptive gamut mapping is presented in which a wide range of published spatial gamut mapping algorithms fit. Two new spatial and color adaptive gamut mapping algorithms are then introduced. Based on spatial color bilateral filtering, they take into account the color properties of the neighborhood of each pixel. Their goal is to preserve both the color values of the pixels and their relations between neighbors. Results of psychophysical experiments confirm the good performance of the proposed algorithms.

Introduction

The fundamental role of a Gamut Mapping Algorithm (GMA) is to manage the color gamut changes between an original image and its reproduction via a given technology (print, photograph, electronic display,...). These changes correspond to shape differences and size reduction of the gamut causing a loss of information. Ideally, a GMA should optimize the reproduction by taking into account the color and spatial distribution of the original image, such that the reproduction is perceived as similar as possible to the original.

In the quest for an optimal reproduction, an impressive number of GMAs have been proposed in the literature. Morovic and Luo have made an exhaustive survey in [1]. The ICC color management flow is based on the first generation, non-adaptive point-wise GMAs [2]. Morovic and Luo classified these classic GMAs into two categories: gamut clipping and gamut compression. Gamut clipping algorithms project color lying outside the output gamut onto its boundary. They usually preserve saturation but clip image details and introduce clipping artifacts. Gamut compression algorithms compress the input gamut onto the output gamut and are better at preserving details but tend to reduce saturation. The next step has been to investigate adaptive algorithms with the selection of an appropriate GMA depending on the image type or directly on the image gamut instead of the input device gamut [3]. To further improve adaptive GMAs, it has been advocated that preservation of the spatial details in an image is a very important issue for perceptual quality [4, 5]. GMAs adaptive to the spatial content of the image, i.e. Spatial Gamut Mapping Algorithms (SGMAs), have been introduced. These new algorithms try to balance both color accuracy and preservation of details, by acting locally to generate a reproduction perceived as close to the original. There are a limited number of publications regarding this recent and important development that was first introduced by Meyer and Barth in 1989 [6].

We distinguish two families of SGMAs which follow different approaches: the first uses iterative optimization tools, the second reinserts high-frequency content in clipped images to compensate for the loss of details caused by clipping.

The optimization family includes algorithms proposed by Nakauchi et al. [7], McCann [4], and Kimmel et al. [8]. Using models of perception of the Human Visual System (HVS), the algorithms minimize the perceived differences between the original and the candidate reproduction by locally modifying the candidate. In these optimization processes, the main difficulty is to define an appropriate criterion to optimize, using a valid perceptual model. Another issue is the lengthy computing time, making these algorithms difficult to use in an industrial context.

Algorithms of the second family are usually sufficiently fast to be implemented in an industrial color flow. They have a less ambitious motivation: to limit or compensate for the loss of details caused by clipping algorithms. Clipping yields good results in terms of saturation but tend to degrade image details in saturated areas. The projection might fail because it projects all non reproducible colors lying on the line of the projecting direction onto the same point on the gamut boundary. If in a local area, several neighboring pixels lie on a same line of projection but with distinguishable colors, the local variations that form the spatial content will be erased (see Fig.1). Similarly, if pixels in a local

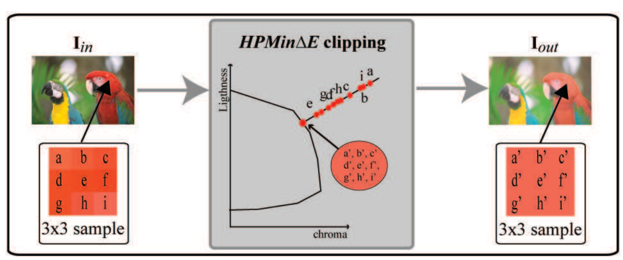

Figure 1. *$HPMin\Delta E$ [9] projects all colors lying outside the gamut and on the line of the projecting direction onto the same point on the gamut boundary, erasing local image variations.*

neighborhood lie on nearby projection lines, they will be mapped to nearby points on the gamut hull, and the local spatial variations may be severely diminished. To prevent these degradations, this family of SGMAs proposes solutions that can be divided in two groups.

In the first group XSGM by Balasubramanian et al. [10] gamut maps the original image using a direction of projection that emphasizes preservation of chroma over luminance.

The parts of the original image that were clipped are high-pass filtered and added to the gamut mapped image. The resulting sum is again gamut mapped using a direction of projection that emphasizes preservation of luminance over chroma. Previously conducted psycho-physical evaluations showed that XSGM obtains good scores but suffers from the presence of halos [11]. Recently, Zolliker and Simon proposed to improve XSGM by using bilateral filtering [12]. The use of such filter eliminates the halos produced in XSGM by the gaussian filters.

In the second group, Meyer and Barth in 1989 [6], Kasson in 1995 [13] and recently Morovic and Wang [14] proposed in MSGM4 to first decompose the image in frequency bands. The low-pass band is gamut mapped then successive clippings are performed during the reconstruction. Results of such an approach depend both on the algorithm used in the image decomposition and on the GMAs successively applied.

In both groups, problems may arise when adding high-pass content to the gamut mapped image: artifacts such as halos and color shifts might be introduced, except for the most recent version of XSGM [12].

Based on the knowledge that can be found in the literature and on our own experience, we have listed conditions that optimal GMAs need to fulfill. First, GMAs need to fully preserve hue, then preserve lightness and chroma as much as possible. Second, they need to preserve spatial information: the color relations between neighboring pixels must be preserved, as does the balance between the frequency bands. Third, they need to avoid the introduction of artifacts such as halos, hue shift or posterization.

In this paper we first introduce a mathematical framework for adaptive gamut mapping algorithms and show that existing algorithms can be considered as special cases of this framework. Two new spatially adaptive GMAs are then introduced within this framework. Finally we proceed to the psychophysical evaluation of our algorithms by conducting a ranking experiment and demonstrate their advantages.

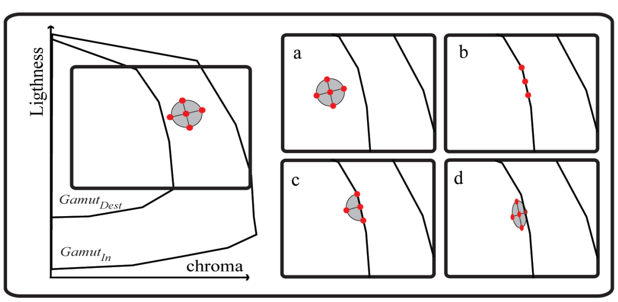

Figure 2. *Results of different gamut mapping strategies in a scenario where the colors of a pixel and its neighbors lie in a hue plane, outside the destination gamut. a) Linear compression: considerable desaturation, and good preservation of local variations, b) Clipping: maximal preservation of saturation, loss of all the local variations in the direction of projection, c) Adaptive Clipping: almost maximal preservation of saturation, loss of half the local variations in the direction of projection, d) Non-linear Adaptive Compression: small desaturation, local variations are preserved but reduced in the direction of projection.*

Mathematical framework for adaptive gamut mapping algorithms

Locally adaptive GMAs often use both the color values of the pixels and the values of their local surrounding. Multi-scale decomposition [15] is an adapted framework for such local image processing and has been used in SGMAs [6,14]. Let note the multidimensional entities with bold characters. The simplest multi-scale decomposition is in two bands: the low-pass band color image $\mathbf{I}_{low}$ contains local means and is obtained by convolution of the original image $\mathbf{I}_{in}$ with a blurring filter. The high-pass band $\mathbf{I}_{high}$ contains local variations and can be obtained by subtracting the local mean $\mathbf{I}_{low}$ from $\mathbf{I}_{in}$ or by dividing $\mathbf{I}_{in}$ by $\mathbf{I}_{low}$.

Once the image is decomposed in two bands, several options are available: $\mathbf{I}_{low}$ might be re-rendered, its lightness range might be rescaled, and it might be gamut mapped (function g in Eq.1). $\mathbf{I}_{high}$ might also be adjusted by a scaling factor, spatially filtered or modified by a more complex function (function k) [16]. Furthermore, the merging of the two adjusted bands can be adjusted (function f). The framework can then be described as follows:

$$\mathbf{I}_{out} = f[g(\mathbf{I}_{low}), k(\mathbf{I}_{high})], \quad (1)$$

$$\mathbf{I}_{out} \in Gamut_{Dest}, \quad (2)$$

where $\mathbf{I}_{out}$ is the image resulting from the SGMA, $Gamut_{Dest}$ is the destination gamut (see Fig.2), f, g and k are the adaptive mapping functions. f, g and k should be chosen such that the SGMA preserves as much as possible the color value of each pixel and the color relation between neighboring pixels.

Color value versus pixel-neighbors relations, a tradeoff

In the case of Hue-Preserving Minimum ΔE clipping [9], $\mathbf{I}_{out} = HPMin\Delta E(\mathbf{I}_{in})$, with $\mathbf{I}_{in}$ the original image and $\mathbf{I}_{out}$ the gamut mapped image (see Fig.1). The level of local color variations $\Delta(\mathbf{p}^i_{out}, \mathbf{p}^j_{out})$ between two neighboring pixels i and j of the gamut mapped image is likely to be lower than the level of their local color variations $\Delta(\mathbf{p}^i_{in}, \mathbf{p}^j_{in})$ in the original image. This can lead to major perceived degradations in the details of the image. To prevent these degradations, SGMAs need to maintain the distance between each pixel and its neighbors. To do so it might be necessary to modify the color value of the mapped pixel or the color value of its neighborhood, or both. A compromise needs to be found between the preservation of the color value of a pixel and the preservation of the color relation with its neighbors.

Special cases: existing algorithms

In this subsection, we show that existing algorithms can be considered as special cases of the above framework:

In Meyer and Barth [6], $\mathbf{I}_{low}$ is obtained by convolution of $\mathbf{I}_{in}$ with a gaussian filter. k is the identity function, g a linear scaling function and f a non-linear chroma compression algorithm followed by a hue and lightness preserving clipping:

$$\mathbf{I}_{out} = f[g(\mathbf{I}_{low}) + \mathbf{I}_{high}]. \quad (3)$$

In MSGM4 [14], $\mathbf{I}_{in}$ is decomposed in 4 bands. $\mathbf{I}_{low}$ is obtained by convolution with a mean filter of each CAM97s2 J, a, b color channel [14] and $\mathbf{I}_{high1}$ by subtracting $\mathbf{I}_{low}$ from $\mathbf{I}_{in}$. This operation is repeated two times by substituting $\mathbf{I}_{low}$ to $\mathbf{I}_{in}$ to obtain $\mathbf{I}_{high2}$ and $\mathbf{I}_{high3}$. k is a linear compression using the ratio of the reproduction medium and original medium lightness ranges.

g is a sigmoidal compression on the lightness J of $\mathbf{I}_{low}$ followed by $HPMin\Delta E$, and f is clipping toward the 50% greypoint (SCLIP) applied sequentially after each step of the reconstruction:

$$\mathbf{I}_{out} = f[f[f[g(\mathbf{I}_{low}) + k(\mathbf{I}_{high1})] + k(\mathbf{I}_{high2})] + k(\mathbf{I}_{high3})]. \quad (4)$$

In Kasson [13] the input image $\mathbf{I}_{in}$ is also filtered, exploiting known spatial-frequency characteristics of the HVS. In this case, f g and k are different for L and c; h is preserved. f_L is a luminance-preserving clipping , g_L is a chroma-preserving clipping followed by a chroma-dependent weighted sum. f_c is a luminance-dependent scaling followed by a luminance-preserving clipping, k_L, g_c and k_c are the identity function:

$$L_{out} = f_L[g_L(\mathbf{I}_{low}) + L_{high}] \text{ , } c_{out} = f_c[c_{in}.(L_{out}/L_{in})]. \quad (5)$$

In XSGM [10], there is no low-pass filtering prior to the initial gamut mapping and g is applied directly to $\mathbf{I}_{in}$. g is $HPMin\Delta E$ clipping, emphasizing the preservation of chroma over luminance. $\mathbf{I}_{high}$ contains the parts clipped by g: $\mathbf{I}_{high} = \mathbf{I}_{in} - g(\mathbf{I}_{in})$, k is a simple high-pass filtering of L_{high}. f is a clipping toward the point on lightness axis with the luminance of the cusp (CUSP), emphasizing the preservation of luminance over chroma:

$$\mathbf{I}_{out} = f[g(\mathbf{I}_{in}) + k(\mathbf{I}_{high})]. \quad (6)$$

In Zolliker and Simon [12], Eq.6 is still valid. f is a clipping GMA and g is any point-wise GMA. k is a more elaborated full color high-pass filtering: the local mean is obtained with bilateral filtering (see Eq.6).

To illustrate the optimization approach, we observe similarity in Nakauchi et al. [7] with XSGM: there is again no low-pass filtering prior to g; f and g are $HPMin\Delta E$; $\mathbf{I}_{high}$ contains the parts clipped by g: $\mathbf{I}_{high} = \mathbf{I}_{in} - g(\mathbf{I}_{in})$. k is a convolution with contrast sensitivity functions and produces the "Perceptual Difference": $PD = k(\mathbf{p}_{high})$. In [7], successive clipping and updating of $\mathbf{I}_{out}$ occur until the decrease of PD falls under a given threshold ε:

$$\mathbf{I}_{out(o)} = f[g(\mathbf{I}_{in}) + k(\mathbf{I}_{in} - g(\mathbf{I}_{in}))], \quad (7)$$

$$\mathbf{I}_{out(i+1)} = f[\mathbf{I}_{out(i)}, PD_{(i)}], \; while \; \Delta PD > \varepsilon. \quad (8)$$

Notice that in all the described SGMAs, if a mapped pixel of $\mathbf{I}_{\overline{low}} = g(\mathbf{I}_{low})$ lies on the gamut boundary, after the sum of $\mathbf{I}_{\overline{low}}$ with $k(\mathbf{I}_{high})$ the resulting pixel in $\mathbf{I}_{out}$ might end up lying outside $Gamut_{Dest}$, the destination gamut. Hence a second gamut mapping by function f is needed.

In the following we propose two new SGMAs which follow the framework as in Eq.1 where g is a point-wise GMA, f and k are locally adaptive functions.

Proposed spatial and color adaptive algorithms

Since it is not easy to determine the appropriate HVS model for gamut mapping [4,17,18] and because optimization processes are too slow to be included in an industrial workflow, we propose in this section two new gamut mapping algorithms which belong to the second group of the second family. However, because their process is fully spatially adaptive and aims at getting an optimal reproduction, they also share properties with the first family. Our adaptive algorithms are described by Eq.1, the diagram in Fig.3 and by the following process:

- Conversion of the original image to the CIELAB color space using the absolute intent of the input ICC profile: $\mathbf{I}_{in}$.
- Decomposition of the CIELAB image in two bands using bilateral filtering (BF): $\mathbf{I}_{low}$ and $\mathbf{I}_{high}$.
- $HPMin\Delta E$ clipping (g) of the low-pass band $\mathbf{I}_{low}$: $\mathbf{I}_{\overline{low}}$.
- Adaptive merging (f and k) of $\mathbf{I}_{\overline{low}}$ and $\mathbf{I}_{high}$: $\mathbf{I}_{out}$.
- Conversion to the CMYK encoding of the output printer using the relative colorimetric intent of its ICC profile.

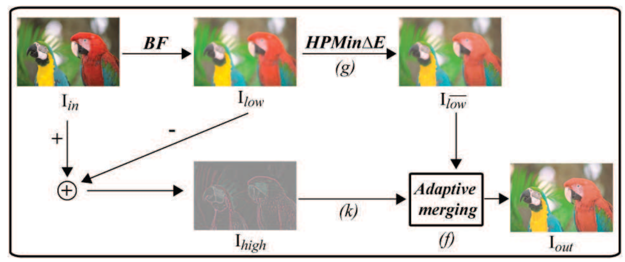

Figure 3. *Diagram of proposed framework for SCACOMP and SCACLIP.*

Multiscale decomposition

Pixel-neighbors relation

To compare the values of the pixels with the values of their local surrounding, we decompose the image in two bands. The low-pass band $\mathbf{I}_{low}$ contains local means. Note that degradation by clipping mostly occurs in a neighborhood in which several pixels have nearby color values (see Fig.1). Consequently the relation between a pixel and its neighbors with similar values needs to be carefully handled. Therefore we compute a weighted local mean where each neighbor is given a weight, which is function of both the geometric distance and the colorimetric ΔE_{ab} distance to the central pixel. This mean is computed using a five-dimensional bilateral filtering algorithm.

5D bilateral filtering in CIELAB space

5D Bilateral Filtering (BF) in the CIELAB space, proposed by Tomasi and Manduchi in [19], is a combined spatial domain and color range filtering. Let $L_{BF} = BF(L)$, $a_{BF} = BF(a)$, $b_{BF} = BF(b)$ denote the three channels of the filtered image. The L_{BF} value of pixel i, L^i_{BF}, can be obtained as follows (similar expressions for a^i_{BF} et b^i_{BF}):

$$L^i_{BF} = \frac{\sum_{j \in \mathbf{I}_{in}} [r(\mathbf{x}^i, \mathbf{x}^j) \; s(\mathbf{p}^i, \mathbf{p}^j) \; L^j]}{\sum_{j \in \mathbf{I}_{in}} [r(\mathbf{x}^i, \mathbf{x}^j) \; s(\mathbf{p}^i, \mathbf{p}^j)]}, \quad (9)$$

where $\mathbf{I}_{in}$ is the original image, $r(\mathbf{x}^i, \mathbf{x}^j)$ measures the geometric closeness between the locations $\mathbf{x}^i$ of pixel i and $\mathbf{x}^j$ of a nearby pixel j. $s(\mathbf{p}^i, \mathbf{p}^j)$ measures the colorimetric similarity between the colors (L^i, a^i, b^i) and (L^j, a^j, b^j) of pixels i and j.
In our implementation, $r(\mathbf{x}^i, \mathbf{x}^j)$ and $s(\mathbf{p}^i, \mathbf{p}^j)$ are gaussian functions of the euclidean distance between their arguments:

$$r(\mathbf{x}^i, \mathbf{x}^j) = e^{-\frac{1}{2}(\frac{||\mathbf{x}^i - \mathbf{x}^j||}{\sigma_r})^2}, \; s(\mathbf{p}^i, \mathbf{p}^j) = e^{-\frac{1}{2}(\frac{\Delta E_{ab}(\mathbf{p}^i, \mathbf{p}^j)}{\sigma_s})^2}, \quad (10)$$

where the scale parameters σ_r and σ_s play an essential role in the behavior of the filter. Tomasi and Manduchi explore different values, and present black and white images processed with $\sigma_r = 3pixels$ and $\sigma_s = 50\Delta E$, yet the size of the processed images are not specified. The setting of σ_r should depend on the image size and the conditions of visualization. Zolliker and Simon [12] have applied the filter in their algorithm with $\sigma_r = 4\%$ of the image diagonal and $\sigma_s = 20\Delta E$. They found that values of σ_r in the range of [2 - 5]% of the image diagonal and σ_s values in the range of [10-25] ΔE show good performance. In our implementation, we have set the values to $\sigma_r = 1\%$ of the image diagonal and $\sigma_s = 25\Delta E$ (for images printed at 150 dpi, at the size [9-15] cm by [12 - 20] cm, viewed at a distance of 60 cm).

Decomposition in two bands

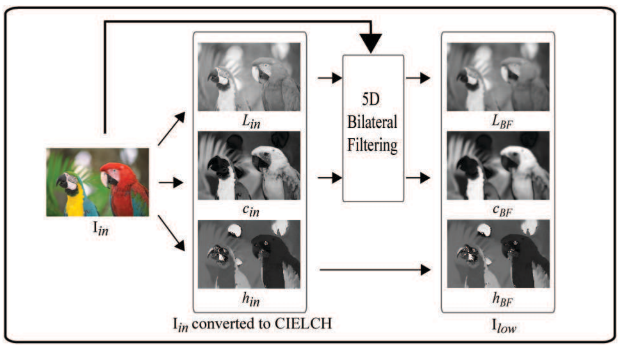

Figure 4. *Computation of the low-pass band* $\mathbf{I}_{low}$.

First, the original CIELAB image is converted to the polar representation CIELCH, i.e. Lightness, chroma and hue. To compute the low-pass band $\mathbf{I}_{low}$, we propose to filter only the two channels L_{in} and c_{in} of the original image $\mathbf{I}_{in}$, using 5D bilateral filtering as described above (Eq.9-10). The h_{in} channel is not filtered, to keep the hue unaltered by our SGMA. Nevertheless, since the 5D bilateral filter involves ΔE_{ab} distance, the hue will be well taken into account in the filtering of L_{in} and c_{in} channels. The low-pass band $\mathbf{I}_{low}$ is thus defined as:

$$\mathbf{I}_{low} = (L_{BF}, c_{BF}, h_{in}), \tag{11}$$

where $L_{BF} = BF(L_{in})$ and $c_{BF} = BF(c_{in})$ (see Fig.4).

The high-pass band $\mathbf{I}_{high}$ is then calculated by taking the difference of $\mathbf{I}_{in}$ and the low-pass band $\mathbf{I}_{low}$:

$$\mathbf{I}_{high} = \mathbf{I}_{in} - \mathbf{I}_{low} = (L_{in} - L_{BF}, c_{in} - c_{BF}, 0). \tag{12}$$

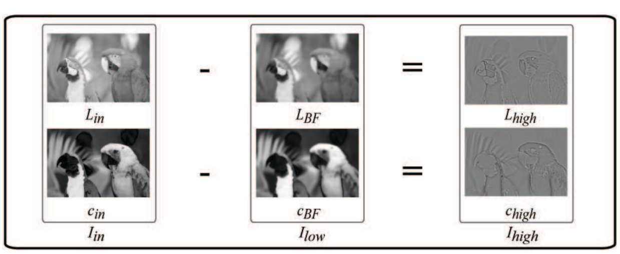

Figure 5. *Computation of the high-pass bands* L_{high} *and* c_{high} *of channels* L_{in} *and* c_{in}*. The hue channel* h *is not filtered.*

Clipping of the low-pass band

The first step of our adaptive algorithms is the gamut mapping of the low-pass band. The goal of this mapping is to preserve as much as possible the color of each pixel, leading to the use of $g = HPMin\Delta E$ resulting in the clipped image $\mathbf{I}_{\overline{low}}$:

$$\mathbf{I}_{\overline{low}} = HPMin\Delta E(\mathbf{I}_{low}). \tag{13}$$

Note that the *hue* channel is left unaltered by $HPMin\Delta E$: $h_{\overline{low}} = h_{low} = h_{in}$. The next step is the adaptive merging of $\mathbf{I}_{\overline{low}}$ and $\mathbf{I}_{high}$ involving the functions f and k.

Adaptive merging of the high-pass band

We aim to merge the mapped low-pass band $\mathbf{I}_{\overline{low}}$ with the high-pass band $\mathbf{I}_{high}$ while preserving as much as possible the local variations contained by $\mathbf{I}_{high}$. We propose two locally adaptive algorithms to map the high-pass content by taking into account the local 5D neighborhood defined by the bilateral filtering.

Discussion

According to the properties of the bilateral filtering (Eq.9-10), local spatial variations contained by $\mathbf{I}_{high}$ present only low color variations. Therefore, each pixel and its neighbors are more likely to be projected to a same little area of the gamut boundary if f is a clipping GMA, resulting in a strong diminution of the variations present in $\mathbf{I}_{high}$. To avoid this situation, f and k need to be locally adaptive functions with the following objectives for a pixel $\mathbf{p}_{out}$ of the resulting image $\mathbf{I}_{out}$:

- $\mathbf{p}_{out}$ is as close as possible to $\mathbf{p}_{in}$ of $\mathbf{I}_{in}$,
- the color variations of $\mathbf{p}_{out}$ with its neighbors are the closest to the color variations of $\mathbf{p}_{in}$ with its neighbors,
- $\mathbf{p}_{out} \in Gamut_{Dest} \cap \wp$ (plane of constant hue h_{in} of $\mathbf{p}_{in}$).

Since the first two requirements might be antagonistic, $\mathbf{p}_{out}$ results of a compromise. A weighted sum can be used here:

$$\begin{cases} \mathbf{p}_{out} \in (Gamut_{Dest} \cap \wp), \\ \mathbf{p}_{out} = \arg\min_{\mathbf{p}}[w\,\Delta(p, \mathbf{p}_{in}) + (1-w)\Delta(\mathbf{p}_{high}, (\mathbf{p} - \mathbf{p}_{\overline{low}}))], \end{cases}$$

where $w \in [0,1]$ is a weight.

- If $w = 1$, k becomes $HPMin\Delta E$ cliping.
- If $w = 0$, only the color variations between the pixel and its neighbors will be preserved, not the pixel value.
- In intermediate cases $w \in]0,1[$, the result might be obtained by an optimization algorithm.

Fast solutions can be deployed to maintain the computational time at a reasonable level. A new tradeoff comes to light: computation time versus quality of the result.

In the next sections, we propose two alternative and fast algorithms that provide approximations of the best obtainable results. They are based on the same framework: decomposition in two bands $\mathbf{I}_{high}$ and $\mathbf{I}_{low}$ using 5D bilateral filtering, followed by clipping of the low-pass band $\mathbf{I}_{low}$. Then adaptive merging of $\mathbf{I}_{high}$ and $\mathbf{I}_{\overline{low}}$ using local adaptive implementation of the two families of pointwise GMAs: compression and clipping.

Spatial and color adaptive compression (SCACOMP)

We propose an adaptive compression algorithm to preserve the color variations between neighboring pixels contained by $\mathbf{I}_{high}$. The concept is to project each pixel lying outside $Gamut_{Dest}$ toward the center, more or less deeply inside the gamut depending on its neighbors.

First, $\mathbf{I}_{high}$ is added to $\mathbf{I}_{\overline{low}}$ and the sum is mapped using SCLIP:

$$\mathbf{I}_S = SCLIP(\mathbf{I}_{\overline{low}} + \mathbf{I}_{high}). \quad (14)$$

Then we compute the difference $\mathbf{I}_{offset}$ between $\mathbf{I}_S$ and the newly constructed image $(\mathbf{I}_{\overline{low}} + \mathbf{I}_{high})$:

$$\mathbf{I}_{offset} = \mathbf{I}_S - (\mathbf{I}_{\overline{low}} + \mathbf{I}_{high}). \quad (15)$$

At the given spatial position $\mathbf{x}^i$, for each pixel j in the neighborhood, we project the color vector $\mathbf{p}^j_{offset}$ on the direction of $\mathbf{p}^i_{offset}$. If the result is greater than the norm $||\mathbf{p}^i_{offset}||$, $\mathbf{p}_j$ is taken into account and pushes $\mathbf{p}^i_S \in \mathbf{I}_S$ toward the 50% greypoint of $Gamut_{Dest}$ (see Fig.6). Each neighbor's contribution to the shifting of pixel i is weighted by w^j_{BF} defined by BF (see Eq.9):

$$w^j_{BF} = \frac{r(\mathbf{x}^i, \mathbf{x}^j)\, s(\mathbf{p}^i, \mathbf{p}^j)}{\sum_{j \in \mathbf{I}_{in}} (r(\mathbf{x}^i, \mathbf{x}^j)\, s(\mathbf{p}^i, \mathbf{p}^j))}, \quad (16)$$

and:

$$\mathbf{p}^i_{out} = (\mathbf{p}^i_{\overline{low}} + \mathbf{p}^i_{high}) + w^i_{shift}\, \mathbf{p}^i_{offset}, \quad (17)$$

where:

$$w^i_{shift} = \sum_{j \in \mathbf{I}_{in}} w^j_{BF}\, max\Big(\frac{\mathbf{p}^j_{offset} \cdot \mathbf{p}^i_{offset}}{||\mathbf{p}^i_{offset}||^2}, 1\Big), \quad (18)$$

"$\cdot$" denotes the scalar product and w^i_{shift} is superior or equal to 1. Therefore the resulting color value lies in the gamut, between the gamut boundary and the 50% greypoint of $Gamut_{Dest}$.

Spatial and color adaptive clipping (SCACLIP)

To maintain the content of $\mathbf{I}_{high}$, we also explore the possibility of setting the direction of the projection as a variable: for each pixel the optimal mapping direction will be chosen so that the local variations are best maintained.

To get faster results, the choice can be restricted to a set of directions. In our implementation, the mapping direction will be chosen within directions proposed in published algorithms, i.e. between $f_1 = HPMin\Delta E$, $f_2 = CUSP$ *and* $f_3 = SCLIP$ [1]. First, $\mathbf{I}_{high}$ is added to $\mathbf{I}_{\overline{low}}$ and the 3 mappings f_n, $n \in \{1,2,3\}$, are run (see Fig.7). Then for each mapping the difference $\mathbf{I}_{\overline{high\_n}}$ between the result of the mapping and $\mathbf{I}_{\overline{low}}$ is computed. This difference can be regarded as the result of the mapping of $\mathbf{I}_{high}$:

$$\mathbf{I}_{\overline{high\_n}} = f_n(\mathbf{I}_{\overline{low}} + \mathbf{I}_{high}) - \mathbf{I}_{\overline{low}}\ ,\ n \in \{1,2,3\} \quad (19)$$

In $\mathbf{I}_{high}$ we compute the energy $E^{\mathbf{I}}_{high}$ corresponding to the weighted sum of the norms of $\mathbf{p}^j_{high}$ for pixels j in the neighborhood of the pixel i, and similarly the energy E^i_n in each $\mathbf{I}_{\overline{high\_n}}$:

$$E^i_{high} = \sum_{j \in \mathbf{I}_{in}} w^j_{BF}\, ||\mathbf{p}^j_{high}||\ ,\ E^i_n = \sum_{j \in \mathbf{I}_{in}} w^j_{BF}\, ||\mathbf{p}^j_{\overline{high\_n}}||, \quad (20)$$

where w^j_{BF} are the weights of the bilateral filter used in the decomposition of the image (see Eq.16).

Then the direction of projection for which E^i_n is the closest to E^i_{high} is selected for the pixel i:

$$\mathbf{p}^i_{out} = f_{select}(\mathbf{p}^i_{\overline{low}} + \mathbf{p}^i_{high}), \quad (21)$$

$$select = \arg\min_n(|E^i_n - E^i_{high}|),\ n \in \{1,2,3\}. \quad (22)$$

Because the process is scanning the image pixel by pixel, some pixels $\mathbf{p}^j$ of the neighborhood have been processed before. For these pixels, $\mathbf{p}^j_{\overline{high\_n}}$ are replaced by results $\mathbf{p}^j_{out}$ in the computation of E^i_n. Therefore, anterior decisions are taken into account and $\mathbf{I}_{out}$ depends on the processing order of the pixels.

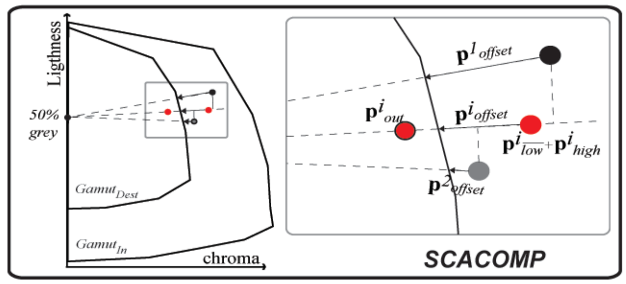

Figure 6. *SCACOMP: $\mathbf{p}^1_{offset}$ (j=1) contributes to the shifting of $(\mathbf{p}^i_{\overline{low}} + \mathbf{p}^i_{high})$ toward the 50 % greypoint, unlike $\mathbf{p}^2_{offset}$ (j=2).*

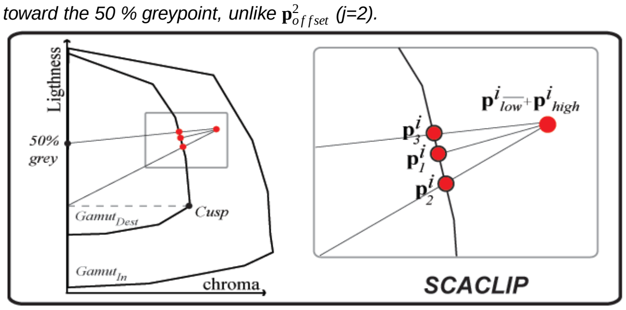

Figure 7. *SCACLIP: $(\mathbf{p}^i_{\overline{low}} + \mathbf{p}^i_{high})$ is mapped toward 3 directions, the optimal direction will be chosen so that the local variations are best maintained.*

Psychophysical experiment

In this section, we present our evaluation of selected SGMAs by a psychophysical experiment following the CIE's guidelines [9]. A total of 22 images were used in this experiment: PICNIC and SKI as recommended by the CIE, along with 6 images from the Kodak Photo CD Sample and 4 sRGB images from the ISO 12640-2:2004 standard [20]. 8 images SCID-LAB from the draft of the ISO 12640-3 converted to Adobe RGB 98 using relative colorimetric intent, and 2 Adobe RGB 98 images (courtesy of Pr. Farup). These images were converted to CIELAB using the absolute colorimetric intent of their profiles. All the images were then gamut mapped using 5 different GMAs. The destination gamut was the gamut of an OCE TCS-500 printer using OCE Standard paper and the printer's highest quality setting. The resulting images were then converted from CIELAB to the device CMYK using the relative colorimetric intent. In order to get high resolution prints, the processed images were printed on an Epson Stylus Pro 7600 using Epson Photo Luster Paper on formats [9-15] cm by [12-20] cm.
The following 2 GMAs and 3 SGMAs have been evaluated:

- HPMINΔE, hue-angle preserving minimum ΔE^*_{ab} clipping,
- SGCK, chroma-dependent sigmoidal lightness mapping and cusp knee scaling performed with the software ICC3D [21],
- Z-HPMINΔE [12], implemented using *HPMinΔE* as the pointwise GMA,
- SCACOMP, our adaptive compression algorithm,
- SCACLIP, our adaptive clipping algorithm.

In our rank order experiment the test panel was constituted by 7 female and 8 male. The observers were presented with a reference image on an EIZO ColorEdge CG221 display at a Color Temperature of 6500 Kelvins, along with 5 printed gamut-mapped candidate in a viewing booth GretagMacBeth The Judge II at a CT of 5000 Kelvins. The observers viewed simultaneously the monitor and the printed images from a distance of approximately 60 cm. For each image, the observers were asked to arrange the candidates according to the decreasing quality of the reproduction with respect to the original reference image. It was suggested to make their decision based on different parts of the image, to evaluate the fidelity of the reproduction of both colors and details, and look for possible artifacts. Thus it is the accuracy of reproduction of the images which was compared, not the pleasantness. Results in Fig.8 show that on average over the 22 images and 15 observers, SCACLIP obtains the best scores, followed by Z-HPMINΔE, SCACOMP, SGCK and HPMINΔE. On average over the 22 images, 12 of the 15 observers ranked SCACLIP first, two ranked Z-HPMINΔE first, and one ranked SCACOMP first. When considering only the 10 Adobe RGB 98 images, the ranking order changes: SCACLIP is first, followed by SCACOMP, Z-HPMINΔE, SGCK and HPMINΔE.

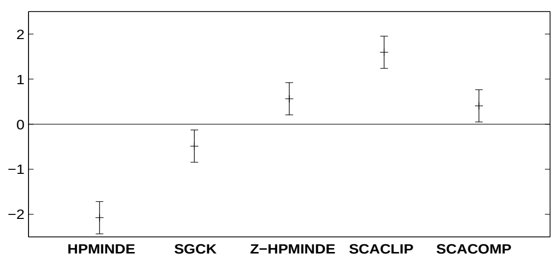

Figure 8. *Z-scores resulting of our ranking experiment, average over 22 images and 15 observers.*

Conclusions

A framework for adaptive mapping has been introduced. Within this framework, two new locally adaptive spatial gamut mapping algorithms have been presented, SCACOMP and SCACLIP, which offer a nice compromise between the preservation of the color values and the preservation of the color relation between neighboring pixels. Psychophysical experiments show that SCACLIP outperforms both pointwise GMAs and our implementation of Z-HPMINΔE.

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