Spatial gamut mapping algorithms for cross-display color reproduction

Hung-Shing Chen
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Abstract — Owing to the fast developments of computer networks and color imaging technologies, there is a tendency towards remote proofing in the printing or textile industries. More cases such as cross-display color matching will occur in the future information society. The problems of color mismatching we usually find in cross-display devices have been widely discussed today. In this paper, to achieve equivalent color matching between a sRGB monitor and an Adobe RGB monitor, the spatial gamut mapping algorithm (SGMA), which introduces sigmoidal tone mapping, multi-mapping paths, and unsharp mask (USM) operation into a sRGB color-management system, is proposed. According to the designs of USM locations, this proposed SGMA can be further developed into pre-USM, post-USM, and double-USM types. Besides, two critical image characteristics, edge map and color histogram, are investigated to establish the relationship between image content and SGMA. The psychophysical experimental results show that double-USM SGMA obtains better color matching than the other spatial types.

Keywords — Spatial-gamut-mapping algorithm, unsharp mask.

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1 Introduction

The development of gamut mapping algorithms (GMAs) is one of the key issues in digital workflows in the printing or textile industries. It is also highly expected to establish useful color-management solutions, which applies color gamut mapping to overcome color-mismatching problems of cross-display color-reproduction systems using remote proofing technologies. The same color image which is applied as two individual displays shows different color appearances. For example, the color appearance of a pair of cross-display color-reproduction systems, such as a sRGB monitor and an Adobe RGB monitor, is hard to match if there is no color management linked to each other.

As shown in Fig. 1, conventional GMAs use the concepts of device-to-device mapping where color mapping is performed from the input device’s gamut to the output device’s gamut. However, device-to-device mapping cannot satisfy the visual effects completely because it does not take the image’s characteristics into account. Hence, to achieve better gamut mapping, image-dependence approaches to GMAs need further study. Thus far, the image-dependent algorithms that consider the image’s spatial characteristics have become new technologies in the GMA field. These new types of GMAs, called spatial gamut mapping algorithms (SGMAs), are expected to result in more pleasing color matching than ever before.

According to Morovič’s surveys (2008) (see Table 1), SGMAs are classified into three types of categories. The first type is the algorithm that applies color-by-color gamut mapping and adds low spatial frequencies to the mapped results. These types of SGMAs were developed for Fourier transforms in the frequency domain or spatial operations in the spatial domain. The former was developed by Meyer and Barth (1989); the latter by Barth (1989) and Bala et al. (2000, 2001), Morovič and Wang (2003), Zolliker and Simon (2007), and Kolas and Farup (2007).

The second type develops the GMA based on Retinex theory, which is a well-known computational model for deal-
ing with human color constancy. The SGMAs developed by Kolas, McCann (1999), and Kimmel et al. (2005) belong to this type. The third category is to develop the algorithm of image difference minimization, which is regarded as a mathematical optimization program to determine the mapped image that is perceptually closed to a given source and inside the destination gamut. The SGMAs developed by Nakauchi et al. (1996) and Kimmel et al. (2005) belong to this type. However, few efforts have been done on multi- or single mapping paths in designing SGMA. One of our aims is to develop the SGMA based on multi-mapping paths, which possibly applies to cross-display color-reproduction system.

The second aim of this paper is to provide a proper color-transform stage of cross-media color reproduction which fits SGMA. Transitional GMAs could be divided into five- or six-stage transform. MacDonald suggested a five-stage-transform in cross-media color reproduction to improve color-reproduction quality. In this transform, device characterization, color appearance model, and gamut mapping belong to essential elements [see Fig. 2(a)]. Morovič further introduced a six-stage transform of cross-media color reproduction, where image enhancement is suited to pixel-based GMAs in the pursuit of different rendering intensions [see Fig. 2(b)]. It can be seen that he added image enhancement into the five-stage transform besides the original three elements. However, two types of conceptual stages mentioned above fit for pixel-based GMAs; it is not clear whether they could be applied to SGMAs. Therefore, this paper is also investigates which stage transform fits the SGMA.

To match a reference on the Adobe RGB monitor with wide color gamut, we tested the proposed SGMA on the sRGB general monitor.

### 2 SGMA design

The flowchart of a general SGMA is demonstrated in Fig. 3, where $Y$ denotes the luminance (lightness) component and $C_1$, $C_2$ denote two opposing chrominance components. $YC_1C_2$ components are the color signals derived from $YCrCb$ or CIELAB color space. The basic model was developed by Bala et al. It combines two pointwise gamut mappings ($G_1$, $G_2$) with an intermediate spatial error feedback ($F$). Firstly, the nearest point mapping is suggested to be applied in $G_1$ operation. It can preserve gamut-mapped images as vivid as possible. However, because parts of the lightness (-luminance) information could be lost in the $G_1$ process, a spatial filter $F$ is chosen in the spatial error feedback process to compensate for luminance error. Finally, the second pointwise gamut mapping $G_2$ is used to preserve the chroma component. In this paper, we improved the above SGMA framework in terms of varying the mapping path, tone mapping, and spatial-filter location. The structure comparisons between Bala’s method and the proposed one are arranged in Table 2.

> **TABLE 2 — Comparison of SGMAs.**

<table>
<thead>
<tr>
<th>Bala et al. (2000, 2001)</th>
<th>Our work (Exp. 1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Color space</td>
<td>CIE LAB ($YC_1C_2$)</td>
</tr>
<tr>
<td>Mapping path</td>
<td>Near points on gamut boundary</td>
</tr>
<tr>
<td>Mapping method</td>
<td>■ 1st stage: chroma preservation clipping ($G_1$) + USM</td>
</tr>
<tr>
<td></td>
<td>■ 2nd stage: lightness preservation clipping ($G_2$)</td>
</tr>
<tr>
<td>Filter operation</td>
<td>Linear high-pass filter (inner-USM)</td>
</tr>
<tr>
<td>Filtering time</td>
<td>1 time</td>
</tr>
</tbody>
</table>
steps as “USM operation” in our algorithm (see Fig. 3). However, the issue of tone mapping and gamut mapping path was not further discussed in Bala's original framework. Therefore, we use “SM-mapping (i.e., sigmoidal compression plus multi-focus points)” to replace “Gamut mapping G2” of Bala’s framework in the latter experiment (i.e., Exp 1), and evaluate the performances of the SGMAs which combine different tone mappings and gamut mapping paths.

The linear spatial filter named USM (Unsharp Mask) in this study is performed using Eqs. (1) and (2). This type of inner-USM manipulation was first introduced by Bala et al. (2001) into their SGMA. It can be thought that USM is likely to achieve edge enhancement by adding to the image’s lightness (-luminance) component during the spatial gamut mapping process.

\[ Y'_i = Y_i + \Delta Y_{i,USM} \]  

(1)

\[ \Delta Y_{i,USM} = \mu \times \left( \frac{1}{N^2} \sum_{j \in S} \Delta Y_j \right) \]  

(2)

In this study, \( Y_i \) and \( Y'_i \) represent the input and output lightness levels at pixel \( i \), respectively. \( \Delta Y_{i,USM} \) is the lightness feedback level of USM operation at pixel \( i \). That is, Eq. (1) means that the output lightness level \( Y'_i \) is the sum of the input lightness level \( Y_i \) and the lightness feedback level \( \Delta Y_{i,USM} \) at pixel \( i \). Then, Eq. (2) defines \( \Delta Y_{i,USM} \), where \( \Delta Y_i \) is the lightness difference before and after G1 mapping at pixel \( i \). \( \Delta Y_j \) is the lightness difference at pixel \( j \), where \( j \) represents the pixel position around the pixel \( i \). \( S \) is a \( N \times N \) local neighborhood around pixel \( i \), and filter gain \( \mu \) is used to adjust the sharpness degree around pixel \( i \). The settings of filter gain \( \mu \) and filter size \( N \) in Eq. (2) can affect how the USM works. However, they are determined by a trial-and-error approach at this stage. A further work will be performed on the parameter optimization of USM’s design. We refer to Bala’s suggestion here (2000, 2001). The USM size is set to \( 15 \times 15 \) (i.e., \( N = 15 \)) for pictorial images. In additions, \( \mu \) is set to 0.4 so as to obtain a better enhancement effect for our test images. The concept of USM-based SGMA is shown in Fig. 4. When \( Y_i \) is set to the broken line in Fig. 4(a) and \( \Delta Y_{i,USM} \) is the one in Fig. 4(b), the \( Y'_i \) after USM operation could be regarded as the result of Fig. 4(c), which is the sum of \( Y_i \) and \( \Delta Y_{i,USM} \).

On the other hand, the gamut mapping path is also an important issue in designing general spatial-invariant GMAs. Here, the gamut mapping path is defined as follows: the predetermined path in a color space or color plane which makes all colors in the source image map towards the destination gamut. The focal point is used to build the predetermined path in a color space or color plane. Usually, the gamut mapping path is selected in a given constant-hue plane, and the numbers or geometric positions of the focal point are designed to determine the mapping directions which map each source color towards the assigned focal point. However, this issue was not clear in SGMAs until now.

The basic mapping approach of source colors is compressed along lines which pass through the middle of the lightness axis, which was first proposed by Sara (1984). Johnson et al. (1992) proposed the CARISMA algorithm also having a single focal point on the constant-hue plane—an initial lightness mapping. Ito and Katoh (1995) first designed a GMA that performs a four-region compression on a constant-hue plane. They designed a point \( K \) along the line between the lightness axis and the destination cusp that divides the source gamut into four regions, which are (A) the colorimetric region, (B) the region where the colors are compressed towards point \( K \), (C) the dark region where the colors are compressed towards the white point, and (D) the highlight region where the colors are compressed towards the black point. Büring and Herzog (2002) further proposed a twist to the usual way of mapping colors.
along straight lines by introducing curvature to the mapping path.\textsuperscript{18} Since 2000, several efforts have revealed that the GMAs based on multiple focal points work better than the ones with a single focal point because multiple focal points can avoid excessive lightness shifting in gamut-mapped images.\textsuperscript{18–21}

Figure 5 shows two concepts of the gamut mapping path: (a) multi-mapping paths and (b) single mapping path. The work of multi-mapping paths represents a solution of selecting proper positions of multiple focal points on the lightness axis to determine gamut mapping paths. In this research, the image’s lightness division (ILD) is utilized to determine proper positions of multiple focal points according to Eqs. (3) and (4) (see Fig. 6)\textsuperscript{19};

\[ p_i = \frac{\sum_{j=1}^{L_{ij}} f_{ij}}{\sum_{j=1}^{L_{ij}} f_{ij}} \quad i = 1 - n, \]  

\[ k = \text{Round} \left( \frac{\text{total pixel number}}{n} \right), \]  

where \( L_{ij} \) represents the \( j \)-th lightness value in the \( i \)-th lightness interval and \( f_{ij} \) represents the accumulative pixel numbers at the \( L_{ij} \) interval. It means the image’s lightness range is divided into \( n \) intervals, where the lightness interval includes the same \( k \) integer of the color sample. Finally, each image is divided into \( n \) lightness intervals, and \( n \) focal points are obtained on the lightness axis using ILD operation. In this study, an appropriate \( n \) value is selected as 10 according to previous research.\textsuperscript{19} To compare it with ILD operation, we also select the manipulation of the single mapping path, where the focal point is selected on the lightness axis towards the cusp point of sRGB’s color gamut.

Next, we introduce GMA studies based on vividness-priority preservation. The vividness attribute in gamut-mapped images is mainly influenced by tone mapping. Generally, tone mapping can be classified into mapping for lightness or for chroma. Most of the tone mapping is preferred to be applied to lightness more than chroma. Nonlinear tone mapping or clipping for chroma is a benefit to obtaining a more vivid effect. However, artificial contours easily occur in gamut-clipped images. Figure 7 demonstrates three types of tone mapping types in generic GMAs, i.e., clipping, linear mapping, and sigmoidal mapping.\textsuperscript{3} Note that sigmoidal mapping is widely used in conventional photographic color reproduction because it works well for enhancing middle tones and preserving highlight and shadow details in an image.\textsuperscript{22}

Ito and Katoh (1995) used hard clipping to apply to lightness and chroma in their proposed GMA.\textsuperscript{17} Hard clipping is easily performed in general GMA; however, it tends to lose the gradations at high-saturation areas. MacDonald et al. (2002) suggested a soft-clipping function to adjust the relationship between source chroma and destination chroma.\textsuperscript{23} Buring and Herzog (2002) also introduced a knee function to deal with the chroma factor in his proposed GMA. By adjusting the parameter \( \lambda \), the different shapes of knee function could produce different vividness effects for mapped images.\textsuperscript{24} In this paper, the assigned tone-mapping

\begin{figure}[h]
  \centering
  \includegraphics[width=\textwidth]{figure5.png}
  \caption{Gamut mapping paths. (a) Multi-mapping paths. (b) Single mapping path.}
  \label{fig:gamut_mapping}
\end{figure}

\begin{figure}[h]
  \centering
  \includegraphics[width=\textwidth]{figure6.png}
  \caption{Image’s lightness division (ILD).}
  \label{fig:ild}
\end{figure}

\begin{figure}[h]
  \centering
  \includegraphics[width=\textwidth]{figure7.png}
  \caption{Tone-mapping types in GMAs.}
  \label{fig:tone_mapping}
\end{figure}
type will calculate the colorimetric Euclidean distance along the line to compress input colors into the sRGB's gamut, if mapping paths are determined. The sigmoidal function is performed to achieve non-linear sigmoidal mapping according to Eq. (5);

\[
C_{out} = t \left( \frac{C_{in}}{C_{in_{\max}}} \right)^{\alpha} \frac{C_{out_{\max}}}{C_{in_{\max}}} \left( \frac{C_{in}}{C_{in_{\max}}} \right)^{\beta} + \gamma
\]

where \(C_{in_{\max}}\) and \(C_{out_{\max}}\) represent the maximum colorimetric distances within the input and output gamut, respectively. Colorimetric distance is the Euclidean distance between source color and destination color along the mapping line in the \(L^* - C_{ab}^*\) plane. \(C_{in}\) and \(C_{out}\) represents the input/output colorimetric distance, respectively; \((t, \alpha, \beta, \gamma)\) are the adjustment coefficients of the sigmoidal shape, and the conditions of \(t - \gamma = 1\) and \(\beta - \alpha > 1\) must be satisfied. Table 3 indicates three cases of \((t, \alpha, \beta, \gamma)\) parameter settings of the sigmoidal function corresponding to Eq. (5). Figure 8 shows an example of the sigmoidal shapes (i.e., S1, S2, and S3 curves) setting different parameters, in which \((C_{in_{\max}}, C_{out_{\max}}) = (120, 100)\). The result in the figure indicates that the S2 curve with \(t - \gamma = 1\) and \(\beta - \alpha > 1\) has a more reasonable sigmoidal shape. Here, a coefficient combination of \((t, \alpha, \beta, \gamma) = (1.8, 2.0, 3.5, 0.8)\) is the experiential setting for obtaining better tonal rendering, which implies a symmetrical s-curve shape could maintain more abounding details at the highlight and shadow areas. The optimization of the \((t, \alpha, \beta, \gamma)\) coefficient combinations will be continually worked on in the future.

### 3 SGMA evaluation

We attempted SGMA evaluations in terms of image characteristics, display characteristics, and GMA performance as follows.

#### 3.1 Image characteristics

It is evident that image content strongly affects SGMA performance. Therefore, some critical image characteristics are needed to further investigate the relationship between image content and SGMA. In this paper, two useful image characteristics, edge map and color histogram, are, respectively, analyzed in each test image.

Edge map represents the 2-D map showing the sharpness change in the brightness component of an image. It can be used to examine high-frequency information which comes from edge variation of the test image. Here, edge map in lightness (CIE \(L^*\)) component of an image is detected by the Canny edge-detection method. The Canny method applies two thresholds to the gradient in lightness component; a high threshold for low edge sensitivity and a low threshold for high edge sensitivity. It has been widely reported that the Canny edge detector is a useful approach. It uses a filter based on the first derivative of a Gaussian filter and further utilizes four edge-direction detecting filters to detect horizontal, vertical, and diagonal edges of an image, and finds the magnitude and direction of the best edge.\textsuperscript{25,26}

![FIGURE 8 — Shapes of sigmoidal functions.](image)

### TABLE 4 — Test images.

<table>
<thead>
<tr>
<th>(a) Parrots</th>
<th>(b) Wool-1</th>
</tr>
</thead>
<tbody>
<tr>
<td>(c) Wool-2</td>
<td>(d) Mandolin</td>
</tr>
</tbody>
</table>

### TABLE 3 — Parameter settings of sigmoidal function.

<table>
<thead>
<tr>
<th>Curve</th>
<th>(t)</th>
<th>(\alpha)</th>
<th>(\beta)</th>
<th>(\gamma)</th>
<th>Limitation 1</th>
<th>Limitation 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>S1</td>
<td>2.4</td>
<td>2.0</td>
<td>3.5</td>
<td>0.8</td>
<td>(\beta - \alpha &gt; 1)</td>
<td>(t - \gamma &gt; 1)</td>
</tr>
<tr>
<td>S2</td>
<td>1.8</td>
<td>2.0</td>
<td>3.5</td>
<td>0.8</td>
<td>(\beta - \alpha &gt; 1)</td>
<td>(t - \gamma = 1)</td>
</tr>
<tr>
<td>S3</td>
<td>1.2</td>
<td>2.0</td>
<td>3.5</td>
<td>0.8</td>
<td>(\beta - \alpha &gt; 1)</td>
<td>(t - \gamma &lt; 1)</td>
</tr>
</tbody>
</table>

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Besides, 8-bit RGB color signals in each pixel of an image are transformed into CIE LCh values according to sRGB encoding. According to the lightness/chroma/hue distributions, a color histogram of an image could be classified into a lightness histogram, chroma histogram, and hue histogram, respectively. They could be used to inspect the relationship between the image’s color characteristics and SGMA performance.

We attempt to analyze the image content in terms of an edge map and color histogram. Therefore, each image characteristics will be inspected according to the classifications of “edge map,” “lightness histogram,” “chroma histogram,” and “hue histogram.” The “edge map” is produced from the image’s lightness (CIE L*) channel. Meanwhile, the “lightness histogram,” “chroma histogram,” and “hue histogram” are calculated according to the frequency of times each pixel occurs in lightness/chroma/hue component of the test images. The number of dominant color hues for each image was further obtained according to the proportion of dominant hue-color pixel’s numbers to total pixel’s numbers. In this research, the threshold of dominant hue-color is

<table>
<thead>
<tr>
<th>Name</th>
<th>Source</th>
<th>Resolution</th>
<th>Color encoding</th>
<th>File format</th>
<th>Record format</th>
</tr>
</thead>
<tbody>
<tr>
<td>Parrots</td>
<td>Kodak test images</td>
<td>768 x 512</td>
<td>sRGB encoding</td>
<td>TIFF</td>
<td>8-bit RGB</td>
</tr>
<tr>
<td>Wool-1</td>
<td>ISO 12640-3, CIELAB/SCID</td>
<td>1000 x 800</td>
<td>Adobe RGB encoding</td>
<td>TIFF</td>
<td>8-bit RGB</td>
</tr>
<tr>
<td>Wool-2</td>
<td>ISO 12640-2, CIELAB/SCID</td>
<td>1200 x 900</td>
<td>sRGB encoding</td>
<td>TIFF</td>
<td>8-bit RGB</td>
</tr>
<tr>
<td>Mandolin</td>
<td>ISO 12640-3, CIELAB/SCID</td>
<td>1120 x 1400</td>
<td>Adobe RGB encoding</td>
<td>TIFF</td>
<td>8-bit RGB</td>
</tr>
</tbody>
</table>

**TABLE 7 — Color-characteristic descriptions of test images.**
defined as follows: the ratio of their color pixel in an image must be larger than 15%.

As shown in Table 4, four types of natural images are chosen to evaluate the GMA performance. They are called “parrots,” “wool-1,” “wool-2,” and “mandolin,” which are selected from Kodak test images, ISO 12640-2, and ISO 12640-3. The image states are listed in Table 5. To examine the relationship between image content and SGMA performance, it is necessary to investigate the image characteristics according to an edge map and color histogram.

The detected edge maps are drawn using white dots in Table 6. It shows that the Canny operator is effective in detecting edge information, which are approximately in accordance with our visual observations.

In addition, the analytical results of color histograms, including “lightness histogram,” “chroma histogram,” and “hue histogram” of the test images, are also arranged in Table 7. Table 8 further lists the data of the edge ratio/mean lightness value/mean chroma value and dominant hue-color number of each image. Compared with the other images, the above result demonstrates that “mandolin” image shows quite different characteristics in the edge map (i.e., edge ratio = 26) and lightness histogram (i.e., mean lightness value = 51).

On the other hands, when we analyze hue histograms of test images, the dominant hue-color numbers in “parrots,” “wool-1,” “wool-2,” and “mandolin” images are 3, 1, 2, 0, respectively. Note that the “mandolin” image is bright and flat, owing to no dominant hue-color in it. Therefore, the “mandolin” image could be seen as a type of high-key content of more edge information and flat tone. We will discuss the relationship between the “mandolin”-like image and its SGMA’s performance later.

### 3.2 Display characteristics

Table 9 lists color-measurement instruments and display equipment used in this paper. It is necessary to calibrate the color primaries and tone characteristics of color displays before the psychophysical experiment. Two well color-calibrated LCD monitors are set up as our experimental test platforms; one is ColorEdge CE240W (EIZO) calibrated with the sRGB setting and the other is ColorEdge CG221 (EIZO) calibrated with the Adobe RGB setting. The spectrophotometer X-rite Eye-One and calibration software EIZO ColorNavigator are used to calibrate the above two monitors. Finally, the spectroradiometer Konica-Minolta CS-1000A is utilized to inspect color accuracies of calibrated LCD monitors. A total of 324 colors which are located along CIE LCh color-gamut boundaries of sRGB monitor are produced as a test color chart (see Fig. 9). The 324 color elements of a test color chart are displayed on a full screen of a calibrated LCD monitor individually to compute color differences between reference colorimetric values and measured colorimetric values. For a sRGB-calibrated LCD monitor (i.e., EIZO ColorEdge CE240W), the maximum/minimum/average color difference ΔE*ab values are

---

**TABLE 8 — Image-characteristic information.**

<table>
<thead>
<tr>
<th>Name</th>
<th>Edge ratio</th>
<th>Mean lightness value</th>
<th>Mean chroma value</th>
<th>Dominant hue number</th>
</tr>
</thead>
<tbody>
<tr>
<td>Parrots</td>
<td>15%</td>
<td>47</td>
<td>30</td>
<td>3</td>
</tr>
<tr>
<td>Wool-1</td>
<td>23%</td>
<td>37</td>
<td>24</td>
<td>1</td>
</tr>
<tr>
<td>Wool-2</td>
<td>10%</td>
<td>35</td>
<td>32</td>
<td>1</td>
</tr>
<tr>
<td>Mandolin</td>
<td>26%</td>
<td>51</td>
<td>23</td>
<td>0</td>
</tr>
</tbody>
</table>

**TABLE 9 — Instruments and display equipment.**

<table>
<thead>
<tr>
<th>Instrument and equipment</th>
<th>Manufacturer</th>
<th>Condition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spectrophotometer</td>
<td>X-rite Eye-One</td>
<td>Monitor calibration</td>
</tr>
<tr>
<td>Calibration software</td>
<td>EIZO ColorNavigator</td>
<td>Monitor calibration</td>
</tr>
<tr>
<td>Spectroradiometer</td>
<td>Konica-Minolta CS-1000A</td>
<td>Monitor measurement</td>
</tr>
<tr>
<td>sRGB LCD monitor</td>
<td>EIZO ColorEdge CE240W</td>
<td>Luminance = 82 cd/m², γ = 2.2, White point = 6502 K</td>
</tr>
<tr>
<td>Adobe RGB LCD monitor</td>
<td>EIZO ColorEdge CG221</td>
<td>Luminance = 84 cd/m², γ = 2.2, White point = 6504 K</td>
</tr>
</tbody>
</table>

**FIGURE 9 — Test color chart based on sRGB color boundary points.** (a) Test color chart. (b) sRGB color boundary points.
2.3/0.3/1.2, respectively. For Adobe RGB-calibrated LCD monitor (i.e., EIZO ColorEdge CG221), the maximum/minimum/average color difference $\Delta E^*_{ab}$ values are 2.8/0.1/1.0, respectively. Therefore, the well color-calibrated ColorEdge CE240W and ColorEdge CG221 could be regarded as standard sRGB monitor and Adobe RGB monitor, respectively.

3.3 GMA performance

The SGMA types based on three types of USM locations in the gamut mapping process are examined in this paper, i.e., pre-USM, post-USM, and double-USM types. The main differences among them are where USM operation is set in spatial gamut mapping process. As shown in Figs. 10–12, “SM-mapping” represents gamut mapping that combines sigmoidal tone mapping and multi-mapping paths using ILD operation, and “USM image” means an image after USM operation.

Pre-USM type is designed to put the USM operation in front of SM mapping in the five-stage transform (see Fig. 10). Moreover, to put the USM operation behind SM mapping in the same five-stage transform is called a post-USM type, which runs the function in compensation for lost lightness information during the SM-mapping process (see Fig. 11). Double-USM type means to combine two processes of pre-USM and post-USM that could perform both edge enhancement and lightness compensation simultaneously (see Fig. 12).

The psychophysical experiment is hoped to make a color-matching comparison between the original image on the reference monitor (i.e., Adobe RGB monitor) and the mapped ones on the test monitor (i.e., sRGB monitor). As the pair-comparison method is adopted, two LCD monitors are viewed in a dark room by 12 young observers with normal color vision, who are mostly 22–28 years old. Each observer is asked to select the one from a pair of mapped images on the sRGB monitor to match the reference one on the Adobe RGB monitor. Under the assumption of Case V in Thurstone’s law of comparative judgment, the data from visual assessment experiment were analyzed to generate the z-score values. 31

Figure 13 shows the experimental flowchart in this paper. Two types of psychophysical experiments, Exp 1 and Exp 2, are performed according to the following procedures. Firstly, 12 test GMAs which introduce different parameter combinations (i.e., tone mapping, mapping direction, and USM filter) are tested in Exp 1 to determine which is the optimal candidate. Next, according to the optimal candidate having USM operation from the pre-experiment, three USM-based SGMA s were further designed in Exp 2 to evaluate the ranking according to USM locations in the
gamut-mapping process. In this paper, the ILD method which determines multi-mapping paths is introduced into the proposed SGMA.

The experimental contents are described as follows:

**[Exp 1]** Optimal parameter combination (OPC) evaluation: Exp 1 is to evaluate the optimal parameter combination (OPC) among test GMAs. As can be seen from Table 10, 12 test GMAs are inspected by pair comparison analysis and 66 pairs of method combinations are produced. The “s-curve” in Table 10 means sigmoidal tone mapping. Each test GMA includes combinations of tone mapping (i.e., clipping, linear, and sigmoidal mapping), mapping path (i.e., single point/ILD), and USM operation (i.e., with or without). For example, GM8 means GMA with sigmoidal tone mapping, ILD multi-mapping paths, and USM operation. Among 12 test GMAs, GM2 with clipping, single mapping path, and USM operation is similar to Bala et al. framework, it could be seen as a comparative index in Exp 1. The test images rendered by 12 test GMAs are evaluated in psychophysical experiments to select the superior method of the highest ranking. In additions, the performances of USM-based types will be inspected to compare with the other spatial-invariable GMAs. As a result, totally 3168 times are executed in Exp 1 according to the following combinations.

\[
12 \text{ observers} \times 4 \text{ images} \times 66 \text{ pairs} = 3168 \text{ combinations.}(6)
\]

**[Exp 2]** Optimal location combination (OLC) evaluation: Exp 2 is to evaluate optimal USM location combinations (OLC) among test SGMA. According to the evaluated results of pre-experiment, the optimal candidate of the highest ranking is selected as an index of test USM-based type in this experiment and we call it the “pre-USM” type. Then three types of USM-based SGMA will be further defined according to where the USM operation is designed in the gamut-mapping process. In Exp 2, “pre-USM” means that the USM operation lies forward of the SM mapping. The “post-USM” means that USM operation lies behind the SM mapping. It can be that SM mapping and USM operation in the post-USM type approximately corresponds to the positions of “image enhancing algorithm” and “accurate GMA” in Morović’s six-stage transform, respectively. Therefore, pre-USM, post-USM, and double-USM types shown in Figs. 10–12 will be compared in this experiment. These SGMA are further evaluated by pair-comparison analysis. As a result, totally 144 times are executed in Exp 2 according the following combinations.

\[
12 \text{ observers} \times 4 \text{ images} \times 3 \text{ pairs} = 144 \text{ combinations.}(7)
\]
4 Experimental results

Figure 14 shows the evaluated result of Exp 1, which is expressed by score means and 95% confidence intervals. The x axis represents the GMA method and the y axis represents mean z-score. The result demonstrates that the best four evaluation rankings are GM 8, GM 7, GM12, and GM11 averaged. It is evident that the GMAs having an ILD parameter are superior to the ones with a single focal point.

For test images of “parrots,” “wool-1,” and “wool-2,” the rankings of USM-based types are higher than the ones without USM totally (i.e., GM 2 > GM1, GM 4 > GM 3, GM 6 > GM 5, GM 8 > GM 7, GM 10 > GM 9, GM 12 > GM 11). As expected in advance, the test SGMAs introducing USM operation with little edge sharpness (i.e., μ = 0.4) have better color matching in cross-display color reproduction. On the other hand, we can also observe that the GMAs with sigmoidal tone mapping (i.e., GM 5, GM 6, GM 7, GM 8) are averagely better than the ones with linear mapping or clipping. It hints that non-linear tone mapping using a sigmoidal function is effective in keeping the highlight and shadow details in a gamut-mapped image.

As a result, it reveals that GM 8 which introduces USM operation, sigmoidal tone mapping, and ILD mapping direction works well in Exp 1. Therefore, we select GM 8 as a USM-based candidate in Exp 2, which is called the “pre-USM” type.

As shown in Fig. 15, the evaluation result in Exp 2 shows that double-USM type has better agreement in the images of “parrots,” “wool-1,” and “wool-2,” excluding the “mandolin” image. The “mandolin” image has more edge information and a brighter appearance than the other ones; it hints that the double-USM type tends to cause over-enhancement and make gamut-mapped images become worse. Therefore, it can be further developed into pre-USM type, post-USM type and double-USM type to examine the color-matching effects according to the USM location in the SGMA process. For most natural images, the psychophysical experimental results show that the double-USM type obtains a better matching effect than the others. However, the double-USM type tends to cause over-enhancement and make gamut-mapped images become worse. It hints that the double-USM type will be a choose to obtain better matching results for most bright images with general edge distributions.

In this research, it also demonstrates that a gamut-mapped image shown on a sRGB monitor is possible to simulate color appearance of an Adobe RGB display using the proposed spatial gamut mapping. A further study will be performed on parameter optimizations in sigmoidal tone mapping and USM operation. We will also attempt to use other non-linear spatial filters applied to SGMA in the future.

5 Conclusions

To solve color-mismatching problems which frequently occur between a sRGB general monitor and an Adobe RGB wide-color-gamut monitor, the spatial-based GMA combined with linear filter operation, SM mapping applied to an sRGB monitor is proposed. The linear filter operation is designed according to USM (Unsharp Mask) operation, which has a better edge-enhancement effect in the gamut-mapping process. SM mapping means the operation combines sigmoidal tone mapping and multi-mapping paths. The work of multi-mapping paths is formed by using image’s lightness division (ILD), which can determine the proper positions of multiple focal points on the lightness axis. Meanwhile, sigmoidal tone mapping is adopted to enhance middle tone and preserve the highlight and shadow details when the dynamic range of the gamut-mapped images become smaller.

It can be further developed into pre-USM type, post-USM type and double-USM type to examine the color-matching effects according to the USM location in the SGMA process. For most natural images, the psychophysical experimental results show that the double-USM type obtains a better matching effect than the others. However, the double-USM type tends to cause over-enhancement and make gamut-mapped images become worse. It hints that the double-USM type will be a choice to obtain better matching results for most bright images with general edge distributions.

In this research, it also demonstrates that a gamut-mapped image shown on a sRGB monitor is possible to simulate color appearance of an Adobe RGB display using the proposed spatial gamut mapping. A further study will be performed on parameter optimizations in sigmoidal tone mapping and USM operation. We will also attempt to use other non-linear spatial filters applied to SGMA in the future.

References


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