EVALUATION OF SPATIAL GAMUT MAPPING ALGORITHMS

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ABSTRACT

We propose an independent evaluation of Spatial Gamut Mapping Algorithms (SGMAs) by a psychophysical experiment comparing five gamut mapping algorithms, two point-wise and three spatially adaptive applied to fifteen images. Results show that reproduction from SGMAs were rated best, and indicate that among SGMAs, observers attached more importance to the preservation of saturation and of global contrast than to the rendering of details. The results of this psychophysical experiments are then compared to selected Image Quality Metrics (IQMs) to investigate their possible utilization in the implementation and evaluation of new GMAs. The comparison demonstrates that while IQMs do not present a conclusive correlation, they are still able to extract useful information about the local distortion caused by the gamut mapping algorithms.

1. INTRODUCTION

The fundamental role of a gamut mapping algorithm (GMA) is to manage the loss of information caused by the shape deformation and generally the size reduction of the color gamut between an original image and its reproduction via another technology (print, photograph, electronic display). There are an impressive number of proposed GMAs in the literature. Morovic and Luo have made an exhaustive survey in [1–3]. They classified the classic point-wise GMAs into two categories: gamut compression and gamut clipping. The ICC color management is based on this first generation of non-adaptive GMAs [4]. The next step has been to investigate the selection of an appropriate GMA depending on the image type, and the adaptation of GMAs directly to the image gamut instead of the input device gamut [1–3]. To further improve GMAs, it has been advocated that preservation of the image details is a very important issue for perceptual quality [5, 6]. 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. There are a limited number of publications regarding this recent and important development that was first introduced by Meyer and Barth in 1989 [7], followed by Nakauchi et al. [8, 9], Balasubramanian et al. [10], McCann [5], Morovic and Wang [11], and more recently Kimmel et al. [12]. In this study, we propose an independent evaluation of three SGMAs and two point-wise GMAs, by comparing them with each other. Psychophysical experiments are conducted as recommended by The Commission Internationale de l'Eclairage (CIE).

Newly implemented GMA are typically evaluated using psychophysical experiment [1–3, 6, 13]. Conducting a psychophysical experiment is not very convenient as it involves a panel of observers, time consuming sessions and an experimental room with specialized equipment. If instead a robust mathematical model of the observers' perception could be used, one would have a much more flexible evaluation tool to compare GMAs and maybe optimize them. It could even provide local quality indexes allowing a finer analysis. Many models of the human visual system have been proposed, and several image quality metrics, based on these models, can be found in the literature.

Before using these metrics to evaluate the quality of GMAs, it is necessary to investigate if they present a correlation with the human perception. Recently, Eriko Bando et al. [14] have launched the evaluation, by comparing the measure obtained with three of these metrics, CIELabΔE_{ab}, S-CielabΔE_{ab} [15], and iCAM [16], with results of paired comparison experiments. They could find no correlation. In this experiment, we have selected four metrics that we thought to be appropriate. We propose to compare them with the results of our psychophysical experiment.

The first part of this paper provides the details of the experiment, followed by an analysis of the results. In the second part, we compare these results with the measures obtained with a selection of Image Quality Metrics

2. EVALUATION OF SPATIAL GAMUT MAPPING ALGORITHMS

In this section, we present our evaluation of selected SGMAs by a psychophysical experiment following the CIE's guide-

lines, with fifteen images and a panel of 22 observers.

2.1. CIE's Guidelines

The CIE and its Technical Committee 8-03 have published in 2004 a technical report providing guidelines for the evaluation of the cross-device and cross-media color image reproduction performance of GMAs [17]. GMAs are evaluated using a psychophysical method and a pool of observers. The guidelines cover numerous aspects of GMA evaluation including test images, media, viewing conditions, measurement, gamut boundary calculation, gamut mapping algorithms, color spaces and experimental method. Three different psychophysical methods are proposed in the guidelines: matching, category judgment and pair comparison. The latest is by far the most popular and is recommended by the CIE. We use it in our evaluation. In pair comparison, the observer is presented with a reference image along with pairs of candidate gamut-mapped images. The observer is asked to pick the "closest"or "most accurate" reproduction with respect to the original image.

2.2. Images

A total of fifteen images (Fig. 1 and 2) were used in this experiment: PICNIC and SKI (ima5 and ima6 in Fig.1) as recommended by the CIE, along with eight images from the Kodak Photo CD Sample and five S-RGB images from the ISO 12640-2:2004 standard [18]. The original images were converted to CIELab and gamut mapped using the different GMAs. The output gamut was the gamut of an OCE TCS-500 printer using OCE Draft paper and the printer's *Presentation* mode. It was measured by a spectrophotometer Spectrolino using GretagMacBeth MeasureTool 5.0.4.

ima1, ima2, ima3, ima4, ima5, ima6, ima7

Fig. 1. Set A

imb1, imb2, imb3, imb4, imb5, imb6, imb7, imb8

Fig. 2. Set B

2.3. Point-Wise and Spatial GMAs Selected

In our psychophysical experiment, in accordance with the CIE's guidelines [17], we evaluate the two point-wise GMAs HPMINDE and SGCK and compare them with the following three Spatial GMAs: XSGM proposed by Bala et al [10], RETGM proposed by McCann and based on Retinex [5] and MSGM4 proposed by Morovic et al. [11].

- HPMINDE, hue-angle preserving minimum ΔE^*_{ab} clipping [17]: this algorithm keeps colors belonging to the intersection of the original and reproduction gamuts unchanged and only alters original colors that are outside the reproduction gamut. This is done in the CIELab space by clipping, these points being projected onto the nearest point (smallest ΔE^*_{ab} color difference) of the reproduction gamut surface belonging to the same hue-angle (h_{ab}) plane.

- SGCK, chroma-dependent sigmoidal lightness mapping and cusp knee scaling [17]: this method keeps perceived hue constant, compress lightness and chroma along lines toward the point on the lightness axis having the same lightness as the cusp of the reproduction gamut, using a knee function.

- XSGM: this gamut mapping aims at preserving spatial luminance variations [10]. Balasubramanian et al. process the image through a standard point-wise clipping GMA, and calculate the difference between the original luminance Y and the gamut mapped image luminance Y'. The difference is spatially filtered with a high pass filter, and added back to the gamut mapped luminance, in order to enhance edges. The resulting image is again gamut mapped, using another clipping algorithm that clip colors onto the gamut surface by projecting them toward a different direction.

- RETGM: the spatial GMA proposed by John McCann [5] is based on the Retinex model, stressing the importance of spatial radiance ratios in human vision. The algorithm starts with the original image and a candidate image resulting from a classic gamut mapping. It computes local ratios in a multi-scale decomposition of the original, and then locally modifies the colors of the multi-scale decomposition of the candidate image by forcing it to present the same local ratios as the original.

- MSGM4: the spatial GMA proposed by Morovic and Wang [11] assumes that when considering spatial accuracy, the high frequency components, i.e. the details, are more important to image quality than low frequency components. After a spatial frequency-based decomposition of the image, they manage to compress the gamut of the low pass band and to reconstruct the image. Then

they apply a GMA again to map the remaining colors lying outside the gamut. By doing so, they try to preserve as much as possible the high frequency content, possibly sacrificing the dynamic of the low frequency content.

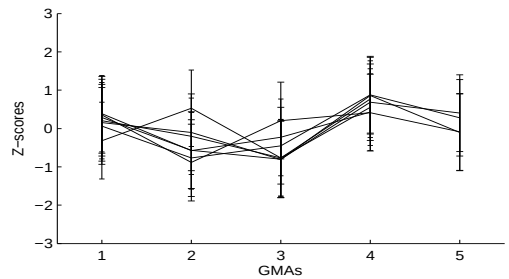
Source code for HPMINDE and SGCK is provided in 'C' on the CIE Division 8 website. In order to be sure that the SGMAs used in our experiments were exactly as in the articles describing them, we asked their authors to process the images. Images from the sets A and B were gamut-mapped with XSGM by Raja Bala et al. using a filter size of 10x10 and a gain of 1.0. Images from the set A, (ima1-7) where gamut-mapped with MSGM4 by Jan Morovic. RETGM was implemented by using Brian Funt's Matlab code [19] and the help of John McCann. McCann algorithm starts with two images, the original and a gamut mapped candidate. In our implementation, we map the candidate with HPMINDE, then we run the Retinex algorithm, then clip the resulting candidate using HPMINDE to clip any pixel that could have been moved out of the gamut by Retinex.

2.4. Psychophysical Experiment

Twenty-two persons constituted the test panel, seven female and fifteen male. Paired comparison was used, and the observers were presented with a reference image along with a pair of candidate gamut-mapped images on an Apple Cinema 23 inch display at a Color Temperature of 6500 Kelvins. The monitor was characterized with a spectrophotometer Minolta CS1000. The background surrounding the monitor was mid gray, illuminated by a D65 fluorescent lamp. The observers viewed the monitor from a distance of approximately 80 cm. We wrote our experiments in Matlab, using the Psychophysics Toolbox extensions [20].

For each image pair, the observers were asked to indicate which of the two candidate images was the best 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. There was no time restriction to answer, and the average response time was approximately of 17 seconds. The observer was forced to reply before accessing the next test.

For each observer, the experiment was split in four sessions. In session one, the seven images of Set A and the five GMAs were compared for a total of 70 pairs. After a short break of a few minutes, session two started where the eight images of Set B and four GMAs, (HPMINDE, SGCK, XSGM and RETGM) were compared for a total of 48 pairs. After a break of minimum one hour and usually a few days, the observers proceeded to session one and two again. Thus each observer had to compare all the pairs of images twice, but in another random order.



1:HPMINDE, 2: SGCK. 3:XSGM, 4: RETGM, 5: MSGM4

Fig. 3. Z-scores and standard deviations of ima2, ima3, ima4, ima7, imb2, imb4 and imb6, images for which RETGMA obtains the best Z-score

2.5. Results

The raw results of the experiment were converted to Z-scores. The Z-score associated with the ith observation of a random variable x is given by $z_i = \frac{(x_i - \overline{x})}{\sigma}$, where $\overline{x}$ is the mean and σ the standard deviation of all observations.

2.5.1. Results per image

Looking at the results per image, we find that for fourteen of the fifteen images, SGMAs obtain the best Z-score. The 15 images can be separated in two main groups based on the preferred GMA: a group for which RETGMA is ranked best and a group for which XSGM is ranked best.

RETGMA obtain the best Z-score for 7 images (ima2, ima3, ima4, ima7, imb2, imb4 and imb6, see Fig. 3). For these images, XSGM results present halos, and RETGMA results are more contrasted and saturated.

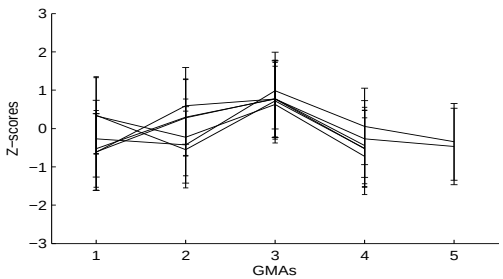
XSGM obtained the best Z-score (see Fig. 4) for 6 images (ima1, ima6, imb1, imb3, imb5, imb8). For these images, RETGMA results show shifts of chroma and clipping artifacts.

MSGM4 obtains the best Z-score for image ima5.

For a single image, imb7, the point-wise GMA HPMINDE is preferred.

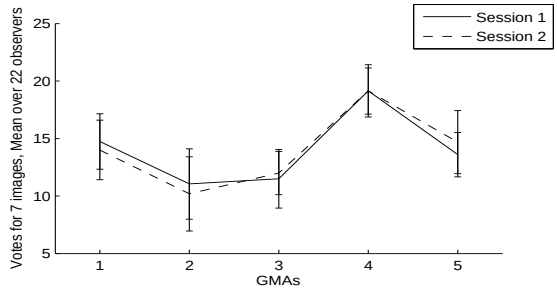
2.5.2. Mean results

Since MSGM4 was evaluated only on Set A, we will discuss the results on the sets A and B separately. In this sub section, we consider for each GMA the accumulated preference count over images. Fig. 5 shows for each of the five GMAs the mean for the twenty-two observers of the accumulated preference count over the seven images of set A. Fig. 6 shows for each of the four GMAs (HPMINDE, SGCK, XSGM and RETGM) the mean for the twenty-two observers of the accumulated preference count over the fifteen images of both sets



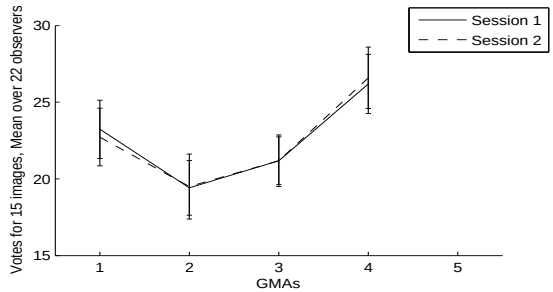
1:HPMINDE, 2: SGCK. 3:XSGM, 4: RETGM, 5: MSGM4

Fig. 4. Z-scores and standard deviations of ima1, ima6, imb1, imb3, imb5, imb8, images for which XSGM obtains the best Z-score



1:HPMINDE, 2: SGCK. 3:XSGM, 4: RETGM, 5: MSGM4

Fig. 5. Mean votes for five GMAs (22 observers, 7 images of set A)



1:HPMINDE, 2: SGCK. 3:XSGM, 4: RETGM

Fig. 6. Mean votes for four GMAs (22 observers, 15 images of sets A and B)

A and B. In the following, we name this mean 'mean vote'. In both cases, the mean votes for each session over the twenty-two observers are very consistent, even if individual results for each observers varied from the first to the second session. The variability might have been caused by the presence of very similar pairs and of pairs showing differences but having the same perceived quality. The observers were forced to make a choice and this added noise to their results. We believe that it would be relevant to add a 'no preference' option into the protocol.

We observe also that the standard deviation of the SGMAs is smaller than that of the point-wise GMAs. This indicates a better consensus of opinions for the SGMAs.

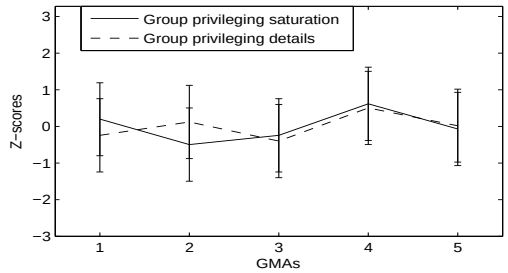
For set A (See Fig. 5), in the first session, the ranking is: RETGM, HPMINDE, MSGM4, XSGM, and at last, SGCK. At the second session, the mean vote of the two point-wise GMAs slightly decreases and the mean vote of the three SGMAs slightly increases. The ranking has changed and MSGM4 is now preferred to HPMINDE.

In Fig. 6, we note that the mean vote over the fifteen images of sets A and B are similar to the mean vote of the set A alone. During the experiment, a few observers declared that overall, the set B was more difficult to evaluate than set A. Indeed the results confirm these declarations as we observe a larger dispersion of the results per observers for the set B and a lesser differentiation of the GMAs. Some of them also complained that images PICNIC and SKI were difficult to evaluate.

2.5.3. Results by category of observers

Looking at individual results, we discern two categories: Sixteen observers who preferred on average HPMINDE over SGCK, and six observers who preferred on average SGCK over HPMINDE. HPMINDE preserves the saturation but often suppresses details in the most saturated parts of the image and introduces artifacts. In the other hand, SGCK preserves details and doesn't introduce artifacts, but at the expense of the saturation. Based on these properties, we argue that observers who preferred HPMINDE over SGCK are more sensitive to the fidelity of the saturation than the details. These are usually 'non-experts' observers. Whereas observers who preferred SGCK over HPMINDE are more sensitive to the fidelity of the detail than the saturation, and are usually 'experts' observers. Given their difference of preference on point-wise GMAs, the judgment of the two groups might be different on SGMAs. In Fig. 7, we see that actually the two groups have a very similar opinion on SGMAs. These results indicate once again a stronger consensus on the quality of SGMAs.

We also looked at a possible difference of judgment between female and male observers, but found no significant bias.



1:HPMINDE, 2: SGCK. 3:XSGM, 4: RETGM, 5: MSGM4

Fig. 7. Mean Z-scores for observers by preference : saturation versus details preservation

2.6. Discussion

The psychophysical experiment shows a worryingly large variation of results among observers and images. The CIE recommends a large pool of observers and Morovic et al in [21] insist on the necessity to use a large number of test images, but the number of images is limited by the necessity to keep the length of the test under one hour. Nonetheless, the consistency of our results from the first session to the second session is a good indicator of the validity and reliability of the experiment. As mentioned earlier, we believe that the observer should be allowed to answer 'no opinion' to the test.

SGMAs obtain the best ratings on fourteen of fifteen images and a stronger consensus than point-wise GMAs. This clearly corroborates that image-dependent SGMAs present a significant progress in the field. The GMAs tested here have specificities that might explain the ratings given:

- HPMINDE images are well saturated but in the most saturated parts of some images we note that details have disappeared and artifacts have appeared.
- SGCK images are not very saturated but no details have disappeared and no artifats have appeared.
- XSGM produces images saturated with a lot of high frequency local details but sometimes showing halos near strong edges.
- RETGMA also produces images saturated and well contrasted, with natural rendering of local details but sometimes showing large shifts of chroma.
- MSGM4 does a nice job on preservation of local details but images suffer of a lack of saturation compared to other SGMAs.

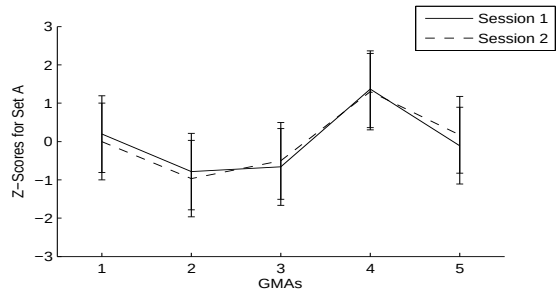
Given these observations, the criteria that seem to matter to the observers, when evaluating SGMAs, are first the saturation and global contrast, and second the preservation of details and the lack of artifacts.

3. QUALITY METRICS FOR COLOR IMAGES

Image quality metrics (IQMs) provide a measure of the difference between two images. In this section, we measure the difference between original and gamut-mapped images with four IQMs, CIELabΔE_{ab}, S-CielabΔE_{ab} [15], iCAM [16], and an extension to color images of SSIM [22]. We compare these measures with the results of our psychophysical experiment on SGMAs for the set A (In Fig. 8).

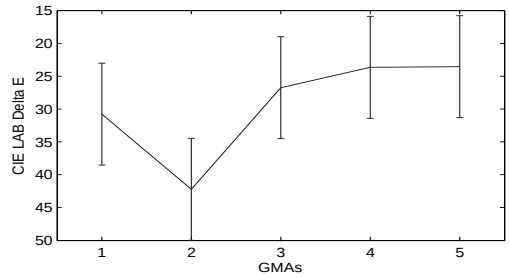
3.1. CIELabΔE_{ab}

The simplest and most widely used IQM is the CIELabΔE_{ab}, a pixel-wise measure corresponding to the Euclidean distance measured between two color points in CIELab space. As it was developed to compare patches of constant colors, it should be of limited accuracy for more complex images.



1:HPMINDE, 2: SGCK. 3:XSGM, 4: RETGM, 5: MSGM4

Fig. 8. Z-scores over the 22 observers for the 7 images of Set A



1:HPMINDE, 2: SGCK. 3:XSGM, 4: RETGM, 5: MSGM4

Fig. 9. CIELabΔE_{ab}, mean over the 7 images of Set A

$$\Delta E_{ab}(x,y) = (\Delta L(x,y)^2 + \Delta a(x,y)^2 + \Delta b(x,y)^2)^{1/2}$$
$$IQM_{Lab} = Mean_{x,y}(\Delta E_{ab}(x,y))$$

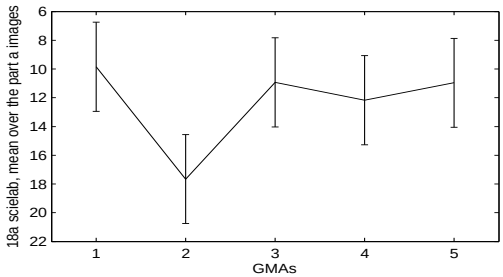
Results in Fig. 9 are to be compared with Z-scores in Fig. 8. We find that the three SGMAs provide the smallest ΔE_{ab}, followed by HPMINDE, and then by SGCK which produces the largest errors. This does not correlate well with the observers' judgment, except for SGCK which observers disliked due to its strong de-saturation.

3.2. S-CielabΔE_{ab}

S-CIELab ΔE_{ab}, introduced by Zhang et al. [15] is an evolution of CIELab ΔE_{ab} and is more elaborated. It includes spatial filtering to model the Contrast Sensitivity Function of the Human Visual System. Results in Fig. 10 resemble CIELabΔE_{ab}'s results (in Fig.9). SGCK is again penalized by its de-saturation, HPMINDE is now the best rated followed by the three SGMAs which obtain approximately the same scores. Comparing them to the Z-scores (see Fig. 8), we can find no correlation.

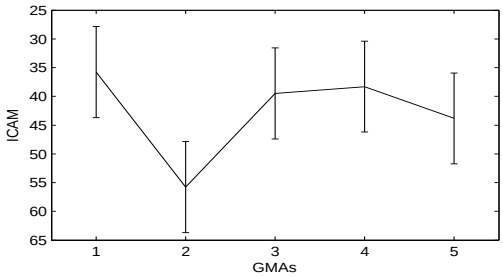
3.3. iCAM

iCAM, proposed by Fairchild and Johnson [16] is an image appearance model, based on a modular framework, that in-



1:HPMINDE, 2: SGCK. 3:XSGM, 4: RETGM, 5: MSGM4

Fig. 10. S-CIELab ΔE_{ab}, mean over the 7 images of Set A



1:HPMINDE, 2: SGCK. 3:XSGM, 4: RETGM, 5: MSGM4

Fig. 11. iCAM difference, mean over the 7 images of Set A

cludes spatial filtering, spatial frequency adaptation, spatial localization, local contrast detection and a color difference map. iCAM can be used as a difference metric. Fig. 11 shows results similar to the above tested metrics.

3.4. Structural Similarity, SSIM

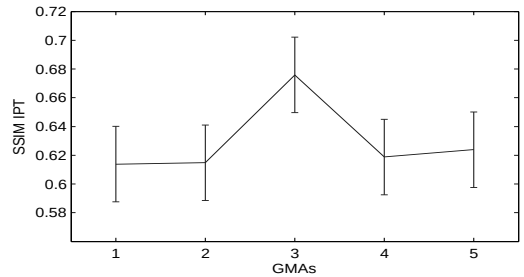
Structural Similarity Based Image Quality Assessment, proposed by Wang et al. [22], follows a different approach. The authors regard the structural information in an image as those attributes that reflect the structure of objects in the scene, independent of the average luminance and contrast. Wang et al. propose a universal image quality index that combines with a geometrical mean the comparison of luminance, contrast and structure : $l(x,y), c(x,y)$ and $s(x,y)$ respectively.

$$SSIM(x,y) = [l(x,y)].[c(x,y)].[s(x,y)]$$

In order to use it in the evaluation of GMAs, we need to adapt it to color images and we compute separately SSIM on each channel of the image in color space IPT [23]. Then we combine the three $SSIM_{channel}$ with a geometrical mean, following recommendations by the authors:

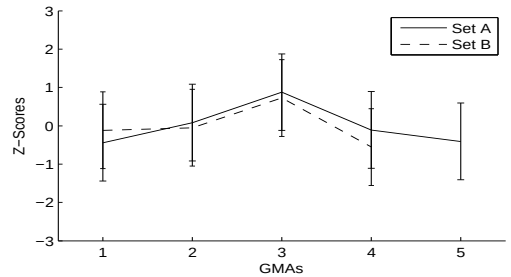
$$SSIM - IPT(x,y) = \\ SSIM_I(x,y).SSIM_P(x,y).SSIM_T(x,y)$$

Results in Fig. 12 show that XSGM obtains the best score from SSIM-IPT followed by the four other GMAs with a lower but similar score. Once again, we do not observe a



1:HPMINDE, 2: SGCK. 3:XSGM, 4: RETGM, 5: MSGM4

Fig. 12. SSIM-IPT, mean over the 7 images of Set A



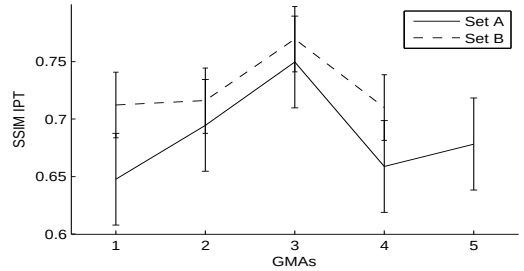
1:HPMINDE, 2: SGCK. 3:XSGM, 4: RETGM, 5: MSGM4

Fig. 13. Z-scores, mean over the images for which XSGM obtained the best rating

strong correlation with the Z-scores over the 7 images; however, we notice similarities with Fig. 4. We decide to focus on the 6 images for which XSGM obtained the best rating, as shown in Fig. 4: we compare the mean of the Z-scores in Fig. 13 and SSIM-IPT results in Fig. 14. The results appear here well correlated but must be considered carefully before generalization and necessitate further investigations.

3.5. Discussion

Three metrics, CIELAB, S-CIELAB and iCAM provide similar results, where SGCK obtains bad scores, and the three SGMAs good scores at almost the same level. They are able



1:HPMINDE, 2: SGCK. 3:XSGM, 4: RETGM, 5: MSGM4

Fig. 14. SSIM-IPT, mean over the images for which XSGM obtained the best rating

to predict loss of saturation. SSIM-IPT's results are very different: XSGM obtains the best score and the other GMAs obtain similar results. SSIM-IPT is able to predict good structural similarity, but apparently not color accuracy. Given that we tested a beta version of SSIM-IPT, future improvements might occur. In the current state, no conclusive correlation between the IQMs results and observers' Z-scores is made, thus we won't use them for global assessment of GMAs. Nevertheless, we believe that IQMs can be used during the development of new GMAs to measure accuracy of colors and details, leaving the final evaluation to observers.

4. CONCLUSIONS

In this study we have proposed an independent evaluation of spatial gamut mapping algorithms by a psychophysical experiment. We learned that for fourteen out of fifteen images, the reproduction perceived as best was the result of a SGMA, and that among SGMAs observers attached more importance to the fidelity of saturation and global contrast than to the fidelity of details. The results also indicated a stronger consensus on the quality of the SGMAs. In the second part, we compared the results of the experiment with Image Quality Metrics and found that none presented a strong correlation with observers Z-scores. Nevertheless, the IQMs results suggested that they could be used for the evaluation of prototype of GMAs, by extracting information about the local distortions of saturation and spatial detail caused by gamut mapping algorithms.

5. ACKNOWLEDGMENTS

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7. BIOGRAPHY

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