The Role of Image Statistics on Cross-Media Gamut Mapping

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Abstract: A universal gamut mapping algorithm (GMA) which performs well for any images in color reproduction between different media would be highly desirable. However, various GMAs have previously been reported to have image–dependent behavior. In order to deal with this problem, recent studies focus on image adapted solutions. Nevertheless, these solutions normally were developed based on a predetermined image characteristic which is incapable of optimizing all types of reproductions. The present study hence investigates various image statistics and their related GMA performance for a better understanding of their correlation. In this paper, the process to identify important image statistics is proposed and an automatic approach to choose the best-suited GMAs for a certain image is also demonstrated.

Introduction

Color gamut mapping refers to the transformation of an image by mapping its colors to fit the gamut of a destination medium. In graphic communications, displays and printers are commonly regarded as the source and the destination media respectively. As a typical printer gamut is smaller than that of a display, how to minimize the change of color appearance through the display-to-printer image transformation is an issue that is being intensively studied. Various kinds of gamut mapping algorithms (GMAs) have been proposed in recent years (Morovic and Luo, 2001). Most of the researches intended to derive a single model which ideally ought to perform well for a wide range of images and conditions. However, reviewing the literatures, one can see that the performance of GMAs has almost invariably been reported to depend on the image contents.

In order to deal with this problem, recent studies focus on image adapted solutions. These solutions normally were developed based on a predetermined image characteristic such as image gamut or lightness histograms (Morovic and Luo, 2001). Yet, an investigation on GMA performance showed that none of them is the dominant factor in controlling the outcomes (Sun and Morovic, 2002). Since

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a single model is hard to cover all images' need, we'd better try another way to solve this problem: finding the best-suited GMA from a range of GMAs for an image based on its statistics. Therefore, the present study aims to investigate various image statistics to see what kings of statistics are particularly important on predicting the GMA performance. Once the key statistics can be extracted, an automatic approach can be derived to optimize the selection of GMAs based on the limited image statistics.

Methods

A psychophysical experiment was set up in which observers were shown an original on a CRT display and a number of laser-printed reproductions of it in a viewing booth. The observers were asked to give estimation about the similarity between the reproductions and their original. The observers' responses were recorded so as to summarize the GMA performance. On the other hand, originals were analyzed on base of three types of image statistics: 1D color, 3D color and texture information. There were 63 items coming from the three categories to be tested. Because many of the items could be useless in the prediction of GMA performance, two-stage selection was first performed to eliminate most of 3D color statistics. The 1D color and texture parameters were then selected using the Principal Component Analysis (PCA) (Jackson, 1991). The variations of the statistics also provided useful hints for the parameter reduction. The resulted principal factors were used to predict the best-suited GMA via the Byers Classifier. To save the computation cost, we prefer limited parameters as possible. Our goal therefore was to maximize the performance of GMA selection while minimizing the numbers of factors in the image statistics.

Gamut Mapping Algorithms

Four GMAs were used to generate the reproductions. They were denoted as SKNEE, XSGM, HP and USMHP. The first, SKNEE, is a compression-type gamut mapping algorithm which is capable of keeping image contrast during the mapping (Braun and Fairchild, 1999). XSGM was proposed by Bala et al. (2001). It applies a two-stage gamut mapping with one spatial filtering process in the implementation. The algorithm features to keep spatial details during the mapping and a 5-by-5 spatial filter in this study was used on lightness plane to extract the spatial information of the original. HP stands for 'hue-preserved minimum deltaE clipping'. In the algorithm, original colors are assigned to the printer gamut while minimizing color differences without change the hue angle. Saturation of an image can be preserved mostly by this GMA. The forth algorithm, USMHP, is similar to the HP except on thing that the former applies a well-known Unsharp Masking technique (USM) to the originals before gamut-map the image. This algorithm also applies a 5-by-5 spatial filter on lightness plane in this study to maintain the sharpness of the image.

To achieve a high-fidelity color reproduction, newly proposed CIECAM02 (J,a_c,b_c) color space (Moroney *et al*., 2002) was used for gamut mapping as well as image transformation. The CRT display was first adjusted to D65 to fulfill the IEC 61966-2.1 standard (IEC, 1999) and the view booth also fitted the standard to minimize the involvement of chromatic adaptation. The viewing environment was set up as "dim". All test images have 0.5 cm white borders and were displayed against a uniform gray background. A ViewSonic 17" CRT was characterized using the CIE recommended GOG model (Berns, 1996) with a mean error of 0.90 ΔE^*_{ab} based on 27 test samples. The destination medium was Epson AcuLaser C4000 laser printer. We chose toner-saver mode with plain papers to generate our prints to ensure that the colors produced by each GMA were significantly different. The printer was categorized by inverse 3D LUTs with tetrahedral interpolation (Hung, 1993) which would generate a mean error of $3\Delta E^*_{ab}$.

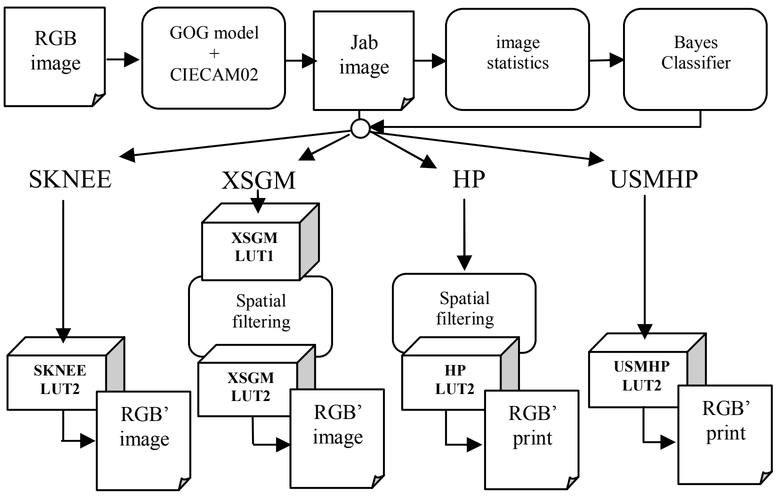

Figure 1: The structure of the proposed color reproduction system

All test images were transformed from sRGB space to (J,a_c,b_c) space based on the GOG model to ensure the originals displayed on the CRT can be reproduced closely on the laser printer. The four GMAs were implemented in between to minimize the visual difference across the two devices. 3D LUTs with tetrahedral interpolation was used for gamut mapping. To avoid quantization errors, all data were stored in 16-bit per channel. The resolution (interval) of the 3D LUTs were set as (4,5,5) for (J,a_c,b_c) channels respectively. In terms of the computation cost, XSGM is greater than all the rest and USMHP also needs more time to complete the work. Refer to Figure 1, LUT1 is used for (J,a_c,b_c) to (J',a_c',b_c') conversion but LUT2 directly transferred colors from (J,a_c,b_c) to gamut-mapped printer's signals (i.e., (R',G',B')). Since the color mapping was performed in the device-independent (J,a_c,b_c) color space, the image statistics also were counted under the space.

Visual Assessment

100 images including portraits, night scenes, landscapes, architectures, commercial posters were regarded as originals in the study. The pixel dimensions of the test images are 800x600 on average, but they were resized into 400x300 for display and the prints were rescaled to fit the image size on the screen. 10 observers were asked to score the 100 originals along with their 400 reproductions under D65 illumination. The viewing booth and the display were toward different directions (with a 90 degree angle) to avoid the observers performing a simultaneous comparison between the original and its reproductions. The observers were asked to score the magnitude of image differences between the pair of images using category judgment method. Eight categories was used, where number zero indicated a perfect match and number seven represented the worst case you can imagine.

The experimental data were summarized using the Mean-Category-Values method (Bartleson, 1984) to identify the best-performed GMA for each original. A Guassian-type Byers Classifier (Sonka et al., 1999) was used to predict the best-performed GMA via various image statistics extracted from the originals. Here, we performed a T-TEST on individual image set to see if our prediction has no significant difference to the observers' judgment (10 observations for each side). For example, if the classifier predicts that the best-suited GMA for image K was XSGM but the observers preferred HP, what we can do is to compare the raw observers' responds of the image on the two GMAs. Assuming the raw responds for XSGM and HP were matrix X_K and Y_K respectively (10 observations for each matrix), we would use T-TEST to determine the accuracy of our prediction. 0.1 is the significant level used throughout the study.

Image Statistics

The present study took into account three types of image statistics: 1D color, 3D color and texture information. The following is their specification:

One-dimensional (1D) color statistics including image summaries and color histograms have been widely used for manual color tuning. Where, Lightness (J), Chroma (C) and hue (h) are the three attributes containing the most important color information. Hence, the (J,a_c,b_c) originals were converted into (J,C,h) space to perform the statistics. Color histogram is the best tool to illustrate the whole picture of the 1D color distributions. However, the histograms contain too much information and hence are inconvenient for on-line image analysis. For this reason, we selected six image summaries, arithmetic mean, standard deviation, skewness, kurtosis, 3rd percentile and 97th percentile to describe the feature of a 1D image color histogram. The reason of using 3rd and 97th percentiles rather than the minimum and maximum is the latter would be seriously influenced by color extremes which only occupies a very small area in the image. 3rd and 97th percentiles hence can better represent the dynamic range of the image histograms. Six statistics with lightness (J) and chroma (C) result in 12 variables. These variables are denoted as L_MEAN, L _STD, L _SKEW, L _KURT, L_3RD, L_97TH, C_MEAN, C_STD, C_SKEW, C_KURT, C_3RD and C_97th.

Due to the circular nature of hue, it's meaningless to count the mean or dynamic range of a hue histogram. The hue histogram hence was divided into eight segments (from 0 to 360 degrees, 45 degrees each) to count the percentage of image's color on the eight primary hues. If a color is nearly neutral, its hue becomes less important. Hence, the statistics only took chromatic colors ($C > 20$) into account. Together with the former, now we have 20 items to depict images' 1D color information.

A specific color cannot be located by 1D color information. For example, the proportion of skin tone cannot be identified by a 1D lightness histogram or a 1D chroma histogram. Therefore, we separated the (J,C,h) color space into 27 blocks to specify the images' 3D color distributions. In previous study, we found that 3D histograms with more hue segments would be useful in image retrieval (Sun *et al*., 2003). In the model, 27 regions were obtained by equally dividing hue angles into eight segments (0, 45, 90, 135, 180, 225, 270 and 315 degrees); three sections for chroma (C=20 and 50 as the thresholds); three lightness sections (J=40 and 70 as the thresholds) for low-chroma regions and two sections (J=55 as the threshold) for mid-chroma regions; no lightness separation for high-chroma regions. The 27 histograms are denoted as W1 to W27. So far, 1D and 3D image statistics contain 47 items in total.

Images' multi-spectral texture information can be obtained by Fourier or wavelets transform. However, they are time-consuming in their computations and no standard statistics can be applied for comparison. Hence, the study used simple spatial filters to extract the texture information. In image processing, Sobel filters have been commonly used for extracting an image's contours (Gonzalez and Woods, 2001). The contours are important features on image recognition. However, its impact on color reproduction is still unknown. Actually, Sobel filters are capable of extracting not only contours but also texture information. The study thus used Sobel filters with 3 different angular magnitudes, 0, 45 and 90, to extract the texture information from different orientations. On the other hand, simple 3-by-3 high-pass filter also was poplar for texture analysis. The filter hence is concerned in the study as well. Because previous studies showed that texture recognition is more correlated to lightness rather than chroma and hue, we only use lightness plane of an original to perform the spatial filtering. The gray level of the filtered lightness-image was then summarized in terms of arithmetic mean, standard deviation, skewness and kurtosis. The four statistics with the four filters form 16 texture variables. Together with the previous, now we have totally 63 variables.

Psychophysical Results

The 400 reproductions were evaluated by 10 observers. However, we found that some bright images only have very small score differences on the four GMAs. This kind of images could introduce noises for image analysis. Hence, in the following discussions, 33 originals with their 132 reproductions having a maximum mean-score difference on the 4 GMAs less than one categorical unit were excluded.

In terms of the mean scores of the 77x4 reproductions, most of observers preferred USMHP (see Table 1). The reason could be that the images lost spatial details intensively due to the gamut difference between the two devices are huge. By using the previous introduced T-TEST, we found that the USMHP would have no significant different to the number one GMA on 77.9% of images. But the algorithm is costly. We should avoid using it if possible. If we randomly select a GMA for use, 47.4% images will regard it as the number one under the significant level of 0.1. Both the averaged number one, USMHP, and the number two, XSGM, require high computation cost. If we can use simple image analysis to determine which GMA is suitable, the quality of reproductions could be enhanced and the cost could be reduced. The accuracy of the proposed automatic approach should be higher than 47.4%, otherwise we just need to randomly select one of the GMAs.

Table 1: GMA performance expresses in different ways.

GMAs	mean score	the best / all images	the best in T-TEST / all images
SKNEE	4.82	18.2%	23.4%
XSGM	4.16	31.2%	46.8%
HP	4.22	18.2%	41.6%
USMHP	3.88	32.5%	77.9%
random selection	4.27	25.0%	47.4%

Note: the lower the mean score, the better the color reproduction

Stage 1 Reduction

63 variables are too many for on-line image analysis. To shorten the time and enhance the performance, some of the variables have to be eliminated. We start from 3D color histograms because previous studies suggested that the histograms are the key factor controlling the image-dependent behavior (Sun and Morovic, 2002). Observing the states of the images' 3D histograms, we found some of them only cover very little amount of image pixels. We believe this sort of histograms is helpless in the GMA prediction. Hence, in the first stage reduction, we counted each histogram. If the value in a histogram was lower than 1% of the total image pixels and the case happened on more than 81.8% images (=100%-18.2%), the histogram will be removed from the list. Under the above criteria, the eliminated items were W8, W11, W12, W15, W16, W18, W19, W23, W24, W26 and W27. After the first stage reduction, 16 (=27-11) 3D histograms left for the second run.

Stage 2 Reduction

We put all 63 variables into the Byers classifier individually to see the accuracy of our prediction. The average accuracy to predict the best-suited GMA was 50.8%. It suggests that the GMA performance cannot be predicted well using a single statistical parameter. Multiple parameters should be used to enhance the accuracy. In order to select the limited items to enhance the accuracy, second stage reduction was performed. We made an assumption that: if a single item performs the task (predicting the best-suited GMA) badly, it is likely to interfere the performance of a group of items. Such a single item therefore should be removed from the list. The 16 3D histograms hence were further reduced to 9 variables based on how accurate each item can solely predict the visual results. The accuracy of random GMA selection, 47.4%, was the threshold. If the accuracy cased by a signal parameter was lower than the threshold, the item would be removed. In the stage, 5 items were eliminated. They are: W7, W9, W14, W17, W20, W22 and W25. Through the two-stage reduction, only 9 3D histograms survived for the GMA selection.

Stage 3 Reduction

In the third stage, Principal Component Analysis (PCA) was employed to extract the important variables among 1D color and texture information. The PCA can only tell you which variables are representative but it cannot show you which variable is important on GMA selection. Therefore, we divided 1D color into 3 subgroups. To reduce the number of variables in the final solution, only one principal factor was extracted to represent the variables in the subgroup. The first subgroup is the statistics of lightness where L_MEAN was the principal factor of L_MEAN, L_STD, L_SKEW, L_KURT, L_3RD and L_97TH. On the other hand, C_MEAN was the representative of the six chroma-type parameters. H6 was the primary factor for the eight 1D hue histograms. In terms of the 16 texture factors, we found S45_SKEW is the key parameter to represent the whole family.

The Performance of the Combined Variables

After the 3-stage reduction, now we have 9 variables from 3D histograms and 4 principal parameters from 1D color and texture information. The accuracy on predicting the well-suited GMA was counted using the T-TEST method mentioned earlier. The results are shown in Table 2.

Table 2: The GMA performance of 9 to 13 principal factors.

Accuracy %	9 3D hist.	+ L_MEAN	+ C_MEAN	+ H6	+ S45_SKEW
no. of factors	9	10	11	12	13
SKNEE	92.9	92.9	100	100	100
XSGM	91.7	87.5	95.8	100	100
HP	78.6	85.7	85.7	85.7	100
USMHP	84.0	88.0	88.0	88.0	84.0
All images	87.0	88.3	92.2	93.5	94.8

As can be seen, after carefully choosing a number of variables from the 63 image statistics, we can use their combinations to enhance the accuracy of automatic GMA selection up to 94.8%. Note that this type of study always needs a great number of image data; but it will be a hard work for observers. Hence, in this study, we use all available data to model the image characteristics without using an independent data set to test its performance. The accuracy should be reduced a bit if we have a large independent data set to test, but we believe the methodology in this study is still valid for researches who planning to conduct similar studies.

Table 3: Pixel frequencies of the 77 images in 9 selected 3D color histograms. The starts indicate the deletion.

Pixel %	W1	W2	W3	W4	W5	W6	W10	W13	W21
SKNEE	32%	14%	8%	11%	2%	1%	1%	2%	32%
XSGM	31%	5%	9%	8%	3%	5%	1%	2%	31%
HP	23%	5%	6%	5%	1%	2%	4%	1%	23%
USMHP	39%	7%	7%	4%	2%	2%	3%	2%	39%
max-min	16.1%	9.3%	*3.3%	6.6%	*2.1%	3.9%	*3.6%	*1.1%	4.7%

Stage 4 Reduction

In the previous section, we introduced 13 parameters to prediction GMA performance; however, the number is still a little bit high for on-line calculation. Therefore, we try to reduce the number of the 9 selected 3D histograms. What has been done is firstly to average image histograms for its best-suited GMA (see Table 3). And then, calculate the difference between maximum and minimum average values for each histogram. If the difference is too small, we assume that the factor is incapable of differentiating the images for GMA selection. We reduced the number of factor from 9 to 5 based on the above rule and the performance of the rest 9 factor-combination is shown in Table 4.

Table 4: The GMA performance after four-stage factors reduction.

Accuracy %	5 selected W	+ L_MEAN	+ C_MEAN	+ H6	+ S45_SKEW
no. of factors	5	6	7	8	9
SKNEE	78.6	78.6	78.6	85.7	100
XSGM	75.0	79.2	91.7	87.5	91.7
HP	64.3	64.3	64.3	64.3	92.9
USMHP	80.0	80.0	80.0	88.0	88.0
All images	75.3	76.6	80.5	83.1	92.2

Image Characteristics vs. GMA performance

Finally, we select 9 principal factors for automatic GMA selection. It's interesting to see whether any patterns which potentially influence the GMA performance can be found within the data. To this end, we summarize the image statistics of the 9 factors for their best-suited GMA. The results are shown in Table 5. The W1 is close to black, the W2 represents mid-gray, the W4 and W6 cover deep red and greed when the W21 dominates saturate yellow. The L_MEAN and the C_MEAN represent the overall lightness and colorfulness of an image. The H6 correlates to deep blue and the S45_SKEW represents the amount of textures. When close look at the data, we might say:

Table 5: Image statistics associated with their best-suited GMAs.

	W1	W2	W4	W6	W21	L_MEAN	C_MEAN	H6	S45_SKEW
SKNEE	32%	<u>14%</u>	11%	1%	2%	39.5	28.6	<u>10%</u>	6.5
XSGM	31%	5%	8%	5%	3%	39.4	23.1	23%	<u>5.3</u>
HP	<u>23%</u>	5%	5%	2%	<u>6%</u>	34.1	<u>34.6</u>	35%	6.2
USMHP	39%	7%	4%	2%	2%	36.0	25.4	29%	<u>5.4</u>
average	32%	7%	7%	3%	3%	36.8	28.2	23%	5.7

1. When HP was favorable, the images normally contained less black (W1). The explanation could be that the HP model clips black colors intensively. If an image has large proportion of black, the model would give you a poor reproduction.

2. When an image contained a lot of mid-gray (W2), SKNEE would be the

best choice because the model preserves mid-tone using a sigmoidal function.

3. As the HP was designed mainly for minimizing the lost of saturation, the model was favorable for images with high chroma (C_mean) and saturate yellow (W21).

4. If an image contains large proportion of saturate blue (H6), SKNEE won't be a good choice because it might map the colors toward black if the lightness of primary blue and black are close on your destination gamut.

5. If an image has more texture on it, the S45_SKEW statistics will be lower. In such case, spatial models like XSGM or USMHP could be useful for color reproduction.

Conclusions

Gamut mapping is the key element for cross-media color reproduction. As a universal GMA is hardly to be found, we proposed an intelligent approach to automatic select the best-suited GMA for the original via image analysis. There are too many parameters can be used for the image analysis, therefore, we need to extract the key factors from a range of image statistics to optimize the speed of process and to enhance the accuracy of GMA prediction. In this study, 63 statistical items representing either color or texture information of 77 images were prepared. By a four-stage reduction, about 9 principal factors were extracted for automatic GMA selection. Carefully examining the principal statistics, one could have a change to find many clues to identify the advantage and disadvantage of each GMA. The clues would be useful in the development of new gamut mapping solutions.

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