The Influence of Image Histograms on Cross-Media Colour Image Reproduction

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Abstract

This paper is part of a study aimed at quantifying the effects of identifiable image characteristics on how images that have them are reproduced. After having investigated the impact of image gamuts, the effect of image histograms will be considered in this paper. To do this, the paper first discusses the development of methods for generating sets of images that have the same image histogram in a channel independent way. Once sets of images that have the same histogram are generated, reproductions are made using a range of gamut mapping algorithms (GMAs) and the performance of these is evaluated psychophysically. The influence of image histograms on image reproduction is then judged on the basis of comparing the performance of GMAs for sets of images which differ in their histograms with their performance for sets in which the images do not differ in terms of this image characteristic. The results showed that none of the image histograms types tried here have a significant effect on GMA performance with the exception of the LC image histograms in the plain paper experiment.

Introduction

Studies on cross-media colour image reproduction have almost invariably reported that the performance of different solutions depends on the characteristics of the images used for testing them and they have often hypothesised about which characteristic is of importance in this respect. However, these hypotheses were normally made on the basis of images which differ from each other by more than just the identified characteristic. We have therefore embarked on a systematic study of the impact of various image characteristics on cross-media colour image reproduction and have in previous papers introduced a framework for this[1] as well as the results of looking at the image gamut characteristic,[2] which has shown not to be of importance from this point of view.

It is then the aim of the present paper to turn to more complex image characteristics – image histograms – and see what role they play in determining cross-media reproduction. Image histograms are characteristics which have been widely used for image enhancement[3] and pattern recognition[4] and they have also been utilised as parameters for adjusting tone reproduction in GMAs.[5] There are several types of image histograms, including lightness, chroma and hue histograms, which could be useful in gamut mapping. However, only lightness histograms have been investigated before[5] and no previous study has used test images with the same histograms – i.e. equi-histogram images. That is, the importance of image histograms in gamut mapping has not been assessed.

Evaluating the influence of the image histogram characteristic on gamut mapping can be done by having sets of images which differ in image histogram and corresponding sets of images which do not.[1] If GMA performances are more similar when using equi-histogram images than when using originals, it would suggest that image histograms could be an important factor for gamut mapping.

In this study four sub-experiments were conducted and they are referred to by the properties of the originals in them: SI- source images having different histograms; sets of images where either L-, C- or LC-histograms matched. To prepare these tests, the originals of the sub-experiments have to be generated first. Four images, CG, MUS, SKI and STR,[4] were used directly for the SI-set and were regarded as the source image data for generating the originals of the L-, C- and LC-match sets. The 'L-match set" represents a set where all the images have the same lightness histogram and the C- and LC- sets are images which match in chroma or both lightness and chroma respectively. The methods for generating the equi-histogram originals will be detailed in the next section.

Image Histogram Matching

Image histogram matching aims to generate an image that matches a predetermined (target) histogram and there are several approaches that could be used for this. These include methods based on using the cumulative distribution function,[3] a sort-matching algorithm[6] or a histogram metric like the Earth Mover's Distance (EMD).[7] Of these EMD is the most promising approach and it is a metric that provides the minimised sum of cross-bin distances (errors) between original and target histograms. As this algorithm provides optimised distances between two histograms, these distances could be used to assign colour values from the original to the target images. However, EMD involves the use of iterative, linear programming techniques and the processing is hence expensive for increasing bin numbers and it can give errors when the optimisation finds not a global but a local minimum. However, existing techniques either are not exact in the match they provide, are impractical for large images or involves the use of iterative, linear programming techniques which can give errors when the optimisation finds not a global but a local minimum. To overcome these problems, an Exact Histogram Matching (EHM) algorithm[8] was derived for this project. It is a simple, non-iterative algorithm, which is suitable for both large-size images and histograms having large numbers of bins and which results in a multi–valued transformation of the original image whereby enabling it to exactly match the target histogram.

In these tests, the mean histogram of the four source images was regarded as the target histogram. The reason for using the mean as the target is to make approximately equal changes to each of the four source images. As the total number of pixels was different for each image, each image's percentage rather than frequency histogram was used for the histogram averaging.

To evaluate the difference between two image histograms, match distance[7] - d_M which uses cumulative histograms for dissimilarity measures was used as it is easy to implement and provides reasonable results corresponding to human vision. However, the scale of the metric is dependent upon both total pixel and bin numbers. There is no fixed maximum in the metric and the absolute value is therefore difficult to interpret. A modification was therefore made and is shown in Equation 1. Here d_M, t, o, H^c, n and *bins* represent modified match distance, target, original, cumulative histogram, total number of pixels and bin-numbers of the image histogram respectively. In the modified metric, zero represents no difference between histograms and 100 is the result one would get when comparing a completely black image with a completely white one in lightness terms.

$$d_M = \frac{100}{(bins-1)} \sum_{i=1}^{bins} \left| \frac{H_{ti}^c}{n_t} - \frac{H_{oi}^c}{n_o} \right| \qquad \textit{Equation 1}$$

Note that, in this study, the number of bins for both lightness and chroma histograms was set as to 256 and that intervals were 1/2.55 and 1/2 units for lightness and chroma respectively.

Problems of Image Histogram Matching

The EHM algorithm mentioned above can provide an exact histogram match of any two images in a channel independent way whereby "channel independent" means that when images are histogram matched, this is done on a channel–by–channel basis. This is simpler and much faster than methods dealing with simultaneous adjustment of multiple channels (e.g., Lab pixel–to–pixel matching based on 3D–histogram). However, when using such channel independent matching techniques, some colours can be transformed to outside the original medium gamut and methods for overcoming this problem are needed.

Solving Out–of–Gamut Problems

For the L–match experiment, after the EHM calculation, one can easily use a lightness–preserving chroma clipping (LPCC) GMA to bring all out–of–gamut colours onto the gamut boundary without changing the lightness histogram.

In the case of the C–match experiment, simply using a chroma–preserving lightness clipping (CPLC) GMA might not be sufficient as those colours which are more chromatic than their medium gamut cusps will map to the cusp and the histogram will not match the target. Both the CPLC GMA and an approach where EHM followed by hue–preserving min. ΔE clipping iterate (referred to as IHEC here) have been tested. The number of iterations of IHEC was set as to be ten and based on a single target histogram which is the averaged C–histogram of the four source images. The results showed the IHEC approach to be superior to CPLC only for the STR image.

The case of the LC–match experiment is even more complex as the chroma histogram will change when trying to maintain the lightness histogram and vice versa and as it is therefore a dilemma to fit both lightness and chroma histograms simultaneously. An iterative approach was used where EHM was first applied for matching the target histograms and this was followed by a GMA for bringing all colours in–gamut. As image histograms could still mismatch after the GMA, the process was iterated. In this approach, there are three key components: GMA, target histogram and number of the iterations and their influence has also been evaluated. There were five GMAs (LPCC, CPLC, hue–preserving min. ΔE clipping [HEC], cusp clipping, image–to–medium gamut compression towards the cusp) that have been tested using two iterations of the approach and the overall results showed that HEC performed best.

There are two possible approaches to generating target histograms for histogram matching. One way is to use a single–target histogram (the mean histogram of the source images) in all iterations. The other way is to create a new target histogram for each iteration, which is based on the histograms of the four gamut–mapped images from the previous iteration. As more than one target histogram is used during such an iterative process, it will be called a multi–target approach. A comparison of these approaches for the C- and LC-match sets is illustrated in Figure 1. As can be seen, the iterative method can effectively decrease the mean errors in all four cases and the errors stabilise after a few iterations. In comparing the single– and multi–target approaches, the multi–target one was significantly superior in the LC–histogram matching case. However, the single–target approach performed better for C–histogram matching.

Based on the above evaluation, multi-target HEC with ten iterations was used for generating the originals of the LC-match set. Using this approach, the mean match distances (d_Ms) between histograms of pairs of images in the

LC-match set were 0.02 and 0.05 for the lightness and chroma histograms respectively. To put these values, which should ideally be zero (i.e. a perfect match), into perspective, the mean d_Ms in the source image set were 5.53 and 3.77 for lightness and chroma respectively. Another way of evaluating the final gamut–corrected originals of the LC-match set is to compare them with the histogram–match images which, however, contain some out-of-gamut pixels by looking at the 99^{th} percentiles of the difference distributions. These ranged between 0.66 and 1.32 depending on the different images and were less than the threshold (1.9 ΔE^*_{ab}) for perceiving image differences suggested by Uroz et al.[9] The colour differences between the exact histogram–match image and the gamut–corrected image can therefore be considered insignificant.

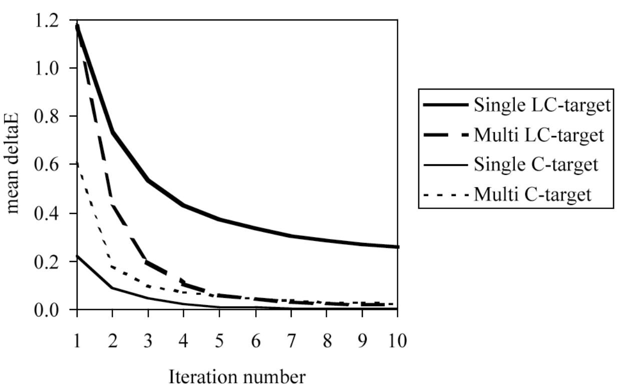

Figure 1. Mean colour difference (ΔE97s2) between histogram–match image and gamut–mapped images obtained using different target histograms in the HEC approach.

Experimental Setup

Once the originals are produced, the second step is to generate reproductions for the experiment. A CRT monitor characterised using a second-order gamma model with a mean error of 0.88 ΔE_{97s2} was the original medium. An inkjet printer characterised using an inverse 10^3 3D LUT with tetrahedral interpolation and a mean error of 2.08 ΔE_{97s2} units was the reproduction medium. Each of the equi-histogram originals were reproduced using four GMAs: CARISMA [Ca], GCUSP [Gc], SKNEE [Sk] & WCLIP [Wc] [4] using the CAM97s2 colour space. Two substrates: high-resolution (hi-res) paper and plain paper, were used, resulting in a total of 128 reproductions.

Finally, a psychophysical experiment with 15 colour-normal observers was carried out using the paired comparison technique in a binocular simultaneous viewing setup to obtain a measure of the GMAs differences. In the technique, all pairs of reproductions were be shown to observers alongside the original, the observers were asked to judge which of each pair of reproductions was closer to the original in terms of appearance.

Results

The relative accuracy (z-score) results of the experiment with 95% confidence intervals for each GMA are shown in Figure 2. The overall accuracy rankings of the four GMAs from the best to the worst were WCLIP, SKNEE, GCUSP and CARISMA. Looking at these z-scores does not directly show how image histograms influence GMA performance and a metric, named overall MD (overall mean of differences), is used to provide a single value for the agreement between sets of z-scores for different sets of images. The reason of choosing this metric over others (e.g., Pearson's correlation) is because it has the same unit as the z-scores and as it is sensitive to both correlation and range differences between sets of z-scores. The steps for obtaining the overall MD for a given substrate and histogram matching setup are as follows:

1. For each pair of images calculate four absolute differences (D) between pairs of z-scores which belong to the same GMA but to different images (i.e. D_1 is the difference between the z–score of GMA_1 for image 1 and GMA_1 for image 2 of the pair; D_2 relates to GMA_2, etc.).
2. For each pair of images, average the four Ds from step 1 – these averaged results are referred to as MD and represent the agreement between the GMAs' performance for a pair of images.
3. Average the MDs from all pair combinations of the four images (i.e. 6 pairs). The result will be referred to as the overall MD and represents the agreement among the z-scores for the four images under a given setup.

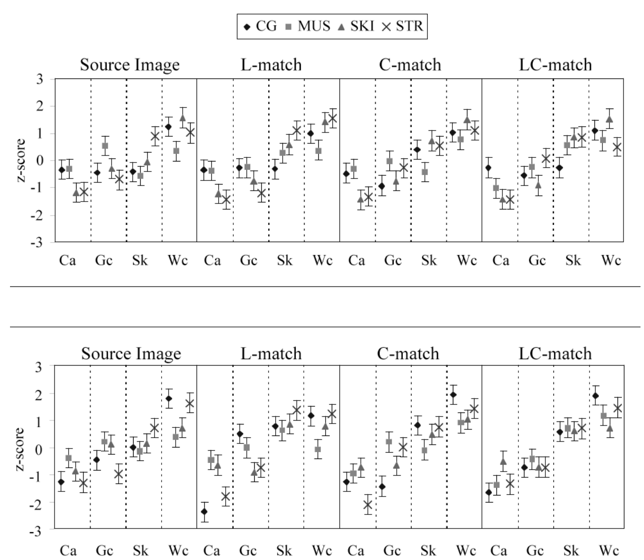

Figure 2. z-score for each GMA (Ca, Gc, Sk & Wc) in the test. Above: hi-res paper, bottom: plain paper.

Based on this method, the overall MDs for each histogram matching set and using the two substrates was calculated and is shown in Figure 3. In the diagram, the error bars represent the 95% confidence interval of the dataset and zero overall MD represents an exact agreement of GMA performances for the four different images. The overall results show that for the plain paper substrate, the LC-match set gives a better agreement among GMA performances for the four images. In all other cases MDs for the various histogram match setups were not significantly different from those for the SI set. Concerning the difference of overall MDs resulting from the four matching techniques, larger variance was observed in the plain paper sets which could be due to the larger gamut difference that the GMAs were used for overcoming there.

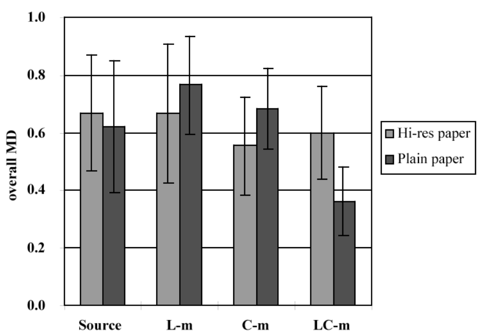

Figure 3. Overall results of the image histogram test in terms of MD metric.

Discussion

The LC-match set (for the plain paper substrate) showed lower overall MDs than the other sets in this test. This suggests that when there are larger gamut differences between original and reproduction media, the agreement of GMA performances can be better for images having similar lightness and chroma histograms. This is already a useful direction to follow in the development of automatic colour reproduction systems as LC image-histograms could be used as an initial criterion for choosing what GMA to apply. It is also interesting to note that single channel (L- or C-) matching showed little difference from the source image set and that significant differences were obtained when the two channels were used simultaneously. This suggests that the agreement of GMA performances could be even better when more channels are used for the image histogram matching.

Looking at the differences caused by substrate, the overall MDs between the hi-res paper set and the plain paper set were evaluated and the results showed that performance variation was highest for the CG image and lowest for the MUS image (i.e. the image with a larger gamut and uniformly–coloured areas was more sensitive to changes than the image with a smaller gamut). On the other hand, the differences between matching setup (i.e. L–, C– or LC–match) did not influence the order of the scores. Overall MDs for individual images for different histogram matching setups were also calculated and the results showed that some images (especially the MUS image) were sensitive to varying the histogram matching setup but others were not.

Conclusion

As some reductions of differences between results for individual images can be seen from the comparison of source and LC-match sets, it is suggested that the image histogram has under some circumstances got an effect on GMA performances. Full 3D histogram matching therefore should be investigated next before moving on to examine more complex image characteristics in terms of how they influence the performance of cross-media colour image reproduction. However, these results still show that it is not one of these image histogram characteristics that is responsible for the differences between how the individual test images are reproduced. Finding such an image characteristic involves looking to more characteristics that are more complex. Once a characteristics is found that influences inter–image reproduction differences, it will enable a greater degree of automation in cross–media colour image reproduction.

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Biography

Mr. Pei-Li Sun received his bachelor and master degrees from the Department of Graphic Communications of the Chinese Culture University in Taipei, Taiwan, 1994 and 1996 respectively. He is currently working at the Colour & Imaging Institute of Derby University towards his PhD on the topic of the Influence of Image Characteristics and Gamut Differences on Colour Gamut Mapping.