Methods for Investigating the Influence of Image Characteristics on Gamut Mapping

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Abstract

The aim of this paper is to give an overview of statistical, spatial and cognitive image characteristics which could influence the performance of gamut mapping algorithms. In addition to reviewing these characteristics, a general method for evaluating their importance in the above context is given whereby this method is based on the creation of sets of images which either share or differ in terms of given characteristics in known ways. The psychophysical evaluation of the reproductions of such image sets can then yield information about their relative impact on the performance of the gamut mapping algorithms used. Having such information would be of great benefit when trying to improve the performance of colour reproduction systems in general and gamut mapping in particular.

Introduction

Gamut mapping refers to the transformation of an image by mapping its colours into the gamut of a reproduction medium. How to make the mapping optimal is an issue that is being intensively researched and various kinds of gamut mapping algorithms (GMAs) have been proposed in recent years[1]. An important characteristic of these approaches is that they attempt to solve the gamut mapping problem by using a single model which ideally ought to give good results for a wide range of images and conditions – in other words it is intended to be universal.

Of equal importance to the development of solutions is also their psychophysical evaluation which has again been carried out by a number of workers.[1–7] Reviewing these studies, one can see that the performance of GMAs has almost invariably been reported to depended on the characteristics of the test images used. Indeed this is not a surprising result – in the graphic arts, parameters of electronic colour scanners have long been adjusted according to image characteristics (e.g., different settings are used for "hi–key" or "low–key" images). Note, however, that these adjustments may be carried out for achieving pleasant, rather than perceptually accurate reproductions.

Attempts have also been made to take into account image characteristics in the gamut mapping process. The most straightforward way of doing this is to start from the original image's gamut rather than from the gamut of the original medium.[4,7–9] Indeed this has been reported to result in better reproductions, even though it does not remove the influence of image characteristics entirely. More recently, work has also been carried out to take into account the influence of image histograms on lightness mapping, which has again been reported to give better results.[10] Various studies have also reported good correlations between the percentage of out–of–gamut pixels[3] or chroma ranges[11] and the performance of GMAs. In addition to claims about these easily quantifiable factors influencing colour reproduction, there are suggestions that higher–level, cognitive image characteristics (e.g. image type) also play a decisive role.[12]

What can be seen for the above overview is the suggestion of some image characteristics as influences on colour reproduction. However, these suggestions are made on the basis of images which differ from each other by more than just the identified characteristic. Hence, it is the intention of this paper to present methods for creating such sets of test images, whose members differ from each other by a single characteristic in a known way. Alternatively, where methods for isolating a single characteristic are not available, ways will be suggested for isolating the characteristic by studying its influence in conjunction with a set of other well–known characteristics.

Set against the above background, the aim of this paper is to propose methods for evaluating the influence of individual image characteristics on cross–media reproduction in general and gamut mapping in particular. This will be done by first reviewing and defining the most prevalent image characteristics, then suggesting methods for generating test images which isolate them and finally by suggesting a data analysis method for obtaining the relative importance of a number of characteristics.

Review and Definition of Image Characteristics

It is suggested here that the characteristics of static colour images can be divided into three major groups – statistical, spatial and cognitive – whereby the characteristics presented here are not those which are claimed to influence colour reproduction, but those which have been identified by the authors as being image characteristics and therefore having the potential to do so. Also, the following is not intended to provide a literature survey of the work that deals with the identified characteristics but merely to serve as a sketch of what they are. And finally, the examples in the following sections are given in terms of greyscale images which makes the illustration of some of the characteristics difficult and limited. Hence, where possible analogies have been used (image colour naturalness has been illustrated by something more akin to image tone reproduction naturalness).

Statistical Image Characteristics

Statistical image characteristics refer to properties of images when they are treated as unordered sets of colours. Some of these characteristics, such as colour histograms, are widely used in colour correction (retouching), image recognition and image enhancement applications. Traditionally in the graphic arts an image statistic taken as a parameter for colour reproduction was the tonal range of an image. At present, one–dimensional "tone reproduction" has been replaced, or at least complemented, by three–dimensional "gamut mapping" so that the 3–D tonal range of an image, referred to as its "image gamut", can be used as a parameter as well. In this paper, three statistical image characteristics – image colour histogram, image summary and image gamut – will be considered and are defined as follows.

Image Summary

An image summary is defined as a *single–valued description of an image involving information from the entire image* (e.g., the mean and standard deviation of an image's colours, the image's dynamic range). See Figure 1 for an example of a set of images with the same mean.

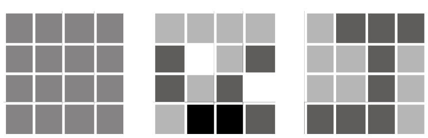

Figure 1. Equi–mean test images.

In some cases using simple image summaries (rather than a complex histogram) can lead to the identification of some higher–level image characteristics (e.g., hi–key or low–key). It would be valuable to understand whether some complex image characteristics can be successfully detected using simple image summaries, as this would make it easier to develop new GMAs that make choices on their basis.

Image Gamut

An image gamut refers to the *subset of a colour reproduction medium's gamut determined by an image's colours*. Many studies report that the performance of GMAs depends on image contents. However, there is no experimental basis for showing which factor (image type, image gamut…) influences gamut mapping most. To avoid unnecessary gamut mapping, many gamut mapping solutions use the original image's gamut rather than that of the original medium and it is reported that better results are obtained in this way. It is also claimed in some studies that it is the size of an image's gamut that determines how well it is reproduced using different GMAs.[11] For a set of images showing the same scene but having different gamuts see Figure 2.

Figure 2. Images with progressively decreasing gamuts (ten per cent reduction compared to preceding image's gamut).

Having a better understanding of the image gamut's influence in isolation could well lead to new ways of improving the performance of colour reproduction solutions.

Image Colour Histogram

An image's colour histogram refers to a representation of the *frequency distribution* of its colours. To do this, colour space is first quantised into "bins" along its dimensions, so that each "bin" represents a subspace of colour space and the number of image pixels having a colour from that subspace is stored for it. Note, that these histograms can be calculated for colour spaces of various dimensions (e.g. 1–D lightness space; 2–D chromaticity space; 3–D lightness, chroma and hue space; etc.). For an example of images showing different scenes but having similar histograms see Figure 3 where the frequency versus lightness distributions of the two images are shown.

Image colour histograms have long been used in image processing, but they are only now being considered in the context of colour reproduction.[10] It would therefore be of interest to understand their influence more systematically and clearly.

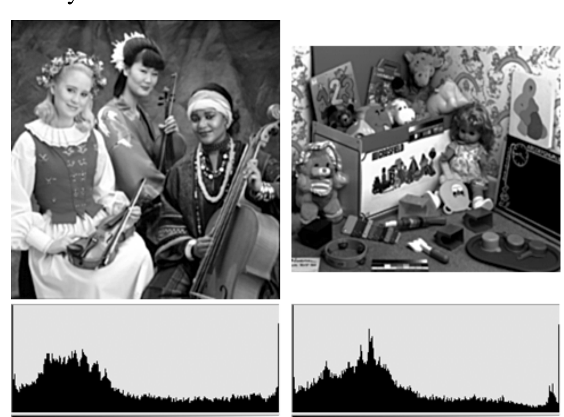

Figure 3. Images and their histograms.

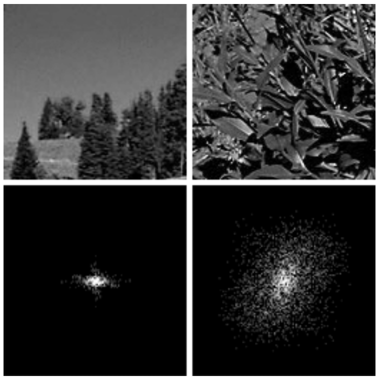

Figure 4. Two images(top row) and visualisations of their Fourier transforms (bottom row).

Spatial Image Characteristics

In recent years, the influence of spatial characteristics on human and robot vision has been studied extensively and its importance in colour imaging has also been recognised.[13] In the past, most of image processing only depended on colour histograms. If maintaining the histogram will still result in a variety of effects on gamut mapping, it might be necessary to be concerned not only with statistical but also spatial image characteristics. The spatial image characteristics considered here will be spatial frequency, local colour contrast, sharpness and image layout and they are defined as follows.

Spatial Frequency

In optics and vision science, spatial frequency is defined by the *number of cycles of a sine–wave per unit distance or angular subtense*, which is related to the reciprocal of the period – the distance between adjacent peaks.[14] Working with complex images, however, it is difficult to use sine–waves and define their peaks directly. However, it is possible to transform an image into a spatial frequency domain using, for example, the Fourier transform whereby this frequency domain representation of the image can then be altered. Figure 4 shows an example of images and their Fourier transforms whereby the closer to the centre a pixel is in the Fourier transform visualisation, the lower the spatial frequency it represents and the lighter the pixels the more dominant the corresponding frequency. Such a spatial frequency domain representation can show the approximate spatial frequencies in an image.

Image Sharpness

Figure 5. Images with progressively decreasing sharpness.

Sharpness refers to the *noticeable extent of the edges of objects and eventually of fine detail and texture* within an image. There have been many attempts to relate perceptual sharpness to physical measures, e.g., Nijenhuis *et al.*[15] suggested a number of equations to do this on the basis of psychophysical experiments they carried out. Sharpness plays an important role when the visual system attempts to recognise objects within an image. Pleasantness is also influenced by sharpness (e.g. portraits are often preferred to have some blur). Some GMAs, in particular clipping, will result in loss of detail in images which can also change the sharpness of an image (see Figure 5 for different levels of sharpness).

Local Colour Contrast

Local colour contrast ($LCC_{i,j}$) is defined as the *colour differences between a colour element and its proximal field* in an image (Equation 1).

$$LCC_{i,j} = \frac{1}{(2p+1)^2 - 1} \sum_{m=-p}^{p} \sum_{n=-p}^{p} \Delta E_{[(i,j)\leftrightarrow(i+m,j+n)]} \tag{1}$$

Here (*i,j*) are pixel co–ordinates in an image and *2p+1* is the size of a pixel's proximal field (e.g. it could extend 2° around the image). To calculate the colour difference •E in the above formula, S–CIELAB[16] can be used to take into account spatial characteristics or one can use a weighted colour difference formula (e.g., CMC(l:c)[17] or CIE94[18]). Note, that the summation of colour differences could also be done in a distance–weighted way which would give more importance to closer pixels.

Contrast sensitivity is a hot issue in vision research and it is a common result that contrast sensitivity depends on spatial frequency, temporal frequency and local colour contrast. Since gamut mapping is a transformation which can vary local colour contrast, it is a factor that ought to be investigated.

When studying image characteristics, it might be also useful to use a Local Colour Contrast Index (LCCI) which is a summary of local colour contrasts in an image and can be defined in the way shown in Equation 2.

$$\mathrm{LCCI} = \frac{1}{i_{\max} \times j_{\max}} \sum_{i=0}^{i_{\max}} \sum_{j=0}^{j_{\max}} LCC_{i,j} \tag{2}$$

Here i_{max} and j_{max} represent image dimensions.

Image Layout

The *spatial relationship of the different parts of an image*, defined by Groff[19] as orientation, will here be referred to as image layout. There have not been many studies looking at this issue, which might nonetheless have some impact on colour reproduction. For an example of a pair of images differing only in image layout see Figure 6.

Figure 6. Images differing only in image layout.

Cognitive Characteristics

Cognitive image characteristics are ones which need to be considered most carefully, as they are the most difficult ones to extract automatically from images. Most studies use different types of images to evaluate GMAs, they often obtain different results for these and frequently the conclusion is drawn that gamut mapping will always need some human input to tell it about image characteristics that cannot be extracted computationally. If this is indeed the case, then it would be very difficult to aim for fully–automatic cross–media colour image reproduction. If, however, it is sufficient to understand easily computable image characteristics to make gamut mapping decisions, then such a system might be within our current reach. The three cognitive image characteristics discussed here – image colour naturalness, image type and image content – are defined as follows.

Image Colour Naturalness

The *agreement between perceived and memory colours of familiar objects* (e.g., skin, grass, sky....) will be called colour naturalness (Figure 7). Indeed, attempts have been made recently to quantify the naturalness of image colours[20], which would allow for the use of this characteristic in automatic colour reproduction. As colour naturalness is an image quality factor, its better understanding could also show whether memory colours influence the judgement of both "accurate" and "pleasant" colour reproduction.

Figure 7. Images differing in naturalness.

Image Type

The image type characteristic refers to an image's *membership in a set of images which are similar in terms of some overall feature*. Examples of such types are portrait, outdoor scene, computer graphic, high–key, business graphic, etc. (Figure 8). It is often claimed that different types of images may need different GMAs, whereby image type can in some cases also determine reproduction intents. For instance, the reproduction intent for natural scenes might more frequently be accurate reproduction while the reproduction intent for business graphics might be one where colour "purity" is the aim.[12]

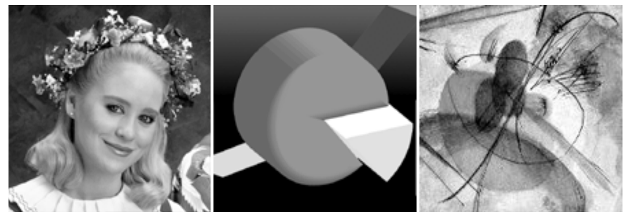

Figure 8. Images differing in type.

Image Content

Image content is defined as *that which is shown in an image, regardless of whether it can be recognised to represent objects in our environment or not* (Figure 9). To determine, whether gamut mapping decisions need to be made on the basis of this particular characteristic is of great importance for understanding whether automatic colour reproduction is possible without having a model of image perception and recognition.

Figure 9. Images differing primarily in image content.

Methods for Testing the Influence of Individual Image Characteristics

What follows is the description of methods for the evaluation of the influence of some of the characteristics discussed in the previous sections. The approach taken here is to generate such sets of test images which either differ only in a single characteristic or which only share a single characteristic.

Image Gamut Test

It has been suggested[11] that image gamuts are a factor influencing the performance of gamut mapping algorithms when reproducing the corresponding images. However, this suggestion was made on the basis of results from an experiment where the individual test images differed in virtually every image characteristic discussed in the previous section.

To verify this proposition, it is possible to create a set of test images which have the same gamut, but which differ in terms of the other characteristics (Figure 10). This can be done by first choosing a set of images where each image is of a different type, has different histograms, spatial characteristics, image gamuts, etc. (images $O_{11\text{–}41}$ in Figure

11). The image gamut of one of these images (e.g. G_1 of image O_{11}) can then be chosen and all other images can be gamut mapped in a way where their image gamut is the original gamut and where the chosen image gamut is the target gamut (resulting in images O_{12-42}). The condition for this to work well is that all original test images ought to have colours in the same regions of colour space.

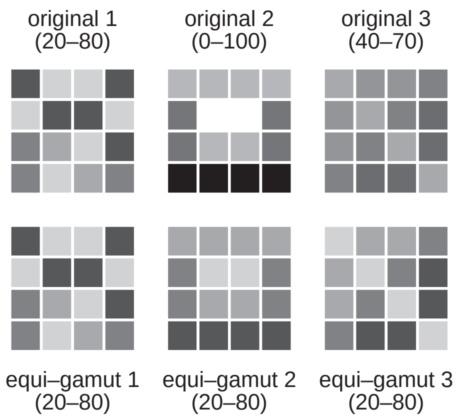

Figure 10. Equi–gamut test images (values in brackets indicate intensity ranges).

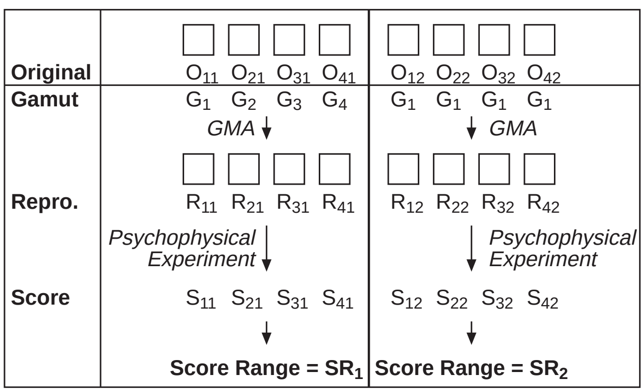

Figure 11. Equi–gamut test work–flow.

To then determine whether image gamut influences the behaviour of a set of GMAs, these images can be used for making reproductions both of the original set (R_{11-41}) and of the equi–gamut set (R_{12-42}). Two sets of psychophysical experiments are then conducted whereby the experiment on the original images and their reproductions results in scores S_{11-41} (having a range of SR_1) and the experiment on the equi–gamut images and their reproductions results in scores S_{12-42} (having a range of SR_2). If then the results from the equi–gamut set produce smaller differences (i.e. $SR_2 < SR_1$) then this would suggest that the image gamut indeed influences the performance of gamut mapping algorithms.

Alternatively, one could select a single original test image and then generate versions of it having different gamut sizes by gamut mapping it to scaled versions of the original image gamut. If the psychophysical evaluation of the resulting gamut mapped images would give similar results for each of the test images (having different gamuts, but having the same image content, image type, etc.) then this would indicate that the image gamut does not play a significant role in colour reproduction using the chosen set of GMAs.

Image Colour Histogram Test

To understand whether an images histogram influences its reproduction, one can use an analogous method to the one presented in the previous section. In this case, however, test images would be generated as follows: first, calculate the images histogram with as many bins as there are possible colours at the image's bit depth (e.g. if it is an 8 bit RGB image then there are 2^{24} possibilities); second, generate an image having same dimensions as the original image by going through the histogram and outputting colours based on the values in it. For example, the histogram can be scanned systematically and colours output in such a way that pixels of the same colour would be next to each other when the image's row's are placed in a single row (Figure 12). Alternatively colours could be chosen from the histogram at random and/or placed into the equi–histogram test image in a different pattern (e.g. a spiral).

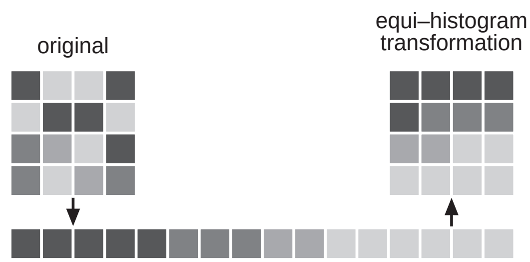

Figure 12. Equi–historam test images.

Evaluation of Characteristics Which Cannot Be Isolated

Even if methods are not found for perturbing certain characteristics in isolation, the above general framework can still be used if perturbations of this characteristic can be achieved in conjunction with perturbing other characteristics in known ways. For example, if no method is found for isolating spatial frequency, the importance of this characteristic can still be assessed if images can be created which vary only in spatial frequency and local colour contrast (experiment A). If, in addition to this the importance of local colour contrast in isolation is known then the importance of spatial frequency can be deduced from the results of this experiment and experiment A. Alternatively, if it is possible to create images that vary only in spatial frequency and image layout then the results of this experiment together with experiment A can yield information about the relative importance of the characteristics involved.

The above hypothetical example was given just to illustrate the possibilities of perturbing images in known ways even if this perturbation cannot be restricted to a single characteristic.

Summary

The work presented in this paper represents preliminary suggestions of methods for the investigation of the role of image characteristics in cross–media image reproduction. This approach is aimed at showing which factors influence gamut mapping most significantly and are therefore priorities for further research. The methods proposed here will be particularly useful for better understanding the problems of gamut mapping, for developing new models which take these factors into account and possibly for aiding a consistent interpretation of previous experimental results.

Further the general framework suggested here is also applicable for the evaluation of the influence of image characteristics on other applications (e.g. image enhancement, database indexing, etc.).

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