Deriving colour palettes from images of natural landscapes

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ABSTRACT

The colours of natural landscapes represent important information about the character of the region in which the landscape is based. The colours extracted from the natural landscapes are considered as the harmonious colour arrangements that could provide a pleasing visual experience to human. In this study, methods to develop colour palettes based on analyses of digital images of natural landscapes are explored. A psychophysical experiment in which participants select five colours that are representative of digital images of landscapes is first described; this generates data that can be used as ground-truth data against which other (more automatic) methods could be evaluated. Automatic methods for generating colour palettes from images using cluster analysis in RGB and CIELAB colour space. A colour-difference metric was used to compare the palettes generated from the designers to automatically generated palettes. There was no statistically significant effect of colour space (RGG v. CIELAB) on the colour differences between visual palettes and those derived using cluster analysis.

Keywords: *colour, landscape, natural landscape*

INTRODUCTION

Natural landscape is one of the most important inspirations for designers. A wide range of colours and colour combinations naturally exist in natural landscapes. There are also abundant colour characteristics of regions, which result from various combinations of rock types, vegetation, local architecture material and soil (Bell 2008). These colours can be used in different design areas including architecture, landscape architecture and urban design, for example, to deliver characteristics to buildings or other infrastructures that enable these structures to blend with their natural surroundings. The particular colour combinations from the natural landscape can be built into a colour palette for designers to inform their design themes. Furthermore, colour palettes are also quite important to image analysis, manipulation and other areas (Ciocca et al. 2019).

Colour palettes that represent images or scenes are generally extracted manually by designers. However, even experienced designers may need to extend substantial effort to build a colour palette from scratch. Many automatic extraction approaches have been developed to inspire designers to build their colour palettes. Cluster analysis is one of the most common automatic methods (Lin and Hanrahan 2013). A previous study concluded that K-means is fast and efficient to generate different colour regions in images which have closed results to human perceptions (Shmmala and Ashour 2013). Some studies have found that CIELAB provided better performance than RGB space when cluster analysis was used for image segmentation (Mathur and Purohit 2014). In this work, colours obtained by K-means in CIELAB and RGB colour space were compared with the colours that were visually extracted from images by designers using a colour-difference metric.

EXPERIMENT

A psychophysical experiment was conducted to obtain the colour palettes selected by subjects from natural landscape images. Figure 1 shows all 10 nature landscape images. 30 participants with different design background were recruited to each select 5 key colours for each image which represent the image and could possibly be used in their design work. The digital images were displayed on a computer (HP DreamColor LP2480zx – a 24-inch LCD Backlit monitor) in a darkened room. The images were displayed one at a time and there were 10 digital images in total (each of which represented a natural landscape). The images were displayed on a uniform grey (CIELAB L* = 50) background. For each image, each participant was requested to select five colours and hence obtain a colour palette that represents the image. This was done by the participant clicking on an area of the image using a mouse in a GUI that was written using the MATLAB programming environment. The number of colour in the colour palette was previously investigated by a questionnaire taken by the same design-background participants. 70% of subjects selected five as a reasonable and workable number with regards to colour selection from landscape images. Furthermore, a previous study shows that five is one of the most common values for the size of colour palettes (O'Donovan et al. 2011). In total, 150 colour (5 key colour $\times$ 30 participants) collected for each image from the experiment and these were used as the visual colour palettes in this study.

ANALYSIS

Figure 2 shows the palettes that were obtained for one of the landscape images as an example. As seen in Figure 2, the colour palettes named DESIGNER are the original colour palettes selected by the 30 subjects. Each row represents one participant, and each column indicates the order of human selection for each image (the left-most colour being the first colour that was selected). Ideally we require a single 5-colour palette that represents the visual selections. However, during the experiment, there were no rules imposed about the order of selection. The order of the colours for each participant were therefore modified. This amounts to changing the order of the colours in each row of the 30 $\times$ 5 DESIGNER palette to minimise the colour differences between the colours in each column. This process results in the NEW ORDER palette (see Figure 2 for example). The point about changing the order is to allow the colours in each column to be averaged together and this produces the 5 $\times$ 1 palette VISUAL DATA. This 5 $\times$ 1 palette is representative of the visual selections and is used as the ground-truth against which the palettes produced by cluster analysis will be compared.

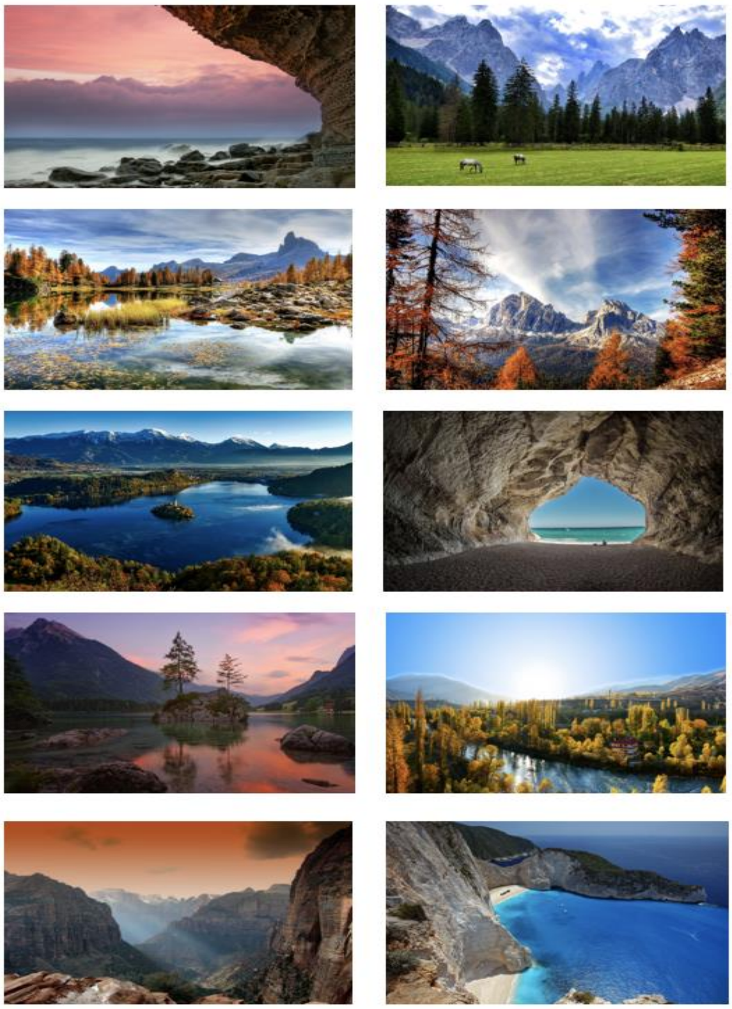

Figure 1: Representation of the 10 natural landscape images used in this experiment.

Figure 2: Example data representation for Image 3 in the experiment. The raw colour palettes obtained visually are labelled as DESIGNER and the visual data shows the average colour palette (VISUAL DATA) produced by the participants. The VISUAL DATA colour palette is compared with the colour palettes produced by cluster analysis using RGB and CIELAB colour spaces.

Subsequently, an automatic method for generating colour palettes from each image was developed using cluster analysis. The cluster analysis, specifically K-means (with K = 5), was performed in several different colour spaces including RGB and CIELAB. These are the computed colour palettes as shown in Figure 2.

The colour palettes generated by the automatic clustering method were compared with the colour palettes that were derived from the psychophysical data using a quantitative method that has previously been published (Pan and Westland 2018) that was referred to as the minimum colour difference model. Briefly, for each colour in the first colour palette, the closest colour in the second colour palette is found and this minimum colour difference is recorded. This results in 5 colour differences. The same process is repeated for each of the colour in the second palette, in this case finding the closest colour in the first palette, to produce 5 more colour differences. The colour difference between the palettes is then given by the average of these 10 colour differences.

RESULTS

Figure 3 and Table 1 show the colour differences (calculated according to the method published by Pan and Westland 2018) between the visual colour palettes and the colour palettes obtained automatically from RGB and CIELAB colour spaces. Overall, the colour differences between visual data and RGB-derived data ($\Delta E = 12.71$) are slightly higher than the visual data compared to the CIELAB-derived data ($\Delta E = 12.05$). However, a two-tailed t-test was used and the difference between the colour differences derived from the two colour spaces was not statistically significant ($p = 0.82$).

However, the fact that the RGB- and CIELAB-derived colour palettes are equally similar to the visual palettes does not indicate that the RGB- and CIELAB-derived colour palettes are the same. To test for this similarity the colour differences were calculated, using the Pan and Westland (2018) method, between the RGB- and CIELAB-derived colour palettes. The mean colour difference was 6.10. This suggests that the RGB- and CIELAB-derived colour palettes are similar but not identical. It may help the reader to note that the colour difference between the RGB- and CIELAB-derived colour palettes for image 3 (as illustrated in Figure 2) was 7.58.

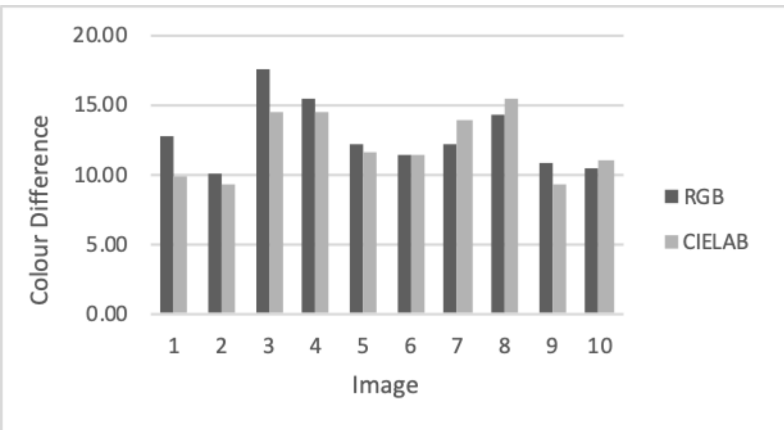

Figure 3: Colour difference between visual data and the computed colour palette from different colour spaces (RGB and CIELAB) for each of the 10 images.

Colour difference		
Image	**RGB**	**CIELAB**
1	12.78	9.90
2	10.11	9.34
3	17.59	14.39
4	15.40	14.37
5	12.20	11.51
6	11.37	11.42
7	12.09	13.78
8	14.27	15.49
9	10.79	9.24
10	10.48	11.07
Mean	12.71	12.05
Standard deviation	2.39	2.29
Variance	5.71	5.25
p-value	0.82	

Table 1: The colour difference values between visual data and the computed colour palettes from different colour space (RGB and CIELAB).

CONCLUSIONS

In this study, cluster analysis using K-means was performed in two different colour spaces (RGB and CIELAB). The choice of different colour space did have some effect (though not necessarily a significant one) on the colours that were extracted. However, there was no significant effect of colour space on the average colour difference between the visual palettes and the palettes derived from cluster analysis. This works suggests that cluster analysis might be a suitable way to extract colour palettes from digital images and that the colour space in which the cluster analysis is performed is relatively unimportant. Although some work has suggested that perceptual colour spaces such as CIELAB should be preferred to spaces such as RGB, other studies have contested this (Chavolla et al. 2018). Some alternative methods, including eye tracking, for automatic palette generation will be explored in future work.

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