Developing an Automatic Method for Generating Colour Palettes from Landscape Images

By

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The candidate confirms that this submitted work is her own and that appropriate credit has been given where reference has been made to the work of others.

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Abstract

In the design process, particularly in landscape, architecture and urban design, colour is a vital element. Designers often use a specific colour palette to clarify their ideas or colourise their plans. Landscape is one of the most significant inspirations for designers; in light of the specific colour matching in the landscape, designers can build a colour palette with the local to indicate the theme of their plan. For instance, a typical landscape view with red bricks, greenish moors and blue sky as well as the white cloud in the United Kingdom. This suggests that a colour palette derived from landscapes can represent particular characteristic features of a place, which can relate to the themes and emotions of the designers. Designers often work on colour palette generation based on subjective colour assessment.

However, this work focuses on not only the subjective but the objective method to extract colour palettes from landscape images. This work was mainly divided into four parts, colour-palette generation by designers (novice and professional designers), predicting visual colour differences between pairs of colour palettes, and colour palette extraction using either K-means clustering or an eye-tracking system. A psychophysical experiment in which 30 (design-based) participants each selected five colours from each of a set of images was first conducted to archive the designer extraction method and the palettes collected from this method were used as the ground-truth data against other (more automatic) methods in this research. The palette difference prediction metric was explored based on the second experiment in which a total of 95 pairs of palettes were rated for visual difference by 20 participants. This leaded to one algorithm (MICDM), which was used as the measure to compare the palette extraction using K-means clustering methods in RGB and CIELAB colour spaces. The eye-tracking experiment was undertaken with the same participants and image stimulus to obtain the eye-tracking data. The eye-tracking data was analysed and modified into colour palettes as the extraction method from the eye-tracking data.

Overall, the experiments and methods described in this work performed to generate colour palettes from landscape images. The palette extraction from eye tracking performs better than K-means clustering, and may have future application to design.

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Chapter 1. Introduction

1.1 Background

Colour plays a vital role in the design area. Using colour is a particular creative and ubiquitous part of the design process. Suitable harmonic colours used together in design projects can improve the visual aesthetics. A collection of colours in design is usually called a colour palette. Colour palettes are often visually generated by designers from images or from other inspirations based on the designer's aesthetic perspective with respect to either a design brief or the designer's own colour preferences (Moretti and Lyons, 2002; Luo, 2006). Different colour palettes can be used to deliver different colour meanings or carry specific colour emotions (Bartram *et al.*, 2017).

However, the process of colour-palette selection can be difficult for non-professional designers. Harmonious colour combinations can improve visual satisfaction and produce a pleasing response (Moretti & Lyons, 2002; Museros *et al.*, 2020). The colour combinations that occur in landscapes, especially in natural landscapes, are often considered to be harmonious and consistent (Feng *et al.*, 2018). Also, various materials naturally exist in nature that provide different colour combinations. The specific colour combinations found in certain natural areas can be identified as the evidence of the characteristics of the local landscapes (Bell, 2008). Due to the wide range of colour combinations and the abundant colour characteristics in landscapes, landscapes remain one of the most common inspirations for designers and artists.

Colour selection is one of the key operations in various design fields. Although it is a process that is normally carried out manually by people, there are computational methods that aim to automatically extract colours from images. Since it is likely that humans may be able to perform this task well (indeed, in this thesis user-derived colours are used as the ground-truth data) this raises the question of why we might develop such automatic methods. There are two possible reasons. Firstly, the amount of data in the world is growing rapidly (for example, about 100 million images are uploaded to Instagram alone each day). It is possible to imagine workflows where colour palettes are extracted from hundreds or thousands of images and it may simply be impossible for this to be accomplished manually in any reasonable amount of time. Secondly, although experienced designers may be able to extract colours quickly and accurately this may not be true for less experienced designers; in such cases, automatic methods might act as tools or even could be relied upon entirely.

1.2 Aims

The aim of the research is to explore automatic methods for generating colour palettes from images. One application of this work could be to form the basis of a digital tool that could be used by inexperienced designers or which could be used instead of manual colour selection in high-volume image workflows. Although the context of the work is landscape images, many of the findings could be applied to other imaging applications.

In order to achieve this aim the following objectives are carried out:

- To understand and analyse the colours selected by designers and to collect a set of manually selected colour palettes as a set of ground-truth data against which to benchmark the automatic methods.

  To develop a method for quantifying the difference between colour palette palettes (a difference-prediction metric) to enable the performance of different algorithms and methods to be quantified.
- To develop and compare different methods for automatically generating colour palettes.

1.3 Overview

Eight chapters are included in this thesis. Chapter 1 introduces the general background, aims and structure of the research. Chapter 2 reviews the colour knowledge and previous studies related to this research. Chapter 3 reports an experiment in which designer's select colour palettes from landscape images to generate ground-truth data to act as a benchmark of subsequent automatic method performance. Chapter 4 introduces the colour-palette difference prediction method so that the performance of any automatic method can be quantified in comparison to human or visual data. This chapter includes a psychophysical experiment using the semantic differential scale method to quantify visual differences between pairs of palettes. Chapter 5 describes automatic colour palette extraction using K-means clustering. Both CIELAB and RGB colour spaces were used and compared with each other and with the visual data from Chapter 3. Chapter 6 focuses on colour palette extraction using eye tracking. The eye-tracking experimental process and the data analysis are described. Also, the colour palettes generated from the eye-tracking method were compared with those from the visual method in Chapter 3. Chapter 7 summarises the performance of the three different methods (visual, clustering and eye tracking) that are explored within this thesis. Two different ways of comparing the methods are described. Chapter 8 summaries the findings and contextualises the research.

Chapter 2. Literature Review

This chapter begins with a basic review of key aspects of colour (section 2.1), including how humans observe, describe and manage colour. This is followed by section 2.2 which summarises and explains colour knowledge in the design and art area. Previous studies into automatic colour-palette extraction are reviewed (section 2.3). Finally, based on the literature reviewed in this chapter, the main research questions are described in section 2.5.

2.1 Colour Fundamentals

Colour is one of the most essential elements in our daily life. Yet, because we see colour in different ways based on different illumination types and intensities (even the left and right eye of one person might see colour slightly differently) it is not easy to describe colour precisely (Best, 2012). Indeed, it can be argued that our colour experiences are private sensations that can only be known to ourselves. The 20th Century, however, saw the emergence of a field known as colour measurement. This was based primarily on a system of colorimetry known as the CIE (Commission Internationale de l'Éclairage) system and this system is now ubiquitous in industrial manufacturing, digital colour systems and in parts of design. The CIE system will form a key cornerstone of the work in this thesis and so it will be described in the following sections and its relationship to colour perception will be discussed.

2.1.1 Visual System

Colour is often described as the outcome of the interaction of light sources, objects and the visual system (Berns, 2000) though we should be aware that objects are not always required in this process since colour can also result from viewing light sources directly. However, reflected or emitted light enters our eyes and is imaged on the retina, the inner lining of the eyeball, where light receptors absorb part of the incident light and generate a signal that is ultimately analysed by our brain. The absorption, scattering, and focusing properties of the cornea, lens, and intraocular fluids (aqueous and vitreous humour) all affect the quality of the retinal image (and are illustrated schematically in Figure 2-1).

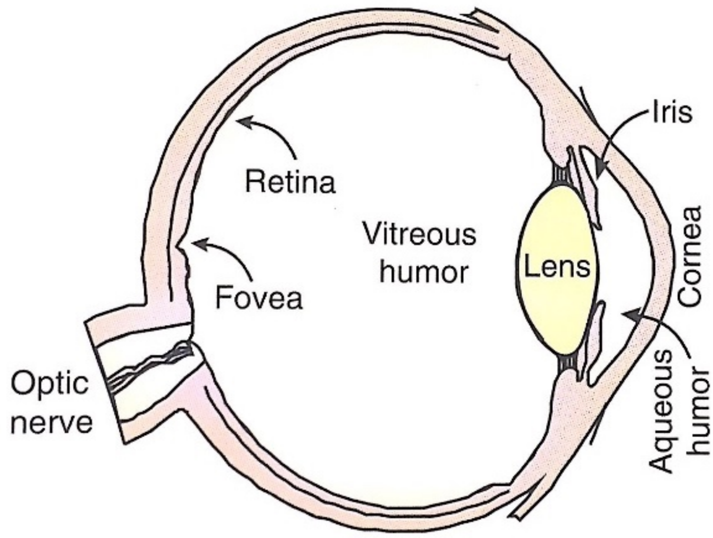


Figure 2-1 The cross section of the human eye (Berns, 2000).

Rods and cones are two kinds of photoreceptors, so-named because of their shape. Rods can detect tiny amounts of light and enable us to see the shape of objects in very low light conditions (so-called scotopic vision or scotopic conditions); because there is only one type of rod they do not allow colour vision but simply enable us to see in shades of grey. With increasing intensity of light, we move from scotopic vision to photopic vision; the rods become inactive and colour vision is mediated by the responses of three types of cones.

The three types of cones respond maximally to different wavelengths in the visible spectrum. It was hypothesised by Thomas Young (1802) - and later Hermann von Helmholtz (1866) - that the human eye contains three sensors, each of which is able to receive separate signals from different spectral regions. As shown in Figure 2-2, the three types of cones are maximally responsive in the short, middle and long wavelength regions of the spectrum and are hence referred to as S, M and L cones (Best, 2012). The spectral responsivity curves in Figure 2-2 can be interpreted as the relative probabilities that each cone will absorb a photon of light at each wavelength.

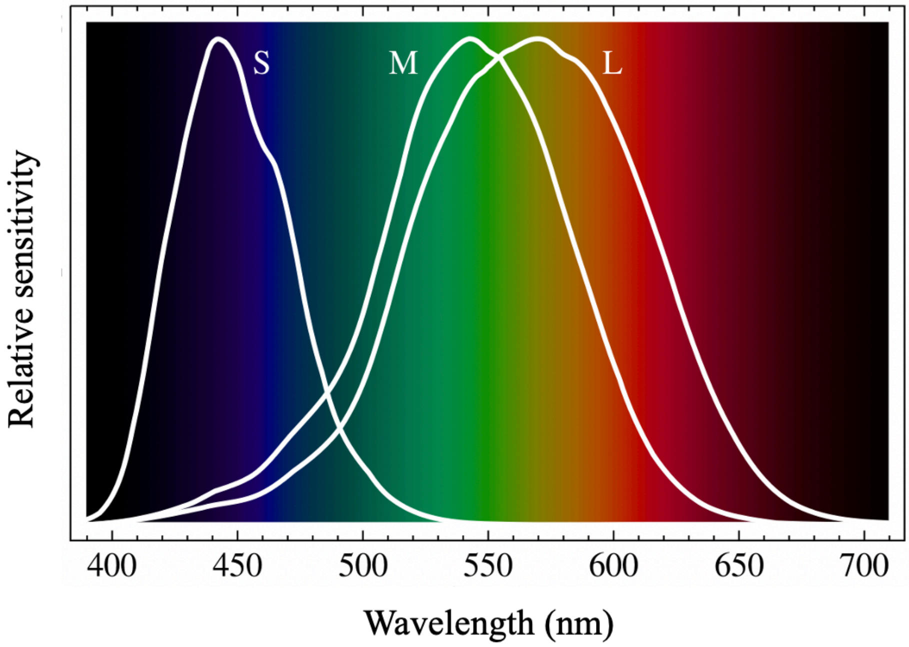


Figure 2-2 S, M, L cones spectral responsivity (Best, 2012).

2.1.2 Spectral Colour

The electromagnetic spectrum comprises of energy of widely different wavelengths and includes ranges that correspond to radio ways, microwaves, x-rays and gamma rays. The energy of each photon changes with wavelength. The human eye can only respond to a small part of the electromagnetic spectrum and we refer to this part as the visible spectrum. The definition of light is somewhat ambiguous. Some people define light as the whole electromagnetic spectrum and then describe the part that we can see as visible light; others, however, define light as only that part of the visible spectrum that we can see. As illustrated in Figure 2-3, the visible spectrum is roughly from 360nm to about 780nm (Fraser *et al.*, 2009). In the 18th Century Newton (1952) described the spectrum as the set of seven 'rainbow' colours, which are red, orange, yellow, green, blue, indigo and violet (often taught in schools with the mnemonic Richard Of York Gave Battle In Vain). The idea of seven colours in the visible spectrum as identified by Newton continues today although with some controversy; some people argue that there are only six bands of colour rather than seven, whilst others argue that hundreds of distinct hues can be seen in the spectrum under the right conditions.

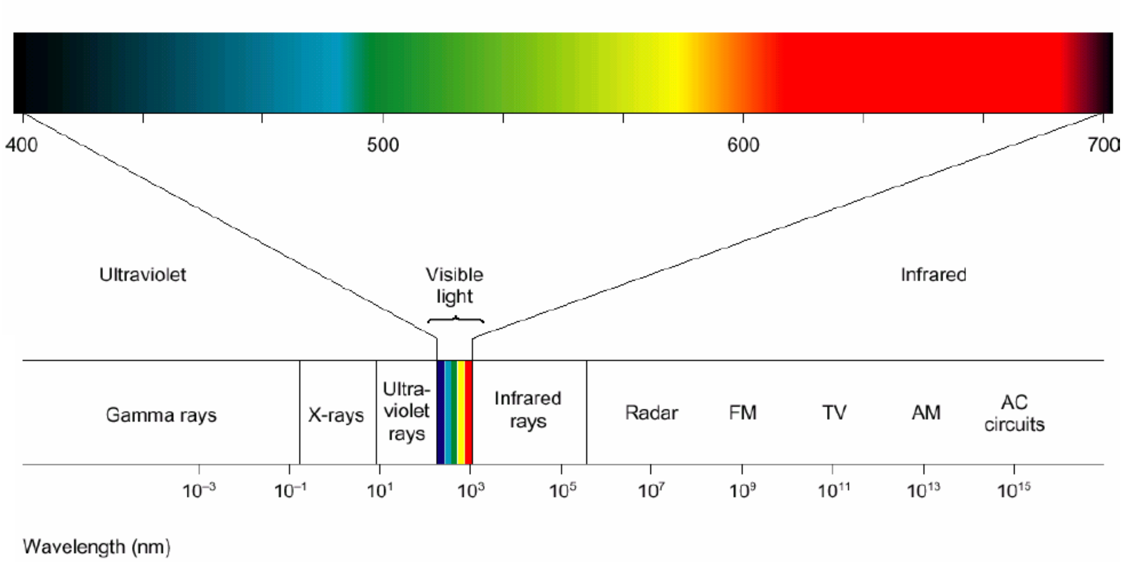


Figure 2-3 The electromagnetic spectrum showing the visible spectrum and a representation of the colours that are associated with it.

We now understand that there are inherently distinguishable terms of colour perception including hue, saturation and brightness. According to hue, saturation and brightness, colour in various parameters can be characterised by colour measurement systems, which include the subjective Munsell and Ostwald systems and the quantitative CIE colour system (Best, 2012).

It should be noted that in recent years it has been established that a small number of females have four classes of cones and therefore may have tetrachromatic vision as opposed to trichromatic vision (Jordan & Mollon, 1993). It has also been determined that visual pigments also exist in other parts of the retina (in the retinal ganglion cells rather than in the cones and rods) but it is believed that these pigments send signals to the centre of the brain (rather than to the visual cortex) and hence are not thought to be involved in colour vision (Provencio, 2000; Westland *et al.*, 2017).

2.1.3 Colour Appearance Phenomenon

The CIE system of colorimetry is discussed later (see section 2.1.5). However, if two stimuli have identical CIE XYZ tristimulus values then the colours of the two stimuli as perceived by an observer with normal colour vision should be the same.

This is only true if certain constraints are met, including the retinal locus of stimulation, the angular subtense, and the luminance level. Additionally, the surrounds, backgrounds, size, shape, surface characteristics need to be identical when the two stimuli are viewed. Therefore, if any of the viewing conditions differ, the two stimuli may no longer match even if they have the same CIE XYZ values. That colour appearance can change depending upon various factors is often described as colour-appearance phenomena (Fairchild, 1998). Some of these colour-appearance phenomena are described below.

Hunt Effect and Stevens Effect

The Hunt effect refers to an increase of colourfulness with an increase of luminance. The colour appearance of objects changes significantly with the overall illuminance level. The Stevens effect refers to perceived lightness contrast increasing with increasing luminance, which is a close relative of the Hunt effect (Fairchild, 1998). The Hunt effect and the Stevens effect are illustrated in Figure 2-4, where both colourfulness and lightness increase as luminance increases.

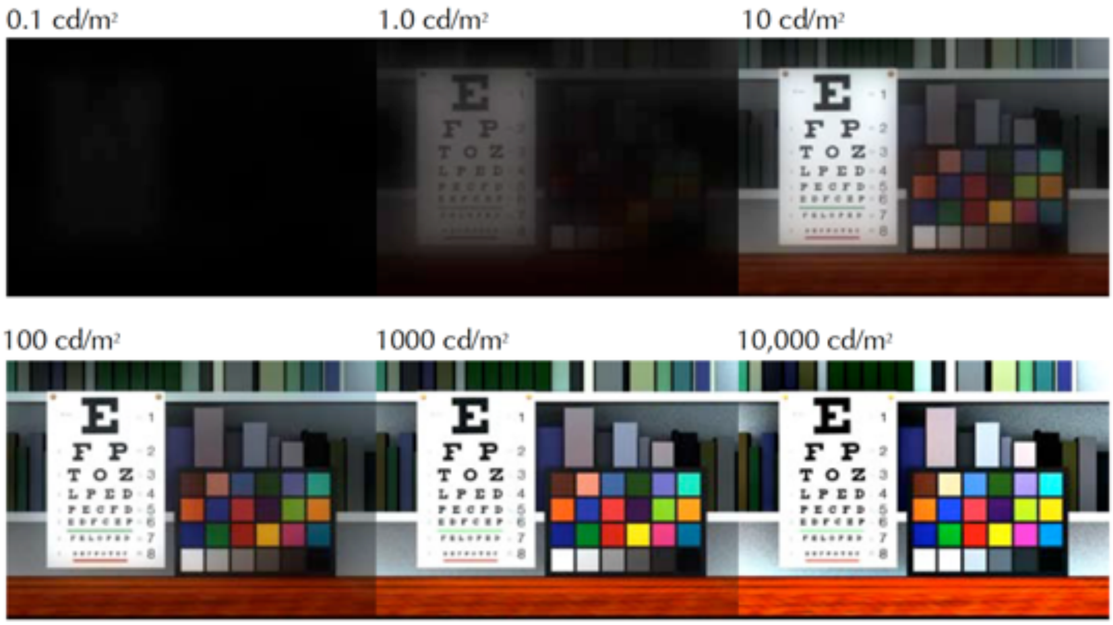
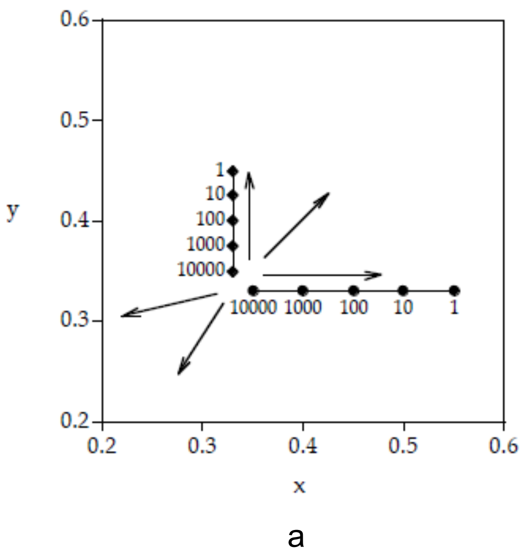


Figure 2-4 Hunt and Stevens effect (as the level of illumination increases, the colour in the figure becomes more colourful and lightness contrast increases, dark colours look darker and vice versa).

Hunt (1952) collected corresponding colour data by haploscopic matching. There were different viewing conditions for each eye to adapt and match between the stimuli presented in each eye. Figure 2-5a is a schematic representation of Hunt's results and shows that a stimulus of low colorimetric purity at 1000cd/m^2 matches a stimulus of high colorimetric purity at 1cd/m^2. This means, as the luminance increases, the perceived colourfulness also increases (Fairchild, 1998).

The Stevens effect (Stevens and Stevens, 1963) can be illustrated in Figure 2-5b. The relationship between relative brightness and relative luminance presents straight lines, which shows the relative brightness increases with increasing adapting luminance of four different adaption levels (Fairchild, 1998). Stated more directly, as the luminance is increased, dark colours look darker and light colours look lighter.



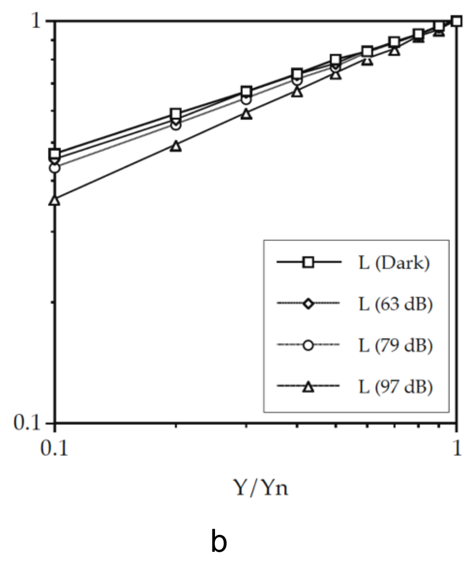


Figure 2-5 Diagrams to show (a) Hunt effect and (b) Stevens effect (Fairchild, 1998).

Chromatic Adaptation

Chromatic adaption is one of the most important colour-appearance phenomena, which is that the human visual system has the capability to adjust to a wide range of colour illumination in order to approximately preserve the undistorted appearance of the coloured object (Fairchild, 1998). A typical application is the automatic white balance mode in digital cameras, which can overcome the impact of the external environment to achieve colour temperature control and correction. It determines the reference white of the screen to achieve the white balance adjustment.

2.1.4 Colour space

A colour space is a specific way of organising colours. Many colour spaces are three-dimensional and different colour spaces make different information about the colours more of less explicit. Some colour spaces are organised systematically whilst others are more arbitrary. The RGB colour space refers to a way of organising colour using red, green and blue coordinates (Stokes *et al.*, 1996). Note, however, that there is more one colour space based on RGB. One of the most notable RGB colour spaces is called sRGB.

sRGB Colour Space

In the late 20th Century there were many different RGB systems (many different standards and many implementations of these standards) and this was not helpful for colour fidelity. In order to improve the then-current colour management strategies and build a method to control colour of the operating system and the internet, a couple of organisations including Integrated Colour Management (ICM), International Colour Consortium (ICC), Hewlett-Packard Co. and Microsoft worked together to bring out a new standard RGB colour space, sRGB. The sRGB colour space was published as the formal international standard IEC 61966-2-1 (IEC, 1999).

Furthermore, the sRGB colour space can support the internet, device drives and operating systems, which is a complementary method to the rest of colour management methods. Through sRGB colour space, people are able to view data directly on the monitors rather than modification. In addition, a substantial degree of consistency and reasonable output expectations can be ensured by using in-gamut sRGB data. In summary, sRGB colour space is able to benefit a boarder range of users by expending and utilizing availability of colour management (Stokes *et al.*, 1996; IEC, 1999).

Device-Independent Colour Space

Apart from the RGB colour space, there are several other colour spaces. RGB and CMYK spaces are normally described as being device-dependent colour spaces, while the CIE colour spaces are device-independent. To achieve good colour fidelity between various devices and systems, it is insufficient to specify colour in a way that depends on a specific device. Therefore, it has become necessary to use CIE colour spaces as device-independent colour spaces. For example, CIELAB (to be discussed later in section 2.1.6) and Yxy pertain to the CIE system and present a way to specify colour which is independent of any devices and is a more accurate method. In brief, device-independent colour spaces can be regarded as the specification of the colour (Sharma, 2004).

2.1.5 CIE System of Colorimetry

In 1931, the CIE system was introduced by the Commission Internationale de l'Éclairage and it has become an internationally accepted standard system. It is able to specify spectral colour according to tristimulus values, which are the three additive CIE primaries X, Y and Z and used to determine colour matches by the standard observer (Schanda, 2007). However, as mentioned previously, colour is a perception and a private experience; it is not accessible to engineering measurement. One can argue therefore that strictly speaking the CIE system of colorimetry is not a method that actually measures colour. Sometimes it is referred to as a system of specification. However, in fact the CIE system is concerned with specifying whether two physical stimuli will be a visual match. It does this by calculating tristimulus values (XYZ) but the values of the XYZ values are somewhat arbitrary; had different primaries been used in the CIE system then different tristimulus values would have resulted. The key feature, however, is that if the tristimulus values are the same for two stimuli then these two stimuli will be a visual match (to the average observer) and this is independent of the actual primaries used in the system.

CIE Standard Colorimetric Observers

The 1931 CIE standard colorimetric observer was introduced as a standard basis to specify colorimetric quantities for both technical and commercial purposes. Prior to this, there were two experimental determinations performed during the 1920s. Wright (1929) measured the colour matching [1] functions with ten observers and Guild (1932) measured seven observers whose colour vision was verified to be normal. The two experiments had similar methods in principle. The same viewing conditions were adopted, a 2° visual angle subtended by a bipartite field and surrounded by darkness (Smith & Guild, 1931). At the meeting of the Colorimetry Committee of the CIE in 1931, the colour matching functions from Wright and Guild were combined and defined as the 2° standard observer or the *1931 standard observer*, which is assumed to represent the colour matching results of human with normal colour vision. In 1964, the CIE put forward an additional standard observer with a larger visual angle 10°. It is referred to as the 10° supplementary standard observer (Berns, 2000).

The CIE Chromaticity Diagram and Chromaticity Coordinates

Although a colour stimulus can be described by three tristimulus values (e.g. XYZ), it is sometimes useful to calculate chromaticity coordinates, x, y and z defined thus:

$$x = \frac{X}{X+Y+Z} \qquad y = \frac{Y}{X+Y+Z} \qquad z = \frac{Z}{X+Y+Z} = 1 - x - y \qquad \textbf{2.1}$$

By definition, the three chromaticity coordinates sum to unity and this means that for many purposes it is possible to refer to only two of them (by convention this tends to be *x* and *y*). The x and y values can be plotted in a rectangular coordinate system defined as the CIE xy chromaticity diagram (as illustrated in

[1] 3 different primary colours were chosen, the observer was shown single-wavelength stimuli and asked to match it with a weighted combination of the primaries. The amounts of the primaries used to match each wavelength are known as the colour-matching functions.

Figure 2-6). The diagram represents colour by hue and excitation purity. The outline includes all the perceivable hues by normal human vision and the spectral colours. The differences between two colours can be easily shown in the diagram by their coordinates. Additionally, it is possible to compare colour saturation using the diagram by creating a line between the illuminant chromaticity coordinates and the point on the outline. The closer a point is to the horseshoe spectral locus the more saturated it is (Xiao, 2006; Schanda, 2007).

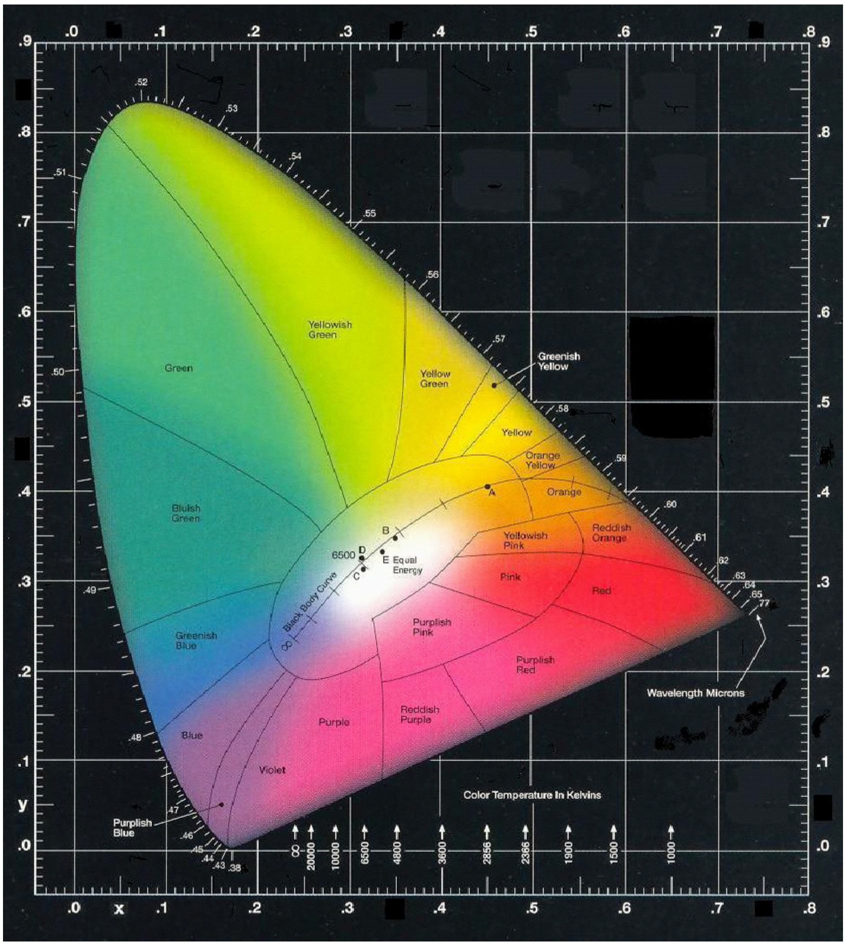


Figure 2-6 CIE xy chromaticity diagram (Xiao, 2006).

2.1.6 CIELAB

The CIE xy chromaticity diagram is not visually uniform, which means the simple geometrical distance between two colours in this space does not correspond well to the perceived colour difference. Therefore, in 1976, the CIE proposed two new more perceptually uniform colour spaces for colour specification, CIELAB and

CIELUV. CIELUV is mainly used in lighting and displays. The CIE 1976 L^*, a^*, b^* (CIELAB) colour space is frequently used in the colorant and graphics arts industries and other areas. Figure 2-7 shows the CIELAB colour space, in which L* represents lightness range from 0 (black) to 100 (white), a* represents redness-greenness and b* represents yellowness-blueness.

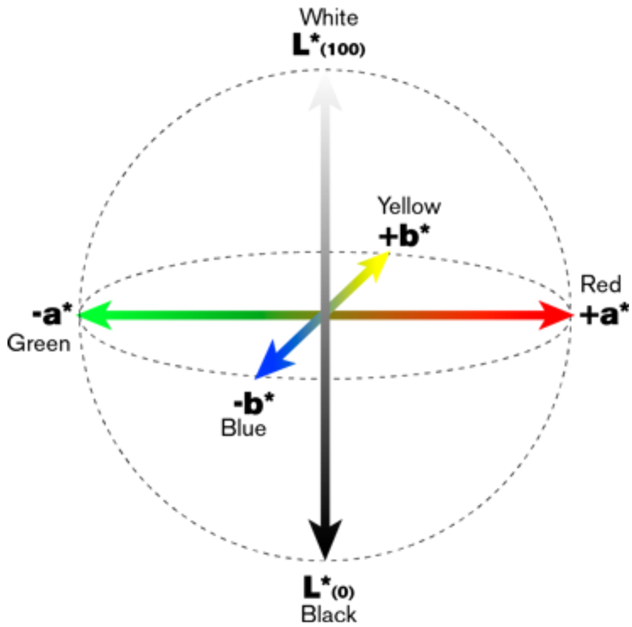


Figure 2-7 The three-dimensional CIELAB colour space (Yaopey, 2020).

The CIELAB equations for are given in Equation 2.2.

$$L^* = 116 f\left(\frac{Y}{Y_n}\right) - 16$$

$$a^* = 500 \left[f\left(\frac{X}{X_n}\right) - f\left(\frac{Y}{Y_n}\right)\right] \tag{2.2}$$

$$b^* = 200 \left[f\left(\frac{Y}{Y_n}\right) - f\left(\frac{Z}{Z_n}\right)\right]$$

where

$f(X/X_n) = (X/X_n)^{1/3}$ for $(X/X_n) > (6/29)^3$

$f(X/X_n) = (841/108)(X/X_n)^{1/3} + 4/29$ for $(X/X_n) \leq (6/29)^3$

$f(Y/Y_n) = (Y/Y_n)^{1/3}$ for $(Y/Y_n) > (6/29)^3$

$f(Y/Y_n) = (841/108)(Y/Y_n)^{1/3} + 4/29$ for $(Y/Y_n) \leq (6/29)^3$

$f(Z/Z_n) = (Z/Z_n)^{1/3}$ for $(Z/Z_n) > (6/29)^3$

$f(Z/Z_n) = (841/108)(Z/Z_n)^{1/3} + 4/29$ for $(Z/Z_n) \leq (6/29)^3$

where X_n, Y_n and Z_n are the tristimulus values of the reference white.

Colours can be defined by L^*, ${C_{ab}}^*$and h_{ab} via Equation 2.3.

$$h_{ab} = tan^{-1}(b^*/a^*)$$

$$C^*{}_{ab} = \sqrt{a^* + b^*} \qquad \textbf{2.3}$$

CIELAB Colour Difference Formula

The distance (colour difference) between two points that represent two stimuli in the CIELAB colour space can be quantified through the CIELAB colour difference formula. The distance is defined as $\Delta E^*{}_{ab}$. The equations are listed below.

$$\Delta E^*{}_{ab} = \sqrt{\Delta L^{*2} + \Delta a^{*2} + \Delta b^{*2}} \qquad \textbf{2.4}$$

or

$$\Delta E^*{}_{ab} = \sqrt{\Delta L^{*2} + \Delta {H^*{}_{ab}}^2 + \Delta {C^*{}_{ab}}^2}$$

where

$$\Delta H^*{}_{ab} = 2\ \sin(\Delta h_{ab}/2) \sqrt{C^*{}_{ab,1} - C^*{}_{ab,2}}$$

2.1.7 Advanced Colour Difference Equation

The CIELAB colour difference equation has been widely used in industry; however, by the 1980s it was already understood that although CIELAB was more visually uniform that the original 1931 system it was far from perfect. A number of studies revealed that CIELAB colour differences could not accurately predict visual colour differences (Clarke *et al.*, 1984; McDonald & Smith, 1995). This led to a whole plethora of so-called optimised colour difference equation including CMC, JPC79, BFD and CIE94. These equations calculate colour differences in the CIELAB colour space but in ways that are more complex than the simple Euclidean distance between two points. Currently the CIE standard for the evaluation of small colour differences (where the CIELAB DE is less than 5) is the CIEDE2000 equation (Luo *et al.*, 2001). CIELAB is still recommended for small colour differences. Both CIELAB and CIEDE2000 equations will be used in this thesis. The CIEDE2000 equations are list below in Equation 2.5. The *L**, *a** and *b** values are calculated using CIELAB formula (Equation 2.2).

$$\Delta E_{00} = \sqrt{\left(\frac{\Delta L'}{k_L S_L}\right)^2 + \left(\frac{\Delta C'}{k_C S_C}\right)^2 + \left(\frac{\Delta H'}{k_H S_H}\right)^2 + R_T \left(\frac{\Delta C'}{k_C S_C}\right)\left(\frac{\Delta H'}{k_H S_H}\right)}$$

$$L' = L^*$$

$$a' = (1 + G)\, a^*$$

$$b' = b^* \qquad \textbf{2.5}$$

$$C' = \sqrt{a'^2 + b'^2}$$

$$h' = \tan^{-1}(b'/a')$$

where

$$G = 0.5 \times \left(1 - \sqrt{\frac{\overline{C^*{}_{ab}}^7}{\overline{C^*{}_{ab}}^7 + 25^7}}\right)$$

$$\Delta L' = L'_2 - L'_1$$

$$\Delta C' = C'_2 - C'_1$$

$$\Delta H' = 2\sqrt{C'_2 C'_1}\ \sin \Delta h'/2$$

where

$$\Delta h' = h'_2 - h'_1$$

$$S_L = 1 + \left(0.015\ (\overline{L'} - 50)^2 \Big/ \sqrt{20 + (\overline{L'} - 50)^2}\right)$$

$$S_C = 1 + 0.045\,\overline{C_{ab}{}'}$$

$$S_H = 1 + 0.015\,\overline{C_{ab}{}'}\,T$$

where

$$T = 1 - 0.17\cos\left(\overline{h_{ab}{}'} - 30°\right) + 0.24\cos\left(2\overline{h_{ab}{}'}\right) + 0.32\cos\left(3\overline{h_{ab}{}'} + 6°\right) - 0.20\cos(4\overline{h_{ab}{}'} - 63°)$$

$$R_T = -\sin(2\Delta\vartheta)\,R_C$$

$$\Delta\vartheta = 30\exp\left[-\left(\overline{h'} - 275°/25\right)^2\right]$$

$$R_C = 2\sqrt{\overline{C'}^7/\overline{C'}^7 + 25^7}$$

2.1.8 Colour Measurement Instruments

Colour measurement instruments measure optical properties of materials such as reflectance, transmission and emission of light (Berns, 2000). The use of the CIE system allows these optical properties to be used to calculate meaningful colour information such as tristimulus values.

Colorimeter

A colorimeter is a device used to measure the CIE tristimulus values of a stimulus (Berns, 2000). Colorimeters can also be used to measure small colour differences due to the high speed and low cost (Ohno, 2000).

Spectrophotometer

A reflectance (or transmittance) spectrophotometer is used to measure spectral reflectance (or transmittance) (Berns, 2000; Schanda *et al*., 2007).

Spectroradiometer

A spectroradiometer is normally designed to measure spectral radiance (unit: W sr-1 m-2 nm-1) or spectral irradiance (unit: W m-2 nm-1) of a light source (Berns, 2000; Ohno,2000).

2.1.9 Colour Management

Considering the different characteristics of varying imaging devices and media, it is inevitable that reproducing colour with different devices will be challenging. For example, as can be seen from Figure 2-8, a stimulus at 500nm produces different camera RGB responses in the Canon EOS 500D and Nikon D5000 devices. The devices have different relative spectral sensitivities and this leads to them recording different RGB values for the same physical stimulus. Since display devices may also differ in their spectral power outputs it follows that the same RGB values might appear to be quite different colours when used on two different displays. Therefore, colour management needs to be used to account for the specific characteristics of each device (Schanda, 2007). In general, colour management refers to the process of using hardware, software, and methodology to control and adjust colour translation among different imaging devices (Sharma, 2004).

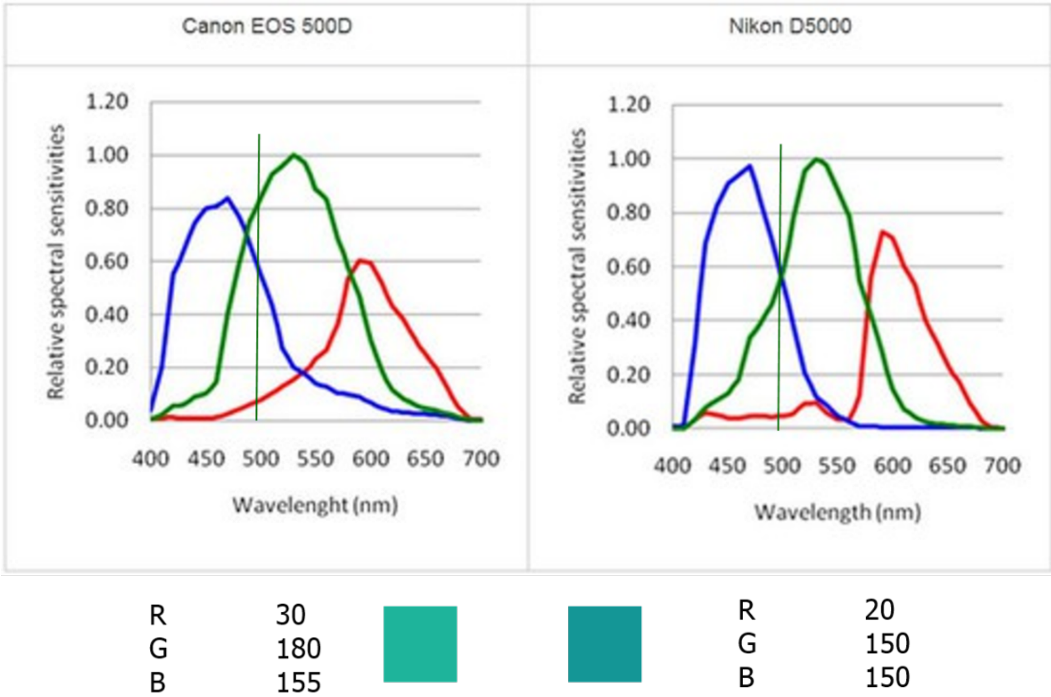


Figure 2-8 Cameras capture device-dependent colour (Westland, 2017).

ICC Colour Management Framework

The colour management framework of the ICC (International Colour Consortium) is the *de facto* standard. The ICC specified the framework of the profile connection space and the format of a profile. The ICC as an independent organisation that was founded in 1993 by eight founding imaging companies (Sharma, 2004).

The ICC proposed two transformations in the colour reproduction process. First, transforming the device colour data into a colorimetric description for the specific viewing condition, which is the profile connection space (PCS). Second, on the contrary, taking the colorimetric description and converting it back to the device colour space data. Based on the two transformations, the parameters for the given colour reproduction medium are stored in a data, which refers to as the "ICC device profile" (ICC, 2004). Overall, in the ICC framework, colour transformations are accomplished among devices based on the profiles of devices by means of the PCS and the rendering intent (Figure 2-9). Thus, it is vital to provide the colour data itself when communicating the colour between different devices (Schanda, 2007).

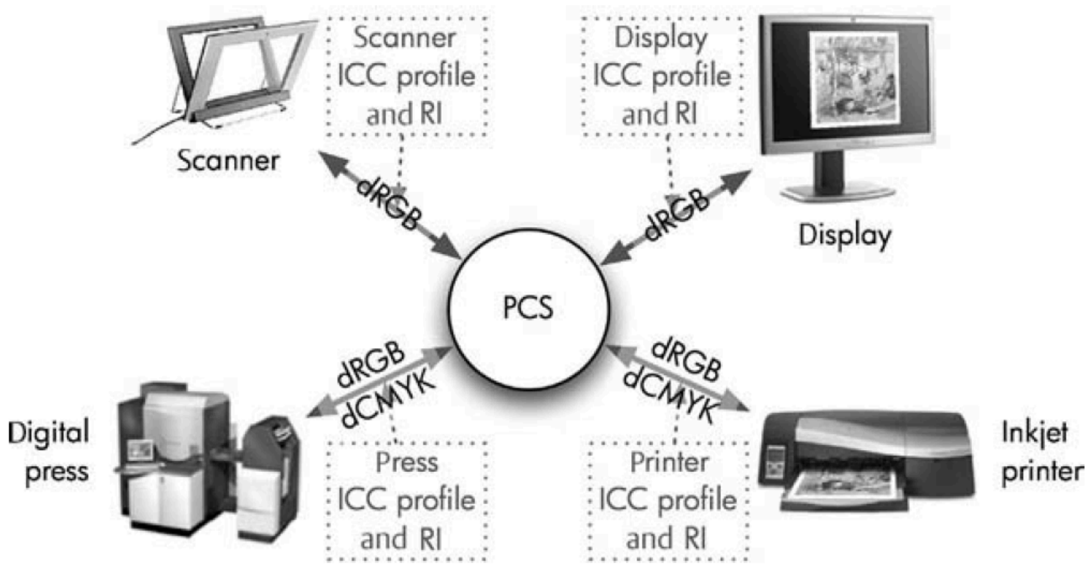


Figure 2-9 ICC workflow sketch (RI- rendering intent). dRGB (device RGB) (Schanda, 2007).

2.2 Colour in Design and Art

Colour is not only a scientific subject as described in the previous sections, but closely related to aesthetic disciplines. Colour as one of the vital elements in the design and art area and usually appears throughout the entire creation procedure. It is one of the fundamental ingredients of art and design. In this section, the colour knowledge in relation to design and art area is reviewed. Firstly, colour order systems (section 2.2.1) are reviewed; conceptual systems that can assist designers and artists to organise colour perceptions. Then, the concept of colour emotion (section 2.2.2) is reviewed to explain the relation between colour and human emotion and to what extent this can be useful for people from a creative background. Section 2.2.3 reviews colour preference and explores the role of colour preference in the design and art field. Section 2.2.4

reviews landscape and colour. Landscape is often a vital inspiration for artists and designers since landscape colours can play an essential role on the creative progress. Finally, the concept of a colour palette is reviewed (section 2.25).

2.2.1 Colour order system

A colour order system is a logical and systematic way to categorise colour perceptions and these are widely used in colour technology (Berns, 2000). A colour order system is constrained with a continuous scale and the appropriately embodied with stable, accurate and precise samples (Fairchild, 1998). In this section, two popular colour order system that are used widely in the design and art field, namely the Munsell system and the Natural Colour System, are summarised.

Munsell Colour System

The Munsell Colour System is one of the most popular colour order systems. It was introduced by the artist and educator Albert H. Munsell in 1905. Munsell's objectives were to create a system to describe colours and educate his students about colours. There are three attributes in this system called Munsell Value, Munsell Chroma and Munsell Hue which correspond with the human appearance attributes: lightness, chroma and hue (see Figure 2-10) (Fairchild, 1998; Hunt & Pointer, 2011; Munsell, 2015). The physical samples of the Munsell System are referred as the Munsell Book of Colour. There are 1500 samples on 40 pages in the Munsell Book of Colour. The arrangement of colours on each page is shown in Figure 2-11 (Hunt & Pointer, 2011). The Munsell Colour System correlates to human colour perception which makes it ideal for designers to make colour communication with the manufacturers who use the same system ('Munsell Colour System', 2013).

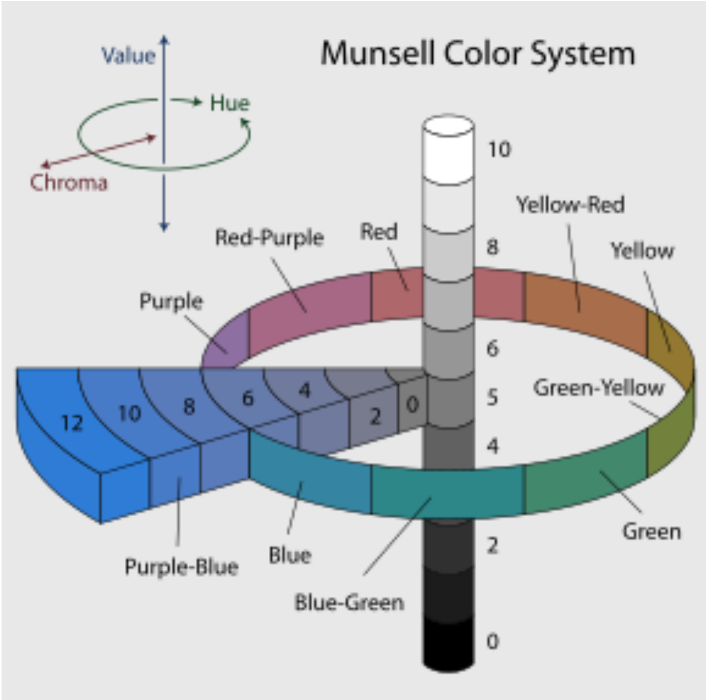


Figure 2-10 The Munsell Colour Order System (Jacobolus, 2007).

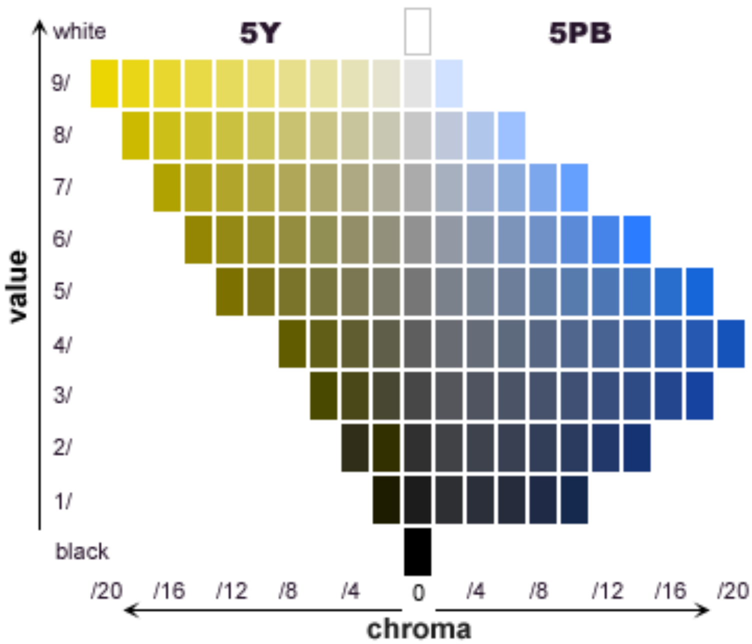
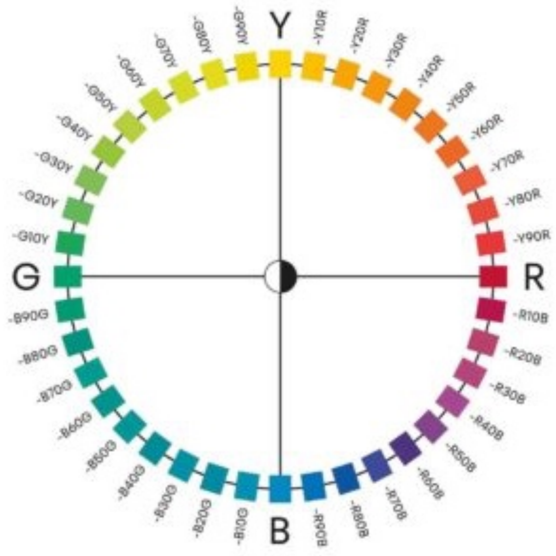


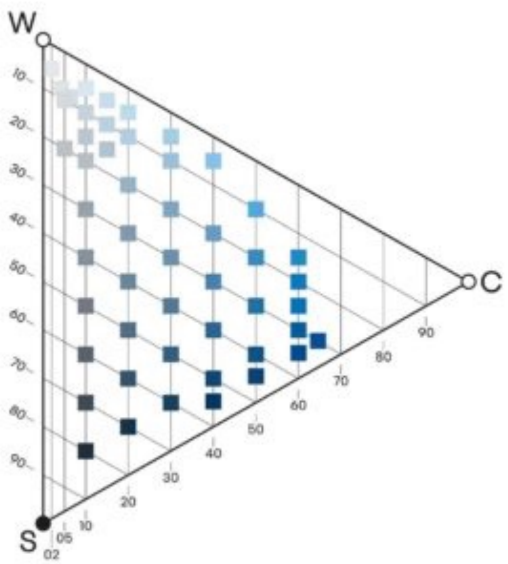
Figure 2-11 Example representation of the Munsell Book of Colour (Xiao, 2007).

Natural Colour System (NCS)

The Natural Colour System was developed in Sweden based on Hering's opponent-colour theory. The system was designed to describe colour perception *per se* which makes it easier for designers, architects and others who have less knowledge of colour physics or physiological attributes of colour stimuli to use. Six elementary colour perceptions are included in the NCS, white (W), black (S), red (R), yellow (Y), green (G) and blue (B). In the system, colour is described as *sc*-Φ (Swedish Standard), where *s* means blackness, *c* means chromaticness and Φ means hue. As shown in Figure 2-12, two diagrams are used to locate the colour, the NCS colour circle (a) and the NCS colour triangle (b). The NCS colour circle represent the hue scale by percentage from two basic colours. For instance, G40Y implies the hue of the colour is 40% yellow and 60% green. The NCS triangle represents the scale of the blackness and chromaticness values with the three variables, W, S and *c*. The sum of three variables is equal to 100 (Hardin & Maffi, 1997; Hård & Sivik, 1981; Hård *et al*., 1996a; Hard *et al*., 1996b).



a



b

Figure 2-12 The Natural Colour System:
a The NCS colour circle b NCS colour triangle
(NCS System-NCS, https://ncscolour.com/ncs/)

Both the Munsell Colour System and Natural Colour System are widely known. However, they have some limitations because of the "manufacturing process and sample choices" (Pastilha *et al*., 2019, p411). According to Pastilha *et al*. (2019), the Munsell Colour System and the Natural Colour System lack sufficient colour samples with low lightness, although these colours frequently appear in natural scenes. This results in some possible insufficient cases when representing natural colours with low lightness levels.

2.2.2 Colour Emotion

Colour is associated with human emotion and can reflect the human mood. Apart from the basic visual perception of colours, meaning can also be evoked by colours. Humans possess the ability to categorise colours into both verbal and nonverbal semantics (Jahanian *et al*., 2017). Relevant feelings or emotions can arise through corresponding colours or colour combinations. For instance, blue symbolises sadness when people say, ‘I am feeling blue’; red can be linked with anger. In general, each colour is associated with more than one emotion. Blue is not only linked with sadness but also with calming, peaceful, quiet, serious and nostalgic. These associations have a long history which can be traced back to the Middle Ages (Gage, 1999; Biggam, 2011; Chen *et al.*, 2020). With regards to different perceptual dimensions of colour, hue, brightness and saturation, they have corresponding categories. Warm colours and cool colours are distinguished by hue. In terms of brightness, brighter colours tend to elicit positive emotions including happy, excited, relaxed and positive. Dark colours are linked with negative feelings like anxious, boring, sad and negative (Hemphill, 1996). D’Andrade & Egan (1974) studied saturated colours are associated with positive response like happy and unsaturated colours related more with negative emotions like sadness.

However, colour emotion association is not always biologically based and pancultural; it varies with cultural background (Elliot & Maier, 2007; Feisner, 2006). Ou *et al.* (2012) conducted psychophysical experiments in the UK, Taiwan, France, Germany, Spain, Sweden, Argentina, and Iran to explore the cross-cultural comparison of colour emotion. A strong effect of culture was evident in the results. A later study explored the colour semiotics between two distinct cultural groups was carried out by Chen *et al.* (2020). Chinese and British participants were recruited in this study and were asked to select three colours for each adjective. Though there were many similarities, the results showed some large differences between Chinese and British participants for some words such as active and bad (see Figure 2-13).

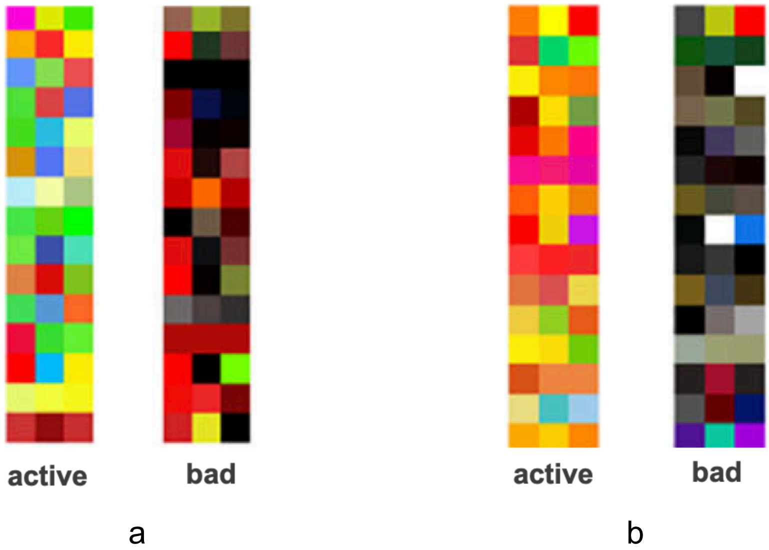


Figure 2-13 The experimental results from the for all three selected colours. a UK participants and b Chinese participants (Chen *et al.,* 2020)

Colour emotion or colour semiotics plays an essential role in art and design. Many artists value the emotional responses of colour more than numeric precision (Shugrina *et al*., 2017). Jahanian *et al.* (2013) note that design is regarded as work that can express its purpose to the audiences, and it is necessary to describe the colour mood of the design. These associations work in conjunction with the principles and elements of design to impact what the artist, architect or designer wishes the viewer to see and feel (Feisner, 2006). With regards to design, colour emotion is related to colour preference which is discussed in the next section.

2.2.3 Colour Preference

Colour affects human emotion and people tend to like colours that evoke positive feelings. This leads to the existence of colour preference. Colour emotion and preference complement one another. However, the vast literature on colour preference has been described as "bewildering, confused and contradictory" (McManus *et al*., 1981, p.651). Individual colour preference can vary but there are still some preference patterns. In general, people tend to prefer cool colours such as blue rather than warm colours such as yellow (McManus *et al.*, 1981; Chen *et al.*,2020). One of the significant early contributions in this area was by Max Lüscher in 1947. In his Lüscher Test, observers were asked to arrange colour samples in order of preference. It was suggested that the preference order indicated personality characteristics of the observers. In this study, in terms of colour preference, blue was found to be the most generally preferred colour and many subsequent studies have confirmed this (Gage, 1999; Stompór-Świderska, 2013). Hemphill (1996) concluded that adults respond more positively to bright colours (white, pink, yellow, blue, purple and green) than to dark colours (black, brown and grey).

The individual variation of colour preference can be affected by gender (Hurlbert & Ling, 2007), age (Lee *et al.*, 2009; Taylor *et al.*, 2013), culture (Ou *et al.*, 2012), context (Jonauskaite *et al.*, 2016), education background (Hanafy & Sanad, 2015). Colour preference is considered to be confusing to some extent because of the existence of various influencing factors.

In common with colour emotion, colour preference also differs according to the different perceptual dimensions, hue, brightness and saturation. Camgöz *et al.* (2002) studied the effects of hue, saturation and brightness on people's preference for foreground-background colour relationships. It was found that colours with the maximum levels of brightness and saturation were more preferred than other brightness-saturation combinations. In terms of hue, blue was found to be the most preferred background.

With regards to industrial applications, especially in the design field, colour preference plays a vital role. In the product design and marketing area, Yu *et al.* (2018) concluded that consumers' purchasing decisions are closely associated with individuals' colour preference when the product has no primary factors (including "colour functionality, colour performance, colour culture and other aspects"). For designers, having a better understanding of colour preference could help reduce the unnecessary waste of products on the market. In general, the colour preference of designers' audiences needs to be considered to satisfy and establish the design requirements. For example, the colour preferences of children and young people were explored for their hospital environment design (Coad & Coad, 2008).

2.2.4 Colour and Landscape

One formal definition of landscape was stated by the Council of Europe as, "an area, as perceived by people, whose character is the result of the action and interaction of natural and/or human factors" (*European Landscape Convention*, 2000. p.2). Landscape has long been as an inspiration to designers and artists. As Leonardo Da Vinci said, "The eye is the window of human body through which it feels its way and enjoy the beauty of the world" (Malla, 2006, p.143). The visual sense has been a primary way for humans to understand and experience the world and landscape from a particularly intriguing source of visual stimulation (Maulan *et al.*, 2006). As proposed by Daniel (2001), Landscape aesthetics is decided by its formal quality including colour, line and form. Our attitudes towards the colours of nature are capable of indicating our preferences to different landscapes (Lee, 2007). In nature, the existence of similar and complementary colour arrangements is common. In landscapes, where there is a wide range of colours and colour combinations, this is particularly so, with the yellows, oranges and reds found during sunrise and the complementary blue sky or ocean with the yellowish sunrise. There is abundant colour variation in different regions, which results from various combinations of rock types, vegetation, local architecture materials and soil (Bell, 2008).

The use of colour is a particularly creative part of the design process; colour decisions occur throughout the entire design procedure (Minah, 2008). Colour is thought to influence people's feelings and there are many theories (and much evidence) that support the idea that colour affects human emotion (Biggam, 2011). Colour can therefore play a central role in the visual landscape experience (Maulan *et al.*, 2006) and designers can use this explicitly in design. For example, as shown in the Figure 2-14 in Reykjavik, the capital of Iceland, most roofs were constructed with red and blue colours to enliven the grey and drab landscape that is common in that area (Bell, 2008).

Figure 2-14 Reykjavik, the capital of Iceland (Bell, 2008).

Designers generally use colour according to basic rules of colour harmony that are represented in a body of knowledge known as colour theory. However, they also often research and identify specific colours or colour combinations discovered in the characteristics of local landscapes (Bell, 2008). The colour combinations in the natural scenes are considered to have the harmonious and consistent colour distribution (Feng *et al.*, 2018). 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.

In general, colour plays a central role in the visual landscape experience and is able to affect people's feelings and instincts. In this sense, it creates useful colour-related jobs for designers, especially for landscape architectures and other designers engaged in the outdoor environment (Thorpert & Nielsen, 2014). An experiment was conducted to test several formulae of colour difference by using twelve images with explanation and questionnaire on the internet (Bishop, 1997). It was concluded that: (1) the CIELAB colour difference formula can be used to estimate perceived colour difference in the landscape; (2) It is convenient to undertake an experiment through the Internet without a specific audience profile.

2.2.5 Colour Palettes

In general, a colour palette is defined as a group of carefully selected harmonious colours used by different types of designers (Best, 2012). Colour palettes (themes or schemes) are ubiquitous in colour design and art. A colour theme is a collection of colour patches that represents the colours used in a design or an image (Liu *et al.,* 2018). Colour scheme was defined by Fisher and Zelanski in 1999 as the aesthetic colour combination which provides pleasing harmonies. Wang *et al.* (2010) referred to colour theme as the colour template can be verbally described. Different colour palettes can communicate different colour meanings or induce different colour emotions (Bartram *et al*., 2017). The particular colour combinations from the natural landscape can be built into a colour palette for designers to inform their design themes. Applying different colour templates to artwork can provide different visual senses (Liu *et al.*, 2018). Often colour palettes are generated by designers for practical application based on their aesthetics with respect to either a design brief or the designers' own colour preferences (Moretti and Lyons, 2002; Luo, 2006). The challenge is to build a colour palette which is aesthetically pleasing and helpful to the design functionality at the same time (Jahanian *et al.*, 2015). Selecting a colour palette from scratch can be difficult (Lin & Hanrahan, 2013), especially for non-professional designers or novices (Feng et al., 2018).

Alternatively, a colour palette may be extracted automatically from an image or a set of images. For example, at the initial stage of a design project like graphic design, designers usually select an inspiration image and generate the colour palette from it. The colour palette will be used through the subsequent design process (Jahanian *et al.*, 2015). Colour palettes can even be generated from a word (Havasi *et al*., 2010; Lindner & Süsstrunk, 2013) which give designers the opportunity to directly receive the colour palette from the corresponding semantic context. More relevant studies related to semantic extraction were reviewed in section 2.3.2.

Furthermore, colour palettes are also quite important to image analysis, manipulation and other areas (Ciocca *et al.*, 2019). The colour palette can be applied to various colour image area; for example, colour quantization techniques and colour indexing. Given various applications and effects of colour palette, extracting the accurate colour palette is important (Delon *et al.*, 2005). Methods of generating colour palettes are the main objectives of this study; therefore recent research into colour palette generation is reviewed in the following section (section 2.3).

2.3 Colour Extraction

As described in the last section, the colour palette is one of the key elements in the design field. Therefore, colour selection is an important operation to obtain colour palettes in various design fields including web design, product design, interior design, built environment design (Brathovde *et al.*, 2019). It is possible to describe an image by naming some of the colours subjectively via the human visual system. Humans have the ability to group colours by similarities and give unique names to each group, albeit it may not be an easy process. These groups can be treated as the colour palette generated manually via the human visual system. Colour palettes can be extracted from different sources not only by a human manually but software automatically. Different sources relate to this progress includes images and words. Artists and designers also learn colouring inspirations form existing colour reference sources with colour combinations examples (Meier *et al.*, 2004). Many websites that allow automatic colour theme extraction have been published, such as Adobe Color (2020), COLOURLovers (2020) and PANTONE Studio (2020). These three commercial websites provide platforms for users to generate colour palettes and to share them with the community.

This section focuses on different methods to extract colours (or colour palettes) from different sources such as images, words and emotions. The subject matter was discussed in five parts in this section: image segmentation (section 2.3.1), semantic extraction (section 2.3.2), saliency extraction (section 2.3.3), machine learning extraction (section 2.3.4), and colour transfer (section 2.3.5).

2.3.1 Image Segmentation

In imaging science, the processes of using mathematical operations to obtain an image of the area with the text, pre-process the specific image segment the individual characters, transform the characters to a form which can be suitable for computer processing, and recognize these characters are defined as digital image processing. Image segmentation is one of the most difficult tasks in image processing (Shapiro & Stockman, 2001). It refers to the process of splitting a digital image into multiple segments, which enable an image to be simplified, meaningful and simpler to analyse. Image segmentation is the process to obtain a group of segments to cover the whole image or contours derived from the image. Furthermore, pixels in the same region share some similar characteristic including colour, intensity, or texture. Regions are differed by the same characteristic (Shapiro & Stockman, 2001; Gonzalez & Woods, 2014). Therefore, colours in the same region can be identified and extracted as the colour palette of one image. However, the challenge of image segmentation is to find the accurate region in view of different image types. Pal & Pal (1993) reviewed the literature on image segmentation techniques. They summarised some existing segmentation methods for colour images based on an Ohlander-type segmentation algorithm (Ohlander *et al.*, 1978), spectrum analysis, clustering techniques, fuzzy c-means methods and methods designed for multispectral images.

K-Means Cluster Analysis

As summarised above, there are several kinds of methods of image segmentation. K-Means cluster analysis is perhaps the most common and is an algorithm that can group pixels based on predefined feature vectors and initial centroids (Hu & Su, 2008). K-means clustering was first described by MacQueen (1967) as a method to partition unlabelled data into a number (K) clusters (Mathur & Purohit, 2014). It has been shown that the method (known colloquially as K-

Means) can extract regions by different colours in an efficient and fast way, and results agree well with human perceptions. In addition, there is evidence that working in a perceptually relevant space such as CIELAB is better than RGB space (Burney & Tariq, 2014; Shmmala & Ashour, 2013).

Delon *et al.* (2005) developed a process to simulate the process of colour extraction from images automatically. Considering the two requirements: “reduction of redundant colours and preservation of rare colours”, a method was proposed which turns colour information into hue, saturation and luminance. The 16- step K-Means approach used is called the ACoPa (automatic colour palette) algorithm. A statistically meaningful set of colour groups (colour palette) can be obtained by this method from any colour images. The results of this research showed the statistical analysis of physical variables enables to assert the perceptual reality. Hassan *et al.* (2017) noted that K-Means is the best algorithm for image segmentation. On the other hand, some previous research has addressed the disadvantages of K-Means. For example, producing an accurate K number is a challenge. Hassan *et al.* developed an automatic K-Means clustering method that determines the number of clusters (K) automatically and which also used two colour spaces (RGB and HSV colour space) to produce better results than a standard K-Means. Feng *et al.* (2018) have also criticised K-Means compared with human performance. High-saliency (but low-frequency) colours may important perceptually but insignificant in the K-Means process. K-Means is one of the most famous clustering methods adopted in some applications based on machine learning (Ciocca *et al.*, 2019). Machine-learning based colour extraction is another commonly used method and is discussed later in section 2.3.4.

2.3.2 Semantic Extraction

Extracting palettes from images or creating them manually are the traditional ways of generating colour palettes. However, starting with words is another way to generate colour palettes in view of the strong association between colours and words. Affective words could be considered as the medium of communicating through colour palettes.

Heer and Stone (2012) indicated that the connection between visual sensory and symbolic cognition is derived from the human capacity of naming colours accurately. In their study, a colour-naming model was generated using a large amount of human colour name judgements. The method was developed from naming certain colour values or conversely the process by providing the colour values of a certain name. The model constructed was then applied to a web-based survey through the scaling method to define how accurate colour is named and the colour difference among colours based on the same colour naming. The colour naming model was adopted in several applications, for example colour dictionary (providing representative colour values by input a colour name) as Figure 2-15 shows.

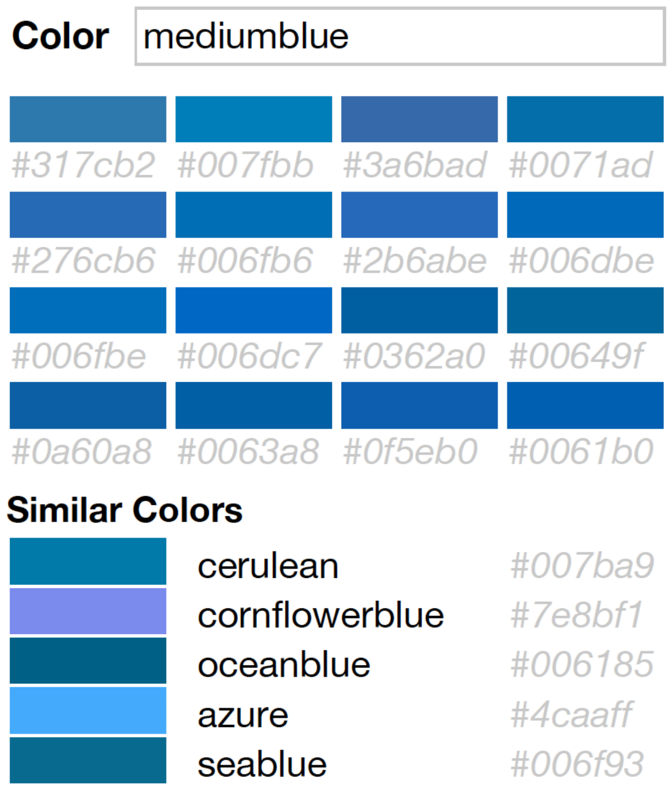


Figure 2-15 Colour dictionary (Heer & Stone, 2012).

A novel method was developed by Lindner and Süsstrunk (2013), which can create colour palettes from words automatically. 100,000 words were chosen from Google n-grams, and each word used to download 60 related images using Google image search. The database was built from these images and colours were extracted using a large-scale statistical method. In addition, the HSV colour space was used in the statistical image-mining process. After these processes, a psychophysical experiment was undertaken to compare this method with Adobe Kuler (Adobe Color).

There are many applications or potential applications involved based on the word-colour association. Kim and Suk (2016) carried out experiments with design-background participants to make the hue selections from images. Designers were then asked to make minor changes in the selected colours according to the emotional words provided. The colour generation framework is illustrated in Figure 2-16. The colour generation model was applied into a prototyped video editing system, which allows users to modify the target video using the video they had with the related affective words.

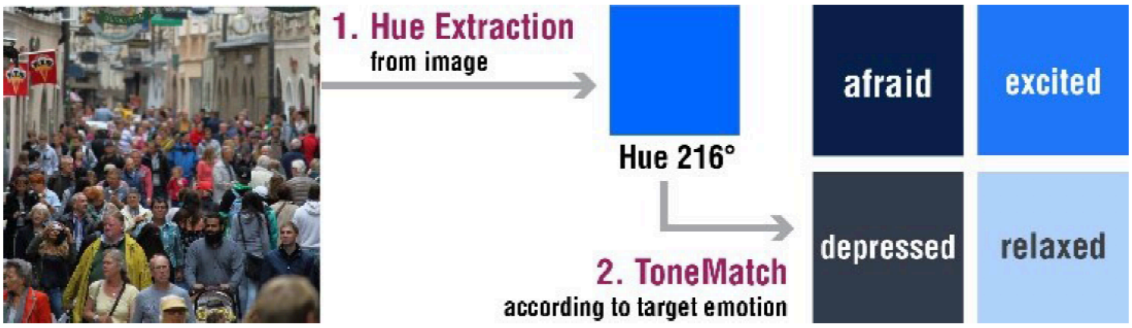


Figure 2-16 Framework of colour generation and optimization (Kim & Suk, 2016).

Cultural differences in the relationship between words and colours is of interest to some researchers. In one study cultural differences were explored using both UK and Chinese participants who each selected three colours for of words (Chen *et al.*, 2020). Furthermore, colour semantic extraction can be adopted into the colourization process. For example, using the context related colour palette to optimize the website interfaces. More related literature will be introduced in section 2.3.5.

2.3.3 Perception and Saliency Extraction

Colour selection in design and art is usually a people-oriented activity. In most design processes, colour selection is a manual and subjective process. Therefore, it is essential to be aware of how humans manipulate and select colours before developing or assessing automatic colour tools for design. However, there is little research about how designers select colours (Sandnes & Zhao, 2015). Kim and Suk (2017) carried out research to study how designers perceive images and colours during their colour design process. In their research, designers were asked to choose one colour which is harmonious with the image and the word presented. It was found that the colour-generation workflow is relatively similar among designers. Designers typically identify a representative colour from the image and then consider the visual effect of the selected colour and image combination. Two distinctive concepts were identified by Kim and Suk; colour-dominance and colour-saliency (see Figure 2-17). In summary, colours selected by colour-dominance represented the majority hue of the images; colours selected by colour-saliency were the most distinctive and salient colours in the images. However, note that participants were only asked to select one colour for each image whereas multiple colours would commonly be selected and used in real design processes.

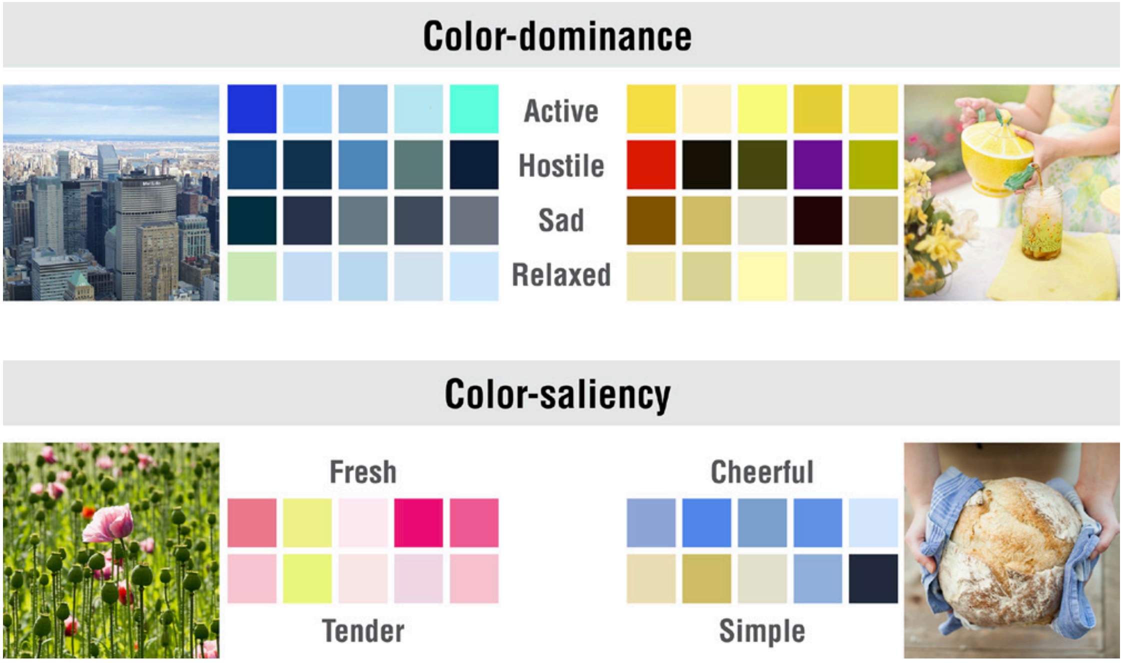
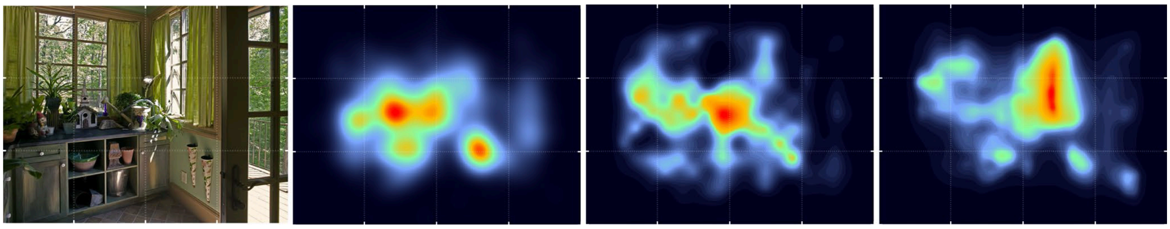


Figure 2-17 Images and selected colours in consideration of different style keywords (Kim & Suk, 2017).

Colour extraction is based on visual attention and images are traditionally used as sources and as inspiration to form a colour palette. Therefore, learning where designers focus on an image or a scene is important. Eye tracking is a viable method to explore eye movements when observers look at an image or scene. Generally, eye tracking techniques are realised through eye tracker which records human fixation and saccade data. Surprisingly, the history of eye tracking dates back to the late 1800s. Eye-tracking techniques have now been developed and applied in different disciplines (Holmqvist & Andersson, 2017). However, eye tracking is interactive and expensive and can be difficult to apply in some cases. Hence, Judd *et al.* (2009) have built a saliency model to predict where people look in a scene without using an eye tracker. They used a large amount of eye-tracking data (from 1003 images) which was collected and used to train their saliency model.

Saliency is one of the image segmentation methods. A saliency map is defined by Niebur (2007) as "a topographically arranged map that represents visual saliency of a corresponding visual scene." Visual saliency (or salience) is described as the subjective visual quality that makes some visual stimulus to appear conspicuous to humans (Itti, 2007). The process of detecting the salient region to model the mechanism of human attention is colour saliency detection (Maity, 2015; Zeng *et al.*, 2017). In recent years, more attention has focused on the relationship between colour saliency and colour extraction from images. A colour saliency model was proposed by Tian *et al.* (2010) to detect salient objects in natural scenes. Jahanian *et al.* (2015) demonstrated the method to extract colour palettes based on the saliency map of images. The method is independent of the saliency map kinds, but the results vary from different kinds of saliency maps. Liu *et al.* (2018, p.554) argued that “colour saliency, colour diversity and images coverage” are essentials to build a colour theme. A novel colour-extraction method was introduced by using saliency analysis for fabric images to obtain the visual attention area. The dominant colours were subsequently selected from both background and foreground colours.

One study found that attention is guided by meaning in real-world scenes, which means that people tend to look at objects that have more meaning that those are salient just in terms of low-level visual features such as contrast. A meaning-based map (see Figure 2-18) was proposed and compared with the attention map (from eye-tracking data) and the saliency map. The results showed that both meanings and saliency took up the distribution of attention; however, only meaning was important when controlling for the relationship between saliency and meaning (Henderson & Hayes, 2017). This suggests that colour saliency should not be the only element to be considered during the colour extraction; the meanings of the scenes should also be taken into account.



Scene fixations a | Attention map b | Meaning map c | Saliency map d

Figure 2-18 Attention (b), meaning (c) and saliency (c) maps for an example scene (a) (Henderson & Hayes, 2017).

2.3.4 Machine Learning Extraction

There have been numerous studies to develop methods to generate colour palettes automatically and in some cases machine learning has been used. Autonomous colour extraction by machine learning is generally based on optimizing different methods. O'Donovan *et al.* (2011) developed an algorithm to predict the aesthetic rating of a colour theme using a first-order linear LASSO regression (Friedman *et al*., 2010) trained online theme datasets (Adobe Kuler and COLOURLover). Lin and Hanrahan (2013) introduced a new way by using LASSO regression model based on the colour palettes human extracted from images. The human-extracted palettes were selected from the 40 colours that running K-means algorithm on the images. The colour extraction interface is illustrated in Figure 2-19. A model was trained for characterizing the colour palettes from human. The innovative part of this research was that they evaluated a new data-driven method similar to O'Donovan *et al.* (2011) but focused more on the colour palettes with the context where the palettes originated. They considered saliency as one of the most valuable elements in the model since "popped out of the image", "caught their eye" or "the most salient colours" are the reasons for participants deciding colours.

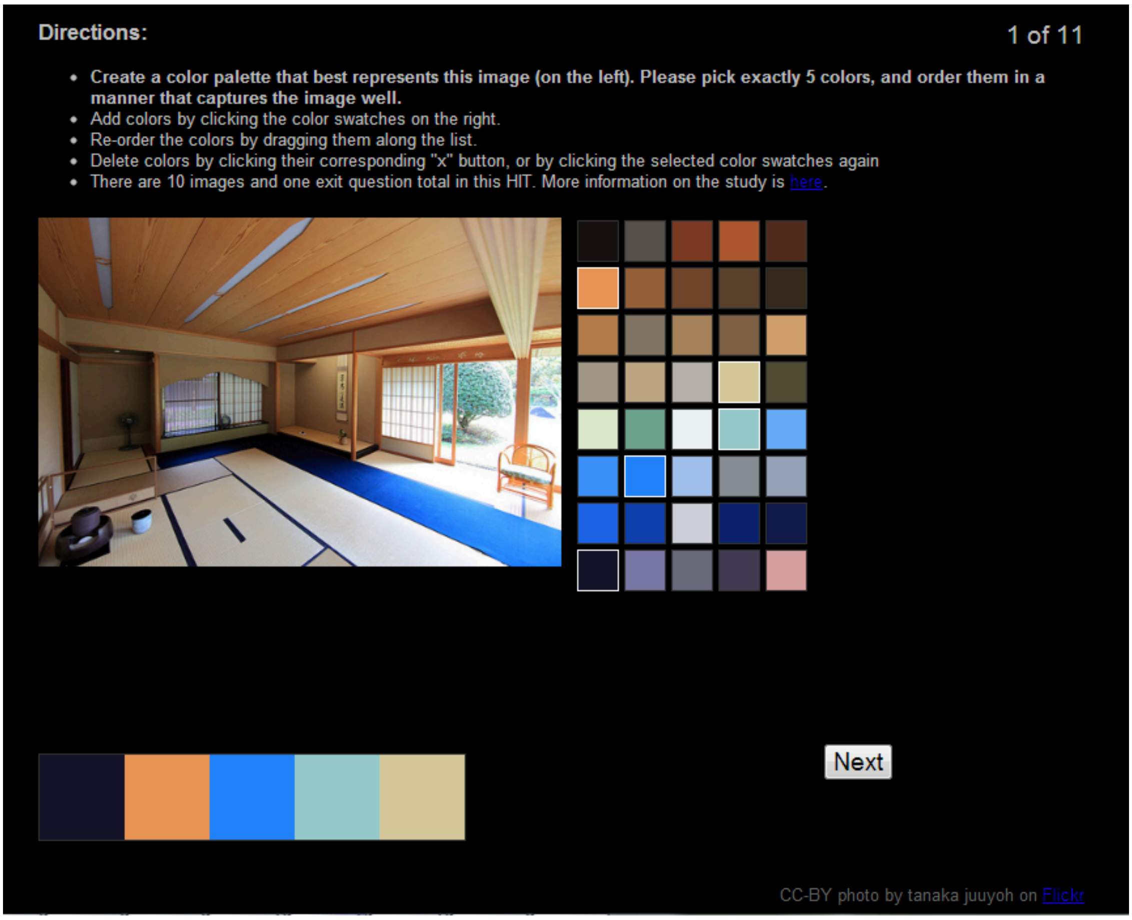


Figure 2-19 Illustration of the interface for human theme extraction (Lin & Hanrahan, 2013).

Based on their dataset, Feng *et al.* (2018) developed a colour-extraction model with a rating image from the colour network. The colour network was built by the pixels selected from the super pixels of image segmentation. In brief, the model is built by three steps, saliency detection and super segmentation, scoring colour themes and training to lean the rating system. K-means clustering is one of the common unsupervised clustering machine learning methods. K-means is widely used of the data-driven models in colour extraction field. Similar to Lin and Hanrahan's work (2013), Weingerl *et al.* (2020) built the human-extracted colour palettes dataset from 25 colours which derived from running K-means algorithm for the images. A novel model was then learned based on this dataset using LASSO regression. K-means is efficient as a fundamental method of data-driven colour extraction, but there are some downsides. Even though both Weingerl *et* *al.* (2020) and Lin and Hanrahan's work (2013) based on the human-extracted colour dataset, the datasets were selected from the results of K-means algorithm.

The data-driven model of colour extraction can not only analyse a single image but also a series of images. Cao *et al.* (2017) described a novel technique called "probabilistic colour palettes" which can analyse a set of artworks from one artist to provide the representative colour palette and the probability distributions of the colour palette (see Figure 2-20).

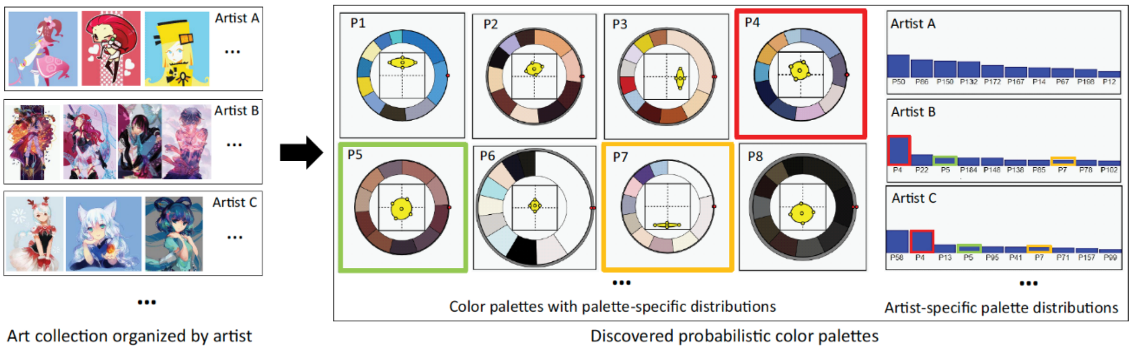


Figure 2-20 Illustration example of colour palettes from a set of art works (Cao *et al.*, 2017).

When it comes to colour semantics for colour palettes, model learning also can be valuable. Liu and Luo (2016) conducted a novel model to extract colour themes with Hierarchical emotions. They analyse the emotion value of each pixel using Ou *et al.* 's (2004) model with 8 representative emotions, warm, cool, heavy, light, soft, hard, passive and active. K-means algorithm was used later to obtain the emotional colour themes. The data-driven approach was subsequently applied to optimise the model. The examples of some emotional colour theme results from different colour emotional spaces are illustrated in Figure 2-21. Learning-based method was used by Jahanian *et al.* (2017) to explore the association between colours and linguistic concepts from designers. Users are able to apply the trained model to link the words to relevant colour palettes, images and design examples. It is a quantified approach to define colour-word topics. Kovacs *et al.* (2019) proposed a learned model of "Context-Aware Search" which produces colour suggestions and the rank of the relevant images by inputting context to the model. This process could increase efficiency of the initial design stages for designers especially the novices. In general, the learning-based approaches of colour semantics provide a more convenient and efficient way for designers to match their linguistic concepts to colour information.

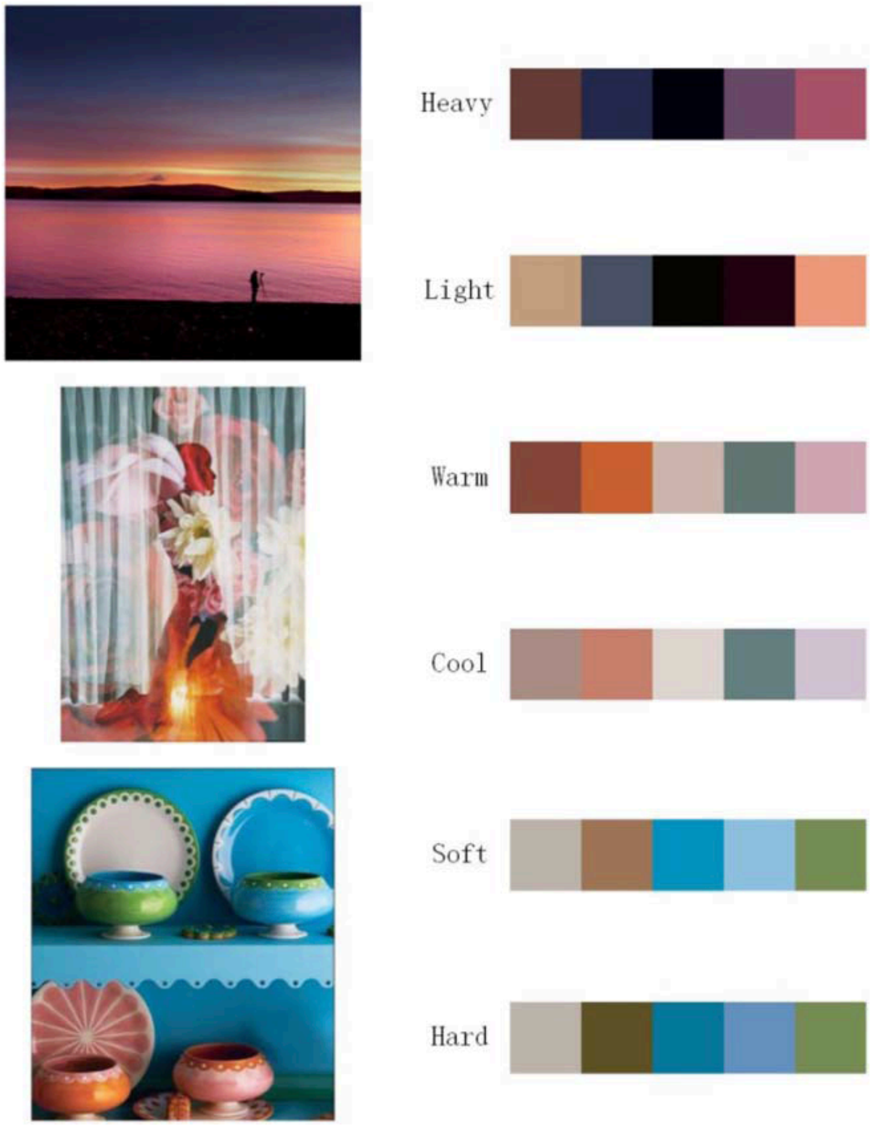


Figure 2-21 Illustration of the emotional colour extraction results by the model (Liu & Luo, 2016).

2.3.5 Colour transfer

The sensation and impression of colour can be influenced by the surrounding colours as well as the overall environment. It means other factors should be considered with regard to colour, such as integral harmony and compatibility. As illustrated in Figure 2-22, there some research has shown that colour is the most important factor need to be modified among different visual elements, when the integration of the landscape photographs needs to be improved (García *et al.*, 2003). Furthermore, the colours in an image or a design such as a magazine cover, website page or packaging usually need to be adjusted for harmony to increase the visual aesthetics. Even though harmony within an image can be subjective to some extent (Baveye *et al.*, 2013), the objective process of colour editing or recolouring is worth investigating. Therefore, colour transformation is essential. There is a large volume of published studies describing colourisation, colour transformation or colour enhancement from colour palettes, images or semantics.

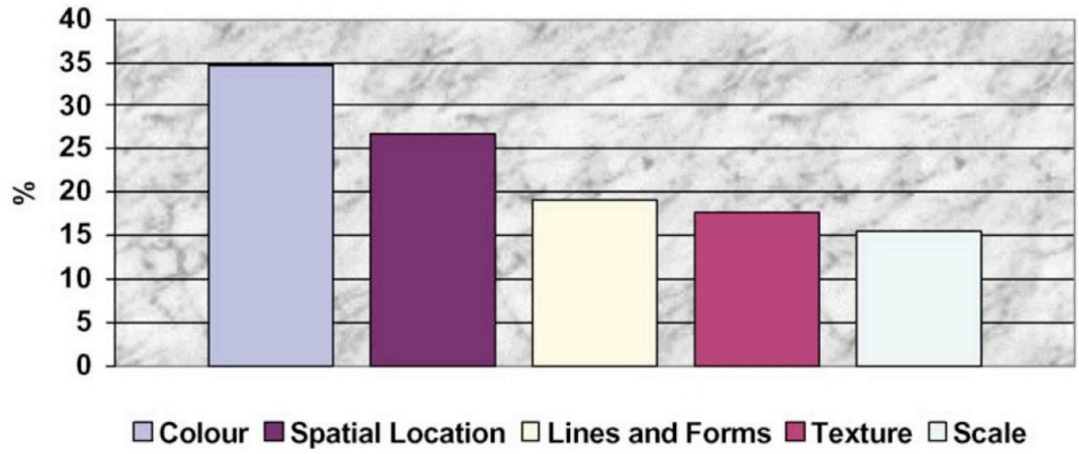


Figure 2-22 Average percentage of occasions in which the visual element was identified as requiring modification (Garcıá *et al.*, 2003).

Colourisation is defined as the process to transfer colour to the greyscale images or movie. It is usually expensive and time-consuming. Segmentation is often a starting point for colourisation and finding the right region boundaries for complex can be challenging (Luan *et al.*, 2007; Levin *et al.*, 2004). Levin *et al.* (2004) introduced a novel approach for colourisation without manual segmentation. The monochrome image can be colourised by scribbling the region with the corresponding colours rather than manually tracing out the detailed boundaries (see Figure 2-23).

Figure 2-23 Illustration of the grayscale images marked with the colour scribbles by the user (left), colourised image from the algorithm (middle), the original colour image for reference (right) (Levin *et al.*, 2004).

To reduce the stroke numbers in the complicated textured images, Luan *et al.* (2007) developed a new method for colourisation for natural images. Similar to Levin *et al.* (2004)'s work, scribbling was used on the very first step but only group regions who shared similar colours need to be scribbled. The subsequent step is colour mapping, in which few pixels with significant luminance differences were chosen by users and transfer colours to them. More strokes can be added to the images if users are not satisfied with the results. This process is shown in Figure 2-24.

Figure 2-24 Illustration of the colourisation process, scribbling strokes (left), then colour mapping (middle), final colourisation result (right)

Other work makes use of colour palettes as intuitive references for colour transformation, enhancement or image colour harmonisation. In general, this process transfers the colours of the images to more visually aesthetic, harmonised or emotionally related colours using various approaches in different fields. Chang *et al.* (2015) designed a simple and efficient recolouring system for novice users. The system involves three components: colour palette extraction based on K-means algorithm, modified palettes via users, the colour transfer algorithm. Some recolouring results are shown in Figure 2-25. The system could be widely used in video recolouring, Duotone reproduction, editing image collections and stroke-based interface.

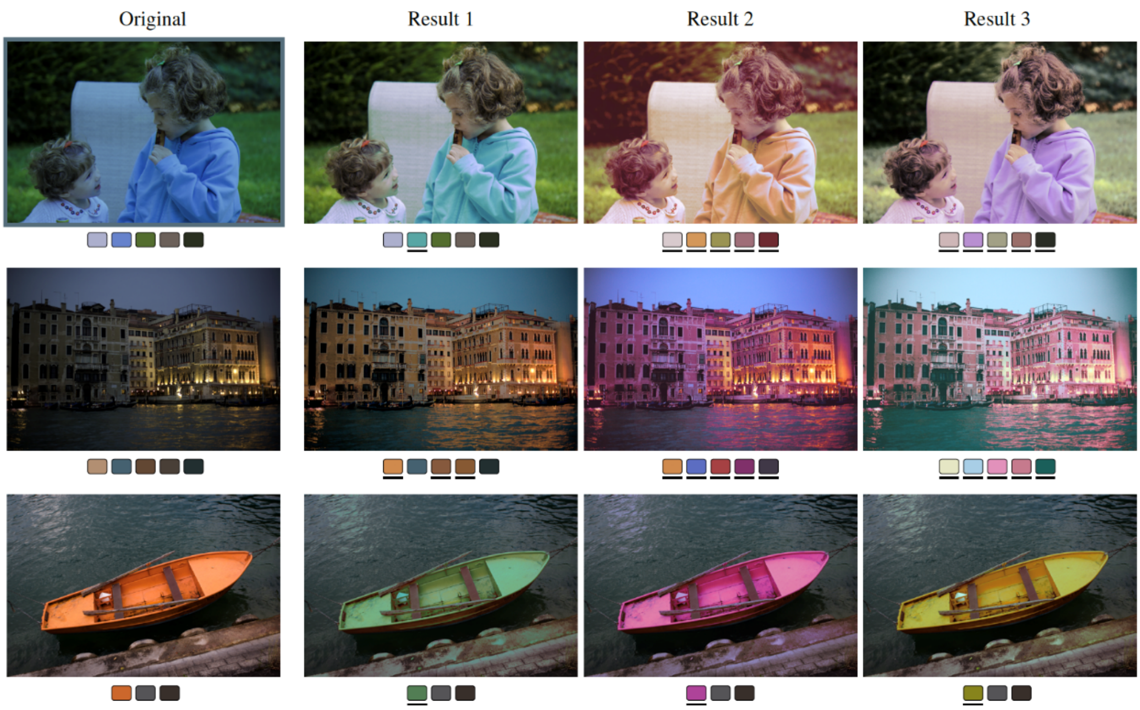


Figure 2-25 Recolouring examples (Chang *et al.*, 2015)

Kim & Suk (2018) developed an image colour adjustment method that used one target colour for harmony in visual design. The Geometric method was used for Wang *et al.* (2019)'s work in palette-based recolouring. Some studies make use of colour-semantic based colour palettes as reference for colour transformation (Hung *et al.*, 2018; Wu *et al.*, 2018).

Web design is a common field for colour transformation since colour is one of the most significant ingredients in a website design for both designing and accessing.

Several works were explored the automatic web page recolouring using different methods including data-driven method (Volkova *et al.*, 2016; Wu & Han, 2018; You *et al.*, 2019). Data-driven methods are popular in colour transfer. However, the learning portion of the recolouring procedure often in the palette extraction part since the referenced colour palettes are important for the whole procedure (Kita & Miyata, 2016; Zheng *et al.*, 2012; Wang *et al.*, 2010; Liu & Luo, 2016).

In summary, colour transformation is a popular topic and much more information has become available on it. However, there are still many problems that demand further research. One of the most important features for colouring is efficiency since the majority of users for method are novices and non-experts or designers for the initial stage of the design.

2.4 Conclusion

The fundamental knowledge of colour (section 2.1), the relationship between design and art (section 2.2) and the related literature (section 2.3) were reviewed in this chapter. Some conclusions have emerged from it:

- Natural images and scenes are one of the most important inspirations for artists and designers since the natural colour combinations are considered as one of the most harmonious colour assemblies.

- Colour extraction is a large research topic and there has been an increasing amount of literature on this topic.

- There have been many approaches related to colour extraction, but there remain issues which still demand attention.

Based on the literature reviewed in this chapter, the main research questions are described in section 2.5.

2.5 Research Questions and Methodological Approach

As reviewed in the section 2.2, colour is closely related to art and design. Landscape is a common inspiration in the process of applying colours to design. For instance, as shown in Figure 2-26, the colour palettes have been manually extracted from different kinds of scenes from one distinctive landscape by an architect (Waygood, 2017). Based on the Natural Colour System (NCS) and subjective judgments of the designer, the colour palettes were classified manually into different tonalities and categories (Figure 2-27). The subjectively selected colour palette can then be used, for example, in the design for a local primary school by drawing from detailed assessment of local colour (Figure 2-28). The project provides an opportunity to reinforce local distinctiveness and develop colour harmony of the target project area.

However, as reviewed in section 2.2.1, NCS has some limitations especially related to natural colours. Besides, the Waygood project (2017) is concerned with abundant design experience. Therefore, in this research, the motivation is to simplify and enhance the work of designers. Based on previous work reviewed in section 2.3, a lot of methods are related to colour extraction. In this research, the aim is to develop the methods to generate colour palettes from landscape images, which simplifies the colour-extraction work of designers.

Figure 2-26 Various colour palettes manually extracted from different kinds of landscape scenes (Waygood, 2017).

Figure 2-27 Different Colour palettes suggested by the designer using NCS (Waygood, 2017).

Figure 2-28 Buildings for Colwall Primary School drawn from detailed manual extracted colour palette from local landscape (Waygood, 2017).

The aim of this research is to explore automatic methods for generating colour palettes from images (Section 1.2). The literature has revealed considerable interest in automatic palette extraction for various applications in science and design. However, this research is grounded in the study of landscape and is inspired by the design work of, for example, Waygood (Figure 2.28). Two potential applications of the work can be identified. Firstly, the findings from this thesis could be used to generate a tool that could assist inexperienced designers (or even non-designers) to generate appropriate selections of colour palettes from images. The proliferation of digital tools such as Adobe Kuler strongly suggest that there is some need (or, at least, appetite) for such tools. Secondly, although experienced designers can accurately generate colour palettes from images given the time, even they might struggle to perform this task well in a future data-driven world. Even today, for example, approximately 100 million images are uploaded to the app Instagram each day. In 2012 it was estimated that 3.5 trillion photographs had been taken since photography was introduced and that 140 billion images had been uploaded to Facebook. Increasingly, these images are being analysed to extract insights into, for example, consumer behaviour or consumer preferences. The work in this thesis is concerned with landscape images but the findings are likely to be transferrable to other domains. The automatic palette generation methods developed in this thesis will not replace today's designers; however, they might enable tasks to be accomplished in the near future that are simply too data intensive to be carried out by humans.

There is therefore no methodological conflict in using palettes generated by humans as ground-truth data against which to evaluate the algorithms and methods developed in this thesis. Chapter 3 of the thesis therefore collects a set of visual data. It is evident that in order to compare colour palettes generated by algorithms developed in this thesis to those visual colour palettes a quantitative method will be required that can predict the visual difference between pairs of palettes. Chapter 4 therefore develops and evaluates such a palette-difference metric and in order to do so collects further psychophysical data. It is clear therefore that the thesis takes an evidence- or data-based approach. At the heart of the thesis is a set of data that describes the colour palettes selected by humans. Psychophysical data is collected in Chapter 4 to shape the development of a palette-difference metric. Quantitative analysis is this used extensively throughout the thesis. Chapters 5 and 6 explore machine learning and eye tracking, respectively, as the basis for algorithms to generate colour palettes. Chapter 7 presents a holistic meta-analysis the work carried out in the thesis. A small amount of qualitative analysis is applied. For example, In Chapter 3 a questionnaire is used to better understand the process by which designers generate colour palettes from images and to explore insights into the role of colour palettes in their design processes.

In summary, the main research questions of the thesis are listed as follows:

- How do designers extract colour palettes from landscape images? Why do designers choose certain colours from the landscape images? Are there any differences or similarities between their colour choices?

- How can we predict the visual similarity or difference between two colour palettes?

- What effective and new methods can be developed for colour extraction?

- What are the differences between different colour-extraction methods? And how do the different methods perform?

Chapter 3. Colour Palette Extraction from Designers

3.1 Introduction

In this chapter, designer-extracted colour palettes were collected as the ground-truth data for this study. An experiment was carried out with 30 designers to generate their colour selections from landscape images. Participants were asked to select five key colours from each image. Some questionnaires were also given to the participants before and after the experiment to help to understand how designers think about and work with colour palettes. The colour palettes selected from 30 participants for each of 30 images were then analysed and reduced to a single 5-colour palette that represents the visual selections for each image. This is done to obtain the ground truth data (*Visual Data*) and will be used to compare the colour palettes produced by cluster analysis in Chapter 5 and eye tracking in Chapter 6.

3.2 Experimental

3.2.1 Stimuli

Landscape photographs were selected as stimuli in this experiment. In total, 30 high-quality landscape photographs were manually selected and downloaded from a copyleft website called Pixabay (2010) website. All images were selected manually but various colour tones and scenes were included intentionally in order to obtain a diversified dataset for use in the following experiment. The images consisted of two different categories: built environment and natural landscape (see Figure 3-1 and Figure 3-2). All photographs were converted and cropped into a fixed size (2560×1600) to simplify subsequent analysis.

Figure 3-1 The 15 built environment photographs.

Figure 3-2 The 15 natural landscape photographs.

3.2.2 Participants

A total of 30 subjects (28 females and 2 males) with normal colour vision according to the Ishihara test participated in the experiment. The average age is 24 years old (ranging from 20 to 35 with standard deviation of 3.8). The participants were from a mixed ethnicity. The study was approved by the University of Leeds Ethics Committee (see Appendix C). All the subjects were students (undergraduates and postgraduates) recruited from the School of

Design, University of Leeds. They were all from different design backgrounds, including textile design, fashion design, fashion marketing, art and design, colour design, product design, graphic design and interior design. Their working experience in design ranged from 0 to 5 years.

3.2.3 Experimental Procedure

The experiment was conducted individually in the psychophysical laboratory in the School of Design, University of Leeds. Figure 3-3 shows the experiment setup. The viewing distance was maintained at approximately 60 cm from the monitor to the eyes of participants. Participants were asked to sign the informed consent form prior to the experiment. An information sheet with the experimental aim was given to participants and the procedure and brief aim of the study were explained.

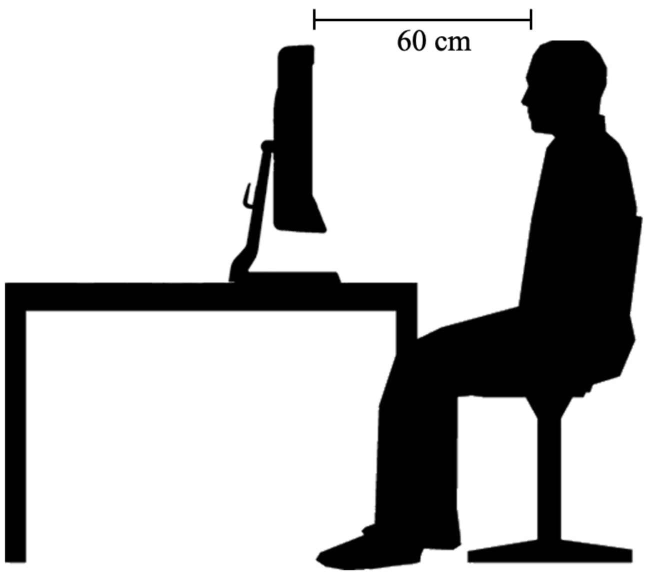


Figure 3-3 The experimental setup.

Participants were then asked to complete the first two questions of the questionnaire on the paper (see Figure 3-4). The experiment was conducted in a darkened room to avoid the distraction of ambient light. Each participant was asked to sit in the darkened environment for 5 minutes to adapt. The experiment was displayed on an LED computer monitor (HP DreamColor LP2480zx – a 24-

inch LCD Backlit Monitor). The whole experiment was designed into two phases and each phase took approximately 10 minutes to complete. Participants were compensated with £5 for their time after the experiment.

1. What is your major or background?

2. In your opinion, how many colours do you want to choose for one image?

Figure 3-4 The two questions for participants to answer prior to the experiment.

In the first phase, participants were asked to free view the 30 landscape photographs and their eye movements were monitored by the eye-tracking system. This phase is described in detail in Chapter six.

In the second phase, the 30 participants were each requested to select 5 key colours for each image which represent the image most and could possibly be used in their future design work. The images were displayed one at a time in a pseudorandom order, against a uniform grey (CIELAB L* = 50 approximately) background. An analysis of previous studies revealed that five is a common number for the size of colour palettes (O'Donovan *et al.*, 2011; Lin & Hanrahan, 2013).

In the experiment participants clicked on an area of the image to select a colour of one pixel using a mouse in a GUI that was written using the MATLAB programming environment. After clicking 5 areas to select desired colours, the colour palettes were shown at the right on the interface (Figure 3-5). No rules were imposed about the selection order because in real life colour selection people usually select colours freely from scratch. The interface allowed for participants to repeat this process or accept the colour palette by clicking the repeat or accept button under the image until they were satisfied with their selections. Each participant was instructed using two test images in a practice session to make sure they fully understood the interface before undertaking the experiment properly. The results of the RGB values for each colour selected by participants were automatically saved as the raw data. The data from the practice sessions were not recorded. In total, 150 colours (5 key colours × 30 participants) were collected for each image from the experiment and these were used as the raw visual colour palettes in this study. After the experiment, participants were asked to answer the rest of the questions in the questionnaire (see Figure 3-6).

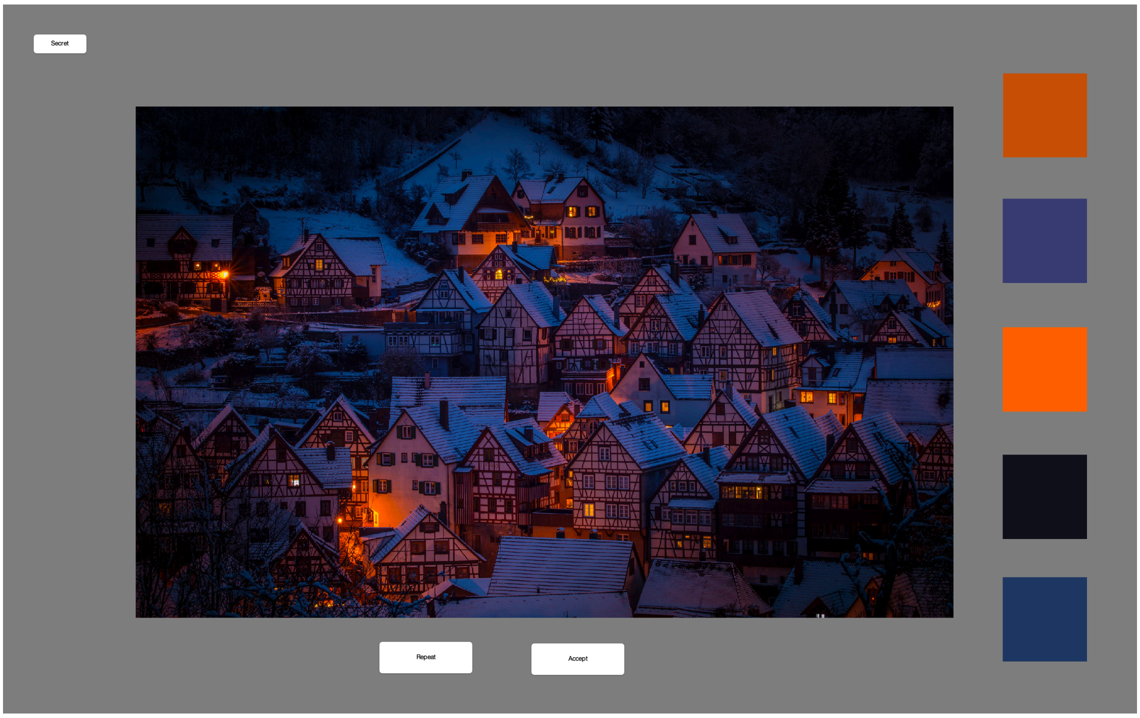


Figure 3-5 The interface for the colour selection experiment (the colours on the right-hand side appear when the participant clicks on the image using the mouse). Note that the participant can reject the choices and start again for that image if they are not happy with the selections.

3. How did you choose those colours? Are there any rules you followed or you just chose them by your first impression?

4. Have you heard of Adobe Kuler (Adobe Color CC)? Do you think that being able to extract a colour palette from an image could be helpful for your future design?

5. In your opinion, what is colour palette?

6. Generally, where do you get the colour inspirations for your design?

Figure 3-6 The rest of the questions for participants to answer following the experiment.

3.2.4 Colour Measurement

No colour management was used before the experiment. Rather, the actual colours selected by each participant were measured to obtain accurate data. The colours selected by participants were automatically recorded as RGB values. After the experiment, the 4500 colours (5 key colours $\times$ 30 participants $\times$ 30 images) were displayed on the computer screen (one at a time) and measured using the Konica Minolta CS-2000 spectroradiometer to obtain the spectral data (see Figure 3-7).

Figure 3-7 Colour measurement of using the Konica Minolta CS-2000.

The device and the screen were turned on and left to warm up for one hour before the measurement. All measurements were carried out in a darkened room to avoid the effects of ambient light. The spectral data were subsequently converted to CIELAB values using the screen's white point which was CIE x = 0.3116, y = 0.3184. The white point of the display was close to the blackbody locus (see Figure 3-8) with a correlated colour temperature of 6659 K. The colour measurements of each patch would be used for subsequent analysis to do CIELAB colour difference calculation.

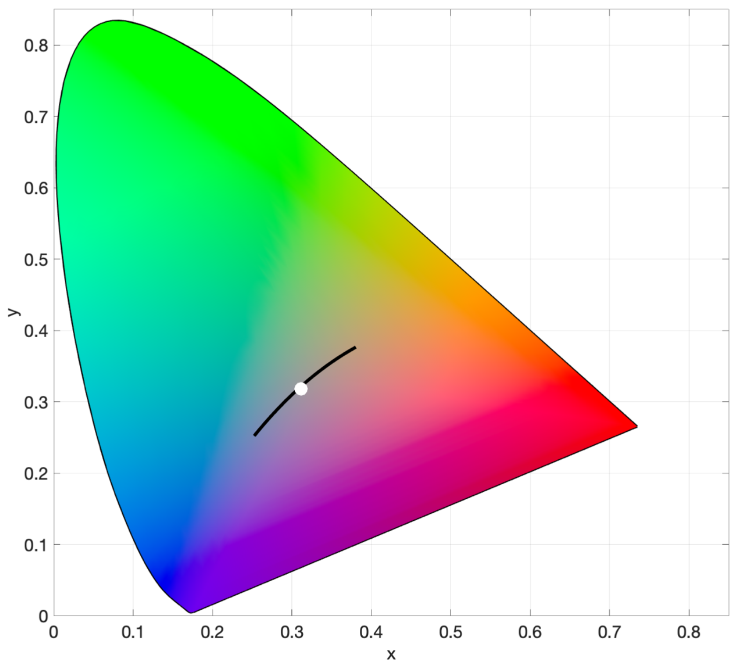


Figure 3-8 Chromaticity plot showing the white point of the display (x=0.3116, y=0.3184) and the Plankian locus between 4000K and 25000 K. The correlated colour temperature of the white point was 6659 K.

3.3 Results

3.3.1 Questionnaire Design

The results from the questionnaire are shown below:

- Question 1: What is your major or background?
  All 30 participants are from different design backgrounds and the details were described in section 3.2.2.

- Question 2: In your opinion, how many colours do you want to choose for one image?
  The answers ranged from 3 to 8, but 5 was the most common response (chosen by 70% of participants) and this is consistent with previously published estimates (O'Donovan *et al.*, 2011; Lin & Hanrahan, 2013).

- Question 3: How did you choose those colours? Are there any rules you followed or did you just choose them based on your first impression?
  The text responses were processed to show a word cloud (Figure 3-9) based on the frequency of word counts.

Figure 3-9 High frequency words of the results from how participants choose the colours.

- Question 4: Have you heard of Adobe Kuler (Adobe Color CC)? Do you think that being able to extract a colour palette from an image could be helpful for your future design?
  More than half subjects (56%) had heard of Adobe Kuler (an online colour palette generator) and some of the participants (13%) had used it for their design work. Almost all subjects (93%) thought that extracting colour palettes from images could be helpful whilst some subjects (10%) thought it may be helpful but that they would need some practice to use such a tool. A few subjects responded that they prefer their own instinct to choose colours. Representative responses are shown below:

“After try to use several times then I will decide to use. I would rely on myself to choose colours mainly and usually. Then I will compare the colours from the programme. It can be a supportive tool. It would help improve confidence and practice early career designers and person from different backgrounds (not design) (Female aged 35, product designer).”

“Yes, it would help designers to come up with new ideas. The colour scheme would benefit while developing new styles (Female aged 23, MA design student).”

“Not really sure, in terms of designing (especially choosing colours), I prefer to rely on my intuition (Female aged 33, interior architect).”

“Yes, you would be able to create a series of designed items that could be linked together (Female aged 20, art and design student).”

“Yes, I believe colour is one of the key components of a successful design and choosing a good colour palette can improve a piece significantly (Female aged 20, fashion design student with experience in painting and art and design).”

- Question 5: In your opinion, what is colour palette?
  There are different answers about the definitions of colour palette; in summary, a colour palette is regarded as a combination of harmonious colours that can represent the image to assist or inspire design work. Typical answers are shown below:

  “Colour palette can show the mood of images and concepts (Female aged 31, fashion designer).”

  “The most dominant or frequently used colours in an image or design (Female aged 20, fashion design student with experience in painting and art and design).”

“Something which shows a harmonious series of colours to assistant people to do design work (Female aged 23, MA design student).”

“It’s colours that go well together, and look good on a page (Female aged 20, fashion marketing student)”

“The summation of colours (Male aged 23, MA design student).”

“A selection of 5 colours which coordinate and complement each other (Female aged 21, fashion marketing student).”

- Question 6: Generally, where do you get the colour inspirations for your design?
  Participants obtain their inspirations from different sources including travel photos, related images, landscape images, personal preference and emotions, trends, feelings, design websites, books, previous design projects from other designers or artists, nature, flowers, daily lives, museums and galleries and cultures. 40% of participants mentioned about images or photographs as the colour inspiration for their design. 23% of participants search colour inspirations from nature or landscapes.

In summary, the results show that a colour palette is regarded by designers as an inspirational tool with harmonious colour combinations to help with design projects. It is an important component in the design process, which can be extracted from images, natures or other sources. Many designers already use automatic tools to generate colour palettes and think such automatic tools could be helpful in their design process, which is consistent with the aim of the study.

3.3.2 Psychophysical Experiment

Through the experiment, 150 colours (5 key colours × 30 participants) were collected for each image, which produced 4500 colour selections (30 images × 150 colours) in total. Figure 3-10 shows the original colour palettes selected by 30 participants for each image from the two types of landscape images (built environment landscape and natural landscape). For each colour palette, the colours in each row are those selected by 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).

Participants tended to first select the colours of the architectures or infrastructures in the built-environment images. For the natural landscape images, participants usually selected the main background colour first. However, there were no obvious differences between the colours selected from the two types of images.

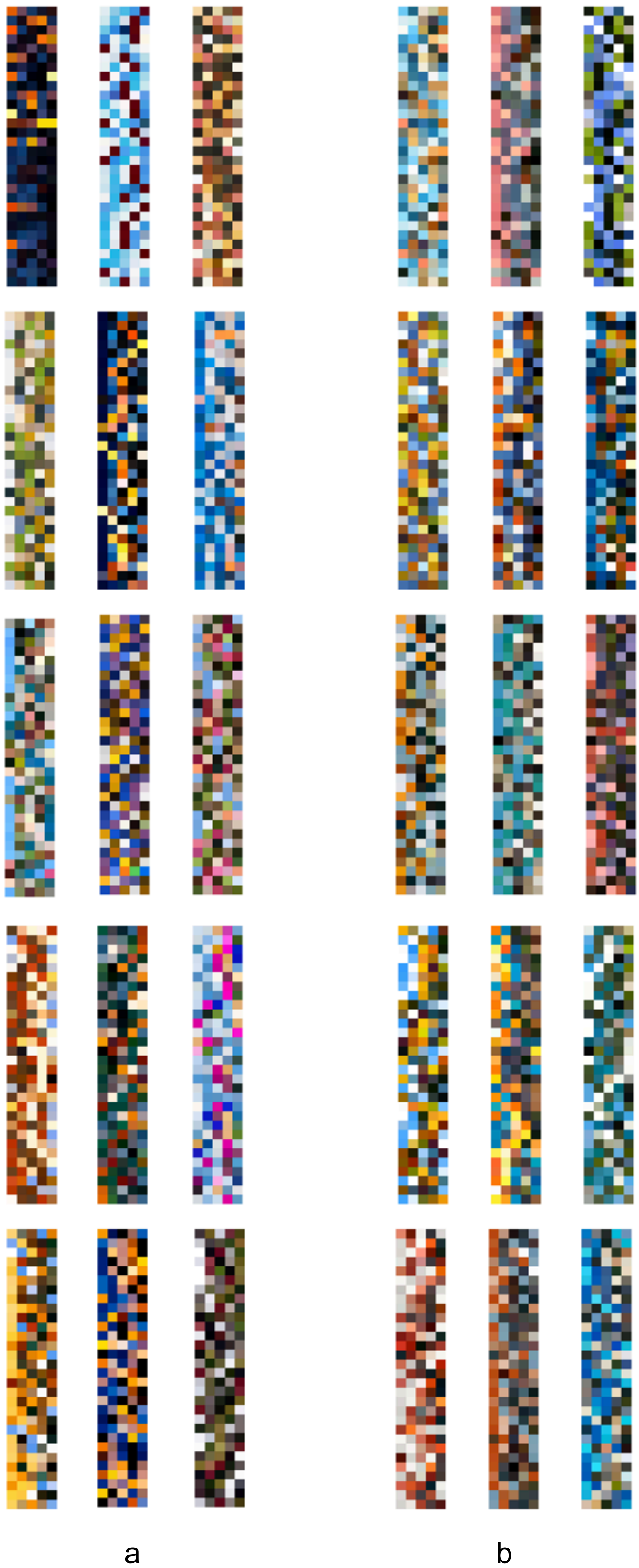


Figure 3-10 Raw colour palettes by designer extraction from 2 types of landscape photographs. (a) built environment palettes (b) natural landscape palettes

Order Modification Metric

Ideally, a single 5-colour palette would be required to represent 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 was therefore modified using the order modification metric. This amounts to changing the order of the colours in each row of the 30 x 5 *Designer* palette to minimise the CIELAB colour differences (using the converted CIELAB values from measured spectral data) between the colours in each column. The CIELAB equations are given in Equation 2.2, section 2.1.6 CIELAB. This process results in the *New Order* palette (see Figure 3-11 for example). The detailed process for order modification is according to the following steps:

1. Set the first row in the *Designer* palette as a reference, calculate the five colour differences between the colours in the first row and the corresponding colours in the second row. The mean of the 5 colour differences is reordered.

2. Then change the colour order of the second row in the *Designer* palette to get every possible colour permutation (5! = 120) of the second row. Step 1 is repeated between the first row (reference) and all 120 possible ordered second rows, resulting in 120 corresponding mean colour differences.

3. Choose the colour arrangement with the minimum mean colour-difference value from all 120 possible ordered second row as the new second row.

4. Step 2 and 3 are repeated successively from 3rd to 30th row to get all new ordered rows from 3 to 30. 29 minimum mean colour differences (calculated from the reference row to the other 29 rows) are recorded at this stage.

5. The sum of the 29 minimum mean colour-difference values is recorded and defined as SUM1.

6. Choose the 2nd row in the *Designer* palette as a reference, repeat step1 to 5 to get another sum of 29 mean colour-difference values. This is defined as SUM2.

7. Choose row 3 to 30 as a reference in sequence and then repeat step 1-5 to get the relative SUM3 to 30.

8. Compare all 30 SUMs to obtain the minimum SUM value. Select that modified order with the minimum SUM value as the *New Order* palette.

The point about changing the order is to allow the colours in each column to be as visually similar as possible (see Figure 3-12 for a better illustration). This allows the colours in one column to be averaged together (using the converted CIELAB values from measured spectral data) which produces the 5 x 1 palette labelled as *Mean New Order*. The median colour of each column in the *New Order* palette is recorded and the 5 median colours from each column are labelled as *Median New Order*. After getting the *Mean New Order* and *Median New Order* colour palettes from all 30 landscape images. The *Median New Order* is defined as the *Visual Data* since the *Mean New Order* palettes blur the colours from the images. The 5 x 1 *Visual Data* palette is representative of the visual selections and is used as the ground-truth data against which the palettes produced by cluster analysis (Chapter five) and eye-tracking system (Chapter six) will be compared. All 30 *Visual Data* palettes are illustrated in Figure 3-13.

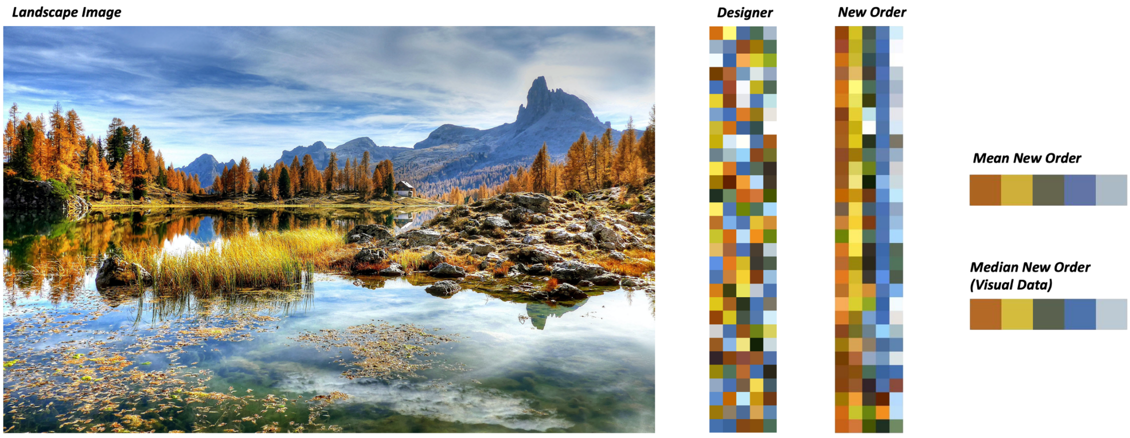


Figure 3-11 Example data representation for one natural landscape image in the experiment. The raw colour palettes obtained visually produced by participants are labelled as *Designer*. *New Order* palette is produced by modifying the colour order in the *Designer* palette. The data shows the average colour palette of New Order is labelled as Mean New Order and the Median New Order palette is defined as the *Visual Data* represent the participants.

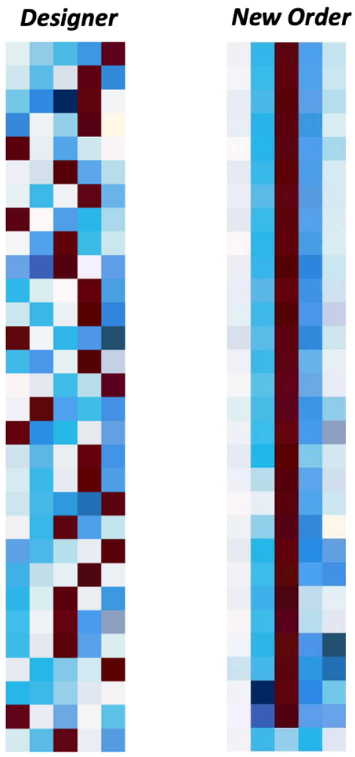
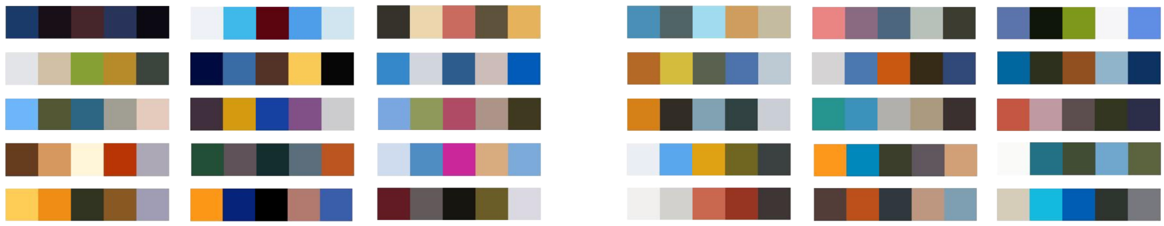


Figure 3-12 Example data representation of *Designer* palette and *New Order* palette from one image in the experiment.



a b

Figure 3-13 All *Visual Data* palettes from 30 landscape images using the order modification metric. (a) built-environment images (b) natural-landscape images

3.4 Summary

In this chapter, a psychophysical experiment and an associated questionnaire were conducted to collect designer-selected colour palettes as ground-truth data for this study. The questionnaire revealed that for most participants 5 colours were appropriate in a colour palette and this is consistent with previously published estimates (O'Donovan *et al.*, 2011; Lin & Hanrahan, 2013). The questionnaire also explored how participants selected colours to represent an image and the word cloud (see Figure 3-9) revealed that 'first impression' was the most common phrase used. This suggests that the process of colour selection is intuitive and not rule-based. The majority of participants were familiar with tools such as Adobe Kuler and some had used such tools in their design work. Most participants agreed that a tool that could automatically extract a colour palette from an image would be useful.

The main psychophysical experiment collected 5-colour palettes for each of 30 landscape images selected by 30 designers. The purpose of this experiment was to collect a set of ground-truth data that could be used to evaluate the accuracy of automatic palette creation methods that will be developed later in the thesis. These data may be valuable to other researchers in the future. It was noted that there was a high level of similarity between the palettes chosen by different participants for the same image. A novel re-ordering algorithm was developed that was shown to be able to reduce the 30 5-colour palettes from each image to a single 5-colour palette for each image that is representative of the participants' selections

Chapter 4. Predicting Visual Similarity between Colour Palettes

4.1 Introduction

A central objective in this study is to develop methods to automatically extract colour palettes from images and to compare these colour palettes to the visual data that was generated in Chapter 3. It is evident, therefore, that a method for predicting the visual similarity or visual difference between two colour palettes is needed so that the performance of any automatic method can be quantified. In this chapter, a psychophysical experiment using the semantic differential scale method was conducted to quantify the visual difference between pairs of colour palettes. Two algorithms were used using the psychophysical data, each based on one of six colour-difference formulae. The colour palette pairs for the experiment were selected from the human-extracted dataset built in Chapter 3. The performance of each algorithm using 6 different colour-difference equations was tested using r^2 and STRESS calculation. The best performance was obtained using the minimum colour-difference algorithm (MICDM) using the CIEDE2000 equation with a lightness weighting of 2.

Most of the work described in this chapter has been separately published (Yang *et al.*, 2020).

4.2 Experimental

4.2.1 Colour-palette Pair Selection

A total of 180 5-colour palettes (90 pairs) were obtained from Chapter 3, which was displayed with the five colours in a horizontal row. Figure 4-1 shows the example workflow for one image in Chapter 3. The number of total pairs is huge so pairs were selected and categorised into 4 groups to ensure that there was a range of colour differences from small to large.

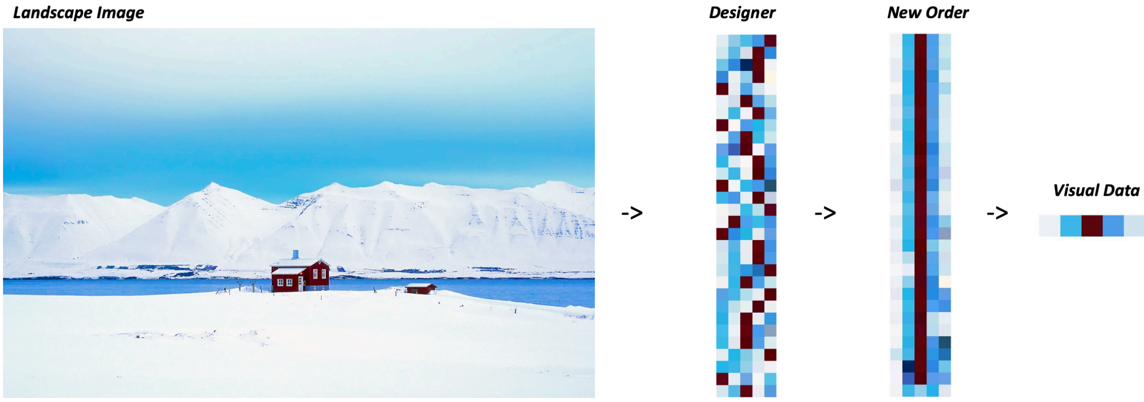


Figure 4-1 Example workflow of the order modification metric representation for one natural landscape image in the Chapter 3.

The details are listed as follows:

- The first group (containing 40 pairs) were randomly selected from all 30 *Visual Data* palettes (see Figure 3-12) of 30 landscape images (see Figure 4-2 for example).

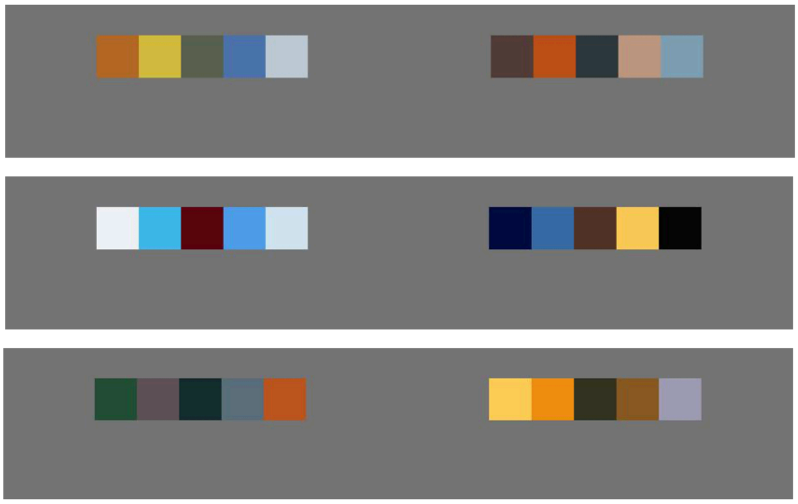


Figure 4-2 Three of the 40 pairs in the first group where the colour palettes were randomly selected from the *Visual Data* palettes.

- The second group (containing 30 pairs) were selected from the colour palettes in the *Designer* palette (see Figure 4-1). The two palettes in each pair are from the raw colour palettes chose by different designers from the same image which are the two different rows in the *Designer* palette of one image (see Figure 4-3 for example).

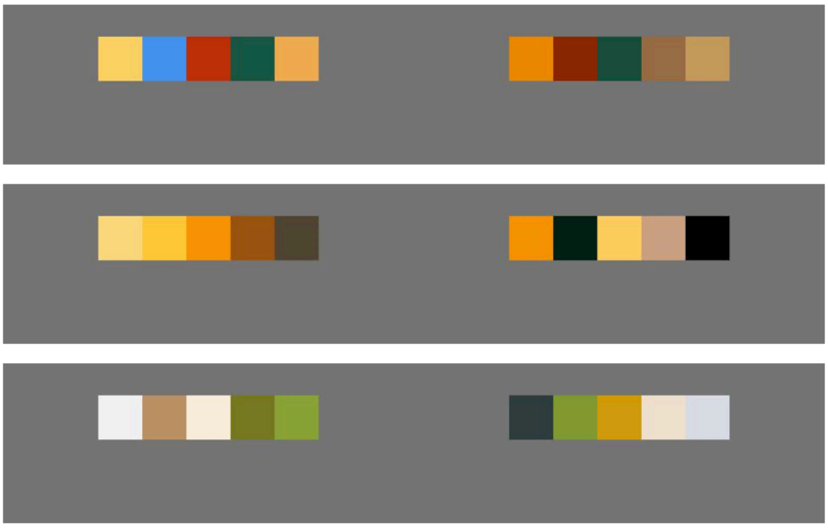


Figure 4-3 Three of the 40 pairs in the second group where the colour palettes were randomly selected from the *Designer* palettes.

- The third group (containing 10 pairs) were selected from *New Order* colour palettes of different images. The two palettes in each pair were two separate rows in one *New Order* palette (see Figure 4-4 for example).

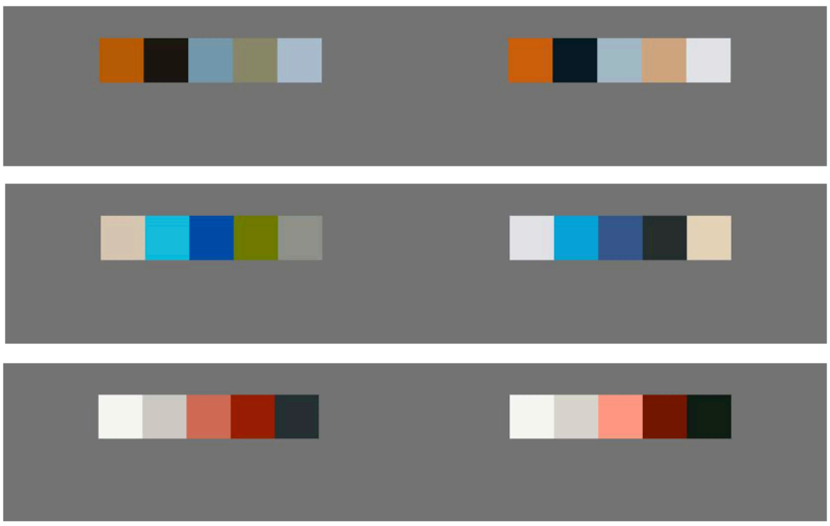


Figure 4-4 Three of the 10 pairs in the third group where the colour palettes were randomly selected from the *New Order* palettes.

- The fourth group (containing 8 pairs) were randomly selected from both the *Designer* and the *New Order* palette in different images. The first colour palette in one pair is from the raw designer-selected palette (*Designer*) in one image. The second palette in the same pair is the modified colour palette (*New Order*) of the first palette, which means the five colours in each palette of two pairs are exactly same, but the order of the colours is changed (see Figure 4-5 for example).

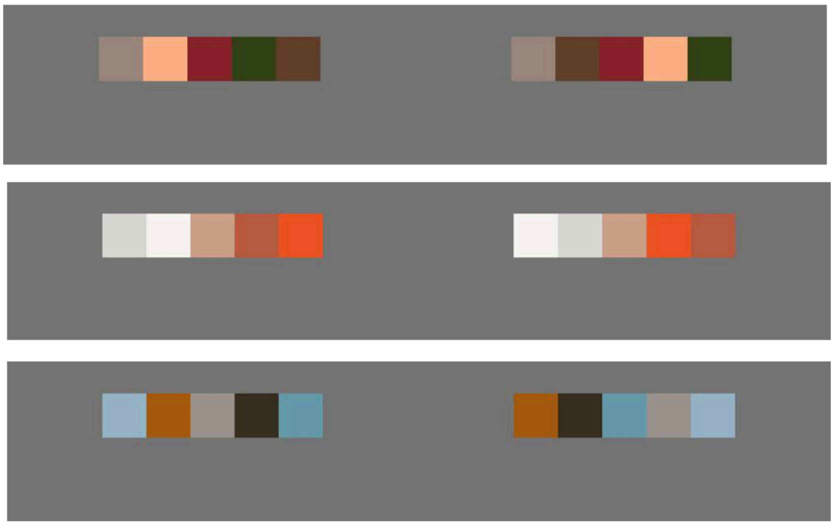


Figure 4-5 Three of the 8 pairs in the fourth group where the colour palettes were randomly selected from the *Designer* and the *New Order* palettes which contains the same 5 colours but different orders in each palette in one pair.

- the fifth group (containing 2 pairs) were randomly selected from the *New Order* palettes in different images. The two colour palettes in each pair are identical including the order and the five colours (see Figure 4-6 for example).

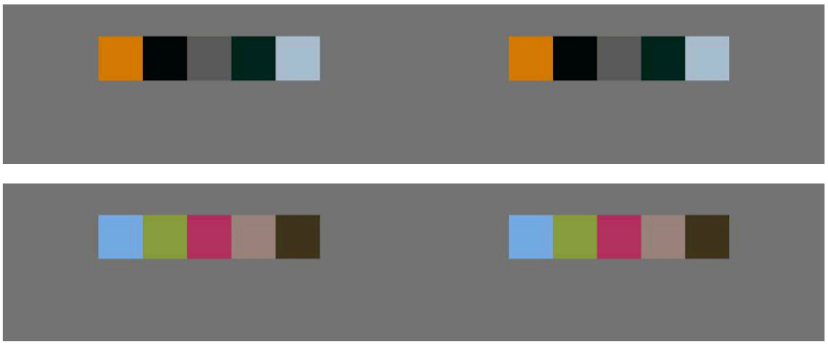


Figure 4-6 The 2 pairs in the fifth group where the colour palettes were randomly selected from the New Order palettes.

Five of the 90 pairs were selected randomly and were duplicated in the experiment to assess intra-observer variability. So that in total, each participant evaluated 95 pairs of palettes. All five groups were summarized in Table 4-1.

Table 4-1 The descriptions and pair numbers of all 5 colour-palette groups.

Group	Description	Number of Pairs
1	Selected from all 30 *Visual Data* palettes. The two palettes in each pair are from different images.	40
2	Selected from the colour palettes in the Designer palettes. The palettes in each pair are from the same images with the raw order.	30
3	Selected from *New Order* colour palettes. The palettes in each pair are from same image with modified order.	10
4	Selected from both the *Designer* and the *New Order* palette. The colours of the two palettes in each pair are identical but with different orders.	8
5	Selected from the *New Order* palettes. The palettes in each pair are identical (same colours and same orders).	2

4.2.2 Hypothesis

The hypothesis is that the visual differences decrease with the group sequences from large to small differences, in which the fifth group has no visual differences and the first group has the biggest visual differences in this study. It means that order or arrangement effects palette colour difference. However, the metrics being considered in this study do not consider the order of the colours in the palettes, the colour palettes in the fourth group contains the same colour with different order (see Figure 4-5); the effect of the order on the psychophysical data could be explored in future work.

4.2.3 Participants

A total of 20 participants (9 males and 11 females) with normal colour vision according to the Ishihara test volunteered to take part in the psychophysical experiment. Their age ranged from 25 to 56 years (mean = 30, standard deviation = 7.50). The participants were from a mixed ethnicity. 20 participants were from different backgrounds which can be divided into two groups: the design background (30%, which includes colour design, product design, textile design, and graphic design), and the non-design backgrounds (which includes business, law, colour science, textile science, mechanical engineering, chemistry, materials and tissue engineering). The purpose of the experiment was briefly explained to all participants when they were recruited.

4.2.4 Experimental Display

Colour-palette pairs were displayed on an LED computer monitor (HP DreamColor LP2480zx— a 24-in. LCD Backlit Monitor) and viewed, from a distance of about 1 m, against a uniform grey background colour (CIELAB L* = 50 approximately). The display of the pairs and the collection of psychophysical data were performed using a computer program written in MATLAB.

4.2.5 Experimental Procedure

The experiment was conducted (with one participant at a time) in the psychophysical lab in the School of Design, University of Leeds. Figure 4-7 shows the experimental setup. Participants were asked to sign the informed consent form prior to the experiment. An information sheet was given to participants to explain the procedure and brief aim of the study. Participants were then instructed orally using the following words:

"For each page you will be shown two colour palettes. We would like to know how different you think those two colour palettes are. Please give your opinion on a scale of numbers from -5 to 5 by clicking the corresponding number on the interface where -5 represent the largest colour difference and 5 represent the most similar (no colour difference) you could think of."

Figure 4-7 The experimental setup.

The experiment was conducted in a darkened room. Each participant was asked to sit in the dark environment for about 5 minutes to adapt to the environment. In the experiment, each participant was requested to view pairs of colour palettes and to indicate for each pair the degree of similarity or difference using a bipolar scale with 10 points (see Figure 4-8) with one extreme (− 5) representing most different and the other extreme (+5) representing most similar. At the beginning of the experiment, participants were shown all of the palettes being used in the experiment (Figure 4-9 shows one of three screens that the participants viewed) to give them an overall impression of the range. A short training session with 5 pages was conducted prior to the main experiment in order to teach the participants about the interface and make sure they fully understand the assessment method. The 95 pairs were presented in a different random order for each participant. There was no time limit for each participant to finish the experiment, but the experiment overall took about 20-30 minutes for each participant.

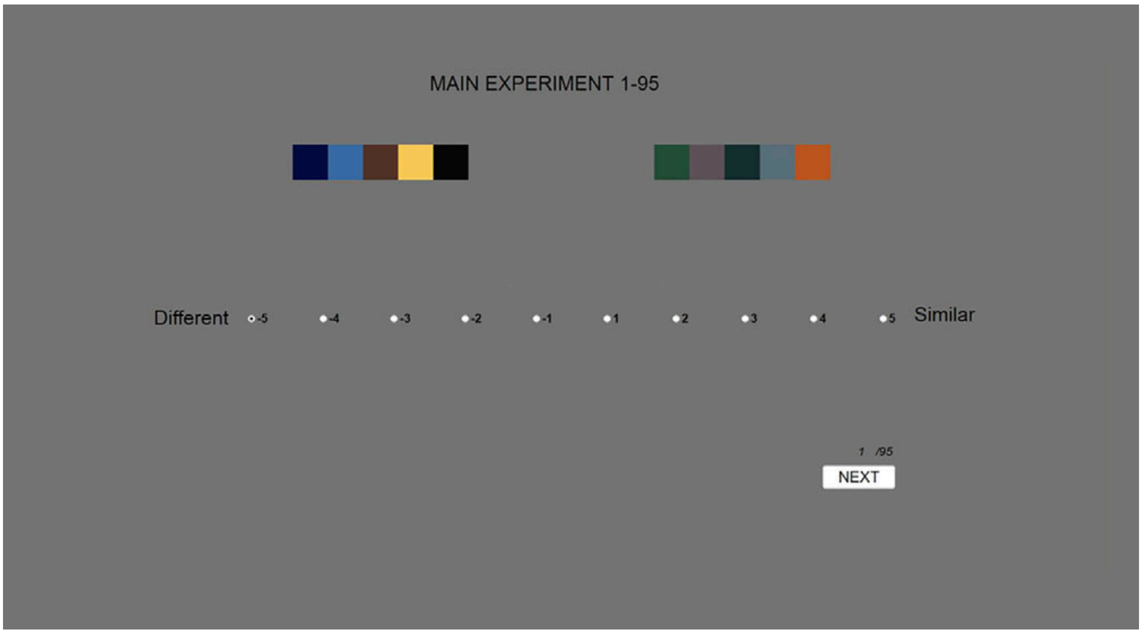


Figure 4-8 The interface for the experiment.

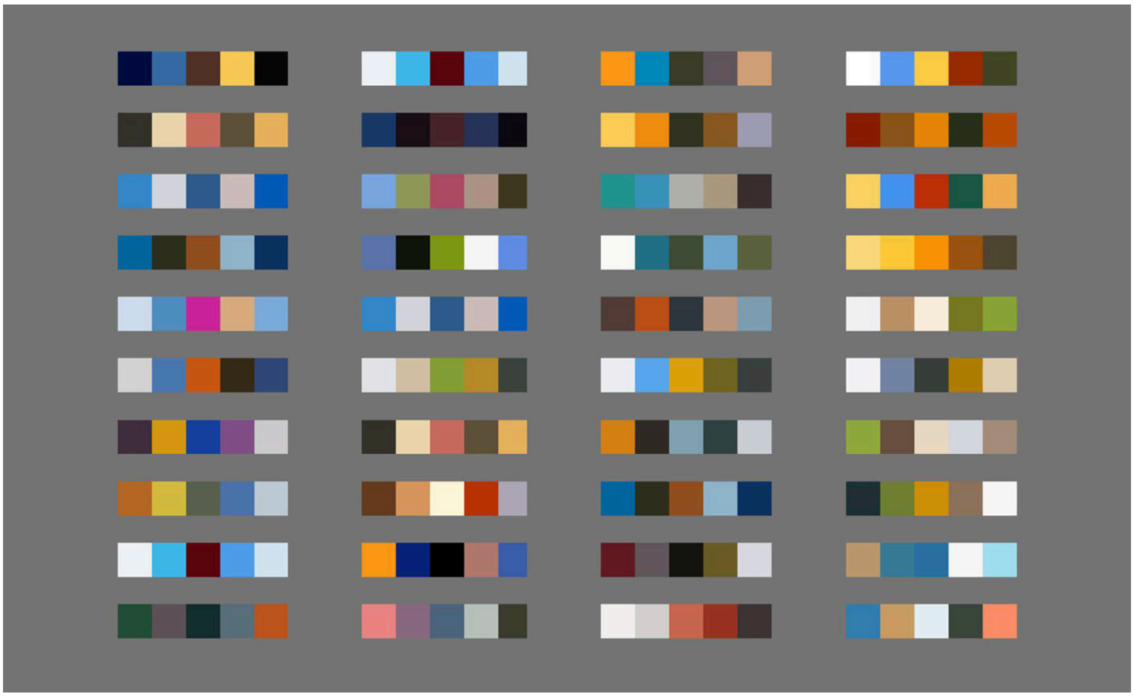


Figure 4-9 A representation of 40 of the 5-colour palettes used in the study.

The results were automatically saved as the data of visual colour difference (ΔV) by the software. The training data were not recorded. The results of the five duplicated pairs were excluded from the main results but were instead used to assess intra-participant repeatability. The ΔV values for each participant were later treated as interval data and were averaged to produce a ΔV value for each pair of palettes (Figure 4-9).

4.2.6 Colour Measurement

After the experiment, the colours of all 95 pairs of colour palettes (in total 95 × 10 = 950 colours) were measured on the screen using the Konica Minolta CS-2000 spectroradiometer. The device and the screen were turned on and left to warm up for one hour before the measurement. All measurements were carried out in a darkened room to avoid the effects of ambient light. Measuring the colours actually used on the screen in this instance is more accurate than using colour management to predict those colours (since what matters is not that the specific colours displayed on the screen but rather the exact colorimetric specifications of the colours that were displayed). The measured spectral data were converted to

CIELAB values using the display white point (CIE x = 0.3116, y = 0.3184). The CIELAB values were used for subsequent colour-difference calculations.

4.3 Results

4.3.1 Colour Difference Calculation

For each pair, the computed colour differences between two colour palettes were examined using two metrics that were also used in a previous study (Pan and Westland, 2018). First is the mean colour-difference model MECDM (referred to as ΔE_M) which is simply the average of the colour differences that result by comparing each patch in one palette with every other patch in the second palette. Since there are five colour patches in each palette, this is the average of 25 colour differences. Second is the minimum colour-difference model MICDM (referred to as ΔE_P; the subscript p is to indicate that it is a palette difference rather than a simple colour difference) which is more complex. The algorithm for calculating ΔE_P is according to the following five steps:

1. For each colour in one palette, the five colour differences between this colour and each of the colours in the second palette are calculated. The minimum of these colour differences is recorded.
2. Step 1 is repeated for all five colours in the first palette, for each finding, their closest corresponding colours in the second palette, resulting in 25 colour differences.
3. The 25 minimum colour-difference values are averaged and the mean value symbolised as m_1.
4. Step 1 to 3 are repeated, but this time for each of the colours in the second palette. In other words, for each of these colours the closest corresponding colour in the first palette is found. The mean value of these 25 colour differences is symbolised as m_2.
5. The values of m_1 and m_2 are averaged to obtain the visual colour difference ΔE_P between the two palettes.

Both ΔE_M and ΔE_P can be implemented using various colour-difference formulae and in this study the following formulae were used: CIELAB, CMC(2:1), CMC(1:1), CIE94, CIEDE2000(1:1:1) and CIEDE2000(2:1:1). The details are described in section 4.3.3.

4.3.2 Rating Score Results

Figure 4-10 shows the distribution of mean rating scores for the 90 pairs of palettes. The mean ratings covered almost the entire range (from -4.55 to 4.88).

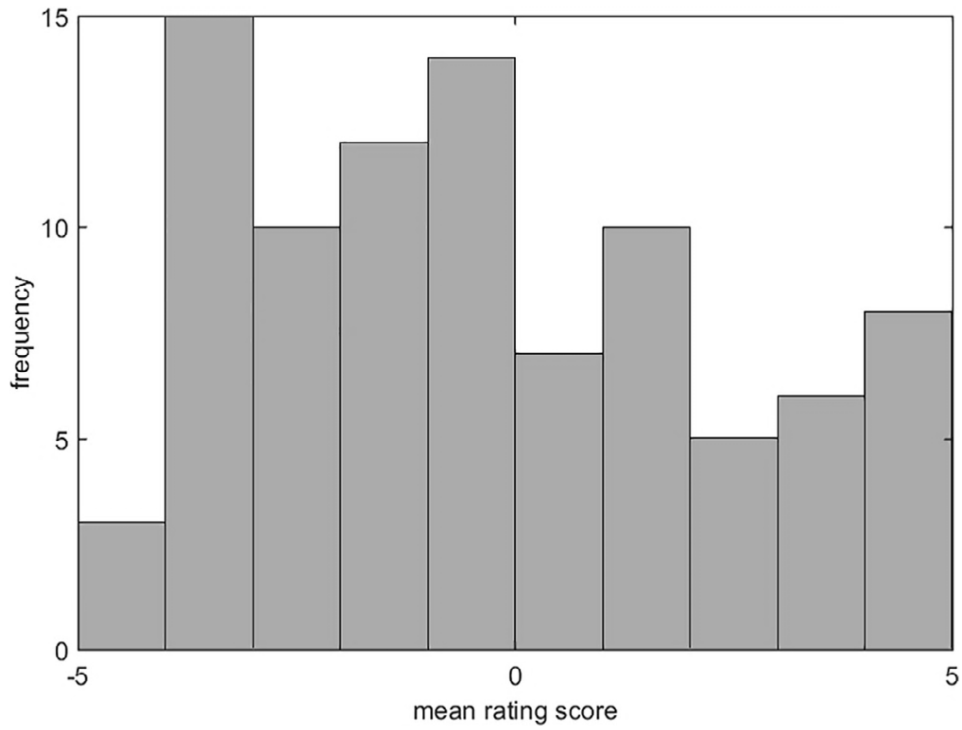


Figure 4-10 Frequency distribution of mean rating scores for the 90 pairs of palettes. Recall that similarity increases with the rating score.

The mean rating scores for the 5 groups as described in the section 4.2.1 are listed Table 4-2. The mean rating score increases as the group number become bigger. In other words, colour order or arrangement in the colour palettes could affect the visual difference, which confirms the hypothesis in section 4.2.2. Figures 4-11 and Figure 4-12 each show the visual ratings of 5 pairs in group 1 and 2, respectively. For example, in Figure 4-11, the pairs have the biggest colour difference in all 5 groups, whereas in Figure 4-12 the pairs have much smaller colour difference.

Table 4-2 The mean rating scores for the 5 groups of colour-palette pairs.

Group	Mean rating score	Number of pairs
1	-2.36	40
2	0.39	30
3	1.00	10
4	4.08	8
5	4.70	2

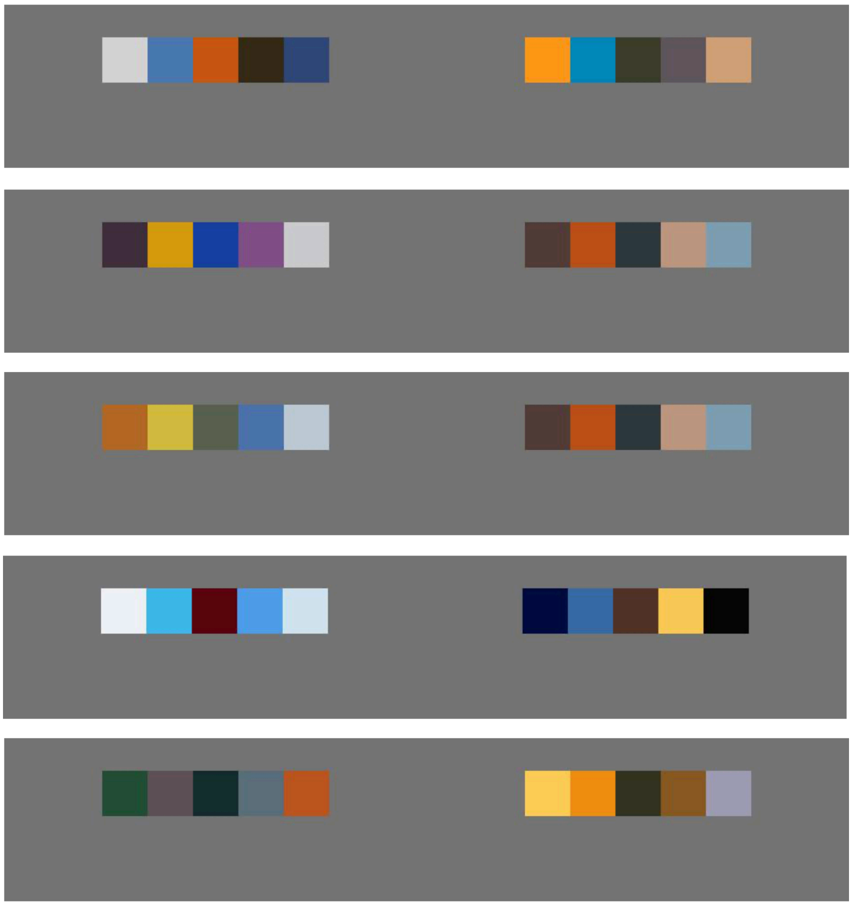


Figure 4-11 5 pairs in the first group which had mean visual ratings of -2.4, -3.7, -2.7, -3.45, and -3.2.

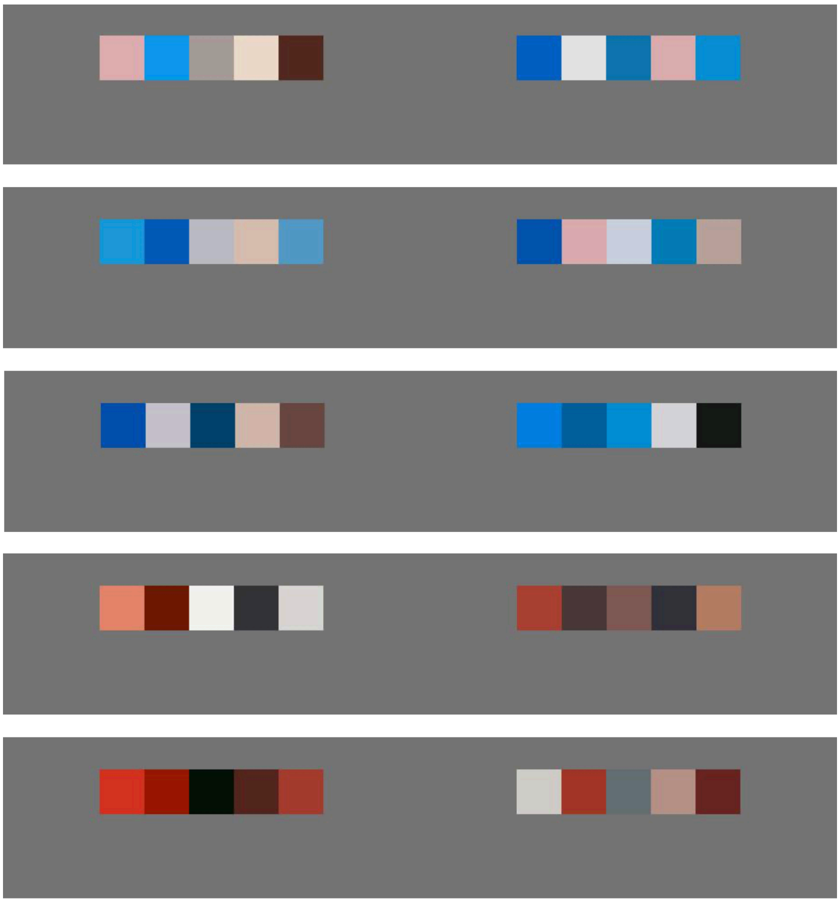


Figure 4-12 5 pairs in the second group which had mean visual ratings of 0.3, 3.9, -1.0, -1.45, and -1.45.

4.3.3 Colour-difference Evaluation

The steps of the colour-difference calculation (ΔE_M and ΔE_P) are described in section 4.3.1. 6 different formulae were implemented and they are: CIELAB, CMC (2;1), CMC (1;1), CIE94, CIEDE2000 (1:1:1) and CIEDE2000 (2:1:1). The performance of difference formulae was analysed using two measures. The first is regression analysis and the value of the coefficient of determination r^2 was reported. The second is the Standardised Residual Sum of Squares (STRESS) measure.

Coefficient of Determination: r^2

The coefficient of determination (r^2) as the square of the correlation is the proportion of variance accounted by distance. r^2 is a common practice in psychological area which provide the measure to predict the performance of the observed outcomes replicated by the regression line (Rao, 1973; Nagelkerke, 1991; Tinsley & Brown, 2000). The r^2 is calculated by the formula in Equation 4.1 (Watier *et al.*, 2014).

$$r^2 = 1 - \frac{\sum_{n-1}^{n}(f(x_i) - Y_i)^2}{\sum_{i-1}^{n}(Y_i - \bar{Y})^2} \quad \textbf{4.1}$$

where Y_i is the y coordinate of the data point. n is the number of the data points. $f(x_i)$ is the trend line function. Y_i is the average of the data points' y coordinates. The value of r^2 is always between 0 and 1 in which the r^2 value close to 1 indicated an acceptable agreement between the data and the trend line, and vice versa the value close to 0 means a poor agreement.

Standardised Residual Sum of Squares (STRESS)

The Standardised residual sum of squares (STRESS) is a statistical index which adopted in multidimensional scaling metric usually be implemented in colour related research. It was recommended to investigate the performance of difference colour-difference formulae through testing the relationship between the perceived and measured colour differences. It has been shown that the STRESS metric is simpler and perform better than other statistical measurements such as PF/3. Besides, STRESS can be used to compare the correlation of visual responses of different observers for the specific colour samples (García *et al.*, 2007; Melgosa *et al.*, 2008). The corresponding equations are as follows:

$$STRESS = 100\sqrt{\frac{\sum(\Delta E_i - f\,\Delta V_i)^2}{\sum \Delta {E_i}^2}} \quad \textbf{4.2}$$

where

$$f = \frac{\sum \Delta E_i \Delta Vi}{\sum \Delta {V_i}^2}$$

where ΔE_i is the measured difference. ΔVi is the perceived difference. f is the logical scaling factor which minimises the STRESS. The value range of STRESS is always between 0 and 100. The ideal model would provide a STRESS value that equals 0.

The squared ration of the STRESS values from two colour-difference formulae can be used to determine whether the two formulae have statistically significantly different at any confidence level (usually 95%). If the squared ratio of two STRESS values is greater than 1, which means the first formula is worse than the second one (Melgosa *et al.*, 2008).

The models (ΔE_M and ΔE_P) to predict the visual difference between the pairs were implemented and the values of r^2 and STRESS calculated between the model predictions and the visual data. Table 4-3 shows the results of r^2 and STRESS values for the two models using each of the six colour difference equations (CIELAB, CMC(2:1), CMC(1:1), CIE94, CIEDE2000(1:1:1) and CIEDE2000(2:1:1). Better performance is indicated by higher r^2 and lower STRESS values.

Table 4-3 Calculation of r^2 and STRESS values for the six colour-difference equations and the two algorithms (MICDM and MECDM).

	r^2		STRESS	
	ΔE_M (MECDM)	ΔE_P (MICDM)	ΔE_M (MECDM)	ΔE_P (MICDM)
CIELAB	0.35	0.82	43.10	19.33
CMC(1:1)	0.21	0.77	41.87	22.99
CMC(2:1)	0.26	0.81	44.06	19.31
CIE94	0.28	0.77	45.54	22.69
CIEDE2000(1:1:1)	0.33	0.83	40.34	18.92
CIEDE2000(2:1:1)	0.39	0.86	39.29	16.93

The order of performance for the two metrics (r^2 and STRESS) is very similar. It is evident that the minimum colour-difference model MICDM performs better than the mean colour-difference model (MECDM). However, according to both r^2 and STRESS, the CIEDE2000 colour difference equation (with a weighting of 2 for Lightness) gives the best performance when all six colour-difference equations are considered.

4.3.4 Statistical Significance of Difference between Colour Difference Formulae

As described in section 4.3.3, the squared ratio STRESS measurement can be used to determine whether there is statistically significantly difference at any confidence level among the colour difference metrics. The squared ratio of the STRESS values follows an *F*-distribution. A two-tailed hypothesis was defined to test the statistical significance between every two colour-difference formulae. The *F* values (squared STRESS ratio) of the ΔE_M model are illustrated in Table 4-4, and the *F* values of the ΔE_P model are in Table 4-5.

For example, the STRESS values for CIELAB and CMC(1:1) in the ΔE_M model are 43.10 and 41.87, respectively. As shown in Table 4-4, the squared STRESS ratio (F) of the two STRESS values is 1.060 (>1), which indicates that the first formula (CIELAB) is worse than the second one (CMC(1:1)). $F_C(0.975; 89; 89) = 0.658$ where the number 89 is from the number of colour pairs (90 pairs in this study) minus 1. The confidence level is $[F_C; 1/F_C] = [0.658; 1.520]$ in which the F_C value represent the lower critical value and the $1/ F_C$ represents the upper critical value. If the F value is greater than the $1/ F_C$, then the first formula is significantly worse than the second one. For the example, the F value equals 1.061 is inside the confidence interval $[F_C; 1/F_C] = [0.658; 1.520]$, so the CIELAB is not significantly worse than the CMC(1:1) in the ΔE_M model.

Note that the underlined values in Table 4-5 show that the metric in the column performs significantly worse than the corresponding metric in the row. The rest of the values show no significant difference between the two metrics. This means that the CMC(1:1) and the CMC(2:1) are significantly worse than the CIEDE2000(2:1:1) in the ΔE_P model. The rest of the values in Table 4-3 and 4-4 show very little or no significant difference.

Table 4-4 Statistical significance of difference between every two of the six difference metric for the ΔE_M (MECDM)model (*F*-test). The value in each cell is the ratio obtained using the squared STRESS values of the column metric divided by the Squared STRESS values of the corresponding row metric.

F **(ΔE_M)**	CIELAB	CMC(1:1)	CMC(2:1)	CIE94	CIEDE2000 (1:1:1)	CIEDE2000 (2:1:1)
CIELAB			1.05	1.12		
CMC(1:1)	1.06		1.11	1.18		
CMC(2:1)				1.07		
CIE94						
CIEDE2000(1:1:1)	1.14	1.08	1.19	1.27		
CIEDE2000(2:1:1)	1.20	1.14	1.26	1.34	1.05	

Table 4-5 Statistical significance of difference between every two of the six difference metric for the ΔE_P (MICDM)model (*F*-test). The value in each cell is the ratio obtained using the squared STRESS values of the column metric divided by the Squared STRESS values of the corresponding row metric.

F **(ΔE_P)**	CIELAB	CMC(1:1)	CMC(2:1)	CIE94	CIEDE2000 (1:1:1)	CIEDE2000 (2:1:1)
CIELAB		1.42		1.38		
CMC(1:1)						
CMC(2:1)	1.00	1.42		1.38		
CIE94		1.03				
CIEDE2000(1:1:1)	1.04	1.48	1.042	1.44		
CIEDE2000(2:1:1)	1.30	1.84	1.301	1.80	1.25	

4.3.5 Observer Variance

Root mean square error (RMSE) is the square root of the mean of the squared errors. It can be examined to measure observer variability includes intra- and inter-observer variability. Higher values mean more biased experimental data. The minimum RMSE value is zero, which indicated the perfect agreement between the two sets of data.

Intra-observer Variance

Intra-observer variance indicated the deviation between the results of each observer's first and repeated trial for those pairs where observers made repeat observations. The corresponding RMSE metric for the intra-observer variance is illustrated in Equation 4.3. A zero value of the intra-observer STRESS means the observer has the same response for two trials.

$$RMSE = \sqrt{\frac{\sum(x1_i - x2_i)^2}{N}} \qquad \textbf{4.3}$$

where $x1_i$ is the assessment response of each observer's first trial, and $x2_i$ is the response of the replicated trial. There are 5 replicated pairs in this study, so N equals 5 in equation 4.3. RMSE values for each observer are then averaged to garner the intra-observer variance for this study. The overall RMSE results of intra-observer variability are summarised in Table 4-6.

Table 4-6 Intra-observer variability in RMSE units.

Observer variability	Intra-observer
Observer 1	2.10
Observer 2	0.45
Observer 3	1.41
Observer 4	0.89
Observer 5	2.32
Observer 6	2.76
Observer 7	4.00
Observer 8	3.82
Observer 9	2.53
Observer 10	0.78
Observer 11	2.37
Observer 12	2.93
Observer 13	0.45
Observer 14	2.57
Observer 15	0.89
Observer 16	2.05
Observer 17	1.61
Observer 18	1.55
Observer 19	1.00
Observer 20	3.32
Mean	1.99

Inter-observer Variance

Inter-observer variance indicated the deviation between the results of each observer and the mean results of all observers. It represents the variance among all observers. A smaller value means all observer in the same experiment provides more similar responses. The corresponding RMSE metric for the inter-observer variance is illustrated in Equation 4.4.

$$RMSE = \sqrt{\frac{\sum(x_i - \bar{x})^2}{N}} \quad \textbf{4.4}$$

where x_i is the visual data in response for each observer, and $\bar{x}$ is the mean assessment responses obtained from all observers. Here N equals 90. The overall RMSE results of inter-observer variability are summarised in Table 4-7.

Table 4-7 Inter-observer variability in RMSE units.

Observer variability	Inter-observer
Observer 1	3.27
Observer 2	2.84
Observer 3	3.55
Observer 4	3.18
Observer 5	3.64
Observer 6	3.25
Observer 7	3.86
Observer 8	4.26
Observer 9	3.39
Observer 10	2.81
Observer 11	2.80
Observer 12	3.84
Observer 13	3.21
Observer 14	3.31
Observer 15	4.01
Observer 16	3.47
Observer 17	2.18
Observer 18	3.71
Observer 19	3.30
Observer 20	2.95
Mean	3.34

The results for both intra- and inter- observer variability are summarised. The intra-observer variability represents the responses between two replicated session for each observer; and the inter-observer variability represents the variance between all observers. Thus, it is reasonable to have higher inter-variability value (3.34) compare to intra-observer variability (1.99).

4.3.6 Comparison with Other Datasets

This chapter has confirmed earlier work that the minimum colour-difference model algorithm is able to make good predictions of the visual difference between colour palettes (Pan and Westland, 2018). In this study, the palettes contained 25 colours arranged in a 5 × 5 block and the r^2 and STRESS values obtained for the MICDM using CIELAB were 0.60 and 20.95, respectively. In this study, with palettes consisting of five colours in a horizontal row the r^2 and STRESS values obtained for the MICDM using CIELAB were 0.82 and 19.33, respectively. There is another dataset with 45 colour-palette pairs from Chen *et al.* (2020), where a similar study was conducted, and where the r^2 and STRESS values obtained for the MICDM (ΔE_P) model using CIELAB were 0.38 and 33.51, respectively. Table 4-8 summarises the values and number of pairs and observers for the three datasets.

Table 4-8 The summarised r^2 and STRESS values of the three different datasets with different size colour palette for the MICDM (ΔE_P) model.

Size of colour palettes	r^2	STRESS	Pair number	Observer number
5	0.82	19.33	90	20
25	0.60	20.95	96	30
45	0.39	33.51	35	30

In other words, better performance is reported in this work (with 5-colour palettes) than reported in the two other studies with 25-colour palettes and 45-colour palettes. It appears that the MICDM (ΔE_P) method works better when there are fewer colours are in the colour palette. The statistical significance of difference between every two of the three datasets are calculated as following:

between datasets of palette size 25 and size 5
$F_C(0.975; 95; 89) = 0.664$, $[F_C; 1/F_C] = [0.664; 1.506]$;

between datasets of palette size 45 and size 5
$F_C(0.975; 34; 89) = 0.547$, $[F_C; 1/F_C] = [0.547; 1.828]$;
between datasets of palette size 45 and size 25
$F_C(0.975; 34; 95) = 0.549$, $[F_C; 1/F_C] = [0.549; 1.821]$.

The squared STRESS ratios are summarised in Table 4-9. The underlined values show that the dataset in the column performs significantly worse than the corresponding dataset in the row. It means that the dataset with the palette size 45 is significantly worse than the datasets with palette size 25 and size 5 in the ΔE_P model. There is no significant difference between the size 5 and the size 25 datasets.

Table 4-9 Statistical significance of difference between every two of the three datasets for the ΔE_P model (*F*-test). The value in each cell is the ratio is obtained using the squared STRESS values of the column dataset divided by the Squared STRESS values of the corresponding row dataset.

F **(ΔE_P)**	**Size 5**	**Size 25**	**Size 45**
Size 5		1.18	<u>3.01</u>
Size 25			<u>2.56</u>

In this study, only 5-colour palettes were investigated and therefore the MICDM algorithm can be used as the model to analyse the difference between different colour palettes.

4.4 Summary

The purpose of this chapter was to develop and test methods for predicting the visual similarity between colour palettes. Several methods have been previously published (Pan & Westland, 2018). However, those previously published methods were evaluated using large 25-colour palettes whereas in this study the colour palettes each consist of just 5 colours, Therefore, new psychophysical data were required with 5-colour palettes (20 participants evaluated the visual difference between 90 pairs of colour palettes). Furthermore, the previously published methods (Pan & Westland, 2018) were based upon the CIELAB colour difference equation whereas the last 50 years have seen considerable advances in sophisticated colour-difference metrics. The work in this chapter, therefore, also compared the use of different colour-difference metrics as the bases for the palette-difference metrics. The results confirmed that the MICDM model was able to make good predictions of the visual difference between colour palettes. The performance on the 5-colour difference set in this chapter was compared with performance with 25-colour and 45-colour palette datasets that were previously published. Interestingly, the MICDM method worked better, the fewer colours in the palettes, and certainly performed well with the 5-colour palettes in this study. The CIEDE2000 colour difference equation (with a weighting of 2 of lightness) gives the best performance compared with the other five colour difference equations that were tested in this chapter. Therefore, the MICDM method using the CIDDE2000 colour difference equation (with a weighting of 2 of lightness) was subsequently used in this study.

Chapter 5. Colour Palette Extraction using K-means Cluster Analysis

5.1 Introduction

In Chapter 3 a set of visual data (colour palettes selected by participants from images) was collected and in Chapter 4 a method for comparing the visual difference between a pair of colour palettes was developed and evaluated. Chapter 5 now looks at methods for automatically extracting a colour palette from an image. As mentioned in Chapter 2 (section 2.3.1), K-means is a fast and efficient way to generate different colour centres that represent clusters in images and is often used to segment the image into different coloured regions that correspond quite well with human image segmentation (Shmmala and Ashour 2013). K-mean is a type of unsupervised machine learning. In this chapter, the colour centres obtained from K-means cluster analysis of images were used to form colour palettes that may be representative of the images. The cluster analysis can, of course, be carried out in different colour spaces and therefore in this study colour palettes obtain from cluster analysis in two colour space (RGB and the more perceptually relevant CIELAB) were compared with the colour palettes (*Visual Data*) that were visually extracted from images by designers I Chapter 3 used the metrics developed in Chapter 4. In section 5.4, the inter-observer variation of designer extraction is quantified, and the K-means clustering generated palettes compared with the raw visual data (*Designer*).

5.2 Data Collection

Cluster analysis is one of the most common automatic methods for colour extraction (Lin and Hanrahan, 2013). The performance of CIELAB and RGB colour spaces using clustering method was investigated by previous studies, which shows that CIELAB colour space is better than RGB colour space (Burney & Tariq, 2014; Shmmala and Ashour, 2013). Therefore, the colour palettes extracted using K-means cluster analysis in both RGB and CIELAB colour spaces have been explored in this chapter. Automatic methods for generating colour palettes from images using K-means clustering have been programmed in MATLAB.

Based on the previous psychophysical palette selection experiment (Chapter 3) and previous studies (O'Donovan *et al.*, 2011; Lin & Hanrahan, 2013) 5 is the most common number of colours in a colour palette and the ground truth data developed consist of 5-colour palettes. In this study therefore, K-means clustering (with K = 5) was used to obtain the colour palettes in both RGB and CIELAB colour space. In total, 60 (30 x 2) colour palettes were collected using the K-means clustering algorithm. All 60 colour palettes from two colour spaces are illustrated in Figure 5-1.

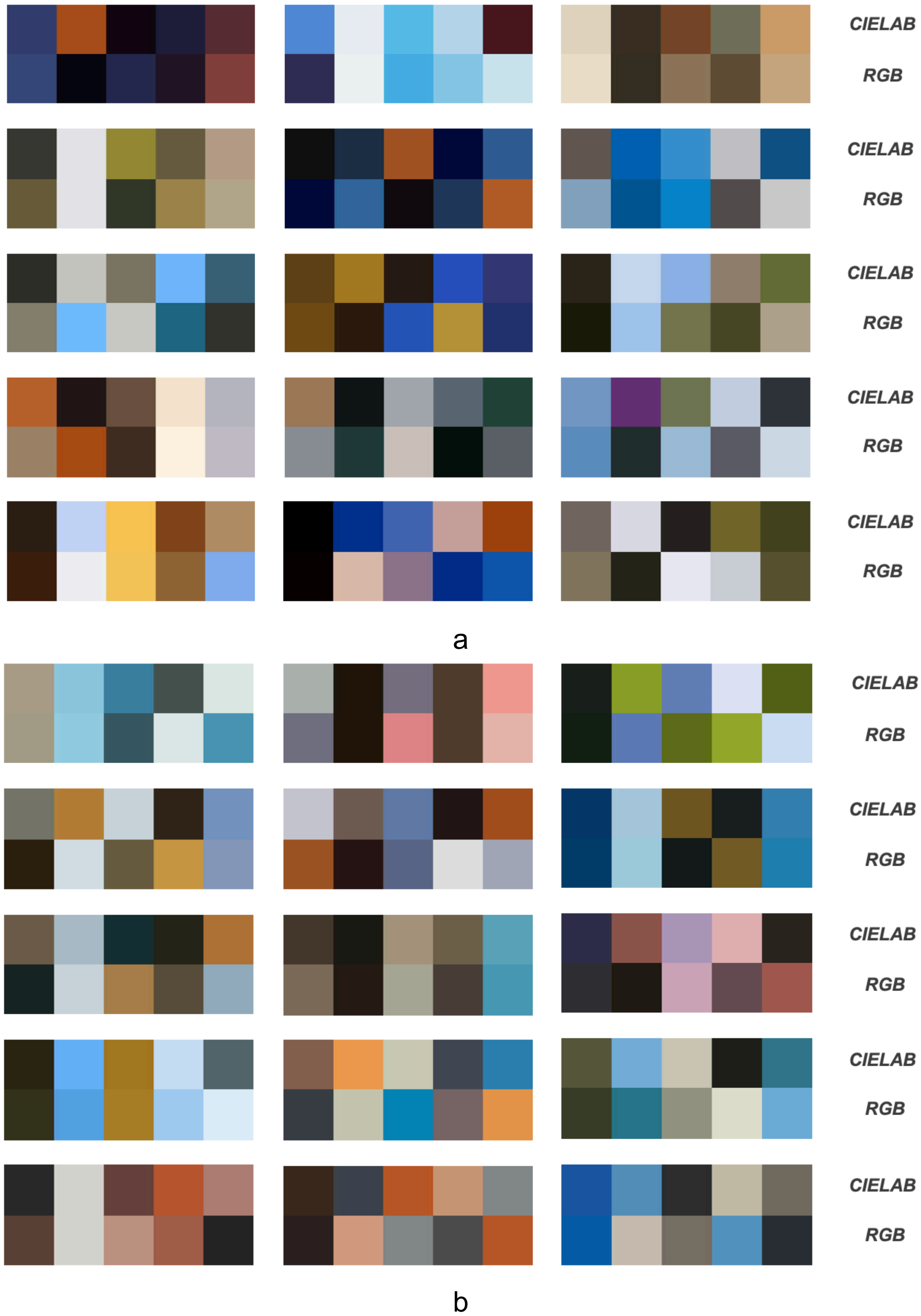


Figure 5-1 All 60 colour palettes from 30 landscape images using K-means clustering in two colour spaces.
(a) built-environment images (b) natural-landscape images

5.3 Comparison with the *Visual Data*

5.3.1 Comparison between *Visual Data* and K-means Colour Palettes

Figure 5-2 shows the three palettes that were obtained using three different methods for one of the landscape images as an example. The colour palettes generated from K-means cluster analysis in CIELAB and RGB colour space are labelled as *CIELAB* and *RGB*, respectively. In Chapter 4, the minimum colour-difference model algorithm MICDM was used to make predictions of the visual difference between colour palettes. Therefore, to compare the colour differences between the K-means clustering colour palettes and the *Visual Data*, the MICDM model (described in section 4.3.1) was used.

Figure 5-2 Example data representation for one natural landscape images in the experiment. The *Visual Data* palette is developed from Chapter 3 to represent the human extraction. The colour palettes generated from K-means in CIELAB and RGB colour space are labelled as *CIELAB* and *RGB*, respectively.

In Chapter 4, the CIEDE2000 colour difference equation (with a weighting of 2 of lightness) provides the best performance compared to the other 5 colour-difference equations using the MICDM model. Thus, the CIEDE2000(2:1:1) formula was used to calculate the colour differences for all 30 images in this chapter. The colour differences (ΔEp_{00}) between *Visual Data (VD)* and the colour palettes obtained automatically from RGB and CIELAB colour spaces are shown in Table 5-1.

Table 5-1 The colour difference values (using CIEDE2000 formulae) between *Visual Data* and the computed colour palettes using K-means clustering from difference colour space (CIELAB and RGB).

VD **vs K-means**	ΔEp_{00}	
Image	***CIELAB***	***RGB***
1	9.46	6.26
2	6.13	11.13
3	8.00	8.05
4	10.64	9.91
5	12.22	12.58
6	8.49	9.20
7	8.63	9.2**5**
8	8.83	12.08
9	9.23	8.30
10	17.07	18.27
11	7.09	7.59
12	10.63	13.52
13	10.88	11.55
14	11.45	11.61
15	11.80	11.54
16	9.09	9.62
17	9.78	9.90
18	12.38	14.17
19	9.16	9.36
20	10.31	9.47
21	17.49	15.94
22	11.24	13.74
23	9.90	10.68
24	11.26	10.70
25	12.69	11.01
26	6.76	10.38
27	7.54	7.07
28	8.60	9.49
29	7.16	8.75
30	8.87	8.30
Mean	10.09	10.65
Standard Deviation	2.61	2.62

The maximum and minimum values for each column of Table 5-1 are underlined. The maximum colour difference using CIELAB colour space is 17.49 CIEDE2000(2:1:1) units and the minimum is 6.13 units. The maximum and the minimum colour-difference values in RGB space are 18.27 and 6.26 CIEDE2000(2:1:1) units, respectively. The mean colour-difference values in CIELAB and RGB spaces are 10.09 and 10.65 units, respectively. It indicates that a better performance using the CIELAB colour space than the RGB colour space. Figure 5-3 shows a better illustration.

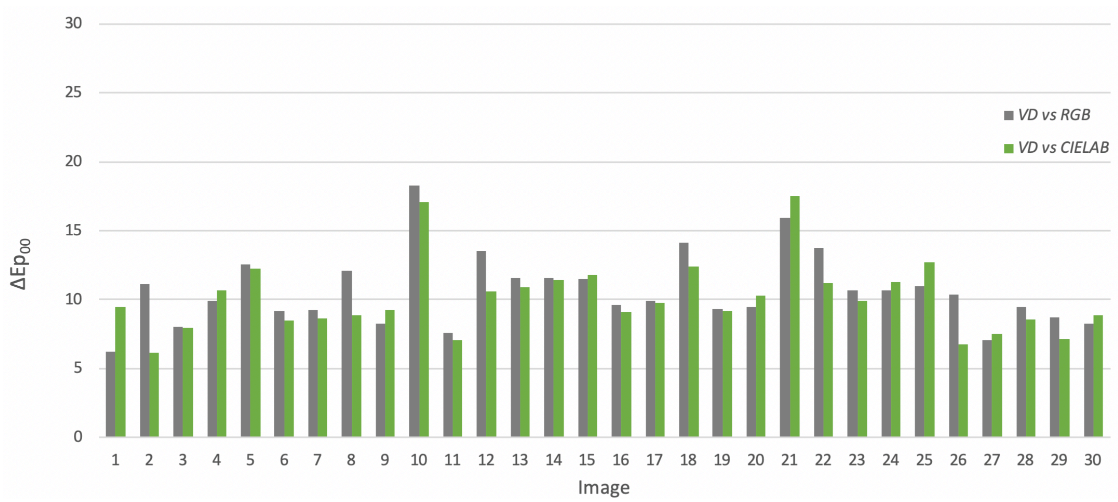


Figure 5-3 Colour difference using the CIEDE2000(2:1:1) formula between *Visual Data* and the computed colour palettes from difference colour space (CIELAB and RGB) for each of the 30 images.

However, the limitation of the new MICDM model is that there is no thresholds set up about palette difference values. The difference between the mean colour-difference values in CIELAB (10.09 units) and RGB (10.65) colour spaces seems small, but if the difference value is noticeable for human is unknown. Also, the statistical difference between the *CIELAB* and *RGB* colour palettes is unknown, which is described in the next section.

5.3.2 Comparison between *CIELAB* and *RGB* Colour Palettes

The *CIELAB* and *RGB* colour palettes were compared using the MICDM model within the CIEDE2000 (2:1:1) colour difference formulae. The results are shown in Table 5-2. The maximum and minimum values in each column are underlined. The mean colour differences between the CIELAB- and RGB-derived colour palettes of all 30 images is 10.09 CIEDE2000(2:1:1) units. Note that the colour difference between *CIELAB* and *RGB* palettes for Figure 5-2 is 10.63 CIEDE2000(2:1:1) units. The statistical difference between CIELAB- and RGB-derived colour palettes is discussed in the next section.

Table 5-2 The colour difference values between *CIELAB* and *RGB* palettes using the CIEDE2000(2:1:1) equation.

CIELAB vs RGB **Image**	**ΔEp_{00}**
1	9.46
2	6.13
3	7.80
4	10.64
5	12.22
6	8.49
7	8.63
8	8.83
9	9.23
10	17.07
11	7.09
12	10.63
13	10.88
14	11.45
15	11.80
16	9.09
17	9.78
18	12.38
19	9.16
20	10.31
21	17.49
22	11.24
23	9.90
24	11.26
25	12.69
26	6.76
27	7.54
28	8.60
29	7.16
30	8.87
Mean	10.09
Standard Deviation	2.61

5.3.3 Statistical Test of Significance Difference between CIELAB and RGB Colour Space

The distribution of colour difference values of are skewed, thus, a non-parametric statistical hypothesis test called the Wilcoxon signed-rank test was used to test the statistical significant difference between the CIELAB- and RGB-derived colour spaces. The Wilcoxon signed-rank test is named after Frank Wilcoxon (1945). It is considered to be the alternative test of the paired Student's t-test for non-normal differences of the related samples (McDonald, 2009).

The *P* values from the colour differences between the *Visual Data* and the computed colour palettes using K-means clustering from different colour spaces (CIELAB and RGB) is 0.000 using CIEDE2000(2:1:1) formulae (see Table 5-3). Therefore, there is a statistically significant difference (with the *P* values of less than 0.05) between computed colour palettes in CIELAB and RGB colour spaces. The CIELAB colour space performed better than the RGB colour space.

Table 5-3 The results of the Wilcoxon signed-rank test.

***VD* vs K-means**	**ΔEp_{00}**	
	CIELAB	***RGB***
P value	0.000	

Even though there is a statistically significant difference between the *CIELAB* and *RGB* colour palettes, the visual threshold among colour-palette difference is still unknown which needs to be explored in future work. Another measurement using inter-observer variability is described in the next section.

5.4 Comparison using Inter-observer Variability

5.4.1 Inter-observer Variation

The inter-observer variability of the human-extraction experiment (Chapter 3) was quantified for all 30 images. The variation in 30 colour palettes of each image was calculated by comparing each observer-extracted palette with each other observer and using the MICDM model to get the colour palette differences (ΔEp). Take one image for example, the inter-observer variation is calculated by comparing each row of the *Designer* palette with every other row to obtain ΔEps, then average them for the final inter-observer variation for each image (see Figure 5-4). There are 435 (30 x 29 x 2) possible ΔEps of the comparing pairs for each image.

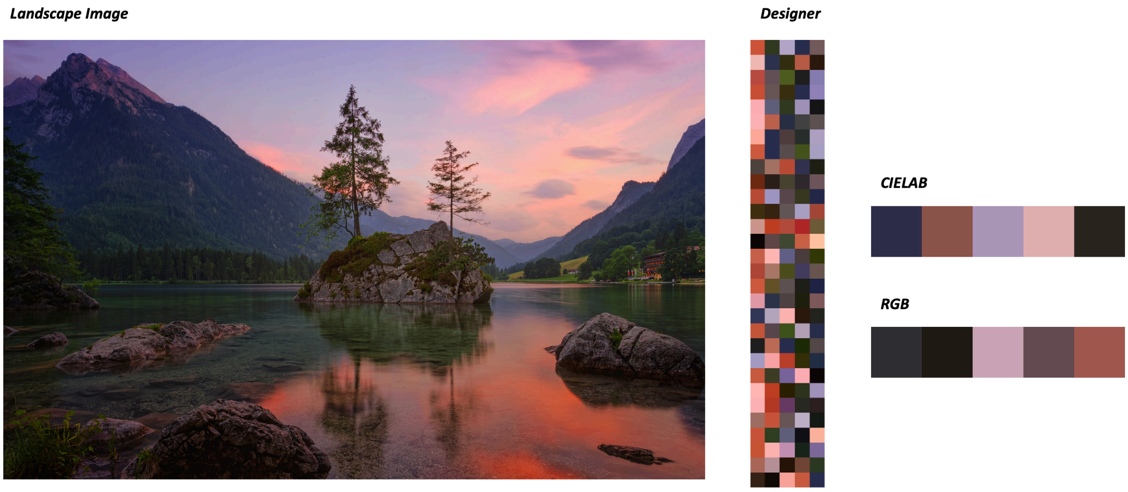


Figure 5-4 Example data representation for one natural landscape images in the experiment. The raw colour palettes obtained visually produced by participants are labelled as *Designer*. The colour palettes generated from K-means in CIELAB and RGB colour space are labelled as *CIELAB* and *RGB*, respectively.

The results of the colour differences are shown in Table 5-4. The inter-observer variability of all 30 images is 9.33 CIEDE2000(2:1:1) units. A limitation here is that the significant level of the difference value is unknown, which results in variability of this method using inter-observer variability. The distributions of all colour-difference values are shown in Figure 5-5.

Table 5-4 The inter-observer variability for each image using the CIEDE2000(2:1:1) formulae.

Inter-observer Variability	ΔEp_{00}
Image	
1	9.65
2	4.24
3	10.00
4	8.53
5	9.09
6	8.22
7	7.73
8	9.13
9	11.33
10	9.89
11	7.14
12	11.02
13	10.67
14	11.90
15	7.94
16	11.90
17	9.40
18	11.32
19	6.37
20	8.97
21	9.70
22	11.17
23	8.90
24	12.14
25	12.16
26	8.59
27	7.65
28	7.86
29	8.38
30	8.94
Mean	9.33
Standard Deviation	1.85

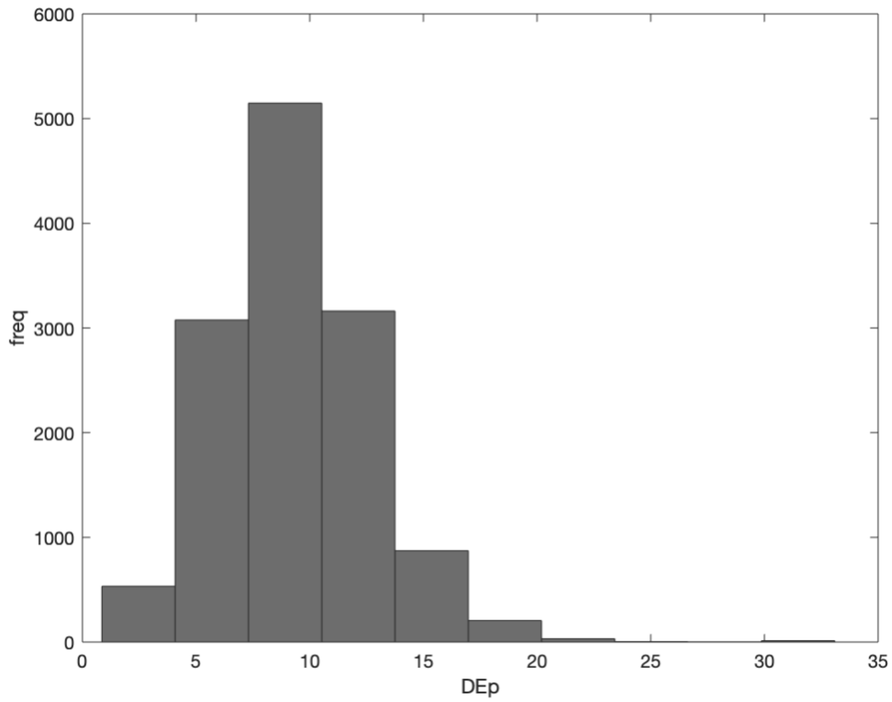


Figure 5-5 Inter-observer variability for the palette extracted from all 30 landscape images. For each image, each observer extracted palette was compared with every other observer and the colour differences were calculated as ΔEps. The frequency distribution of all ΔEp values (using the CIEDE2000(2:1:1) formula).

5.4.2 K-means Clustering Method Performance

In this study, the value of the inter-observer variation is considered as a limit measure to test algorithm performance. The performance of K-means was calculated by obtaining the colour difference (ΔEp) between K-means and the palettes from each observer's colour selection. Take Figure 5-4 as an example, the colour difference between *RGB* (or *CIELAB*) and each row of the *Designer* palette were calculated, and then the mean colour difference for the image was calculated. The average colour difference of all images was then calculated. The results are shown in Table 5-5. The results show the RGB colour space perform slightly better than the CIELAB colour space, which provides an opposite conclusion with the different measurement to test the method performance in section 5.3.2 and 5.3.3. However, the difference between the CIELAB (13.86) and the RGB (13.75) colour spaces is small.

Table 5-5 K-means method performance includes using two colour spaces (CIELAB and RGB) and two colour difference formulae (CIELAB and CIEDE2000(2:1:1)).

K-means Method Performance		
Colour space	CIELAB	RGB
Formula	ΔE_{00}	
error	13.86	13.75

5.4.3 Results

The inter-observer variability of the palette extracted from all 30 images was calculated to be 9.33 CIEDE2000(2:1:1) units, which is smaller than the K-means performance. Besides, the mean colour difference values of each observer were calculated to compare with the values of K-means performance (see Table 5-6). The maximum and minimum values in each column are underlined. It shows that the values of the overall K-means performance (> 13 units) are higher than each observer's performance (< 12 units).

Table 5-6 The inter-observer variability for each observer using CIEDE2000(2:1:1) formulae.

	ΔEp_{00}
Observer 1	8.59
Observer 2	8.85
Observer 3	9.75
Observer 4	9.46
Observer 5	9.13
Observer 6	8.88
Observer 7	8.88
Observer 8	8.52
Observer 9	8.87
Observer 10	11.29
Observer 11	8.64
Observer 12	9.79
Observer 13	11.67
Observer 14	9.32
Observer 15	9.17
Observer 16	9.27
Observer 17	9.29
Observer 18	8.73
Observer 19	9.24
Observer 20	8.95
Observer 21	8.52
Observer 22	9.48
Observer 23	9.01
Observer 24	9.15
Observer 25	9.40
Observer 26	9.42
Observer 27	9.31
Observer 28	10.79
Observer 29	9.62
Observer 30	8.94
Mean	9.33

5.5 Summary

In this chapter, cluster analysis using K-means was performed in two different colour spaces (CIELAB and RGB). The choice of different colour space did have some effect on the colours that were extracted. Two difference measurements were used in this chapter for testing and comparing the K-means method performance in CIELAB and RGB colour space. In section 5.3, the first one was used by comparing the *Visual Data* (5×1 palette summarised from the designer extraction) to the palettes extracted from K-means clustering. The second measurement took inter-observer variability as the limit measure. The palettes extracted from K-means were compared to the raw palette extracted by each designer to obtain the performance values, then compared it with the inter-observer variability value (section 5.4). Using the first measurement method, the K-means clustering within the CIELAB colour space provided better performance than the RGB colour space. There is a statistically significant difference between the *CIELAB* and *RGB* colour palettes. Using the second measurement method, the results show the RGB colour space perform slightly better than the CIELAB colour space, which provides an opposite conclusion with the first measurement. However, the difference between the CIELAB (13.86) and the RGB (13.75) colour spaces is small. Besides, the conclusion from measurement method one is consisted with previous research (Burney & Tariq, 2014; Shmmala and Ashour, 2013). Therefore, the CIELAB colour space might be a better choice than RGB colour space when using K-means extraction method.

An alternative method using eye tracking for palette generation will be explored in the next chapter. The overall comparison among all extraction methods and the corresponding descriptions are summarised in Chapter 7.

Chapter 6. Colour Palette Extraction using Eye Tracking

6.1 Introduction

In this chapter, the eye fixation of participants in this study was explored using an eye-tracking system and colour palettes are extracted using the eye-tracking system. The eye-tracking system and the experiment procedure is described in section 6.2. The process of generating colour palettes from the eye-tracking system is described in section 6.3. The eye-tracking extracted palettes (*Eye Tracking*) are then compared with the *Visual Data* using MICDM model to obtain the colour differences (section 6.4). In section 6.5, the *Eye Tracking* palettes are compared with the raw data of designer extraction (*Designer*) to get the performance value of the eye-tracking extraction.

6.2 Experimental

6.2.1 Eye-tracking System

Eye-tracking systems have been considered as an objective measure to analyse human's observation and perception of landscapes. Real time data is captured objectively using an eye-tracking system (Wang & Sparks, 2016). It provides the eye-movement direction (saccades), the position of eye focuses (gaze points), the gaze path and the fixation durations during people's observation (Dupont *et al*., 2014). The eye-tracking data includes the target fixation and the number of duration of fixations can provide the most dominant information of the stimuli. The saccades and the gaze path data can indicate how the eye focus changes from objects to objects and help track the visual stimulus shift flow in the stimuli (Wang & Sparks, 2016; Wedel & Pieters, 2006; Wedel & Pieters, 2008).

Digital images are frequently used stimuli in eye-tracking studies (Dupont *et al*., 2014; Hägerhäll, 2000; Ode *et al*., 2008; Palmer, 2004; Sevenant, 2010; Tveit, 2009). In this study, the eye-tracking system has been used as a tool for measuring the eye focus on landscape images and for getting the observational eye-tracking data.

As explored in a previous chapter (section 3.3.1), “first impression” and “standout” are two of the highest-frequency words used when participants describe how they choose their colour palettes. Considering these words, it is worthwhile to try to extract the colour palettes from each observer’s patterns of visual attention. Therefore, the aim of the experiment is to analyse the fixation of the participants to obtain the colour palettes.

6.2.2 Eye-tracking Apparatus and Software

The eye-tracking experiment was conducted using the Tobii X2–60 Eye Tracker, developed by Tobii Technology. The eye-tracking data was processed using Tobii Studio software, which provides a platform to visualise and analyse eye-tracking data.

6.2.3 Experimental Procedure

Prior to the experiment, participants were asked to forsake mascara and wear contact lenses instead of glasses to improve the accuracy of the eye-tracking system. Participants were placed in front of the eye tracker and informed to sit comfortably at a distance (around 60 cm) from the eye tracker. They were asked to free view the 30 landscape photographs and their eye movements were monitored by the eye tracker (Figure 6-1).

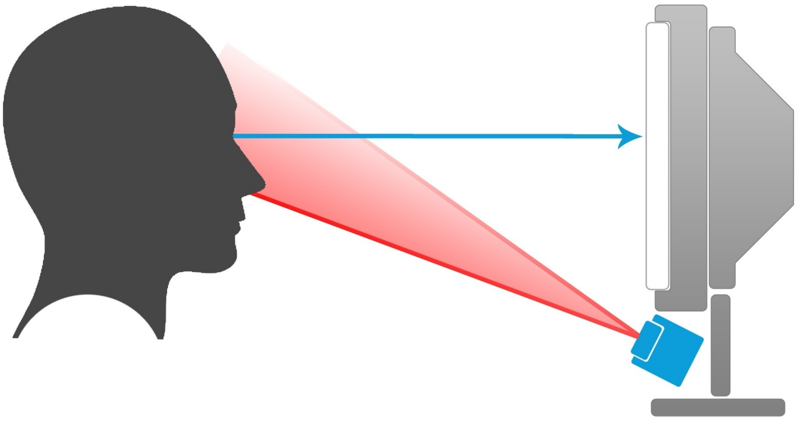


Figure 6-1 The eye-tracking system setup.

Calibration was performed for each participant before the test using a 9-dot calibration procedure to assure the accurate results. As shown in Figure 6-2, a track status box is shown to help adjust the observer position. The two white dots represent the pupils of the observer. The possible calibration results and solutions are shown in Figure 6-3.

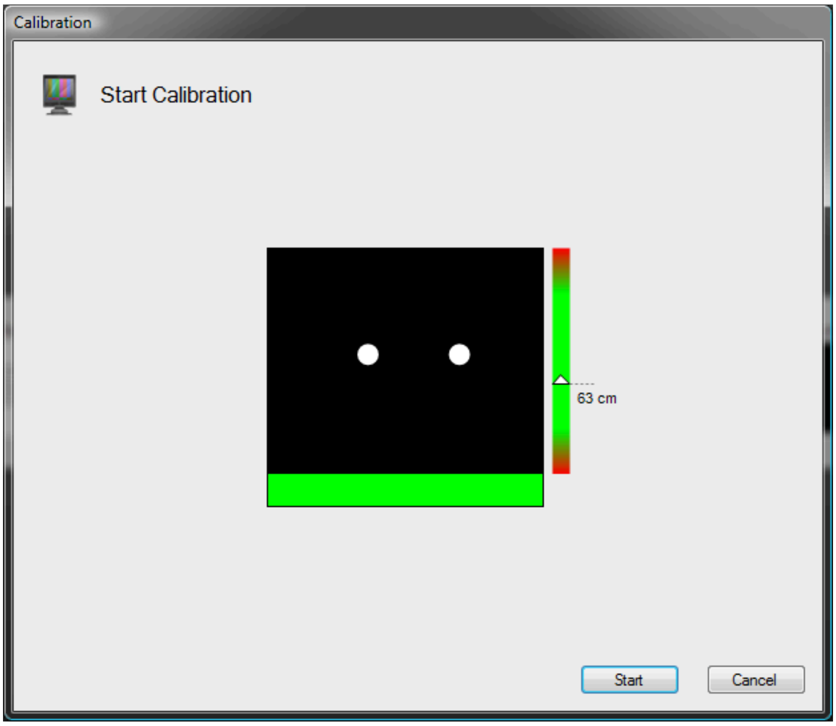
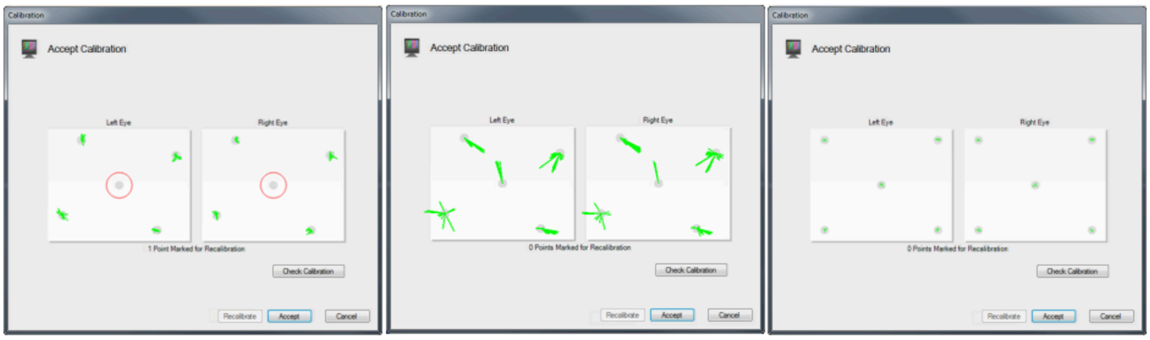


Figure 6-2 The eye-tracking system setup.



Problem: Calibration point missing
Solution: Select and recalibrate the missing point.

Problem: Large errors in calibration
Solution: Check eye-tracker, setup, glasses, and participant. Make new calibration.

Perfect calibration

Figure 6-3 The possible eye-tracking calibration results and solutions.

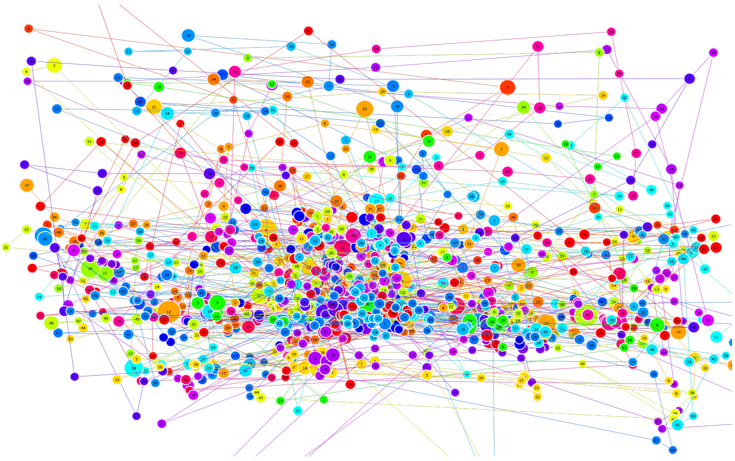
The viewing sequence of all 30 landscape images was randomly displayed to avoid any possible order effect. The background colour of each image was set into a uniform grey (CIELAB L*=50). Between each landscape image, a blank screen with a cross in the centre was placed to bring subjects attention back in the centre of the page and provide consistency of viewing patch for each photograph. The same grey background colour as the photograph pages was set on the cross page. Image pages were set to automatically play for 15 seconds then went into the cross page. The specific display time for the landscape images was investigated from previous similar studies (Berto *et al.*, 2008; De Lucio *et al.*, 1996; Dupont, 2014) and tested prior to the experiment to ensure participants have the right amount of time to look through the whole image.

Observers were requested not to talk while viewing the images to avoid head movements. However, they were allowed to move and rest during the cross pages. No display time was set on the cross page. The cross page would step into the next photograph page by mouse clicking. A practice session with two photographs (different from the 30 landscape photographs) was conducted prior to the main experiment to ensure participants fully understand the experimental procedure.

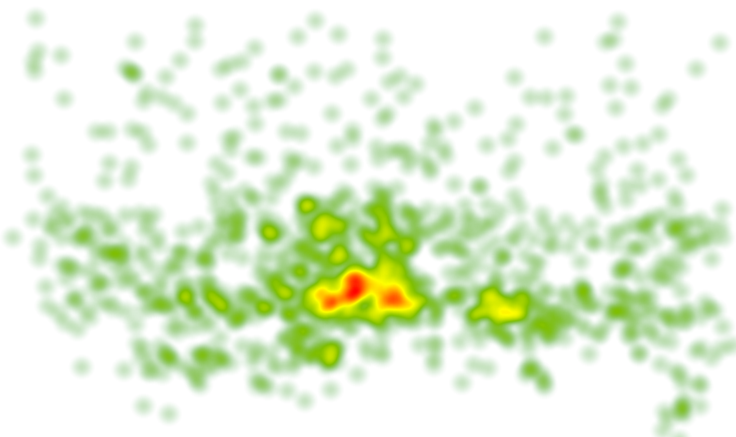
6.2.4 Eye-tracking Data

The eye movements of observers were recorded during the whole experiment. During the recording of each observer, the fixation position (“X, Y” coordinates) with the timestamp were automatically saved into Tobii Studio. Figure 6-4 shows the visualization of the eye-tracking data of one landscape photographs. The gaze plot represents the eye-move sequence and the fixations positions (dots) on the stimuli image. The size of the fixation dots corresponds to the duration of each fixation. The number on each dot represents the gaze order of each observer. Each colour of the gaze plot represents each observer in the experiment. Heat maps shows the general distribution of fixations and gaze points. The heat map uses different colours to represent the number of fixations delivered by observers. From red to green, the number and the duration of fixations decrease, which means that red represents the largest number or the longest time of fixations.

a



b



C

Figure 6-4 Example for eye-tracking data visualization of all 30 observers. (a) stimuli image (b) gaze plot (c) heat map

6.3 Using Eye-tracking to Colour Palette Extraction

In this study, the aim of the experiment was to extract colour palettes from eye-tracking data. According to the questionnaire conducted in section 3.3.1, most observers tend to choose the colours from images by “first impression” and “standout”. Therefore, the colour palettes extracted from the eye-tracking data were collected. As previously, a five-colour palette was produced to represent the eye-tracking extraction of one image. Thus, the first five longest fixation points of each observer from the eye-tracking data were selected for each image and used to identify colours. According to the first five fixation position (“X, Y” coordinates), the pixel of the fixation was located. The RGB values of the fixation pixel were recorded and automatically saved. This was processed in MATLAB (Figure 6-5).

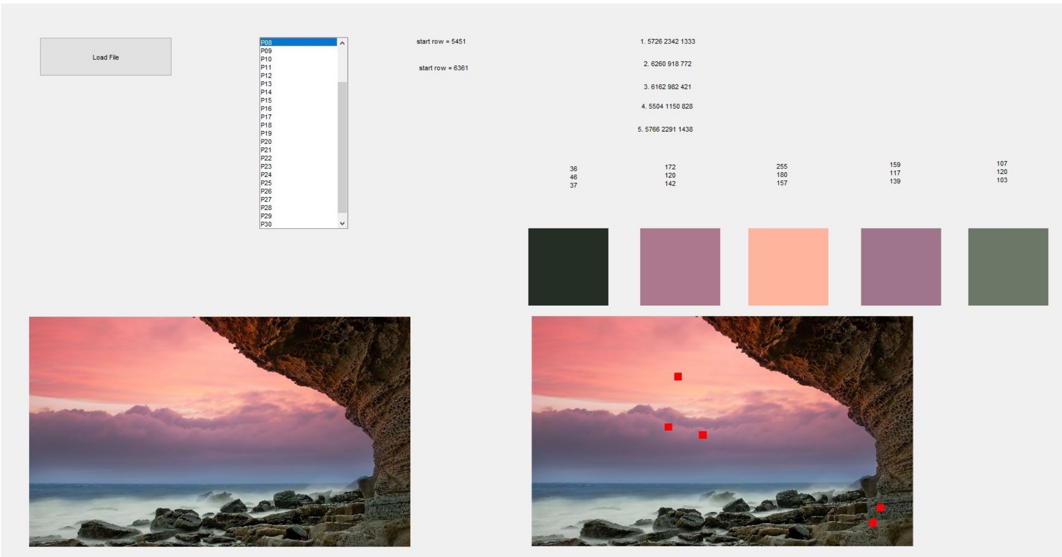


Figure 6-5 The interface for colour extraction from the eye-tracking data. The colour patches on the right-middle part were delivered by selecting each participant’s eye-tracking data on the left side. The RGB values of each colour patch were shown above each colour. The position of each fixation is shown as the small red square one right image.

All eye-tracking data of 30 participants were saved for each image. There were 150 colours (5 colours $\times$ 30 participants) extracted from the eye-tracking data for each image. All raw colour palettes from the eye-tracking data are shown in Figure 6-6.

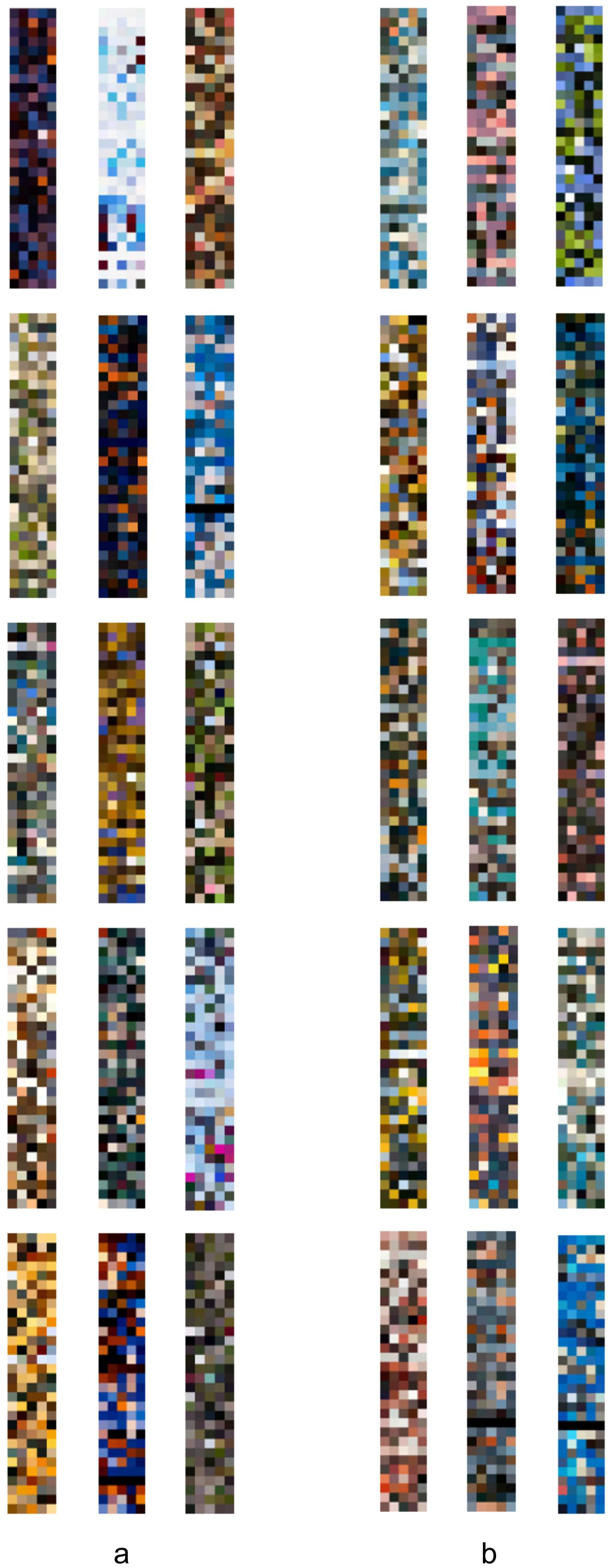


Figure 6-6 Raw colour palettes extracted from the eye-tracking data. (a) built environment palettes (b) natural landscape palettes

It should be noted that there were missing data of the 21st participant in three images due to outside-media (image) fixations. Therefore, there were 145 (5 colours × 29 participants) for these three images. The missing colour palettes from the 21st participant in the three images (located as the 6th palette in the built environment palette and the 14th and 15th palettes in the natural landscape palettes in Figure 6-6) are represented by one black row.

Palette Modification Using Order Modification Metric

The raw colour palettes extracted from the eye-tracking data (*Eye Tracking* palette) were modified using order medication metric (section 3.3.2). This process results in the *New Order ET* palettes. Then the median colours from each column in the *New Order ET* palettes are recorded and labelled as the *ET Palette* (Figure 6-7). The 5 x 1 *ET Palettes* are defined as the representative palette of the eye-tracking extraction. All 30 *ET Palettes* are illustrated in Figure 6-8.

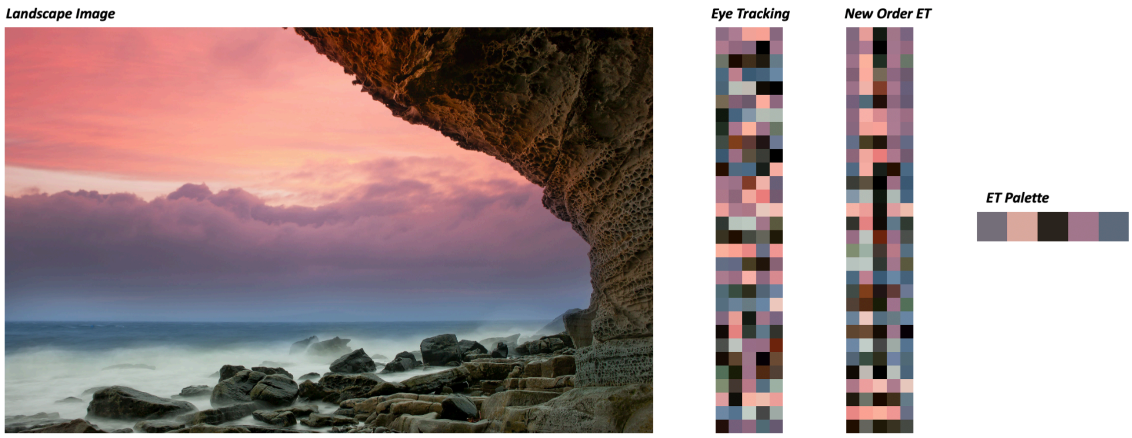


Figure 6-7 Example data representation for one natural landscape image in the experiment. The raw colour palette is collected from the eye-tracking data is labelled as the *Eye Tracking* palette. *New Order ET* palette is obtained by modifying the colour order in the *Eye Tracking* palette. The data shows the median colour palette of *New Order ET* palette is labelled as the *ET Palette.*

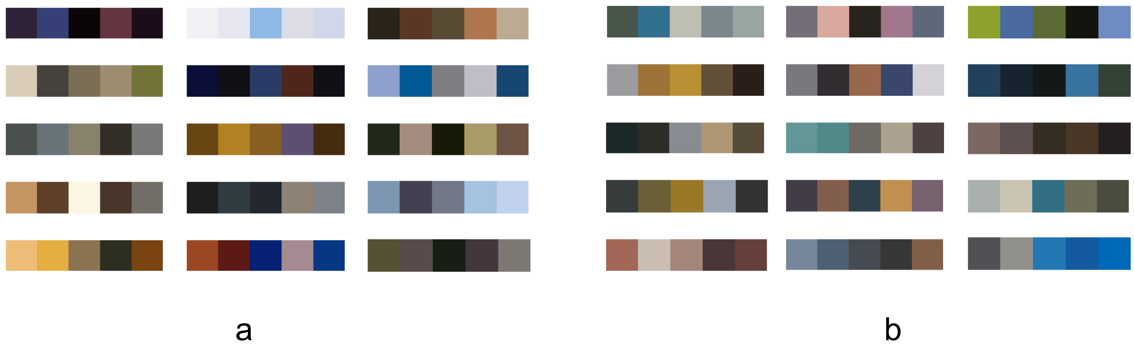


Figure 6-8 All *ET Palettes* from 30 landscape images.
(a) built-environment images (b) natural-landscape images

6.4 Comparison with the *Visual Data*

The *Visual Data* palette (developed in Chapter 3) is used as the ground-truth data in this study. It represents the visual colour selection by designers. Therefore, the colour palettes by the eye-tracking extraction were compared with the *Visual Data*. Figure 6-9 shows two 5 x 1 palettes that represent the designer and the eye-tracking extraction as an example. The minimum colour-difference model algorithm MICDM (Chapter 4) was used to predict the visual difference between the two colour palettes.

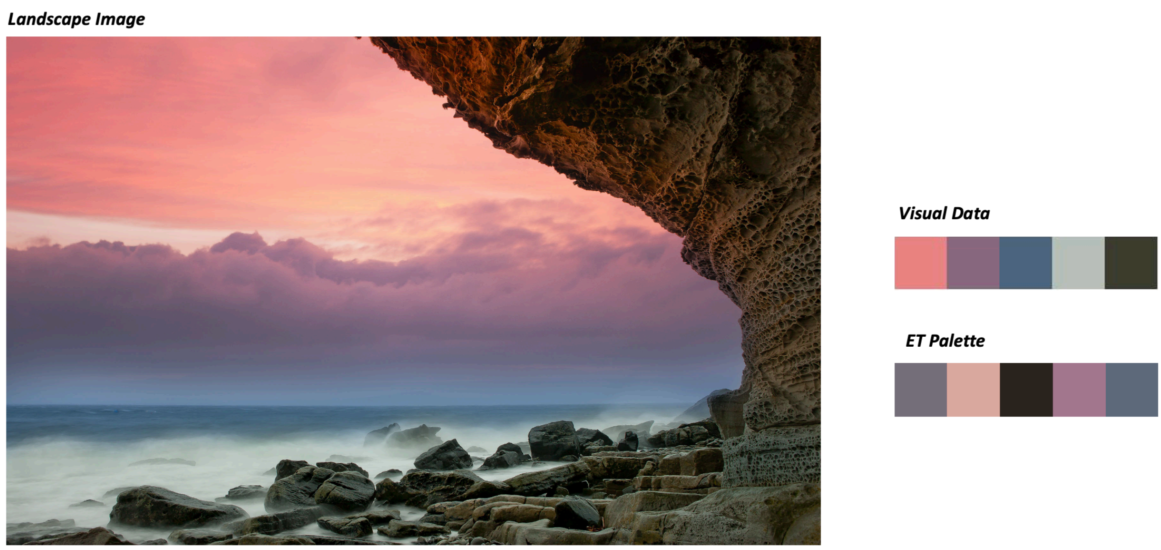


Figure 6-9 Example data representation for one natural landscape images in the experiment.

As explained in Chapter 4, the CIEDE2000 (with a weighting of 2 of lightness) provides the best performance when it comes to predicting the visual difference between 5-colour palettes. Therefore, as in Chapter 5, the CIEDE2000 (2:1:1) formulae was used in the MICDM algorithm to make predictions. The colour differences (ΔEp_{00}) between the *Visual Data* (*VD*) and the *ET Palette* (*ET*) are shown in Table 6-1. The maximum and minimum colour-difference values in Table 6-1 are underlined. The maximum and minimum colour-difference values between visual selection and eye-tracking extraction are 13.96 and 4.32 units, respectively. The mean colour-difference value is 8.84, which is smaller than using the K-means extraction method (Table 5-1). More detailed comparison among extraction methods is in Chapter 7. Figure 6-10 shows a better illustration.

Table 6-1 The colour difference values (using the CIEDE2000 formulae) between *Visual Data* and *ET Palette.*

VD* vs *ET	**ΔE_{p00}**
Image	
1	4.32
2	8.73
3	9.22
4	8.20
5	7.91
6	9.23
7	6.18
8	7.79
9	11.87
10	13.96
11	5.70
12	12.27
13	9.47
14	9.75
15	7.77
16	9.61
17	7.87
18	12.56
19	7.12
20	8.65
21	12.41
22	8.33
23	10.98
24	7.58
25	10.38
26	6.85
27	7.53
28	8.06
29	7.62
30	7.27
Mean	8.84
Standard Deviation	2.20

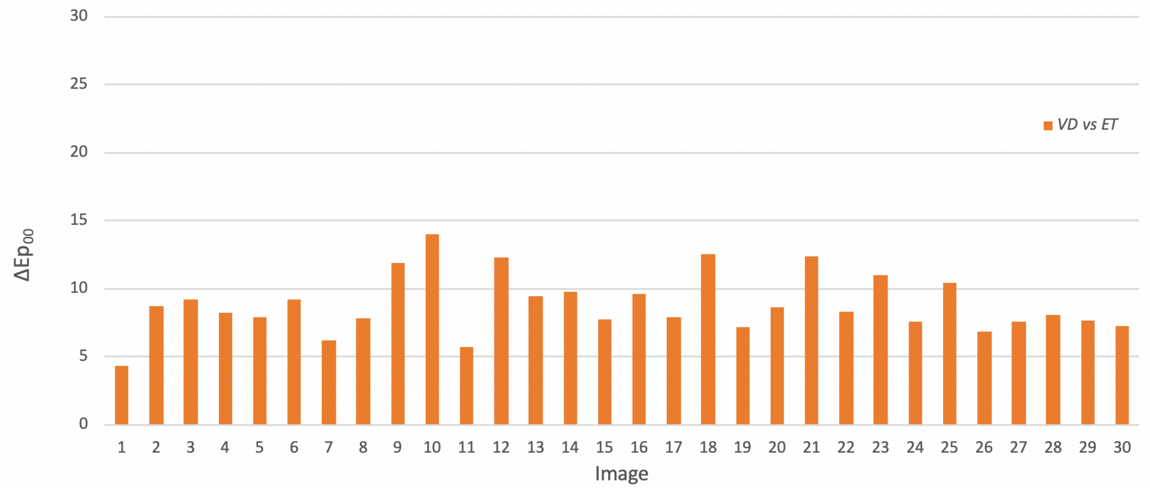


Figure 6-10 Colour difference between Visual Data and ET Palette.

6.5 Comparison Using the Inter-observer Variability

As described in Chapter 5 (section 5.4.1), the inter-observer variability of all 30 landscape images in the designer-extracted experiment was 9.33 CIEDE2000 (2:1:1) units. It shows the variation in colour palettes selected from 30 subjects in 30 images, which provides a limit to measure the method performance. To comparing the eye-tracking method to the designer-extracted method, the calculation is according to the following steps:

1. Each 5 colour palettes selected by one participant in one image is compared with the eye-tracking colour palette from the same participant. The MICDM model with the CIEDE2000(2:1:1) formula is used to obtain the colour difference values between the two palettes.
2. Repeat the first step for the other 29 participants' data, resulting in 30 colour difference values for each image.
3. The 30 colour-difference values are averaged to get one mean value for one image. The one mean value is the error between the *Designer* and the *Eye Tracking* palette (Figure 6-11).
4. Step 1 to 3 are repeated in the other 29 images and there are 30 mean colour-difference values for all 30 landscape images.

5. The 30 mean colour-differences from the 30 images are averaged to obtain the mean performance value of the eye-tracking extraction method.

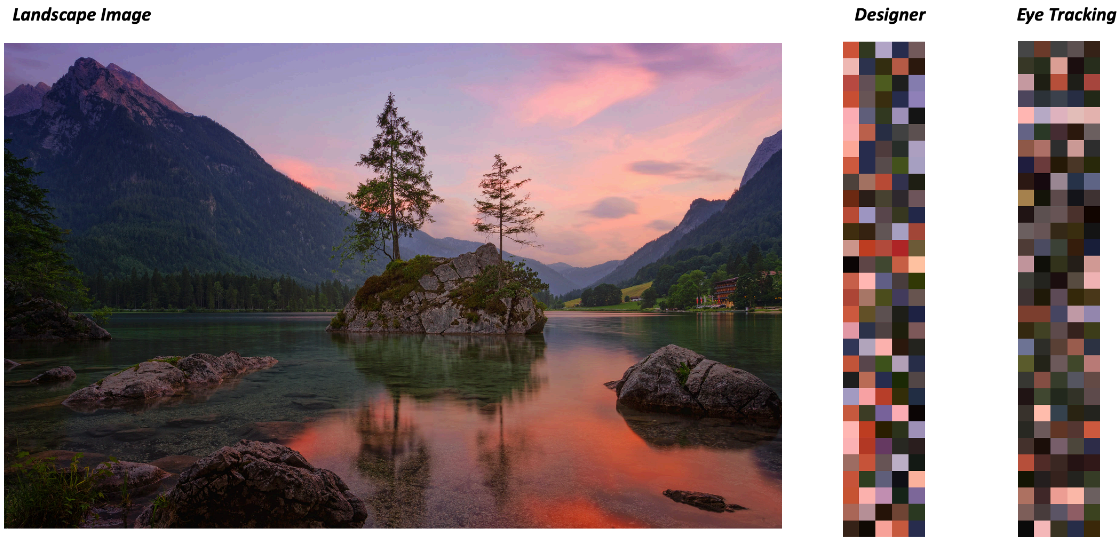


Figure 6-11 Example data representation for one natural landscape images in the experiment. The raw colour palettes obtained visually produced by participants are labelled as *Designer*. The colour palettes generated from the eye-tracking data are labelled *Eye Tracking*.

The performance value of the eye-tracking extraction is 11.79 CIEDE2000 (2:1:1) units, which is bigger than the inter-observer variability (9.33). The performance of the eye-tracking extraction is compared with the performance of the K-mean extraction in Chapter 7. All colour-extraction methods and their performances in this study are described in Chapter 7.

6.6 Summary

In this chapter, using the eye-tracking system for palette generation was explored. The eye-tracking system and the experiment procedure were described in section 6.2. Section 6.3 described the process of generating the colour palettes from the eye-tracking data. Two different measurements were used to test the performance of the eye-tracking extraction method. In section 6.4, the *ET Palette* (5×1 palette summarised from eye-tracking extraction) was compared with the *Visual Data* (5×1 palette summarised from the designer extraction). In section

6.5, the second measurement was used by taking the inter-observer variability as the limit measure. The unprocessed *Eye Tracking* palettes (5×30) was compared with the 5×30 *Designer* palettes (raw data from designer) to obtain the performance value to compare with the inter-observer variability.

Chapter 7. Meta-analysis of the Colour Extraction Methods

7.1 Introduction

Three image-based palette extraction methods have been explored in this study. The first one is by human extraction or the visual method (Chapter 3); the colour palettes were manually generated from the design-based participants in this study. The second extraction method was using K-means clustering to generate colour palettes from images (Chapter 5). Two different colour spaces (CIELAB and RGB) were used in this method and CIELAB was found to be produce palettes that better agree with the visually derived palettes. Eye tracking is the third method which generates the colour palettes from the eye-tracking data provided from the same participants as method one (Chapter 6). The colour palette generated visually by designers is considered as the ideal palette and provides a baseline of the other extraction method. Therefore, the other two methods were compared with the visual method. Two different measurements were used for the comparison. A summary of the comparison between these colour extraction methods and the method performances are described in this chapter. Another possible new method (saliency map extraction) is described at the end of the chapter.

The representative colour palettes extracted from all three extraction methods of one example image are shown in Figure 7-1.

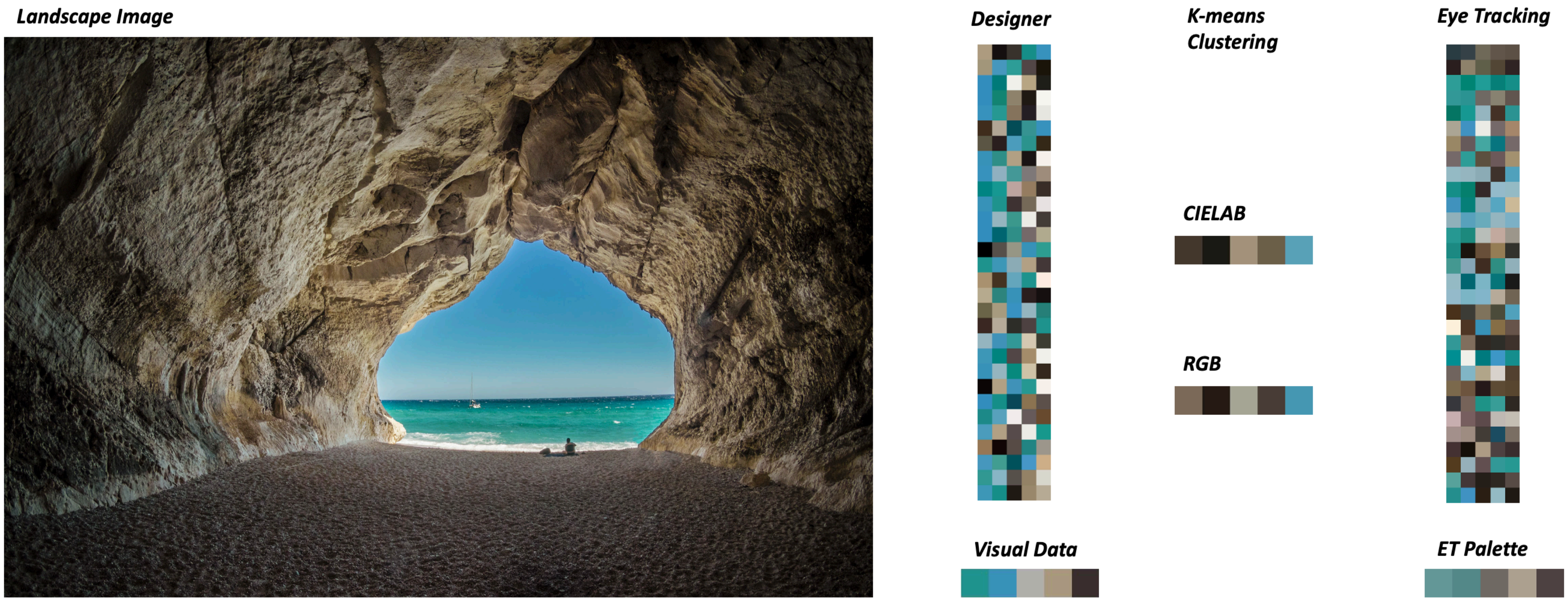


Figure 7-1 Example data representation for one natural landscape images in the experiment. The representative colour palettes are from different extraction methods. The raw colour palettes obtained visually produced by participants are labelled as *Designer*. The *Visual Data* palette is developed from the *Designer* palette. The colour palettes generated from K-means clustering in CIELAB and RGB colour spaces are labelled as *CIELAB* and *RGB*, respectively. The colour palettes generated from the eye-tracking data are labelled *Eye Tracking*. The *ET Palette* is developed from the *Eye Tracking* palette.

7.2 Measurement Method 1: Comparison with the *Visual Data* Palette

The *Visual Data* is the ground-truth data and the baseline in the first measurement method. The colour palettes developed from the other methods (the K-means extraction based in CIELAB and RGB space and the eye-tracking extraction) were compared with the *Visual Data.* The mean colour differences are shown in Table 7-1. The eye-tracking extraction method provides the best results, then the next one is the K-means extraction method within the CIELAB colour space. The K-means method with the RGB colour space has the poorest corelation to the designer selected palette using this measurement. Table 7-2 and Figure 7-2 shows the colour-difference values of each image. More detailed descriptions are listed in section 5.3 and 6.4.

Table 7-1 The method performance using the first measurement by comparing palettes extracted from different methods with the *Visual Data.*

Measurement 1: Method Performance	
Extraction Method	**ΔEp_{00}**
Eye-tracking Extraction	8.84
K-means Extraction (CIELAB)	10.09
K-means Extraction (RGB)	10.65

Table 7-2 The colour difference values calculated by comparing palettes extracted from the eye-tracking data and the K-means clustering using CIELAB and RGB colour space with the *Visual Data.*

Comparison with VD		ΔEp_{00}	
Image	***ET Palette***	***CIELAB***	***RGB***
1	4.32	9.46	6.26
2	8.73	6.13	11.13
3	9.22	8.00	8.05
4	8.20	10.64	9.91
5	7.91	12.22	12.58
6	9.23	8.49	9.20
7	6.18	8.63	9.25
8	7.79	8.83	12.08
9	11.87	9.23	8.30
10	13.96	17.07	18.27
11	5.70	7.09	7.59
12	12.27	10.63	13.52
13	9.47	10.88	11.55
14	9.75	11.45	11.61
15	7.77	11.80	11.54
16	9.61	9.09	9.62
17	7.87	9.78	9.90
18	12.56	12.38	14.17
19	7.12	9.16	9.36
20	8.65	10.31	9.47
21	12.41	17.49	15.94
22	8.33	11.24	13.74
23	10.98	9.90	10.68
24	7.58	11.26	10.71
25	10.38	12.69	11.01
26	6.85	6.76	10.38
27	7.53	7.54	7.07
28	8.06	8.60	9.49
29	7.62	7.16	8.75
30	7.27	8.87	8.30
Mean	8.84	10.09	10.65
Standard Deviation	2.20	2.61	2.62

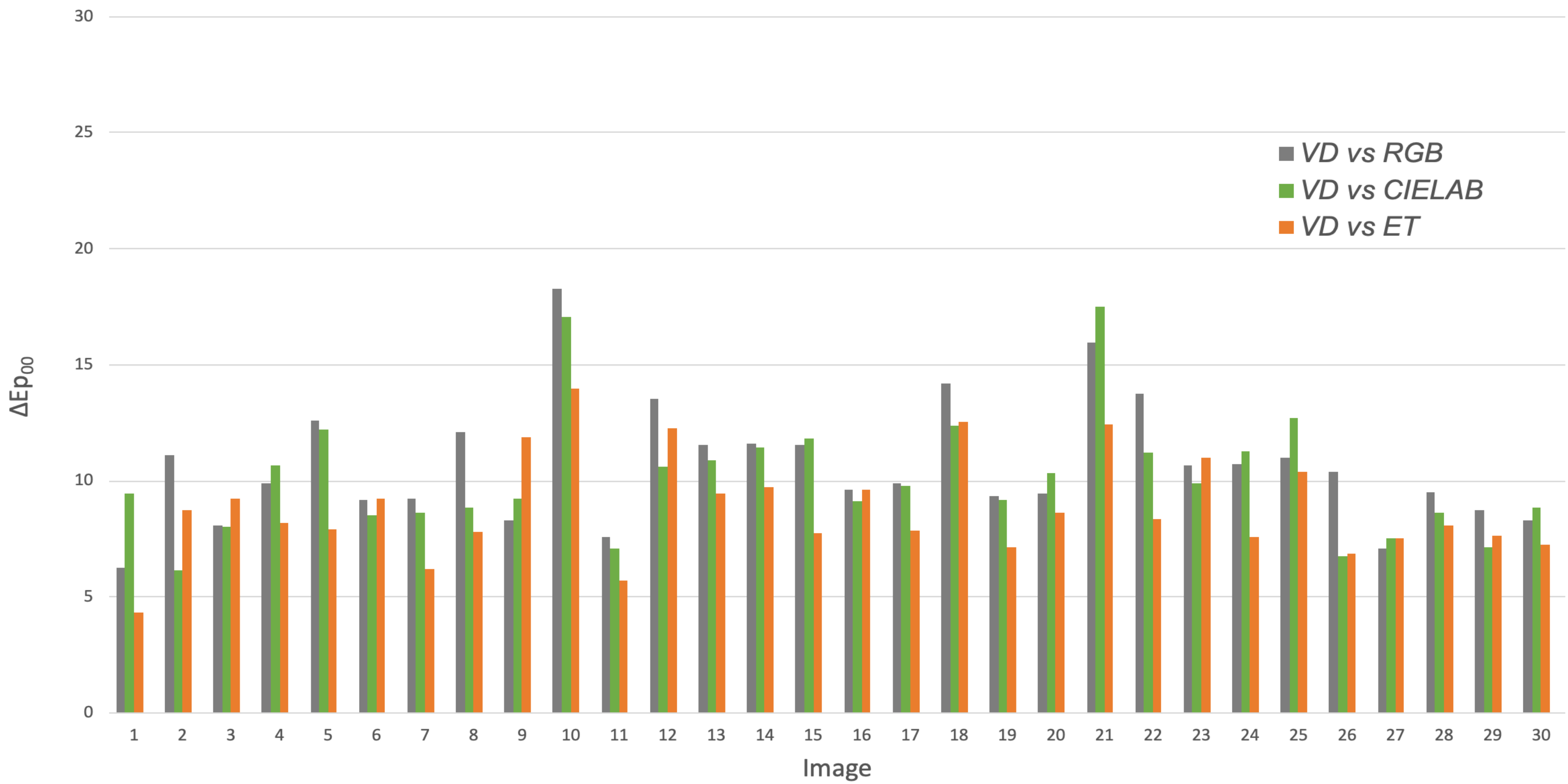


Figure 7-2 Colour difference between *Visual Data* and *RGB*, *CIELAB* or *ET* palettes**.**

7.3 Measurement Method 2: Comparison with the *Designer* Palette

In measurement method 2, the inter-observer variability of the human extraction was used as the limit or baseline on the method performance. The inter-observer variability was operated by comparing each participant's five-colour palette with each other 29 participants' five colour palette to obtain the colour difference values. In other words, each row in the *Designer* palette was compared with the other 29 rows (see Figure 7-1). All 30 images were quantified to obtain the inter-observer variability. Different from measurement 1, the raw palette data from each extraction method were compared rather than the developed colour palette in measurement 2. The *Eye Tracking* palette and the K-means palettes were compared with the *Designer* palette to obtain the performance values of each method. More detailed calculation steps are described in section 5.4 and 6.5. The results are shown in Table 7-3.

Table 7-3 The method performance using the second measurement.

Measurement 2: Method Performance	
Extraction Method	**Performance Value**
Human Extraction (inter-observer variability)	9.33
Eye-tracking Extraction	11.79
K-means Extraction (CIELAB)	13.86
K-means Extraction (RGB)	13.75

7.4 Conclusion

In general, measurement method 1 and 2 drew a similar conclusion; the eye-tracking extraction method provides better performance than the K-means clustering extraction method. However, measurement 1 and 2 provided opposite conclusion about the performance of the K-means extraction within the RGB and

CIELAB colour space. The CIELAB colour space performs better than the RGB space within a statistically significant difference (section 5.3.3, Table 5-3) in measurement 1. In measurement 2, RGB colour space performed slightly better than the CIELAB colour space, but the difference is small. Besides, some work has suggested the CIELAB is preferred to the RGB colour space and the CIELAB performs better than the RGB colour space (Burney & Tariq, 2014; Shmmala and Ashour, 2013). Therefore, measurement 1 might be suitable when testing the performance of K-means extraction method within the RGB and CIELAB colour space.

7.5 An Alternative Automatic Method (Saliency Map Extraction)

The eye-tracking extraction method has the best performance in this study. However, the eye-tracking extraction method requires human observation rather than fully automatic. Recently, researches have explored using computer-generated saliency maps with different-level features to predict the eye fixation without using the actual eye-tracking system (Duan *et al.*, 2014; Judd *et al.*, 2009; Dupont *et al.*, 2016, Huang & Lin, 2019). In 2016, Dupont *et al.* compared saliency maps with eye-tracking focus maps. The GBVS (Graph-based Visual Saliency) algorithm is used to produce the saliency maps automatically from landscape images. The prediction of the saliency map performs better with more natural landscape and fewer buildings. Therefore, a new automatic extraction method can be developed by applying the computer-generated saliency map for natural landscape images. The colour palettes can be extracted from the potential focus area and features of the saliency maps. The saliency map extraction will be developed in future work.

7.6 Summary

This chapter summarised the performance of the three different extraction methods in this research. Two different measurements were used for testing performance. Similar conclusion is received from the two measurements; eye-tracking extraction has the best performance to generate colour palettes from images in this research.

Chapter 8. Discussion

8.1 Summary

Using colour is a particularly creative component of the design process. Landscape is one of the most significant inspirations for designers and artists. 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). In light of the specific colour matching in landscape, designers can build a colour palette to indicate the theme of their plan, for example, to deliver characteristics to the infrastructure or architecture so they can blend in with their natural surroundings and carry the local characteristic of the specific area by applying the colour palettes to the design. However, building a colour palette from scratch needs substantial effort even for experienced designers. It can be rather challenging for novice or non-designer. Therefore, the aim of this research was to develop a colour-palette extraction method, which could help designers generate colour palettes automatically from landscape images. The end purpose is to simplify and enhance the work of designers rather than to replace them.

The first question that was considered is to find out how designers select colours from landscape images to build a colour palette. Thus, a colour-extraction psychophysical experiment (Chapter 3) was carried out to build a ground-truth palette dataset from designer extraction. The colour palette generated visually by designers is considered as the ideal palette and provides a baseline of the other extraction method. Then, a second psychophysical experiment using semantic differential scale (Chapter 4) was carried out to explore the visual difference between the two colour palettes. The MICDM model was used in Chapter 4 to predict the colour difference between two colour palettes. In this study, this model was used to compare the designer extracted palettes to the K-means extracted palettes (Chapter 5) and the eye-tracking extracted palettes (Chapter 6). Besides, the inter-observer variability of the designer-extraction experiment was quantified and considered as another limit measure to test the performance of the K-means and eye-tracking extraction methods. The summary and contributions of each chapter are discussed in Table 8.1.

Table 8-1 The summary of each chapter in this research.

Chapter	Summary
2	**Literature Review** The key aspects of colour, colour knowledge in design and art area, related pervious colour extracted studies were reviewed in sequence in this chapter. Based on the reviewed literature, the research aim and questions were introduced. According to the aim to develop colour extraction method from landscape images, visual colour extraction by designers, colour-palette difference prediction, different colour extraction methods and their performance were set as the research questions. The research questions correspond to the next chapters.

3	**Human (or Designer) Extraction** The questionnaire and the psychophysical experiment have conducted to understand how designers extract colours in this chapter. The results from the questionnaire show that a colour palette is considered as an important element with harmonious colour combinations in the design process to inspire designer and help with design projects. The common size of a colour palette in design was investigated in the questionnaire as well; size 5 was chosen by 70% design-based participants and was used in all extraction methods throughout the entire research. Throughout the experiment, the colour palettes were selected from landscape images and used as the ground-truth dataset for this study. The raw palette for each image was modified into one 1 × 5 palette (*Visual Date* palette) by the order medication metric. The modified colour palettes are considered as the representation of the human extraction. The *Visual Data* palette is considered as the ideal palette and provides a baseline of other extraction methods in this research.

4	**Palette Difference prediction** The visual colour difference between pairs of colour palettes needs to be quantified in this research to test the possible extraction methods performance. A psychophysical experiment using the semantic differential scale method was conducted. Two palette-difference metrics (MECDM and MICDM) from Pan and Westland (2018)'s work with 6 colour-difference formulae were tested using the psychophysical experiment's results. The MICDM within CIEDE2000 (2:1:1) provides the best performance, where the r^2 and STRESS values were 0.86 and 16.93, respectively. The dataset from this experiment (palette size 5) was compared with two other datasets with different size colour palette (size 25 and 45). The results show a better performance with small number palette size (5) using model MICDM. Therefore, the MICDM model was used in this research as the method to prdict the visual colour difference between pairs of plaettes.
5	**K-means Extraction** The extraction method using K-means cluster analysis in two different colour space (RGB and CIELAB) was described in this chapter. The colour palettes obtained using K-means cluster analysis in CIELAB and RGB colour space were compared with the *Visual Data* palettes using MICDM model. The CIELAB colour space performed better than the RGB colour space. Besides, the inter-observer variation of the human extraction method was introduced as the limit measure of methods performance in this research.

6	**Eye-tracking Extraction** This chapter describes the eye-tracking experiment and the process of extracting colour palettes from the eye-tracking data. The “first impression” and colour “standout” were two of the most common reasons for colour selection from images. Therefore, the first five longest fixation points of each observer from the eye-tracking data were selected for each image. The pixel colour of the fixation position was recorded, which became the colour palettes from the eye-tracking system. The raw palette from eye-tracking data of each image was modified into the 5×1 palette using the order medication metric and then compared with the *Visual Data* palette using the model MICDM. The inter-observer variation of the human extraction was used as the limit measure in this method as well.

7	**Meta-analysis of the Colour Extraction Methods** In total, three main image-based palette extraction methods have been explored in this study. The human extraction method was considered as the baseline of the extraction methods, which provides ideal palettes. Thus, the two other methods (K-means and eye-tracking methods) were compared with the human extraction method to obtain the method performances. Two measurement methods were used to compare the performance of three image-based palette extraction methods. First one used *Visual Data* palette as the ideal palettes represent the image and the second used the inter-observer variation as the limit measure. A similar conclusion was determined from the two measurements; eye-tracking extraction provides the best performance for extracting colour palettes from images.

8.2 Limitations

There are several limitations in this research:

- Firstly, there is no defined thresholds for the colour-palette difference prediction model (MICDM). The levels of colour-palette difference values are unknown due to the lack of thresholds. The noticeable, small or big colour difference between pairs of colour palettes is unexplored. In measurement method one, the palettes selected from K-means and eye-tracking methods were compared with the palettes from designers (*Visual Data*) to test the method performances. Therefore, how significant the differences between the different methods is variable in measurement method one.

- Secondly, the limitation of colour-palette size using the MICDM model is unknown. Three datasets with different palette sizes were compared in this research (including size 5, 25 and 45). It appears that smaller size performs better using the MICDM (Section 4.3.6). The more detailed correlation between the palette size and the performance of the MICDM model is unexplored.

8.3 Future Work

The present research has built three main colour-palette extraction methods from the psychophysical experiments and questionnaire conducted in this study. However, based on the findings and limitations of this research, some areas can be improved and design-based application can be implemented in the future.

Future work and possible applications are below:

- In this research, the eye-tracking extraction method provided the best performance. The collection of eye-tracking data requires some human observation. To make the eye-tracking palette extraction fully automatic, the computer-generated saliency maps which predict the eye fixation without using the actual eye-tracking system needs to be explored. The eye-tracking extraction method can be improved by adding the prediction saliency map.

- The fully automatic method improved (from the eye-tracking extraction method) can be applied to future application. An app can be made using the improved eye-tracking extraction method for colour extraction from images which provides the most similar results as the designer selection. The extracted palettes and the corresponding image can be saved into the app as the inspirational mood board for users’ future design projects. Besides, the extracted palette can be linked with similar palettes and the correspondent images using the MICDM model. Various personal palette series can be built for design inspirations.

- Based on the first limitation of this work, future experiment needs to be conducted to test the thresholds of the perceived colour difference between colour-palette pairs. Besides, the order effects in the visual colour-palette prediction needs more exploration.

- How colour-palette size affects the perceived colour difference of colour palettes using the MICDM metric needs to be investigated. The limit of palette size using MICDM model need to be explored.

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Appendix

Appendix A: Publications

This section consists of the published works related to this study.

Journal paper:

Yang, J., Chen, Y., Westland, S., & Xiao, K. (2020). Predicting visual similarity between colour palettes. *Color Research & Application*, *45*(3), 401–408. https://doi.org/10.1002/col.22492

Chen, Y., Yang, J., Pan, Q., Vazirian, M., & Westland, S. (2020). A method for exploring word-colour associations. *Color Research & Application*, *45*(1), 85–94. https://doi.org/10.1002/col.22434

Conference paper:

Yang, J., Westland, S., & Xiao, K. (2017). Developing a Method for Generating Colour Palette from Landscape Images. *Proceedings of 13th AIC Congress 2017*. AIC Congress.

Yang, J., Westland, S., & Xiao, K. (2019). Deriving colour palettes from images of natural landscapes. *Proceedings of the International Colour Association (AIC) Conference 2019*, 351–356.

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RESEARCH ARTICLE

WILEY

Predicting visual similarity between colour palettes

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Abstract

This work is concerned with the prediction of visual colour difference between pairs of palettes. In this study, the palettes contained five colours arranged in a horizontal row. A total of 95 pairs of palettes were rated for visual difference by 20 participants. The colour difference between the palettes was predicted using two algorithms, each based on one of six colour-difference formulae. The best performance (r^2 = 0.86 and STRESS = 16.9) was obtained using the minimum colour-difference algorithm (MICDM) using the CIEDE2000 equation with a lightness weighing of 2. There was some evidence that the order (or arrangement) of the colours in the palettes was a factor affecting the visual colour differences although the MICDM algorithm does not take order into account. Application of this algorithm is intended for digital design workflows where colour palettes are generated automatically using machine learning and for comparing palettes obtained from psychophysical studies to explore, for example, the effect of culture, age, or gender on colour associations.

KEYWORDS

colour, colour difference, colour palettes, design

1 | INTRODUCTION

Data are increasingly being used to optimize design. Recent advances in hardware processing speeds, software, and connectivity are together leading to the availability of huge amounts of data and the ability to process those data in order to generate deep and meaningful insights.[1] As a consequence, we are seeing the emergence of design tools that are driven by machine learning and powered by vast amounts of data. Machine learning is being used to develop, for example, fashion retail forecasting systems.[2,3] However, recent advances in machine learning offer the potential for software to generate original designs. For example, the recent discovery of Generative Adversarial Networks (GANs) has recently received attention[4] for their application to generating fake (but original) images and videos known as "deepfakes" which has some worrying implications.[5] More positive applications of GANs, however, may be the ability to create new original designs and this may pave the way for generative design systems in colour, fashion, and design.[6] Rapid and digital workflows in the operation of these systems will require automatic methods for evaluating and/or comparing colours and designs.[7,8] The work described in this study is concerned with methods for automatically predicting the visual similarity between colour palettes.

Colour palettes are ubiquitous in colour design. A colour palette is a collection of colour patches that represents the colours used in a design or an image. Interest in developing and sharing colour palettes has grown considerably in recent years and has led to a proliferation of digital tools that can generate and share colour palettes. For example, the Adobe Color website[9] allows users to create colour palettes according to different rules for colour harmony; for example, colour palettes that can be described as analogous or complementary.[10] The Adobe website also allows users to generate a colour palette automatically from an image and this can be achieved using a machine-learning technique known as cluster analysis. PaletteGenerator also uses a k-means cluster algorithm to allow users to extract a colour palette from a source image.[11] Other digital resources have focused on allowing users to share their colour palettes with others. For example, the colourlovers website currently incorporates more than 4.6 million palettes that have been generated and shared by users.[12] Colormind is a digital on-line tool that generates colour palettes using deep learning and which allows automatic generation of colour palettes from an upload digital image.[13] Colour Tool allows users to generate colour palettes and incorporates a visualization tool to allow the user to see how the palette may appear in a particular graphical user interface.[14] Many of these websites have associated apps that can be used on smart devices. Typically, these tools generate colour palettes that consist of five colours; however, some allow a variable number of colours to be produced (eg, Palette Generator allows between 2 and 10 colours to be generated automatically from an image). The proliferation of these tools demonstrates a growing demand for tools that can help users to develop harmonious colour palettes quickly and efficiently.

Different colour palettes can communicate different colour meanings or induce different colour emotions.[15] Often colour palettes are generated by designers for practical application based on their knowledge of aesthetics with respect to either a design brief or the designer's own colour preferences.[16,17] Colour palettes may be extracted automatically from an image or a set of images[18] or even generated from a word.[19,20] There are currently no established methods for predicting the visual similarity or visual difference between two colour palettes; the automated design systems that are being developed based on data and machine learning will require the ability to be able to predict similarity between colour palettes.[21,22]

The prediction of colour differences between a pair of colours has of course been of paramount interest to the colour community for nearly a century.[23-25] The last 50 years has seen a number of colour-difference formula being published; the majority of these are based on CIELAB colour space, including CIE94, CMC, and most recently CIEDE2000, which is the current CIE recommendation for small colour differences.[26] CIELAB remains the CIE recommendation for use with large colour differences although there has recently been interest in predicting large colour differences and in using colour-difference metric based on colour-appearance spaces other than CIELAB such as CIECAM02.[27,28] Although evaluating colour differences between a pair of spatially homogenous colours has been widely explored, there has been relatively little research about colour palette difference evaluation. In fact, it can be argued that the case for a pair of spatially homogenous colours is a special case of a more general problem. The more general problem is when we compare a palette of N colours with another palette of M colours. At some point, of course, this problem becomes the problem of image-difference metrics. A number of studies have explored the prediction of image difference. One method, for example, is to calculate the average colour difference on a pixel-by-pixel basis[29] but that assumes that there are corresponding pixels. This will often be the case for pairs of images (where there is, for example, an original image and a distorted version of it); however, this is most often not the case of pairs of colour palettes. More sophisticated algorithms have considered the spatial properties of the images[30] or strongly weight areas in the images that are deemed to be more significant or salient.[29] It is not clear, however, whether such methods could apply to the prediction of palette differences. However, it is clear that the colour-difference formulae that have been developed and tested for use on solid colour patches should serve as the building blocks for image- or palette-difference metrics.

In one recent study, a psychophysical experiment was conducted with pairs of colour palettes, each containing 25 different colour patches.[22] In that study, three different palette-difference metrics were tested using the psychophysical data. The metrics tested were: (1) Single colour-difference model (where the RGB values of each palette were averaged and a single colour difference was calculated between the palettes); (2) Mean colour-difference model (where each patch in one palette was compared to each patch in the second palette and the mean of all of these colour differences was calculated) and (3) Minimum colour-difference model (where each patch in a palette was compared with its closest colour in the other model and the mean of these colour differences was calculated). The coefficients of determination r^2 between each of these metrics and the psychophysical data were 0.35, 0.12, and 0.60, respectively. The Minimum Colour-Difference Model (MICDM) was also the best performing of the three metrics using STRESS, which has become preferred over the coefficient of determination in many colour-difference studies. All of the metrics tested were based on the CIELAB colour-difference formula. Although this finding suggests that MICDM might be useful for predicting visual differences between palettes, there are several questions that emerge. Firstly, how well does the model work when the number of colour in the palettes are much smaller or larger than the 25-colour palettes that were tested? Secondly, since optimized colour-difference formulae such as CIEDE2000 often outperform CIELAB for solid colours, will this also be the case for the MICDM model? Therefore, in this study, a new psychophysical experiment was conducted to obtain the human visual colour differences (ΔV) between colour-palette pairs that each contain only five colours. Note earlier that many of the digital tools that allow users to generate and share colour palettes use 5-colour palettes and therefore it is important to see whether the early work (using 25-colour palettes) applies to these smaller palettes. The MICDM model will be evaluated but will also be extended by testing different colour-difference formulae to compute the colour difference (ΔE) between the palettes.

2 | EXPERIMENTAL

A psychophysical experiment was conducted to quantify the visual difference between pairs of colour palettes that each contain five colours. A semantic differential scale was used as the method to collect the psychophysical data.

2.1 | Participants

A total of 20 participants (9 males and 11 females) with normal colour vision according to the Ishihara test volunteered to take part in the psychophysical experiment. Their age ranged from 25 to 56 years. The purpose of the experiment was briefly explained to all participants when they were recruited.

2.2 | Colour-palette pair selection

A total of 180 colour palettes were obtained from a previous study.[31] Each of the palettes contained five colours that were chosen by participants in that study to represent landscape images. The palettes were displayed with the five colours in a horizontal row (Figure 1 illustrates 40 of the 5-colour palettes). There are 100!/(98!2!) = 4950 possible pairs of these 180 colour palettes but to include all of these pairs would make the experiment too onerous for the participants. Therefore, 90 pairs of palettes were selected from the possible 4950 pairs to ensure that there was a range of differences from small to large (determined informally by one of the authors).

The metrics that are being considered to predict palette colour difference do not consider the order (or the arrangement) of the colours in the palettes. However, eight of the pairs were selected so that the two palettes in each case contained the same colours but in a different order so that the effect of order on the psychophysical data could be explored (see Figure 2).

Further two pairs were selected where the colours and the order of the colours for each pair were identical. For the other 80 pairs of palettes, the colours for each palette in the pair were different from each other.

Five of the 90 pairs were selected randomly and were duplicated in the experiment to assess intraobserver reliability so that in total each participant evaluated 95 pairs of palettes.

2.3 | Display

Colour-palette pairs were displayed on an LED computer monitor (HP DreamColor LP2480zx—a 24-in. LCD Backlit Monitor) and viewed, from a distance of about 1 m, against a uniform gray background colour (CIELAB L^* = 50 approximately). The display of the pairs and the

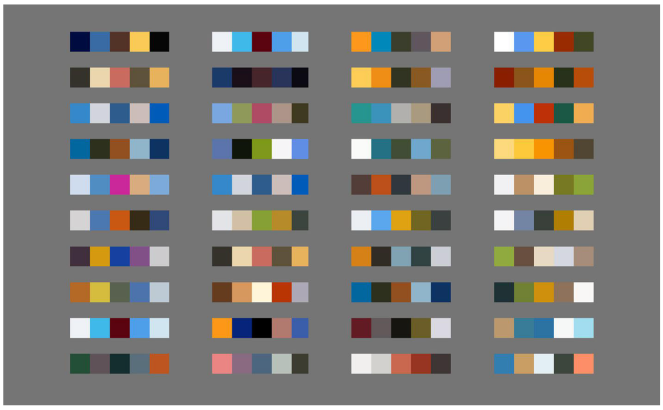

FIGURE 1 A representation of 40 of the 5-colour palettes used in the study

collection of psychophysical data were performed using a computer program written in MATLAB.

2.4 | Experiment design

The experiment was conducted in a darkened room. Each participant was asked to sit in the dark environment for about 5 minutes to adapt to the environment. In the experiment, each participant was requested to view pairs of colour palettes and to indicate for each pair the degree of similarity or difference using a bipolar scale with 10 points (see Figure 2) with one extreme (−5) representing most different and the other extreme (+5) representing most similar. At the beginning of the experiment, participants were shown all of the palettes being used in the experiment (Figure 1 shows one of three screens that the participants viewed) to give them an overall impression of the range. The 95 pairs were presented in a different random order for each participant. There was no time limit for each participant to finish the experiment, but the experiment overall took about 20-30 minutes for each participant. The results were automatically saved as the data of visual colour difference (ΔV) by the software. The results of the five duplicated pairs were excluded from the main results but were instead used to assess intraparticipant repeatability. The ΔV values for each participant were later treated as interval data and were averaged to produce a ΔV value for each pair of palettes (Figure 3).

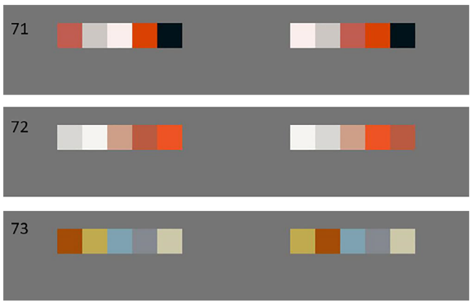

FIGURE 2 Three of the eight pairs where the colours were the same but the order was changed

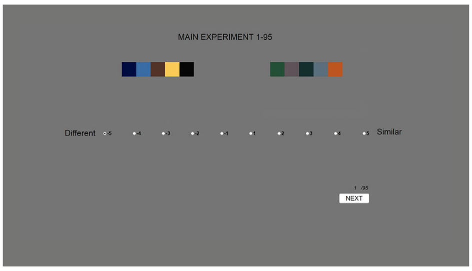

FIGURE 3 Screenshot of the experimental design

2.5 | Analysis

After the experiment, the colours of all 95 pairs of colour palettes (in total $95 \times 10 = 950$ colours) were measured on the screen using a Konica Minolta CS-2000 spectroradiometer. Measuring the colours actually used on the screen in this instance is more accurate than using colour management to predict those colours (since what matters is not that we display specific colours but rather that we know the exact colourimetric specifications of the colours that were displayed). The measured spectral data were converted to CIELAB values using the display white point (CIE $x = 0.3116$, $y = 0.3184$). The CIELAB values were used for subsequent colour-difference calculations. For each pair, the computed colour differences between two colour palettes were examined using one of two metrics that were also used in a previous study (Pan and Westland, 2018). The mean colour-difference model MECDM (referred to as ΔE_{M}) is simply the average of the colour differences that result by comparing each patch in one palette with every other patch in the second palette. Since there are five colour patches in each palette, this is the average, 25 colour differences. The minimum colour-difference model MICDP (referred to as ΔE_{P}) is more complex. The algorithm for calculating ΔE_{P} is according to the following five steps:

1. For each colour in one palette, the five colour differences between this colour and each of the colours in the second palette are calculated. The minimum of these colour differences is recorded.
2. Step 1 is repeated for all five colours in the first palette, for each finding, their closest corresponding colours in the second palette, resulting in 25 colour differences.
3. The 25 minimum colour-difference values are averaged and the mean value symbolized as m_1.
4. Steps 1-3 are repeated, but this time for each of the colours in the second palette. In other words, for each of these colours the closest corresponding colour in the first palette is found. The mean value of these 25 colour differences is symbolized as m_2.

5. The values of m_1 and m_2 are averaged to obtain the visual colour difference ΔE_P between the two palettes

Both ΔE_M and ΔE_P can be implemented using various colour-difference formulae and in this study the following formulae were used: CIELAB, CMC(2;1), CMC(1;1), CIE94, CIEDE2000 (1) and CIEDE2000 (1, 2). Subsequently, two measures were used to analyze the performance of different formulae. The first is regression analysis and the value of coefficient of determination r^2 was reported. The second is the Standardized Residual Sum of Squares (STRESS) measure[32] as shown in Equation 1.

$$STRESS = \sqrt{\frac{\sum (\Delta E_i - f\Delta V_i)^2}{\sum \Delta E_i^2}} \times 100\%, \qquad (1)$$

where $f = \frac{\sum \Delta E_i \Delta V_i}{\sum \Delta V_i^2}$.

3 | RESULTS

Figure 4 shows the distribution of mean rating scores for the 90 pairs of palettes. Note that mean ratings covered almost the entire range (from −4.55 to 4.85).

Figures 5 and 6 show 10 of the palette pairs and their mean visual ratings. In Figure 5, the pairs have relatively large colour difference, whereas in Figure 6 the pairs have much smaller colour difference. These figures are included to give readers an impression of the magnitude and type of colour differences that existed in the palette pairs in this study.

Of the 100 repeat assessments (20 participants × 5 palettes), 36% were exactly the same rating between the first and second attempt. A total of 73% of the repeat assessments were within 1 rating unit of the original assessment. When pooled over all observers, the mean absolute difference between the first and second assessment was 0.45 units.

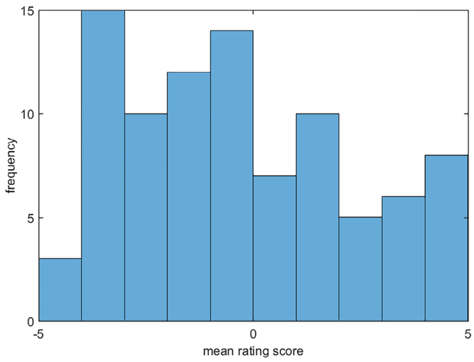

FIGURE 4 Frequency distribution of mean rating scores for the 90 pairs of palettes

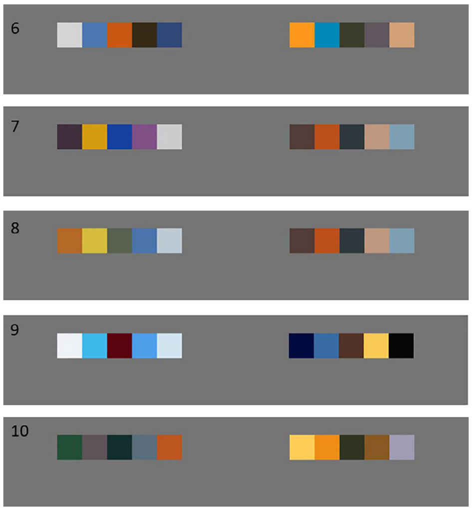

FIGURE 5 Pairs 6 to 10 which had mean visual ratings of −2.4, −3.7, −2.7, −3.45, and −3.2

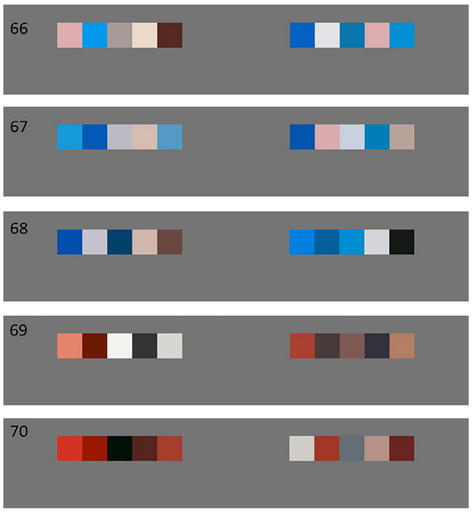

FIGURE 6 Pairs 66 to 70 which had mean visual ratings of 0.3, 3.9, −1.0, −1.45, and −1.45

TABLE 1 Calculation of r^2 and STRESS values for the six colour-difference equations and the two algorithms (MICDM and MECDM)

	r^2		STRESS	
	ΔE_M − MECDM	ΔE_P − MICDM	ΔE_M − MECDM	ΔE_P − MICDM
CIELAB	0.345	0.821	43.10	19.33
CMC(1,1)	0.213	0.768	41.87	22.99
CMC(2,1)	0.256	0.812	44.06	19.31
CIE94	0.281	0.768	45.54	22.69
CIE2000(1,1,1)	0.325	0.832	40.34	18.92
CIE2000(2,1,1)	0.392	0.864	39.29	16.93

The two pairs of palettes that had exactly the same palettes being compared (the same colours in the same order) had average ratings of 4.85 and 4.55, which are close to the maximum rating of 5.0 (when the intraparticipant variability of 0.45 is considered). There were eight pairs that had the same colours but arranged in a different order and the average visual rating was 4.08. Given the intraparticipant variability of 0.45, this does suggest that order or arrangement of colours in the palettes affects the visual differences that were reported.

The models to predict visual difference between the pairs were implemented and the values of r^2 and STRESS calculated between the model predictions and the visual data. Table 1 shows the r^2 and STRESS values for the two models (ΔE_M and ΔE_P) using each of the six colour-difference equations. Note that better performance is indicated by higher r^2 and lower STRESS values.

The order of performance for the two metrics (r^2 and STRESS) is very similar. It is evident that the minimum colour-difference model MICDM performs better than the mean colour-difference model (MECDM). However, according to both r^2 and STRESS, the CIEDE2000 colour-difference equation (with a weighting of 2 of Lightness) gives the best performance when all six colour-difference equations are considered.

4 | DISCUSSION

This work has confirmed earlier work[22] that the minimum colour-difference model algorithm is able to make good predictions of the visual difference between colour palettes. In the earlier study, the palettes contained 25 colours arranged in a 5 × 5 block and the r^2 and STRESS values obtained for the MICDM using CIELAB were 0.60 and 21.0, respectively. In this study, with palettes consisting of five colours in a horizontal row the r^2 and STRESS values obtained for the MICDM using CIELAB were 0.82 and 19.3, respectively. In other words, slightly better performance is reported in this work (with 5-colour palettes) than reported in the earlier study with 25-colour palettes. We have unpublished data for a similar study with 45-colour palettes, where the r^2 and STRESS values obtained for the MICDM using CIELAB were 0.38 and 33.51, respectively.[33] It appears that the MICDM method works better when the fewer colours are in the colour palette. Most applications of colour palettes in design will have relatively few colours in them (typically less than 10) and therefore this work suggests that there can be practical applications of the MICDM algorithm. Note that when there is only one colour in each palette, the well-known colour-difference problem that has been widely studied. The MICDM algorithm in this case simplifies to being the colour difference between the two colour patches. In one analysis of classical colour difference, the STRESS values have been reported for the CIEDE2000 range from about 19-30.[32]

The STRESS value that is reported in this study for the MIDCM algorithm using the CIEDE2000 equation is 16.9 and this was obtained using a weighing of 2 for the Lightness parameter. This study found some evidence that the order or arrangement of the colours in the palette could affect the visual difference and this makes intuitive sense. However, we suggest that the order effect may be relatively unimportant for two reasons. Firstly, the visual colour differences reported in this study for the samples where the order was changed (but the colours in the palettes remained the same) was 4.08 on a scale of −5 to +5 (where 5 indicates maximum similarity). Secondly, the performance of the MICDM algorithm is high (r^2 = 0.86 and STRESS = 16.3) even though this algorithm does not consider the order of the colours in the palettes. Nevertheless, future work may well improve upon the performance of the MICDM algorithm, if the order of colours in the palettes can be included in the algorithm.

The likely application of this work is in digital workflows, where colour palettes are automatically generated. For example, colour palettes have been generated for words or sentences based on semantic knowledge[14] and from automated internet search methods.[21] Other potential applications are in the comparison of colour palettes that are selected by different groups defined by, for example, culture, age, or gender.[34] The method could be used to compare palettes that are generated from various websites (such as Adobe Color and Colormind) and could help to answer questions about how similar the outputs from these different websites are. For many applications, there is no "gold standard", that is, different methods may generate different palettes (given the same input), each of which are equally valid (perhaps as inspiration for, or application to, a design process). However, in other applications, there will be a "correct" or target colour palette (usually derived psychophysically) and in those cases, the metric developed in this work could be used to measure how closely automatically generated colour palettes match the target.

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RESEARCH ARTICLE

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A method for exploring word-colour associations

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Abstract
Strong associations exist between colours and concepts or words. Understanding these associations, sometimes referred to as colour emotions, is important for effective use of colour in art and design. Traditionally the relationships have been systematically explored in experiments where participants scale colours according to bipolar adjectives such as warm-cool. In this article, a method for exploring the relationships between words and colours is suggested and is demonstrated. A psychophysical experiment is described where participants select colours based on words. The data are used to show that many similarities between the word-colour relationships for UK and Chinese participants although some interesting differences are also revealed. The method makes explicit the observation that there is not a one-to-one relationship between words and colours. The method could be used to explore word-colour relationship for specific words and participant groups or could be used to generate ground-truth data for testing methods for automatically generating the word-colour relationships.

KEYWORDS
colour, design, language, semiotics

1 | INTRODUCTION

It is established that strong associations exist between colours and concepts.[1] Colour can also elicit an emotional response and the term colour emotion is often used to describe this.[2] Colours or colour combinations may evoke corresponding feelings such as excitement, energy and calmness.[2-5] It is likely that such colours emotions are triggered by learned associations[6] or shaped by nature although the effect of light on the nonimaging-forming pathways of the human visual systems as a contributing cause cannot be ruled out.[7] It has been noted that people associate blue with calming, depressing, peaceful, quiet, serious, and nostalgic[1]; associate yellow with serene, happy and softly exciting,[8] or warm and sunny; associate green with envy, red with passion, black with death, yellow with cowardice, blue with loyalty.[9] Cherry has explored the link between colour and mood.[5] In terms of object colour at least, cool colours are linked with the moods as calm, serene and comfort whereas warm colours are relevant to stressful and exciting moods.

Colour is differentiated by hue, brightness and saturation.[10] In terms of hue, colours can be categorized into warm colours (eg, orange and red) and cool colours (eg, violet and blue). Brightness and saturation are also significant in colour perception however. Brightness plays an important role in determining lightness or darkness of colour; saturation suggests purity of colour. According to Hemphill, bright colours are linked with positive emotions like happiness, joy and hope.[11] Likewise, Elliot and Maier consider brighter colours as friendly, cultured, pleasant and beautiful.[12] Conversely, dark colours are associated with negative emotions such as boredom and sadness.[13] According to Elliot and Maier, colour may generate associations and responses, and they take meaning of colour as bipartite.[12]

In terms of colour preference there is a huge amount of previous literature. The long history of colour preference research has been described as being "bewildering, confused and contradictory."[14,15] Most recent studies have tended to agree that, on average, people have a preference for cool shades such as blue and a dislike for warmer colours such as yellow and orange but there is still huge individual variation and some systematic differences between gender and culture.[15,16] For example, Choungourian studied people from four countries and identified variance in colour preferences representing individual variation.[17] It was found that the US consumers prefer red and blue, but least like blue-green. However, respondents from Iran and Kuwait preferred blue and green. However, whether there are effects of culture and gender on colour preference, and certainly exactly what those effects are, is still somewhat of an open question.

Although colour can elicit emotional responses, the sorts of associations that colours have are not limited to emotions. For example, the colour pink may be associated with femininity, but this does not necessarily mean that looking at pink (or wearing pink) makes one "feel" more feminine (although it may); it may be that pink is simply associated (cognitively) with the concept of femininity. Such associations are important for the successful application of colour in product design, advertising and marketing.[18] In some case, "meaning" may represent a kind of mental stimulation.[19] Won defined colour meaning in her research thus[20]: "Colour meaning is not about combinations that create pleasing responses (colour harmony), not about the processes with which people understand and react to colour (colour perception), and not about liking a particular colour among alternatives (colour preference). Instead, it is concerned with the meanings that are associated with certain colours." Grieve has argued that colours do not elicit a semiotic response per se[21]; however, this can be interpreted as stating that without the cultural framework in which we live, red, for example, would have no specific meaning and would elicit no semiotic response. Nevertheless, we do live in a cultural framework and empirical studies show that colours do elicit response even when presented without any context.[22] These two views can be reconciled if we understand that colours can have a meaning even when presented without a context because of the associations that become formed when individuals previously encounter that colour in context. People associate colours with experience and memories; a colour may remind someone of a specific object, a certain substance, a person, a period time or a region and this has been referred to as colour association.[23]

Some studies have discussed colour meanings among different cultures and some cross-cultural difference in colour meanings and associations have been identified. The colours themselves may differ because of dependence on lighting conditions, observation position and surrounding especially the adjacent colour and all of these factors can shape the ways of perceiving a specific colour.[19] Moreover, even when people are exposed to the same stimulus colour, the way they perceive that colour, and hence the meanings and emotions incurred, may differ as a result of variability in gender, age, educational background and culture, childhood association and others.[24] Nevertheless, broadly speaking, the empirical data suggest more similarities than differences in colour meanings between cultural groups. Osgood and his colleagues carried out colour-meaning research across 20 countries.[19] They chose participants from high schools and asked them to rate seven (red, orange, yellow, green, blue, black, and white) colours for each of 12 semantic differential items. The results, analyzed using scaling, used "evaluation, potency and activity" as reference, were broadly similar for the 20 countries; blue was the most highly evaluated colour, green and white followed; black and red were the most potent colours; the most active colour was red, whereas gray and black were the most passive colours. In 2000, research indicated some differences and similarities in four cultures (Japan, China, South Korea, and United States).[25] The students from those four countries were asked to summarize the most closely colour associated with 13 words which are often used in describing objects from eight sample colours. As a result, red was associated with love and blue with high quality for all four cultures. Black was consistently associated with powerful and expensive. In contrast, purple associations showed a sharp contrast between three Asian countries (Japan, China, and South Korea) and the United States. In the three Asian countries, purple was associated with expensive products while in the United States purple normally represents inexpensive. Thomas explored cross-cultural similarities and dissimilarities in colour preferences and colour meanings associations in eight cultures (Austria, Brazil, Canada, Colombia, Hong Kong, China, Taiwan, and the United States).[25] In his results, green, white and blue were consistently associated with "calming,", "peaceful," and "gentle" in all eight countries. Green, white and blue were also associated with "pleasant" (Austria, Colombia, United States, and to a lesser extent China and Taiwan) and "beautiful" (Brazil, Hong Kong, China, and United States). However, those three colours also represent unique meanings separately in different countries while they share the meanings in the research. Thomas concluded that no universal meanings can be attributed to specific colours and proposed, instead, a "Spectrum of Colour Meaning."

Colour association may be a more accurate term than colour meaning since it implies that the relationship between colour and concept is the result of a learned association rather than being a property of the colours themselves. Colour association can be divided into concrete and abstract colour associations. Schloss and Palmer argued that colour can be associated with specific objects.[26] For instance, blue is associated with sky, red colour is associated with ripe berries and fruits, and brown is associated with feces and rotten fruit. Moreover, the differences in colour associations between age, areas and environment have been discussed. In Goethe's research,[8] it is suggested that colour associations could be different because of some factors (for instance, women and children, or northern Europeans as opposed to southern Europeans) and hue might not even be the most important element in colour associations.[23] Gage agrees that "the same colour can be found to have quite antithetical connotations in different periods and cultures and even at the same time and place."[1] Tofle et al. also claimed emotional responses evoked by colour as an outcome of learned associations on basis of culture and individual-related features.[6]

In summary, despite Grieve's claim[23] that colours elicit no semiotic response per se, empirical data supports the notion that colours are associated with ideas, concepts, and emotions. Although there is some variation between individuals and between cultural and gender groups, there is a great deal that is agreed upon. These associations may result from human physiological responses or, more likely, from associations with key objects and experiences but nevertheless are relatively robust. Colours may, however, take on quite different meanings and associations when they occur in context (ie, a red dress may take on quite a different meaning to the colour red without any context). Note that this work is restricted to the associations of colour in an abstract sense rather than with any particular instantiation or context. By context, we mean that the colours are not seen as belonging to an object but rather as seen as simple patches (albeit in the context of a background and other colour patches).

The vast majority of experimental work that has been carried out in this field has used a scaling technique called semantic differential scaling.[19] In these studies the participants are presented with a colour and are asked to respond using a slider bar or by otherwise indicating the extent to which the colour is associated with two bipolar adjectives; for example, male-female, soft-hard, old-new. Some computational models have been produced, fitted to the experimental data, that are able to predict the extent to which any given colour can elicit any of these responses.[22] However, in this work, we suggest that there is merit in turning this problem around on its head. That is, rather than starting with a colour and asking to what extent it is, for example, modern, we start with an adjective, such as modern, and ask which colours are associated with this adjective. The reason for this is that in the design process the identification of intended feelings and/or ideas will normally come first, and the designer then seeks colours that can deliver the required message.[20] However, there are obviously a very large number of potential words that could be used as starting points for a colour palette; it is inconceivable that laboratory-based studies such as the one described in this article could provide the required data for this (especially since this might be required in multiple languages). The purpose of this study therefore is to provide some new psychophysical data on the relationship between word and colour. These data could be used as ground-truth data to validate automatic methods that may be developed to predict colours from words.[27,28] In one previously published study, for example, it was suggested that internet scraping could be used to derive the word-colour relationships automatically based on analyses of millions of images.[27] The second purpose of the work is to illustrate the method used in this study to obtain word-colour relationships from laboratory studies and to encourage other researchers to adopt these methods. Finally, we conduct a study with two distinct cultural groups. The aim of the work is not to undertake a cultural comparison (since that would require many more words and more participants than used in the current study). Nevertheless, the comparison of the results of this method used with two cultural groups will enhance the extent to which the method can be evaluated.

2 | EXPERIMENTAL

A total of 30 participants, 15 from the United Kingdom (7 males and 8 females) and 15 from China (9 males and 6 females) all of whom had normal colour vision and were more than 18 years old, were recruited to take part in a psychophysical experiment. The number of males and females in the two groups were approximately equal.

There were two purposes to the experiment:

1. to demonstrate a new method for collecting word-colour associations;
2. to produce psychophysical data that could be used to evaluate the performance of algorithms that automatically generate colour palettes.

In the experiment, 30 target English words were selected. Although to some extent the selection of the 30 words was arbitrary, the words chosen were among the most-frequent words in the English language. A number of websites exist that provide these lists (eg, http://www.wordfrequency.info/).

However, words such as "the" and "a," although frequently occurring, would probably have very weak colour associations. Therefore, 30 words were selected (see Table 1) from a list of the 500 most-frequent words; in selecting the words some attention was paid to whether the words would likely have strong colour associations—in addition, some words were selected because they have been used extensively in other related studies (eg, the word "active"). Chinese translations were made for each of the

TABLE 1 The list of 30 words used in the experiment (note, that before this, each participant was also presented with the words, red, soft, and twelve)

English words	Chinese words	English words	Chinese words
Active	积极的	Married	婚姻的
Bad	坏的	Medical	医学的
Clean	干净的	Modern	现代的
Cold	冷的	Natural	自然的
Cultural	文化的	Old	年老的
Dangerous	危险的	Poor	贫穷的
Dead	死亡的	Powerful	强大的
Female	女性的	Religious	宗教的
Fresh	新鲜的	Rich	富有的
Future	未来的	Safe	安全的
Good	好的	Sweet	甜的
Healthy	健康的	Traditional	传统的
Hot	热的	Unlucky	不幸的
Lucky	幸运的	Urban	城市的
Male	男性的	Young	年轻的

30 words (Table 1). Since typeface may affect the mood or emotion created in the reader, Lanting Hei (兰亭黑) was chosen for the Chinese typeface, since it invokes quite similar responses to Calibri in English from different cultures.[29]

In the experiment, the participants viewed the words (presented one at a time in randomized order) on a PC display (HP DreamColour LP2480zx—a 24-in. LCD Backlit Monitor, max luminance 187 cd/m^2) from a distance of about 80 cm in a darkened room. The UK participants were presented with the English words and the Chinese participants were presented with the Chinese (Mandarin) words. A small reward was given to each participant at the end of the experiment to thank them for their participation.

The words were displayed in a black typeface on a uniform gray (CIELAB $L^* = 50$) background. For each word that was presented (in random order), each participant was requested to perform the following tasks:

1. To select the colour that most represents the word using a typical colour picker.
2. To indicate the strength of association between that colour and the word using a slider bar (in the range 0-100).
3. To then select two more colours that also are associated with the word.
4. To indicate the strength of the association between the three selected colours and the word using a slider bar.
5. To enter text in a box to describe the reasons that they chose the colours that they did (note, however, that in this article this text information has not been analyzed).

No constraints on or recommendations to the participants were made in terms of which colours they selected. For example, participants might choose three colours that were quite similar in response to a word prompt or they might choose three very different colours. Participants were not given any time limit to perform the task. However, each participant took about 45-60 minutes to complete the experiment. Before the experiment, participants were presented with three trial words in order to get used to the paradigm and also to provide some anchor points for the extremes of the slider bars (the use of such anchors has been shown to result in more consistent scaling between participants in such experiments). The three trial words were "twelve," "soft," and "red" and these were chosen because they were thought to have little, moderate, and substantial colour association, respectively. Five Chinese and five UK participants were invited back (1 or 2 days after the experiment) in order to repeat the experiment to provide information about intraobserver variability. The interface for displaying the words, for allowing the participants to select colours, and for automatically randomizing the words and collected the data was written using MATLAB (Mathworks, Natick, Massachusetts (USA)).

The colours selected were automatically recorded as RGB values. After the experiment the colours selected (40 participants × 3 colour selections × 33 words = 3960 colours) by each participant for each word were displayed on the computer screen and measured using a Minolta 2000 Spectroradiometer (Konica Minolta Inc., Chiyoda, Japan) (the spectral data were subsequently converted to CIELAB values using the screen's white point, CIE $x = 0.3116$, $y = 0.3184$).

For each word (and for each nationality, United Kingdom and Chinese) this generated palettes containing 45 colours (3 selections × 15 participants) and 15 colours (1 selection × 15 participants) depending upon whether all three selections from each participant are included or whether only the first selected colour by each participant is used.

The colour measurements of each patch will be used to quantify colour differences within a palette or selection of colours and between palettes. For within a palette, each colour will be compared with each other and the CIELAB colour difference calculated; the mean of these colour differences will be used an indicator of similarity *within* the palette.

For comparing similarity between palettes, a method for quantifying the visual difference ΔE_P between two palettes has been developed by Pan and Westland.[30] The algorithm to calculate the ΔE_P is according to the following five steps given N colours in the palette:

1. For each colour in one palette, the CIELAB colour difference between this colour and each of the colours in the second palette are calculated. The minimum colour difference is recorded.
2. Step 1 is repeated for all the colours in the first palette, for each finding their closest corresponding colours in the second palette, resulting in N colour differences.
3. The N minimum colour difference values are averaged and the mean value symbolized as m_1.
4. Steps 1-3 are repeated, but this time for each of the colours in the second palette. In other words, for each of these colours the closest corresponding colour in the first palette is found. The mean value of these N colour differences is symbolized as m_2.
5. The values of m_1 and m_2 are averaged to obtain the visual colour difference ΔE_P between the two palettes

Smaller values of ΔE_P are associated with greater similarity between two palettes.

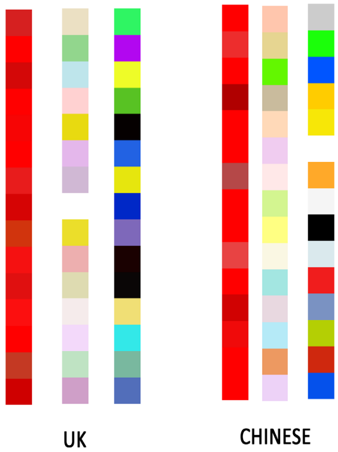

FIGURE 1 The trial results for the UK (left) and Chinese (right) participants. Each row represents the first colours chosen by one of the participants for the words red, soft, and twelve (shown from left to right)

3 | RESULTS

The first colour selected by the UK and Chinese participants for the three trial words are illustrated in Figure 1. The mean strength of association for these words were 98.3 (red), 75.5 (soft), and 33.2 (twelve) for the 15 UK participants and 99.2 (red), 82.0 (soft), and 59.6 (twelve) for the 15 Chinese participants. This confirms the assumption made at the beginning that the words red, soft, and twelve would have strong, moderate, and weak colour associations, respectively. The mean colour difference within each palette was 13.6 (red), 44.4 (soft), and 99.6 (twelve) for the UK participants and

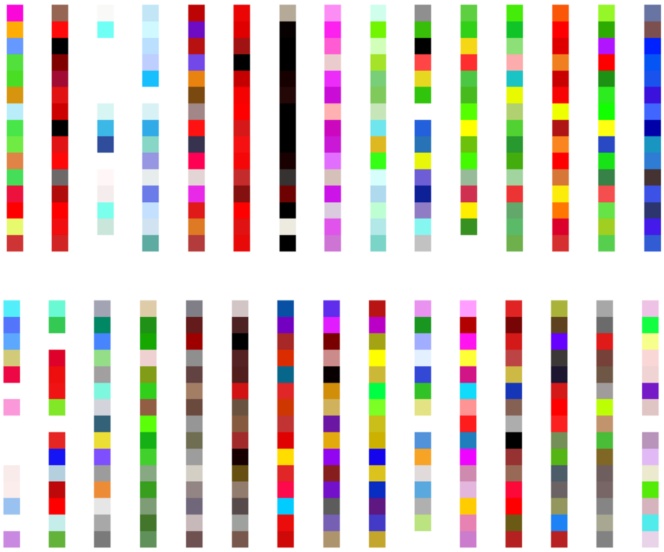

FIGURE 2 The experimental results for the UK participants the first colour selected. The words are, from left to right in the top row (active, bad, clean, cold, cultural, dangerous, dead, female, fresh, future, good, healthy, hot, lucky, male) and in the second row (married, medical, modern, natural, old, poor, powerful, religious, rich, safe, sweet, traditional, unlucky, urban, young)

18.0 (red), 46.7 (soft), and 96.6 (twelve) for the Chinese participants. Based on these three words alone it seems that palettes that are strongly associated with the words contain more self-similar colours than palettes that are weakly associated with the words. This will be tested later for all 30 of the test words.

Figures 2 and 3, respectively, show the first colours selected by the UK and Chinese participants for the 30 test words. For example, for the word "hot" the vast majority of participants selected a red colour whereas for the word "natural" the vast majority of participants selected a green colour. In some cases the colours selected are intuitively what one would expect (ie, for example, there is a large amount of published studies that would equate blue with cold, for example). Note the predominance of pink for female, and the predominance of blue for cold (and compare these to the reds that are generally associated with hot). Visually there are many similarities between the colours chosen by the UK participants and those chosen by the Chinese participants. Even when the colours that were collected were less obviously intuitive (such as the reds and blacks that are associated with bad and the colours associated with active) there is evidence of some common relationship between word and colour. However, some interesting differences can be observed between the UK and

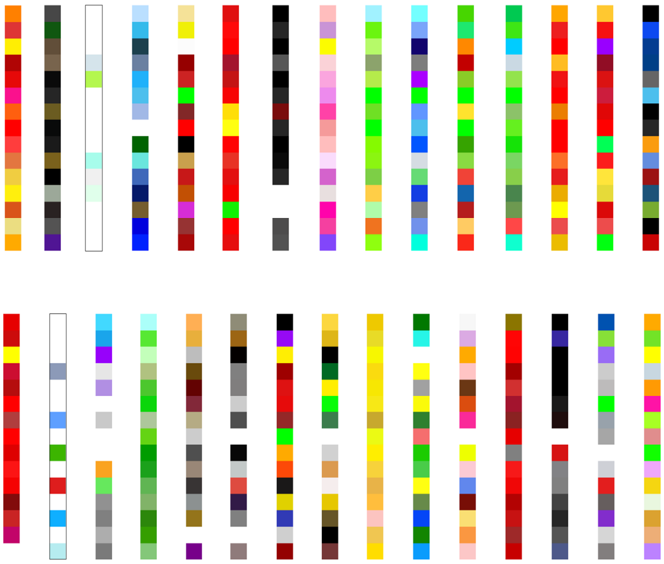

FIGURE 3 The experimental results for the Chinese participants the first colour selected. The words are, from left to right in the top row (active, bad, clean, cold, cultural, dangerous, dead, female, fresh, future, good, healthy, hot, lucky, male) and in the second row (married, medical, modern, natural, old, poor, powerful, religious, rich, safe, sweet, traditional, unlucky, urban, young)

TABLE 2 Visual colour differences ΔE_P between the UK and Chinese colour palettes (smaller values of ΔE_P indicate more similarity between the two palettes)

Word	Difference	Word	Difference	Word	Difference
Dead	5.88	Old	16.73	Male	23.54
Clean	8.89	Dangerous	17.25	Unlucky	23.67
Hot	9.80	Good	17.57	Sweet	25.28
Fresh	12.95	Urban	19.02	Young	26.13
Medical	13.41	Cold	19.02	Future	26.32
Poor	14.38	Female	19.39	Married	27.06
Traditional	14.72	Lucky	19.43	Active	27.64
Natural	15.34	Powerful	20.70	Rich	31.93
Modern	16.10	Cultural	22.35	Bad	36.10
Healthy	16.13	Safe	23.03	Religious	39.64

Note: Based on the first colour selected by each participant for each word.

Chinese colours. For example, red is used much more by Chinese participants in association with traditional and with married. Note also the dominance of red for the word lucky in the Chinese data whereas there is a dominance of green for the same word in the UK data.

However, the similarity between palettes can be quantified using the palette comparison metric ΔE_P. Table 2 lists the ΔE_P values for each of the 30 words where the UK palette is compared with the Chinese palette.

From Table 2 it can be observed that the three words that produced the most similar palettes between the UK and Chinese participants were dead ($\Delta E_P = 5.9$), clean ($\Delta E_P = 8.9$), and hot ($\Delta E_P = 9.8$). The three words that produced the least similar palettes between the UK and Chinese participants were religious ($\Delta E_P = 39.6$), bad ($\Delta E_P = 36.1$), and rich ($\Delta E_P = 31.9$). More work may be needed with the ΔE_P metric to ascertain a threshold value above which palettes may be considered to be visually dissimilar. Words that produce

TABLE 3 Mean strength of association reported by participants

	United Kingdom (1)	United Kingdom (3)	China (1)	China (3)
Red	98.3	95.2	99.2	91.4
Twelve	33.2	23.9	59.6	44.8
Soft	75.5	64.3	82.0	67.2
Active	62.1	58.3	84.9	81.7
Bad	76.3	68.2	82.1	77.4
Clean	85.8	73.9	97.3	88.8
Cold	87.3	83.8	88.1	83.7
Cultural	34.9	35.3	75.8	71.2
Dangerous	87.6	77.9	93.0	86.4
Dead	77.4	71.2	91.5	82.2
Female	75.8	70.6	86.0	80.0
Fresh	79.0	72.9	89.8	86.4
Future	48.4	40.9	83.5	74.0
Good	78.5	63.6	79.7	72.6
Healthy	69.8	65.8	87.2	80.3
Hot	90.7	84.6	89.8	85.1
Lucky	79.0	67.2	90.1	81.2
Male	78.4	63.9	78.7	74.6
Married	68.8	57.5	90.1	79.1
Medical	75.2	72.3	91.6	87.1
Modern	52.6	45.5	79.9	70.7
Natural	82.7	81.8	91.1	83.1
Old	59.2	46.3	86.2	79.8
Poor	58.3	52.2	81.6	71.8
Powerful	70.7	63.8	84.9	73.4
Religious	47.3	45.5	81.4	77.3
Rich	74.6	62.8	89.8	80.3
Safe	55.5	50.9	82.8	73.6
Sweet	63.8	55.1	86.2	80.8
Traditional	49.1	55.7	86.7	79.2
Unlucky	54.4	48.5	81.2	73.6
Urban	68.7	61.3	79.1	75.4
Young	65.0	60.4	82.0	76.5

Note: Data are shown for UK and Chinese participants and based on the first selected colour and on all three colour selections.

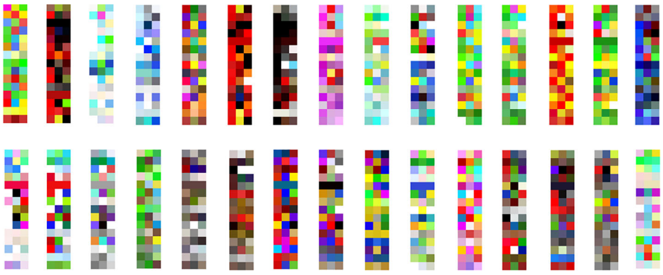

FIGURE 4 The experimental results for the UK participants for all three selected colours. The words are, from left to right in the top row (active, bad, clean, cold, cultural, dangerous, dead, female, fresh, future, good, healthy, hot, lucky, male) and in the second row (married, medical, modern, natural, old, poor, powerful, religious, rich, safe, sweet, traditional, unlucky, urban, young)

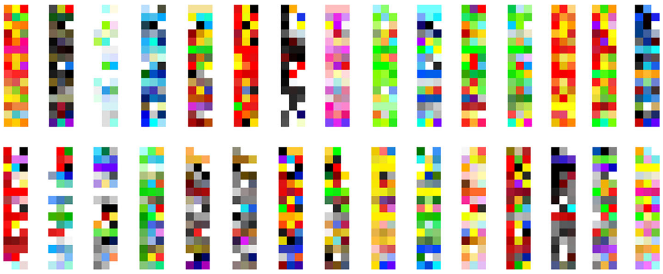

FIGURE 5 The experimental results for the Chinese participants for all three selected colours. The words are, from left to right in the top row (active, bad, clean, cold, cultural, dangerous, dead, female, fresh, future, good, healthy, hot, lucky, male) and in the second row (married, medical, modern, natural, old, poor, powerful, religious, rich, safe, sweet, traditional, unlucky, urban, young)

similar colour palettes for UK and Chinese participants tend to have strong associations. However, words that produce less similar palettes may have weak associations for one or both of the participant groups (eg, the strength of association for the word safe was only 55.5 for UK participants but is 82.8 for Chinese participants). However, the colour associations for the word bad are quite different for the two groups but both groups report strong associations (76.3 and 82.1 for UK and Chinese participants, respectively) for the colours that they select. The strength of the associations are detailed in Table 3. Note that in nearly every case the strength of the association of three selected colours is a little less than for the first selected colour.

The analysis so far has considered the first colour chosen by each participant for each word. Figures 4 and 5 show the colour palettes (3 colours × 15 observers) that result by considering all three colours chosen by each participant. In this figures, each row shows the colours selected by a participant with the left-most colour in each case being the first colour that was selected.

Figure 6 shows the relationship between the self-similarity of the colours in a palette and the strength of the association between word and colour. The left-hand figure shows the average ΔE between the 15-colour palettes that result from considering the first colour selected only and the average strength of the association between the word and colour ($r^2 = 0.20$). The right-hand figure shows the average ΔE between the 45-colour palettes that result from considering all colours selected and the average strength of the association between the word and colour ($r^2 = 0.29$). Correlations are relatively weak but indicate some evidence that palettes that are strongly associated with the words contain more self-similar colours than palettes that are weakly associated with the words. Other metrics that quantify self-similarity of the palettes may show stronger correlations with the visual strength data. For example, the ΔE could be calculated using other colour difference equations such as CIEDE2000.

Recall that five UK and five Chinese participants undertook the experiment twice within a few days in order to investigate intraobserver variability. Intraobserver variability varied greatly between words as would be expected if some words elicit strong associations and other words elicit much weaker associations (or no associations at all). The words dead for example elicited strong associations from UK participants (see Figure 2—where the colours for dead are displayed in the upper row and the seventh column for a visual representation and note that in Table 3 the mean strength association was 77.4). For this word, the mean CIELAB colour difference between the first colour selected by the UK participants during their first and second visit was 2.0. By contrast, the word future has much weaker associations for UK participants (see Figure 2—where the colours for future are displayed in the upper row and the 10th column for a visual representation and note that in Table 3 the mean strength association was 48.4). For this word, the mean CIELAB colour difference between the first colour selected by the UK participants during their first and second visit was 34.6. Participants were more consistent in their choices when the associations between the words and the colours were strongest.

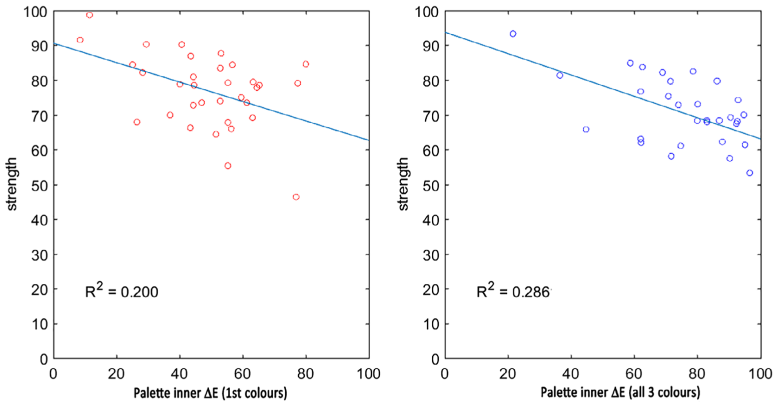

FIGURE 6 Correlation between within-palette Δ*E*s and mean strength of word-colour association for all 33 words used in the study. Note that in general the stronger the association of word and colour, the greater the similarity of the colours within a palette. The left figure shows the correlation for when only the first colour selected is considered (15 colours per word); the right figure shows the correlation for when all three selected colours are considered (45 colours per word)

4 | DISCUSSION

In this article, a new method for exploring the relationships between words and colours has been suggested. The data derived have been used to show, for example, that there are a great many similarities between the word-colour relationships for UK and Chinese participants although some interesting differences were also revealed.

The majority of the published literature explore word-colour relationships by starting from a colour and finding the strength of the relationship between that colour and various terms, often expressed as bipolar adjectives such as weak-strong or warm-cool. It is suggested that there is merit in reversing the experimental paradigm and in this study participants were asked to identify colours that relate to various adjectives. One of the advantages of this method is that it makes explicit the observation that there is not a one-to-one relationship between words and colours. Numerous infographics can be found on the internet that grossly simplify the relationship between colour and meaning, suggesting for example that red means this or green means that. For example, in our data the colours red and blue are found in many of the relationships (see Figures 2–5). The method described in this study could be used by those who wish to explore specific relationships. Nevertheless, for practical use the method is somewhat time-consuming and more efficient methods to obtain the relationships should be sought. In one previous study, it was suggested that internet scraping could be used to derive the word-colour relationships automatically based on analyses of millions of images.[27] Further work may be required to ascertain whether the colour palettes derived using automatic methods are consistent with those derived from psychophysical experiments. In this regard, the data generated in this article can be regarded as test data that could be used to evaluate the performance of internet-based automatic word-colour extraction (the RGB values obtained are available on request from the authors to any researchers who wish to use them). The possibility of automatic extraction of word-colour relationships offers the potential for design tools that allows users to input a word and to be presented with a colour palette—a range of colours that represent that word from which the user can select. Such a system would present obvious and commercially valuable opportunities in design, marketing, and branding. It would also allow a large-scale investigation of differences in word-colour relationships that may exist between cultures, subcultures, or even over time in a way that small-scale laboratory-based studies will always struggle to deliver.

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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 × 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 × 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 × 1 palette VISUAL DATA. This 5 × 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.

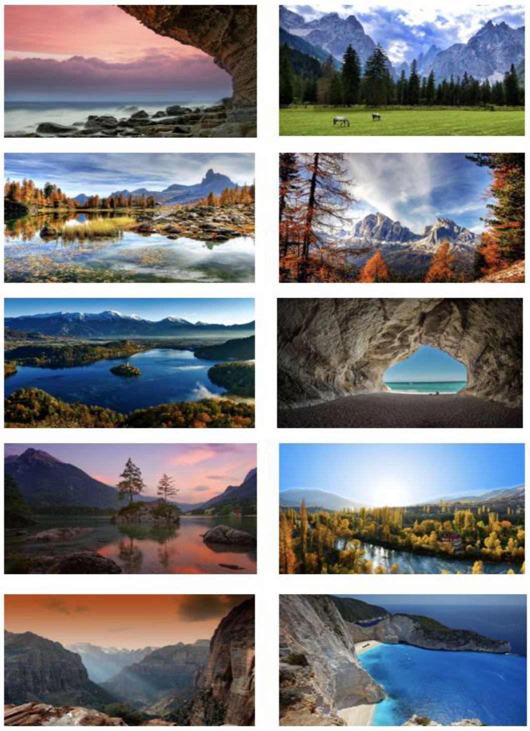

Figure 1: Representation of the 10 natural landscape images used in this experiment.

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.

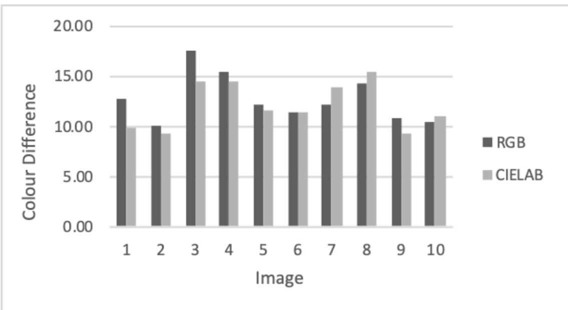

Figure 3: Colour difference between visual data and the computed colour palette from different colour spaces (RGB and CIELAB) for each of the 10 images.

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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Developing a Method for Generating Colour Palette from Landscape Images

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ABSTRACT

In the design process, particularly in landscape, architecture and urban design, colour is a vital element and usually appears in the entire design procedure. Designers generally use a specific colour palette to clarify their ideas or colourize their plans. Moreover, landscape is one of the most significant inspirations for designers; in light of the specific colour matching in landscape, designers can build a colour palette to indicate the theme of their plan. For instance, the typical landscape view with red bricks, green lawn and blue sky as well as the white cloud in the United Kingdom. This suggests that a colour palette derived from landscape can represent particular characteristic features of a place, which can relate to the themes and emotions of the designers. Landscape designers have been working on colour palette generation based on subjective colour assessment. The aim of this study is to develop an objective method to automatically generate colour palettes from landscape images using clustering analysis. A group of landscape images are captured and used as reference database. Clustering methods were applied to those landscape images in both RGB and CIELAB colour spaces. There is some evidence that the clusters that result from CIELAB colour representation are more robust than those that result from RGB colour representation.

KEYWORDS: colour palette, colour imaging, landscape

INTRODUCTION

In nature, the existence of similar and complementary colour arrangements is common. In landscapes, where there is a wide range of colours and colour combinations, this is particularly so, with the yellows, oranges and reds found during sunrise and the complementary blue sky or ocean with the yellowish sunrise. There is abundant colour variation in different regions, which results from various combinations of rock types, vegetation, local architecture materials and soil [1].

Using colour is a particularly creative component of the design process; it often appears throughout the entire design procedure [2]. Colour is thought to influence people's feelings and there are many theories (and much evidence) that support the idea that colour affects human emotion [3]. Colour can therefore play a central role in the visual landscape experience [4] and designers can use this explicitly in design. Designers generally use colour palettes according to the basic rules of colour harmony. However, they also often research and identify specific colours or colour combinations discovered in the characteristics of local landscapes.

This work is concerned with the automatic extraction of key colours in landscapes and the use of those colours to generate a colour palette that represents the colorimetric characteristics of the landscape and could be used in design. A typical application would be to generate a colour palette for use in a building where the architects would like the colours to be consistent with the local landscape and its character. One approach to this would be to segment the image in terms of colour. Unfortunately, there is no universal theory on colour image segmentation and methods that have been used tend to be *ad hoc* [5]. Cluster analysis is often used and one study of its use found that Pillar K-means clustering provided better results than either K-means or Fuzzy C-means clustering [6] although there was no conclusive finding on the relative merits of three colour spaces (RGB, CIELAB or HSV) in which to perform the cluster analysis. A different study, however, concluded that K-means is fast and efficient and segments images by colour in a way that is close to human perceptions [7]. Two recent studies have found that for K-means clustering the use of CIELAB and HSV colour spaces gave better results than RGB [8, 9]. Note, however, that our interest is not exactly in image segmentation but in the extraction of the most common colours in the images.

EXPERIMENTAL

A series of 21 images were captured of an urban landscape during a single day in July at approximately 20-minute intervals between 3pm and 10pm. Figure 1 shows four of these images. The images were captured using a Pentax KP Digital SLR camera mounted on a tripod with a Pentax smc DFA 50mm f/2.8 macro lens. The white-balance was fixed at 6000K and but the shutter speed was adjusted automatically based on the exposure (without the auto-exposure the camera would not be able to capture the dynamic range of the temporal scene).

Figure 1: Four of the 21 images captured at 15:17, 17:17, 19:37 and 21:57.

A LX1010BS lux metre was placed near to the camera and used to measure the illuminance of the ambient sky at the same time that the digital images were captured (see Figure 2). The lux measurements were captured for later analysis but are not used in this paper.

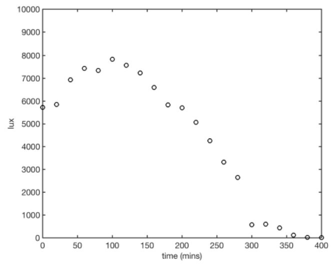

Figure 2: Lux measurements taken at the same time as the digital images (the time is expressed as mins after 15:17, the time at which the first image was captured).

P.

Each of the images were converted from sRGB to CIELAB colour coordinates at each pixel using standard methods [10]. Both sRGB and CIELAB images were processed using MATLAB's *kmeans* command that uses K-means clustering to extract clusters or centroids. A total of 8 centroids were extracted with 10 replicates each time (in which the initial centroids were randomly selected and after which the replicate with lowest error was returned; error in this sense is the distance of the pixels from the centroids). The centroids were ranked according to the populations of the clusters that they represented and the first two of these centroids were selected as being representative of the image.

RESULTS AND DISCUSSION

Figure 3 shows representative colour centroids for two of the images from the series using either sRGB and CIELAB representations. Informally there is a good degree of visual correspondence between the colours in Figure 3 and the two images they represent from Figure 1 but a psychophysical study will be required to better evaluate this.

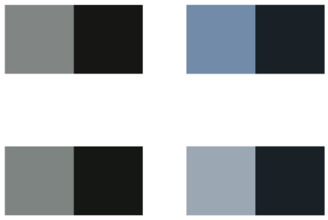

Figure 3: Representative colours for the 15:17 (left) and 21:57 (right) images extracted using RGB (upper row) and CIELAB (lower row) images.

The robustness of the colour-extraction method was assessed by repeated the analysis 6 times. The mean colour difference between the six repeats is then used as a measure of robustness (if the mean DE is zero it means that exactly the same colours are extracted each time). Table 1 shows the mean CIELAB DE for the colours extracted for the four images shown in Figure 1.

Table 1: Colour differences between repeated centroid extractions

	Image 15:17	**Image 17:17**	**Image 19:37**	**Image 21:57**
RGB	8.5	16.4	27.8	15.3
CIELAB	2.0	19.8	18.9	16.9

The colour differences for repeat assessments for Image 15:17 are quite small (ΔE = 2.0 for CIELAB representation) which indicates that the first two components that were extracted from the image were quite stable. However, the colour differences for repeat assessments for some other images is much larger (for example, for Image 21:57 ΔE = 16.9 for CIELAB representation). The most likely reason for this is for Image 15:17, for example, the first two components are dominant and have much greater population than the third component; on the other hand, for Image 21:57, the populations of the first two components are similar to that of the third component which means that when repeated with a different random starting point the second and third component, for example, may flip in order of population. This raises the important question of how many centroids should be extracted for a given image and whether this can be automatically determined for each image. The data in Table 1 are only for four images; however, there is some indication that the use of CIELAB colour leads to more stable estimates of the centroids than does the use of RGB colour space. This tentative finding needs to be explore more using a greater number of images and with images having greater variety.

CONCLUSION

Clustering analysis using K-means is usually used for image segmentation. However, there is evidence that it can be used as a method of automatically extracting key colours from an image. For landscape images this raises the potential that an automatic method could be employed to extract the colour characterization of the landscape images (either for a single image or for a group of related images). In this study both RGB and CIELAB colour representations were used and there was some evidence (albeit based on a small number of images) that more robust extraction of colour clusters occurs with CIELAB colour space and this is consistent with some other published work in image segmentation [8-9]. However, a number of important questions remain. In particular, there is the question of how many colour clusters or centroids should be automatically extracted from an image to form a colour characterization; what effect does this number have on the robustness of the clustering and on the agreement with any visual analysis?

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Appendix B: Questionnaire

This section consists of the questionnaire answers of all 30 participants.

Q. How did you choose those colours? Are there any rules you followed or you did just choose them based on your first impression?

1. I tried to select colours that could represent the overall atmosphere (colour selected from nature such as tree, flowers, stream, mountain and stone, not from artificial things). It relies on person's instinct.
   I select the first colour from the large portion on the image.
2. I think, I've found out background colours and then choose the detail colours. Mood.
3. 1) the colour occupies a very large space; 2) or the colour catches my attention immediately.
4. Evaluate representative colours for the picture.
5. I chose those colours by the feelings the picture gave me and first impression.
6. Based on the space of colours and some by first impression if clear with the type of colours.
7. From the scale of each colour in a picture.
8. Those who take up high proportion or have big influence on the image.
9. First impression.
10. I think in terms of human's nature habit and behaviour, we are more attractive to the 'light' part in the image. (somewhere shinny)
11. According to the colours of main elements in the pictures.
12. I would choose from the colour of the most obvious item (the main focus of the pic) and try to order them with their importance.
13. The colours I saw first and the one I thought were pretty.
14. The colour of environment (light, tree, lake) and first impression.
15. The colour that stood out to me, the most or took up a lot space within the photo.

16. I visually choose a harmonious colour palette with hints of contrasting/ highlighting to make the image stand out.
17. Choose the highlight one and first impression.
18. First impression.
19. Colour tone.
20. I start with the colour accent and choose the gradation that represent the whole image.
21. I chose by my main impression, which colour come into my view quickly. (attracted me first)
22. Tired to pick shades that worked well together to get a representation of the overall image.
23. I chose the colours that were more saturated.
24. First impression for more vibrant/ obvious images.
25. First impression/ what I am most drawn to.
26. I chose the colours based on them standing out + large object.
27. I followed the rule that I should choose the most represented colours, like some outstanding colours or strong contrast colours.
28. Colours which stood out, colours which my eye was drawn to and colours which I liked.
29. Choose the most attractive and the largest scope.
30. First impression. No.

Q. Have you heard of Adobe Kuler (Adobe Color CC)? Do you think that being able to extract a colour palette from an image could be helpful for your future design?

1. 1) After try to use several times then I will decide to use. I would rely on myself to choose colours mainly and usually. Then I will compare colours from the programme. It can be a supportive tool. 2) It would help improve confidence and practice early career designers and person from different background (not design).
2. No.
   I think I can't use it before learning this program.
3. Yes.
   But I don't think that will be helpful for my future design. I don't know the selecting rule of this software, it might select the colour randomly.
4. Not really sure.
   In terms of designing (especially choosing colour), I prefer to rely on my intuition.
5. Yes.
   I thought it would only give me the palette for reference.
6. Yes.
   Yes, it is helpful. I used this way to pick up colour palette for my work usually.
7. Yes.
   Yes.
8. Yes.
   Yes.
9. No.
   I hope so.
10. Yes.
    Yes.
11. Yes, I have heard of it, but I haven't used of it before.
    Yes, I think it is meaningful.
12. Yes and yes.

It would help designers to come up with new ideas. The colour scheme would be benefit while developing new styles.

13. Yes definitely- I currently use Adobe Colour CC.

    Yes.

14. Yes.

    Yes.

15. Yes.

    Yes, you would be able to create a series of designed items that could be linked together.

16. No, I have not heard of it.

    Yes, I believe colour is one of the key components of a successful design& choosing a good colour palette can improve a piece significantly.

17. Yes.

    Yes. The colour collection is important to design.

18. No.

    Yes.

19. No.

    Yes.

20. No, I haven’t.

    Yes, it will be very helpful.

21. Yes.

    Yes, I think so. If I want to design a new product, I can get the colours from relative images.

22. No.

    Yes, I quite enjoy choosing the colours myself but of the tool came up with good solutions, I think it would be useful.

23. No.

    Yes, it could be to help design draw accurate inspiration from landscape images.

24. Yes.

    Yes, would help with complementary text in graphic design.

25. No.

    Yes.

26. No.

    Yes.

27. Yes.

    Yes, it’s very useful and easy to handle. I love to try it in my future design.

28. Yes.

    Yes, it would be useful.

29. No.

    Yes.

30. No.

    Yes.

Q. In your opinion, what is colour palette?

1. It should represent the image of photos with domain, sub colours.
2. Colour palette can show the mood of images and concepts.
3. The panel has some colours on it.
4. Representative picture or object.
5. The colour tones of images and the most representative colour.
6. It is a group of colours which can create harmony phenomenon.
7. Harmonious colours from a picture.
8. Something which shows a harmonious series of colours to assistant people to do design work.
9. It could represent the whole picture's colour by choosing several colours.
10. Colour palette can be used to inspire people with colour selection.
11. The summation of colours.
12. Presenting a style of feeling.
13. It is colours that go well together, and look good on a page.
14. Distinguish different colour.
15. A combination of colours used to make something.
16. The most dominant of frequently used colours in an image or design.
17. Collect colour into same palette, divide them into dark or light colour section.
18. To distinguish different colour species.
19. A series of colours from a design or image.
20. Monochromatic and yellowish pastel.
21. It likes a colour guidance for some specific images or objects.
22. A selection of colours that provide inspiration for design, taken from a common theme or image.
23. A palette of colour representing a theme, mood, atmosphere.
24. Main colours extracted from an image/artwork.
25. A range of colours suitable for an image.
26. A range of colours.
27. It is a kind of summarising tool to help designer have a clear understanding of users' interest colours.
28. A selection of 5 colours which coordinate and complement each other.

29. The colour of things and the contrast.
30. Colours with harmonious match.

Q. Generally, where do you get the colour inspirations for your design?

1. Go to the library or access the internet to see photos and images related to culture like traditional costume, hand writing, patterns, local people's life etc. I am strongly motivated by visual materials. For this reason, I took many photos when I travel. I also use these photos that I took. Sometimes I find things for the inspiration from the academic references or books. But this is not that useful and boring.
2. In general, inspiration motives and sometimes I choose the colour based on my preference and trend.
3. Feeling.
4. Experience: fashion, food, travel, flower, nature, personal emotion, function of the design itself.
5. 1) Does it suitable for my audience? 2) Does it make people comfortable? 3) The function of design. 4) Are these colours harmonious to put together?
6. Pictures taken by me when I travel. Design website (Pinterest).
7. Website, the harmonious colours from a picture in website or from a design of other designers.
8. Beautiful images and other design work.
9. Pictures from the internet.
10. Website Pinterest, images within a particularly theme.
11. From daily life.
12. From pictures and from others' works.
13. Things around me, website Pinterest design layouts.
14. Website, culture, museum, gallery.
15. Nature or other artists.
16. Mainly from natural subjects such as colourful flowers, birds or images of landscapes.
17. Photography.
18. I get the colour inspiration from some images online or books.
19. Photography and nature.
20. Nature and also man-made objects.

21. I usually get the colour from the similar products or the same kind of products by other designers.
22. Varies a lot. I love natural colours, so nature is often used for inspiration but different culture, use of bright colours also inspires me (e.g. I love the bright reds uses in Chinese silks!)
23. I usually go for pastel or monochrome tones as if is personally more usually appealing.
24. Go along with my creative process, no particular inspiration unless something comes along to inspire me in terms of colours.
25. Based on existing artists, and colours which complement each other.
26. Complementary colours.
27. Other people's work but try to change the way to present in case to be similar with others' design.
28. Online research, personal preference or I relate it to the type of project/ time period.
29. Previous product design colours and representative colours.
30. Other design works.

Appendix C: Ethical Approval Certificate

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UNIVERSITY OF LEEDS

Jie Yang
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Arts, Humanities and Cultures Faculty Research Ethics Committee
University of Leeds

26 August 2020

Dear Jie

Title of study: **Developing a method for generating colour palettes from landscape images**
Ethics reference: **LTDESN-088 amendment May 19**

I am pleased to inform you that your amendment to the research application listed above has been reviewed by a delegate of the Faculty of Arts, Humanities and Cultures Research Ethics Committee and I can confirm a favourable ethical opinion as of the date of this letter. The following documentation was considered:

Document	*Version*	*Date*
LTDESN-088 Amendment_form.doc	1	15/05/19
LTDESN-088 recuit email.docx	1	15/05/19
LTDESN-088 Information Sheet.docx	1	15/05/19
LTDESN-088 Informed Consent for Observers.docx	1	15/05/19
LTDESN-088 LightTouchEthicsForm-.doc	1	10/07/18

Please notify the committee if you intend to make any further amendments to the original research as submitted at date of this approval as all changes must receive ethical approval prior to implementation. The amendment form is available at http://ris.leeds.ac.uk/EthicsAmendment.

Please note: You are expected to keep a record of all your approved documentation, as well as documents such as sample consent forms, and other documents relating to the study. This should be kept in your study file, which should be readily available for audit purposes. You will be given a two week notice period if your project is to be audited. There is a checklist listing examples of documents to be kept which is available at http://ris.leeds.ac.uk/EthicsAudits.

We welcome feedback on your experience of the ethical review process and suggestions for improvement. Please email any comments to ResearchEthics@leeds.ac.uk.

Yours sincerely

Senior Research Ethics Administrator, the Secretariat
On behalf of Prof Robert Jones, Chair, AHC FREC
CC: Student's supervisor(s)/ Faculty Research and Innovation Office