Colour statistics of natural and man-made surfaces

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Keywords

Colour, Vision, Statistics

Abstract

The reflectance spectra of natural and man-made surfaces are highly constrained. Statistical analyses have been conducted that confirm that the surface reflectance spectra form a set of band-limited functions with a frequency limit of approximately 0.02 cycles/nm. The reflectance spectra can be represented by a linear-model framework and are adequately described by 6-12 basis functions. However, the spectral properties of surfaces are not so constrained as to allow the human visual system to recover the surface properties from cone excitations. Furthermore, trichromatic colour devices such as scanners and cameras can only capture illumination-specific colour information.

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Sensor Review
Volume 20 · Number 1 · 2000 · pp. 50–55
 · ISSN 0260-2288

Introduction

Traditional image-capture devices such as scanners and digital cameras capture and represent information about real scenes or surfaces based on three broadband photoreceptors often called red, green and blue. The three-dimensional nature of colour is derived from established facts about colour perception in humans and it is important to understand these facts in order to be able to consider the effectiveness of colour representation in trichromatic systems such as scanners.

Figure 1 shows the reflectance curve for a surface, the spectral distributions of a phase of daylight and an incandescent light source, and the colour signals for the surface under each of the two light sources. The colour signal is simply the product of the reflectance of the surface and the energy of the light source at each wavelength.

Colour perception is derived from stimulation by the colour signal of a spatial mosaic of three classes of photoreceptor in the retina, termed short-, medium-, and long-wavelength sensitive cones or L, M and S cones. The peak sensitivity of the L, M and S cones are approximately at 566nm, 543nm and 440nm and the extent of sensitivity of the human visual system spans 380-740nm. Figure 2 shows the spectral sensitivity of the three classes of cone.

Formally, for surfaces under natural illumination we can define the colour signal $S(\lambda)$ thus

$$S(\lambda) = R(\lambda)E(\lambda)$$

where $R(\lambda)$ is the spectral reflectance factor of the surface and $E(\lambda)$ is the spectral energy distribution of the light source, each as a function of wavelength λ. In some sense, at least, the cones sample the colour signal that enters the eye. The cone excitations $\Phi_i (i = L, M, S)$ are given by the integral of the product of the colour signal and the respective spectral sensitivity $\phi_i(\lambda)$ of the cone class thus

$$\Phi_i = \int S(\lambda)\phi_i(\lambda)\delta\lambda.$$

Consequently, it is possible for two non-identical colour signals to give the same set of cone responses. Thus, two spectrally dissimilar surfaces could appear identical under a certain illumination but look different under another illumination. This phenomenon is called metamerism. The

Figure 1 (a) typical reflectance spectrum; (b) relative energy of a phase of daylight (dashed line) and incandescent light (solid line); (c) colour signal of (a) when viewed under the two light sources in (b)

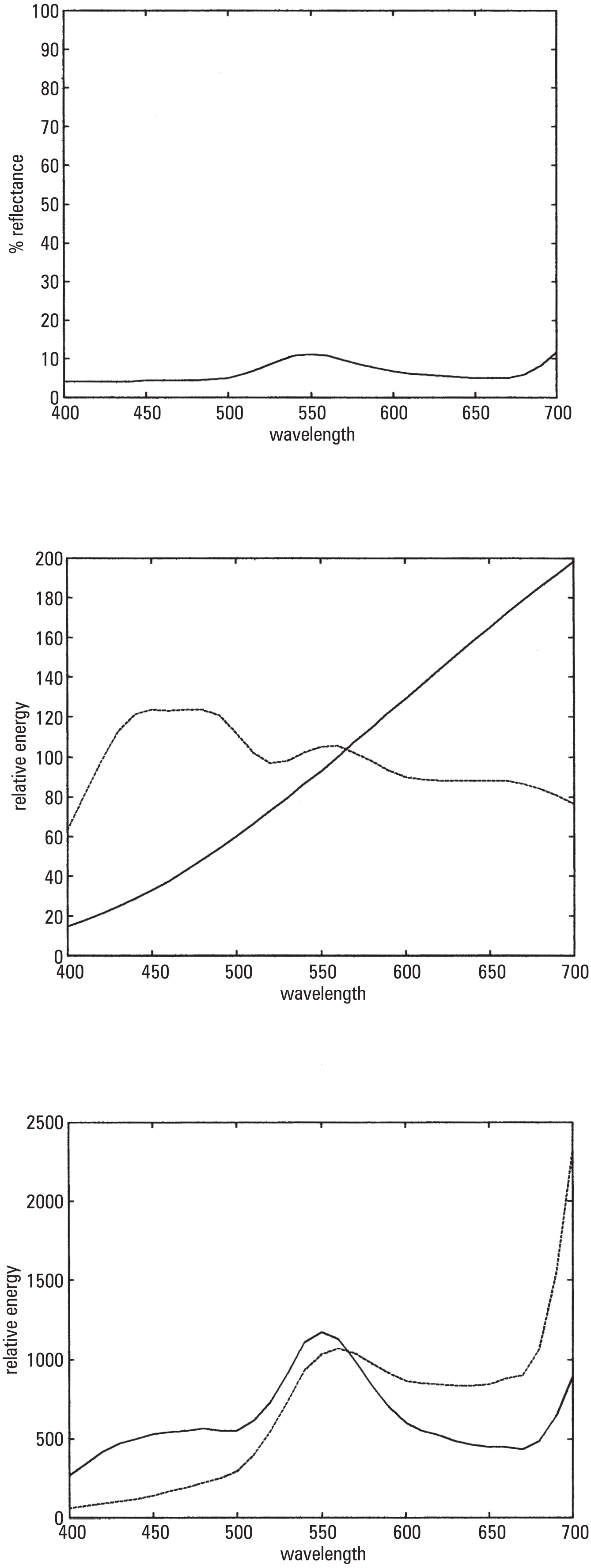
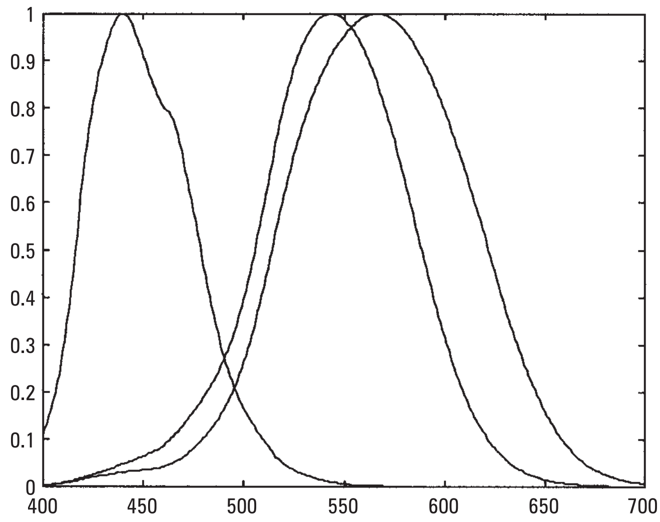


Figure 2 Spectral sensitivities of S, M and L human cone classes



three-dimensional nature of colour perception allows scanners and cameras to capture the colour information from surfaces using three spectrally broad-band sensors rather than measuring the spectral properties of the colour signal.

Another consequence of trichromacy is that the same surface yields different colour signals, and hence different cone responses, when it is viewed under different illuminants. Yet objects appear to us as relatively colour constant; that is, they seem to retain their daylight appearance when viewed under a wide range of different light sources. How is this possible when the colour signal $S(\lambda)$ for a given surface $R(\lambda)$ has a marked dependence on the illuminating source $E(\lambda)$? Many computational models of colour constancy attempt to derive from the cone responses some property that is invariant to changes in the illumination (see Wandell (1997) for a review). It is interesting to consider, therefore, whether it is possible to derive the spectral reflectance of a surface from the three classes of cone responses Φ_L, Φ_M and Φ_S given the constraints on natural surface reflectance functions and light sources.

This study concerns the smoothness of reflectance spectra for natural and man-made surfaces. An analysis of these data provides useful information towards a better understanding of both human colour vision and the limitations of trichromatic colour-measuring devices such as cameras and scanners.

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Linear model framework

One way to quantify the smoothness of the reflectance spectra is to consider their Fourier properties. Fourier analysis allows the reflectance spectra signals to be represented by sinusoids of different spectral frequency (cycles/nm). An estimate of the frequency limit in Fourier space provides an indication of smoothness; the higher the frequency limit in Fourier space the less smooth the spectra are in wavelength space.

An alternative technique to measure smoothness is provided by principal component analysis. Several authors have suggested that naturally occurring spectral-reflectance curves are well fitted by simple models with only a few parameters (Maloney, 1986). Linear models of surface reflectance with n parameters consist of a list of n *basis* surface reflectances $R_j(\lambda)$ for j=1,n. A given surface reflectance $R(\lambda)$ can be fitted using this linear model if it can be expressed as the weighted sum of the n basis surface reflectances thus:

$$R(\lambda) = \sigma_1 R_1(\lambda) + \sigma_2 R_2(\lambda) + \sigma_3 R_3(\lambda) + \ldots + \sigma_n R_n(\lambda),$$

where $\sigma_{j(j=1..n)}$ are the weights (real numbers).

Principal components analysis (PCA) is a multivariate statistical technique that is essentially a method of data reduction. It allows the expression of large data sets with a small number of linear combinations of the original data and a corresponding set of known constants. These linear combinations must be uncorrelated and their constants normalised so that the variance accounted for is not biased by the choice of constant. Thus, principal components, or basis functions, can be computed whose variance is maximum within the original data, and can be used to reproduce a certain percentage of the original data depending on the number of components used.

The claim that most surface reflectances can be fitted using a linear model with few parameters is not a trivial constraint; any function of wavelength across the visible spectrum that ranges between 0 and 1 is potentially a surface spectral reflectance and such functions need not be frequency limited. However, there are well known phenomenological constraints on the statistics of natural surfaces that result from the mechanisms by which natural dyes and pigments interact with light (Nassau, 1983). Figure 1a shows a typical spectrum from the man-made set and it can be observed that it is highly constrained to be a smooth function of wavelength.

Collection and measurement of data

A set of 404 natural surfaces and a set of 279 man-made surfaces were collected. The natural surfaces consisted of leaves, petals and bark from the grounds of Keele University in Staffordshire. The man-made surfaces were composed of individual artists' paints (oil-based) and mixtures of these paints. The spectral reflectance values of the two sets of surfaces were measured between 400nm and 700nm at 10nm intervals using an Ihara S900 reflectance spectrophotometer (0/45 geometry) driven by QC++ colour software.

Fourier analysis of reflectance data

Figure 3a shows a typical reflectance spectrum. Figure 3b shows the Fourier amplitude spectrum of the sample in 3a after the sample was multiplied by a Hanning function. These analyses were carried out using the MatLab software and the Hanning function provided by the MatLab Signal Processing Toolbox was employed.

Since the spectra were sampled at 31 points in the visible range 400-700nm this constrains the maximum detectable frequency to 15 cycles per 300nm or 0.05 cycles/nm.

Estimates of the frequency limit for a particular set were made as follows. The Fourier power spectrum was computed for each sample and a cumulative frequency chart constructed to show the proportion of energy below each frequency. For various candidate frequency limits the proportion of energy contained was computed on a sample by sample basis. The median was computed for the set of n proportions where n is the number of samples in the set. This process was repeated for various candidate frequency limits and the results of this analysis are given in Table I.

We measured frequency limits of between 0.015 cycles/nm and 0.020 cycles/nm for both the natural and man-made surfaces. A similar analysis of a special set of man-made surfaces known as Munsell surfaces showed that 99.9

Figure 3 Example Fourier analysis; (a) typical reflectance spectra (b) Fourier amplitude after Hanning

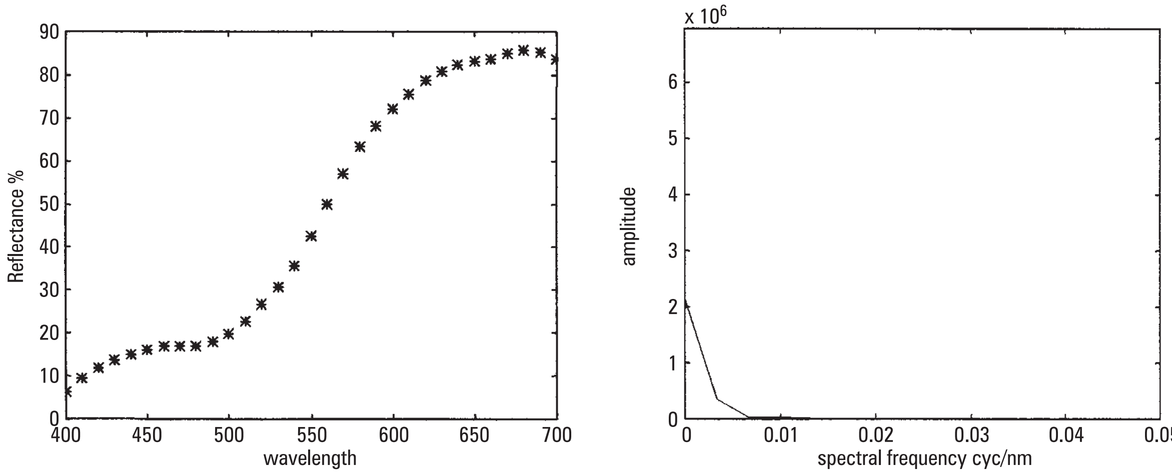


Table I Estimation of frequency limit for natural and man-made spectral reflectance data

	Candidate frequency limit cycles/nm			
	0.005	0.010	0.015	0.020
Data set	**proportion of power below frequency limit**			
Man-made surfaces	0.9966	0.9984	0.9989	1.0000
Natural surfaces	0.9893	0.9958	0.9990	1.0000

percent of the power was at spectral frequencies less than 0.015 cycles/nm (Maloney, 1986).

Principal component analysis

The natural and man-made data sets were subjected to principal components analysis performed using MiniTab. Figure 4 shows the first three basis functions derived from the analyses of the man-made set. The first three basis functions are very similar for each of the data sets and are in close visual agreement with those obtained by other workers (e.g. Skelton, 1997).

Table II shows the proportion of variance accounted for by 1-5 components. The natural and man-made sets allow 95.7 per cent and 97.8 per cent of their variance to be accounted for by a linear model with three parameters.

An analysis of 150 spectral reflectances of Munsell colour samples found that a linear model with only three parameters could account for 0.992 of the variance in the overall fit (Cohen, 1964). A more recent analysis of the 462 samples in the Nickerson-Munsell set found that 0.9916 of the variance could be accounted for by a linear model with only three parameters (Maloney, 1986). In addition, it has been shown that the spectral properties of various phases of daylight can be described with only two to three parameters (Judd *et al.,* 1964).

However, it would be misleading to conclude that reflectance spectra can be adequately represented by three numbers irrespective of the application in which the spectra are used. Despite the fact that three numbers can represent a surprisingly high proportion of the variance, our data are consistent with previous analyses that 6-12 basis functions are really required for an accurate representation (Maloney, 1986). A linear model for representing reflectances has been developed from a group of 5,574 samples of acrylic paint on paper (García-Beltrán *et al.,* 1998). It was found that seven linear components were necessary and sufficient to represent the data accurately. Marrimont and Wandell (1992) have also used linear models to efficiently represent reflectance data and suggest that these could be useful for printer calibration. However, whereas PCA is independent of the sensors in a colorimetric device Marrimont and Wandell describe linear models that are based on the sensors and which could be more efficient for device calibration issues.

Colour gamuts

The *CIE* (Commission Internationale l'Eclairage) tristimulus values *XYZ* were computed for the reflectance spectra of each set using the *CIE* 10° or 1964 standard

Figure 4 First three components of man-made surface set

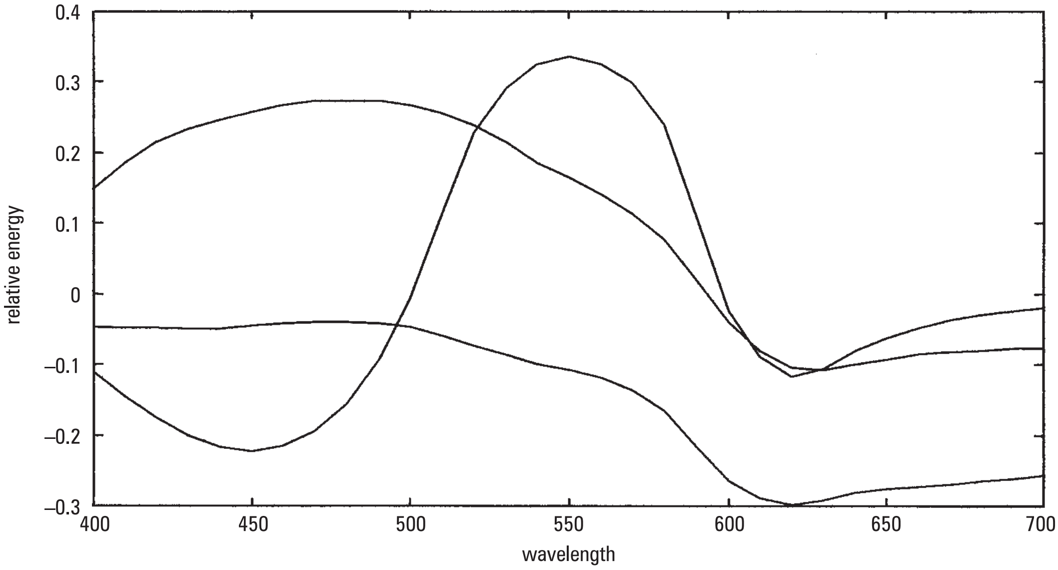


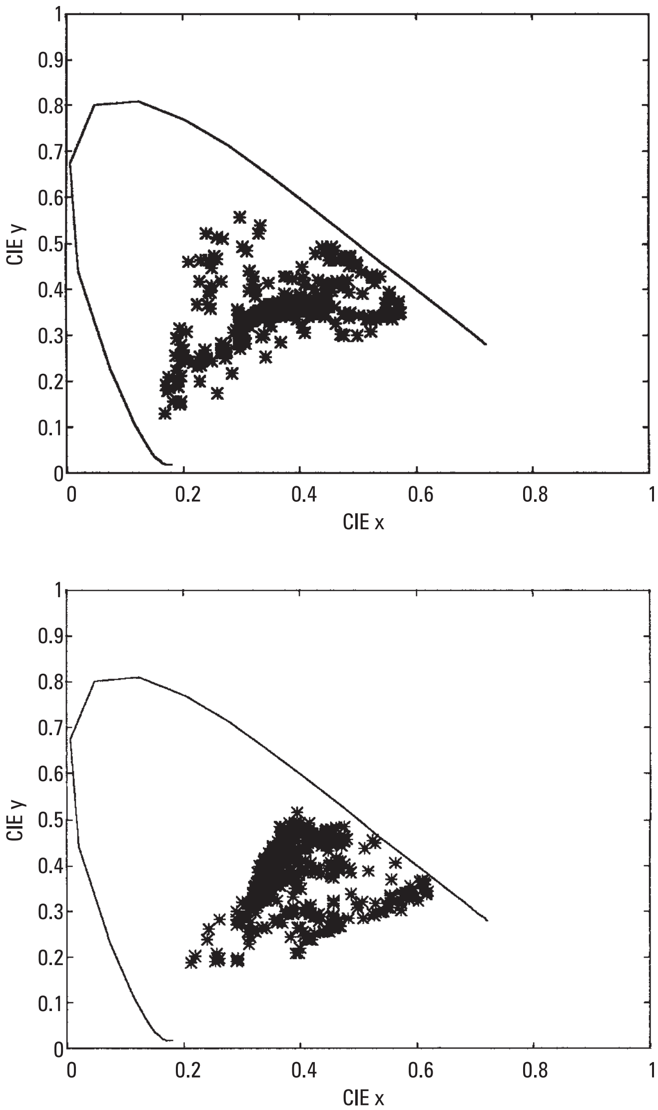
Table II Summary of PCA results

	Number of principal components				
	1	2	3	4	5
Data set	Cumulative % variance				
Pooled	0.733	0.92	0.978	0.990	0.995
Natural	0.685	0.836	0.957	0.984	0.994

observer and *CIE* illuminant *D65*. Figure 5 shows the gamuts of the two sets of data in CIE chromaticity space. The chromaticity coordinates x and y are given by the proportion of tristimulus values $x = X|(X+Y+Z)$ and $y = Y|(X+Y+Z)$ respectively.

There is a relationship between the frequency limit of a set of reflectance spectra and the gamut of colours in a CIE chromaticity diagram (Buchsbaum and Gottschalk, 1984). Thus, a set of frequency-limited functions will allow more and more saturated colours (that is, moving more towards the spectral locus in the chromaticity diagram) as the frequency limit increases. A stimulus on the spectral locus is a point source in wavelength space with an infinitesimally small wavelength interval and thus infinite spectral frequency (cyc/nm). Consequently, it can be observed in Figure 5 that less than half of the space that represents possible colour stimuli is occupied by the gamuts of natural and man-made surfaces. Whilst it is undoubtedly the case that natural reflectance spectra occupy a smaller gamut than the spectra of man-made surfaces, the

Figure 5 CIE xy chromaticity plots under D65 (1964) for man-made (top) and natural (bottom) sets (solid line shows spectral locus)



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chromaticity diagram illustrated in Figure 5 is notoriously non-uniform perceptually and the practical difference between the natural and man-made gamuts (in terms of visual colour difference) is probably quite small.

Discussion

Statistical analyses have been conducted that confirm that the reflectance spectra of natural and man-made surfaces form a set of band-limited functions with a frequency limit of approximately 0.02 cycles/nm. The reflectance spectra can be represented by a linear-model framework and are adequately described by 6-12 basis functions.

However, the spectral properties of surfaces are not so constrained that they allow the human visual system to recover the surface properties from triplets of cone excitations. Although human colour constancy is not in fact perfect (see Foster *et al.*, 1997) it would appear that performance is not consistent with a system that can recover spectral reflectances to the accuracy of just three basis functions. This leaves open the question of how the visual system is able to perform colour constancy for surfaces viewed in different light sources. Furthermore, the analyses confirm that trichromatic colour devices such as scanners and cameras cannot accurately recover surface spectral properties from their illumination-specific RGB values. The amount of information lost from a trichromatic sensor system can be estimated from the statistics of surface reflectance spectra. Thus typical trichromatic image-capture systems only collect information about the appearance of surfaces under the light source under which the image is sampled. The development of imaging systems that can reproduce colour appearance under a wide range of light sources require more than three sensors or need to collect information under more than one light source.

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