Chromatic and achromatic information preserved in natural scenes under illuminant changes

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ABSTRACT

The aim of this study was to determine how much information about surface colour is preserved under changes in daylight illumination. Information was quantified in the sense of Shannon and was estimated separately for chromatic and achromatic attributes of surfaces in natural scenes. Despite the large variation of luminance within natural scenes and the usually restricted gamut of colours, the information from chromatic attributes was only a little less than that from achromatic attributes. As well as providing a basis for object discrimination in natural scenes, chromatic attributes provide an important contribution towards object identification under changes in illuminant.

1. INTRODUCTION

In both natural and built environments, we use colour to help detect and distinguish objects, most notably, from an evolutionary viewpoint, ripe fruits or young leaves among mature foliage[1]. But colour is an imperfect label because we have only three classes of cone receptors in the eye and, in general, spectra need more than three variables to specify them. Thus, even for the perfectly adapted eye, surfaces appearing to have a particular colour under one light need not have the same colour under another[2]. Given this potential for uncertainty, how much information about object identity is actually preserved when the illuminant on a scene changes, and what is the nature of that information?

A priori, it might be assumed that information based on chromatic rather than achromatic attributes would dominate identification performance, simply because of the greater dimensionality of chromatic signals, but a complicating factor is that natural scenes often contain large variations in luminance from point to point, due to differences in the orientation of individual surfaces and in local illumination arising from occlusion and mutual reflectance. These variations and the usually restricted gamut of colours found in natural scenes might therefore suggest that information from achromatic attributes would greatly exceed that from chromatic attributes.

The aim of this study was to compare how much of these two kinds of information, each quantified in the sense of Shannon[3], is preserved under changes in global scene illuminant. Contrary to expectations, it was found that information from chromatic attributes was only a little less than that from achromatic attributes.

2. METHOD

The calculations were based on data acquired with a high-resolution hyperspectral imaging system[4], which was used to record distant and close-up images of a large ensemble of natural scenes drawn from the Minho region of Portugal, which has a temperate climate and variety of vegetation and natural rock formations. Images of scenes were obtained during the summers of 2002 and 2003, almost always under a clear sky or leafy canopy. Particular care was taken to avoid scenes containing object movement. Some typical scenes are shown in Figure 1.

The hyperspectral system, developed from an earlier device[5], was based on a low-noise Peltier-cooled digital camera of spatial resolution of 1344 × 1024 pixels (Hamamatsu, model C4742-95-12ER, Hamamatsu Photonics K. K., Japan) with a fast tuneable liquid-crystal filter (VariSpec, model VS-VIS2-10-HC-35-SQ, Cambridge Research & Instrumentation, Inc., MA) mounted in front of the lens, together with infrared blocking filter. Focal length was typically 75 mm and aperture f/16 or f/22 for depth of focus. The line-spread function of the system was almost Gaussian with SD ~1.3

pixels at 550 nm. Intensity response at each pixel, recorded with 12-bit precision, was linear over the entire dynamic range. Peak-transmission wavelength was varied in 10-nm steps over 400–720 nm; bandwidth (FWHM) was 10 nm at 550 nm, 7 nm at 400 nm and 16 nm at 720 nm. Spectral calibration was verified against test samples[5]. Before acquisition, the exposure at each wavelength was determined automatically so that maximum response was within 86–90% of saturation. Immediately after acquisition, the reflected spectrum from a small flat grey (Munsell N5 or N7) reference surface in the scene was recorded with a telespectroradiometer (SpectraColorimeter, PR-650, Photo Research Inc., Chatsworth, CA), with calibration traceable to the National Physical Laboratory. Images were corrected for dark noise, spatial nonuniformities (mainly off-axis vignetting), stray light, and wavelength-dependent variations in magnification or registration. Spectral-reflectance functions at each pixel were estimated by normalizing the corrected signal against that from the grey reference. Illumination was assumed to be spatially uniform in all scenes: calculations performed with and without cropping of shadows in the scenes yielded similar results[5].

Figure 1: Example scenes reconstructed from hyperspectral data.

In computational simulations, scenes were illuminated by daylights with correlated colour temperatures of first 25000 K and then 6500 K, typical of the north sky and of combinations of the direct sun and sky. The surface colours represented by pixels were labelled within CIELAB colour space[2, 6] in the usual way. Full chromatic adaptation to the sample was calculated from a simple standardized model CMCCAT2000[7]. Colour differences were evaluated with CIEDE2000[8]. Calculations were also made with CMC(*l*:*c*)[8] and other chromatic-adaptation transformations[9].

To calculate the information preserved under changes in illuminant, suppose that each point j in the scene under illuminant 2 is identified with a point i under illuminant 1 having the smallest colour difference. Depending on the particular combination of spectral reflectance and illuminant, this identification may or may not be correct, a situation that can be summarized by a function $p(i, j)$ describing the probability of identifying j with i. From this probability, Shannon's mutual information $I(1; 2)$ was calculated[3, 10]. Informally, $I(1; 2)$ represents the reduction in uncertainty about the sample points under illuminant 1 given knowledge about the points under illuminant 2. Explicitly, $I(1; 2)$ is given by formula

$$I(1;2) = \sum_{i=1}^{n} \sum_{j=1}^{n} p(i,j) \log \frac{p(i,j)}{p(i)p(j)}, \tag{1}$$

where $p(i) = \sum_{j=1}^{n} p(i,j)$ and $p(j) = \sum_{i=1}^{n} p(i,j)$, and n is the actual number of sample points. If the base of the logarithm is 2, then $I(1; 2)$ is expressed in bits. Reliably evaluating Equation (1) can prove difficult when n is very large and the probabilities $p(i, j)$ are very small[11], but an upper bound C on $I(1; 2)$ can be estimated from an analysis of an additive Gaussian noise channel[10]. In principle, if the variances in CIELAB Cartesian coordinates L^*, a^*, b^* over a scene under illuminant 1 are, respectively, var(L^*), var(a^*), var(b^*) and the variances in the differences ΔL^*, Δa^*, Δb^* in coordinates under the new illuminant 2 are var(ΔL^*), var(Δa^*), var(Δb^*), then, in bits,

$$C = \frac{1}{2}\left[\log_2\left(1+\frac{\mathrm{var}(L^*)}{\mathrm{var}(\Delta L^*)}\right)+\log_2\left(1+\frac{\mathrm{var}(a^*)}{\mathrm{var}(\Delta a^*)}\right)+\log_2\left(1+\frac{\mathrm{var}(b^*)}{\mathrm{var}(\Delta b^*)}\right)\right], \qquad (2)$$

providing L^*, a^*, b^* are independent. The differences ΔL^*, Δa^*, Δb^* are not exactly normally distributed, but this is not critical[12]. Equation (2) can be re-expressed in terms of achromatic (lightness) and chromatic (chroma and hue) attributes for use with CIEDE2000[8].

3. RESULTS

Results are summarized in Table 1, which shows, for each of the scenes in Figure 1, the estimated maximum information C in bits partitioned into achromatic and chromatic components under the change in daylight from correlated colour temperature 25000 K to 6500 K. The total information preserved obtained by summing values of C across achromatic and chromatic components (columns 1 and 4) ranged from 9.8 to 12.4 bits. Similar values have been estimated for information derived from cone signals under full von-Kries adaptation under the same illuminant changes[4].

Table 1: Maximum information preserved C in bits for eight natural scenes under a change in daylight from a correlated colour temperature of 25000 K to 6500 K. Scene numbers refer to Fig. 1.

Scene no.	CIELAB attribute			
	achromatic L^*	**red-green** a^*	**blue-yellow** b^*	**chromatic** a^*+b^*
1	6.80	1.98	2.37	4.35
2	6.09	2.43	2.58	5.01
3	6.74	2.31	2.99	5.3
4	5.87	3.00	3.48	6.48
5	6.45	1.89	1.49	3.38
6	5.66	2.39	1.78	4.23
7	5.13	2.83	1.92	4.76
8	7.12	2.25	2.40	4.65
Mean	6.23	2.38	2.38	4.76

On average, 43% of the maximum information preserved was based on chromatic attributes, divided evenly between red-green and blue-yellow. With other combinations of chromatic-adaptation transformations and colour-difference formulas, the percentage of maximum information preserved by chromatic attributes was similar: 38%–40%.

4. CONCLUSIONS

Although the sample of scenes analysed here was small and diverse, the maximum information preserved under an illuminant change did not vary much about a mean of 11 bits. More comprehensive analyses[4] have suggested that the standard deviation of the variation in information over scenes is less than one bit, and this holds over illuminant changes other than the particular one considered here, including changes in daylight from correlated colour temperature of 4000 K to 6500 K and 25000 K to 4000 K.

Despite the anticipated effects of variations in surface orientation and local illumination and the restricted gamut of colours in natural scenes, the information from chromatic attributes was only a little less than that from achromatic attributes, thereby confirming the importance of colour in object identification under illuminant changes, as well as in discrimination[1]. Nevertheless, it was not easy to predict from an informal assessment of the chromatic diversity of scenes which ones would yield the greater information preserved. The information, however, depends not just on chromatic variance, but also on the variance in chromatic differences due to illuminant changes, as Equation 2 makes explicit.

Estimates of the maximum information of the kind described here are based on consideration of physical factors only: the spectral properties of natural reflecting surfaces and illuminants and of the absorption spectra of the eye. Such estimates do not take into account sensory and perceptual limitations on information transmission, although some experimental data suggest that physical factors may provide the principal limit on performance[13]. Interestingly, they do not depend on particular threshold estimates of colour differences, such as $\Delta E*_{ab}$ or ΔE_{00}, according to some metric, since surface-identification performance summarized by information capacity is based on finding the closest match between two surfaces (a "nearest-neighbour" criterion) rather than deciding whether two surfaces are discriminable or not.

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