Information limits on identification of natural surfaces by apparent colour

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Abstract. By adaptational and other mechanisms, the visual system can compensate for moderate changes in the colour of the illumination on a scene. Although the colours of most surfaces are perceived to be constant ('colour constancy'), some are not. The effect of these residual colour changes on the ability of observers to identify surfaces by their apparent colour was determined theoretically from high-resolution hyperspectral images of natural scenes under different daylights with correlated colour temperatures 4 300 K, 6 500 K, and 25 000 K. Perceived differences between colours were estimated with an approximately uniform colour-distance measure. The information preserved under illuminant changes increased with the number of surfaces in the sample, but was limited to a relatively low asymptotic value, indicating the importance of physical factors in constraining identification by apparent colour.

1 Introduction

The perceived colour of a surface depends on its spectral-reflecting properties, the spectral-radiance properties of the illumination, and the spectral-reflecting properties of the other surfaces in a scene. But if variations in the illuminant spectrum are not too extreme, the visual system can compensate through adaptational and other mechanisms for its effects (Arend and Reeves 1986; Bäuml 1999). This is the phenomenon of illuminant colour constancy (Maloney 1999; Foster 2003). Nevertheless, even with a nominally colour-constant visual system, there will usually be some surfaces in a scene that will appear different in colour with a change in illuminant. These residual colour differences are the result of interactions between the illuminant spectrum and surface spectral reflectance that fail to be predicted by the visual system. Some of these failures are related to the phenomenon of metamerism, whereby two surfaces with different spectral reflectances appear identical under one light but not under another (Wyszecki and Stiles 1982).

Are such residual colour differences important in making visual judgments? Suppose perceived surface colour is used to label or identify objects in a scene under different illuminants. As the number of surfaces in the selected sample increases, the information gained from the scene also increases, in a way that can be defined formally by information-theoretic methods. In the presence of residual colour differences, however, there will be errors in identification and a loss in information.

To quantify this information loss, an analysis was made of high-resolution digital representations of rural and urban scenes obtained with a hyperspectral imaging system, which provided estimates of the surface spectral reflectance at 10-nm intervals at each point (pixel) in each scene. In computer simulations, scenes were variously illuminated by daylights of correlated colour temperatures 4 300 K, 6 500 K, and 25 000 K. A random sample of points was drawn from each scene and, after compensation for the effects of chromatic adaptation, was labelled within an approximately perceptually uniform colour space. The reliability of this labelling under changes in illuminant was used to calculate how much information was preserved in each sample.

The information preserved under illuminant changes increased with the size of sample, but was limited to a relatively low asymptotic value, indicating the importance of physical factors in constraining identification by apparent colour.

2 Methods

2.1 Image reflectances

A high-spatial-resolution hyperspectral imaging system was used to acquire data from rural and urban scenes in the Minho region of Portugal. Details of an earlier version of this system have been given in Nascimento et al (2002). The present system used a Peltier-cooled digital camera providing a spatial resolution of 1344×1024 pixels (C4742-95-12ER, Hamamatsu Photonics KK, Japan) with a fast-tuneable liquid-crystal filter (VariSpec, model VS-VIS2-10-HC-35-SQ, Cambridge Research & Instrumentation, MA, USA) mounted in front of the lens, together with infrared blocking filter. For each scene, 33 images were captured at 10-nm intervals with 12-bit intensity resolution at each pixel. The line-spread function of the system was close to Gaussian with standard deviation ~ 1.3 pixels at 550 nm. Images were corrected for dark noise, spatial nonuniformities (mainly off-axis vignetting), stray light, and any wavelength-dependent variations in magnification or registration. The spectral reflectance at each pixel was estimated by normalising the corrected signal against that obtained from a neutral standard consisting of a small planar grey (Munsell N5 or N7) surface placed in the scene whose reflected spectrum was measured with a telespectroradiometer (SpectraColorimeter, PR-650, Photo Research, Chatsworth, CA), with calibration traceable to the National Physical Laboratory. Initially, the illumination was assumed to be spatially uniform in all scenes; the effect of indirect illumination is considered later.

2.2 Representation of surface colours

In computational simulations, scenes were illuminated by daylights with correlated colour temperatures of first 25 000 K and then 6 500 K, or first 4 300 K and then 6 500 K. The surface colours represented by pixels were coded within the three-dimensional colour space CIELAB, commonly used for surface appearance (Fairchild 1998; Westland and Ripamonti 2004). It has coordinates L^*, a^*, b^*, with L^* representing an achromatic attribute, and a^* and b^*, respectively, red–green and yellow–blue chromatic attributes. The procedure was as follows. For each of the three illuminants, the spectrum of the reflected light at each pixel was first converted to tristimulus values. The effects of full chromatic adaptation to the sample were then calculated from a simple standardised model, CMCCAT2000 (see eg Li et al 2002); that is, a fixed linear transformation $\mathbf{M}$, defined by CMCCAT2000, was applied which converted the original tristimulus values X, Y, Z to nominal R, G, B values; these were then scaled by a diagonal (von Kries) linear transform representing full adaptation; and then the inverse transformation $\mathbf{M}^{-1}$ was applied to obtain the 'corresponding colours' X_C, Y_C, Z_C. These X_C, Y_C, Z_C values were then converted to L^*, a^*, b^* values with respect to a reference white achromatic stimulus D65 of luminance 100 cd m^{-2}. Because just-noticeable colour differences do not always have the same CIELAB differences (CIELAB space is perceptually non-uniform), the CIE colour-difference formula CIEDE2000 and the colour-difference formula CMC$(l : c)$ of the Colour Measurement Committee of the Society of Dyers and Colourists (see eg Luo et al 2001) were each used to evaluate the differences ΔE. Additional calculations were made with other plausible values of the chromatic-adaptation transformation $\mathbf{M}$ (Finlayson and Süsstrunk 2000, 2002).

2.3 Information-theoretic measure of object identification

A comprehensive measure of the ability to identify surfaces across a change in illumination, from say illuminant e_1 to illuminant e_2, is provided by the mutual information $I(e_1 ; e_2)$ from information theory (Cover and Thomas 1991; MacKay 2003). Informally, $I(e_1 ; e_2)$

represents the reduction in uncertainty about a sample of surfaces under illuminant e_1 given knowledge about the surfaces under illuminant e_2.

Estimates of $I(e_1; e_2)$ for a fixed pair of illuminants e_1, and e_2 were obtained as follows. Repeated draws of n sample points (pixels) were taken at random, without replacement, from a selected scene. In each draw, each point under illuminant e_2 (CIELAB coordinates L_2^*, a_2^*, b_2^*) was identified with the point under illuminant e_1 (coordinates L_1^*, a_1^*, b_1^*) that was closest to it in colour: its 'nearest neighbour' (the difference between coordinates being defined according to the colour difference ΔE). From these repeated draws, a probability transition matrix was derived, giving the probability $p(i, j)$ of identifying point j under illuminant e_2 with point i under illuminant e_1. From $p(i, j)$, the mutual information $I(e_1; e_2)$ is given by

$$I(e_1; e_2) = \sum_{i=1}^{n} \sum_{j=1}^{n} p(i, j) \log \frac{p(i, j)}{p(i)p(j)} , \tag{1}$$

where

$$p(i) = \sum_{j=1}^{n} p(i, j) \quad \text{and} \quad p(j) = \sum_{i=1}^{n} p(i, j) .$$

If the base of the logarithm is 2, then $I(e_1; e_2)$ is expressed in bits. Numerical estimates will be given later, but, for comparison, upper limits on the information used by observers have been estimated as 29 – 58 bits in some attentive-detection tasks (Verghese and Pelli 1992) and 36 – 49 bits in a partial-report task (Sperling 1960).

Difficulties with the expression given in equation (1) can arise when n is large and the probabilities $p(i, j)$ are small (eg Brillinger 2002). The problem can be circumvented, however, when n is so large that the distribution of colour-code values may be treated as continuous; for then an estimate of an upper bound C on $I(e_1; e_2)$ can be taken from an analysis of the capacity of an additive noise channel, where the noise between input and output corresponds to the differences in code values under illuminants e_1 and e_2. If the noise is distributed normally, then the capacity of this Gaussian channel has a simple formulation in terms of the quotient of the variances of the code values and of the noise (Cover and Thomas 1991). This quotient corresponds in effect to the number of distinguishable code values. Thus, if the variances in the coordinates L_1^*, a_1^*, b_1^* over the selected scene are v_{L^*}, v_{a^*}, v_{b^*} and the variances in the differences $L_2^* - L_1^*$, $a_2^* - a_1^*$, $b_2^* - b_1^*$ are $v_{\Delta L^*}$, $v_{\Delta a^*}$, $v_{\Delta b^*}$, then
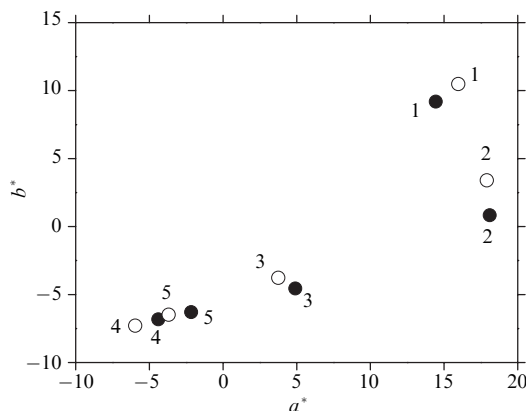
$$C = \frac{1}{2} \left[\log_2 \left(1 + \frac{v_{L^*}}{v_{\Delta L^*}} \right) + \log_2 \left(1 + \frac{v_{a^*}}{v_{\Delta a^*}} \right) + \log_2 \left(1 + \frac{v_{b^*}}{v_{\Delta b^*}} \right) \right] , \tag{2}$$

providing L^*, a^*, b^* are independent. Although the assumption of independence can be justified, neither L^*, a^*, b^* nor the differences ΔL^*, Δa^*, Δb^* are exactly normally distributed. Even so, it may still be shown that equation (2) cannot be exceeded with normally distributed code values and nearest-neighbour identification (Lapidoth 1996).

3 Results
3.1 Mismatches
Figure 1 illustrates how incorrect identifications occur. The solid symbols mark the CIELAB chromatic coordinates (a^*, b^*) of 5 points under the 25 000 K illuminant and the open symbols their coordinates under the 6 500 K illuminant, after full chromatic adaptation. For points 1 – 4, the assumption that each open symbol corresponds to the nearest solid one (ignoring the L^* coordinate) gives the correct identification, but not so for point 5, where the open symbol is closer to the solid symbol for point 4.
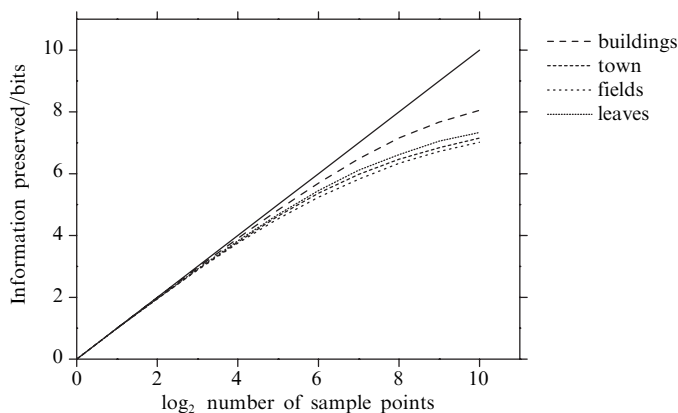
Figure 1. The origin of incorrect identifications. The solid symbols mark the CIELAB chromatic coordinates (a^*, b^*) of 5 points under a daylight of correlated colour temperature 25 000 K, and the open symbols their corresponding coordinates under a daylight of correlated colour temperature 6 500 K (the L^* coordinate has been ignored).

3.2 Information capacity

The curves in figure 2 show the estimated information preserved $I(e_1; e_2)$ under changes in illuminant from 25 000 K to 6 500 K as a function of the logarithm to the base 2 of the number of sample points n. The evaluation of equation (1) was restricted to the range $1 \leqslant n \leqslant 2^{10}$, to avoid the estimation problem (section 2.3). Similar results were obtained with other scenes and scenes cropped to minimise the effects of shadows (as described in Nascimento et al 2002). Under the assumption that performance can be approximated by an additive Gaussian channel, these curves have asymptotes at 9 – 11 bits for these particular illuminant changes. A similar pattern of performance was obtained with changes in daylight illuminant from 4 300 K to 6 500 K.

Critically, the square root of the sum of the variances $v_{\Delta L^*}$, $v_{\Delta a^*}$, $v_{\Delta b^*}$ of the differences in the corresponding values of L^*, a^*, b^* under the two illuminants (see section 2.3) often exceeded 1.0. Since the nominal threshold for a CIELAB (or CIEDE2000) difference to be visually detectable is of this order (or less), it follows that incorrect identifications can occur as a result of clearly discriminable changes in colour appearance, despite full von-Kries adaptation.

Figure 2. Information preserved $I(e_1; e_2)$ under a change in daylight illuminant from e_1 with correlated colour temperature 25 000 K to e_2 with correlated colour temperature 6 500 K as a function of the logarithm to the base 2 of the number of sample points n. The broken curves are for four different scenes and the solid line of unit slope shows the maximum possible value of $I(e_1; e_2)$. Each scene was of size 1344×1024 pixels.

4 Discussion

Because of the nature of physical surfaces and illuminants, there will usually be some surfaces in a scene that will appear different in colour with a change in illuminant. If perceived surface colour is used to label or identify objects in a scene under different illuminants, then these failures in colour constancy will lead to a loss in information. As has been shown here, the information preserved under illuminant changes increases as the number of sample points in the scene increases, but it is eventually limited by an asymptotic value. This asymptote depends, of course, on the magnitude of the change in illuminants. It also depends on the nature of the scenes, although the effect seems not to be large.

Information capacity was estimated here for a perceptual colour space with an approximately uniform colour-difference metric and for the completely adapted eye. How the effects of adaptation are estimated depends to some extent on the nature of the chromatic-adaptation transformation described in section 2.2. Replacing this transformation by one that corresponds to the adaptation of more spectrally sharpened colour mechanisms (Foster and Snelgar 1983; Finlayson and Süsstrunk 2002) may lead to an improvement in performance. Even so, the information capacities described here define relevant physical limits to visual performance, which are rarely considered in experimental studies of surface-colour-matching ability (cf Nascimento et al 2004).

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