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Effectiveness of Digital Camera Sensors in Distinguishing Colored Surfaces in Outdoor Scenes

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Abstract: Five camera sensors were tested in simulations with hyperspectral data from 50 outdoor scenes. There was a marked variation across sensors in the estimated number of distinguishable colored surfaces, unpredicted by previous related estimates.

OCIS codes: (280.4788) Optical sensing and sensors; (330.1710) Color, measurement; (330.6180) Spectral discrimination; (110.3055) Information theoretical analysis

1. Introduction

Using color to classify the elements of a scene is a convenient and efficient solution to many image-processing tasks, including remote sensing, image indexing, and object tracking. But success in any particular classification task is ultimately constrained by the properties of the trichromatic digital camera used to image the scene. For any distribution of reflected spectral radiance across a scene, the triplet of red, green, and blue (R, G, and B) values at each image pixel depends on the spectral sensitivities of the camera sensors and on the level of noise associated with each.

The aim here was to estimate how effectively different camera sensors distinguish the elements of a sample of outdoor scenes solely on the basis of their color. Simulations were based on hyperspectral images, and, as in [1, 2], the spatial properties of the cameras, including demosaicking and size of sensor array, were not considered. The effectiveness of a sensor was quantified by the number of surfaces that could be distinguished. This experimental measure is a generalization of the notion of color sensitivity or input gamut [3-7], normally defined for uniformly sampled colors in some theoretical color space (and sometimes expressed as a percentage of the maximum number, e.g., 256^3, possible [1]). The difference between the two kinds of sample spaces, i.e., outdoor scene colors and theoretical color spaces, is that outdoor scenes rarely contain uniformly distributed colors, being dominated by the browns, greens, and blues of the earth, vegetation, and sky [8]. Yet it is not so much the reduced range of sensor responses that affects the distinguishability of surfaces as the probability of different response values varying within that range [9], owing to differences in the relative abundances of outdoor scene colors. Thus, where triplets of R, G, and B values are sparse, there is little risk of confusing one surface with another, but where triplet values are dense, the risk of confusion is high. Conveniently, Shannon's channel-coding theorem [10] provides a simple way to estimate the number of distinguishable colored surfaces from estimates of the differential entropy of the colors.

In computational simulations, radiance spectra were generated from a set of 50 hyperspectral images of outdoor scenes under a standard daylight. Estimates of the mean number of distinguishable colored surfaces were obtained for five sensors used in commercial digital cameras and, for comparison, for the human eye [2].

The present work should be differentiated from a previous analysis of optimized sensor spectral sensitivities for standard object spectra [11] and from an analysis and ranking of the effectiveness of sensors in identifying colored surfaces in outdoor scenes undergoing changes in illumination [2].

2. Sensor signals and mutual information

Suppose that the spectral sensitivities of the R, G, and B sensor elements (i.e., the combination of lens and color-filter transmittance and photodetector quantum efficiency [12]) are, respectively, $s_R(\lambda)$, $s_G(\lambda)$, and $s_B(\lambda)$ at each wavelength λ, with maximum normalized to unity. Suppose, further, that the scene to be imaged is spatially uniformly illuminated by a fixed illuminant with incident spectral radiance $e(\lambda)$ and that the effective spectral reflectance [13] at each point (x, y) is $\rho(\lambda; x, y)$. The reflected spectral radiance is then given by $c(\lambda; x, y) = e(\lambda)\rho(\lambda; x, y)$. (The assumption of uniform illumination is not necessary, but is included to allow comparison with previous analyses [2]; see also [13].) In the absence of noise, the triplet of values r, g, b at each point x is given by

$$r = \int s_R(\lambda)c(\lambda; x, y)\mathrm{d}\lambda, \quad g = \int s_G(\lambda)c(\lambda; x, y)\mathrm{d}\lambda, \quad b = \int s_B(\lambda)c(\lambda; x, y)\mathrm{d}\lambda, \tag{1}$$

where the integrations are taken over the visible spectrum, and response linearity is assumed [12], without saturation. The triplet of values r, g, b may be treated as an instance of a trivariate continuous random variable U with probability density function (pdf) f_U, say. The differential entropy $h(U)$ of U is defined [10] by

$$h(U) = -\int f_U(u) \log f_U(u) \mathrm{d}u, \tag{2}$$

where the integration is over the response range of the sensors, and $h(U)$ is in bits if the logarithm is to the base 2.

The variable U represents the sensor response without noise. Suppose, now, that noise is included. Assume that it is additive and represented by a trivariate continuous random variable W with pdf f_W, say. Its entropy $h(W)$ is defined in the same way as in (2). Let $V = U + W$. Provided that U and W are independent [4], the mutual information I between the noise-free and noisy variables U and V is given [10] by $I = h(U) - h(W)$. By Shannon's channel-coding theorem [10], the maximum number of colored surfaces in the scene that can be distinguished with this set of sensors is 2^I. For independent channels, this number is much less than $(\mathrm{SNR})^3$, where SNR is the signal-to-noise ratio (mean divided by standard deviation [12, 14]).

3. Differential entropy estimators

Scene reflectances were taken from 50 hyperspectral images of natural rural and urban scenes; see [13] for details of calibration and accuracy and [15] for thumbnail images. The illuminant on each scene was a standard daylight with a correlated color temperature of 6500 K [1], representing approximate average daylight. The camera sensor spectral sensitivities were as follows: an Agilent CMOS sensor array from a Concord EyeQ digital camera, a Foveon X3 sensor array from a Sigma SD9 digital camera, a Kodak frame-transfer CCD sensor array from a Kodak DCS-460 digital camera, a CCD sensor array from a Nikon D1 digital camera, and a Sony interline CCD sensor array from a Hewlett Packard 618 digital camera. Data sources are listed in [2], along with plots of the spectral sensitivities of the sensors, and for the photoreceptors of the eye.

The differential entropy $h(U)$ of each scene was estimated by a k-nearest-neighbor estimator [16, 17], known to be efficient, adaptive, and have minimum bias [18]. It was used in an offset form that converges more rapidly than the original [2, 19]. The noise pdf f_W was assumed, as elsewhere [4], to be Gaussian, with covariance matrix K determined by the SNR, which was set nominally to 100 [14]. The signal in the SNR was taken as the mean sensor response for the scene. Although smaller [12] or larger [1, 5] values could have been used for the SNR, the choice is unimportant since, as long as it is constant, it does not affect the ranking of the sensors. A more comprehensive model of noise based on an affine transformation [4] was not used.

4. Numbers of distinguishable surfaces

The plot of Fig. 1 shows the logarithm of the mean estimated number of distinguishable colored surfaces for the five camera sensors and the eye. There was a marked variation over sensors, with the difference between the largest and smallest estimate reaching 0.91 on the logarithmic scale, corresponding to a ratio of 8.2 on a linear scale.

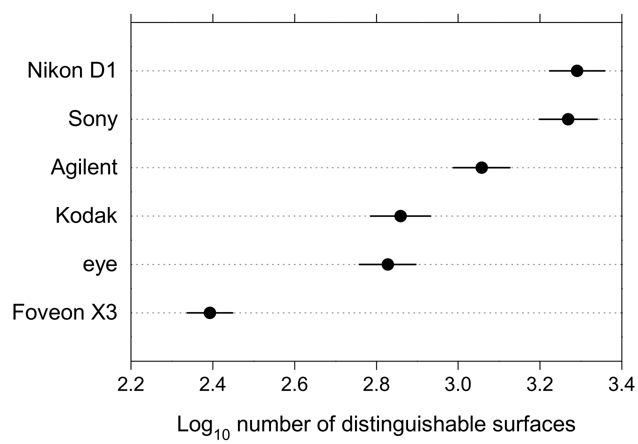

Fig. 1. Logarithm of the mean estimated number of distinguishable colored surfaces for five camera sensors and the human eye. Symbols show means over 50 outdoor scenes and horizontal bars show ±1 standard error of the mean.

5. Discussion

By comparison with conventional input gamut estimates, the number of colored surfaces distinguishable by digital camera sensors in outdoor scenes was found to be low, with a mean value of about 2.2×10^3, excluding data for the eye. Previous analyses [1, 4, 5], based on uniform sample gamuts and larger SNRs, have generated estimates ranging from 1.9×10^4 to 8.4×10^6. It should be noted that the values reported here do not change with the introduction of a noise-free smooth invertible transformation of the sensor signals, such as a colorimetric transformation to CIE coordinates, since mutual information is invariant under such transformations [18].

More useful, however, than the absolute numbers of distinguishable colored surfaces is the ranking of the sensors, since in this analysis it is independent of SNR. The largest number of distinguishable colored surfaces was obtained with the Nikon D1 sensors and, unexpectedly [2], the smallest number with the Foveon X3. Like the photoreceptors of the eye, which produced the next to smallest number, the Foveon X3 sensors have R and G spectral sensitivities which have greater overlap than in other sensors, and which, by implication, have been assumed to be well matched to the color statistics of natural scenes [20].

Nevertheless, it is important to distinguish these measurements of sensor performance from others concerned with the number of identifiable surfaces in scenes undergoing changes in scene illumination, as described in [2]. Sensor noise was not included in those measurements, but external noise due to metamerism was. The mean numbers of surfaces thus derived provided a ranking of the camera sensors. That ranking was the approximate reverse of the present one, with the Foveon X3 sensor delivering the largest number of identifiable surfaces per scene, in fact, 5.7 times more than with the Nikon D1 [2].

The effectiveness of camera sensors in distinguishing colored surfaces in outdoor scenes necessarily depends on sensor spectral sensitivities and on the level of noise associated with each. But determining which sensor is best also depends on the nature of the experimental measure, including whether the scene illumination is fixed or changing and what sources of external noise affect that measure.

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