A MEASURE OF COLOR SENSIBILITY FOR IMAGING DEVICES

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ABSTRACT

We define color sensitivity or effective color depth based on the "number of reliably distinguished colors", using ideas from information theory. This figure of merit allows the comparison of different sensors or cameras and we indicate how it can be used both for the design of imaging devices and to optimize their adaptation to the scene.

1. INTRODUCTION

Imaging devices have very different performances regarding color quality. This is both a fact of common experience and an important issue in the design of camera modules. An obvious measure related to this performance is the *color depth*, i.e., the number of bits used to represent the color of each pixel. However, it is well-known that devices with the same color depth can still have very different performances. An obvious issue is the fidelity of color reproduction which has been studied by many authors [6, 7, 10] and involves delicate psychophysical issues [4]. We introduce in this paper a more basic aspect of color performance, which we call **color sensibility**, based on the number of reliably distinguished colors.

After giving this definition, we check its meaningfulness by computing the figure for different devices (a camera phone, a bridge camera and a reflex camera). We then detail how the various stages of the acquisition of a color image (lenses, color filters, photoelectric sensor, color matrix, tone curve) impact on this figure of merit. We finally illustrate in a simple case how color sensitivity can be used to design camera modules by determining their limiting components or adjust their parameters in response to specific scenes.

2. DEFINITION OF THE COLOR SENSITIVITY

We would like to measure how well the color information in a given scene is captured and transmitted by an imaging device. This kind of measure is standard in information theory [3]: it is the Shannon information capacity of a channel. Estimating this capacity can be quite formidable but information theory establishes that the channel capacity is essentially (the logarithm of) the number of messages that are reliably distinguished despite the noise. Having this in mind, we define color sensitivity as the number of colors of the true image of a typical scene that can are "reliably distinguished" by the imaging device, i.e., not frequently mapped to the same output color. Note that we do not consider here the color sensitivity of the *viewer*.

The typical scene is represented by a collection of probabilities: for each color (x, y, z), $P(x, y, z)$ the probability that this color is contained in the input image. Here (x, y, z) encodes the physical spectral distributions of energy into some fixed color space $\mathcal{I} \subset \mathbb{R}^3$ (say CIE color space XYZ with a fixed choice of luminance scale, see [6]— one could in principle use physical units like cd·m^{-2} for each primary).

Let $F : \mathcal{I} \to \mathcal{O}$ be the imaging chain, seen as a map from scene colors in the space $\mathcal{I}$ to output colors in the (usually discrete) space $\mathcal{O}$, with noise removed. For $u \in \mathcal{I}$, let $\mathrm{vol}(u) \subset \mathcal{I}$ be a set of colors likely to be confused with u after treatment in the device. We define it precisely to be: $\mathrm{vol}_n(u) = \{u' \in \mathcal{I} : \exists u''$ with $F(u'') = F(u)$ and $\max_{i=1,2,3} |u'_i - u''_i| \leq \sigma_i\}$ where σ_i is the standard deviation of the noise n in the ith channel. The **color sensitivity** is then the following function of the transform F and the noise n:

$$CS(F, n) = \int_{\mathcal{I} \cap F^{-1}(\mathcal{O})} \frac{P(du)}{|\mathrm{vol}_n(u)|}.$$

Thus, $CS(F, n)$ is approximately the average number of colors that can be reliably distinguished by the output of the imaging device. It can also be presented as an **effective color depth** $\log_2 CS(F, n)$: the minimum number of bits needed to encode the distinguished colors.

The color sensitivity is a quantitative version, generalized for color, of the classical notion of *tonal range*. We note that there has been a number of attempts to measure color quality of imaging devices but they have been concerned with the question of physical or psychophysical *fidelity* (e.g., [7, 10, 12]). This question, though of obvious importance, is a different aspect than the one quantified by color sensitivity. Our more limited inquiry results in a much more simple and fundamental metric - we can avoid the many delicate issues of color appearance [4].

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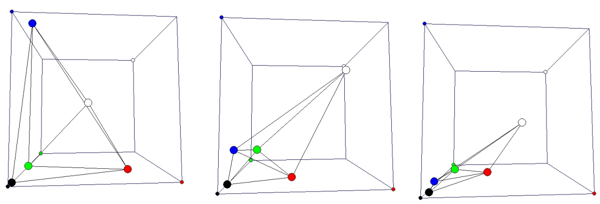

Fig. 1. Color polyhedra obtained theoretically and by the sensors of the 300D and Kph cameras from a color chart. Respective volume as a fraction of $[0, 256)^3$ are $61.3 \cdot 10^{-3}$, $13.4 \cdot 10^{-3}$ and $2.13 \cdot 10^{-3}$.

3. APPLICATION TO THE EVALUATION OF IMAGING DEVICES

We present the results of our studies for a 2 megapixel phone camera[1] (**Kph**, for short), a Kodak P850 bridge camera (**P850**) and a Canon 300D reflex camera with Canon EF 16-35 mm f/2.8L USM lens (**300D**). We evaluated these devices as whole systems outputting images with 24 bits color depth and using default modes when available (especially tungsten illuminant for interior scenes). The color sensitivity for two types of scenes are presented in Table 1.

We first considered scenes with all colors in the sRGB cube (see `http://www.srgb.com`). The first column (titled "volume covered") shows that the camera phone (Kph) and the bridge camera P850 both produce almost all possible colors in the output RGB space, whereas the output of the reflex camera (300D) only covers 89% of this volume. As the color performance of the 300D is obviously much superior to that of the Kph, we see that the number of colors in the output is certainly not a relevant metric.

The second column (title "distinguished colors") of the table gives the color sensitivity (as a percentage of the maximum number of ouput colors, e.g., 256^3 and as an effective color depth. We see that this figure of merit gives a correct ranking: the camera phone has a sensitivity which is much lower than (less than a tenth of) that the bridge camera which is only somewhat less than that of the reflex camera.

The bottom rows account for the same analysis but with colors from a scene. This scene was defined as having the colors in the polyhedron defined by the black, white, red, blue and green patches of a Gretag-Macbeth color checker, normalized by multiplication by the largest factor not causing saturation. The resulting polyhedron are displayed in Figure 1. Thus we took $P(R, G, B)$ to be 1 for colors inside this polyhedron and zero outside. The percentages within parenthesis in the bottom rows of the table give those results as a fraction of the number of colors in the ideal polyhedra (that is, real, not observed by a limited sensor).[2]

[1] This was a camera module still being designed which cannot be named here.

[2] Observe that this fraction can exceed 100%, which just means that the imaging device over-expand the polyhedron (and in fact the camera phone maps part of it outside of the cube).

Camera	Volume covered	Distinguished colors
Kph	99%	0.11% (14.2 bits)
P850	98%	1.40% (17.8 bits)
300D	89%	1.69% (18.1 bits)
Kph	8.3% [136%]	0.009% [0.14%] (10.6 bits)
P850	5.6% [91%]	0.054% [0.88%] (13.1 bits)
300D	5.7% [94%]	0.086% [1.41%] (13.8 bis)

Table 1. Color sensibility as a percentage of 256^3 (effective color depth in parenthesis) with (i) full sRGB cube as input (top rows); (ii) "Gretag scene" with percentages of the ideal case in brackets (bottom rows).

4. ESTIMATING THE COLOR SENSITIVITY

To compute the color sensitivity of digital cameras we must recall how a physical illuminated scene u is transformed into an output image ω by a digital camera with, say, a CCD or CMOS array sensor.

Optics: A lens with aperture given by some effective f-number f collects the light from the scene and brings it on the sensor for a given aperture time t.

Filtering: The light is decomposed by an array of micro-filters in front of the sensor array so as to transmit, ideally, only the red to the red pixels, etc. Thus there is a linear transformation $\mathbf{M}_0$ from u_{XYZ} in the CIEXYZ color space to u in the implicit color space of the sensor.

Sensor array: During exposure, each site of the sensor array accumulates electrical charge proportionally to the number of photons received up to saturation. This charge is then converted to a number between 0 and $2^b - 1$, for some **internal number of bits per channel** b. This results in a linear correspondence between the number of photons and the output except for **the dark current** DC (the output in the absence of light essentially caused by electronic thermal noise), the possible saturation and the **noise**. Apart from the dark current, the noise is caused by the discrete nature of light (shot noise) and the readout noise caused by the sensor amplifier. The **gain**, i.e., the ratio of the number of photons to the output, can usually be adjusted through a parameter g at the level of the analogic-to-digital converter. Therefore, the output of the sensor $v : [0, 1]^2 \to \{0, \ldots, N-1\}^3$ is a so-called **RAW image:**

$$v_i(\mathbf{x}) = \kappa_{2^b} \left(gKu_i(\mathbf{x}) + n(g, Ku_i(\mathbf{x}), \mathbf{x}) + \mathrm{DC} \right)$$

where $\kappa_{2^b}(s) = [\min(\max(s, 0), 2^b - 1)]$ ($[\cdot]$ is the integer part); $K = K_0 t / f^2$ with K_0 reflecting the sensitivity[3] of the sensor for $g = 1$; $n(g, u, \mathbf{x})$ is the noise at place $\mathbf{x}$ given the true value of u and the gain. $\{n(g, u, \mathbf{x})\}_{\mathbf{x} \in [0,1]^2}$ is assumed to be a family of independent Gaussian random variables of zero mean and variance $\sigma^2(g, u)$.

Digital processing: The digital image thus produced by the sensor is then processed. From our point of view the relevant

[3] Recall that the ISO sensitivity of the whole camera (ISO standard 12232:1998) is proportional to the gain, everything else being fixed.

operations are: (i) **white balance**: selective multiplications of ith channel by some number λ_i to compensate for the color of the illuminant; (ii) **color matrix**: a linear transform $\mathbf{M}$ corrects for the spectral sensitivity of the filters by $w_i(\mathbf{x}) = \kappa_N \left(\sum_{i=1}^{3} \mathbf{M}_{ij} v_j(\mathbf{x})\right)$; (iii) **tone curve**: the dynamics of the image is placed within the output dynamics (for instance to produce an image with a given average) by some function $\phi : [0,1) \to [0,1)$ applied to each channel.

The transformation from $\mathcal{I} := [0,N)^3$ to $\mathcal{O} = \{0,\ldots,M-1\}^3$ in the absence of noise is denoted by F.

5. IMPACT OF THE COMPONENTS

We examine the influence of each stage of the making of the digital image on the color sensitivity.

5.1. Sensor Noise

The sensor array itself is of course the core of the camera and the starting point for the computation of the sensitivity. Its limitations are (i) true numerical range, i.e., the difference between the dark current and the saturation value - for the cameras we have analysed it is $N = 2^b - \mathrm{DC}$ (the camera sensors usually do not saturate before the analog-to-digital converter); (ii) the shot and readout noises, which determine the smallest differences that can be reliably discerned.

The standard deviation of the noise for given gain g and at a given input u can often be modeled for cameras by an affine fonction: $\sigma(g,u) = \alpha + \beta g + \gamma u$. By itself, this would produce a color sensitivity $CS = \left(\int_0^N \frac{1}{2\sigma(u,g)/g}\, dU\right)^3 = \frac{g^3}{8\gamma^3} \log^3\left(1 + \frac{\gamma}{\alpha+\beta g}(N/g)\right)$ We obtain, for the Kph $CS = 2.6 \cdot 10^5 = 2.4 \cdot 10^{-4} \times 1024^3$, ($\sigma(g,u) = 1.6 + 1.2g + 0.014u$); and for the 300D $CS = 3 \cdot 10^8 = 4.4 \cdot 10^{-3} \times 4096^3$ ($\sigma(g,u) = 0.03 + 0.03g + 0.025u$). Thus the Kph sensor has an effective color depth of 18 bits whereas the 300D has 28 bits, thus a difference of 10 bits (in comparison with the difference of only 6 bits of their nominal color depths).

5.2. White balance and color matrix

The first stage of the digital processing is the application of the white balance and color matrix. Notice that the color matrix is made necessary by the filters in front of the sensor. This can be seen in the reduction and distortion of the colors from a “scene” made from the Gretag-Macbeth color chart under some fixed illuminant (with exposure chosen so that the image is as bright as possible without saturation and dark current has been substracted). Fig. 1 represents the polyhedra thus observed by various sensors and one can see the severe distortions.

This correction requires a linear transformation which can be quite far from the identity. For instance, for the Kph camera we obtain: $\begin{pmatrix} 2.1 & -0.8 & 0.7 \\ -1.1 & 1.8 & -0.7 \\ -0.8 & -1.7 & 7.6 \end{pmatrix}$ with singular values: 0.9, 2.9 and 7.9.

This is quite dramatic: first, a factor $2.9 \times 7.9 = 22.9$ expands the noise; second, 87% of the RAW gamut is mapped

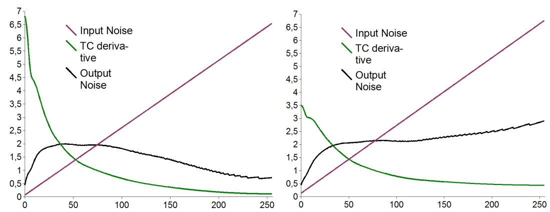

Fig. 2. Noise as a function of the intensity before and after the tone curve for the 300D and Kph camera. Observe that it is always above $0.5/256$.

outside of the RGB gamut and 15% of the RGB gamut is not in the image. Assuming the constant sensor noise, this divides the sensitivity by $22.9/0.13 \approx 176$, i.e., loses 7.5 bits.

The 300D has the following color matrix: $\begin{pmatrix} 1.0 & -0.2 & 0.2 \\ 0.0 & 1.2 & -0.2 \\ 0.1 & -0.4 & 1.3 \end{pmatrix}$ and white balance: $(1.5, 1.0, 1.8)$. Hence the corresponding figures for the reflex camera are $2.6 \times 1.4 \times 1.1 = 4.0$, 73% and 4% giving a division by $0.27/4 = 14.8$ of the sensitivity and a loss of 3.9 bits.

Thus, the strong color mismatch of the Kph camera, increases the difference with the color sensitivity of the 300D by 3.6 bits.

5.3. Tone curve

The tone curve is a non-linear transform applied to each channel before reducing the color depth, usually to 24 bits. It has a two-fold goal: (i) to map the linear color space into a non-linear one like the sRGB which entails a γ of 2.2, this non-linearity taking into account the logarithmic sensibility of the human eye as described by the Weber law; (ii) better adjust the dynamics of the image to the output dynamic range, e.g., by increasing the average luminance of the image. The output color depth is usually smaller than that of the RAW causing a loss of color sensitivity. However, it is usually much less severe than one would expect because of the loss of sensitivity already caused by noise amplified by color treatment especially at the high levels of intensities which are the most contracted by usual tone curves. This is illustrated in Fig. 2. In fact, this stage causes almost no loss in sensitivity: none for the Kph and about 2 bits for the 300D.

6. OPTIMIZING THROUGH COLOR SENSITIVITY

Let us consider the design of a camera around a given sensor. The spectral sensibility of the sensor defines in first approximation the color matrix whereas the white balance is imposed by the (estimated) illuminant.

A first choice for the designer concerns the *color depths* that should be used. These can easily be changed in simulations to determine the lowest bit counts giving maximum color sensitivity. For instance, for the three cameras examined in section 4, these theoretically optimal RAW color depths are 3×9, 3×9 and 3×11 bits, resp. for the Kph, P850 and 300D cameras instead of their actual 3×10, 3×12 and 3×12 bits.

Their digital processing is therefore, in this respect, slightly over-dimensioned, which is perfectly reasonable.

A second choice involves the *target exposure* of the camera, i.e., where the scene colors should be put in the dynamics of the sensor by adjusting the global gain $G = K_0 gt/f^2$ (see Section 4) given a scene and, say, a desired average in the output image. In this way, the tone curve is determined by G (completely if it is just a gamma transform). [4]

To find G, we compute for each possible value the color sensitivity with respect to a color statistics P (see Section 2) reflecting the important colors in the scene so that eventual saturations will be measured by a decrease in color sensitivity. We propose that the target exposure should be determined by maximizing color sensitivity while keeping noise under some tolerance.

These considerations help explain why, for the same scene with an output average of 128, the exposure target is 60 out of 256 for the P850 camera, but only to 36 out of 256 for the 300D. The 300D having much less sensor noise can accomodate a much wider dynamic range, capturating more highlights through a steeper tone curve.

7. CONCLUSION

We have defined and estimated color sensitivity (equivalently the effective color depth which is the base 2 logarithm of this number), a figure of merit pertaining to the richness of the color of imaging devices and based on the number of distinguished colors, in line with standard ideas in information theory.

We have computed it for phone, bridge and reflex cameras and found the results in agreement with expectations. Even though color sensitivity of a sequence of transformations is not in general the product (or even generally a function) of the color sensitivity of the individual transformations, this approximately holds for the devices we analyzed: the effective color depth is that of the sensor (18 bits for the Kph, 28 for the 300D) determined first by the noise and the saturation level of the photosensible array and then by the precision of the analog-to-digital convertor, minus the loss from the spectral mismatch of sensor filters (7.5 and 3.9 bits respectively) with the tone curve mapping to 24 bits losing practically no additional information.

The obvious importance of color quality leads to a potentially important role for color sensitivity. It can assist in the evaluation of existing devices as shown by the examples in Section 3. It can help design whole or parts of imaging devices or setting their parameter as we saw in Section 6 for the choice of RAW color depth or of the exposure target for a given scene.

Of course, color sensitivity does not take into account the fidelity of the output colors to the input colors and the corresponding subtleties of color appearance models [4, 6, 7] which obviously have to be taken into account in the design of imaging devices, and especially their gamut-mapping [1, 11].

Color sensitivity as presented here does not take into account the sensitivity of the human viewer, i.e., the fact that two colors distinguished by the camera in the sense that they produce reliably distinct outputs can nevertheless be indistinguishable to the human eye under specified conditions of reproduction and viewing. Along this line, one could define a perceptual color sensitivity which rewards cameras producing “gamma-corrected” intensities expanding the dynamics at low intensities according to the Weber law of human eye sensitivity.

However, color sensitivity in the version presented here has already a perceptually important signification which is both intuitively clear and theoretically and empirically tractable (with a simple definition, not depending on too many parameters) making it, we believe, a useful new tool.

[4] A given G should be achieved with g as small as possible to maximize the signal-to-noise ratio which is $gKu/(\alpha + \beta g + \gamma Ku)$.

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