

Presentation of calibrated images over the web

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ABSTRACT

This paper considers the problem of delivering calibrated images over the web with the precision appropriate for psychophysical experimentation. We are interested only in methods that might be employed by a remote participant possessing nothing other than a computer terminal. Therefore, we consider only purely psychophysical methods not requiring any measurement instruments or standards. Because of this limitation, there are certain things we can *not* determine, the most significant of which is the absolute luminance. We present solutions for three particular problems: *linearization*, also known as *gamma correction*; determination of the *relative luminances* of the display primaries; and *colorimetry*, i.e. determining the chromaticity of the primaries.

Keywords: gamma correction, calibration, colorimetry, psychophysics

1. INTRODUCTION

The recent explosion in the number of people world-wide who are accessing the "web" via the internet provides exciting new possibilities for experimental psychologists to collect data from a subjects pool the size of which would have been inconceivable just two decades ago. Several experimenters have already exploited this opportunity; for example Nakayama¹ collected face recognition data from over 22,000 subjects! In this example, which was concerned with memory for faces, the results are not expected to depend critically on accurate calibration of the subjects' displays: changes in display characteristics to some extent mimic changes in illumination of the faces in the stimuli, and human face perception is robust with respect to these types of variation. But for many experiments in low- and mid-level vision, precise calibration *is* important; in this paper we will explore methods for achieving presentation of calibrated images to remote subjects, where the calibration is performed by the subjects themselves, making only psychophysical judgments.

John Krantz at Hanover College has put together a list of psychological experiments available on the web (<http://psych.hanover.edu/research/exponnet.html>). Figure 1 shows the numbers of experiments in a variety of categories assigned by Krantz. Of the 360 experiments listed at the time of writing of this paper, only 3 links are given under the heading "Sensation and Perception." While this does not necessarily represent an unbiased sample, the fact is that most psychophysical research employs relatively small numbers of subjects, tested using precisely-controlled stimuli that are difficult if not impossible to reproduce over the web. Nevertheless, there are a number of advantages to studying perception using the large subject populations available over the web. Large subject populations are essential for the study of individual differences. A recent survey of individual differences in perception can be found in a recent textbook by Mather;² these include the decline in acuity with age, and gender differences in mental rotation tasks. Wilmer and Nakayama³ have reported individual differences in motion perception that correlate with eye movement behaviors, and Wilmer⁴ argues persuasively that individual differences are an under-utilized resource.

While most of the ideas presented in this paper originated as solutions to the problem of conducting psychophysical experiments over the web, there are other disciplines which have a need for precision display of images. A prime example is medical imaging: it is becoming increasingly common for specialists to "read" radiological images in electronic form, at remote sites. The current standard for medical images is called Digital Imaging and Communications in Medicine (DICOM), which is an integrated format containing patient information in addition to image data. DICOM images now allow at least one lossy compression method (JPEG), but the medical field has long had concerns with respect to lossy compression, due to uncertainties concerning the importance of the lost information, and concerns over liability. Similar concerns over the accuracy of displayed

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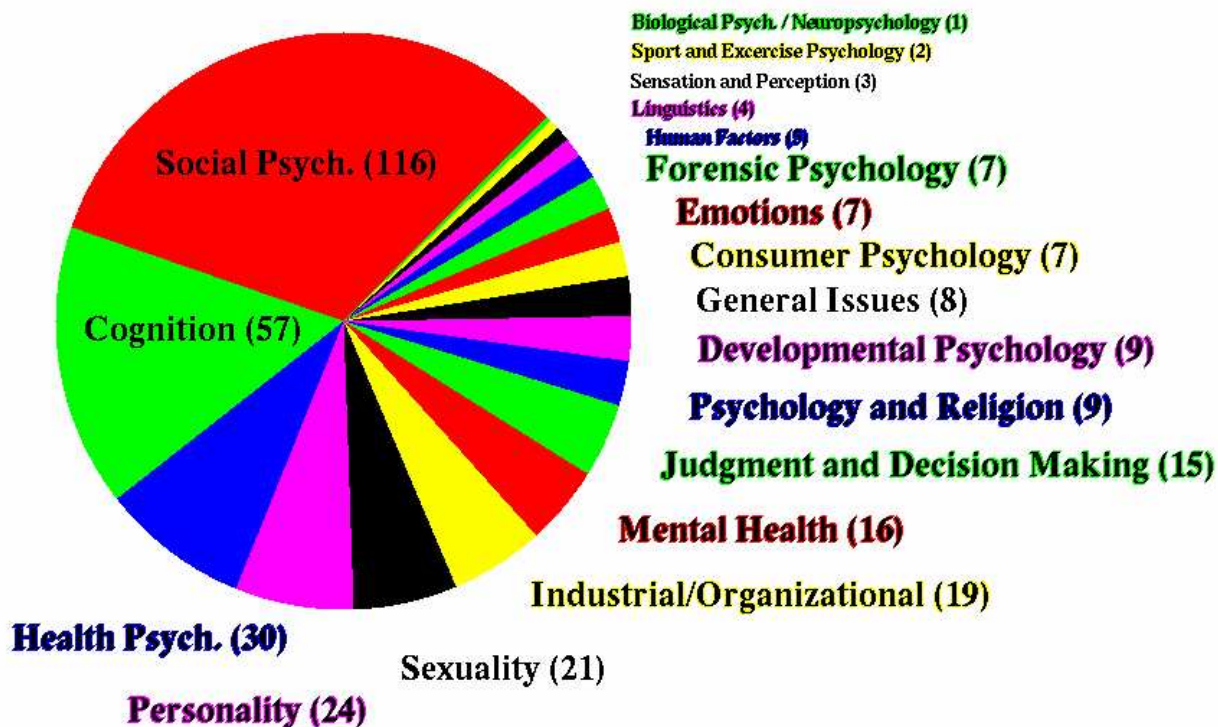


Figure 1. Distribution of 360 psychological experiments on the web, using categories assigned by John Krantz of Hanover College.

information make web-based delivery of medical images problematic; nevertheless, development of web-based systems for delivery of medical images are being studied.⁵⁻⁷

Faithful reproduction of medical images is considered to be important, and a premium price is exacted for "medical" display monitors. While some of the added cost is undoubtedly due to safety features not normally present on standard computer displays, such as waterproofing and electrical isolation, medical monitors are required to conform to performance standards and have a high degree of stability. The irony of this is that many of the images displayed on such monitors are provided at a higher-bit depth than can normally be displayed on a conventional display, and so physicians are provided with software image display tools to transform the image data to make the features of interest visible; to the extent that this process is done "by eye" (as opposed to "by the numbers"), little benefit is afforded by using a calibrated display.

One of the first attempts to address the problem of calibration of remote displays using only human visual judgments was made by Lavin, Silverstein and Zhang.⁸ One of the problems they considered was determination of the pixel size, which they solved by assuming the subject had access to a common object to be used as a reference standard: a dollar bill. We return to this idea in section 4.

The human visual system has a remarkable capacity to adapt to the average light level in an environment, so that the visual appearance of images generally depends primarily on their *contrast*. Thus, the contrast of a target or other display element is often the variable of interest in perceptual research. In order to accurately represent a stimulus specified in terms of contrast, it is necessary to know the relative luminances corresponding to the various pixel settings; this problem is known as *display linearization*, or *gamma correction*. The latter term refers to the *gamma nonlinearity* sometimes incorporated in display devices such as cathode-ray tubes (CRT's), relating output light intensity to input voltage. This is typically a power function with an exponent near 2; this provides relatively small steps of luminance at low levels (where human discrimination is good), and larger steps at high luminance (where discrimination of small-amplitude steps is relatively poor).

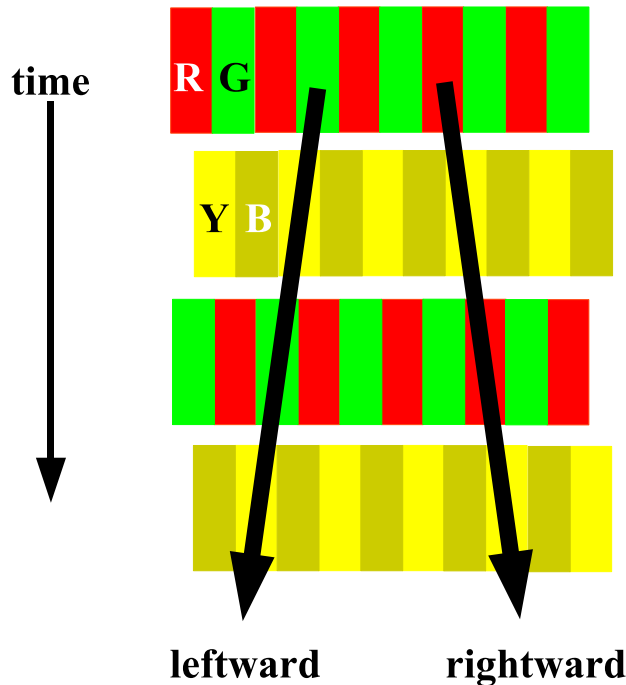


Figure 2. Schematic diagram showing the four frame sequence in the Anstis and Cavanagh motion nulling paradigm. Red and green stripes alternate with yellow and brown stripes in spatial quadrature; the perceived direction of motion depends on the relative luminances of the red and green bars.

2. DETERMINATION OF THE RELATIVE LUMINANCES OF THE PRIMARIES

In 1983, Anstis and Cavanagh⁹ introduced a motion-nulling technique for the determination of an individual's equiluminance settings. This technique was the inspiration for the method of gamma correction presented below in the section 3, and so we begin by reviewing it here.

The question the technique seeks to answer is how much of one primary (say, red) is required to produce exactly the same response in the human visual system's luminance channel as a given amount of another primary (say, green). This is traditionally done using a technique called *heterochromatic flicker photometry* (HFP), in which two lights are alternated in rapid succession, while the relative intensities are varied to minimize the perceived flicker. HFP yields results which differ from side-by-side brightness matches, and, because HFP obeys a number of useful algebraic laws such as linearity and additivity, it is used to operationally define luminance.

The Anstis and Cavanagh technique relies upon the fact that, under a wide range of conditions, the perception of motion is determined by the luminance channel alone. The stimulus display (depicted schematically in figure 2) consists of opposing motions carried by different color components; the amplitudes of the components are varied to obtain a motion null. Depending on the spatial and temporal parameters, the appearance near the null setting may be either flicker with no motion, or a bistable percept with leftward and rightward motions both seen at different times, in large part determined by eye movements. The influence on the percept of eye movements can be reduced by eccentric viewing of the stimulus while holding fixation on a stationary target.

The technique was introduced not as a calibration procedure, but rather as a technique for the assessment of color vision. Using a calibrated monitor, subjects with normal color vision will be expected to produce settings in a restricted range, while various forms of anomalous color vision produce different patterns of results. Because moving stimuli generally produce reflexive tracking eye movements, the technique can be used to assess the color vision of infants,¹⁰ and other non-verbal animals. The technique has even been used to measure the color vision of guppyfish, by observing the direction they swim when the stimulus was presented through the walls of their tank.¹¹

While the technique can be used with a calibrated monitor to assess the color vision of a subject, we can conversely use it with a normal subject to calibrate a monitor. In addition, for many vision experiments we are more interested in subject-dependent calibrations than in results from a photometer; this is particularly important for the creation of equiluminant stimuli, because subject-dependent factors such as pre-retinal absorption of light by the lens and macular pigment tend to cause nominally equiluminant stimuli (set using a photometer) to contain small but significant luminance artifacts for individual subjects.

We describe the procedure formally by introducing the following notation: let R_b^t represent the level of the red component in bar b in frame t , where $b \in \{1, 2, 3, 4\}$ and $t \in \{1, 2, 3, 4\}$. The bar index b represents not the bars shown in figure 2, but rectangular regions on the screen making up half of each bar. Thus, the upper left-most red bar in the figure is formed by the union of bars 1 and 2, the yellow bar below it from bars 2 and 3, and so on. The green component is similarly represented by G_b^t . In order to generate the appearance shown in figure 2, we impose the constraints:

$$R_1^1 = R_2^1 = R_2^2 = R_3^2 = R_3^3 = R_4^3 = R_4^4 = R_1^4 = R_4^4 = R_0 + \Delta R, \quad (1)$$

$$R_3^1 = R_4^1 = R_1^2 = R_4^2 = R_1^3 = R_2^3 = R_2^4 = R_3^4 = R_0 - \Delta R, \quad (2)$$

$$G_1^1 = G_2^1 = G_1^2 = G_4^2 = G_3^3 = G_4^3 = G_2^4 = G_3^4 = G_0 - \Delta G, \quad \text{and} \quad (3)$$

$$G_3^1 = G_4^1 = G_2^2 = G_3^2 = G_1^3 = G_2^3 = G_1^4 = G_4^4 = G_0 + \Delta G. \quad (4)$$

In practice, we fix ΔR , and have the subject vary ΔG to obtain a null. Because the green component generally carries the most luminance, a good null can be obtained with this procedure even when ΔR is chosen to be the maximum. If gamma calibration (described in the following section) is performed first, and the quantities in equations 1-4 are used to control component luminances, then varying ΔR and ΔG will change neither the mean luminance nor the mean chromaticity, which is desirable from the standpoint of maintaining a constant state of chromatic adaptation. It is similarly desirable to maintain a neutral state of chromatic adaptation, by adding a blue component B_0 to each color, so that (R_0, G_0, B_0) is a neutral gray. We introduce the symbol C_b^t to represent the color of bar b on frame r , $C_b^t = (R_b^t, G_b^t, B_b^t)$. Then we can generalize the procedure as follows:

$$C_1^1 = C_2^1 = C_3^3 = C_4^3 = C_0 + \Delta_1 - \Delta_2, \quad (5)$$

$$C_3^1 = C_4^1 = C_1^3 = C_2^3 = C_0 - \Delta_1 + \Delta_2, \quad (6)$$

$$C_2^2 = C_3^2 = C_1^4 = C_4^4 = C_0 + \Delta_1 + \Delta_2, \quad \text{and} \quad (7)$$

$$C_1^2 = C_4^2 = C_2^4 = C_3^4 = C_0 - \Delta_1 - \Delta_2, \quad (8)$$

where Δ_1 and Δ_2 represent color-difference vectors $(\Delta R, \Delta G, \Delta B)$. Thus, to implement the example given in equations 1-4 above, we would set $\Delta_1 = (\Delta R, 0, 0)$ and $\Delta_2 = (0, \Delta G, 0)$. By fixing the color directions of Δ_1 and Δ_2 (i.e., maintaining constant ratios between the components), we can adjust the relative amplitudes to obtain luminance matches between color vectors in arbitrary color directions. Rather than match red to green, we could make matches between arbitrary color directions. At least two linearly independent pairs of directions must be tested to calibrate all three color components; testing additional directions provides a consistency check.

3. A MOTION-NULLING METHOD FOR GAMMA CALIBRATION

In this section we present a motion-nulling method for gamma calibration that is directly analogous to the luminance matching procedure described in the previous section. Instead of matching color-difference vectors, however, in this case we are matching spatial mixtures of difference gray levels (halftones).

The procedure is illustrated schematically in figure 3. The figure is similar to figure 2, except that instead of having bars of a solid color, each bar is composed of a checkerboard pattern of subelements. Let $S_{b,c}^t$ represent the setting of check $c \in 1, 2$ in bar b in frame t . Then, to implement the stimulus shown in figure 3, we would set

$$S_{1,1}^1 = S_{2,1}^1 = S_{2,1}^2 = S_{3,1}^2 = S_{3,1}^3 = S_{4,1}^3 = S_{1,1}^4 = S_{4,1}^4 = S_1, \quad (9)$$

$$S_{1,2}^1 = S_{2,2}^1 = S_{1,2}^2 = S_{4,2}^2 = S_{3,2}^3 = S_{4,2}^3 = S_{2,2}^4 = S_{3,2}^4 = S_2, \quad (10)$$

$$S_{3,1}^1 = S_{4,1}^1 = S_{3,2}^1 = S_{4,2}^1 = S_{1,2}^2 = S_{2,2}^2 = S_{3,2}^2 = S_{4,2}^2 = S_0, \quad (11)$$

$$S_{1,1}^3 = S_{2,1}^3 = S_{1,2}^3 = S_{2,2}^3 = S_{1,2}^4 = S_{2,2}^4 = S_{3,2}^4 = S_{4,2}^4 = S_0. \quad (12)$$

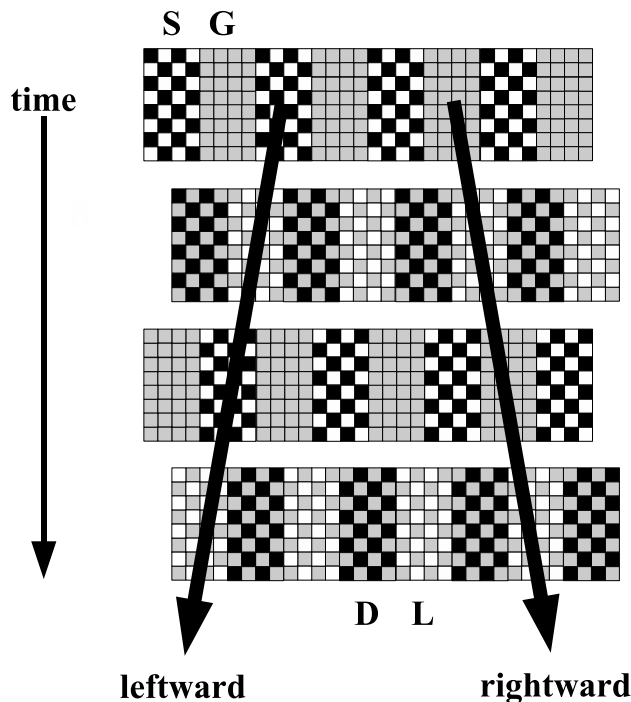


Figure 3. Schematic diagram showing the four frame sequence used for gray level bisection. Stippled (S) and gray (G) stripes alternate with light (L) and dark (D) stripes in spatial quadrature; the perceived direction of motion depends on the luminance of the variable gray pixels.

In the example shown in figure 3, S_0 is an intermediate gray, S_1 is white, and S_2 is black. In practice, we fix the endpoints S_1 and S_2 , and adjust S_0 to obtain a null. If we let $L(S)$ represent the luminance produced by the display when setting S is applied, then at the null point

$$L(S_0) = \frac{L(S_1) + L(S_2)}{2}. \quad (13)$$

The function $L(S)$ is generally non-linear, and is often well-approximated by a power function:

$$L(S) = S^\gamma. \quad (14)$$

Because the Greek letter gamma (γ) is traditionally used for the exponent in this formula, it has become common to speak of the "gamma" of the display, and the function $L(S)$ is often called the *gamma function* of the display. The goal of *gamma calibration* is to invert the gamma function, in order to tell us what setting is required to produce a certain desired luminance; it is common to implement this using a table. Because most computer video boards represent each color component of a pixel with an 8 bit byte, it is common to think of gray levels as going from 0 to 255. A simple approach to linearization is therefore to map images through a look-up table (LUT) with 256 entries; each entry corresponds to the setting appropriate for the desired luminance. But because of the form of the gamma nonlinearity, this approach results in insufficient sampling at low luminances. One approach¹² to this problem is to simply increase the size of the table, and use more bits to represent the desired imagery. For example, we might represent a desired image with floating point numbers in the range 0-1, map these to 12 bit integers by multiplying by 4095 and rounding, and then use the resulting integers as indices into a 4096-entry table of 8 bit pixel settings.

Our goal is to determine enough points on the gamma function that intermediate points can be obtained by interpolation. Perhaps the simplest method is *recursive bisection*. Using the notation introduced above, we let S_1 represent the minimum setting, $S_1 = L^{-1}(0)$, and S_2 the maximum setting, $S_2 = L^{-1}(1)$. Then by adjusting

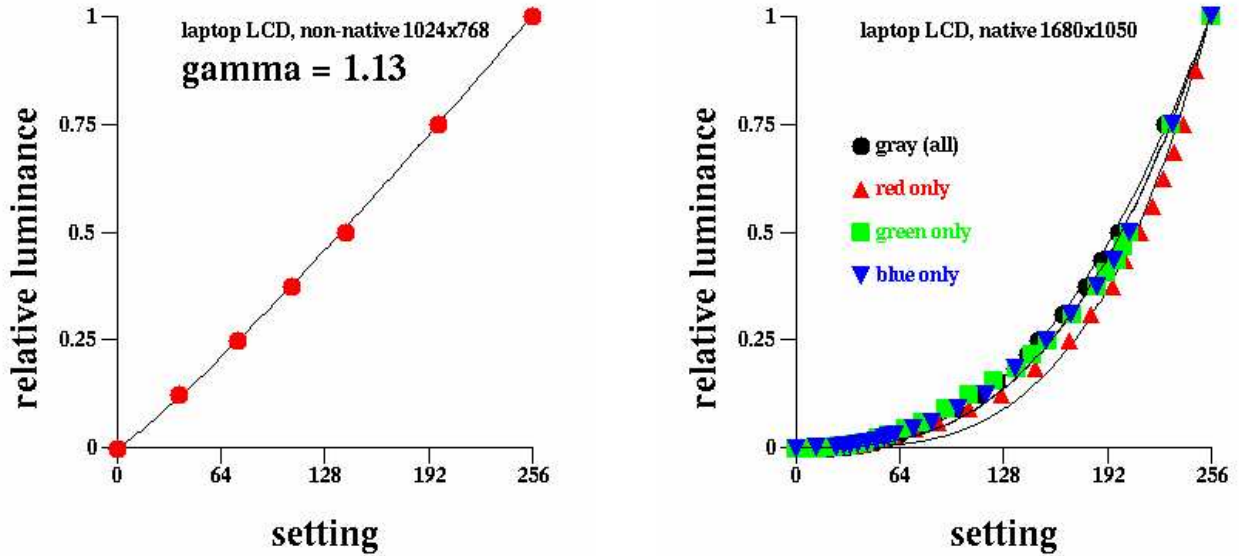


Figure 4. Gamma functions obtained using the motion nulling procedure. The left panel shows the function obtained when the laptop display is driven at a resolution of 1024x768, while the right panel shows functions obtained when the same display is driven at its native resolution of 1680x1050.

S_0 to attain a null, we have bisected the range, and know that $S_0 = L^{-1}(0.5)$. In a similar fashion, we can find the setting $S_3 = L^{-1}(0.25)$ by bisecting S_1 and S_0 ; $S_4 = L^{-1}(0.75)$ can be found by bisecting S_0 and S_2 . We halt the recursion when the bisector setting is within integer precision of the mean of the endpoint settings, indicating that we have reached a linear region of the gamma function.

Figure 4 shows gamma functions obtained using this procedure on the LCD screen of the author’s laptop computer. The left-most panel shows results obtained when the display resolution was set to be 1024x768 - significantly lower than the native resolution of 1680x1050, this lower resolution was used when developing the slides for the conference presentation, being a common projector resolution. In this case, the function obtained was nearly linear, being best-fit by a power function with an exponent of 1.2. This is not that surprising when we consider that in order to display low-resolution imagery on a high-resolution screen, in-between pixels must be assigned values synthesized by interpolation. Thus, our checkerboard pattern that is nominally made up of just S_1 and S_2 pixels will in fact have a number of pixels set to intermediate values.

The right hand panel of figure 4 shows strikingly different results, obtained when the display is driven at its native resolution of 1680x1050. In this case, we estimate a gamma exponent of 2.62 when we perform the procedure with gray modulation (identical settings applied to the red, green and blue pixel components). A curious phenomenon was observed in this situation, however: at the null point, a color difference was noted between the black/white checkerboard pattern and the luminance-matched uniform gray.

One explanation for the unexpected color difference could be that the different color components have slightly different gamma functions. The calibration procedure was repeated, testing the red, green and blue color components separately, and different gamma values were indeed found for red ($\gamma = 3.49$), green ($\gamma = 2.88$) and blue ($\gamma = 2.86$).

There are several problems with this as an explanation of the hue shift, however; first, one would expect the gamma value obtained for gray patches to be close to the mean of that obtained for the components, but, in fact, the value is lower than *all* of the component gamma functions. Another problem is that one would then predict subtle hue shifts when displaying different shades of gray or a gray-scale ramp, but this seems not to be the case. The result appears to be due to some sort of component-dependent spatial interaction between the light and dark pixels in the checkerboard texture. This is somewhat reminiscent of the non-linear spatial interactions

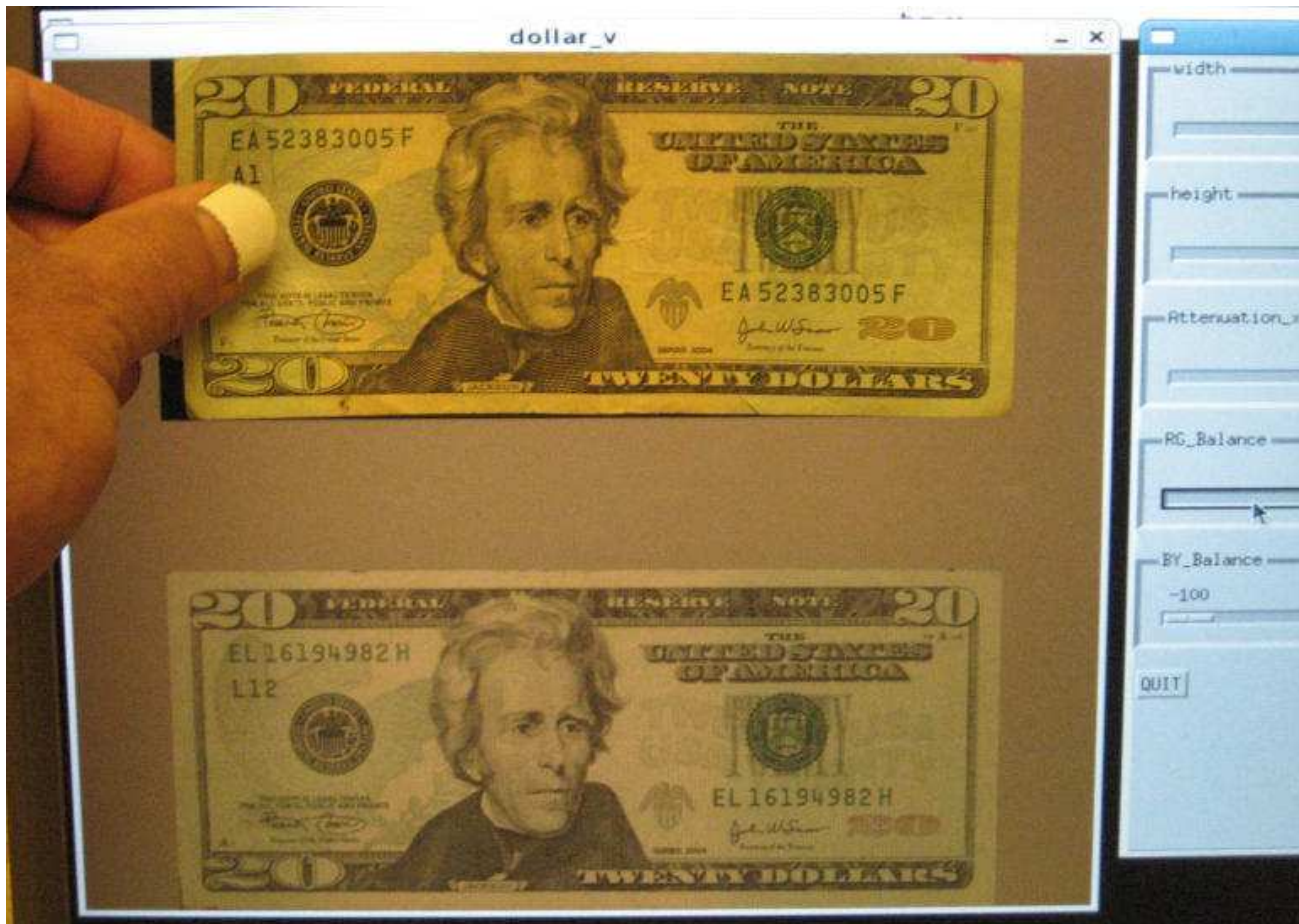


Figure 5. Attempt to match the appearance of a twenty dollar bill by adjusting the color balance of a scanned image of the bill displayed on a laptop screen. Under the fluorescent lighting conditions shown, the laptop display was not capable of matching the yellow in the bill.

observed with some cathode ray tube (CRT) displays.¹³ The basic observation is that the mean luminance of a halftone pattern does not increase linearly with the proportion of white pixels (as would be expected if each white pixel always contributed the same incremental luminance), but rather exhibits an expansive non-linearity. This effect was well-fit by a model in which the video signal was low-pass filtered prior to being subjected to the gamma non-linearity. The model was confirmed (for the single CRT tested) when an estimate of the time constant τ of a simple exponential filter, obtained by applying the model to various halftones to fit the measured luminance-vs-dot-density function, could predict the mean luminance vs. halftone amplitude function.¹³ The resulting failure of spatial independence is sometimes referred to as the *adjacent pixel non-linearity*; a simple and fast method to correct for it based on table look-up has been demonstrated.¹⁴

A quick and simple check for this problem can be done by comparing the mean luminance of a pattern of fine vertical black and white stripes with that of the same pattern rotated 90 degrees so the stripes become horizontal. If video bandwidth is a problem, then the modulation amplitude of the vertical stripes will be attenuated, and the mean luminance will be reduced, compared to the horizontal stripes. This check was performed on the laptop display described above, but no difference was observed. Thus, this type of mechanism cannot be responsible for the unexpected color shift and variation in gamma exponents described above.

4. COLORIMETRIC CALIBRATION

In this section, we present an outline for a procedure for performing *relative colorimetric calibration* by executing a series of color matches. To perform a true colorimetric calibration, it would be necessary to have a matching standard of known chromaticity; we assume that this is too much to expect from the average remote participant. However, following Lavin, Silverstein and Zhang,⁸ we consider it reasonable to assume that participants might have access to a standard object: a twenty dollar bill. (Although the discussion here is conducted in the context of the currency of the United States, other currencies could be accommodated in a similar manner.) The chromaticity of a reflective object such as a dollar bill depends not just on the object itself, but on the spectral content of the light which illuminates it. As the illumination environment of the remote participant is unknown, it would seem we have little hope of gaining much information about the color of their display from a match to a reflective sample. However, we might assume that the participants are adapted to their local illumination environment, so that a white piece of paper will appear white. In this case, a match between a screen patch and the piece of paper would at least tell us how to make a patch that appears white in the local environment. And if we can make two more matches to a pair of independent colors whose chromaticities are known *relative* to the local white, then we have achieved our goal of relative colorimetric calibration.

When Lavin *et al.*⁸ proposed using a dollar bill for spatial calibration, the currency of the United States was printed using just black and green inks, and thus did not possess sufficient chromatic variation to enable a complete relative calibration. Beginning in the fall of 2003, however, a new design of the \$20 bill was issued, having substantially greater chromatic variation, and potentially enabling relative calibration of all three display primaries. We now describe our attempt to implement such a procedure.

The first step was to obtain a scanned image of the standard object (in this case, a \$20 bill). Ideally, this would be done using a calibrated scanner, but our initial attempt was performed with an uncalibrated scanner (Hewlett Packard Officejet All-in-one, model 7210). (Scanned images are also available on Wikipedia: http://en.wikipedia.org/wiki/Federal_Reserve_Note.)

In the scanning process, the spectral distributions reflected by the sample are converted to RGB triples with filters designed to approximate linear combinations of the human color-matching functions, and assuming standard chromaticities for the red, green and blue display primaries. In the case where the ambient illumination under which the matches are made is identical to the illumination source used in the scanner, *and* the display primaries have the expected standard chromaticities, then a good match should be obtained between the actual bill and the display by simply scaling the raw RGB values to equate the luminances. We do not generally expect all of these conditions to hold, however, and thus expect that some sort of transformation of the RGB values will be necessary to obtain a match. We let \mathbf{c} represent the scanned RGB values for a particular pixel in the image, and \mathbf{c}' the display RGB values necessary to obtain a match to the corresponding location in the sample. The appropriate transformation can be described by a 3×3 matrix \mathbf{M} :

$$\mathbf{c}' = \mathbf{M}\mathbf{c}, \tag{15}$$

or, in expanded notation,

$$\begin{vmatrix} r' \\ g' \\ b' \end{vmatrix} = \begin{vmatrix} a & b & c \\ d & e & f \\ g & h & i \end{vmatrix} \begin{vmatrix} r \\ g \\ b \end{vmatrix}. \tag{16}$$

Matches to three linearly independent colors \mathbf{c}_1 , \mathbf{c}_2 , and \mathbf{c}_3 are sufficient to allow determination of the elements of \mathbf{M} ; we stack three equations of the form of equation 16, but rearrange the terms so that the 9 coefficients of \mathbf{M} appear as a vector on the right, and the RGB values of the three colors samples populate a sparse matrix we call \mathbf{C} :

$$\begin{array}{c}
\left| \begin{array}{l} r'_1 \\ g'_1 \\ b'_1 \\ r'_2 \\ g'_2 \\ b'_2 \\ r'_3 \\ g'_3 \\ b'_3 \end{array} \right| = \left| \begin{array}{cccccccccc} r_1 & g_1 & b_1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & r_1 & g_1 & b_1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & r_1 & g_1 & b_1 & 0 \\ r_2 & g_2 & b_2 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & r_2 & g_2 & b_2 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & r_2 & g_2 & b_2 & 0 \\ r_3 & g_3 & b_3 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & r_3 & g_3 & b_3 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & r_3 & g_3 & b_3 & 0 \end{array} \right| \left| \begin{array}{l} a \\ b \\ c \\ d \\ e \\ f \\ g \\ h \\ i \end{array} \right|.
\end{array} \tag{17}$$

We solve for the coefficients of \mathbf{M} by inverting \mathbf{C} , and applying the resulting inverse matrix to the match settings (the vector on the left side of equation 17).

While the approach presented above is completely general, we may often expect that \mathbf{M} may have a simpler form. In particular, a simple shift of color balance might be achieved when \mathbf{M} is a diagonal matrix:

$$\mathbf{M} = \left| \begin{array}{ccc} \lambda_R & 0 & 0 \\ 0 & \lambda_G & 0 \\ 0 & 0 & \lambda_B \end{array} \right|. \tag{18}$$

The three elements of such a matrix are completely determined by a single match.

Regardless of the form of \mathbf{M} , the quality of the transformation can be assessed by applying \mathbf{M} to the entire image, and comparing the result to the test object. Figure 5 shows an attempt to do this, after manual adjustment of λ_R , λ_G , and λ_B , to match the yellowish-white center border. Much to the author's surprise, this proved impossible to accomplish using the laptop display pictured in figure 5. The figure shows an actual bill held in front of an appropriately-sized black rectangle (to insure that the bill is seen by reflected, not transmitted light), above a transformed version of the data from the scanner. Although not obvious in the color version of the figure, given the additional color transformations done by the camera which captured the image, λ_B has been set to 0, and the display is still incapable of matching the yellow of the paper viewed under fluorescent light. The large differences in color temperature between typical displays and indoor lighting may make this technique impractical. However, further investigation is warranted. In particular, the new five dollar bill, issued in 2008, has a large purple "5" on the reverse side, which can probably be matched well under artificial light. A subsequent test performed with a different display, under a different fluorescent illuminant did allow the yellow of the twenty dollar bill to be matched, but at present it is not clear how unusual the situation encountered with the laptop display is.

5. IMPLEMENTATION

Computer programs that implement the procedures described in this paper were implemented in the QuIP scripting language for demonstration during the conference presentation. QuIP (QUick Image Processing) consists of a command interpreter coupled to a number of libraries providing a range of functions, encompassing creation, manipulation, and display of images and other data structures. The QuIP interpreter is written in the C programming language, and has been under continuous development since 1982 when the author was a graduate student. The present implementation runs on various flavors of the UNIX operating system with the X11 window system used for display and graphical interaction. The current development platform is Linux with XFree86; in 2008, the software was ported to Apple Computer's Mac OSX in an hour or two. Previously, development was performed under version 6 UNIX, SunOS, and SGI's IRIX.

Work is currently underway for a public open-source release of QuIP under the NASA Open Source Agreement (NOSA). More information about the software (along with downloadable code in the near future) can be found at <http://quip.arc.nasa.gov>.

In 2004, the author and a computer scientist named Constantinos Stratelos created an implementation of QuIP in the Java programming language, with the ultimate goal of allowing QuIP scripts (which currently can run only on machines with the QuIP software installed) to be run by a Java applet, allowing remote users to run the software using any Java-enabled browser.

6. SUMMARY

We have presented psychophysical approaches to display linearization and determination of the component relative luminances based on motion nulling. Both of these procedures rely upon the ability to present animated stimuli on the remote display; prior to using these procedures, a check for smoothness of animation will probably be useful. Despite potential problems posed by this and other issues, the world-wide web provides a vast array of potential experimental subjects which has been underutilized to date in the area of sensation and perception. It is hoped that this paper may help to change that in the future.

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