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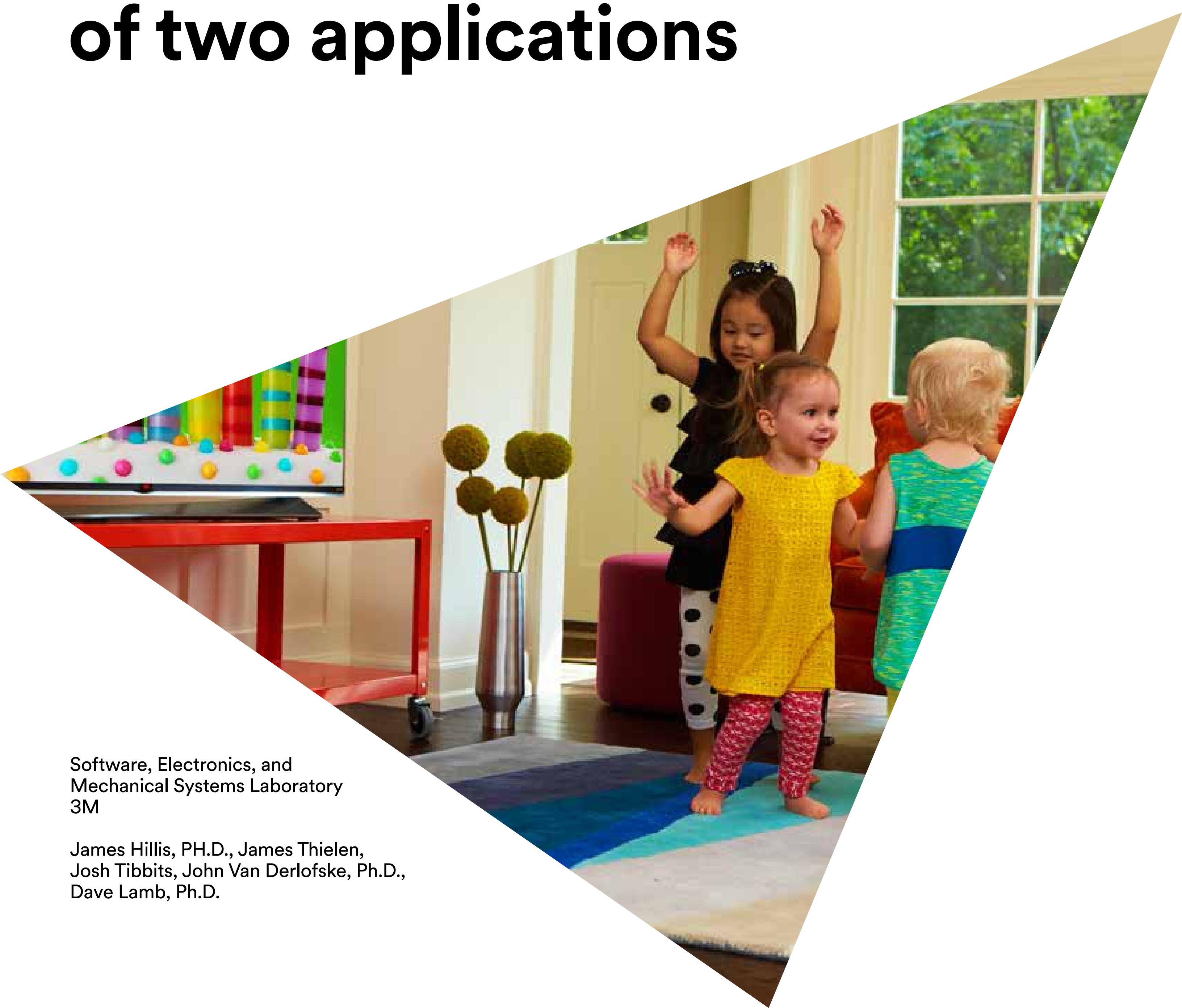
Achieving BT. 2020 color with LCDs: A tale of two applications



Software, Electronics, and
Mechanical Systems Laboratory
3M

James Hillis, PH.D., James Thielen,
Josh Tibbits, John Van Derlofske, Ph.D.,
Dave Lamb, Ph.D.

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Abstract.

One constraint on a complete transition to the ITU BT.2020 broadcasting standard is the limited availability of displays that achieve the recommended color space. However, several technologies are capable of coming close. Our research addresses the question of how close the primaries must be to the standard to be acceptable for different applications (e.g. professional vs. consumer). In previous research, we measured color difference detection thresholds for colors along the Rec. 2020 boundary with simple test patterns. In our current study, we measured color discrimination rates for photographic images rendered in color spaces near Rec. 2020 in two tasks: (1) images viewed sequentially and (2) images viewed side-by-side. We discuss how to use these data to define tolerance criteria for different applications and examine if prototype quantum-dot enabled LCDs meet these criteria.

Keywords.

Rec. 2020, color, quantum dots

Introduction

The International Telecommunications Union (ITU) published recommendations (ITU-R BT.2246-2 & BT.2020[1]) for ultra high-definition television (UHD) that include an expanded color reproduction capability. Current mass-produced television technology is unable to achieve this standard exactly. However, several technologies, such as lasers, quantum dots and OLEDs, can come close. An important question therefor is: how close must the color primaries come to the targeted standard to be considered Rec. 2020-compliant? The present study was designed to help establish guidelines for qualifying displays as Rec. 2020-compliant.

Consistent with the ITU's goal of developing the standard to "enhance visual experience", we consider visual experience the foundation for qualifying displays. Specifically, we would consider a display Rec. 2020 color-compliant if it was perceptually indistinguishable from a true Rec. 2020 display. We have therefore undertaken studies that measure human color discrimination performance for displays with color primaries that deviate from the Rec. 2020 target.

The ability to distinguish between displays with different color primary coordinates depends on, amongst other things, the individual, the task the individual is performing, and the content they are working with. For example, differences that are detectable to colorists proofing a single image for distribution may not be detectable to home viewers watching dynamic content. While mass-produced general-purpose displays cannot easily correct for differences between individual perception and specific content, markets have developed for critical applications, such as displays targeted at content distributors, professional photographers and in-home entertainment. It is therefore useful to establish criteria for Rec.2020 compliance for these various applications.

In previous work[2], we used a "no missing colors" criteria for displays aimed at professionals that master content for distribution. This criterion implied that any color difference detectable on a 'perfect' Rec. 2020 display (e.g. detectable at a boundary in a test pattern with a very small color difference, or in a color gradient), would also have to be detectable in a "Rec. 2020 compliant" display. This experiment involved test patterns designed to maximize the likelihood that a color difference would be detected. Here, two studies are presented that used photographic images to gain insight into color difference detection rates under more typical viewing conditions.

The first study was designed to simulate conditions for professionals grading content to meet color fidelity criteria. Participants were given control to toggle between two images presented sequentially in the same spatial location and instructed to scrutinize the images for any detectable color difference. The images were either physically identical, or one of the two was processed to simulate an inaccuracy in a display primary color coordinate. Participants were in a dark room, free to move about and allowed to toggle between the images as many times as they wished. After scrutinizing each image pair, the participant indicated whether the images appeared to be the same, or different. The data collected across the range of participants gives an estimate of the probability that a color difference would be detected for an average observer across a range of images for the set of primary inaccuracies we simulated.

The second study was aimed at developing guidelines for consumer level displays. Consumers typically make purchasing decisions based on side-by-side inspection of displays. Under these conditions, a display could be considered Rec. 2020-compliant if its images were perceptually indistinguishable from images presented on an adjacent, true Rec. 2020 display. Therefore, in this experiment, images were presented side-by-side. Participants were again free to move around and scrutinize the color in the images before indicating if they saw the images as the same or different.

In both experiments, we tested inaccuracies in three color directions for each of the three primaries, resulting in a total of nine conditions. Specifically, we simulated inaccuracies in the red primary as it shifted toward green, blue, and white; in the blue primary as it shifted toward red, green, and white, and in the green primary as it shifted toward red, blue, and white. Also, because of the special importance of skin tones in color reproduction, we measured difference detection rates for each of the nine color directions, using images with and without skin tones.

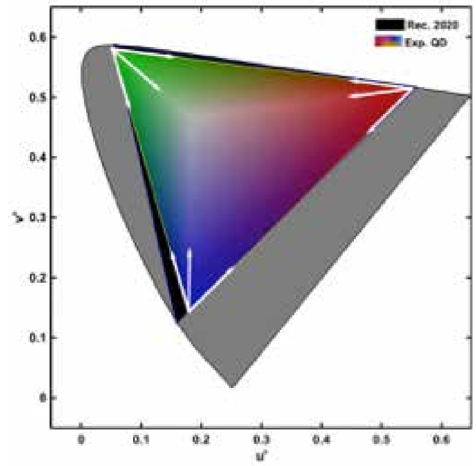

Figure 1. CIE 1976 chromaticity coordinates for Rec. 2020 color gamut (black), the gamut of the display used in the experiment (Exp. QD - colored), and the color primary mislocated vectors tested in the experiment (white).

Methods

Materials

We used a modified LG 31” 4096×2160 pixel (17:9 aspect ratio) 31MU97-B display to present images. The display was modified with 3M™ Quantum Dot Enhancement Film (3M QDEF) and blue LEDs to expand the color gamut. This modification achieves 93% coverage of the Rec. 2020 color space and is shown in Figure 1 with the Rec. 2020 color space for comparison.

Coordinates of the display and the Rec. 2020 standard are also provided in Table 1. The gamma functions and spectral power distribution of each color channel were measured with a Photo Research 670 spectroradiometer. All images were processed for this display’s color space and gamma functions, not the Rec. 2020 color space.

	Rec. 2020 primary coordinates		Modified LG primary coordinates	
	u’	*v’*	*u’*	*v’*
R	0.5570	0.5170	0.5510	0.5150
G	0.0560	0.5870	0.0520	0.5810
B	0.1590	0.1260	0.1790	0.1430

Table 1 CIE 1976 coordinates for Rec. 2020 and the modified LG monitor used in the study.

The display was controlled using a Windows 7 computer equipped with a 10-bit per color channel NVidia Quadro K-4200 video card and DisplayPort output connection. Images were processed and controlled using Matlab version 2013b software and the Psychophysics Toolbox[3].

Images and image processing. RAW format images were captured with a Nikon D7000 DSLR camera. RGB sensor values were converted to CIE L*a*b* using the camera profile generated with the X-Rite Color Checker system. Horizontally-oriented 4298×3264 resolution images were reduced to 2098×1080 to fit on half the screen in both experiments, using a bicubic interpolation in Matlab. Similarly, vertically-oriented images were reduced to 1640×2160 resolution. This was done for both side-by-side and sequential procedures so that any differences between the studies could not be attributed to image size.

L*a*b* coordinates were converted to CIE 1931 XYZ coordinates using a standard 3×3 linear matrix transform. A linear model was then employed to convert XYZ to RGB by using Matlab to solve for the 3×3 matrix M in XYZ*M = RGB. Next, L*a*b* images were converted to RGB coordinates through the linear model. These images, representing the *full-color* image representation for the display, were then stored in TIFF format, using 16-bit ICCLAB encoding.

To present images and generate versions of the images that would simulate the impact of displays with inaccurate primaries on the image colors, the ICCLAB-encoded images were loaded into Matlab and converted to 64-bit floating point numbers, scaled from zero to one. The full-color standard was presented as 10-bit per-channel color images through the Psychophysics Toolbox imaging pipeline. To create and present the “inaccurate” images, a 3×3 linear transformation from XYZ to RGB and its inverse was generated for the targeted inaccuracy. We then computed the XYZ values expected to be emitted from such a display and converted these XYZ values to the RGB values of the display we used in the experiment.

As described in the introduction, we simulated the impact of the each of the three primaries shifted in three directions. We chose to keep the white-point constant on each of the simulated displays so we could isolate the impact of primary locations on the detectability of color differences between images. The effects of the simulations on image colors for each of the nine conditions is shown in Figure 2. The panels are arranged with red, green, and blue primaries in columns and their titles (e.g. *r toward g* refers to the condition where the red primary is shifted toward the green primary).

In examining the color shifts shown in Figure 2, it is important to keep in mind that the magnitude and direction of each vector in the field is a consequence of both (1) the magnitude and direction of the *one* primary shifted in the simulation, and (2) the fact that we maintained a fixed white point. We chose to fix the white point in part because such changes are often readily detected and previous unpublished internal research showed no systematic changes in judgments of image quality with detectable white point changes. By fixing the white point in the present study, saturated colors are shifted more than unsaturated colors.

It is also important to keep in mind that we were trying to simulate what would happen to the colors of a Rec. 2020 specific image when shown on a display with one of the primaries mislocalized, as shown in Figure 2 (i.e. as if the manufacturer believed the display was perfectly compliant and thus made no effort to map the Rec. 2020 colors to the display color space). As such, the simulation is agnostic as to whether saturation, hue, or both are altered.

Consider for example, the simulation of moving the red primary toward the green primary (top left panel). The bottom right most vector along the gamut boundary indicates how the primary is mislocated. So, when this simulated display receives a [1 0 0] RGB Rec. 2020 signal, it would show the color at the tip of the vector rather than the intended color at the vertex of the triangle. The remainder of the vectors shows a sampling of what would happen to the intended Rec. 2020 RGB signal when shown on this simulated display. In this case, the magnitudes of the vectors in CIE 1976 coordinates are largest along the red-blue boundary. Colors along the line connecting the white point to the location of the blue primary are practically unchanged. Meanwhile, colors above this line are shifted toward the line while colors above it are shifted upward toward it.

A similar bisector line (colors remain practically unchanged) can be seen in the top six panels where the

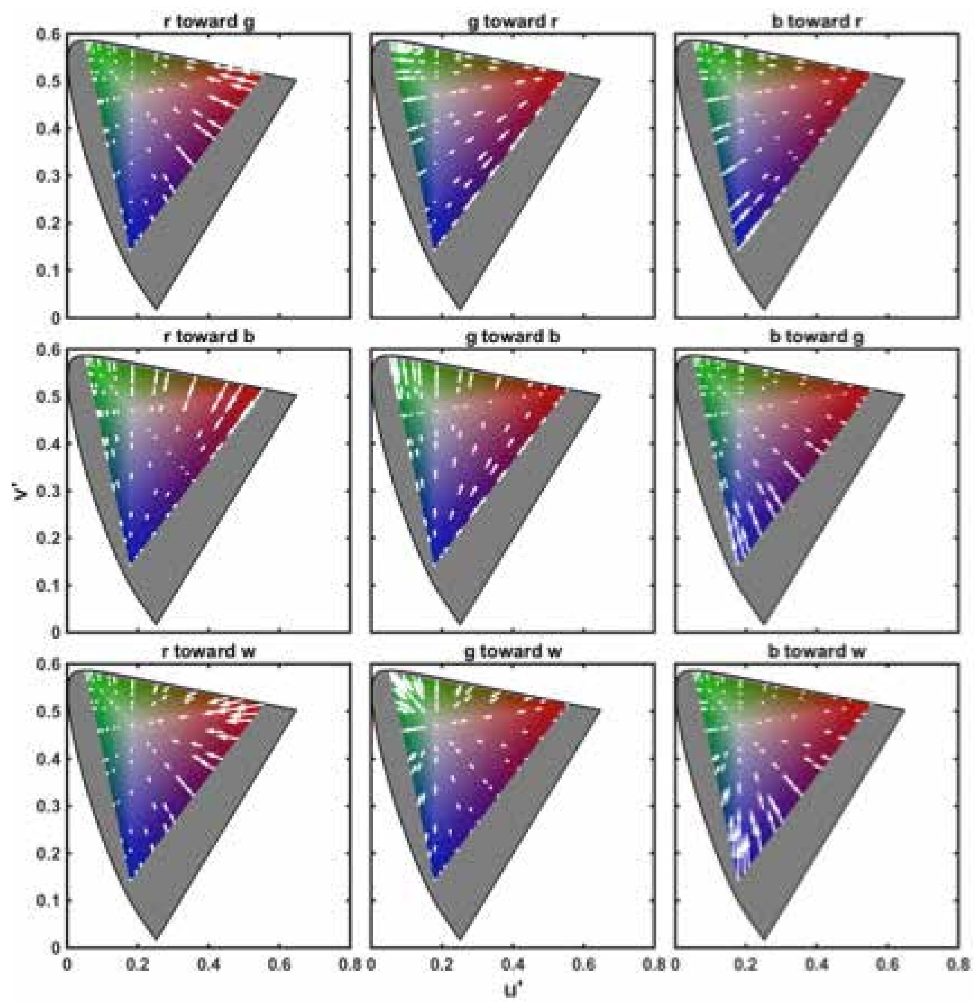

Figure 2. Color shifts resulting from the nine simulated primary direction shifts.

simulation involved moving the primaries along the gamut boundary. For the simulation of a primary color mislocated toward the white point (bottom row of panels), the colors along the opposite boundary remain practically unchanged. Note that for simulations where the primary is moved along the color boundary (top six panels), the colors on the opposite boundary shift along that boundary. This results from the need to change the relative intensities of the two primaries opposite to the one that is shifted in order to maintain the white point.

Forty-nine images with skin tones and 59 images without skin tones were selected for the experiment. All scenes for all images were illuminated by sunlight when recorded, and most of the images were highly colorful. The majority of images with skin tones were captured at an outdoor picnic where there were many children's games that included colorful objects. There were man-made and non-man-made objects in both image sets.

Procedure

The goal of these studies was to determine the probability of detecting color differences for images presented on displays that deviate from the target Rec. 2020 color space. We tested deviations along the directions shown in Figure 1. To sample difference detection probabilities, the magnitude of these vectors was controlled adaptively on a trial-by-trial basis. Selection of magnitudes was controlled using the Psi adaptive "staircase" method[4]. This method uses Bayesian updating of prior parameter estimates for the function relating color vector magnitude to the probability of difference detection. After each trial, a posterior distribution of likely values for the slope and position of this function is computed. A magnitude is then selected for the next trial to maximize the expected information for updated parameter values on the subsequent sample (i.e. to maximize expected reduction of parameter uncertainty).

We used a Gumbel cumulative distribution function ($F(x; \alpha, \beta) = 1 - e^{-10^{-\beta(x-\alpha)}}$) to model the relationship between the difference magnitudes to probability of detection. The prior distribution for the position of the curve, α, was uniform across CIE ΔE_{2000}[5] values ranging from 0 to 20. The prior for the slope, *ß*, was again uniform across a range of values from 0 to 1.5.

Each experimental session consisted of three adaptive staircases that terminated after 30 trials. There was one staircase for each of the three primaries and one test direction for each. The combination of three vectors for the three sessions were: (1) *r* toward *g*, *g* toward *b*, and *b* toward *r*; (2) *r* toward *b*, *g* toward *r* and *b* toward *g*; and (3) *r*, *g*, and *b* toward the white point, *w*, where *r*, *g*, *b*, and *w* refer to red, green, blue, and white respectively. The trial type was randomly selected on a trial-by-trial basis so participants could not know which of the three conditions was being tested on any trial. In addition, each session included 20 "catch trials" where there was no physical difference between the photographs (total of 110 trials per session). This ensured adequate sampling to estimate participants' *false alarm rates* (aka *guess rates*).

Each session consisted of images with skin tones or images without skin tones. So, for each of the sequential and side-by-side tasks, participants made their observations in six sessions (12 sessions in total). Images were presented in random order with the constraint that all images were shown once before they were repeated; again with a new randomly selected order. For each skin-tone session, each of the 49 images was shown twice and 12 images were shown three times. For each of the sessions of images without skin-tone sessions, each of the 59 images was shown once and 51 of the images were shown twice. The particular color distortion applied to each image was determined by the random ordering of trial type. Each session lasted about 20 minutes.

Participants

To date, 13 volunteers (five female and eight male, ages ranging from 20 to 47) from within 3M completed both the sequential and side-by-side tasks.

Results

To compare across conditions and establish average difference detection rates, data from all participants was pooled and fit with a Gumbel CDF. Two parameters were added to the model: the first representing a rate at which participants indicated a difference when there was no difference (a “guess-rate”, γ, aka “false alarm” rate) and a second representing a rate for key press error (lapse rate, λ) so the functional form was: $F(x; \alpha, \beta) = \gamma + (1-\gamma-\lambda)(1-e^{-10^{-\beta(x-\alpha)}})$. Parameters were selected based on a maximum likelihood criterion.

Data and fits for the sequential task for images with and without skin tones are shown in Figure 3. The x-axis represents distance from the primary in CIE ΔE_{2000} units. The y-axis represents the proportion of times observers indicated a difference between the images. Results of each of the nine conditions are shown in different panels. Panels are arranged as Figure 2 (red, green and blue primaries are in columns) and are labeled at the top. The size of each data point represents the relative number of trials that were shown at that ΔE_{2000} value.

In all but one condition (*r toward b*) there was practically no difference between results for images with and without skin tones. The similarity of the data for eight of the conditions across image type runs somewhat contrary to participants reports that the sessions with skin tones seemed more difficult than the session without. Results of the *r toward b*, where skin tones are pushed toward the white point, were the only condition that was consistent with these reports. Here, larger differences in the ΔE_{2000} value were required for images with skin tones before the participants could reliably detect an image difference.

Overall, these results indicate that *for the particular manipulations we considered*, the fidelity of skin tones does not measurably reduce color difference detection rates. Participant reports and the nature of the distortions simulated for the experiment (Fig. 2) suggest rather that differences were most easily noticed in the saturated colors.

It is also noteworthy that the slope of the psychometric function relating difference detection rates to the ΔE_{2000} metric on the x-axis is shallower in the *r toward b* case. For this color direction and location, the ΔE_{2000} metric predicts that people are very sensitive to relatively small chromaticity changes in the CIE 1976 coordinate system. It is our understanding, however, that the ΔE_{2000} metric has been extrapolated from data on less saturated colors to this region. It is therefore possible that it is not accurate for this color location and test direction. Thus, the shallower

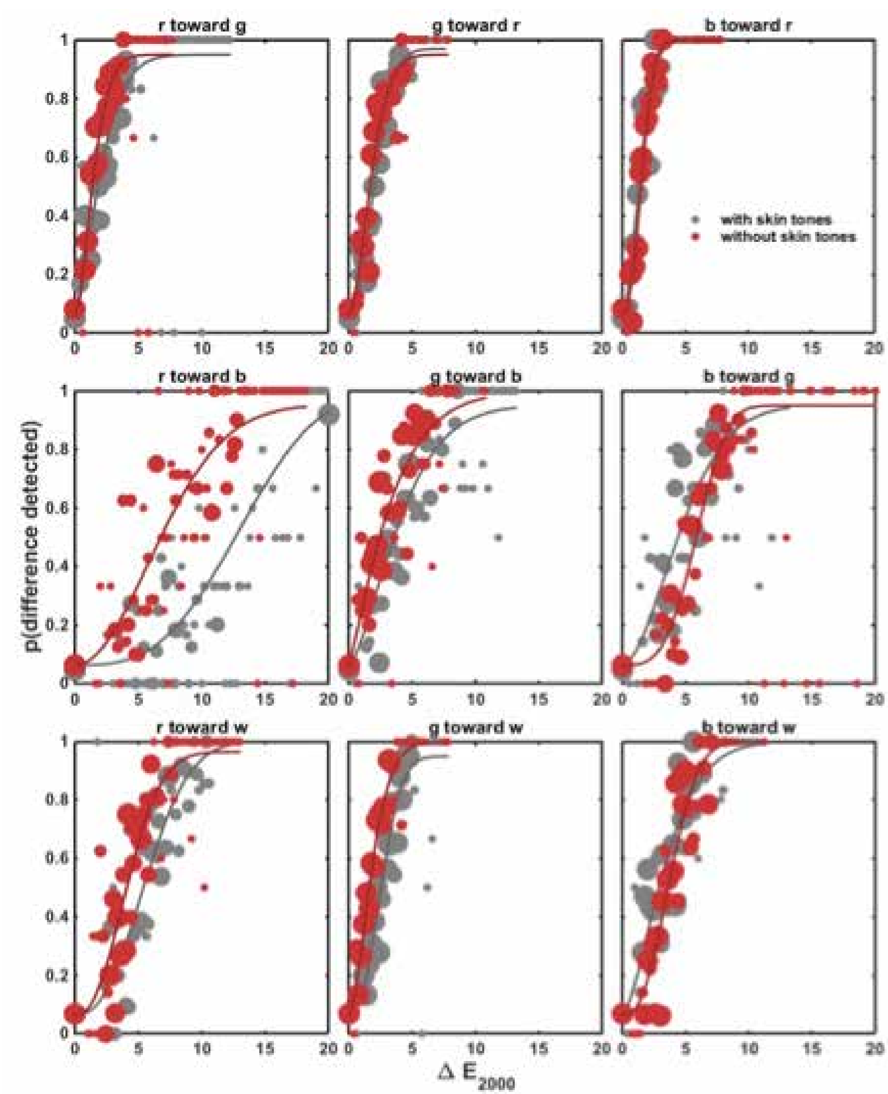

Figure 3. Results for the nine conditions for the sequential presentation for images with and without skin tones.

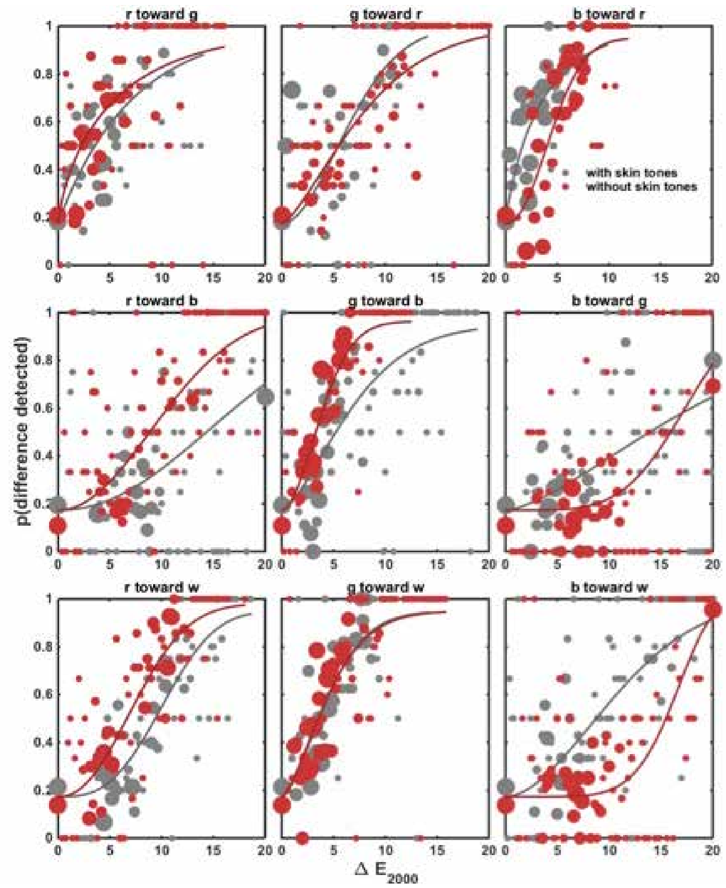

Figure 4. Results for the nine conditions for the side-by-side presentation for images with and without skin tones.

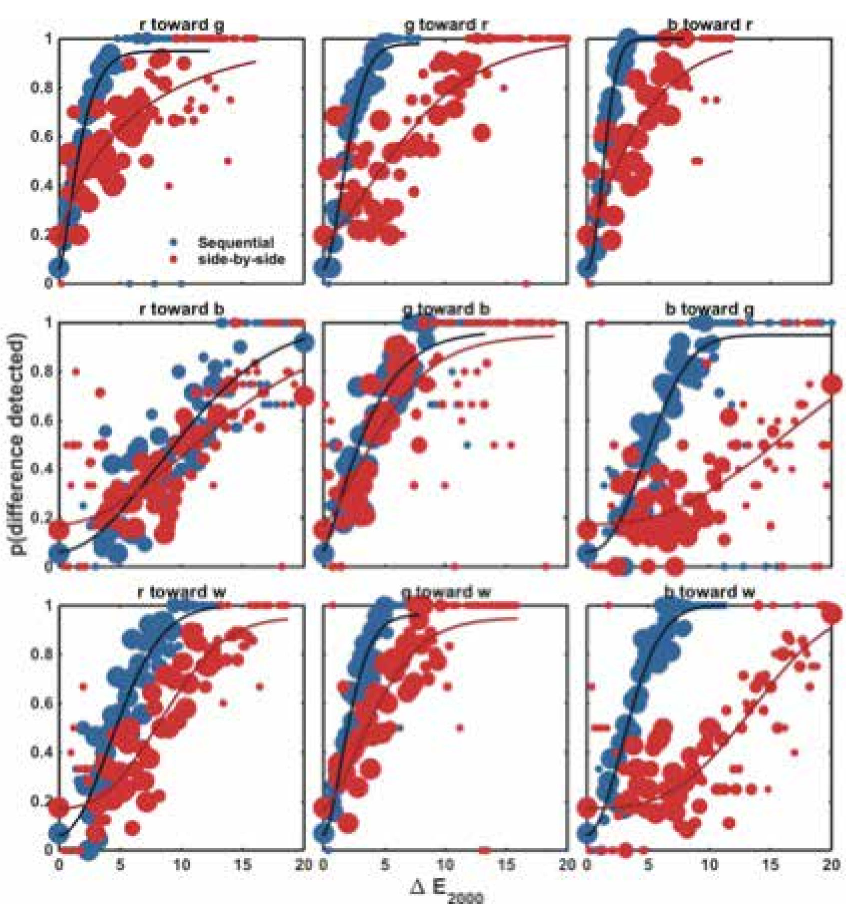

Figure 5. Results for the nine conditions for the side-by-side and sequential presentation with data for each pooled across image type (1430 samples per curve fit)

slope in this condition may reflect inaccuracy in the metric, rather than explanations related to other factors in the experiment (e.g. image content).

Figure 4 shows data and fits for the side-by-side task for images with and without skin tones are shown in the same format as the sequential. Again we observed no systematic difference between the two image types. One striking observation however is that, compared to the sequential task, larger differences in the ΔE_{2000} value were required for color differences to be reliably detected. To show this more clearly, we pooled and re-fit the data across skin-tone and non-skin-tone image types for the sequential and side-by-side tasks and plotted them in Figure 5.

The results shown in Figure 5 are consistent with the idea that different display applications will require different guidelines for establishing Rec. 2020 compliance. That is, tasks involving comparison of colors in close sequence and the same spatial location (e.g. a colorist fine tuning colors on a static image) will require a display with more accurately placed primaries than a consumer application where only side-by-side comparison affects experience and decisions.

To set such guidelines, two things are required. The first is to transform the data shown in Figure 5 into chromaticity coordinates, typically used to specify the color primaries. The model fits to the data plotted in CIE 1976 coordinates in Figure 6.

The top and bottom row of panels of Figure 6 show the results for the sequential and side-by-side tasks, respectively. Columns correspond to the red, green, and blue primaries. Each gray level corresponds to 2.5% increments in detection rates *above the guessing (false alarm) rate*. That is, the darkest level is 2.5% above the rate at which participants indicated a difference when there was no difference. The next lighter level corresponds to 5%, and so on (values indicated in 10% intervals along the red gamut boundary). In the sequential and side-by-side tasks, the guessing rates were 6.27% and 17.31% respectively. These figures include values up to a 50% difference detection rate. Inferring from our sample to the population: a 50% difference detection rate indicated that there would be a 50:50 chance that a randomly-selected person would detect a difference between a randomly-selected image shown on a true Rec. 2020 display and an uncorrected, inaccurate display. We believe values greater than a 50% difference detection are unacceptable for most applications. This may seem conservative given that we don't know if such differences would bother observers/consumers. We assume, however, that most people would prefer to see the content as it was originally intended to be seen.

Interestingly, the difference-detection contours in Fig. 6 do not follow the shapes of the 1 ΔE_{2000} discrimination ellipses shown around each of the color primaries. The ellipse around the red primary, for example, is much narrower in the direction of blue than green (a ratio of 0.19). The ratio of distance along the red-blue:red-green axes for the difference detection contours, on the other hand is only about .5 (note the u' and v' axes do no have equal scales in order to show detail in the contours so distances appear distorted); much smaller than indicted by the ΔE_{2000} metric. This lack of agreement with the ΔE_{2000} metric runs counter to our previous research aimed at establishing a "no missing colors" criterion. This may not be too surprising given that the method used in that experiment was similar to the experiements used to develop the ΔE_{2000} color difference formula (side-by-side comparison of uniform color patches) while the present experiment involved judgements of color differences in photographic images. It is however a cautionary result in regard to the application of basic colorimetric quantities to more complex judgements of color differences.

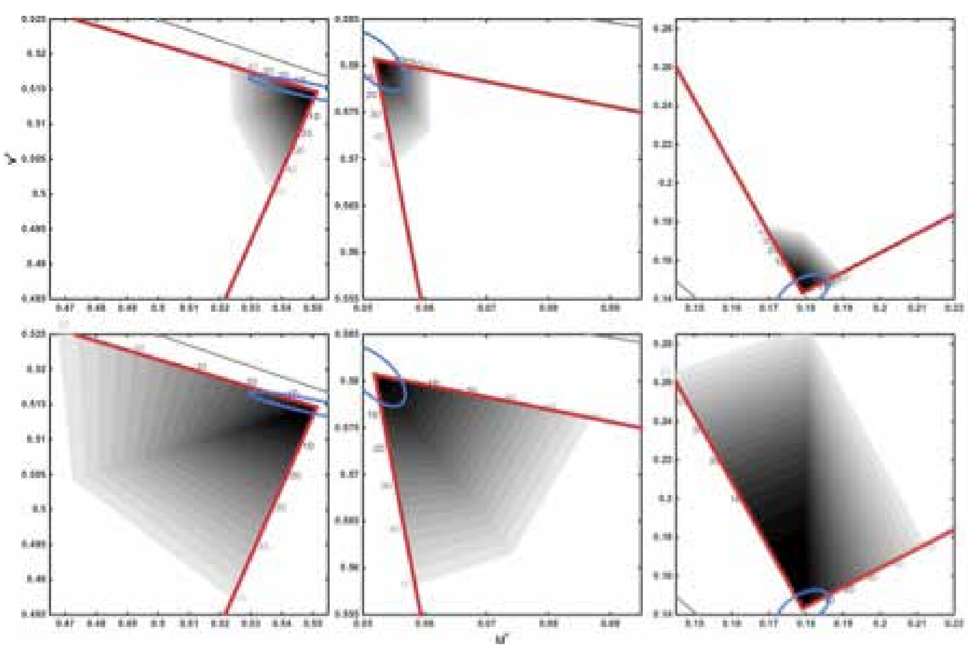

Figure 6. Difference detection rate contours in CIE 1976 coordinates for the sequential (top panels) and side-by-side (bottom panels) tasks for primary deviations from the red, green and blue primaries (left, middle and center respectively). The blue ellipses represent 1 from each of the three coordinates.

The second and more challenging step in setting guidelines is to distill data like these into an indicator of Rec. 2020 color compliance for different applications. Below, we discuss some of the factors we consider important in using these data to inform such decisions.

Discussion

Our experiments were designed to estimate the probability that calibrated images shown on a display with inaccurate color primaries would be detectably different from a true Rec. 2020 display. The aim of the study was to determine difference detectability rates "on average" for photographic images. So a 50% difference detection rate means that, for a randomly-selected person and randomly-selected image, the differences between an image shown on a display with a mislocated primary and a true Rec. 2020 display would be detected about half of the time. We believe these data form a reliable, perceptually-based foundation for establishing guidelines to qualify displays as Rec. 2020-compliant. How we use such data to establish guidelines is a matter for discussion within the broadcasting and display industries. Here are a couple of possibilities.

First, data such as these could be used to develop a continuous scale for qualifying Rec. 2020 color quality. For example, quality could be measured by computing the proportion of times a display with a given set of color primaries can be expected to be visibly different from a true Rec. 2020 display. Such a metric could be expressed as "this display is indistinguishable from an ideal Rec. 2020 display for x% of content and viewer combinations". Figure 7 provides an example of how such a scale would work and how the difference-detection rates could be used to help display designers optimize a system for a Rec. 2020 signal.

In this figure, we translated and rotated the detection rate contours from our experimental display primary positions (red lines) to Rec. 2020 coordinates (black lines). The white polygons at each vertex correspond to the "no-missing colors" criterion established in previous research[2]. The top and bottom panels correspond to data from sequential and side-by-side tasks. The red, green and blue primaries are represented in the left, middle and right panels.

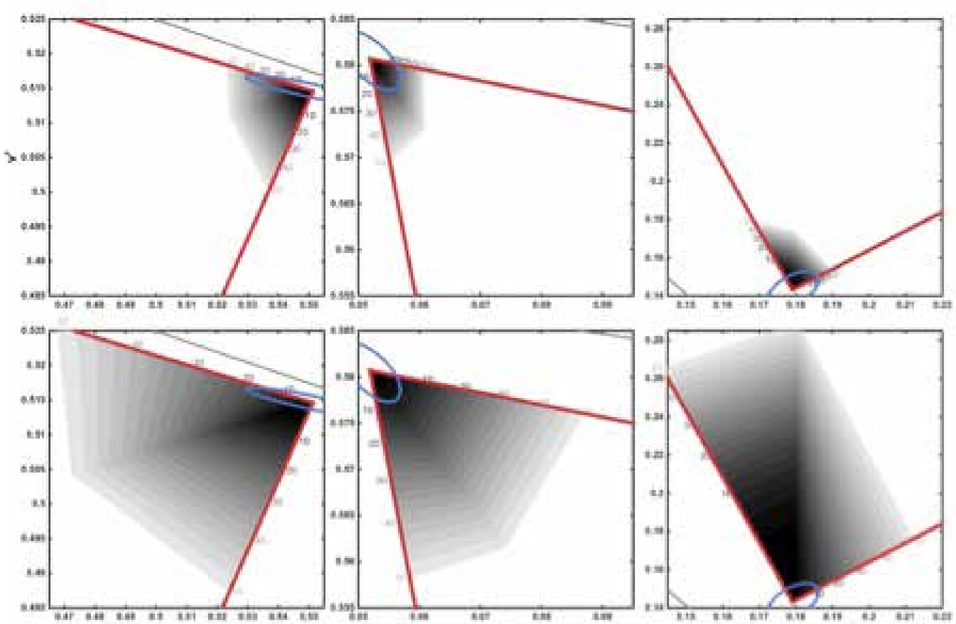

Figure 7. Difference detection rate contours translated and rotated from the experimental display (red lines) to the Rec. 2020 boundary (CIE 1976 coordinates for sequential and side-by-side (top and bottom) red, green and blue primary locations (left to right). White polygons show tolerances developed with a "no missing colors" criterion. The cyan lines represent the color gamut of a modeled QD enhanced display with the same LCD panel as the experimental display.

To demonstrate the potential advantage of using the criteria of minimizing difference in detection rates as opposed to another metric (e.g. maximizing coverage) we performed further modeling of a QD enabled display with the same LCD panel as the experimental display.

Peak wavelengths of the QDs in the prototype used in the present study (red lines in Fig. 7) were chosen in part to maximize *area coverage* of the Rec. 2020 color for a the set of LCD panels that are currently available on the market. While the red primary is clearly in a good location, moving the green QDs to a longer wavelength would push the green primary into a region that could reduce the likelihood that the display would be distinguishable from a true Rec. 2020 display[1]. In QD enabled LCDs, the location of the blue primary is partly controlled by the selection of LEDs that also have flexibility in regard to their spectral output. Shifting the blue LEDs to a longer wavelength would also push the blue primary into a better location. The cyan line in Fig. 7 shows a modeled system composed of the LCD panel used in the experimental QD prototype and red, green, and blue peak QD wavelengths at 457.5, 530.8 and 642.8nm. Based on the data presented in this paper, using QDs with these peak wavelengths would provide a display with color difference detection rates of 5%, 22.5% and 27.5% (46.6% overall assuming independence) for the red green and blue primaries. This compares 2.5, 27.5 and 35% (54.1% assuming independence) for the experimental prototype.

Computing expected difference detection rates as above would not only help display designers but could form the basis for a continuous metric for Rec. 2020 compliance. Such a metric would have direct meaning in terms of the expected proportion of time a display would show colors that are noticeably different from a true Rec. 2020 display. Development of this scale would require a larger sample of images and participants than those used in the present study. Ideally, it could be built from a model of difference detection rates based on pixel output and spatial pooling that mimics human performance (e.g. based on sCIELAB[6]). This would make it feasible to test a larger image set and establish more reliable estimates of expected difference detection rates. Further research is required to develop and test such a model.

The second approach would be to find consensus within the broadcasting and display industries on an acceptable level of difference detection rates for qualifying a display as Rec. 2020-compliant. Figure 8 provides an example of how such a guideline could be applied. In this figure, we show the 25% detection rate contours from Rec. 2020 coordinates (blue lines). (The choice of 25% was selected here only as a basis for this demonstration.) The white, black and grey polygons boundaries correspond to a "no-missing colors" criterion established in previous research[2], and "25% difference" detection rates for sequential and side-by-side image judgments. Importantly, the guidelines would state that each of the three primaries must fall within the application-specific polygon for the display to be qualified as Rec. 2020-compliant. Such a criterion would be easier to implement than the continuous metric described above but would be less informative. Nonetheless, it would provide a clear and perceptually meaningful target for display designers. Either method would also allow manufacturers, given the variance due to production methods, to establish criteria that ensure color in the same display models always look the same to consumers.

As indicated above, our data allow for difference detection rate estimates in the population when ***one*** of the Rec. 2020 primaries is mislocated. So the contours shown in Figure 8 should only be applied for 25% difference detection rates when two of the primaries are perfectly placed. But what happens when more than one of the color primaries is mislocated? Until we obtain data to address this question directly, we can compute bounds on how mislocalization of more than one primary would impact detection rates.

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[1] This is also true if some color management was introduced; that is, software could move the green to a point where the line crosses the gray zone and this may actually improve performance in terms of detectable differences from Rec. 2020.

As an upper bound, we make the simplifying assumption that the impact of each primary on difference detection rates is independent. In this case the probability detection rates would be:

$$p=p(\Delta R)+p(\Delta G)+p(\Delta B)-p(\Delta R\cap\Delta G)-p(\Delta R\cap\Delta B)-p(\Delta R\cap\Delta B)+p(\Delta R\cap\Delta G\cap\Delta B)$$

where p is the difference detection probabilities and $p(\Delta R)$, $p(\Delta G)$, $p(\Delta B)$ refer to the conditional probability of detection given the difference in red, green, and blue from the primaries. From the point of view of the display industry, this would be a "best case scenario" as it would create the most liberal tolerance. A "worst case scenario" would be one where the human observer combines the difference signal created by mislocalization of the primaries in a statistically optimal fashion. If we assume that the noise in each difference detector is uncorrelated, a statistically-optimal detector reduces to a weighted sum:

$$\hat{\Delta} = \sum_{i=1}^{3} w_i \Delta_i \text{ where the weight } w_i = \frac{r_i}{\sum_{i=1}^{3} r_i}$$

such that w_i is proportional to the reliability, r_i, of the difference signal (defined as the inverse variance of the difference signal $r_i=1/\sigma^2$.

In summary, guidelines based on either the continuous scale or discrete approach would provide a target for the development of display systems (QD-enhanced LCDs and other technologies). Either metric would help to minimize the likelihood of a detectable difference from a true Rec. 2020 color signal. QD enabled LCDs with existing panels achieve a high degree of compliance. Even better color fidelity is achievable with coordination between LCD panel makers who choose and design color filter sets and the back-light unit designers.

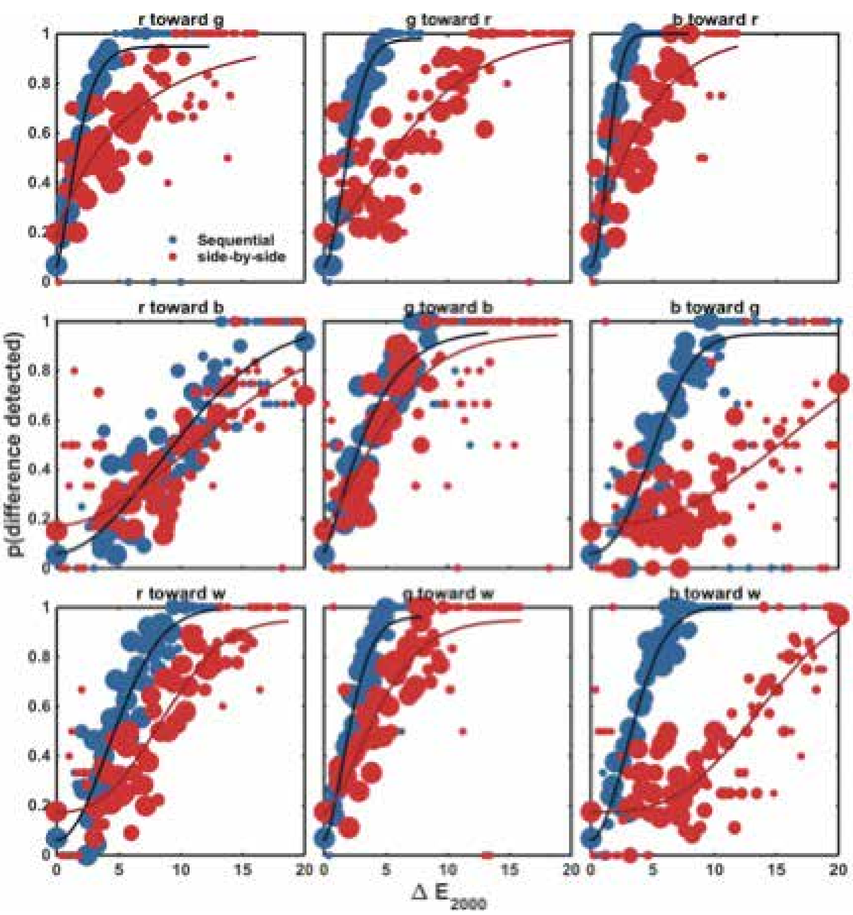

Figure 8. Twenty-five percent difference detection rate contours in CIE 1976 coordinates for the "no-missing color" (white), sequential (black) and side-by-side (gray) tasks shown at the Rec. 2020 red, green and blue primary location (left to right). The red and cyan lines represent the color gamut of the display used in the present study and a modeled QD enhanced LCD.

Conclusions

The introduction for this session of the SMPTE Technical Conference refers to the largely market-driven “wild card” world of displays. While this is unlikely to change in the near future, the “wild card” nature of the industry is in part due to the absence of metrics that have a clear relationship to the users’ experience. In this paper we have demonstrated:

1. methods that provide a foundation for the development of a perceptually meaningful manufacturing tolerance criteria and display qualification
2. that guidelines for achieving Rec. 2020 color compliance should depend on the intended display application (e.g. consumer vs professional)
3. that QD enhancement of *existing* LCDs *without any color management* has a high level of compliance for consumer applications. Matching color filter design to QDs and introducing color management will only improve their compliance.

Developing a metric based on the methods presented in this paper would give manufacturers a clear and perceptually meaningful target for design and would likely lead to better and more predictable quality for the home theater experience. We recommend the development of such a color qualification for displays to be able to claim Rec. 2020 compliance. Such information would help consumers choose a display that matches the experience they wish to have and may help reduce the “wild card” nature of the display industry. Our hope is to work with other industry members and standards organizations to develop guidelines that ensure a better quality experience across a range of display applications.

Acknowledgements

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References

1. ITU-R BT.2020, “Parameter values for ultra-high definition television systems for production and international programme exchange”. International Telecommunication Union. Aug. 2012

2. J. M. Hillis, J. Thielen, J. Tibbits, A. Lathrop, D. Lamb and J, Van Derlofske, “17.1: Invited Paper: Closing in on Rec. 2020: How Close Is Close Enough?”, *SID Symposium Digest of Technical Papers*, 46(1) pp. 223–226, June 2015

3. D. H. Brainard, D. H. The Psychophysics Toolbox. *Spatial Vision*, 10:433-436, 1997

4. L.L. Kontsevich & C.W. Tyler, “Bayesian adaptive estimation of psychometric slope and threshold”, *Vision Research*, 39(16):2729-37, August 1999

5. M. R. Luo, G. Cui, and B. Rigg, “The development of the CIE 2000 colour-difference formula: CIEDE2000,” *Color Research and Applications*, 26(5):340–350, Oct. 2001

6. Zhang, X. & Wandell, B, “A spatial extension of CIELAB for digital color image reproduction”, *Society for Information Display Journal*, 5, pp. 61-64, 1997

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