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A color characterization model for APL dependent OLED displays

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Abstract

Several studies in the past have proposed models to characterize the colorimetry of displays, most of which have poor performance for OLED displays. This is primarily due to the dependency of the colorimetry of OLED panels on the Average Pixel Level (APL) of the content displayed on them. In this study, a workflow is proposed to characterize the colorimetry of APL dependent OLED panels based on the power consumption of actual pixel-content of the displayed scene. The method performed well with a mean of mean CIEDE2000 of 19 natural images as 2.18 units.

Introduction

Predictability is key for characterizing the colorimetry of a display. A characterization model aids in understanding how a device's colorimetry behaves. There are two types of characterization models:

1. Physical
2. Empirical

Physical models rely on the established relationships between the device's physical properties and its colorimetric output [1], [2]. For instance, Cathode Ray Tube (CRT) displays were typically characterized using the Gain Offset Gamma (GOG) model [3]. Printers can be characterized using the Yule-Nielson, Kubelka-Munk, or Neugebauer models [2]. These models operate under the assumption that the devices are consistent and behave predictably. For example, all CRT displays are assumed to follow the GOG model due to the physical properties of the electron gun, which has a power law relation output luminance with respect to driving voltage. The power law relationship is not due to CRT phosphors, contrary to popular belief [4]. However, physical models do not apply to LCD or OLED displays. Studies have shown that the GOG model performs poorly for LCD displays due to variations in RGB primaries and differences in backlights and polarizers among different manufacturers [5]. The same applies to OLED displays, making it impractical to use a single physics-based model for LCD or OLED displays, although the latter technology has additional challenges to address as well, as discussed later.

Empirical models, on the other hand, establish relationships between device space and colorimetry by measuring a large population of colors. These models often utilize multidimensional interpolation or neural networks to fit the data. However, they can be complex and tend to perform poorly near the gamut boundary points [1], [2].

The International Color Consortium (ICC) workflow addresses these issues by creating ICC profiles [6] that capture a device's colorimetry using Look-Up Tables (LUTs). A display device is characterized, and the data is encoded and stored in these LUTs. The ICC profiles use an empirical approach combined with interpolation. Not all points in the LUT lattice, such as a 33x33x33 node lattice for RGB space, are measured. Instead, a smaller sample is measured, and the remaining lattice points are interpolated from this data. Several interpolation methods exist, such as tetrahedral or trilinear, with no strict guidelines from the ICC on which algorithm to use for creating LUTs [7].

Although, the colorimetry for a display can be easily encoded into 3-D Look Up Tables (LUTs) using ICC profiles, there are drawbacks. ICC profiles only hold true for the calibration status for which they are created. The workflow in the ICC paradigm is always calibration followed by characterization of the calibrated behavior encoded into an ICC profile. So, if the calibration status of the display changes, the ICC profile information does not hold true. As an example, the ICC profile created for a display (laptop or standalone monitors) for a specific peak luminance (200 cd/m^2) cannot describe the colorimetry of the same display when its peak luminance is changed (either via On Screen Display (OSD) controls or auto-brightness algorithms). For OLED displays, this problem is even more pronounced because of the absence of channel independence and chromaticity constancy.

OLED displays have an even bigger challenge to address. The colorimetry of most OLED panels (except reference or master monitors) is dependent on content which drives the Average Pixel Level (APL) of the display. Though there is not a widely accepted definition of APL, a general definition is given by Poynton as "For image data having the "gamma correction" of video, the weighted average corresponds to BT.601 luma, or average pixel level, APL." [4]. The average luminance of an OLED display is driven by the power it consumes [8] thereby affecting its color characteristics. For example, for a white window, a smaller window in the presence of no background in the frame consumes less power and can use the remaining power to produce higher luminance while the same content when shown together with a background image has much higher power requirements for the overall frame, and thus produces lesser luminance resulting in lesser absolute color gamut. This is implemented because of Automatic Brightness Limiter (ABL) algorithms implemented in OLED panel to limit overall power consumption of a panel, and the limiting algorithm is often non-linear. Several studies in the past have tried to characterize OLED displays. Ashraf et al. tested various regression models and found out that a 4th degree polynomial model was able to characterize a multi-primary OLED display well [9]. The outcome of this study was to build an inverse characterization model to map CIEXYZ values to device RGB values. This is important for cases where specific CIEXYZ values need to be reproduced on a display device. This study however ignores the impact of the APL of an image, which has a direct impact of the absolute gamut of an OLED display. A study from Sun et al. [10] proposed two models (PLCC and polynomial regression) to minimize the color errors arising because of the effect of background image. Both models however assume chromaticity constancy, that is often not observed in reality in OLED displays [8]. Sun et al. [10] proposed a Piecewise Linear assuming Chromaticity Constancy (PLCC) based compensation model (name PC model) for HDR OLED displays. The models works better than 3D-LUT, SMPTE-2084 (refer to [10]) or the original PLCC model [10] but this study also did not consider the effect of average pixel level on OLED colorimetry and the whole study was conducted with a 4% window size. Overall, it was found during literature survey that building a color characterization model based on the varying background displayed on an OLED has not been achieved yet. This also meant that if a model could take into account the effect each background has on the overall colorimetry of the OLED display, then such a model could be plausible. This hypothesis effectively meant a way to connect colorimetry to the background image on an OLED display. For this it is important to define a metric that can describe a background image.

As mentioned earlier, the average luminance of an OLED display is driven by the power it consumes. Studies by Gerhardt et al. [11], [12] proposed a methodology to predict the lifetime of an OLED display based on the power consumption of different images. With this algorithm, the LifeTime (LT) of an OLED display is calculated. The work done in our present study takes inspiration from such studies and puts forward a new way to connect the power consumption of an image with the colorimetry that the display will portray in its presence. Thus, a color characterization model for an automatic brightness limiting algorithm enabled OLED display is put forward, which takes into consideration the actual pixel-wise composition of an image background displayed and predicts the colorimetry of an OLED display.

Method

The OLED Panel: An eight inches AMOLED panel was used for this study. The panel had a MIPI Display Serial Interface [13] which had an HDMI input. The HDMI input was used to display stimulus on this display using Windows and Psychtoolbox-3. The peak luminance of the display for a 2% APL white was 650 cd/m^2. The OLED Panel used for the current study had APL dependent ABL. This meant that based on the content of the frame buffer, the power of the OLED panel is regulated/limited. If the APL was high, the peak luminance was reduced, and vice versa. Apart from this, there was also an additivity failure between primaries.

As can be seen in *Figure 1*, the sum of the red, green and blue primaries did not add up to the luminance of white. This was observed for all gray levels. Moreover, the difference between the sum of the red, green and blue primaries with the white was not the same across all gray levels, which made a characterization model based on an associated loss function difficult.

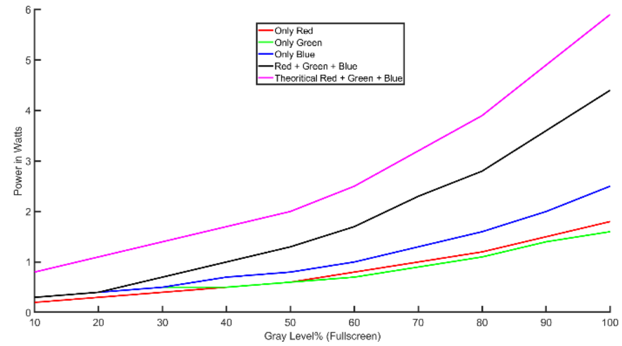

Figure 1: *Power consumption of R, G and B channels of the OLED display showing additivity failure.*

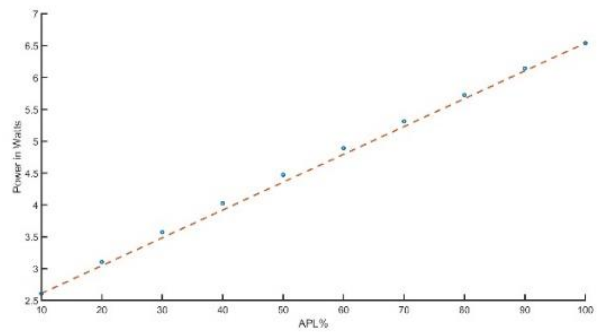

Figure 2: *For different APL levels, a linear increase in power consumption was observed. A pure white pattern is shown in this example (R=G=B=255).*

The testing done for this research showed that similar power consumption between two different images resulted in similar peak white luminance and overall color gamut volume. For example, the power consumption of

Figure **3** are 3.4 (complex image) and 3.5 (30% APL White) Watts (W) respectively, resulting in peak white luminance of 585 and 575 cd/m^2 respectively and their overall color gamut was also comparable.

***Figure 3**: Left: A natural image having a power consumption of 3.4 Watts and Right: A white having 30% APL on the display having a similar power consumption of 3.5 Watts, both resulting in similar absolute color gamuts.*

Taking inspiration from this finding, it was clear that if a procedure can be designed to calculate the power consumption of an image, its gamut should be similar to a white pattern with a similar power consumption. Thus, the approach to calculate the gamut of the OLED display comprised of two stages:

1. Calculate the power requirements of the displayed image on a pixel by pixel basis.
2. Interpolate the colorimetric values based on the power consumed by each pixel to find the colorimetry of each pixel.

Stage 1:

1. Create a power (Watts) database for a regular grid of RGB values shown full screen (100% APL respectively, see **Figure 4**, left). The granularity of the R, G and B values is 0.1, 0.1 and 0.1 on a scale of 0 to 1, thereby resulting in 1331 combinations. This defines how much power a particular combination of RGB consumes when displayed full screen.
2. Divide this power by the resolution of the display to convert full screen power to per pixel power for the RGB combinations.
3. Create a 3-D interpolation model to convert RGB values of a pixel to the power consumed by this combination using point 1 and 2.
4. Apply this model pixel wise for any image rescaled to the resolution of the display used for creating the power database in point 1 to convert any image to the power it will consume if displayed on the display panel used in point 1.

The peak power consumption of the panel was for a full screen white (full screen R, G, B = 255, 255, 255) at ~6.5W while for no content shown on the panel (full screen R, G, B = 0, 0, 0) is was ~2.1W.

Stage 2:

Different window sizes of white patterns were displayed on the display panel (see **Figure 4**, right) and their power consumption was recorded using the ChargerLab Power-Z KM003C voltmeter [14]. This was done using the integration of the database saving feature of the voltmeter with MATLAB and the patterns were shown synchronized with the data recording using Psychtoolbox (PTB-3) [15]. For each of these white patterns, 175 RGB color combinations (2% APL) were displayed and their colorimetry was recorded using an i1 X-Rite Display colorimeter by integrating ArgyllCMS libraries with MATLAB [16]. This colorimeter was used despite using an OLED display because of the reliable implementation of correction matrix needed for a colorimeter reducing the calibration needed for the instrument, and making it less dependent on the exact type of display technology [17]**.** With this dataset, the color characteristics and gamut volume of the white patterns for a particular power usage can be calculated which in turn could be linked to any RGB image having similar power requirements of the white pattern. This dataset was created for 10 area coverage cases for the display panel ranging from a white pattern covering the entire width of the panel but 10% to 100% of the height of the panel in steps of 10% increments. The colorimetry of any other power consumption could be interpolated by using the colorimetry data of these 11 cases (10 white patterns and 1 for no content (pure black background but displaying the 175 RGB colors)) using 3-D interpolation.

***Figure 4**: Setups showing the AMOLED panel connected to the ChargerLAB KM003C Voltmeter which is saving live power consumption data to a MySQL database via its software. Left: Stage 1 dataset is captured by displaying 1331 RGB combinations full screen. Right: Whites at different APL levels (different heights) is displayed (60% in the example), with 175 RGB colors displayed on top and measured with a colorimeter.*

The schematic of the workflow can be seen in Figure 5. The first stage captures the power consumption pattern of the OLED panel by displaying sequential full screen RGB patterns (1331 in total). Using this data, power/pixel is calculated for the display panel. For any image (for example, the sunflowers image shown in Figure 5), the RGB values of each pixel is used to calculate the power consumption of the image using the data from stage 1. Let us assume that the total power consumption of this image was X Watts. Stage 2 data provided the power consumption of pure white patterns covering different APL levels for 11 cases (10 measured with different white percentages and one with no white pattern) as well as the associated colorimetry. Stage 2 dataset was then used to interpolate the colorimetry for X Watts using 3-D interpolation.

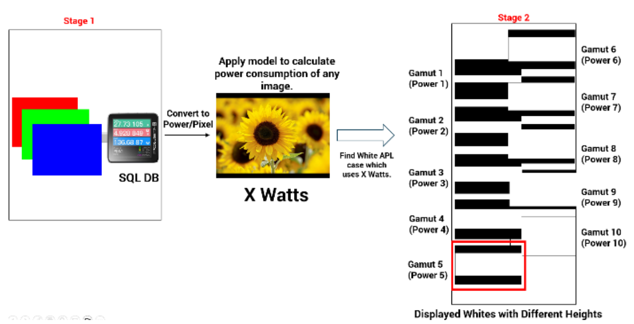

***Figure 5**: Schematic describing an example of the workflow for predicting the colorimetry of an APL dependent OLED display panel.*

Verification of the model

Nineteen images from the DXOMARK perceptual images dataset were used as backgrounds for verifying the performance of the algorithm (see **Figure 6**). The 19 images were representative of varied APL cases. The power consumption of these 19 background images (displayed with PTB-3) was calculated with the methodology explained above (Stage 1) and the real consumption was also recorded using the integration of the ChargerLAB

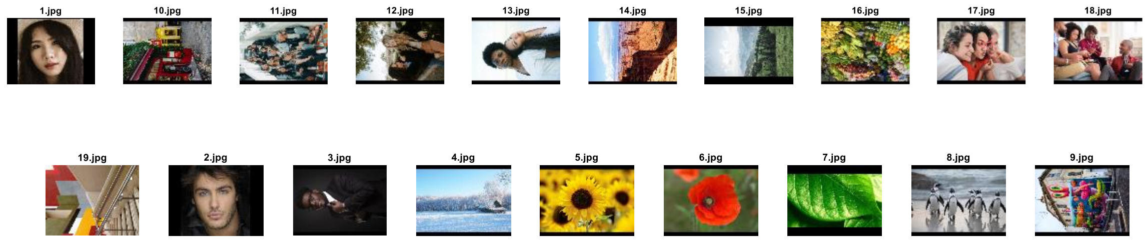

***Figure 6**: Left: DXOMARK perceptual images dataset comprising of 19 images having varied contents.*

	Stage 1			Stage 2	
Image Name	**Power (W) Calculated by Algorithm [A]**	**Power (W) Measured by VoltMeter [B]**	**Power Prediction Error % [A-B]**	**Predicted CIEDE2000 Mean**	**Predicted CIEDE2000 95 %ile**
'1.jpg'	2.78	2.88	-3.37	0.48	1.42
'10.jpg'	3.05	3.19	-4.34	1.00	1.76
'11.jpg'	3.50	3.66	-4.35	2.09	2.79
'12.jpg'	3.23	3.37	-4.29	1.58	2.20
'13.jpg'	4.58	4.83	-5.09	4.78	6.23
'14.jpg'	3.97	4.18	-4.92	3.49	4.65
'15.jpg'	3.70	3.84	-3.51	2.72	3.55
'16.jpg'	3.29	3.34	-1.46	1.49	2.15
'17.jpg'	3.76	3.91	-3.72	2.79	3.62
'18.jpg'	3.79	3.97	-4.48	2.87	3.70
'19.jpg'	3.57	3.68	-3.21	2.23	2.97
'2.jpg'	2.64	2.71	-2.45	0.61	1.49
'3.jpg'	2.42	2.47	-2.06	0.71	1.52
'4.jpg'	4.56	4.83	-5.56	4.72	6.15
'5.jpg'	3.77	3.68	2.60	2.44	3.34
'6.jpg'	3.01	3.04	-1.06	1.13	1.81
'7.jpg'	3.02	2.95	2.25	0.95	1.70
'8.jpg'	3.76	3.91	-4.01	2.84	3.69
'9.jpg'	3.56	3.76	-5.29	2.61	3.44
MEAN			3	2.18	3.06

***Table 1:** Performance of the power consumption based OLED color characterization model.*

Voltmeter application with MATLAB. With this, the accuracy of the power model with the real power consumption was calculated (see **Table 1**). Afterwards, the images were displayed with PTB-3 and on top of them, 175 RGB color patches sized 2cm by 2cm were displayed and their colorimetry was recorded using a colorimeter (see **Figure 7**), referred to as C_1.

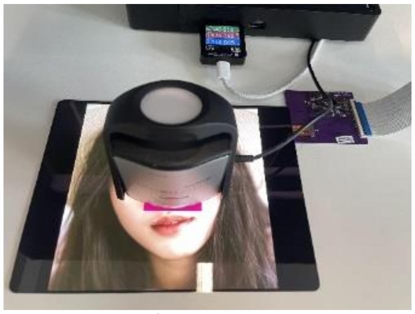

***Figure 7**: Setup to collect verification ground truth data by capturing the colorimetry of 175 RGB color patches displayed on the top of 19 DXOMARK perceptual images. These colorimetric measurements are compared with the predicted colorimetric values with the results of stage 2 and quantified using CIEDE2000.*

Using the predicted power (from stage 1 power model), the colorimetry of the 175 RGB patches displayed on top of each of the 19 images was also predicted (using the dataset and interpolation methodology of Stage 2), referred to as C_2. The mean color difference using CIEDE2000 between 175 C_1 and C_2 RGB colors was calculated for the 19 images-background cases to quantify the performance of the entire workflow (see **Table 1**).

Results

It was found that the power prediction model had an average error of **-3** percent. The mean and 95 percentile CIEDE2000 for the predicted colorimetry of the 175 RGB color patches displayed on top of the 19 background images can be seen in **Table 1**. For all 19 images combined, the mean of mean and the mean of 95 percentile CIEDE2000 was 2.18 and 3.06 units respectively, indicating good performance.

Conclusion and Future Work

As the colorimetry prediction of the combined model was found to be good, such an approach could be used to create forward characterization models for APL/content dependent OLED displays. This data could be used as an input to ICC profiling software (such as Argyll CMS) to encode the forward and reverse direction characterization of such displays into an ICC profile. Reverse characterization data from such ICC profiles can be used as reliable models to predict RGB values to reproduce specific CIEXYZ values on such displays [18]. In the future, the authors aim to use this approach to reproduce target CIEXYZ values for conducting various psychophysical experiments using this OLED panel. The authors also aim to refine this model further to make it adaptable for cases where the display's peak brightness is changed by using its OSD controls. For example, if the display peak brightness is limited to 50 cd/m^2 instead of 650 cd/m^2, a scaling factor would be needed for this model.

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Adrien Carmone *graduated in 2011 from Polytech Paris-Saclay with an engineering degree in opto-electronics. He started at Renault working on driving assistance systems. In 2019, he joined DXOMARK as a Camera Image Quality engineer and transitioned to the Display Image Quality team, where he led the design of display testing protocols.*