Characterization of iPhone Displays: A Comparative Study

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This paper reports a comparative study on evaluating the performance of six display characterization models applied to mobile displays of four Apple iPhones belonging to three different models (3GS, 4 and 4S). The characterization models evaluated include three PLCC (Piecewise Linear interpolation assuming Constant Chromaticity coordinates) models, the PLVC (Piecewise Linear interpolation assuming Variation in Chromaticity) model, Tamura-Tsumura-Miyake masking model with one principle component (MM) and modified masking model with two principle components (MMM). The results showed that PLCC3, MM and MMM models are among the best models for all tested iPhone displays. Our study also revealed that different models are ranked differently on two iPhones of the same model (iPhone 4), which suggests that the intra-model consistency may be an issue for smart phone displays.

1 Introduction

Color devices (displays, cameras, scanners, printers, etc.) are normally working in a device-dependent color space which is determined by the underlying physical mechanism of the color capturing or rendering process. For color displays, this device-dependent color space is normally a RGB space because most displays depend on three additive primaries R, G and B to reproduce colors. In order to allow accurate color reproduction across different color devices using different color spaces, a common approach is to relate different device-dependent color spaces to a single (standard) device-independent color space (e.g. CIE 1931 XYZ). The process of linking a device-dependent color space to a device-independent color space is called characterization of that color device. It is also called profiling in the context of color management where the outcome of the characterization process is called a device's profile and the selected device-independent color space is called a profile connection space.

Characterization of color displays has been widely studied in the literature and many characterization models have been proposed over the years. Most previous studies focused on computer monitors and TVs of relatively large sizes. Some characterization models have been adopted by the display industry for color characterization and calibration purposes. By contrast, small displays on portable devices like smart phones have received much less attention despite their recent rapid growth in the consumer electronics market. Different from larger displays, modern mobile displays like those used on iPhones often have a super-high resolution but lack a built-in color management mechanism. This makes it difficult to directly apply previous research results on larger displays to mobile displays. This paper tries to meet this gap in reporting our comparative study on benchmarking six display characterization models applied to Apple's iPhone displays.
To conduct the comparative benchmarking study, we used the LUT model, which represents the relationship between the two related spaces as a 3-D look-up table from the display's RGB space to CIE 1931 XYZ space, as the *reference* model for calculating the estimation error of six other models. The LUT reference model was built from data measured by uniform sampling on a regular lattice of the display's RGB cube. The other six display characterization models studied in this paper include

- three variants of the PLCC (Piecewise Linear interpolation assuming Constant Chromaticity coordinates) model with a colorimetric transform matrix **T**:
  - PLCC1 (**T** estimated from primaries at their maximum intensity) [1, 2],
  - PLCC2 (**T** estimated with linear regression) [3],
  - PLCC3 (**T** estimated with linear regression and extended with nonlinear terms for channel interaction) [4, 2],
- the PLVC (Piecewise Linear interpolation assuming Variation in Chromaticity) model [5, 6, 7],
- Tamura-Tsumura-Miyake masking model (MM) and modified masking model (MMM) [8].

The rest of the paper is organized as follows. The next section gives a brief overview of related work. Section 3 explains our experimental setup for collecting raw data about iPhone displays. An analysis on various properties of the tested iPhone displays is given in Sec. 4 which offer useful information about what models may work better. The comparative study of different models applied to the iPhone displays is described in Sec. 5. The last section concludes the paper with future work.

2 Related Work

In this section we review some related work about display characterization. Please note it is not our intention to give a complete survey of related work. Instead, we will mainly focus on models and techniques that directly related to the comparative studies we performed. Throughout the paper we use CIE 1931 XYZ space as the profile connection color space.

2.1 Modeling of Tone Reproduction Curves (TRCs)

For color displays, the relationship between the input digital value in a color channel and the output luminance (brightness) on the display is normally not linear but follows a nonlinear curve called a tone reproduction curve (also called an EOCF/EOTF – Electro-optical Conversion/Transfer Function – in different contexts). Therefore, one integral part of most characterization models is a model of TRCs of the R, G and B channels. TRCs of CRT displays have a typical "gamma"-form due to the physics behind the electron gun. However, new generation displays based on liquid-crystal technology normally don't follow the gamma-form, but can be better modeled by a sigmoidal S-shaped function [9]. Most manufacturers choose to "correct" their LCDs to mimic the behavior of CRT displays, so the gamma model may still be used to represent their TRCs. Our experimental data revealed that the TRCs of all the studied iPhone displays match the gamma model quite well, so in this paper we still use the standard gamma models as summarized in [10].
The most general form of the gamma models is the so-called GOGO (gain-offset-gamma-offset) model:

$$y = (ax + b)^\gamma + c.$$

In the above equation x is the input and y is the output, whereas a, b, and c are parameters. Fixing some or all of the parameters yields simpler models:

- $c = 0$: GOG (gain-offset-gamma) model, represented by $y = (ax + b)^\gamma$.
- $b = 0$: GGO (gain-gamma-offset) model, represented by $y = (ax)^\gamma + c$.
- $a = 1, b = c = 0$: G (simple gamma) model, represented by $y = x^\gamma$.

2.2 3-D LUT Model

The most straightforward model of characterizing a display is the 3-D LUT model, which simply uses a look-up-table (LUT) of $((R, G, B), (X, Y, Z))$ entries to represent the relationship between the 3-D RGB device-dependent color space and the profile connection space CIE XYZ. If all (R, G, B) values are covered in this 3-D LUT, then the model is an accurate representation of the display's color profile. However, the space for storing the whole 3-D LUT is too much to be convenient in many applications. For instance, for an 8-bit RGB space, the whole 3-D LUT model will require $2^{8\times3} \times (3 + 8 \times 3) \approx 453$ MB if (X, Y, Z) values are stored as double-precision floating-point numbers. In addition, having a too large 3-D LUT also means that a large number of measurements have to be performed on the display which can be very time-consuming and costly.
In practice, a 3-D LUT consists of only a small number of sampled (R, G, B) points from the whole 3-D RGB space and the missing points are estimated via interpolation. Different sampling schemes and interpolation methods have been proposed to reduce the overall errors of reproducing the complete 3-D LUT (e.g. [11]).

2.3 Other Display Characterization Models

While the 3-D LUT model requires storing a number of $((R, G, B), (X, Y, Z))$ entries, other models of display characterization aim to use a mathematical model with a smaller number of parameters to achieve the same goal. There are mainly two groups of models: physical models and numerical models, where the former are based on modeling of the

physical display processes and the latter merely use a mathematical model (e.g. an n-order polynomial model) to approximate the raw data without considering if the model has any physical meaning. Hybrid models can be devised by mixing the two models.
In the following we briefly introduce all the six display characterization models that were implemented and evaluated for iPhone displays in this work. Unless otherwise stated, the XYZ value of the display's black level is always subtracted from all the measured XYZ values that are used for estimating the model parameters and then added to the predicted XYZ values at the end.

2.3.1 PLCC models

We start with the models of the PLCC (Piecewise Linear interpolation assuming Constant Chromaticities) family which make the following assumptions about the properties of a display (which are stricter compared with other more advanced models):

- the chromaticities of the primaries are constant;
- there is no channel interaction (PLCC3 model relaxes this restriction however).

PLCC models were designed for the characterization of CRT monitors, which follow the above assumptions very well. As the assumptions make the models fast and easy to implement, they are still used for LCDs.
A PLCC model consists of two independent stages. At first RGB values are linearized by a nonlinear function, then a linear transformation represented by a matrix $\mathbf{T}$ is applied:

$$\begin{bmatrix} X & Y & Z \end{bmatrix}^T = \mathbf{T} \begin{bmatrix} R_l & G_l & B_l \end{bmatrix}^T .$$

If R_l, G_l and B_l are all normalized to be a value in $[0, 1]$, substituting the three color primaries $(R_l, G_l, B_l) = (1, 0, 0), (0, 1, 0)$ and $(0, 0, 1)$ into the above equation, the matrix $\mathbf{T}$ can be estimated as follows:

$$\mathbf{T} = \begin{bmatrix} X_R & X_G & X_B \\ Y_R & Y_G & Y_B \\ Z_R & Z_G & Z_B \end{bmatrix},$$

where X_{ch}, Y_{ch} and Z_{ch} represent the XYZ values of the primary chromaticity of a given channel $\mathrm{ch} \in \{R, G, B\}$ at its maximum intensity.
The linearization of RGB channels could be performed with one of the gamma models described in Sec. 2.1 or with three 1-D LUTs. When the LUTs are used, normally only a number of selected channel values are sampled and other missing values are estimated with the help of a linear interpolation method. To guarantee high accuracy of such a linearization procedure the measurements for building the LUTs should be preformed with a sufficiently high sampling rate.
Once $\mathbf{T}$ is estimated, the 1-D LUTs of TRCs can be computed by calculating the linearized RGB values for the raw RGB values which represent primaries. Such a model is called PLCC1 in our paper.
Instead of using the XYZ value of the color primaries one could estimate the matrix $\mathbf{T}$ with the help of linear regression [3] from a number of measured $((R, G, B), (X, Y, Z))$ pairs. We call this edition PLCC2.

Finally, the linear transformation can be extended to include additional terms to model channel interaction [4, 2]:

$$\begin{bmatrix} X & Y & Z \end{bmatrix}^T = \mathbf{T} \begin{bmatrix} R_l & G_l & B_l & R_l^2 & G_l^2 & B_l^2 & R_lG_l & G_lB_l & R_lB_l & R_lG_lB_l \end{bmatrix}^T.$$

This enhanced PLCC model is called PLCC3 in this paper.

2.3.2 PLVC model

The PLVC (Piecewise Linear interpolation assuming Variation in Chromaticities) model [6] relaxes the assumption in PLCC about the constancy of the primary chromaticities. This model was recently advocated by Thomas *et al.* [7] who showed a good performance of PLVC applied to LCDs. This model merges the two stages of PLCC models, the linearization and the linear transformation, into one. Given an RGB value, the XYZ tristimuli are computed as following:

$$\begin{aligned} X(R,G,B) &= R_X + G_X + B_X \\ Y(R,G,B) &= R_Y + G_Y + B_Y \\ Z(R,G,B) &= R_Z + G_Z + B_Z, \end{aligned}$$

where R_X is a 1-D LUT containing X values of input values in the form of $(R,0,0)$ and other notations have a similar meaning. When a 1-D LUT does not cover all values in a channel, the missing values are computed with a linear interpolation method.

2.3.3 Tamura-Tsumura-Miyake masking models

The masking model proposed in [8] relaxes the second assumption of PLCC models – the absence of channel interaction. The main idea here is to decompose a color into three color components, the primary color (selected from red, green, blue), the secondary color (selected from cyan, magenta, yellow), and the grey color, in a special way. After that the corresponding XYZ values of the three color components are summed up. The word "masking" comes from the fact that the three masking color components are masked one after the other. In the following, we give an example to explain the model.

Let us consider the color $(R,G,B) = (50,200,100)$. The intensity of the grey color, is set to be equal to the intensity of the minimum channel value, which is 50 for the given example. The mix of the other two color channels will decide the second color component. In the given example the other two channels are green and blue which are mix to decide the the second color as cyan. Its intensity will be the intensity of the next minimum channel value minus the intensity of the grey color component: $100 - 50 = 50$. The third color component is the color of the channel with a maximum intensity. In the example, it is green. Its intensity equals to the intensity of the maximum channel minus the intensity of the second color: $200 - 100 = 100$.

After the three color components are obtained, the masking model calculate the an approximation value of the corresponding XYZ value as a sum of approximated XYZ values of the three color components. Denoting the approximated XYZ value of a color (R,G,B) by $\widehat{T}(R,G,B)$ and assuming $R < B < G$, the process can be represented by

$$\widehat{T}(R,G,B) = \widehat{T}(R,R,R) + \widehat{T}(0,B-R,B-R) + \widehat{T}(0,G-B,0).$$

This formula can be built by analogy for other cases. The approximate value $\widehat{T}(\cdot)$ is obtained using the principal component analysis (PCA). In the case of the cyan color, it is done as follows:

$$\widehat{T}(0,x,x) = C(x)\left[X_{\mathrm{PCA(cyan)}} \quad Y_{\mathrm{PCA(cyan)}} \quad Z_{\mathrm{PCA(cyan)}}\right]^T,$$

where $\left[X_{\mathrm{PCA(cyan)}} \quad Y_{\mathrm{PCA(cyan)}} \quad Z_{\mathrm{PCA(cyan)}}\right]^T$ is the first principal component of the XYZ values of the cyan color at all measured intensities and $C(x)$ is calculated as follows:

$$C(x) = \left[X_{\mathrm{PCA(cyan)}} \quad Y_{\mathrm{PCA(cyan)}} \quad Z_{\mathrm{PCA(cyan)}}\right] T(0,x,x).$$

The modified masking model enhances the basic masking model by incorporating the second principal component to increase the accuracy of the approximation of $\widehat{T}(\cdot)$. This improves the performance of the model, since the tristimulus values XYZ are changing in a nonlinear manner.

3 Experimental Setup

Data collection could be very tedious and time consuming if performed by hand. In the case of ordinary displays connected to a PC with a Windows/Linux operating system it could be easily automated by means of a simple cross-platform application which instructs a spectroradiometer to take measurements and displays a series of color patches on the display in a synchronized manner. However programming environments of mobile devices are much more versatile and a common programming framework across different mobile platforms is absent. For instance, one has to use Objective-C to develop an iOS application for iPhone and Java or C/C++ to develop an Android application. There are also another mobile platforms emerging such as Windows Mobile 8, Firefox OS and Tizen. To overcome the difficulties of developing different control applications for all platforms separately we propose a web-based solution. We make use of the WebSocket API in the the new HTML5 standard which allows bi-directional, full-duplex communications between a web browser and a server. Here, the smart phone runs a web browser and a PC runs a web server and the control software of the spectroradiometer. As long as the smart phone's web browser supports WebSockets, the framework can run without any problem. Considering the HTML5 will finally replace older editions of HTML in near future, we expect all future web browsers and servers will support HTML5 and WebSockets.

Figure 1 depicts the architecture of our measurement setup. The measurement procedure functions as follows. At the beginning two corresponding connection links are established: serial communication between the spectroradiometer and the control software and WebSocket-based communication between the smart phone and the control software. Then measurement cycles take place. One measurement cycle consists of:

1. sending an RGB value to the web page;
2. receiving an acknowledgment that the color of the web page was successfully set;
3. instructing a spectroradiometer to perform a measurement;
4. receiving of a measurement data from the spectroradiometer.

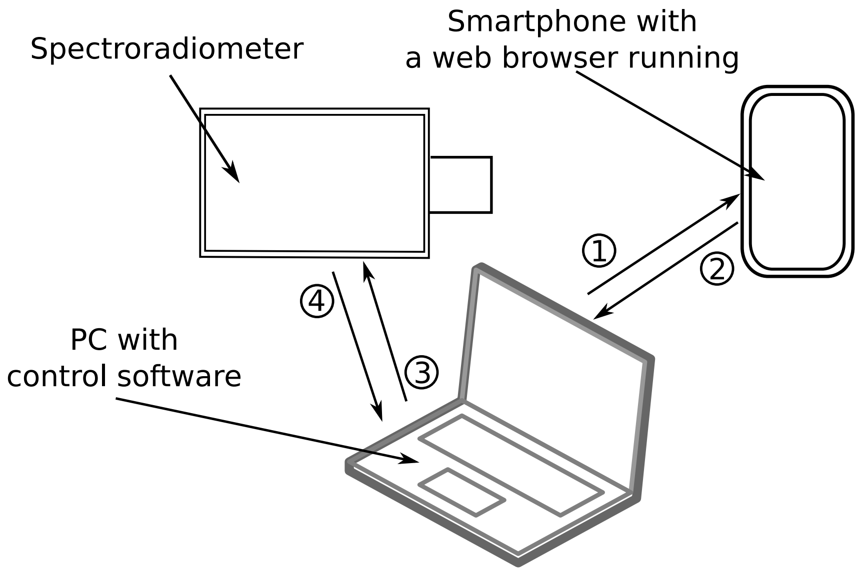


Figure 1: The illustrative diagram of the measurement setup. The numbers denote the orders of messages.

Once all the measurements are done both communication links are closed. Such a setup allows us to perform completely unattended measurements of various displays including those of smart phones.

In our study we tested four iPhones of three different models: one iPhone 3GS, two iPhones 4 and one iPhone 4S, all of which are equipped with a liquid crystal display. A Konica Minolta spectroradiometer CS-2000 was used to measure the CIE 1931 XYZ values of the color patches shown on the tested iPhone displays. The measurements were performed in a dark room. An iPhone was put to be perpendicular to the spectroradiometer at a distance of approximately 35 cm. The level of brightness of the displays was set to the maximum and the tristimuli of its central region were measured.

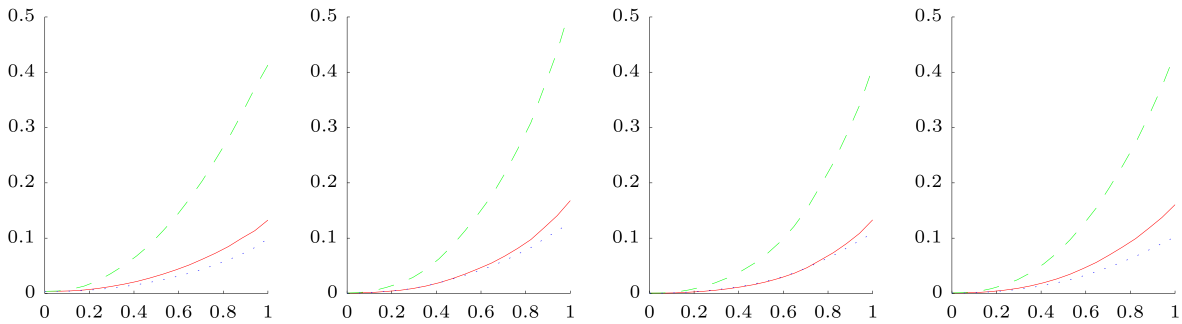
To be an accurate reference for validating other models, the LUT model requires a large number of samples of the device's RGB cube. We sampled the cube uniformly as $15 \times 15 \times 15$ cells, which lead to $18 \times 18 \times 18 = 5832$ samples in total per iPhone display. The measurement of each data set took approximately 15 hours. Compared with previous work, we collected a much larger dataset which makes our results more accurate.

4 Properties of iPhone Displays

Before we compare the performance of different display characterization models, we first report our analysis on some key properties of the measured iPhone displays. These properties also give useful clues about what characterization models may perform better.

4.1 Tone Reproduction Curves (TRCs)

All the four sets of TRCs of the tested iPhone displays have a typical "gamma"-curve form (see Figure 2). The measurements show that the nature of the TRCs remains the same across three different iPhone models: the TRCs of the red and blue channels are similar and can potentially be modeled by one equation, whereas the TRC of the green channel differs so it should be modeled separately. The two iPhones of the same model (iPhone 4) behave almost identically.

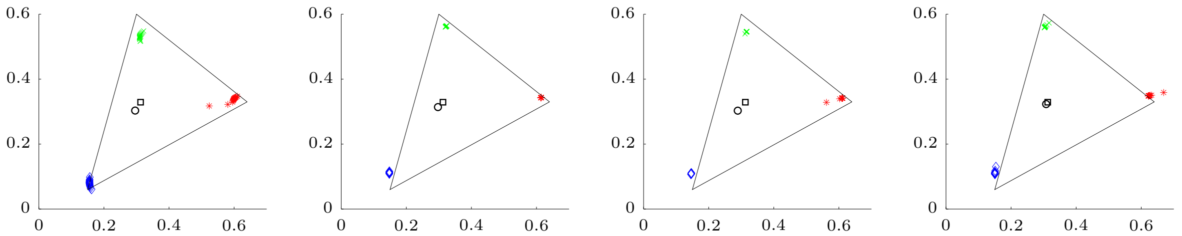


(a) iPhone 3GS (b) iPhone 4S (c) iPhone 4 (1) (d) iPhone 4 (2)

Figure 2: Non-normalized TRCs: solid line – red channel, dashed line – green channel, dotted line – blue channel.

4.2 Chromaticities of Color Primaries

Previous testing results on mobile displays (e.g. those at `http://www.displaymate.com/mobile.html`) have shown that the gamuts of most mobile phone displays including all iPhone models differ significantly from that of the sRGB space. This was also confirmed by our data (see Figure 3). The primary chromaticities were rather unstable for the display of the oldest iPhone model (3GS). They have been stabilized however in later generations of iPhones, there are only outliers in the red channel at the lowest intensities. Finally, the primary chromaticities of the newest iPhone display were very stable.



(a) iPhone 3GS (b) iPhone 4S (c) iPhone 4 (1) (d) iPhone 4 (2)

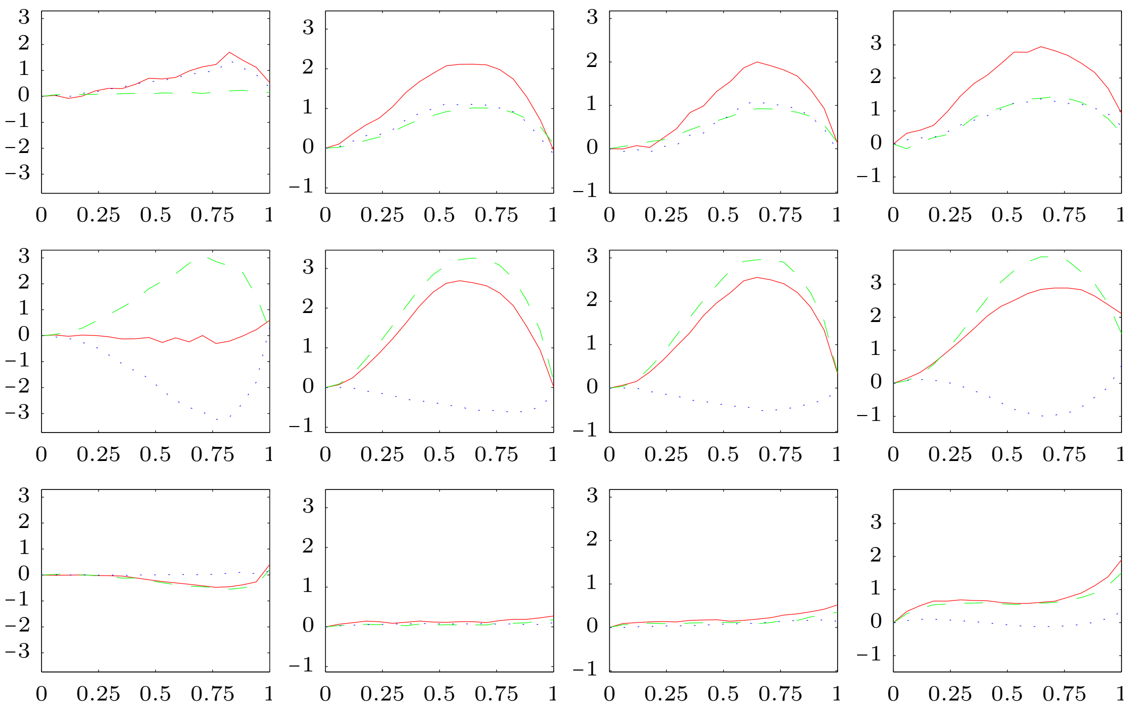
Figure 3: Primary chromaticities of tested iPhone displays. Red (stars), green (crosses), and blue (diamonds) markers represent corresponding primary chromaticities at different intensity levels. The black circle and the square represent white points of displays and that of the sRGB color space, respectively. The triangle represents the gamut of sRGB color space.

4.3 Channel Interaction

One reason why display characterization is not a trivial problem is the existence of interactions between different color channels, i.e., each color channel can be influenced by the other one or two channels in a nonlinear manner. In order to have an idea of the amount of channel interaction of iPhone displays we tested, we employed the metrics proposed by Bastani *et al.* [12] which is defined as follows for the red channel:

$$\mathrm{CI}_R(v,a,b) = 100 \times \frac{\overline{Y}(v,a,b) - \overline{Y}(0,a,b) - \overline{Y}(v,0,0)}{\overline{Y}(255,255,255)},$$

where $\overline{Y}(v,a,b)$ is the measured luminance value of the color $(R,G,B) = (v,a,b)$ minus that of the black color, $Y(0,0,0)$. The CI_X metric reflects the normalized change in luminance of the channel X, $X \in \{R,G,B\}$, when the other two channels are set to values a and b, respectively. The metric is built by analogy for the other two channels. For the four iPhone models we tested, Figure 4 shows the functions CI_R, CI_G and CI_B, which reveal a considerable amount of channel interaction for the red and green channels (although for iPhone 3GS the channel interaction is less serious for the red channel).



(a) iPhone 3GS (b) iPhone 4S (c) iPhone 4 (1) (d) iPhone 4 (2)

Figure 4: Channel interaction metrics of the four iPhones' displays. From top to bottom: $\mathrm{CI}_R(v,a,b)$, $\mathrm{CI}_G(v,a,b)$ and $\mathrm{CI}_B(v,a,b)$. In each plot, the three lines correspond to: 1) $a = 255$, $b = 255$ (solid line); 2) $a = 0$, $b = 255$ (dashed line); 3) $a = 255$, $b = 0$ (dotted line).

Table 1: Measurements used for estimating parameters of the characterization models.

Model	Measurements Used	Number of Measurements
PLCC1	primaries at different intensities	$3 \times 18 = 54$
PLCC2	all	5832
PLCC3	all	5832
PLVC	primaries at different intensities	$3 \times 18 = 54$
MM	primaries, secondaries and grey at different intensities	$(3 + 3 + 1) \times 18 = 126$
MMM	primaries, secondaries and grey at different intensities	126

5 Performance Comparison of Different Characterization Models

For each of the six models we tested, a subset of the measured RGB cube was used for estimating the model parameters. Table 1 shows which measurements were used for each model. The number of samples used for this purpose is uniquely determined by the model itself. For PLCC1 and PLVC models, 18 measurements uniformly sampled in each channel (with a sampling distance of 15) were used to estimate both the linear matrix $\mathbf{T}$ and the 1-D LUTs which also include the three primaries at the maximum intensity and and the black level. For PLCC2 and PLCC3, a subset of the whole measurements can be used, but we decided to use all the measurements to maximize their performance. For the MM and MMM models, the PCA of each channel was done based on 18 measurements.

After the parameters had been estimated, the performance of each model was validated on the whole set of measured colors by calculating some statistics of color differences between the estimated XYZ values and the measured ones. For the color difference calculation the CIE76 and CIEDE2000 standards were used. The former, although already very old, is still used in similar studies. We have included it so that our study can be easily compared to what were reported in previous work. The performance of the six characterization models is shown in Table 2, where the column "95 ptl" denotes the maximum value of color difference in 95% of all results when ranked in an ascending order.

Observing the data in Table 2, we can see that in all of the cases the simplest model PLCC1 has the worst performance. This could be explained by the fact that this model does not account for the variation in primary chromaticities and for the channel interaction. PLCC2 model having the same structure, but with an optimized linear transformation decreased the mean error. In the case of iPhones 4 and 4S this decrease is substantial. However, at the same time the maximum error increased for all iPhone displays and the 95th percentile increased for the display of the iPhone 3GS. The conclusion can be made that although PLCC1 and PLCC2 can successfully predict a certain set of XYZ with an acceptable accuracy, their simplistic structure does not allow them to predict the tristimulus values of the whole RGB cube.

PLVC model accounts for the change in primary chromaticities. That is why it has brought improvement in the performance for the display of iPhone 3GS. However, for the displays with constant primary chromaticities the improvement was marginal.

As a whole, the PLCC3, masking (MM), and modified masking (MMM) models performed the best. However, taking into account that the MM and MMM needed much less measurements for model parameter estimation and were only marginally worse they can be considered preferable to PLCC3. When comparing MM and MMM, the latter

Table 2: Performance of characterization models.

iPhone	Model	ΔE^*_{76} mean	ΔE^*_{76} max	ΔE^*_{76} std	ΔE^*_{76} 95 ptl	ΔE^*_{00} mean	ΔE^*_{00} max	ΔE^*_{00} std	ΔE^*_{00} 95 ptl
3GS	PLCC1	3.48	11.36	2.10	7.60	1.75	4.56	0.94	3.43
	PLCC2	3.18	14.21	2.48	8.93	1.41	8.97	1.10	3.61
	PLCC3	1.32	4.55	0.78	2.77	0.61	2.38	0.36	1.32
	PLVC	1.78	5.25	1.18	3.93	0.97	3.59	0.72	2.23
	MM	2.51	7.93	1.40	5.26	1.24	3.34	0.66	2.41
	MMM	**0.73**	**3.23**	**0.46**	**1.56**	**0.36**	**2.01**	**0.22**	**0.79**
4(1)	PLCC1	2.55	6.05	1.15	4.46	1.53	3.76	0.77	2.82
	PLCC2	1.67	6.53	0.89	3.17	0.92	3.09	0.51	1.90
	PLCC3	**0.89**	3.41	0.58	2.18	**0.47**	1.49	0.27	0.99
	PLVC	2.23	6.05	1.11	3.90	1.39	3.61	0.75	2.64
	MM	0.94	**2.57**	**0.49**	**1.85**	0.53	**1.68**	**0.26**	**1.00**
	MMM	0.93	3.32	0.57	1.97	0.53	1.51	0.31	1.11
4(2)	PLCC1	4.42	8.09	1.56	6.66	2.42	6.69	1.13	4.26
	PLCC2	2.62	9.18	1.27	4.74	1.35	4.15	0.70	2.70
	PLCC3	**1.31**	7.71	0.82	2.93	**0.68**	2.70	0.40	1.42
	PLVC	4.18	8.07	1.56	6.35	2.32	6.65	1.13	4.17
	MM	2.57	4.97	0.92	3.96	1.34	3.14	0.60	2.42
	MMM	1.50	**4.60**	**0.72**	**2.80**	0.78	**2.14**	**0.37**	**1.47**
4S	PLCC1	3.11	7.06	1.32	5.44	1.79	4.40	0.87	3.23
	PLCC2	1.86	8.25	1.03	3.64	1.01	3.81	0.56	2.08
	PLCC3	**0.94**	**5.09**	0.67	2.37	**0.50**	**3.35**	0.31	1.12
	PLVC	2.64	6.79	1.27	4.69	1.60	4.18	0.83	2.97
	MM	1.13	6.77	**0.56**	**2.08**	0.59	2.80	**0.29**	**1.11**
	MMM	1.05	6.24	0.61	2.12	0.58	2.95	0.32	1.14

has improved performance considerably only for the displays of the iPhone 3GS and the second iPhone 4.

The results on the two iPhones 4 showed that they behave rather differently. All models perform much better on the first iPhone 4. Such discrepancies can also be observed in Fig. 4c)-d) where the chromaticities of the red primaries do not match for the two iPhones 4. The reason of these discrepancies remains unclear, but the results do shed some lights on the consistency of color reproduction across different devices of the same iPhone model.

6 Future Work

There are three lines of future research. The first one involves further study on the intra-model consistency of mobile phone displays, inspired by the visible discrepancies in the results of the two iPhone 4 devices. Since we only tested one device for other two iPhone model (3GS and 4S), more research is needed to clarify if different iPhone models have different levels of consistency in their color reproduction capabilities.

The second research line covers investigations on improvements to existing models. Not only those good models will be considered for further improvement, but also those performing relatively poor but computationally light. We will also investigate which minimal subset of the measured cube can be used for estimating parameters of PLCC2 and PLCC3 models so that they perform at the same level as when all the measurements are used. The third line of research is to study more mobile phone models particularly those based on Android OS produced by Samsung, HTC and Google. Since most high-end Android phones are using AMOLEDs other than Super LCDs as their displays, we expect there will be a big difference in the performance of the characterization models studied.

References

[1] R. S. Berns, R. J. Motta, and M. E. Gorzynski. CRT colorimetry. Part I: Theory and practice. *Color Research & Application*, 18(5):299–314, 1993.

[2] N. Katoh, T. Deguchi, and R. S. Berns. An accurate characterization of CRT monitor (II) proposal for an extension to CIE method and its verification. *Optical Review*, 8:397–408, 2001.

[3] O. Arslan, Z. Pizlo, and J. P. Allebach. CRT calibration techniques for better accuracy including low-luminance colors. In *Color Imaging IX: Processing, Hardcopy, and Applications*, volume 5293 of *Proceedings of the SPIE*, pages 286–297. SPIE, 2003.

[4] P. Bodrogi and J. Schanda. Testing a calibration method for colour CRT monitors. a method to characterize the extent of spatial interdependence and channel interdependence. *Displays*, 16(3):123–133, 1995.

[5] W. W. Farley and J. C. Gutmann. Digital image processing systems and an approach to the display of colors of specified chrominance. Technical Report HFL-80-2/ONR-80, Virginia Polytechnic Institute and Slate University, Blacksburtf, VA, USA, 1980.

[6] L. Del Jiménez Barco, J. A. Díaz, J. R. Jiménez, and M. Rubi no. Considerations on the calibration of color displays assuming constant channel chromaticity. *Color Research & Application*, 20(6):377–387, 1995.

[7] J.-B. Thomas, J. Y. Hardeberg, I. Foucherot, and P. Gouton. The PLVC display color characterization model revisited. *Color Research & Application*, 33(6):449–460, 2008.

[8] N. Tamura, N. Tsumura, and Y. Miyake. Masking model for accurate colorimetric characterization of LCD. *Journal of the Society for Information Display*, 11(2):333–339, 2003.

[9] Y. Kwak and L. MacDonald. Characterisation of a desktop LCD projector. *Displays*, 21(5):179–194, 2000.

[10] N. Katoh, T. Deguchi, and R. S. Berns. An accurate characterization of CRT monitor (I) verifications of past studies and clarifications of gamma. *Optical Review*, 8(5):305–314, 2001.

[11] V. Monga, R. Bala, and X. Mo. Design and optimization of color lookup tables on a Simplex topology. *IEEE Transactions on Image Processing*, 21(4):1981–1996, 2012.

[12] B. Bastani, B. Cressman, and B. Funt. Calibrated color mapping between LCD and CRT displays: A case study. *Color Research & Application*, 30(6):438–447, 2005.