Cross-media color reproduction and display characterisation

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1 Introduction

Digital images today are captured and reproduced using a plethora of different imaging technologies (e.g. digital still cameras based on CMOS or CCD sensors, Plasma or Liquid Crystal Displays, inkjet or laser printers). Even within the same type of imaging technology there are many parameters which influences the processes, resulting in a large variation in the ”color behaviour” of these devices.

It is therefore a challenge to achieve color consistency throughout an image reproduction workflow, even more so since such image reproduction workflows tend to be highly distributed and generally uncontrolled. This challenge is relevant for a wide range of users, from amateurs of photography to professionals of the printing industry. And as we try to advocate in this chapter, it is also highly relevant to researchers within the field of image processing and analysis.

In the next section we introduce the field of cross-media color reproduction, including a brief description of current standards for color management, the concept of colorimetric characterization of imaging devices, and color gamut mapping. Then, in Section 3 we focus on state of the art and recent research in the characterization of displays. In Section 4 we consider methods for inverting display characterization models; this is an essential step in cross-media color reproduction, before discussing quality factors, based on colorimetric indicators, briefly in Section 5. Finally, in Section 6 we draw some conclusions and outline some directions for further research.

2 Cross-media color reproduction

When using computers and digital media technology to acquire, store, process, and reproduce images of colored objects or scenes, a digital color space is used, typically *RGB*, describing each color as a combination of variable amounts of the primaries red, green, and blue. Since most imaging devices “speak” *RGB* one may think that there is no problem with this. However every individual device has its own definition of *RGB*, that is, for instance for output devices such as displays, for the same input *RGB* values, different devices will produce significantly different colors. It usually suffices to enter the TV section of an home electronics store to be reminded of this fact.

So therefore, the *RGB* color space is usually not standardized, and every individual imaging device has its own definition of it, i.e. its very own relationship between the displayed or acquired “real-world” color and the corresponding *RGB* digital color space. Achieving color consistency throughout a complex and distributed color reproduction workflow with several input and output devices is therefore a serious challenge; achieving such consistency defines the research field of cross-media color reproduction.

The main problem is thus to determine the relationships between the different devices’s color “languages,” analogously to colour “dictionaries.” As we will see in the next subsections, a standard framework has been defined (color management system), in which dictionaries (profiles) are defined for all devices; between their native color language and a common, device-independent language. Defining these dictionaries by characterizing the device's behaviour is described in Section 2.2–2.2, while Section 2.3 addresses the problem of when a device simply does not have rich enough "vocabulary" to reproduce the colors of a certain image.

2.1 Color Management Systems

By calibrating color peripherals to a common standard, Color Management System (CMS) software and architecture makes it easier to match colors that are scanned to those that appear on the monitor and printer, and also to match colors designed on the monitor, using for example CAD software, to a printed document. Color management is highly relevant to persons using computers for working with art, architecture, desktop publishing or photography, but also to non-professionals, as for example, when displaying and printing images downloaded from the Internet or from a Photo CD.

To obtain faithful color reproduction, a Color Management System (CMS) has two main tasks. First, colorimetric characterization of the peripherals is needed, so that the *device-dependent* color representations of the scanner, the printer, and the monitor can be linked to a *device-independent* color space, the Profile Connection Space (PCS). This is the process of *profiling*. Furthermore, efficient means for processing and converting images between different representations are needed. This task is undertaken by the Color Management Module (CMM).

The industry adoption of new technologies such as CMS depends strongly on standardization. The International Color Consortium (ICC, `http://www.color.org`) plays a very important role in this concern. The ICC was established in 1993 by eight industry vendors for the purpose of creating, promoting and encouraging the standardization and evolution of an open, vendor-neutral, cross-platform color management system architecture and components.

For further information about color management system architecture, as well as theory and practice of successful color management, refer to the ICC specification [ICC, 2004] or any recent textbooks on the subject, such as "Color engineering", [Green and MacDonald, 2002].

Today there is wide acceptance of the ICC standards, and different studies such as one by Schläpfer et al. [1998] have concluded that color management solutions offered by different vendors are approximately equal, and that color management has passed the breakthrough phase and can be considered a valid and useful tool in color image reproduction.

However, there is still a long way to go, both when it comes to software development (integration of CMS in operating systems, user-friendliness, simplicity, etc.), research in cross-media color reproduction (better color consistency, gamut mapping, color appearance models, etc.), and standardization. Color management is a very active area of research and development, though limited by our knowledge on the human perception process. Thus in the next sections, we will briefly review different approaches to the colorimetric characterization of image acquisition and reproduction devices.

2.2 Device colorimetric characterization

Successful cross-media color reproduction needs the calibration and the characterization of each color device. It further needs a color conversion algorithm, which permits to convert color values from one device to another.

In the literature, the distinction between calibration and characterization can vary substantially, but the main idea usually remains the same. For instance, some authors will consider a tone response curve establishment as a part of the calibration, others as a part of the characterization. These difference does not mean too much in practice and is just a matter of terminology. Let us consider the following definition:

The **calibration** process put a device in a fixed state, which will not change with time. For a color device, it consists in setting up the device. Settings can be position, brightness, contrast, and sometimes primaries and gamma, etc.

The **characterization** process can be defined as understanding and modeling the relationship between the input and the output, in order to control a device for a given calibration set-up. For a digital color device, this means either to understand the relationship between a digital value input and a produced color for an output color device (printer, display) or, in the case of an input color device (camera, scanner), to understand the relationship between the acquired color and the digital output value. Usually, a characterization model is mostly static, and is relying on the capability of the device to remain in a fixed state, thus on the calibration step.

As stated above, the characterization of a color device is a modeling step, which permits to relate the digital value that characterizes the device and the actual color defined in a standard color space, such as *CIEXYZ*.

There are different approaches to modeling a device.

One can consider a **physical** approach, which will aim to determine a set of physical parameters of a device, and uses these in a physical model based on the technology definition. Such an approach has been extensively used for CRT displays, and also for cameras it is quite common. In this case, the resulting accuracy will be constrained by how well the device fits the model hypothesis and how accurate the related measurements were taken. Commonly a physical device model consists in a two steps process. First, a linearization of the intensity response curves of the individual channels, i.e. the relation between the digital value and the corresponding intensity of light. The second step is typically colorimetric linear transform (i.e. a 3x3 matrix multiplication). The characteristics of the colorimetric transform is based on the chromaticity of the device primaries.

Another approach consists in fitting a data set with any **numerical** model. In this case, the accuracy will depend on the number of data, on their distribution and on the interpolation method used. Typically a numerical model would require more measurement, but would make no assumption on the device behavior. We can note that the success of such a model will depend also on the capacity of the model to fit with the technology anyway.

For a numerical method, depending on the interpolation method used, one have to provide different sets of measures in order to optimize the model determination. This implies to first define which color space is used to make all the measures. The

CIEXYZ color space seems at first to be the best choice considering that some numerical method would use its vectorial space properties successfully, particularly additivity, in opposition with *CIELAB*. An advantage is that it is *absolute* and can be used as an intermediary color space to a uniform color space, *CIELAB*, which is recommended by the *CIE* for measuring the color difference when we will evaluate the model accuracy (the ΔE in *CIELAB* color space). However, since we define the error of the model, and often the cost function of the optimization process as an Euclidean distance in *CIELAB*, this color space can be a better choice.

These sets of measures can be provided using a specific (optimal) color chart, or a first approach can be to use a generic color chart, which allows to define a first model of characterization.

However, it has been shown that it is of major importance to have a good distribution of the data everywhere in the gamut of the device and more particularly on the faces and the edges of the gamut, which is roughly fitting with the edges and faces of the *RGB* associated cube. These faces and edges define the color gamut of the color device. The problem with acquisition device such as cameras is that the lighting conditions are changing, and it is really hard to have a dedicated data set of patches to measure for every possible conditions. Thus, optimal charts have been designed, which color patches spectral characteristics are made in order not to relatively vary with changing of a given number of illuminants [MAIER and RINEHART, 1990]. [1]

Another possibility is that, based on a first rough or draft model, one can provide an optimal data set to measure, which takes into account the non-linearity of the input device. There are several methods to minimize errors due to the non-linear response of devices. By increasing the number of patches, we can tighten the mesh's sampling. This method can be use to reach a lower error. Unfortunately, it might not improve much the maximum error. To reduce it, one can decide to over-sample some particular area of the color space. The maximum error is on the boundaries of the gamut, since there are fewer points to interpolate, and in the low luminosity areas, as our eyes can easily see small color differences in dark colors. Finally, one can solve this non-linearity problem by using a non-linear data set distribution, which provides a quite regular sampling in the *CIELAB* color space.

Characterization of input devices

An input device has the ability to transform color information of a scene or an original object into digital values. A list of such devices would include digital still cameras, scanners, camcorders, etc. The way it transforms the color information is usually based on (three) spectral filters with their highest transmission or resulting color around a Red, Green and Blue part of the spectrum. The intensity for each filter will be related to the *RGB* values. A common physical model of such a device is given as

$$\rho = f(\nu) = \int L(\lambda)R(\lambda)S(\lambda)\mathrm{d}\lambda, \tag{1}$$

[1] COMMENT: .. With more or less success. This paragraph needs citation and improvement, maybe redistribute a part to the next subsection? STILL?

where ρ is the actual digital value output, v is the non linearized value, $L(\lambda)$, $R(\lambda)$, $S(\lambda)$ are the spectral power distribution of the illuminant, the spectral reflectance of the object, and the spectral sensitivity of the sensor, including a color filter.

The input device calibration includes the setup of the time exposure, the illumination (for a scanner), the contrast setup, the color filters, etc.

In the case of input devices, let us call the forward transform the transform which relates the acquired color with the digital value, e.g. conversion from *CIEXYZ* to *RGB*. Meanwhile the inverse transform will estimate the acquired color given digital value caught by the device, e.g. converts from *RGB* to *CIEXYZ*.

The input device characterization can be done using a physical modeling or a combination of numerical methods. In the case of a physical modeling, the tone response curves will have to be retrieved; the spectral transmission of the color filters may have to be retrieved too, in order to determine their chromaticicities, thus establishing the linear transform between intensity linearized values and the digital values. This last part requires usually a lot of measurements, and may requires the use of a monochromator or an equivalent expensive tool. In order to reduce this set of measurements, one need to make some assumptions and to set some constraints to solve the related inverse problem. Such constraints can be the modality of the spectral response of a sensor or that the sensor response curve can be fitted with just a few number of the first fourier coefficients [Barnard and Funt, 2002], [Sharma and Trussell, 1993], [Sharma and Trussell, 1996], [Finlayson et al., 1998]. Such models would mostly use the *CIEXYZ* color space or another space which has the additivity property.

Johnson [1996] gives advices to achieve a reliable color transformation for both scanner and digital cameras. In this article, one can find diverse characterization procedures, based on the camera colorimetric evaluation using a set of test images. The best is to find a linear relationship to map the output values to the input target (each color patch). The characterization matrix, once more, provides the transformation applied to the color in the image. In many cases the regression analysis shows that the first order linear relationship is not satisfactory and a higher order relationship or even non-linear processing is required (log data, gamma correction or S-shape for example). Lastly, if a matrix cannot provide the transformation, then a LUT (Look Up Table) will be used. Unfortunately, the forward transform can be complicated and quite often produces artifacts [Johnson, 1996]. Possible solutions to the problems of linear transformations encountered by Johnson are least-squares fitting, non linear transformations or look-up-tables with interpolation. In the last case, any scanned pixel can be converted into tristimulus values via the look-up-table(s) and interpolation is used for intermediate points which do not fall in the table itself. This method is convenient for applying a color transformation when a first order solution is not relevant. It can have a very high accuracy level if the colors are properly selected.

The colorimetric characterization of a digital camera was analyzed by Hong et al. [2001]. An investigation was done to determine the influence of the polynomial used for interpolation and the possible correlation between the RGB channels. The channel independence allows us to separate the contribution of spectral radiance from the three channels. Hong et al. [2001] also checked the precision of the model with respect to the training samples data size provided and the importance of the color precision being either 8 or 12 bits. According to the authors, there are two categories of color characterization methods: either spectral sensitivity based (linking the spectral sensitivity to the CIE color matching functions) or color target based (linking color patches to the CIE color matching functions). These two solutions lead to the same results, but the methods and devices used are different. Spectral sensitivity analysis requires special equipment like a radiance meter and a monochromator; while a spectrophotometer is the only device needed for the color target based solution. Typical methods like 3D lookup tables with interpolation and extrapolation, least square polynomials modeling and neural networks can be used for the transformation between *RGB* and *CIEXYZ* values, but in this article, polynomial regression is used. As for each experiment only one parameter (like polynomial order, number of quantization levels, or size of the training sample) changes, the ΔE^*_{ab} difference is directly linked to the parameter.

Articles published on this topic are rare, but characterization of other input devices with a digital output operates the same way. Noriega et al. [2001] and Gatt et al. [2003] further propose different transformation techniques. These articles discuss the colorimetric characterization of a scanner and a negative film. In the first article [Noriega et al., 2001], the authors decided to use least squares fitting, look up tables and distance weighted interpolation. The originality comes from the use of the Mahalanobis distance used to perform the interpolation. The second article [Gatt et al., 2003] deals with the negative film characterization. Distance weighted interpolation, Gaussian interpolation neural networks and non-linear models have been compared using Principal Component Analysis. In these respective studies, the models were trained with the Mahalanobis distance (still using the color difference as a cost function) and neural networks.

Characterization of output devices

An output device will be any device that will reproduce a color. In this category fall printers, projection systems, monitors.

In this case, the input to the device is a digital value, and we will call the forward transform the transform that predicts the color displayed for a given input, e.g. *RGB* to *CIEXYZ*. The inverse or backward transform will then define which digital value we have to input to the device to reproduce a wanted color, e.g. *CIEXYZ* to *RGB*.

The characterization approach for the output devices and media is similar to that of input devices. One have to determine a model based on a set of measured color patches.

The main advantage of output devices is the fact that we could do a dynamic characterization process, i.e. we may use a small set of color to yield a draft model, then create an optimal color chart, which will allow an accurate color characterization of the output device. With printers, this would require a bit of manual intervention, with displays this could be fully dynamic and automatic.

2.3 Color gamut considerations

A color gamut is the set of all colors that can be produced by a given device or that are present in a given image. Although these sets are in principle discrete, gamuts are most often represented as volumes or blobs in a 3D color space using a gamut boundary descriptor [Bakke et al., 2010]. When images are to be reproduced between different devices, the problem of gamut mismatch has to be addressed. This is usually referred to as color gamut mapping. There is a vast amount of literature about the gamut mapping problem. Fortunately, much of this was summarized by Morovic and Luo [2001].

To keep the image appearance, some constraints are usually considered while doing a gamut mapping:

- Preserve the grey axis of the image and aim for maximum luminance contrast.
- Reduce the number of out of gamut colours.
- Minimize hue shifts.
- Increase the saturation.

CIELAB is one of the most often used color space for gamut mapping, but there are deficiencies in the uniformity of hue angles in the blue region. To prevent this shift, one can use Hung and Berns' data to correct the *CIELAB* color space [Braun et al., 1998]. To map a larger source gamut into a smaller destination gamut of a device with a reduced lightness dynamic range, often a linear lightness remapping process is applied. It suffers from a global reduction in the perceived lightness contrast and an increase in the average lightness of the remapped image. It is of the utmost importance to preserve the lightness contrast. An adaptive lightness rescaling process has been developed by Braun and Fairchild [1999]. The lightness contrast of the original scene is increased before the dynamic range compression is applied to fit the input lightness range into the destination gamut. This process is known as a sigmoidal mapping function, the shape of this function aids in the dynamic range mapping process by increasing the image contrast and by reducing the low-end textural defects of hard clipping.

We can categorize different types of pointwise gamut mapping technics (See Figure 1); **gamut clipping** only changes the colours outside the reproduction gamut while **gamut compression** changes all colours from the original gamut. The knee function rescaling preserves the chromatic signal through the central portion of the gamut, while compressing the chromatic signal near the edges of the gamut. The sigmoid-like chroma mapping function has three linear segments; the first segment preserves the contrast and colorimetry, the second segment is a mid-chroma boost (increasing chroma) and the last segment compresses the out of gamut chroma values into the destination gamut.

Spatial gamut mapping has become an active field of research in the recent years [Kimmel et al., 2005, Farup et al., 2007]. In contrast to the conventional color gamut mapping algorithms, where the mapping can be performed once and for all and stored as a look-up table, e.g., in an ICC profile, the spatial algorithms are image dependent

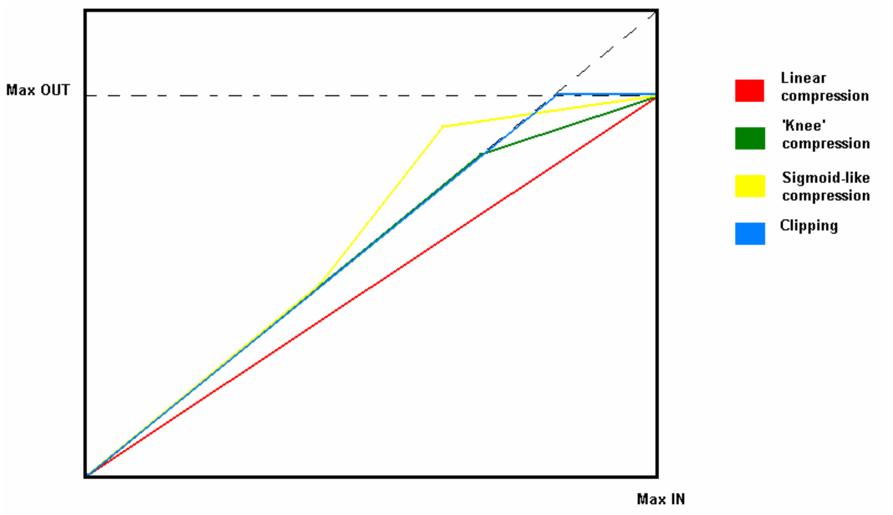


Fig. 1. Scheme of typical gamut mapping techniques.

by nature. Thus, the algorithms have to be applied for every single image to be reproduced, and make direct use of the gamut boundary descriptors many times during the mapping process.

Quality assessment is also required for the evaluation of gamut mapping algorithms, and extensive work has been carried out on subjective assessment [Dugay et al., 2008]. This evaluation is long, tiresome, and even expensive. Therefore objective assessment methods are preferable. Existing work on this involves image quality metrics, for example by Bonnier et al. [2008] and by Hardeberg et al. [2008]. However, these objective methods can still not replace subjective assessment, but can be used as a supplement to provide a more thorough evaluation.

Recently, Alsam and Farup [2009] presented a novel, computationally efficient, iterative, spatial gamut mapping algorithm. The proposed algorithm offers a compromise between the colorimetrically optimal gamut clipping and the most successful spatial methods. This is achieved by the iterative nature of the method. At iteration level zero, the result is identical to gamut clipping. The more we iterate the more we approach an optimal, spatial, gamut mapping result. Optimal is defined as a gamut mapping algorithm that preserves the hue of the image colors as well as the spatial ratios at all scales. The results show that as few as five iterations are sufficient to produce an output that is as good or better than that achieved in previous, computationally more expensive, methods. Unfortunately, the method also shares some of the minor disadvantages of other spatial gamut mapping algorithms: halos and desaturation of flat regions for particularly difficult images. There is therefore much work left to be done in this direction, and one promising idea is to incorporate knowledge of the strength of the edges.

3 Display color characterization

This section will study in depth display colorimetric characterization. Although many books investigate color device characterization, they mostly focus on printers or cameras, which have been far more difficult to characterize than displays during the CRT era; thus, mostly a simple linear model and a gamma correction were addressed in books when considering displays. With the emergence of new technologies used to create newer displays in the last fifteen years, a lot of work has been done concerning this topic, and a new bibliography and new methods have appeared. Many methods have been borrowed from printers or camera though, but the way to reproduce colors and the assumptions one can do are different when talking about displays, so the results or the explanation of why a model is good or not are slightly differents. We propose to discuss the state of the art and the major trends about display colorimetric characterization in this section.

3.1 State of the art

Many color characterization methods or models exist; we can classify them in three groups. In a first one, we find the models, which tend to model physically the color response of the device. They are often based on the assumption of independence between channels and of chromaticity constancy of primaries. Then, a combination of the primary tristimulus at the full intensity weighted by the luminance response of the display relatively to a digital input can be used to perform the colorimetric transform. The second group can be called numerical models. They are based on a training data set, which permits optimization of the parameters of a polynomial function to establish the transform. The last category consists of 3D Look Up Table (LUT) based models. Some other methods can be considered as hybrid. They can be based on a dataset and assume some physical properties of the display, such as in the work of Blondé et al. [2009].

3D LUT models

The models in the 3D LUT group are based on the measurement of a defined number of color patches, i.e. we know the transformation between the input values (i.e. *RGB* input values to a display device) and output values (i.e. *CIEXYZ* or *CIELAB* values) measured on the screen by a colorimeter or spectrometer in a small number of color space locations (see Figure 2). Then this transformation is generalized to the whole space by interpolation. Studies assess that these methods can achieve accurate results [Bastani et al., 2005, Stauder et al., 2007], depending on the combination of the interpolation method used [Kasson et al., 1995, Amidror, 2002, Bookstein, 1989, Nielson et al., 1997, Akima, 1970], the number of patches measured, and on their distribution [Stauder et al., 2007] (note that some of the interpolation methods cited above cannot be used with a non-regular distribution). However, to be precise enough, a lot of measurements are typically required, i.e. a $10 \times 10 \times 10$ grid of patches measured in Bastani et al. [2005]. Note that such a model is technology independent since no assumptions are made about the device but that the display will always have the same response at the measurement location. Such a model needs high storage capacity and computational power to handle the 3D data. The computational power is usually not a problem since Graphic Processor Units can perform this kind of task easily today [Colantoni and Thomas, 2009]. The high number of measurements needed is a greater challenge.

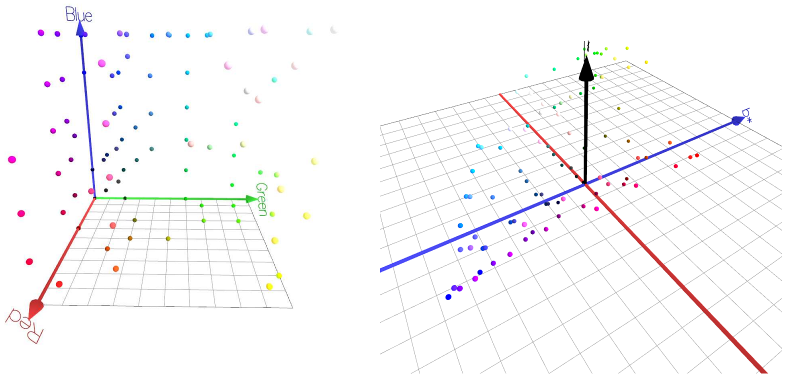


Fig. 2. 3D lookup table for a characterization process from *RGB* to *CIELAB*.

Numerical models

The numerical models suppose that the transform can be approximated by a set of equations, usually an n-order polynomial function. The parameters are retrieved using an n-order polynomial regression process based on measurements. The number of parameters required involves a significant number of measurements, depending on the order of the polynomial function [Green and MacDonald, 2002]. The advantage of these models is that they take into account channel inter-dependence by applying cross components factors in the establishment of the function [Katoh et al., 2001a,b, Tamura et al., 2003]. More recently, an alternative method has been proposed by Wen and Wu [2006] who removed the three-channel crosstalk from the model, considering that the inter-channel dependence is only due to two-channel crosstalk, thus reducing the required number of measurements. They obtained results as accurate as when considering the three-channel crosstalk.

Radial Basis Function (RBF) permits to use a sum of low order polynomials instead of one high order polynomial and has been used successfully in different works [Colantoni and Thomas, 2009], [Colantoni et al., 2005], [Stauder et al., 2006], [Stauder et al., 2007]. Mostly polyharmonc splines are used, which include Thin Plate Splines (TPS) that Sharma and Shaw [2006] used for printers too. TPS are a subset of polyharmonic splines (bi-harmonic splines). Sharma and Shaw [2006] recalled the mathematical framework and presented some applications and results for printer characterization. They showed that using TPS, they achieved a better result than in using local polynomial regression. They showed that by using a smoothing factor, error in measurement impact can be avoided at the expense of the computational cost that optimize this parameter, similar results were observed by Colantoni and Thomas [2009]. However, Sharma and Shaw [2006] did not study data distribution influence (but they stated that the data distribution can improve the accuracy in their conclusion) neither the use of other kernels for interpolation. This aspect have been studied by Colantoni and Thomas [2009], which main improvement were in the optimization of the selection of the data used to build the model in an iterative way.

Physical models

Physical models are historically widely used for displays, since the CRT technology follows well the assumptions cited above [Cowan and Rowell, 1986, Berns et al., 1993a, Brainard, 1989]. Such a model typically first aims to linearize the intensity response of the device. This can be done by establishing a model that assumes the response curve to follow a mathematical function, such as a gamma law for CRT [Cowan, 1983, Berns et al., 1993b,a, Sharma, 2003], or a S-shaped curve for LCD [Yoshida and Yamamoto, 2002, Kwak and MacDonald, 2000, Kwak et al., 2003]. Another way to linearize the intensity response curve is to generalize measurements by interpolation along the luminance for each primary [Post and Calhoun, 1989]. The measurement of the luminance can be done using a photometer. Some approaches propose as well a visual response curve estimation, where the 50% luminance point for each channel is determined by the user to estimate the gamma value [Cowan, 1983]. This method can be generalized to the retrieval of more luminance levels in using half toned patches [Neumann et al., 2003, Mikalsen et al., 2008]. Recently a method to retrieve the response curve of a projection device using an uncalibrated camera has been proposed by Bala and Braun [2006], Bala et al. [2007] and extended by Mikalsen et al. [2008]. Note that it has been assumed that the normalized response curve is equivalent for all the channels, and that only the gray level response curve can be retrieved. In the case of a doubt about this assumption, it is of use to retrieve the three response curves independently. Since visual luminance matching for the blue channel is a harder task, it is of use to perform an intensity matching for the red and green channel, and a chromaticity matching or gray balancing for the blue one [Klassen et al., 2005]. This method should not be used with projectors though, since they show a large chromaticity shift with the variation of input for the pure primaries.

A model has been defined by Wyble and Zhang [2003], Wyble and Rosen [2004] for DLP projectors using a white segment in the color wheel. In their model, the characteristics of the luminance of the white channel is retrieved with regard to additive property of the display, given the four-tuplet (R,G,B,W) from an input (d_r,d_g,d_b).

The second step of these models is commonly the use of a 3×3 matrix containing primary tristimulus values at full intensity to build the colorimetric transform from luminance to an additive independent color space. The primaries can be estimated by measurement of the device channels at full intensity, using a colorimeter or a spectroradiometer, assuming their chromaticity constancy. In practice this assumption does not hold perfectly, and the model accuracy suffers from that. The major part of the non constancy of primaries can be corrected by applying a black offset correction [Jimenez Del Barco et al., 1995]. Some authors tried to minimize the chromaticity non-constancy in finding the best chromaticity values of primaries (optimizing the components of the 3×3 matrix) [Day et al., 2004]. Depending on the accuracy required, it is also possible to use generic primaries such as *sRGB* [Anderson et al., 1995] for some applications [Bala and Braun, 2006, Bala et al., 2007], or data supplied by the manufacturer [Cowan, 1983]. However, the use of a simple 3×3 matrix for the colorimetric transform leads to inaccuracy due to the lack of channel independence and of chromaticity constancy of primaries. An alternative approach has been derived in the masking model and modified masking model, which takes into account the cross-talk between channels [Tamura et al., 2003]. Furthermore, the lack of chromaticity constancy can be critical, particularly for LCD technology, which has been shown to fail this assumption [Brainard et al., 2002, Kwak and MacDonald, 2000]. The Piecewise Linear assuming Variation in Chromaticity (PLVC) [Farley and Gutmann, 1980] is not subject to this effect, but has not been widely used since Post and Calhoun [1989] demonstrated that among the models they tested in their article, the PLVC and the Piecewise Linear assuming Chromaticity Constancy (PLCC) models were of equivalent accuracy for the CRT monitors they tested. The last one requiring less computation, it has been more used than the former one. These results have been confirmed in studies on CRT technology [Post and Calhoun, 1989, 2000], especially with a flare correction [Jimenez Del Barco et al., 1995, Thomas et al., 2008a]. On DLP technology when there is a flare correction, results can be equivalent [Thomas et al., 2008a]. However, the PLVC can give better results on LCDs [Thomas et al., 2007, 2008a].

Other models exist, such as the 2-steps parametric model proposed by [Blondé et al., 2009]. This model assumes separation between chromaticity and intensity, and is shown to be accurate, with average ΔE^*_{ab}'s around 1 or below for one DLP projector and a CRT monitor. The luminance curve is retrieved, as for other physical models, but the colorimetric transform is based on 2D interpolation in the chromaticity plane based on a set of saturated measured colors.

The case of subtractive displays

An analog film projection system in a movie theater was studied by Alleysson and Susstrunk [2002]. A Minolta CS1000 spectrophotometer was used to find the link between the RGB colors of the image and the displayed colors. For each device, red, green, blue, cyan, magenta, yellow and grey levels were measured. The low luminosity levels didn't allow a precise color measurement with the spectrophotometer at their disposal. For the 35 mm projector, it was found that the color synthesis is not additive, since the projection is based on a subtractive method. It is difficult to model the transfer function of this device, the measures cannot be reproduced as both measure and projection angles change, moreover, the luminance is not the same all over the projected area. The subtractive synthesis, by removing components from the white source, cannot provide the same color sensation as a cinema screen or a computer screen, which are based on additive synthesis of red, green and blue components. Subtractive cinema projectors are not easy to characterize as the usual models are for additive synthesis. The multiple format transformations and data compression led to data lost and artifacts.

Ado [2002] shows the gamut differences between CRT monitors (*RGB* additive method) and printed films (*CMY* dyes subtractive method). The main problem for a physical modeling is the tone shift. In a matching process from a CRT to a film, both gamut difference and mapping algorithm are important. During the production step, the minor emulsion changes and chemical processes can vary and then make small shifts on the prints, leading to a shift on the whole production. An implementation of a 3D LUT was successfully applied to convert color appearance from CRT to film display.

3.2 Physical models

Display color characterization models

Physical models are easily invertible, do not require a lot of measurements, require a little computer memory, and do not require high computing power so they can be used in real time. Moreover, the assumptions of channel independence and chromaticity constancy are appropriate for the CRT technology. However, these assumptions (and others such as spatial uniformity, both in luminance and in chromaticity, view angle independence, etc.) do not fit so well with some of today's display technologies. For instance the colorimetric characteristic of a part of an image in a Plasma Display is strongly dependent of what is happening in the surrounding [Choi et al., 2007] for energy economy reasons. In LC technology, which has become the leader for displays market, these common assumptions are not valid. Making such assumptions can reduce drastically the accuracy of the characterization. For instance, a review of problems faced in LC displays has been done by Yoshida and Yamamoto [2002]. Within projection systems, the large amount of flare induces a critical chromaticity shift of primaries.

In the same time, the computing power has become less and less a problem. Some models not used in practice because of their complexity can now be highly beneficial for display color characterization. This section provides definitions, analysis and discussion about display color characterization models. We do not detail hybrid methods or numerical methods in this section because they show less interest for modelling purpose, and we do prefer to refer the reader to the papers cited above. 3D LUT based method are more considered in the part concerning model's inversion.

In 1983, Cowan [1983] wrote what is considered to be the pioneer article in the area of physical models for display characterization. In this work, the author stated that a power function can be used, but is not the best to fit with the luminance response curve of a CRT device. Nevertheless, the well known ”gamma” model that considers a power function to approximate the luminance response curve of a CRT display is still currently widely used.

Whichever shape the model takes, the principle remains the same. First, it estimates the luminance response of the device for each channel, using a set of functions monotonically increasing such as Equation 2. Note that the results of these functions can also be estimated with any interpolation method, since the problem of monotonicity that can arise during the inversion process is taken into account. This step is followed by a colorimetric transform.

Response curve retrieval

We review here two types of models. The models of the first type are based on functions, the second type is the PLCC model. This model is based on linear interpolation of the luminance response curve and its accuracy has been demonstrated by Post and Calhoun [1989] who found it the best among the models they tested (except in front of the PLVC model for chromatic accuracy).

For function based model, the function used is the power function for CRT devices, which is still the most used, even if it has been shown that it does not fit well LC technology [Fairchild and Wyble, 1998]. It has been shown that for other technologies, there is no reason to try to fit the device response with a gamma curve, especially for LCD technology that shows a S-shape response curve in most cases (Figure 3) and a S-curve model can be defined [Yoshida and Yamamoto, 2002, Kwak and MacDonald, 2000, Kwak et al., 2003]. However, the gamma function is still often used, mainly because it is easy to estimate the response curve with a few number of measurements, or using estimations with a visual matching pattern.

The response in luminance for a set of digital values input to the device can be expressed as follows:

$$\begin{array}{c} Y_R = f_r(D_r) \\ Y_G = f_g(D_g) \\ Y_B = f_b(D_b), \end{array} \tag{2}$$

where f_r, f_g and f_b are functions that give the Y_R, Y_G and Y_B contribution in luminance of each primary independently for a digital input D_r, D_g, D_b. Note that for CRT devices, after normalization of the luminance and digital value, the function can be the same for each channel. This assumption is not valid for LCD technology [Sharma, 2002], and is only a rough approximation for DLP based projection systems, as seen for instance in the work of Seime and Hardeberg [2003].

For a CRT, for the channel $h \in \{r, g, b\}$, this function can be expressed as :

$$Y_H = (a_h d_h + b_h)^{\gamma_h}, \tag{3}$$

where $H \in \{R, G, B\}$ is the equivalent luminance from a channel $h \in \{r, g, b\}$ for a normalized digital input d_h, with $d_h = \frac{D_h}{2^n - 1}$. D_h is the digital value input to a channel h and n is the number of bits used to encode the information for this channel. a_h is the gain and b_h is the internal offset for this channel. These parameters are estimated empirically using a regression process.

This model is called Gain-Offset-Gamma (GOG) [Berns, 1996, CIE, 1996, Katoh et al., 2001b]. If we make the assumption that there is no internal offset and no gain, $a = 1$ and $b = 0$, it becomes the simple ”gamma” model.

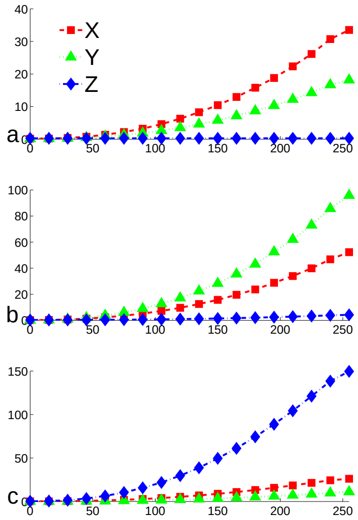


Fig. 3. Response curve in X, Y and Z for an LCD display in function of the digital input for respectively the red(a), green(b) and blue(c) channel.

Note that for luminance transforms, polynomials can be fitted better in the logarithmic domain or to cube root function than in the linear domain because the eye response to signal intensity is logarithmic (Weber's law). For gamma based models, it has been shown that a second order function with two parameters such as $Log(Y_H) = b_h \times Log(d_h) + c_h \times (Log(d_h))^2$ [2] gives better results[Cowan, 1983] and that two gamma curves should be combined for a better accuracy in low luminance[Arslan et al., 2003].

For a LCD, it has been shown by Kwak and MacDonald [2000], Kwak et al. [2003] that a S-shape curve based on 4 coefficients per channel can fit well the intensity response of the display.

$$Y_H = A_h \times g_h(d_h) = A_h \times \frac{d_h^{\alpha_h}}{d_h^{\beta_h} + C_h}, \tag{4}$$

with the same notation as above, and with A_h, α_h, β_h and C_h parameters obtained using the least-squares method. This model is called S-curve I.

The model S-curve II considers the interaction between channels. It has been shown in [Kwak and MacDonald, 2000, Yoshida and Yamamoto, 2002, Kwak et al., 2003] that the gradient of the original S-curve function fits the importance of the

[2] Note that Post and Calhoun [1989] added a term to this equation, which became $Log(Y_H) = a + b_h \times Log(d_h) + c_h.(Log(d_h))^2$.

interaction between channels. Then this component can be included in the model in order to take this effect into account.

$$\begin{aligned} Y_R &= A_{rr} \times g_{Y_RY_R}(d_r) + A_{rg} \times g'_{Y_RY_G}(d_g) + A_{rb} \times g'_{Y_RY_B}(d_b), \\ Y_G &= A_{gr} \times g'_{Y_GY_R}(d_r) + A_{gg} \times g_{Y_GY_G}(d_g) + A_{gb} \times g'_{Y_GY_B}(d_b), \\ Y_B &= A_{br} \times g'_{Y_BY_R}(d_r) + A_{bg} \times g'_{Y_BY_G}(d_g) + A_{bb} \times g_{Y_BY_B}(d_b), \end{aligned} \tag{5}$$

where $g(d)$ and its first-order derivative $g'(d)$ are

$$g(d) = \frac{d^\alpha}{d^\beta + C}, \quad g'(d) = \frac{(\alpha - \beta)x^{\alpha+\beta-1} + \alpha C x^{\alpha-1}}{(x^\beta + C)^2}. \tag{6}$$

To ensure the monotonicity of the functions for the S-curve models I and II, some constraints on the parameters have to be applied. We let the reader to refer to the discussion in the original article [Kwak et al., 2003] for that matter.

For the PLCC model, the function f is approximated by a piecewise linear interpolation between the measurements. The approximation is valid for a large enough amount of measurements (16 measurements per channel in Post and Calhoun [1989]). This model is particularly useful when no information is available about the shape of the display luminance response curve.

Colorimetric transform

A colorimetric transform is then performed from the (Y_R, Y_G, Y_B) "linearized" luminance to the *CIEXYZ* color tristimulus.

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} X_{r,max} & X_{g,max} & X_{b,max} \\ Y_{r,max} & Y_{g,max} & Y_{b,max} \\ Z_{r,max} & Z_{g,max} & Z_{b,max} \end{bmatrix} \times \begin{bmatrix} Y_R \\ Y_G \\ Y_B \end{bmatrix} \tag{7}$$

where the matrix components are the tristimulus colorimetric values of each primary, measured at their maximum intensity.

Using such a matrix for the colorimetric transform supposes perfect additivity and chromaticity constancy of primaries. These assumptions have been shown to be acceptable for CRT technology [Cowan and Rowell, 1986, Brainard, 1989].

The channel inter-dependence observed in CRT technology is mainly due to an insufficient power supply and an inaccuracy of the electron beams, which meet inaccurately the phosphors [Katoh et al., 2001a]. In LC technology, it comes from the overlapping of the spectral distribution of primaries (the color filters), and from the interferences between the capacities of two neighboring sub pixels [Seime and Hardeberg, 2003, Yoshida and Yamamoto, 2002]. In DLP-DMD projection devices, there is still some overlapping between primaries and inaccuracy at the level of the DMD mirrors.

Considering the assumption of chromaticity constancy, it appears that when there is a flare [Katoh et al., 2001a], either a black offset (internal flare) or an ambient flare (external flare), added to the signal, the assumption of chromaticity constancy is not valid anymore. Indeed, the flare is added to the output signal and the lower the luminance level of the primaries, the more the flare is a significant fraction of the resulting stimulus. This leads to a hue shift toward the black offset chromaticity. Often the flare has a ”gray” (nearly achromatic) chromaticity, thus the chromaticities of the primaries shift to a ”gray” chromaticity (Figure 4, left part). Note that the flare ”gray” chromaticity does not necessarily correspond to the achromatic point of the device (Figure 4). In fact, in the tested LCD devices (Figure 4, a, b, e, f), we can notice the same effect as in the work of Marcu et al. [2001]: the black level chromaticity is bluish because of the poor filtering power of the blue filter in the low wavelength.

The flare can be taken all at once as the measured light for an input $(d_{r,k}, d_{g,k}, d_{b,k}) = (0,0,0)$ to the device. Then it includes ambient and internal flare.

The ambient flare comes from any light source reflecting on the display screen. If the viewing conditions do not change it remains constant, can be measured and taken into account, or can be simply removed in setting up a dark environment (note that for a projection device, there is always an amount of light that lights the room, coming from the bulb through the ventilation hole).

The internal flare, which is the major part of chromaticity inconstancy at least in CRT technology [Katoh et al., 2001a], is coming from the black level. In CRT technology, it has been shown that in setting the brightness to a high level, the black level increases to a non-negligible value [Katoh et al., 2001a]. In LC technology, the panel let an amount of light passing through due to a leakage of the crystal to stop all the light. In DLP technology, an amount of light can be not absorbed by the ”black absorption box”, and is focused on the screen via the lens.

On Figure 4, one can see the chromaticity shift to the flare chromaticity with the decreasing of the input level. We have performed these measurements in a dark room, then the ambient flare is minimized, and only the black level remains. After black level subtraction, the chromaticity is more constant (Figure 4), and a new model can be set up in taking that into account [Jimenez Del Barco et al., 1995, Hardeberg et al., 2003, Katoh et al., 2001a,b].

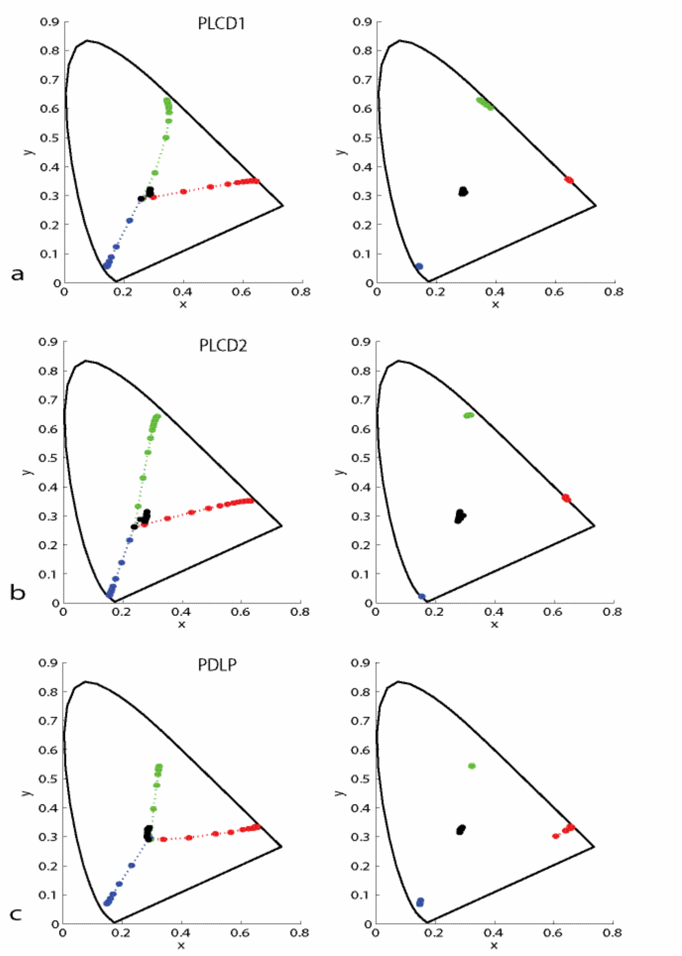
The gamma models reviewed above have been extended in adding an offset term. Then the GOG can become a Gain-Offset-Gamma-Offset (GOGO) model [Katoh et al., 2001a,b, IEC:61966-3, 1999].

The previous equation 2 becomes:

$$Y_H = (a_h d_h + b_h)^{\gamma_h} + c, \tag{8}$$

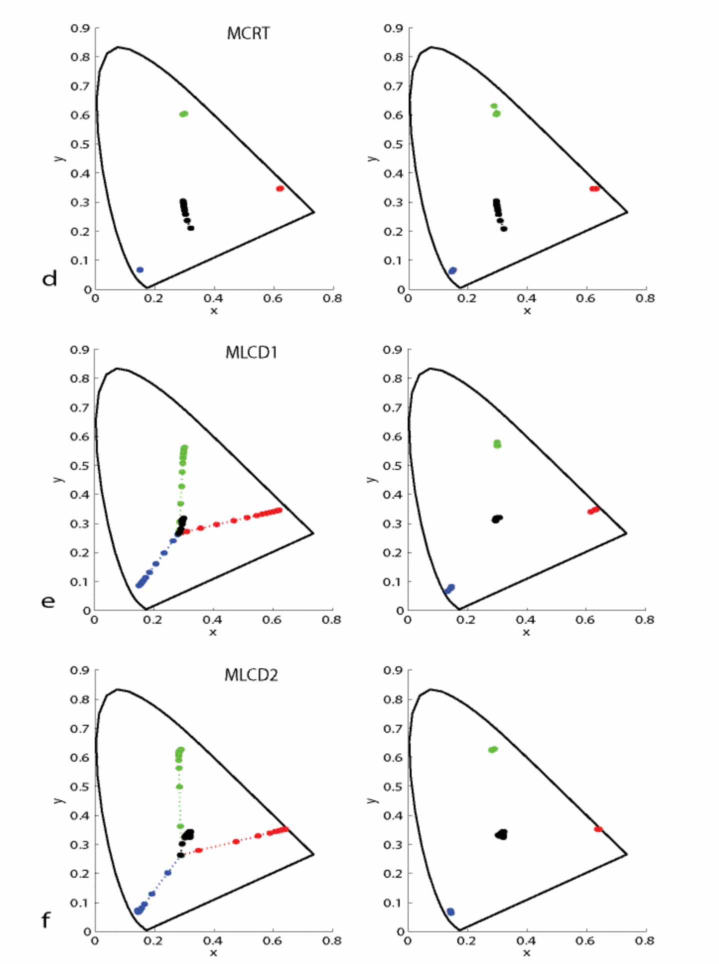
where c is a term containing all the different flares in presence. If we consider the internal offset b_h as null, the model becomes Gain-Gamma-Offset (GGO) [IEC:61966-3, 1999].

A similar approach can be used for the PLCC model. When the black correction [Jimenez Del Barco et al., 1995] is performed, we name it PLCC* in the following. The colorimetric transform used then is the Equation 9 that permits to take the flare into account during the colorimetric transformation. For the S-curve models, the black offset is taken into account in the matrix formulation in the original papers.



(a) abc

Fig. 4. Chromaticity tracking of primaries with variation of intensity. The left part of the figure shows it without black correction. On the right, one can see the result with a black correction performed. All devices tested in our PLVC model study are shown, a-PLCD1, b-PLCD2, c-PDLP, d-MCRT, e-MLCD1, f-MLCD2. Figures from [Thomas et al., 2008a].



(b) def

Fig. 4. Chromaticity tracking of primaries with variation of intensity. The left part of the figure shows it without black correction. On the right, one can see the result with a black correction performed. All devices tested in our PLVC model study are shown, a-PLCD1, b-PLCD2, c-PDLP, d-MCRT, e-MLCD1, f-MLCD2. Figures from [Thomas et al., 2008a]

If we consider that mathematically, the linear transform from the linearized *RGB* to *CIEXYZ* needs to associate the origin of *RGB* to the origin of *CIEXYZ* in order to respect the vectorial space property of additivity and homogeneity. Thus the original transform of the origin of *RGB* to *CIEXYZ* needs to be translated of $[-X_k - Y_k - Z_k]$. However, in doing that we modify the physical reality and we need to translate the result of the transformation of $[X_k Y_k Z_k]$. We can formulate these transforms such as in Equation 9.

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} X_{r,max} - X_k & X_{g,max} - X_k & X_{b,max} - X_k & X_k \\ Y_{r,max} - Y_k & Y_{g,max} - Y_k & Y_{b,max} - Y_k & Y_k \\ Z_{r,max} - Z_k & Z_{g,max} - Z_k & Z_{b,max} - Z_k & Z_k \end{bmatrix} \times \begin{bmatrix} Y_R \\ Y_G \\ Y_B \\ 1 \end{bmatrix} \tag{9}$$

The A_k's, $A \in \{X,Y,Z\}$, come from a black level estimation.

Such a correction permits to achieve better results. However, on the right part of Figure 4, one can see that even with the black subtraction, the primary chomaticities do not remain perfectly constant. On Figure 4, right-a, it remains a critical shift especially for the green channel.

Several explanations are involved. First, there is a technology contribution. For LC technology, the transmittance of the cells of the panel changes within the input voltage [Yeh and Gu, 1999, Brainard et al., 2002]. This leads to a chromaticity shift when changing the input digital value. For different LC displays, we notice a different shift in chromaticity; this is due to the combination back-light/LC with the color filters. Since the filters transmittances are optimized taking into account the transmittance shift of the LC cells, the display can achieve good chromaticity constancy. For CRT, there are less problems due to the same phosphors properties, as well for DLP as the light and the filters remain the same.

However, even with the best device, there is still a small amount of non-constancy. This leads to a discussion about the accuracy of the measured black offset. Indeed, the measurement devices are less accurate in the low luminance. Berns et al. [2003] proposed a way to estimate the best black offset value. A way to overcome the problems linked with remaining inaccuracy for LCD devices has been presented by Day et al. [2004]. It consists in the replacement of the full intensity measurement of primary chromaticities colorimetric values by the optimum values in the colorimetric transformation matrix. It appears that the chromaticity shift is a major issue for LCD. Sharma [2002] stated that for LCD devices the assumption of chromaticity constancy was weaker than the channel inter-dependence.

More models that linearize the transform exist. In this section we presented the ones that appeared to us as the more interesting, or the more known.

Piecewise Linear model assuming Variation in Chromaticity

Defining the Piecewise Linear model assuming Variation in Chromaticity (PLVC) in this section has many motivations. First, it is the first display color characterization model introduced in the literature as far as we know. Secondly, it is an hybrid method, considering that it is based on data measurement and assumes a small amount of hypothesis on the behavior of the display. Finally there is a section in next chapter devoted to the study of this model.

According to Post and Calhoun [1989], the first persons who have introduced the PLVC were Farley and Gutmann [1980] in 1980. Note that it preceded the well known article from Cowan [1983]. Further studies have been performed afterward on CRT [Post and Calhoun, 1989, 2000, Jimenez Del Barco et al., 1995], and recently on more recent technologies [Thomas et al., 2007, 2008a]. This model does not consider the channel inter-dependence, but does model the chromaticity shift of the primaries. In this section, we recall the principles of this model, and some features that characterize it.

Knowing the tristimulus values of X, Y, and Z for each primary as a function of the digital input, assuming additivity, the resulting color tristimulus values can be expressed as the sum of tristimulus values for each component (i.e. primary) at the given input level. Note that in order not to add several times the black level, it is removed from all measurements used to define the model. Then, it is added to the result, to return to a correct standard observer color space [Jimenez Del Barco et al., 1995, Post and Calhoun, 2000]. The model is summarized and generalized in Equation (10) for N primaries, and illustrated in Equation (11) for a three primaries *RGB* device, following an equivalent formulation as the one given by Jimenez Del Barco et al. [1995].

For an N primary device, we consider the digital input to the i^{th} primary, $d_i(m_i)$, with i an integer $\in [0,N]$, and m_i an integer limited by the resolution of the device (i.e. $m_i \in [0,255]$ for a channel coded on 8 bits). Then, a color $CIEXYZ(\ldots,d_i(m_i),\ldots)$ can be expressed by :

$$\begin{array}{l} X(\ldots,d_i(m_i),\ldots) = \sum_{i=0,j=m_i}^{i=N-1}[X(d_i(j)) - X_k] + X_k \\ Y(\ldots,d_i(m_i),\ldots) = \sum_{i=0,j=m_i}^{i=N-1}[Y(d_i(j)) - Y_k] + Y_k \\ Z(\ldots,d_i(m_i),\ldots) = \sum_{i=0,j=m_i}^{i=N-1}[Z(d_i(j)) - Z_k] + Z_k \end{array} \quad (10)$$

with X_k, Y_k, Z_k the color tristimulus coming out from a $(0,\ldots,0)$ input.

We illustrate this for a three primaries *RGB* device, with each channel coded on 8 bits. The digital input are $d_r(i)$, $d_g(j)$, $d_b(l)$, with i, j, l integers $\in [0,255]$. In this case, a $CIEXYZ(d_r(i),d_g(j),d_b(l))$ can be expressed by :

$$\begin{array}{l} X(d_r(i),d_g(j),d_b(l)) = [X(d_r(i)) - X_k] + [X(d_g(j)) - X_k] + [X(d_b(l)) - X_k] + X_k \\ Y(d_r(i),d_g(j),d_b(l)) = [Y(d_r(i)) - Y_k] + [Y(d_g(j)) - Y_k] + [Y(d_b(l)) - Y_k] + Y_k \\ Z(d_r(i),d_g(j),d_b(l)) = [Z(d_r(i)) - Z_k] + [Z(d_g(j)) - Z_k] + [Z(d_b(l)) - Z_k] + Z_k \end{array} \quad (11)$$

If the considered device is a *RGB* primaries device, thus the transformation between digital *RGB* values and *RGB* device's primaries is as direct as possible. The A_k, $A \in \{X,Y,Z\}$ are obtained by accurate measurement of the black level. The $[A(d_i(j)) - A_k]$, are obtained by one dimensional linear interpolation with the measurement of a ramp along each primary. Note that any 1-D interpolation method can be used. In the literature, the piecewise linear interpolation is mostly used.

Studies of this model have shown good results, especially on dark and mid-luminance colors. When the colors reach higher luminance, the additivity assumption is less true for CRT technology. Then the accuracy decreases (depending on the device properties). More precisely, Post and Calhoun [1989, 2000] stated that chromaticity error is lower for the PLVC than for the PLCC in low luminance. This is due to the setting of primaries colorimetric values at maximum intensity in the PLCC. Both models show inaccuracy for high luminance colors due to channel interdependence. Jimenez Del Barco et al. [1995] found that for CRT technology, the higher level of brightness in the settings leads to a non-negligible amount of light for a (0,0,0) input. This light should not be added three times, and they proposed a correction for that [3]. They found that the PLVC model was more accurate in medium to high luminance colors. Inaccuracy is more important in low luminance, due to inaccuracy of measurements, and in high luminance, due to channel dependencies. Thomas et al. [2008a] demonstrated that this model is more accurate than usual linear models (PLCC, GOGO) for LCD technology, since it takes into account the chromaticity shift of primaries that is a key features for characterizing this type of display. More results for this model are presented in the next chapter.

4 Model inversion

4.1 State of the art

The inversion of a display color characterization model is of major importance for color reproduction since it provides the set of digital values to input to the device in order to display a desired color.

Among the models or methods used to achieve color characterization, we can distinguish two categories. The first one contains models that are practically invertible (either analytically, or in using simple 1D LUT)[Cowan and Rowell, 1986, Post and Calhoun, 1989, Berns et al., 1993b,a, Jimenez Del Barco et al., 1995, Katoh et al., 2001a,b], such as the PLCC, the black corrected PLCC*, the GOG or GOGO models. The second category contains the models or methods, which are not practically invertible directly. and that show difficulties to be applied. Models of this second category require other methods to be inverted in practice. We can list some typical problems and methods used to invert these models:

- Some conditions have to be verified, such as in the masking model [Tamura et al., 2003].
- A new matrix might have to be defined by regression in numerical models [Katoh et al., 2001a,b, Green and MacDonald, 2002, Wen and Wu, 2006].
- A full optimization process has to be set up for each color, such as in S-curve model II [Kwak and MacDonald, 2000, Kwak et al., 2003] in the modified masking model, [Tamura et al., 2003] or in the PLVC model [Post and Calhoun, 1989, Jimenez Del Barco et al., 1995, Thomas et al., 2008b].

[3] Equation 10 and Equation 11 are based on the equation proposed by Jimenez Del Barco et al. [1995], and take that into account.

- The optimization process can appear only for one step of the inversion process, as in the PLVC [Post and Calhoun, 1989] or in the S-curve I [Kwak and MacDonald, 2000, Kwak et al., 2003] models.
- Empirical methods based on 3-D LUT (lookup table) can be inverted directly [Bastani et al., 2005], using the same geometrical structure. In order to have a better accuracy, however, it is common to build another geometrical structure to yield the inverse model. For instance, it is possible to build a draft model to define a new set of color patches to be measured [Stauder et al., 2007].

The computational complexity required to invert these models makes them seldom used in practice, except the full 3-D LUT, which major drawback is that it requires a lot of measurements. However, these models do have the possibility to take into account more precisely the device color-reproduction features, such as interaction between channels or chromaticity inconstancy of the primaries. Thus, they are often more accurate than the models of the first category.

4.2 Practical inversion

Models such as the PLCC, the black corrected PLCC*, the GOG or GOGO models [Cowan and Rowell, 1986, Post and Calhoun, 1989, Berns et al., 1993b,a, Jimenez Del Barco et al., 1995, Katoh et al., 2001a,b] are easily inverted since they are based on linear algebra and on simple functions. For these models it is sufficient to invert the matrix of Equation 7. Then we have:

$$\begin{bmatrix} Y_R \\ Y_G \\ Y_B \end{bmatrix} = \begin{bmatrix} X_{r,max} & X_{g,max} & X_{b,max} \\ Y_{r,max} & Y_{g,max} & Y_{b,max} \\ Z_{r,max} & Z_{g,max} & Z_{b,max} \end{bmatrix}^{-1} \times \begin{bmatrix} X \\ Y \\ Z \end{bmatrix} \quad (12)$$

Once the linearized $\{Y_R, Y_G, Y_B\}$ have been retrieved, the intensity response curve function is inverted as well to retrieve the $\{d_r, d_g, d_b\}$ digital values. This task is easy for a gamma based model or for an interpolation based one. However, for some models such as the S-curve I, an optimization process can be required (note that this response curve can be used to create a 1D LUT).

4.3 Indirect inversion

When the inversion becomes more difficult, it is of use to set an optimization process using the combination of the forward transform and the color difference (often the euclidean distance) in a perceptually uniform color space, such as *CIELAB*, as cost function. This generally leads to better results than usual linear models, depending on the forward model, but is computationally expensive, and can not be implemented in real time. It is then of use to set a 3-D LUT based on the forward model. Note that it does not mean that an optimization process is useless, since it can help to design a good LUT.

Such a model is defined by the number and the distribution of the color patches used in the LUT, and by the interpolation method used to generalize the model to the entire space. In this subsection, we review some basic tools and methods. We distinguish works on displays from more general works, which have been performed in this way either in a general purpose or especially for printers. One of the major challenge for printers is the problem of measurement, which is really restrictive, and many works have been carried out in using a 3-D LUT for the color characterization of these devices. Moreover, since printer devices are highly non-linear, their colorimetric models are complex. So it has been customary in the last decade to use a 3-D complex LUT for the forward model, created by using an analytical forward model, both to reduce the amount of measurements and to perform the color space transform in a reasonable time. The first work we know about creating a LUT based on the forward model is a patent from Stokes [1997]. In this work, the LUT is built to replace the analytical model in the forward direction. It is based on a regular grid designed in the printer *CMY* color space, and the same LUT is used in the inverse direction, simply in switching the domain and co-domain. Note that in displays, the forward model is usually computationally simple and that we need only to use a 3-D LUT for the inverse model. The uniform mapping of the *CMY* space leads to a non-uniform mapping in *CIELAB* space for the inverse direction, and it is common now to re-sample this space to create a new LUT. To do that, a new grid is usually designed in *CIELAB* and is inverted after gamut mapping of the points located outside the gamut of the printer. Several algorithms can be used to re-distribute the data [Chan et al., 1997, Groff et al., 2000, Dianat et al., 2006] and to fill the grid [Shepard, 1968, Balasubramanian and Maltz, 1996, Viassolo et al., 2003].

Returning to displays, let us call source space the independent color-space (typically *CIELAB* or alternatively *CIEXYZ*), the domain from where we want to move, and destination space, the *RGB* color space, the co-domain, where we want to move to. If we want to build a grid, we then have two classical approaches to distribute the patches in the source space, using the forward model. One can use directly a regular distribution in *RGB* and transform it to *CIELAB* using the forward model; this approach is the same as used by [Stokes, 1997] for printers, and leads to a non-uniform mapping of the *CIELAB* space, which can lead to a lack of homogeneity of the inverse model depending on the interpolation method used (See Figure 5). An other approach can be to distribute the patches regularly in *CIELAB*, following a given pattern, such as an hexagonal structure [Stauder et al., 2007] or any of the methods used in printers [Chan et al., 1997, Groff et al., 2000, Dianat et al., 2006]. Then, an optimization process using the forward model can be performed for each point to find the corresponding *RGB* values. The main idea of the method and the notation used in this document are the following:

- One can define a regular 3-D grid in the destination color space (*RGB*).
- This grid defines cubic voxels. Each one can be split into five tetrahedra (See Figure 6).
- This tetrahedral shape is preserved within the transform to the source space (either *CIEXYZ* or *CIELAB*).

- Thus, the model can be generalized to the entire space, using tetrahedral interpolation [Kasson et al., 1995]. It is considered in this case that the color space has a linear behavior within the tetrahedron (e.g. the tetrahedron is small enough).

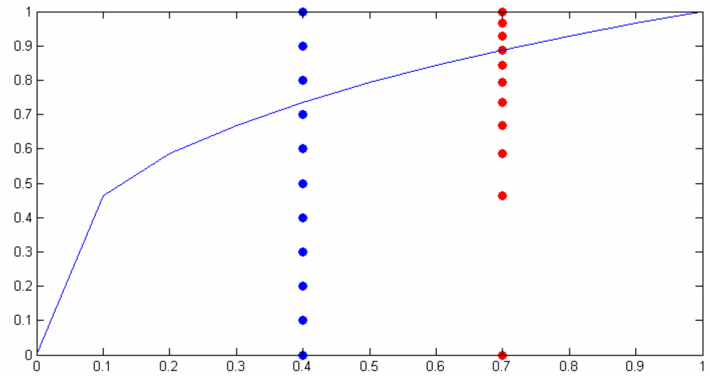


Fig. 5. The transform between *RGB* and *CIELAB* is not linear. Thus while using a linear interpolation based on data regularly distributed in *RGB*, the accuracy is not the same everywhere in the colorspace. This figure shows a plot of regularly distributed data in a linear space (blue dot, left) and the resulting distribution after a cubic root transform (that mimics *CIELAB* transform)(red dots, right).

The most used way to define such a grid is to take directly a linear distribution of points on each digital d_r, d_g, and d_b axis as seeds and to fill up the rest of the destination space. A tetrahedral structure is then built with these points. The built structure is used to retrieve any *RGB* value needed to display a specific color inside the device's gamut. The more points are used to build the grid, the more the tetrahedra will be small and the interpolation accurate. Each vertex is defined by $V_{i,j,k} = (R_i, G_j, B_k)$, where $R_i = d_i$, $G_j = d_j$, $B_k = d_k$, and d_i, d_j, $d_k \in [0,1]$ are the possible normalized digital values, for a linear distribution. $i \in [0, N_r - 1]$, $j \in [0, N_g - 1]$, and $k \in [0, N_b - 1]$ are the indexes (integers) of the seeds of the grid along each primary, and N_r (resp. N_b, N_g) is the number of steps along channel R (resp. G, B).

Once this grid has been built, we define the tetrahedral structure for the interpolation following Kasson et al. [1995]. Then we use the forward model to transform the structure into *CIELAB* color space. An inverse model has been built. According to the non-linearity of the *CIELAB* transform, the size of the tetrahedra is not anymore the same as it was in *RGB*. In the following section, a modification of this framework is proposed that makes this grid more homogeneous in the source color space where we perform the interpolation; this should lead to a better accuracy, following Groff et al. [2000].

Let us consider the PLVC model inversion as example. This model inversion is not as straightforward as the matrix based models previously defined. For a three primaries display, according to Post and Calhoun [1989], it can be performed defining

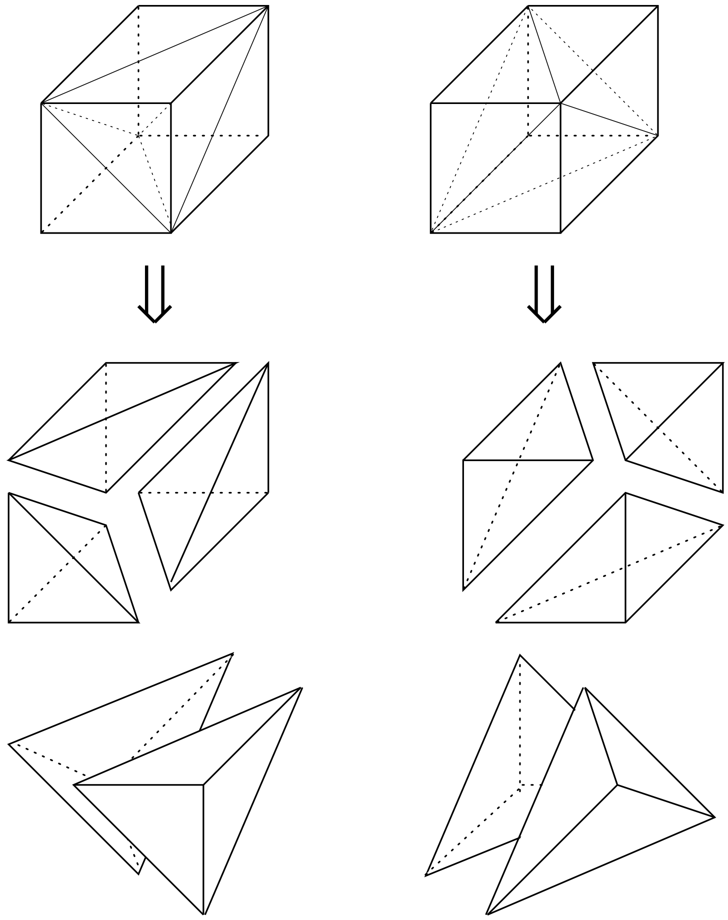


Fig. 6. The two ways to split a cubic voxel in 5 tetrahedra. These two methods are combined alternatively when splitting the cubic grid to guarantee that no coplanar segments are crossing.[5]

all subspaces defined by the matrices of each combinations of measured data (note that the intercepts have to be subtracted, and once all the contributions are known, they have to be added). One can perform an optimization process for each color [Jimenez Del Barco et al., 1995], or define a grid in *RGB*, such as described above, which will allow us to perform the inversion using 3D interpolation. Note that Post and Calhoun have proposed to define a full LUT considering all colors. They said themselves that it is inefficient. Defining a reduced regular grid in *RGB* leads to the building of an irregular grid in *CIELAB* due to the non-linear transform. This irregular grid could lead to inaccuracy or a lack of homogeneity in interpolation, especially if it is linear. Some studies addressed this problem [Thomas et al., 2008c,b]. They built an optimized Look Up Table, based on a customized *RGB* grid.

5 Quality evaluation

Colorimetric characterization of a color display device is a major issue for the accurate color rendering of a scene. We have seen several models that could possibly be used for this purpose, each of these models have their own advantages and weaknesses.

This section discusses the choice of a model in relation with the technology and the purpose. In the following, we explicit what is the need, then we discuss the evaluation of a model depending on the purpose. Before to conclude, we propose a qualitative comparison of some display characterization methods.

5.1 Purpose

Like any image processing technique, a display color characterization model has to be chosen considering needs and constraints. For color reproduction, the need is mainly the expected level of accuracy. The constraints depend mainly on two things: the time and the measurement. The time is a major issue, because one may need to minimize the time of establishment of a model, or its application to an image (computational cost). The measurement process is critical because one may need to have access to a special device to establish the model. The constraint of money is distributed on the time, the software and hardware cost, and particularly on the measurement device. We do not consider here some other features of the device, such as spatial uniformity, gamut size, etc. but only the result of the point-wise colorimetric characterization.

In the case of displays, the combination needs vs constraints seems to be in agreement. Let us expose two situations:

- The person who needs an accurate color characterization (such as a designer or a color scientist) has often a color measurement device available, is working in a more or less controlled environment, and does not mind to spend 15-20 minutes every day to calibrate his/her monitor/projector. This person may typically want to use an accurate method, an accurate measurement device, to take care of the temporal stability of the device, etc.
- The person who wants to display some pictures in a party or in a seminar, using a projector in an uncontrolled environment does not need a very accurate colorimetric rendering. That is fortunate, because he/she does not have any measurement device, does not have much time to perform a calibration or to properly warm up the projector. However, this person needs the colors not to betray the meaning she/he intends. In this case, a fast end-user characterization should be precise enough. This person might use a visual calibration, or even better, a visual/camera based calibration. The method should be coupled to a user-friendly software for making it easy and fast.

We can see a duality between two types of display characterization methods and goals: the consumer, end-user purpose, which intends only to keep the meaning and aesthetic unchanged through the color workflow, and the accurate professional one, which aims to have a very high colorimetric fidelity through the color workflow. We see also through these examples that the constraints and the needs are not necessarily going in the opposite direction.

In the next section, we will relate the quality of a model with colorimetric objective indicators.

5.2 Quality

Once a model is set-up, there is a need to evaluate its quality to confirm we are within the accuracy we wanted. In this section, we discuss how to use objective indicators for assessing quality.

Evaluation

A point-wise quality evaluation process is straightforward. We process a digital value with the model to obtain a result and compare it in a perceptually pseudo-uniform color space, typically *CIELAB*, with the measurement of the same input. Figure 7 illustrates the process.

The data set used to evaluate the model should be obviously different than the one used to yield the model. The distribution of this data can be either distributed regularly or following a random distribution. Often, authors are chosing an evaluation dataset distributed homogeneously in the *RGB* device space. This is a good choice, since it will cover the whole device possibility. This can also be a good choice for the comparison of one method over different devices. However, if one want to relate the result to the visual interpretation of the signal throughout the whole gamut of the device, it might be judicious to select an equiprobably distributed data set in a perceptual color space. This means that most of the data will fall into low digital values.

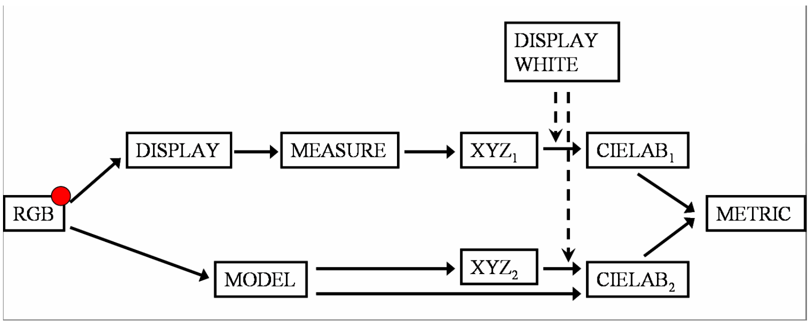


Fig. 7. Evaluation of a forward model scheme. A digital value is sent to the model and to the display. A value is computed and a value is measured. The difference between these values represents the error of the model in a perceptually pseudo-uniform color space.

Quantitative evaluation

Once we have an estimation of the model failure, we would like be able to say how it is good or not for a given purpose. The ideal colorimetric case is to have an error below the Just Noticeable Difference [6](JND). Kang [1997] stated on page 167 of his book that the JND is of 1 ΔE^*_{ab} unit. Mahy et al. [1994] study assessed that the JND is of 2.3 ΔE^*_{ab} units. Considering that the *CIELAB* color space is not perfectly uniform, it is impossible to give a perfect threshold with an euclidean metric[7]. Moreover, these thresholds have been defined for simultaneous pair comparison of uniform color patches. This situation almost never fit with a display use, it may then not be the best choice when comparing color display devices.

In the case of ΔE^*_{ab} thresholds for color imaging devices, many thresholds have been used [Abrardo et al., 1996, Hardeberg, 1999, Schläpfer, 1993, Stamm, 1981]. Stokes et al. [1992] found a perceptibility acceptance for pictorial images of an average of 2.15 units. Catrysse et al. [1999] used a threshold of 3 units. Gibson and Fairchild [2000] found acceptable a characterized display that has a prediction error average of 1.98 and maximum of 5.57, while the non-acceptable has at the best an average of 3.73 and a maximum of 7.63 using ΔE^*_{94}.

Following is a set of thresholds that could be used to quantify the success of the color control depending on the purpose. In Table 1, we distinguish between accurate professional color characterization, which purpose is to ensure a really high quality color reproduction, and a consumer color reproduction, which aims only at the preservation of the intended meaning, and relate the purpose with objective indicators.

Considering the professional reproduction, let us consider the following rule of thumb. If we want to reach a good accuracy we need to consider two indicators: the average and the maximum error. Let us consider the average: from 0 to 1 is considered good, from 1 to 3 acceptable, and over 3 not acceptable. If now we consider the maximum, from 0 to 3 is good, from 3 to 6 is acceptable, over is not acceptable. If we compare this scale with the rule of thumb used by Hardeberg [1999], it makes sense since below three it is hardly perceptible, the same if we look at the work of Abrardo et al. [1996]. If we look at the JND proposed by Kang [1997] or Mahy et al. [1994] it seems to make sense since in both cases, the *good* is under the JND. In this case we would prefer results to be good, and it may be possible to discard a couple model/display if it does not satisfy this condition. In the case of this professional reproduction, it could be better to use the maximum error to discard a couple model/display. Considering the consumer prediction, we propose to consider that from 0 to 3 it is good, from 3 to 6 it is acceptable, and over 6 it is not acceptable. In this case we would rather accept methods that shows average results up to 6, since it should not spoil the meaning of the reproduction. This is basically the same than

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[6] A JND is the smallest detectable difference between a starting and secondary level of a particular sensory stimulus, in our case two color samples.

[7] The JND while using ΔE^*_{00} should be closer to one than with other metrics but has still been defined for simultaneous pair comparison of uniform color patches.

the rule of thumb proposed by Hardeberg [1999], *perceptible but acceptable* being the basic idea of preserving the intended meaning.

Table 1. This table shows the set of thresholds one can use to assess the quality of a color characterization model, depending on the purpose.

<table>
<tr><td>ΔE^*_{ab}</td><td colspan="2">Professional</td><td>Consumer</td></tr>
<tr><td></td><td>Mean ΔE^*_{ab}</td><td>Max ΔE^*_{ab}</td><td>Mean ΔE^*_{ab}</td></tr>
<tr><td>$- < 1$</td><td>good</td><td rowspan="2">good</td><td rowspan="2">good</td></tr>
<tr><td>$1 \leq - < 3$</td><td>acceptable</td></tr>
<tr><td>$3 \leq - < 6$</td><td rowspan="2">not acceptable</td><td>acceptable</td><td>acceptable</td></tr>
<tr><td>$6 \leq -$</td><td>not acceptable</td><td>not acceptable</td></tr>
</table>

5.3 Color correction

The different approaches presented in the previous sections are characterized by different parameters, such as the accuracy on a given technology, the computational cost, the number of measurements required, etc.

The accuracy of the color rendering depends on the choice of both the method and the display technology and features.

Display characteristics, such as temporal stability or spatial uniformity have to be taken into account. Some of these parameters are studied in the literature, for instance in [Thomas and Bakke, 2009, Bakke et al., 2009]. However, Table 2 presents a qualitative summary of different display colorimetric characterization models based on quality thresholds from Table 1, and on the experimentation on several displays of different models in relation with the nature and number of measurements needed. The complete quantitative analysis of these models are presented in the literature [Colantoni and Thomas, 2009], [Thomas et al., 2008a], [Mikalsen et al., 2008].

We only focus on five models that are a representative sampling of existing ones: The Piecewise Linear assuming Variation in Chromaticity (PLVC) model [Post and Calhoun, 1989, Jimenez Del Barco et al., 1995, Thomas et al., 2008a], Bala's model [Bala and Braun, 2006, Bala et al., 2007, Mikalsen et al., 2008], an optimized polyharmonic splines based model [Colantoni and Thomas, 2009], the offset corrected Piecewise Linear assuming Chromaticity Constancy model (PLCC*) and the Gain-Offset-Gamma-Offset (GOGO) [Cowan and Rowell, 1986, Post and Calhoun, 1989, Berns et al., 1993b,a, Jimenez Del Barco et al., 1995, Katoh et al., 2001a,b].

Table 2. Qualitative interpretation of different models based on Table 1. The efficiency of a model is dependent on several factors: the purpose, the number of measurements, the nature of the data to measure, the computational cost, its accuracy, etc. All these parameters depend strongly on each display.

Model	PLVC	Bala	PLCC*	Polyharmonic splines	GOGO
Type of measurement	54 (*CIEXYZ*) measures	1 to 3 visual tasks for 1 to 3 pictures	54 (Y) measures 3 (*CIEXYZ*)	216 (*CIEXYZ*) measures	3 to 54 (Y) measures 3 (*CIEXYZ*)
Technology	dependent	dependent	dependent	independent	CRT
Purpose	Professional or Consumer	Consumer	Professional or Consumer	Professional	Consumer

6 Conclusion and perspectives

Successful color-consistent cross-media color reproduction depends on a multitude of factors. In this chapter we have reviewed briefly the state of the art of this field, focusing specifically on displays.

Device colorimetric characterization is based on a model, which can successfully predict the relationship between the media value and the color itself. A model can be based on knowledge on the device technology, then a few measurement or evaluation is necessary. A numerical model based on measure only can be used too, which requires usually more measurement, and requires to take care of more aspects, such as an interpolation method and the distribution on the training data set.

Point-wise colorimetric characterization of displays is something that is working considering objective indicators. Within this chapter, we reviewed different means to achieve this result. Display technology is evolving really fast. New technology might requires the definition of other types of models. For instance, this happened with the emergence of multi-primaries devices, which means more than three primaries, there are some works that adress the transform from a set of N-primaries and a 3-D colorimetric data.

This chapter only treated on point-wise, static models. A research direction could be to define dynamic models, which could take into account the spatial uniformity, the temporal stability, etc.

Within the last section of this chapter, we mainly wanted to show how we can evaluate the quality of a couple display/color characterization model with the tools we have in hands and to give an idea of how to select a model for a given purpose.

In summary, the choice of a couple display/color characterization model depends on the purpose. However, all the considerations we discussed are taking into account colorimetric objective indicators. In the case of complex images, indicators based on pointwise colorimetry show their limit. As far as we know, there are no comprehensive work addressing color fidelity and quality for complex color images on displays based on more human indicators. But there are some research initiated in this direction.

Furthermore, to reach an efficient perceived quality of displayed images, we need to relate the work on image quality metric and and the display color rendering quality. That means to define an objective indicator for color image quality viewed on displays related to the accuracy of the color rendering.

This point of view could be of benefit, particularly while considering new "intelligent" displays that adapt backlight to the image content. Such displays makes a static model inefficient.

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