Displays

Using single-shot 3D look-up-tables for color reproduction of display monitors

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Abstract:	Color, as represented by display monitors, is a primary cue for many professionals in fields like digital photography, design, and medicine. Therefore, reproduction of the colors of a reference display in a second display is crucial for color consistency across multiple displays in such scenarios. It requires the color characterization of the displays and a color reproduction method that is able to cope with differences in overall brightness and different black levels of the displays. Characterization of display monitors is usually performed with specific equipment (\eg, colorimeters, spectrometers). This type of professional equipment is not readily available and requires exhaustive measurements of each monitor, making it a tedious and slow process. Alternatively, manually performing the color reproduction task by tuning the settings of the display monitors is also time-consuming and leads to subjective results. In this work, we show that a consumer camera, such as a DSLR or cellphone camera, can be used to accurately perform color reproduction of display monitors, without needing to be photometrically calibrated. We use a single-shot taken with an uncalibrated camera to characterize the displays to 3D look-up-tables and used these in a new nonlinear optimization scheme to match the colors of one display to another. Experimental validation of the color reproduction framework is performed using real data and we compare our approach to another camera-based method showing that we are able to obtain consistently better results.
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Dear editors of Elsevier's Displays journal,

We wish to submit an original research article entitled *Color reproduction and characterization of display monitors using a camera* for consideration by the Displays journal.

In this paper, we report on a method for display characterization and color reproduction of display monitors. More specifically, we describe a new camera-based method to perform display characterization using a single phtograph, which is then used to perform color reproduction between two or more displays in a new framework that outperforms current literature. This is particularly important for calibrating display monitors in scenarios where exhaustive measurements are not viable or traditional display calibration equipment is not available.

We believe this work falls well within the scope of your journal and that it would be of interest to your readership because it is a new approach to the topic of color reproduction that provides robust results.

Thank you for your consideration.

Best Regards,

Pedro Rodrigues

Highlights

- We propose a method for display monitor characterization using a consumer camera.
- A 3D look-up-table is created from a single shot of the display.
- We perform color reproduction invariant to the black levels and overall brightness.
- Non-linear optimization allows for the use of LUTs and better gamut mappings.

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Using single-shot 3D look-up-tables for color reproduction of display monitors

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A R T I C L E I N F O

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A B S T R A C T

Color, as represented by display monitors, is a primary cue for many professionals in fields like digital photography, design, and medicine. Therefore, reproduction of the colors of a reference display in a second display is crucial for color consistency across multiple displays in such scenarios. It requires the color characterization of the displays and a color reproduction method that is able to cope with differences in overall brightness and different black levels of the displays. Characterization of display monitors is usually performed with specific equipment (*e.g.*, colorimeters, spectrometers). This type of professional equipment is not readily available and requires exhaustive measurements of each monitor, making it a tedious and slow process. Alternatively, manually performing the color reproduction task by tuning the settings of the display monitors is also time-consuming and leads to subjective results. In this work, we show that a consumer camera, such as a DSLR or cellphone camera, can be used to accurately perform color reproduction of display monitors, without needing to be photometrically calibrated. We use a single-shot taken with an uncalibrated camera to characterize the displays to 3D look-up-tables and used these in a new nonlinear optimization scheme to match the colors of one display to another. Experimental validation of the color reproduction framework is performed using real data and we compare our approach to another camera-based method showing that we are able to obtain consistently better results.

1. Introduction

Color gamut is the subset of visible colors that a color output device, such as a display monitor or projector, is able to represent. Two display monitors usually have different color gamuts, due to having different RGB primaries, different ranges of luminance, and different in-monitor color mapping functions. This is a critical point for applications that require color reproducibility on different displays, since each display will represent differently the same image.

One application where color reproduction across displays is crucial is in arrays of display monitors. It requires all the displays to be calibrated to each other to avoid color inconsistencies. Professionals in the fields of digital photography and design also need to perform display characterization and calibration regularly. Color is also an important cue for diagnosis in medical applications where imaging is an integral part of the diagnosis, such as medical endoscopy. If a practitioner is used to a display with a specific color gamut, a change to a completely different

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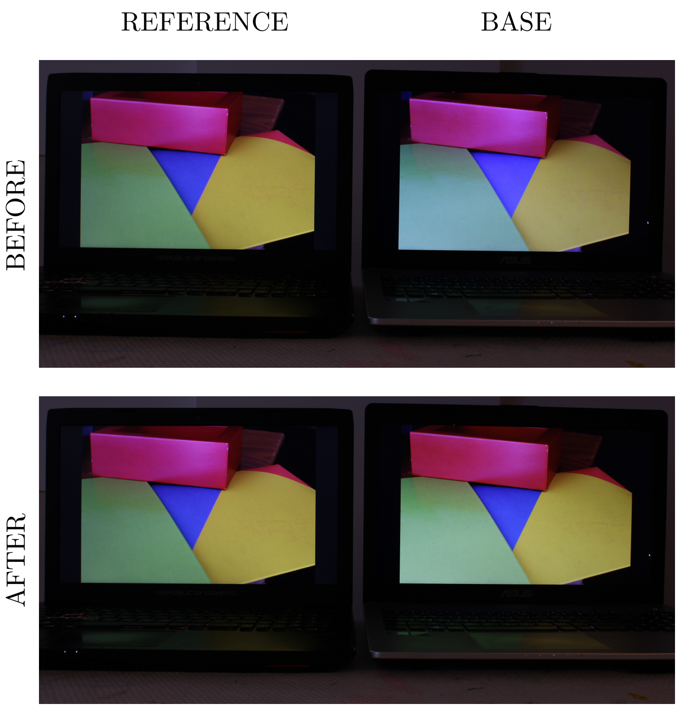


Fig. 1. DLSR stills of two displays showing the same input image: before (top) and after (bottom) the color reproduction correction to one of the displays.

display can interfere with diagnosis ability. In fact, display calibration is known to significantly improve practitioner efficiency [1].

Display monitors are usually equipped with a control board that transforms the input discrete logic levels (*i.e.*, the RGB values image or frame to be shown) by a given function. This board has internal memory that stores color parameters which could be changed in a calibration scenario. The display calibration process thus consists in finding the values for the parameters in order to obtain a certain color response (*e.g.*, the BT.709, a recommendation for HDTV from ITU-R — Radiocommunication Sector of the International Telecommunication Union). Currently, this calibration requires precise measuring equipment (*e.g.*, a spectrometer) and a framework that is time consuming for the individual in charge of the calibration procedure. For medical applications, besides the necessary display characterization, display manufacturers often must produce new displays with characteristics similar to the displays already deployed and known by the physicians. This leads to a time-consuming trial-and-error process of manual selection of the parameters available to the user, such as brightness, contrast, and temperature.

The main goal of our work is to provide a fast and automatic color reproduction framework for display monitors using a consumer camera. In other words, the same image being displayed in two different displays provides different color output results (see Fig. 1). Therefore, the goal is to estimate which is the best transformation that can be done to the input image of one of the displays so that its' color output matches the other's (see Fig. 2).

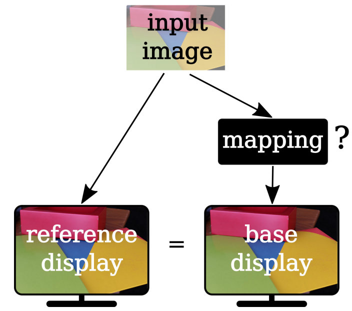


Fig. 2. The goal of the work is to find which transformation must be done to the image in the base display so that the color output of the base and reference displays is similar.

Literature has been published on the subject of projector display characterization using specialized measuring equipment (colorimeters, spectroradiometers, spectrometers) [2, 3, 4]. Display monitor characterization using specialized equipment [5] has also been discussed in the literature. However, this specialized equipment can be expensive and can lead to a tedious and time consuming process for display characterization, where each color must be sequentially shown by the display to be measured individually.

Cameras are known to be able to measure with acceptable accuracy the colorimetric properties of display projectors [6]. Using a camera as a colorimeter has the advantage of being able to take measurements of multiple color patches simultaneously. Therefore, a complete characterization of a display could potentially be produced from a single photograph.

Regarding projector display characterization using cameras, the authors of [6, 7] propose a method that requires the user to visually define the mid-gray level of the display, which introduces subjectivity. Other approaches [8, 9] are targeted to multi-projector arrays where overlap and registration can be used for performing matches between displays and estimating the required mapping functions. Jung *et al.* [10] propose an automatic characterization of display monitors using cameras. However, they used a linear mapping for the calibration and assume that the display monitors are similar in terms of overall luminance. In Post *et al.* [11], the authors aim to calibrate an immutable camera-display system where the display only shows the video streaming of one single camera. That camera is used to calibrate the camera-display system. However, showing images/frames from other camera equipment is not viable.

The main contributions of the present work are a display monitor characterization procedure using a single image taken with a consumer camera and a color reproduction framework for matching the color properties of two or more display monitors that:

- reduces the execution time for display characterization to mere seconds, while still using a comprehensive display model;
- allows for the relaxation of camera acquisition param-

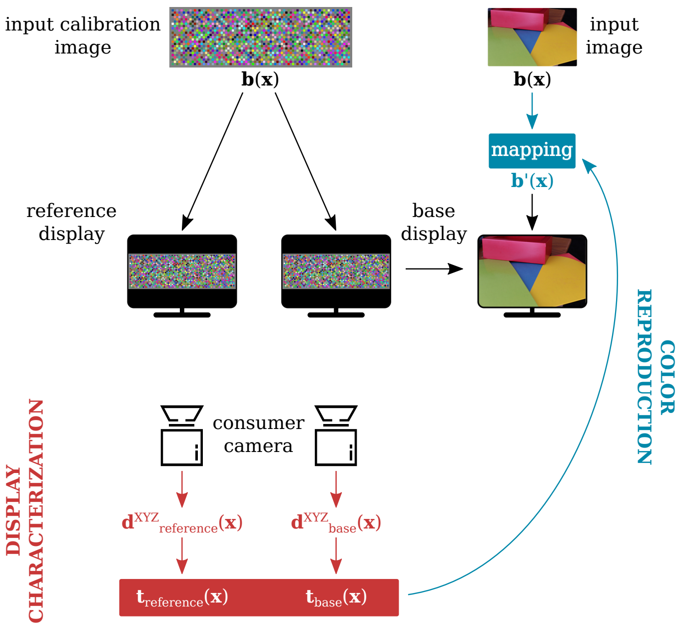


Fig. 3. Schematic overview of the display characterization and color reproduction framework.

eters, namely the exposure and the distance to the displays;

- allows for color matching of displays with different overall brightness and different levels of black;
- estimates a parameterized mapping function that outperforms the state-of-the-art methods.

2. Overview and Models

To quickly recreate the colors of a reference display monitor in a base display, the method proposed in this work will use a consumer camera (such as a DSLR camera or a smartphone camera) to take a single photo of each display, which are showing a known calibration image. Fig. 3 shows a schematic representation of the process.

An exhaustive description of the method will be provided in section 3. First, however, for an easier interpretation of the present work, this section defines the notation used and the main model equations on which this work is based. We discuss the assumptions about the radiometry involved in capturing an image of a display monitor, we describe the display models that are used, as well as the mapping function that is used to transform incoming images on the base display for it to match the reference display. We also propose new images that will be fed to the displays and specify the perceptual metric used in this work.

2.1. Notation

Matrices are represented by symbols in a sans serif font, *e.g.*, A. Vectors and vector functions are represented by bold symbols, and scalars are denoted by plain font letters, *e.g.*, $\mathbf{x} = (x, y)^\mathsf{T}$ and $\mathbf{f}(\mathbf{x}) = \left(f_x(\mathbf{x}), f_y(\mathbf{x})\right)^\mathsf{T}$.

2.2. Camera Measurements

Since we will be using estimation procedures involving minimization of color as measured by the camera, characterization of the camera response must be considered. Photometric calibration of the camera is not mandatory in our algorithms. Modeling the display monitors without a calibrated camera, means that we will model the display and the camera together. As long as the same camera is used for imaging both the base and the target displays, color reproduction using our method is possible. The minimization space will be warped in relation to visual perception, but this is not crucial to obtain good results.

In this work, we use cameras shooting in RAW mode that are then transformed to a canonical color space, the CIEXYZ, using dcraw [12]. For applications other than color reproduction, the display characterization described in this work is still feasible, however, photometric calibration may be required.

In addition, the cameras that are used do not suffer from significant vignetting and, thus, it will not be considered throughout the rest of the work. Geometric calibration of the cameras is also not considered in this work. It was observed that it was not necessary as long as we use the calibration images that we propose.

2.3. Display Monitors

Regarding the display monitors, there are a few assumptions that need to be satisfied experimentally. For imaging the display monitor we assume that there are no external lights and that the monitor radiance is point-wise isotropic. The latter may not reflect the reality for some types of monitors [5], but we minimize this effect by fixating the camera far from the monitor and fronto-parallel to the monitor. It comes that,

$$\mathbf{d}^{\text{XYZ}}(\mathbf{x}) = \alpha \mathbf{l}^{\text{XYZ}}(\mathbf{x}) \tag{1}$$

where $\mathbf{d}^{\text{XYZ}}$ is the acquired image in the CIEXYZ space, $\mathbf{x}$ is a scene point (in this case a point on the monitor), $\mathbf{l}^{\text{XYZ}}$ is the radiance and α is the camera exposure. For simplicity, the equation is written in the CIEXYZ color space, but it could easily be extended to use other relevant color spaces.

Given the mentioned assumptions, the radiance can be then measured up-to-scale directly by a camera. Additionally, modeling of a display monitor can be done directly from the values measured by the camera.

In this work, we used a 3D look-up-table (LUT) as a model for the display monitors. Note that for a complete 3D LUT with 8-bit axis one would need 256^3 measurements. This is not feasible. Nevertheless, accurate representation of the display can still be achieved with a minimum of 1000 measurements [7].

The camera has a striking advantage over the colorimeter/spectrometer, as it can perform all 1000 measurements in a single image. This approach is impractical with other, more standard, measurement equipment, where only a single color can be measured at a time. The 3D LUT is built directly from a single acquired image $\mathbf{d}$ as a series of measurements, for instance 1000 different colors spread out through the RGB space as explained in section 2.5. The remaining values are retrieved by interpolation. We formalize the model as

$$\mathbf{d}^{\mathrm{XYZ}}(\mathbf{x}) = \mathbf{t}(\mathbf{b}(\mathbf{x})). \tag{2}$$

where $\mathbf{b}$ is the input image, *i.e.*, the image fed to the display, and $\mathbf{t}$ is the 3D LUT, an $\mathbb{R}^3 \to \mathbb{R}^3$ function.

Other models were considered, such as the PLCC* and the PLCC model [7]. However, better results were obtained with the LUTs.

2.4. In-monitor Mapping Function

Not all operations are permitted for color correction in display firmware and/or software dedicated for display. For instance, there is no 3D LUT in most display monitors firmware. There are only a few specific operations that can be performed. In this work, it is assumed that the allowed operations are a matrix multiplication, $\mathsf{R}_{3\times3}$, followed by a function $\mathbf{h}$, composed of three $\mathbb{R} \to \mathbb{R}$ functions, one for each channel. Thus, to transform the input image $\mathbf{b}$ to a new image $\mathbf{b}'$ that compensates for the differences between two monitors, we have

$$\mathbf{b}'(\mathbf{x}) = \mathbf{h}(\mathsf{R}\mathbf{b}(\mathbf{x})). \tag{3}$$

In this instance, we have used 4th-order polynomials for function $\mathbf{h}$, as it presented a good trade-off between complexity and results.

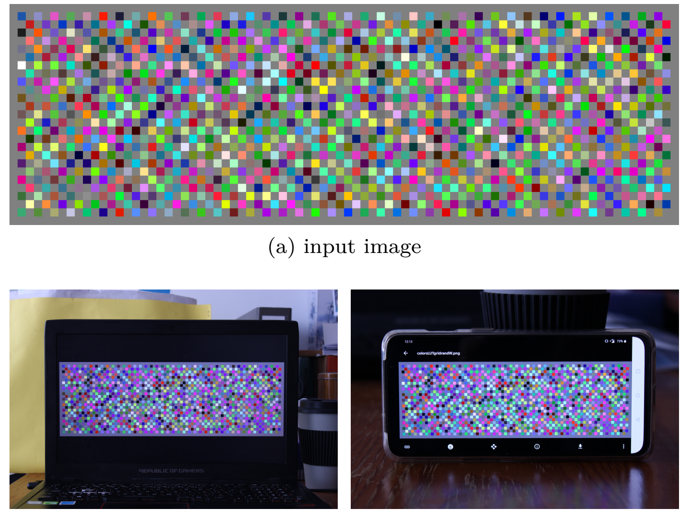
Although this is not a standard transformation, this is can be used in many display manufacturers as it is composed by traditional color operations and gamma curve manipulations. Our method, however, is not closed off to other mapping functions. In fact, we have also tested another mapping where only the matrix multiplication is used, as in [10]. Formally,

$$\mathbf{b}'(\mathbf{x}) = \mathsf{R}\mathbf{b}(\mathbf{x}). \tag{4}$$

2.5. Input Calibration Image

The input image used for display characterization is shown in Fig. 4. The image has 1000 color patches that correspond to the values on a 10 by 10 by 10 grid in the RGB color space. Each patch is surrounded by gray patches to reduce spatial overlap between colors due to camera blur and/or defocus, and to attenuate spatial color variation present in some display technologies. For instance, a pure black patch surrounded by red pixels can have a different reading than one surrounded by green pixels.

Another potential source of error is when there is no consistency across the entire display. For example, due to a non-uniform backlight in LCDs. This could lead to changes in the measured colors in some regions of the display. The gray patches could also be used to normalize for this aspect. However, in our tests, as long as the camera is fronto-parallel and far from the display monitors, this operation was not necessary. Positioning the camera in such way also ensures that, from the point view of the camera, violations in the assumption that the display radiance is point-wise isotropic, are less noticeable.



(a) input image

(b) reference display

(c) base display

Fig. 4. Image fed to the display monitors: (a) 1000-color image used for modeling the display models and to estimate the parameters for color reproduction mapping; (b) example of an image acquired with a DSLR camera of a reference display showing the characterization image; (c) example of an image acquired with a DSLR camera of a base display showing the characterization image.

2.6. Perceptual Metric

The $u'v'$ chromaticity plane provides a good two-coordinate color description. It can be directly transformed from the CIEXYZ color space. Within this color plane, the perceived difference between two colors can be expressed as an euclidean distance, $\Delta_{u'v'}(\mathbf{d}_1, \mathbf{d}_2)$. This metric can effectively be used as a color distance metric [13], and will be used to quantitatively evaluate the models and to perform display matching.

3. Color Reproduction

To achieve color reproduction we combine the concepts disclosed in the previous sections. For an overview of the complete process, please check algorithm 1.

Before any optimization, the single-frame measurements acquired with the camera must be transformed into a LUT. The LUT is populated with the median pixel values taken from the corresponding color patches shown on screen. This is done for both the base and the reference displays. Since we are using the 1000-color image proposed in section 2.5, we end up with LUTs that have 10×10×10 triplets of XYZ values. In this work, we use linear interpolation to obtain the remaining values since more complex interpolation methods did not seem to provide better results.

The goal of the color reproduction procedure is to find what new image $\mathbf{b}'(\mathbf{x})$ must be given to the base display so

Algorithm 1 Display monitor color reproduction algorithm.

Require: look-up table for reference display, $\mathbf{t}_{\text{reference}}$
1: obtain look-up table for base display, $\mathbf{t}_{\text{base}}$
2: estimate κ_1 and κ_2 — equation (9)
3: estimate R and $\mathbf{h}^{-1}$ — equation (11)
4: estimate $\mathbf{h}$ — equation (11)
5: non-linear refinement of R and $\mathbf{h}$ — equation (12)

that the measured LUTs of both the base and the reference displays are equivalent. For simplicity, let us first define $\mathbf{b}_\rho$ and $\mathbf{b}'_\rho$ as a shorthand for the colors being displayed in patch ρ of, respectively, the images $\mathbf{b}(\mathbf{x})$ and $\mathbf{b}'(\mathbf{x})$. Formally,

$$\begin{aligned} \mathbf{b}_\rho &= \mathbf{b}(\mathbf{x}_i), \quad \forall i \in \mathcal{P}_\rho \\ \mathbf{b}'_\rho &= \mathbf{b}'(\mathbf{x}_i), \quad \forall i \in \mathcal{P}_\rho \end{aligned} \tag{5}$$

where $\mathcal{P}_\rho$ is the set of pixel indexes that correspond to a color patch ρ. Then,

$$\mathbf{t}_{\text{base}}\left(\mathbf{b}'_\rho\right) \equiv \mathbf{t}_{\text{reference}}\left(\mathbf{b}_\rho\right), \quad \forall \rho \tag{6}$$

where $\mathbf{t}_{\text{base}}$ and $\mathbf{t}_{\text{reference}}$ are, respectively, the measured LUTs of the base and the reference displays. In fact, we must know, not only $\mathbf{b}'$, but how $\mathbf{b}'$ can be obtained from $\mathbf{b}$. Combining (3) and (6) we have that

$$\mathbf{t}_{\text{base}}\left(\mathbf{h}\left(\mathsf{R}\mathbf{b}_\rho\right)\right) \equiv \mathbf{t}_{\text{reference}}\left(\mathbf{b}_\rho\right), \quad \forall \rho. \tag{7}$$

The unknowns are the in-monitor mapping function, composed by the matrix R and the polynomials $\mathbf{h}$. However, we still need to define how the comparison between the two displays must be performed.

There are multiple factors that must be considered when comparing two displays. Among the factors that make this comparison non-trivial is the variable camera exposure. The gamuts of the displays are also important in this comparison. Not only the color gamut defined by the 3 primary colors of the display but also the full 3D gamut of the display. The gamut of display is in reality defined, not only by its primary colors, but also by the brightness range for each color that can be represented. Different displays can have very different overall brightness values (*e.g.*, cellphones and some medical displays have more brightness than other traditional displays). How black is the pure black of a display is another factor that must be taken into account (*e.g.*, OLED displays can achieve darker levels of black than other types of displays). The full 3D gamuts must be considered in the comparison, because the in-monitor mapping function that we need to estimate should not change the overall brightness of the base display or how dark the black level is, which would happen if a direct comparison of the two display were to be used. This is not desirable because, in the one hand, brighter displays should not lose their brightness when being matched to a reference with less brightness, on the other hand, a base display with less overall brightness cannot be matched directly to a brighter reference. Similarly, a darker pure black is a desirable characteristic that should not be changed to accommodate a reference with a brighter black level. Additionally, camera exposure and distance of the camera to the display can also have an effect similar to differences in brightness between the displays. The present work aims to achieve display monitor color reproduction without the need to have static camera exposure or to have similar displays being photographed at the same distance. This allows for color reproduction of a wide variety of displays and relaxation of acquisition settings. All these factors haven been taken into consideration when defining how to compare the LUTs of two displays.

Nonlinear optimization is used to estimate the in-monitor mapping function. In this way, we are able to perform the optimization with a cost function related to the human perception of color differences. However a good initialization is required for good results and fast optimization. To perform the comparison between the two LUTs in both the initialization and nonlinear refinement stages, two unknown scalars were introduced, a scaling and a shift. These scalars will compensate for the differences in the camera exposures, in the distances of the camera to the display, in the brightness of the pure black of the displays, and in the overall brightness.

3.1. Initialization

The initialization is performed in three optimization steps.

The first step is to match the codomains of the two LUTs. To compare the two LUTs in the initialization stage we define

$$\mathbf{t}_{\text{base}}(.) = \kappa_1 + \kappa_2 \mathbf{t}_{\text{reference}}(.) \tag{8}$$

where κ_1 and κ_2 are unknown scalars, the aforementioned scalars for scaling and shift. These scalars are estimated using L^2-norm with equations of the form

$$t_{\mathrm{Y,base}}(.) = \kappa_1 + \kappa_2 t_{\mathrm{Y,reference}}(.) \tag{9}$$

where t_{Y}, an $\mathbb{R}^3 \rightarrow \mathbb{R}$ function, is the Y channel of the LUT $\mathbf{t}$. The reasoning for using the channel Y instead of using a quantity that better relates to human perception, such as lightness L^* (CIELUV), is that this change would require the definition of a white point, which is not crucial for our approach. The values that are outside the common codomain are ignored for the rest of the initialization.

From (7) and (8), we can write

$$\mathbf{h}\left(\mathsf{R}\mathbf{b}_\rho\right) = \mathbf{t}_{\text{base}}^{-1}\left(\kappa_1 + \kappa_2 \mathbf{t}_{\text{reference}}\left(\mathbf{b}_\rho\right)\right), \quad \forall \rho. \tag{10}$$

At this point the right hand side of the equation is fully known/initialized. It will be denoted as $\mathbf{b}'^{*}_\rho$, as this could be used for a first approximation of $\mathbf{b}'(\mathbf{x})$. Thus,

$$\mathbf{h}\left(\mathsf{R}\mathbf{b}_\rho\right) = \mathbf{b}'^{*}_\rho, \quad \forall \rho. \tag{11}$$

For the second step, the set of equations defined in (11) can used to estimate R and the inverse of $\mathbf{h}$, one channel at a time, without additional unknowns. This convex optimization problem was performed with quadratic programming and linear inequality constraints on the monotonicity of the polynomials.

Finally, in the third step, the direct $\mathbf{h}$ is estimated using the matrix R that was estimated in second step. This estimation of $\mathbf{h}$ is necessary since the polynomials used for $\mathbf{h}^{-1}$ are not invertible. In this way, we are able to estimate R without assuming a linear $\mathbf{h}$, which in turn gives a more accurate initialization for both R and $\mathbf{h}$. The estimation in the third step is also performed for each channel independently, using quadratic programming and linear inequality constraints on the monotonicity of the polynomials.

3.2. Nonlinear Refinement

For the nonlinear optimization the cost function we will be composed of two metrics: the aforementioned perceptual metric and a metric comparing the brightness of the color patches. This second metric ensures that the relationships between the color patches are maintained. Without it, the brightness of the colors could lose its meaning.

The comparison used here to match the codomains of the two LUTs takes the form of (9). It still uses a shift κ_1 and scaling κ_2 in the Y channel. However, κ_1 and κ_2 are not refined for. They are taken as constants for the nonlinear refinement.

The optimization problem can be written as

$$\min_{\mathbf{h}(.),\mathsf{R}} \frac{1}{N_\rho} \sum_\rho \epsilon_\rho^{\text{chromaticity}} \left(\mathbf{h}(.), \mathsf{R}\right) + \lambda \frac{1}{N_\rho} \sum_\rho \epsilon_\rho^{\text{brightness}} \left(\mathbf{h}(.), \mathsf{R}\right) \quad (12)$$

with

$$\epsilon_\rho^{\text{chromaticity}} \left(\mathbf{h}(.), \mathsf{R}\right) = \Delta_{u'v'}\left(\mathbf{t}_{\text{base}}\left(\mathbf{h}\left(\mathsf{R}\mathbf{b}_\rho\right)\right), \mathbf{t}_{\text{reference}}\left(\mathbf{b}_\rho\right)\right) \quad (13)$$

and

$$\epsilon_\rho^{\text{brightness}} \left(\mathbf{h}(.), \mathsf{R}\right) = \left|\kappa_1 + \kappa_2 t_{\text{Y,reference}}\left(\mathbf{h}\left(\mathsf{R}\mathbf{b}_\rho\right)\right) - t_{\text{Y,base}}\left(\mathbf{b}_\rho\right)\right|. \quad (14)$$

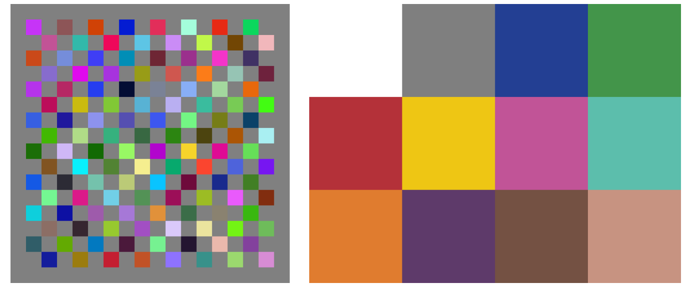
Within the cost function, some values of transformed image $\mathbf{b}'(\mathbf{x})$ (see (3)) may be outside the range of possible values. We used absolute colorimetric rendering intents to bring them back into the cube of possible values.

Note that κ_1 and κ_2 are only used to compare the two LUTs. They will not be used after the optimization is performed. Only R and $\mathbf{h}$ are needed.

4. Results

In this section, we will discuss the evaluation procedures and their results.

The cameras used in this work were: (C1) a digital single-lens reflex Canon EOS 600D (Canon Inc., Tokyo, Japan) with a standard Canon EF-S 18-55mm F3.6-5.6 IS II lens, and; (C2) a smartphone camera, the OnePlus 7 (OnePlus Technology Co., Ltd., Shenzhen, China) built-in camera.



(a) (b)

Fig. 5. Images fed to the display monitors: (a) the image with 128 randomly-chosen colors that was used for quantitative assessment of the models and the mapping; (b) the image with 12 colors used for qualitative visual assessment.

The monitors used for evaluation are: (D1) an ASUS N56VZ (ASUSTeK Computer Inc., Taipei, Taiwan) laptop display; (D2) an ASUS ROG GL553V laptop display; (D3) an OnePlus 7 OLED display; and (D4) the same ASUS ROG GL553V display with manual color settings. For experimental validation, in addition to the 1000-color image (see Fig. 4), two additional images were displayed in each monitor and photographed by the camera. One image with 128 randomly generated colors (quantitative assessment), and another with 12 hand-picked colors to match the colors used in the X-Rite (X-Rite, Inc., MI) ColorChart (qualitative assessment). See Fig. 5.

A few values for the optimization parameter λ were tested (see equation (12)). The best results were obtained with $\lambda = 1$. Regarding the in-monitor mapping function, 4th-order polynomials were used for function $\mathbf{h}$.

4.1. Color Reproduction

For evaluating the color reproduction framework we resort to the 128-color input calibration image. One shot of the display is taken with the camera before correction and another after correction using the parameters R and $\mathbf{h}$. For these results, only the DSLR camera (C1) was used. Table 1 shows the results. For comparison, we implemented a version of our approach where only a 3×3 matrix R is estimated as the in-monitor mapping function, as in (4), instead of both R and $\mathbf{h}$. We also provide baseline results using our implementation of the method proposed by Jung *et al.* [10], which also estimates only a 3×3 matrix.

The baseline method reduces the color perception metric by an average of 46%. Our approach achieves better metrics for all tested cases and is able to achieve an average reduction of 68% and up to 84%.

The simpler version of our approach (estimation of only R) is able to outperform the baseline method for all cases. These improvements are due to the fact that we use a cost function based in color perception and to the better

Table 1. Initial and final $\Delta_{u'v'}$ metric (average±standard deviation) for the color reproduction frameworks. Each line corresponds to a different display monitor pair. The lines are sorted by the perceptual metric obtained before corrections.

base	reference	before correction	Jung *et al.*	ours (R only)	ours
D3	D2	0.028 ± 0.025	0.017 ± 0.019	0.013 ± 0.016	**0.012 ± 0.016**
D2	D3	0.028 ± 0.025	0.015 ± 0.013	0.013 ± 0.011	**0.013 ± 0.011**
D2	D1	0.039 ± 0.027	0.025 ± 0.028	0.018 ± 0.017	**0.017 ± 0.016**
D3	D4	0.045 ± 0.028	0.022 ± 0.018	0.016 ± 0.014	**0.010 ± 0.009**
D2	D4	0.051 ± 0.039	0.032 ± 0.029	0.017 ± 0.013	**0.008 ± 0.006**
D3	D1	0.056 ± 0.036	0.024 ± 0.019	0.020 ± 0.017	**0.019 ± 0.016**
D1	D4	0.057 ± 0.050	0.027 ± 0.024	0.018 ± 0.015	**0.011 ± 0.009**

codomain matching, *i.e.* 3D gamut matching, between the two displays. By using the 3D LUTs and by using scaling and shift parameteres in the brightness channel, we are able to achieve better results, even when estimating the same transformation (only R).

Figs. 6 and 7 show the optimization results for the different display monitor pairs. Figs. 6 presents the distances of the colors, in the chromaticity plane, of some pairs of base-reference display monitors. In this figure, one evaluate how the distances between the colors of the base and the reference displays are improved with our framework. In addition, the chromaticity diagram is shown to allow for visual assessment of what the color distances in the $u'v'$ plane represent in terms of visual perception of color distances.

In Fig. 7 one can visually assess the results of the calibration. Note that it is not expected that the colors are matched in terms of brightness as the display monitors might have different overall brightness. Only the tone of the color is supposed to match. The 4 colors in the bottom right corner of the base displays are perceptually closer to the reference. Only one color patch, the white patch of display D3, seems to not be completely corrected. This is expected, because we are estimating an in-monitor mapping function that must be implemented in real applications. It is not a perfect transformation that is able to map correctly all possible colors. Nevertheless, all other color patches seem to be perceptually closer to the reference image.

4.2. Colorimeter Comparison

In this experiment we want to show if a calibration with our method is able to match that of a hardware specifically designed for display monitor calibration. For that purpose, we used a Datacolor Spyder 3 Elite (Datacolor, NJ), which is a colorimeter for display calibration usually used in professional setups, such as professional digital photography, where color accuracy is very important.

The colorimeter was used to calibrate one of the display monitors to a standard color space by using an unknown mapping function. We then tried to match the mapping performed by the colorimeter with our camera-based method, by using camera shots of the display showing our input calibration image before (base) and after (reference) the colorimeter calibration. A perceptual metric of zero would mean that the colorimeter and our method lead to the same result. Nevertheless, small differences are expected due to measurement errors and differences in the mapping function.

The results are shown in Table 2. For these results, only the DSLR camera (C1) was used.

The results also show the potential of using this method to calibrate display monitors to standard color spaces, such as the BT.709, without having photometrically calibrated cameras. Since, in that case, a camera shot of the reference display already calibrated to the standard color space would be necessary.

4.3. Camera Cross-validation

For the final experiment, we aim to demonstrate the robustness of the method across different cameras. Since the cameras are not previously calibrated photometrically, results will differ. To assess this problem we performed cross validation using both cameras, a DSLR camera (C1) and a smartphone camera (C2). The displays used in this test were: D2 as base display and D4 as reference display.

The results are shown in Table 3 and confirm that photometric calibration of the cameras is not necessary to obtain robust results.

5. Conclusions

We have provided a framework for color reproduction across display monitors using a single image taken with a common camera, such as a smartphone camera. This work is relevant in many different applications. In a medical context, color reproduction is crucial as color information acquired from a video camera will be seen by surgeons and other physicians through many monitors, both in and out of the operating room. In more generic applications, digital photography displays and multi-display arrays can also be calibrated with the proposed method.

Our method was able to achieve better results than other camera-based methods (Jung *et al.* [10]) for this type of problem, and it was shown to be robust across cameras even without photometric calibration. Additionally, our method can be easily extended to other in-monitor mapping function, as long as initialization of those mapping functions is feasible.

Table 2. Initial and final $\Delta_{u'v'}$ metric (average±standard deviation) for the color reproduction frameworks. For this test, the reproduction frameworks must use a monitor calibrated with a colorimeter as a reference display and the same display before correction as the base display.

before correction	Jung *et al.*	ours (R only)	ours
0.053 ± 0.037	0.015 ± 0.013	0.012 ± 0.012	**0.007 ± 0.008**

Table 3. Initial and final $\Delta_{u'v'}$ metric (average±standard deviation) for the proposed color reproduction framework. For this test, our approach is evaluated using cross-validation of different cameras.

acquisition camera	before correction	validation with C1	validation with C2
C1	0.051 ± 0.039	0.007 ± 0.007	0.008 ± 0.008
C2	0.046 ± 0.035	0.007 ± 0.006	0.007 ± 0.006

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References

[1] A. Badano, C. Revie, A. Casertano, W.C. Cheng, P. Green, T. Kimpe, E. Krupinski, C. Sisson, S. Skr??vseth, D. Treanor, P. Boynton, D. Clunie, M.J. Flynn, T. Heki, S. Hewitt, H. Homma, A. Masia, T. Matsui, B. Nagy, M. Nishibori, J. Penczek, T. Schopf, Y. Yagi, H. Yokoi, Consistency and standardization of color in medical imaging: a consensus report, Journal of Digital Imaging 28 (2014) 41–52.

[2] L. Seime, J.Y. Hardeberg, Colorimetric characterization of LCD and DLP projection displays, Journal of the Society for Information Display 11 (2003) 349–358.

[3] J.Y. Hardeberg, L. Seime, T. Skogstad, Colorimetric characterization of projection displays using a digital colorimetric camera, in: M.H. Wu (Ed.), Procedings of SPIE on Projection Displays IX, volume 5002, 2003, pp. 51–61. doi:10.1117/12.473865.

[4] M. Brown, A. Majumder, R. Yang, Camera-based calibration techniques for seamless multiprojector displays, IEEE Transactions on Visualization and Computer Graphics 11 (2005) 193–206.

[5] D.H. Brainard, D.G. Pelli, T. Robson, Display characterization, in: Encyclopedia of Imaging Science and Technology, John Wiley & Sons, Inc., Hoboken, NJ, USA, 2002. doi:10.1002/0471443395.img011.

[6] R. Bala, R.V. Klassen, K.M. Braun, Efficient and simple methods for display tone-response characterization, Journal of the Society for Information Display 15 (2007) 947–957.

[7] J.B. Thomas, Colorimetric Characterization of Displays and Multi-display Systems, Ph.D. thesis, Université de Bourgogne, 2009.

[8] E.S. Bhasker, P. Sinha, A. Majumder, Asynchronous distributed calibration for scalable and reconfigurable multiprojector displays, IEEE Transactions on Visualization and Computer Graphics 12 (2006) 1101–1108.

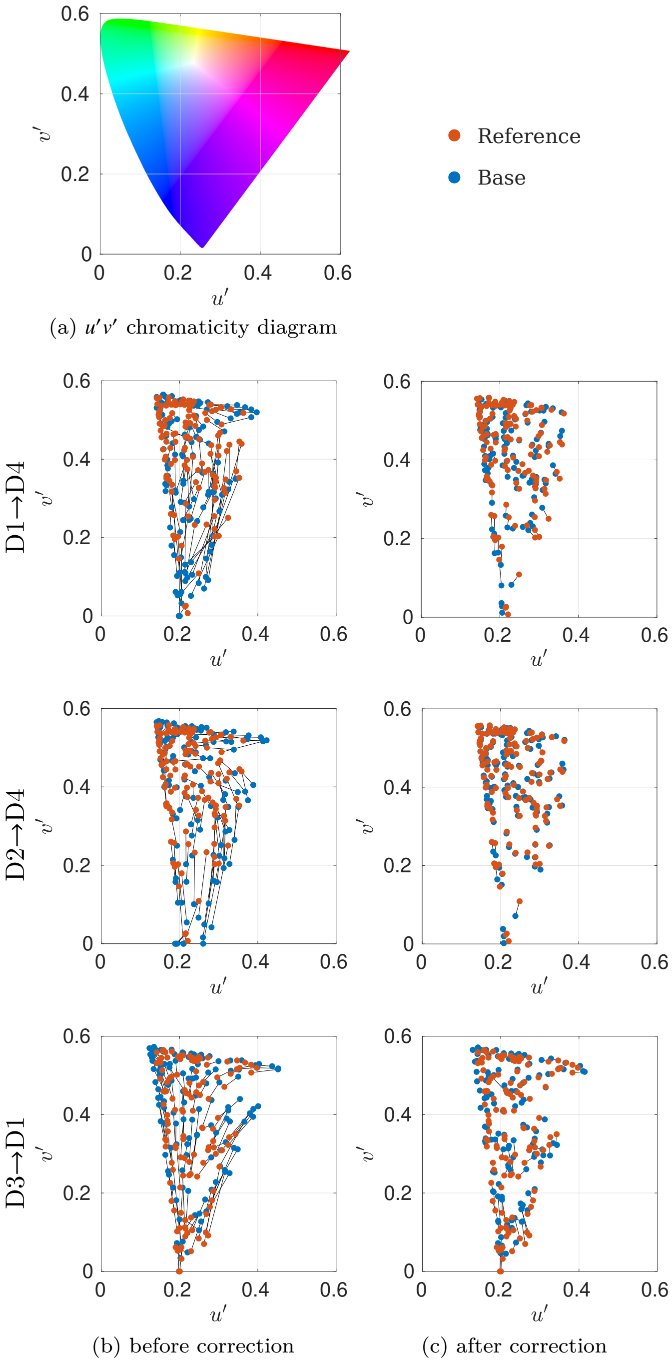
[9] E. Bhasker, R. Juang, A. Majumder, Registration techniques for using imperfect and partially calibrated devices in planar multi-projector displays, IEEE Transactions on Visualization and Computer Graphics 13 (2007) 1368–1375.

[10] J.Y. Jung, S.W. Kim, S. Park, B.D. Choi, S.J. Ko, Camera-based color calibration method for multiple flat-panel displays using smartphone, Journal of Display Technology 12 (2016) 1777–1784.

[11] M. Post, P. Fieguth, M.A. Naiel, Z. Azimifar, M. Lamm, FRESCO: Fast radiometric egocentric screen compensation, in: 2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW), IEEE, 2019, pp. 1899–1906. doi:10.1109/CVPRW.2019.00241.

[12] D. Coffin, Decoding raw digital photos in Linux, 2015. URL: https://www.dechifro.org/dcraw/, (accessed 01 October 2019).

[13] CIE, Chromaticity difference specification for light sources, 2014. URL: http://files.cie.co.at/738_CIE_TN_001-2014.pdf, (accessed 01 October 2019).

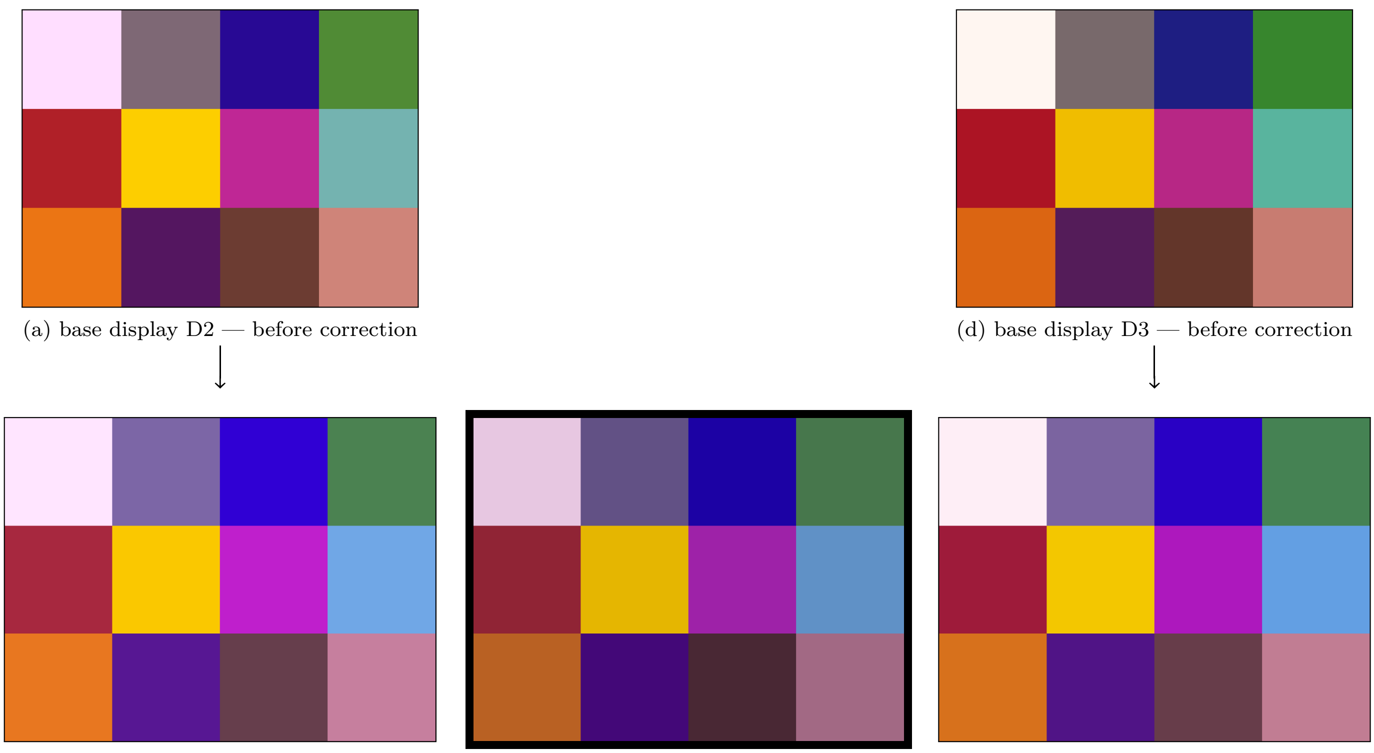


(a) $u'v'$ chromaticity diagram

(b) before correction

(c) after correction

Fig. 6. Color distances before and after the application of color reproduction framework as represented in the $u'v'$ chromaticity plane. Plot (a) shows the CIE 1976 UCS (uniform chromaticity scale) diagram, *i.e.*, the $u'v'$ diagram. The distances were taken with the DSLR camera and are relative to the 128-color validation image. The red dots represent colors in the reference display and the blue dots represent colors in the base display.



(a) base display D2 — before correction

(d) base display D3 — before correction

(b) base display D2 — after correction

(c) reference display D1

(e) base display D3 — after correction

Fig. 7. Color patches imaged with the DSLR camera. The patches are shown here in the sRGB color space for qualitative assessment of the improvements obtained with the color reproduction framework. Each column relates to a different display monitor. The first and the third columns relate to the base displays that were calibrated to match the reference display represented in the second column. Note that the 4 colors in the bottom right corner of the base displays are perceptually closer to the reference display.

Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐ The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: