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Colour Correction Using Modified Root Polynomial Regression

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***Abstract*— Cameras record three colour responses (RGB) which are device dependent. Camera coordinates are mapped to a stan-dard colour space such as XYZ - useful for colour measurement - by a mapping function e.g. the simple 3 × 3 linear transform (usually derived through regression). This mapping, which we will refer to as LCC (linear colour correction), has been demonstrated to work well in the number of studies. However, it can map RGBs to XYZs with high error. The advantage of the LCC is that it is independent of camera exposure. An alternative and potentially more powerful method for colour correction is polynomial colour correction (PCC). Here, the R,G and B values at a pixel are extended by the polynomial terms. For a given calibration training set PCC can significantly reduce the colorimetric error. However, the PCC fit depends on exposure i.e. as exposure changes the vector of polynomial components is altered in a non-linear way which results in hue and saturation shifts. This paper proposes a new polynomial-type regression loosely related to the idea of FRACTIONAL polynomials which we call 'Root-Polynomial Colour Correction' (RPCC). Our idea is to take each term in a polynomial expansion and take its K^{th} root of each K-degree term. It is easy to show terms defined in this way scale with exposure. RPCC is a simple (low complexity) extension of LCC. The experiments presented in the paper demonstrate that RPCC enhances colour correction performance on real and synthetic data.**

INTRODUCTION

The problem of colour correction arises from the fact that camera sensor sensitivities cannot be represented as the linear combination of CIE colour matching functions. The violation of the Luther conditions results in camera-eye metamerism that is certain surfaces while different to the eye will induce the same camera responses and vice-versa. While colour correction can-not resolve metamerism per se, it aims at establishing the best possible mapping from camera RGBs to device independent XYZs.

The literature is rich in descriptions of different methods attempting to establish the mapping between RGBs and XYZs. Methods include: three dimensional look-up tables, least-squares linear and polynomial regression and neural networks.

Despite the variety of colour correction methods reported in the literature the simple 3 × 3 linear transform is not easily challenged. First, if we assume that reflectances can be represented by 3 dimensional linear model (approximately the case), then under a given light the mapping from RGB to XYZ has to be a 3 × 3 matrix. Marimont and Wandell extended the notion of modelling surface reflectances using linear models

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by proposing that a linear model should account only for that part of the reflectance which can be measured by a camera or a human eye or in general any set of sensors (under different lights). They found that typical lights and surfaces interact with typical cameras as if reflectances and illuminants were well described by the 3 dimensional linear models.

Fig. 1 illustrates the problem. We map the scene physical colours at a number of exposures using PCC and plot the corresponding chromaticities. One can clearly see the chromatic shifts induced by the PCC as one scales the intensity of the light. The red lines show that the scene physical input chromaticity might be mapped to a range of outputs depending on exposure.

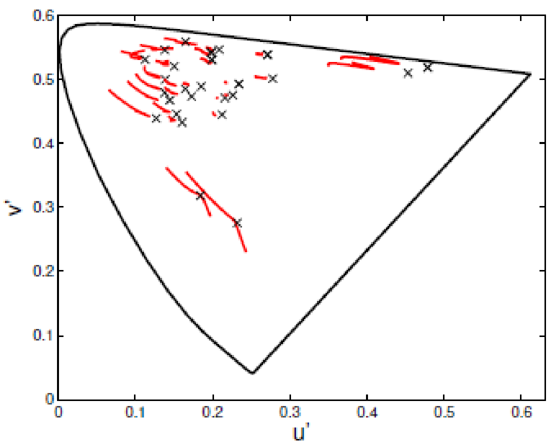

Fig. 1. Selection of reflectances from the SFU 1995 dataset and their true U′V′ coordinates (x) chromatic shifts produced by the polynomial model of the 4th degree (red solid lines).

A real image example of the problem is presented in Fig. 2. Fig. 2a contains an image of the colour checker captured with the NIKON D70 camera and colour corrected with the polynomial model of the 4th degree. Fig. 2b shows the same image with double the exposure time before it was corrected by the same transform. One can see that the colours of some patches have changed as the exposure changed e.g. an orange patch is corrected to pink as exposure changes.

Other examples of PCC failure are shown in Fig. 3. The scene containing the Macbeth colour chart and a pepper fruit under the D65 illuminant was captured with the Specim VNIR hyperspectral camera [1] and integrated with the sRGB sensors (shown in Fig. 3a). Next, the scene was integrated with Foveon sensors and colour corrected by the 4th degree PCC (shown in Fig. 3b). This image shows a relatively good colour correction when compared with the sRGB image. However, when we look at the image that was colour corrected after the illumination level was increased (shown in Fig. 3c), we can see that some colours were rendered inaccurately (e.g. the cyan patch and the pepper highlight). Note, that these patches are still below the sensor saturation level (the white point in the original image).

In this paper, we develop a new Root Polynomial Colour Correction (RPCC). By taking the kth root of k-degree polynomial terms, we show RPCC is independent of exposure (like LCC).

The rest of the paper is organised as follows. In Section II, we describe the PCC and a few other alterations to the LCC.

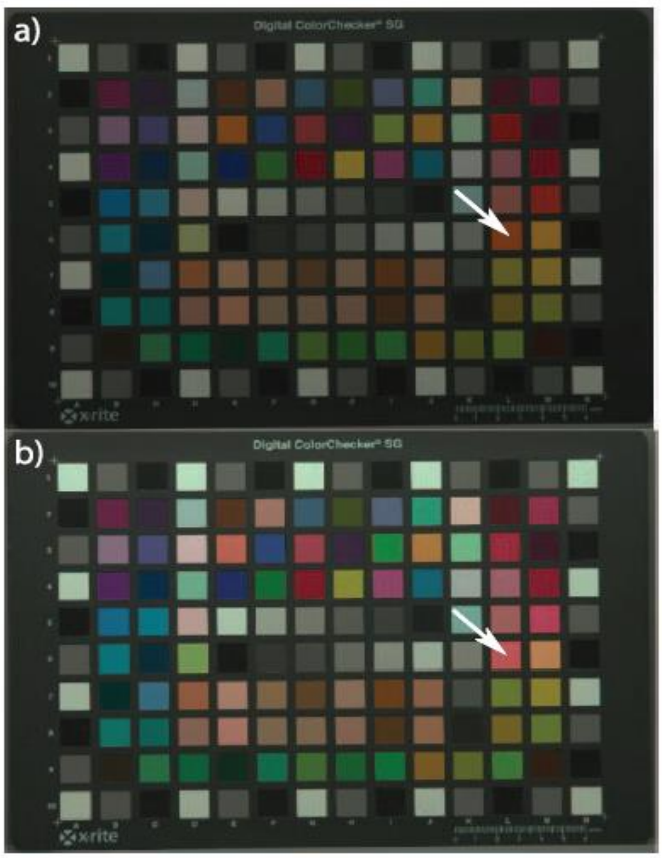

Fig. 2. X-rite SG colour chart captured with NIKON D70 camera and colour corrected using the polynomial model of the 4th degree (a). The image RGB values were multiplied by 2 before applying the same colour correction transform (b). A sample pair of patches with high error has been marked with arrows.

POLYNOMIAL COLOUR CORRECTION

Let ρ define a three element vector representing the three camera responses and Q their corresponding tristimulus values. A simple 3 × 3 colour correction transform is written as:

$$Q = M\rho \qquad (1)$$

The matrix M is generally found by some sort of least-squares regression. Let us denote a set of N known XYZs for a reflectance target as Q and the corresponding camera responses as the 3 × N matrix R. We find the least-squares mapping from R to Q using the Moore-Penrose inverse:

$$M = QR^T (RR^T)^{-1} \quad (2)$$

In polynomial regression, vector ρ is extended by adding additional polynomial terms of increasing degree. Formally, let ρ denote responses from N sensors. Then, the set of up to K^{th} degree polynomial terms in N variables is defined as:

$$P_{K,N} = \{\rho^\alpha : |\alpha| \leq K\} \quad (3)$$

where $\alpha = (\alpha_1, ..., \alpha_N)^T$ is a *multi-index* that is n-tuple of non-negative integers and its size is defined as $|\alpha| = \alpha_1 + ... + \alpha_N$ [22]. In multi-index notation, $\rho^\alpha = \prod_{i=1}^{N} \rho_i^{\alpha_i}$. There are $\left(\binom{N}{K}\right) = \binom{N+K-1}{N-1} = \binom{N+K-1}{K}$ different multi-indices of size K [23], and so, that many polynomial terms of degree K. It can be shown that the number of polynomials of up to K^{th} degree in N variables is $h = \binom{N+K}{N} - 1 = \binom{N+K}{K} - 1$.

For a typical case when $N = 3$ i.e. $\rho = (r, g, b)^T$, the polynomial expansions of the 2^{nd}, 3^{rd} and 4^{th} degree investigated in this work are given by the sets $P_{2,3}, P_{3,3}$ and $P_{4,3}$, which after ordering are defined by the following vectors:

$$\begin{aligned}
\rho_{2,3} &= (r, g, b, r^2, g^2, b^2, rg, gb, rb)^T \\
\rho_{3,3} &= (r, g, b, r^2, g^2, b^2, rg, gb, rb, \\
&\quad r^3, g^3, b^3, rg^2, gb^2, rb^2, gr^2, bg^2, br^2, rgb)^T \\
\rho_{4,3} &= (r, g, b, r^2, g^2, b^2, rg, gb, rb, \\
&\quad r^3, g^3, b^3, rg^2, gb^2, rb^2, gr^2, bg^2, br^2, rgb, \\
&\quad r^4, g^4, b^4, r^3g, r^3b, g^3r, g^3b, b^3r, b^3g, \\
&\quad r^2g^2, g^2b^2, r^2b^2, r^2gb, g^2rb, b^2rg)^T
\end{aligned}$$

ROOT-POLYNOMIAL COLOUR CORRECTION

For fixed exposure, polynomial regression really can deliver significant improvements to colour correction. However, in reality the same reflectance will also induce many different brightness's for the same fixed exposure and viewing con-ditions. As an example, due to shading the same physical reflectance might induce camera responses from zero to the maximum sensor value. Clearly, for this circumstance we want the colour of the object (hue and saturation) to be constant throughout the brightness range. As shown in Fig. 1-3 simple polynomial regression does not preserve object colour.

The starting point of this paper was to ask the following question. Is there a way we can use the undoubted power of polynomial data fitting in a way that does not depend on exposure/scene radiance? We make the observation that the terms in any polynomial fit each have a degree e.g. R, RG and R^2B are respectively degree 1, 2 and 3. Multiplying each of R, G and B by a scalar k results in the terms kR, k^2RG and k^3R^2B. That is the degree of the term is reflected in the power to which the exposure scaling is raised. Clearly, and this is our key insight, taking the degree-root will result in terms

which have the same k scalar: $(kR)^{1/1} = kR$, $(k^2RG)^{1/2} = k(RG)^{1/2}$, $(k^3R^2B)^{1/3} = k(R^2B)^{1/3}$. For a given p^{th} degree

polynomial expansion, we take each term and raise it to the inverse of its degree. The unique individual terms that are left are what we use in Root-Polynomial Colour Correction.

Formally, the set of up to K^{th} degree root-polynomial terms in N variables is defined as:

$$\overline{P}_{K,N} = \left\{\rho^{\frac{\alpha}{|\alpha|}} : |\alpha| \leq K\right\}$$

Strictly speaking all root-polynomial terms are multi-variable polynomials (monomials) of degree 1 as we took the p^{th} root of every p^{th} degree polynomial term.

EXPERIMENTS

To measure the performance of the RPCC, we performed both real camera experiment and synthetic data simulations, which are given in the following subsections. For both types of data, we compared the performance of RPCC with the LCC and PCC up to degree of four. We also compared the above with the colour correction using tri-linear LUT interpolation implemented as suggested. Here, we used 13x13x13 LUT and employed the Graph Hessian Regularize also described in the above references. And finally we tested the HPPCC. As suggested by the author we partitioned the hue circle into twelve slices and performed sample section based on relative susceptibility to noise.

Real camera experiments

We performed two real camera characterisations. The experimental set-up was as follows. The X-rite SG colour chart was positioned in a viewing box, illuminated with a D65 metamer produced by Gamma Scientific RS-5B LED illuminator and imaged with Nikon D70 and Sigma SD15 cameras. We also measured XYZs of each of the 96 patches using a Photo Research PR-650 spectrophotometer (see Fig. 5a). The linear 16-bit images were extracted from the camera raw images using DCRAW [1] (Nikon) and PROXEL X3F [2]

(Sigma) packages. The 96 patches were manually segmented and for the purpose of this exercise we used the average RGB of each patch. The dark levels were captured with the lens cap on and subtracted from the average camera responses. Resulting RGBs and measured XYZs were used to derive a set of colour correction models as described in the earlier sections. The models were evaluated using the leave-one-out method i.e. we built the model using all but one of the surfaces from the dataset and tested that model on the remaining patch; we repeated this for all the patches in the dataset and calculated mean E in the CIELUV colour space. The results of the validation can be seen in the second column (original exposure) in Table I.

The remaining two columns contain the results of performing colour correction on the same image data after multiplying all RGBs by the factors of $\frac{1}{2}$ and 2 and excluding those patches whose at least one sensor response (R, G or B) exceeded the corresponding sensor response of the white patch at the original exposure. This ensures that we are not taking into account those patches which in the real situation would be clipped. Thus, after multiplying RGBs by the factor of 2, we are left with 66 out of the original 96 patches for the Nikon camera and with 73 patches for the Sigma camera (see the last rows of Table I).

Fig. 5a-d allow us to compare the colour correction errors visually. Fig. 5a contains the sRGB SG chart patches, whereas the remaining figures contain the patches that were synthesised from the manually segmented average Nikon D70 RGBs that were multiplied by 2 (simulating light intensity increase) and colour corrected using PCC of degree 3 (Fig. 5b), 4 (Fig. 5c) and RPCC of degree 4 (Fig. 5d). These figures correspond to the errors reported in Table I in column *multiplied by 2*. It can be clearly seen that as Table I suggests, the errors for the PCC of degree 3 and 4 are significant, which is particularly visible for some green as well as pink and red patches. In contrast the high degree RPCC result in Fig. 5d does not manifest these chromatic errors.

Table I shows that the RPCC performs better than the LCC and is invariant with respect to the change of illumination intensity. It is also clear that PCC fails under the change of illumination condition. The smaller errors for the Nikon sensors than those for the Sigma suggest that the former are more colorimetric than the latter. The LUT method provides comparable performance to the PCC, i.e. it outperforms the LCC for the original exposure, but is not exposure invariant so it is clearly worse than RPCC as the exposure level is varied.

Against our expectations, HPPCC does not provide clearly better results than the LCC.

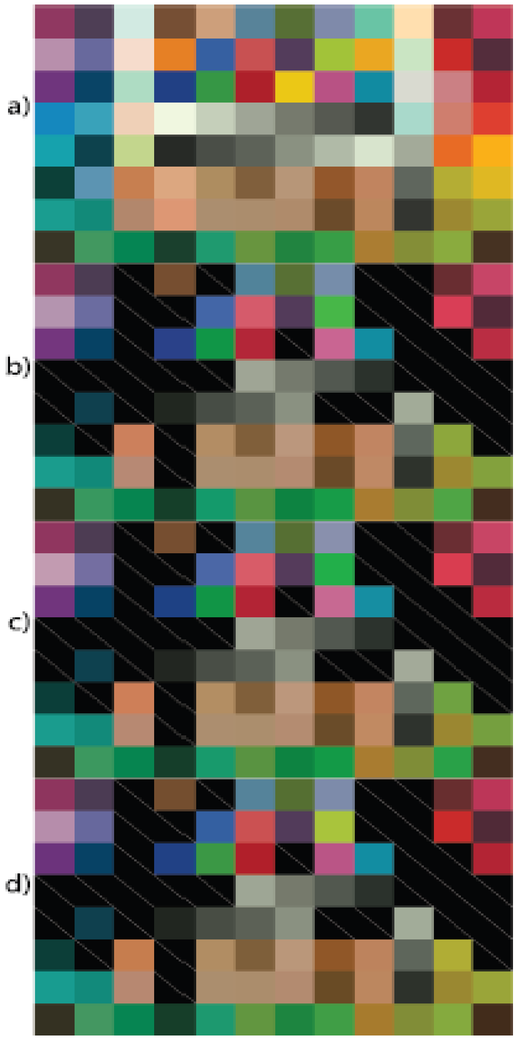

Fig. 5. SG chart synthesised from the spectrophotometer measurements (a). SG chart patches (66) captured with Nikon D70, multiplied by 2 and corrected with **polynomial of degree 3** (b), **degree 4** (c) and **root-polynomial of degree 4** (d). The patches that are crossed over have been removed as they were clipped following the multiplication. Note, these are synthetic patches derived from RGB averages.

CONCLUSIONS

'Root-Polynomial Colour Correction' builds on the earlier widely used polynomial models, but unlike its predecessors is invariant to the change of camera exposure and/or scene irradiance. The results presented in this paper show that this algorithm outperforms linear regression and offers a significant improvement over polynomial models when the exposure/scene irradiance varies. RPCC falls firmly into the well established family of linear and polynomial colour correction and therefore certain improvements to the last methods presented earlier in the literature (such as white-point preserving method) can be applied for RPCC case as well.

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