Colour Correction Toolbox

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ABSTRACT

For a camera image, the RGB response from the imaging sensor cannot be used to drive display devices directly. The reason behind this is two-fold: different cameras have different spectral sensitivities, and there are different target output spaces (e.g. sRGB, Adobe RGB, and XYZ). The process of mapping from captured RGBs to an output colour space is called colour correction. Colour Correction is of interest in its own right (*e.g.* for colour measurement), but it is also an important part of the colour processing pipelines found in digital cameras. In this paper, we look at the problem of mapping device RGB values to corresponding CIE XYZ tristimuli. We make three contributions. First, we review and implement a range of colour correction algorithms. We benchmark these algorithms in experiments using both synthetic data (so we can numerically assess a wider range of cameras) and real image data. In our second contribution, we develop an ensemble method to combine colour correction algorithms to further enhance performance. For the methods tested, we find there is small extra power in combining the methods. Our final — and perhaps most important contribution — is to provide an open source colour correction MATLAB toolbox for the community, implementing the algorithms described in the paper. As well, all our experimental data is provided.

KEYWORDS: Colour correction, Image reproduction, CIELAB colorimetric values

INTRODUCTION

The problem of colour correction arises from the fact that cameras do not measure colour in the same way as human vision. Imaging sensors in the camera do not have the same spectral sensitivity as the cone cells in the human eye. The spectral sensitivities for cameras do not perfectly satisfy the Luther conditions, i.e. they are not a perfect linear transformation of the cone sensitivities [1]. Violation of the Luther conditions can result in metamerism between cameras and the eye. This happens when two lights with different spectrum power distributions introduce different responses to the eye but the same response to cameras, and vice versa [2]. There has been sustained research interest in correcting camera colour measurements to colour spaces that are referenced to the human visual system since it is easier to measure the quality of colour reproduction in such colour coordinates. Common target colour spaces include sRGB, CIE XYZ [3], CIE Lab [4] and cone responses.

Colour contributes to the decision process when humans make visual judgements. This means that accurate colour reproduction is important when a computer vision system attempts to replicate the process [5]. On the image capturing side, colour correction involves mapping the device specific camera RGBs to device independent colour space such as sRGB. In the image reproduction side, colour correction involves mapping device independent colour spaces to the colour spaces of the image reproduction device [6]. For displays, this can be the display specific RGB; for printers, this can be the printer specific CMYK [7]. In this work, we explore different methods which map an (R, G, B) triplet p to the corresponding (X, Y, Z) triplet x. To evaluate the performance of colour correction algorithms, we then convert colours from CIE XYZ colour space to CIE Lab colour space. In CIE Lab colour space, the Euclidean distance between two colour coordinates tolerably corresponds to the perceived colour difference [8].

COLOUR CORRECTION ALGORITHMS

Linear Colour Correction [9]

The simplest and most commonly used colour correction method is linear colour correction. Let P and X denote $3{\times}N$ matrices representing camera RGBs and the corresponding XYZs, in linear colour correction, we find the $3{\times}3$ matrix M which minimises:

$$\min_{M} \|MP - X\|_F \tag{1}$$

The $3{\times}3$ regression matrix is found in closed form using the Moore-Penrose pseudoinverse:

$$M = XP^{\intercal}[PP^{\intercal}]^{-1} \tag{2}$$

The $3{\times}3$ colour correction matrix is well-justified when reflectance can be approximated by a 3D linear model [10]. If we adopt this approximation, then under a given illuminant, the mapping between RGB to XYZ is necessarily a $3{\times}3$ matrix.

An advantage of linear colour correction is that it unaffected by scene radiance/exposure changes. This is known as exposure invariance.

Polynomial Colour Correction [11]

To reduce colour reproduction error, one can use polynomial colour correction (PCC) instead [11]. This is achieved by modifying Eq. 1 by adding into P extra rows containing polynomial component terms. For example, for 2nd PCC, rows with the following terms need to be added: $r^2, g^2, b^2, rg, rb, gb$. P becomes a $9{\times}N$ matrix and M has the dimension of 3×9. For third order PCC, in addition to the rows with second order polynomial terms, rows with the following terms need to be added: $r^3, g^3, b^3, rg^2, gb^2, rb^2, gr^2, bg^2, br^2, rgb$, P then has the dimension of $19{\times}N$ and M has dimension of $3{\times}19$. Higher order polynomial terms can also be derived. However, PCC above the 3rd degree does not tend to be used often, due to the potential for overfitting — when overfitting occurs, the colour correction matrix produces images with excessive noise. Overfitting can be avoided by using regularisation [12]. Under polynomial colour correction, brightness changes may result in a hue shift, PCC does not have exposure invariance [2].

Root-Polynomial Colour Correction [13]

Root polynomial colour correction (RPCC) [13] provides better performance than linear colour correction, while preserving the important property of exposure invariance. This is achieved by adding rows with root-polynomial terms into P in Eq. 1. For example, for second order RPCC, rows with the following terms need to be added: $\sqrt{rg}, \sqrt{gb}, \sqrt{rb}$. For third order RPCC, the following terms need to be added in addition to the second order root polynomial terms: $\sqrt[3]{r^2g}, \sqrt[3]{r^2b}, \sqrt[3]{rg^2}, \sqrt[3]{rb^2}, \sqrt[3]{g^2b}, \sqrt[3]{gb^2}$. The polynomial degree of the added terms is always 1. Exposure invariance is a property that follows from the inverse root.

Hue Plane Preserving Colour Correction [14]

A hue plane is a geometrical half-plane defined by the neutral axis and a chromatic colour. In hue plane preserving colour correction, the colour spaces are divided in sub-regions defined by hue planes. In order to map RGBs to XYZs, a $3{\times}3$ matrix is learned and applied in each subregion separately [14]. These matrices can also be constrained to preserve the whitepoint. The sub-regions can also be flexibly chosen in number and position to regularise and optimise results, while constraining continuity across hue planes. Hue plane preserving colour correction provide significantly higher colorimetric accuracy compared to linear colour correction, while maintaining exposure invariance. Its performance is comparable to root-polynomial colour correction.

Colour Correction by Angular Minimisation [15]

Most colour correction algorithms are sensitive to the brightness difference in training RGBs and XYZs. In order to avoid that problem either the lighting field has to be uniform, or the radiance of each individual colour patch need to be measured. Both of these are hard to accomplish.

Colour correction by angular minimisation avoids the problem of uniform lighting field by ignoring the magnitude differences between the RGB and XYZ vectors, and minimising the angular differences between them. This results in a 3×3 colour correction matrix that is exposure invariant [15]. The minimisation process is a search procedure which may not converge to global minimum.

Homography Colour Correction [16]

In mathematics, a homography is a mapping between two projective spaces. Finlayson et al. showed that the mapping between RGB and XYZ is well related by a homography [16], and this homography can be solved using Alternating Least Square algorithm.

Like colour correction by angular minimisation, homography colour correction is exposure invariant. A uniform lighting field is not required for capturing the training data. Advantageously, homography colour correction discards less information during training.

Maximum Ignorance Colour Correction [17]

The maximum ignorance (MI) approach to colour correction is a method which operates without an explicit calibration data set. Instead, the transform used for colour correction is defined to be the mapping which best takes the device response functions onto the XYZ matching curves. The effective statistical assumption made here is that all possible spectra, with both positive and negative power at each wavelength, all occur with equal likelihood. This approach can be justified, as Horn [9] and Vrhel and Trussell [18] have shown, in that perfect colour correction for any colour stimulus is possible if and only if the device sensitivities are a linear transform from the colour matching functions.

Maximum Ignorance with Positivity Colour Correction [17]

Maximum ignorance with positivity colour correction (MIP) is similar to MI colour correction, as it does not require an explicit calibration data set. The major difference for this method is that the colour signal is assumed correctly to be strictly positive and equally likely [17].

MIP improves on the conventional MI zero-calibration method by providing a better statistical assumption, as negative spectral power does not make physical sense. It also provides substantially improves colour correction performance.

ENSEMBLE COLOUR CORRECTION

Here we propose a new colour correction algorithm, presented here for the first time. We call this method Ensemble Colour Correction. Ensemble colour correction provides a method for combining multiple methods of colour correction. In fact, it has been shown that combining multiple algorithms together may be of use for improving accuracy, *e.g.* in improving results for illuminant estimation methods [19].

Assuming we have m constituent colour correction algorithms, and n colour patches in our training set, the RGB and XYZ matrices follow a row-wise format (we use $3\times n$ matrices to store RGBs and XYZs), The training process for our ensemble colour correction is as follows:

1. The m colour correction algorithms are trained.
2. Each colour correction algorithm is then applied to the training RGBs, in order to obtain estimated XYZs for each method.
3. The estimated XYZs are combined row-wise forming a $3n\times m$ matrix (which is denoted by eXYZ).
4. Regression is performed between the eXYZ matrix and the true XYZ matrix, with the regression coefficients termed the *ensemble matrix*.

RESULTS

Experiment 1: Regression-based colour correction

For regression-based colour correction algorithms (that is all colour correction algorithms other than maximum ignorance-based methods), we used a 140-patch X-Rite ColorChecker Digital SG for performance evaluation. Under *uniform* D65 illumination, we measured the XYZs of the colour checker using a Photo Research PR-670 spectroradiometer. We then photographed the colour checker using a Nikon D70 camera. The colour correction experiments were performed using three-fold cross-validation. For the Ensemble Method, the ensemble consists of Homography, Second Order Root-polynomial and Hue Plane Preserving methods.

Table 1. CIELAB ΔE for regression-based colour correction algorithms

Method	Mean	Median	95%	Max
Linear least squared [9]	2.95	2.06	8.34	23.06
Second order polynomial [11]	2.39	1.94	6.35	8.01
Second order root-polynomial [13]	1.97	1.47	4.57	5.52
Homography [16]	2.65	2.19	5.48	12.91
Hue Plane Preserving [14]	2.05	1.63	5.5	10.41
Angular Minimisation [15]	2.69	2.26	6.76	11.87
Ensemble method	1.86	1.52	4.74	5.87

Experiment 2: Maximum-ignorance based colour correction

Maximum ignorance colour correction algorithms require the spectral sensitivity curve of the camera. We were not able to obtain the spectral sensitivity for the Nikon D70 camera, so a Nikon D5100 was used instead. We decided to collect colour checker data outdoor. In order to avoid change in lighting condition and save time, we used a 24-patch X-Rite ColorChecker Classic instead. Under cloudy daylight, the XYZ values of the colour checker were measured using a Photo Research PR-670. Then the colour checker was photographed. The spectral sensitivity for the camera we used can be found in [20]. As maximum ignorance-based colour correction was trained using the spectral sensitivity curve and data from the colour checker was not used for training, cross validation was not performed.

Table 2. CIELAB ΔE for maximum ignorance-based colour correction algorithms

Method	Mean	Median	95%	Max
Maximum Ignorance	5.32	4.46	12.22	13.61
Maximum Ignorance with Positivity	3.99	3.66	8.25	9.35

COLOUR CORRECTION TOOLBOX

We created a new Colour Correction Toolbox, a MATLAB toolbox for running colour correction experiments. It is provided under the MIT License. It contains the implementation of all the algorithms described above. The toolbox can train colour correction algorithms, and apply the algorithms on RAW images or matrices containing device-specific RGB values. Test data sets are shipped with the toolbox. The toolbox also contains a utility function for extracting RGB values from colour checker images. The toolbox also provides the facility for evaluating colour correction functions. Cross-validation can be optionally performed.

For more information on colour correction toolbox, please visit:
https://github.com/fangfufu/Colour_Correction_Toolbox.

CONCLUSION

In this paper, we provide three contributions. First, we reviewed a range of colour correction functions. Our second contribution is developing an ensemble method for combining assorted colour correction algorithms. The ensemble method for colour correction marginally improves the performance of its constituent colour correction algorithms. Our final and perhaps most important contribution is providing the community with a Colour Correction Toolbox.

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