Color Calibration of Digital Camera Using Polynomial Transformation

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Abstract

In the case of digital cameras, device dependent values describe the camera's response to incoming spectrum of light. Transformation from one device space to another has to be defined separately in each case. Device dependent values are not colorimetric and don't necessarily provide a good starting point for transformation between device spaces.

We converted the device dependent digital camera RGB values to reflectance spectra, which is used as the device independent color representation. If the spectral power distribution of original and reproduction are identical, a spectral color reproduction is achieved. From spectra, it is possible to calculate response in any color space under arbitrary light sources. We calculated the corresponding results also for direct RGB-CIELAB conversion.

In testing phase we modeled the color calibration of a digital camera as a regularized polynomial regression problem. In polynomial regression, strong adaptation of the model to training data can cause problems. Measurement data includes noise that has effect on the complexity of the estimated function, especially when a high order polynomial is used. Effects of overfitting to training data can be dampened by using regularization methods [3]. Two regularization methods, Tikhonov regularization and Truncated Singular Value Decomposition, were tested in order to reduce overfitting.

We used Munsell Matte color set (1269 samples) and Macbeth chart (24 samples) in calibration. Analysis of results for different training sets show that the "quality" of the training set is the most important part of the model. As the size of the training set becomes larger, the performance of polynomial model improves. When small training set is used, it must be chosen carefully. With randomly chosen small training sets polynomial model is a very unstable method.

Introduction

Digital color cameras capture the spectrum of physical stimuli by filtering the incoming color signal through color filters with different spectral transmittances. In the case of digital cameras (non-colorimetric), the device dependent RGB values describe this response to color. If we want to transform camera RGB values to device independent space, we need to define the mapping separately for each device. This mapping can be done for example via least-squares regression method. Values in device independent color spaces like CIE XYZ, CIELAB and sRGB are light source dependent, so we should calculate separate representations for each illumination condition. If we convert the device dependent RGB values to reflectance spectra, by using spectra it is possible to calculate any needed color information using arbitrary light sources.

The goal of this study was to investigate whether reflectance-estimation method can be used for color camera calibration. We tested the model using training sets of different sizes. We calculated the results for polynomial transformation in explicit spectral reconstruction and in CIELAB reconstruction. This method has been used for example in [2], [4] and [5]. Method was evaluated by using a colorimetric measure and a spectral measure with values from two digital cameras.

Munsell data set was divided into three different sets: training set, test set and validation set. Training set was used to construct the model for chosen polynomials and parameters. Test set was used to find the best combination of model parameters (degree of polynomial and regularization parameter). Final evaluation of the model was done with validation set.

Methods

The color calibration of digital camera can be defined as an approximation problem

$$XW \approx Y, \tag{1}$$

where the transformation matrix W maps the camera response values (matrix $X \in \mathbb{R}^{l\times 3}$) to CIELAB values (matrix $Y \in \mathbb{R}^{l\times 3}$) or high-dimensional spectra (matrix $Y \in \mathbb{R}^{l\times n}$). Here l is the number of samples and n denotes the number of components in the spectrum. Unknown coefficients of this model can be obtained from least squares approximation using pseudoinverse approach and known RGB-CIELAB or RGB-spectrum pairs for calculation. So the approximate solution for the problem (1) can be calculated as

$$\hat{W} = (X^T X)^{-1} X^T Y = X^\dagger Y. \tag{2}$$

Method solves for the training set $min_W \|XW - Y\|_F$, where $\|\|_F$ denotes the Frobenius norm. This linear model can be extended to higher order polynomials by adding terms $R^2, G^2, B^2, RG, RB, GB, \ldots$ to matrix X [2], [4], [5]. In testing phase, we used 1^{st}, 2^{nd}, 3^{rd} and 4^{th} degree polynomials with 3, 10, 20 and 35 terms, respectively. Models with 10, 20 and 35 terms include also a constant term 1.

It is possible that for the higher order polynomials, the solution starts oscillating and overfitting is obtained because the polynomial adapts to the given training data too accurately but fails to generalize well for test data. Effect of noise in the measured data also provides false information for the estimated function. Regularization is a method where we use some additional constraints for limiting the capacity of the resulting function to overfit the data. In Tikhonov regularization [3] we add multiple of identity matrix to equation (2). The solution with regularization can be written as

$$\hat{W}_r = (X^T X + \lambda I)^{-1} X^T Y, \tag{3}$$

where λ is the regularization parameter. Truncated singular value decomposition [3] is another simple regularization method for the capacity control. This means that we discard small singular values of matrix X, when computation for matrix W is performed ($Rank(X) = k$):

$$X = USV^T = \sum_{i=1}^{k} \sigma_i u_i v_i^T = \sum_{i=1}^{p} \sigma_i u_i v_i^T + \sum_{i=p+1}^{k} \sigma_i u_i v_i^T$$
$$= U_1 S_1 V_1^T + U_2 S_2 V_2^T. \qquad (4)$$

We can use only first p singular values for the calculation of matrix W in equation (2). In this case, pseudoinverse $X^\dagger$ for matrix X can be stated as $X^\dagger = V_1 S_1^\dagger U_1^T$. We tested these both methods, and concluded that the Tikhonov method performs slightly better than the truncated SVD. Generally the difference between these two methods was very small, so the final results have been presented only for Tikhonov method.

We have used the following error measures for evaluating the CIELAB and spectral estimation:

ΔE for CIELAB and spectral estimation

$$\Delta E = \sqrt{(L^* - \tilde{L}^*)^2 + (a^* - \tilde{a}^*)^2 + (b^* - \tilde{b}^*)^2}, \qquad (5)$$

where L^*, a^*, and b^* are the original CIELAB values, and $\tilde{L}^*$, $\tilde{a}^*$, and $\tilde{b}^*$ are in CIELAB case the estimated CIELAB values and in spectral case CIELAB values calculated from estimated spectra.

Root Mean Squared Error (RMSE) for spectral estimation

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n} (s(i) - \tilde{s}(i))^2}{n}}, \qquad (6)$$

where n is number of wavelength components in spectra, s is the original spectrum and $\tilde{s}$ is the reconstructed spectrum.

Experiments

For testing purposes, we had RGB data of GretagMacbeth ColorChecker (24 samples) and Munsell Book of Color - Matte Finish Collection (1269 samples) acquired with Fujifilm Finepix S1 Pro and Canon A20 Powershot digital cameras under daylight simulation light source. Spectra of both sets were sampled from 400 nm to 700 nm with 5 nm step. Munsell spectra are from University of Joensuu Color Group Spectral Database [1].

At first, Munsell set was divided into 3 parts: training, testing and validation set consisting of 635, 317 and 317 samples, respectively. We used random sets of 200, 50, and 24 samples from Munsell training set and Macbeth set as final training sets. For each set size, we had two different sets picked randomly from Munsell training set. Regularization parameter for Tikhonov regularization and degree of polynomial were chosen so that ΔE errors for test set were minimized. Chosen model parameters were validated using a separate validation set. Validation set results are presented in Tables 1 and 2. Illustrations of estimation results for spectral estimation are shown in Figures 1 - 4 and for CIELAB estimation in Figures 5 and 6.

We tested the performance of polynomial model in two cases: when estimating 1) CIELAB values and 2) spectra from RGB. We evaluated the color difference between original and estimated data using CIELAB ΔE error measure, and error in spectral estimation using RMSE measure. We tested how the number of polynomial terms affects the estimation performance, and if the regularization by Tikhonov regularization would improve the results. Abbreviations used in Tables 1 and 2: Avg. = average error, Std. = standard deviation of error, Max. = maximum error.

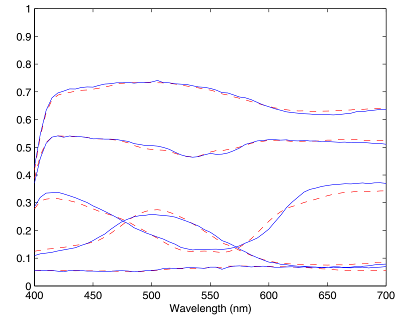

Figure 1. *Good spectral estimation - training set: Munsell 200/II, camera: Fuji. Solid line: original spectra, dashed line: estimated spectra.*

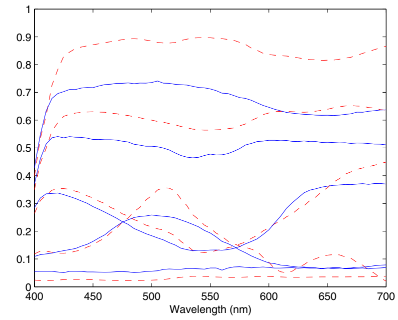

Figure 2. *Bad spectral estimation - training set: Macbeth, camera: Fuji. Solid line: original spectra, dashed line: estimated spectra.*

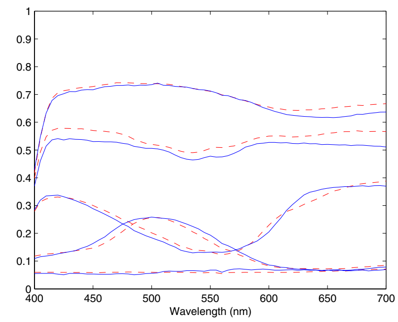

Figure 3. *Good spectral estimation - training set: Munsell 200/II, camera: Canon. Solid line: original spectra, dashed line: estimated spectra.*

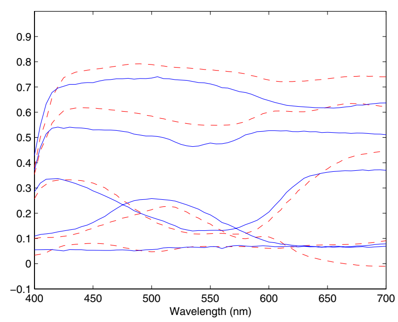

Figure 4. *Bad spectral estimation - training set: Macbeth, camera: Canon. Solid line: original spectra, dashed line: estimated spectra.*

Table 1: Error values for Fujifilm camera

Training set	ΔE in CIELAB estimation				ΔE in spectral estimation				RMSE in spectral estimation			
	Avg.	Std.	Max.	terms	Avg.	Std.	Max.	terms	Avg.	Std.	Max.	terms
Munsell 200 / I	1.95	1.06	7.84	20	2.56	1.92	11.07	20	0.021	0.013	0.091	20
Munsell 200 / II	1.98	1.06	6.90	20	2.11	1.23	7.72	35	0.020	0.015	0.093	35
Munsell 50 / I	2.20	1.26	11.60	10	3.37	2.47	13.18	10	0.026	0.017	0.140	10
Munsell 50 / II	2.31	1.36	10.40	10	4.10	3.71	20.21	10	0.028	0.017	0.113	10
Munsell 24 / I	2.73	1.48	9.99	10	4.29	3.70	19.60	10	0.033	0.021	0.122	10
Munsell 24 / II	2.66	1.60	11.63	10	3.50	3.00	18.24	10	0.031	0.021	0.136	10
Macbeth	4.99	2.80	16.85	10	6.49	3.26	17.80	20	0.060	0.043	0.216	20

Table 2: Error values for Canon A20 camera

Training set	ΔE in CIELAB estimation				ΔE in spectral estimation				RMSE in spectral estimation			
	Avg.	Std.	Max.	terms	Avg.	Std.	Max.	terms	Avg.	Std.	Max.	terms
Munsell 200 / I	3.66	2.40	13.65	20	3.07	2.11	12.45	20	0.022	0.015	0.109	20
Munsell 200 / II	3.16	1.94	12.18	35	2.87	1.83	11.87	35	0.022	0.015	0.080	35
Munsell 50 / I	5.24	3.89	23.32	10	4.74	3.15	22.16	10	0.032	0.023	0.128	10
Munsell 50 / II	4.52	2.78	15.77	20	4.74	3.57	19.91	10	0.030	0.020	0.138	10
Munsell 24 / I	6.92	4.56	23.64	10	5.33	4.49	27.81	10	0.035	0.024	0.120	10
Munsell 24 / II	6.65	4.44	25.36	10	5.24	3.56	18.49	10	0.035	0.025	0.145	10
Macbeth	6.43	3.50	19.59	10	6.20	3.48	20.02	10	0.042	0.020	0.113	10

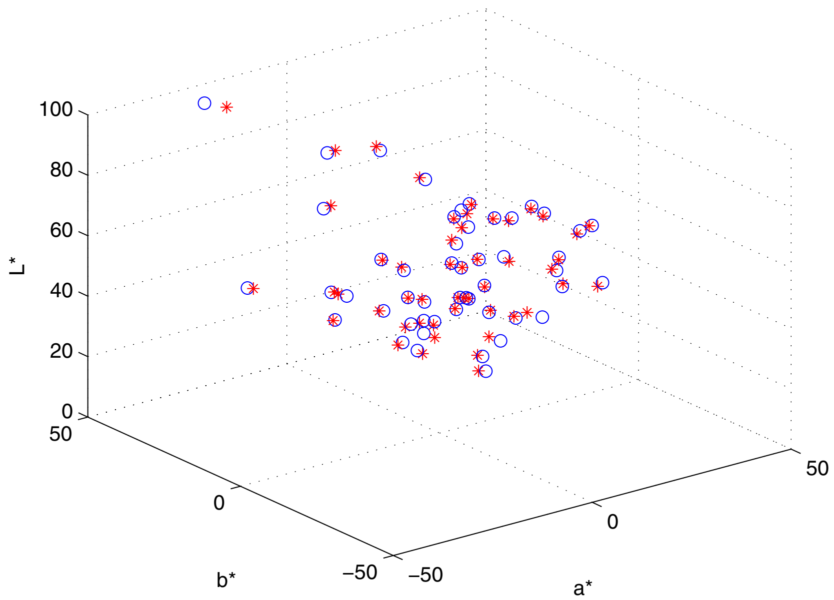

Figure 5. *Good CIELAB estimation - training set: Munsell 200/I, camera: Fuji. Circles: original values, stars: estimated values.*

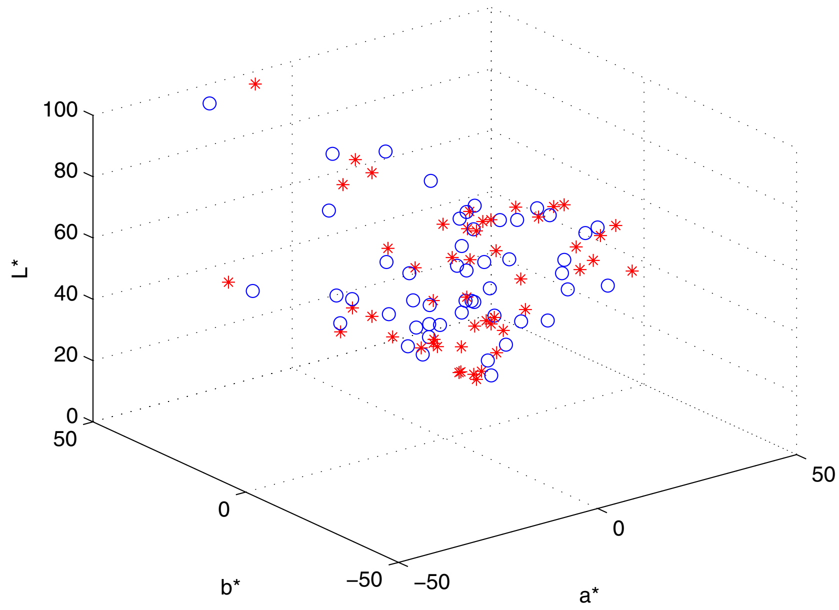

Figure 6. *Bad CIELAB estimation - training set: Munsell 24/I, camera: Canon. Circles: original values, stars: estimated values.*

Discussion

The performance of color calibration via spectral estimation depends on camera. For Canon A20 camera, the spectral estimation gives better performance than the direct CIELAB estimation. The behavior is opposite for Fujifilm camera, which clearly shows stronger performance in direct CIELAB estimation in terms of maximal color difference. There are large differences between the two cameras. In overall, the color calibration results for low-cost Canon are worse than for the Fujifilm camera.

Regularization is important when we use higher order polynomials and small training sets for the transformation. On the other hand, large regularization terms have to be used usually in cases when the degree of the polynomial is already too high for the training set. If the degree of polynomial was properly chosen, the effect of regularization was small or it wasn't needed at all.

Size of the training set is obviously a very important factor in the training process, which can be seen clearly from the results. Maximum errors for both the CIELAB and RMSE measures have the lowest values when the largest training sets are used. The best performing polynomial usually was the 2^{nd} degree polynomial, even for the training set of 50 samples. The largest training set benefitted from the use of 3^{rd} and 4^{th} degree polynomials. From the smallest sets only Macbeth chart gave reasonable results when the 3^{rd} degree was used. Despite of this, the obtained results for Macbeth training set were usually worse than for the other sets containing 24 samples.

It can be seen that there are also quite large deviations between results for the training sets with same size. This deviation is smallest between the largest training sets. This suggests that training set should be chosen carefully if small sets are used in training.

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Author Biography

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