

Dynamic camera spectral sensitivity estimation

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Abstract—In large-scale series production the time for evaluating the camera spectral sensitivity is strongly limited and measured in units of seconds because of production and economic constraints. To estimate variation of spectral sensitivity properties, manufacturers usually precisely measure only a few sensors (the golden set) and use these measurements to perform quick estimation of any other sensor in the released pack. The main drawback of this approach is that the worst color reproduction error cannot be controlled for a particular device: instability of device production process usually causes significantly different sensors, which may not be included in the golden set. In that case the camera will work with low accuracy during the lifetime. To overcome this problem, we consider a new approach to camera spectral sensitivity estimation during its operation. The main idea is based on consistency estimation of images and average scenes spectra. Users receive such a combination of data in practice, for instance modern phone devices have built-in integral spectrometers. Also, the proposed approach can be considered in the scope of classical problem statement of spectral sensitivity estimation with color charts. In the paper we investigated the accuracy of the method of spectral sensitivity estimation based on the basis calculation with singular value decomposition of the sensitivities from the golden set in combination with different types of regularization.

Keywords— *dynamic camera calibration, spectral sensitivity estimation, golden set, quality of color reproduction, color patches.*

1. INTRODUCTION

We consider the problem of evaluating the spectral sensitivity of a sensor in operation, without the use of laboratory equipment and color targets [1]. Such formulation is rare because of the high accuracy requirements for this problem, which is difficult to achieve under uncontrolled conditions. The only example of a similar problem statement is the work [2], where the authors propose to perform the calibration based on averaged sky spectra. They calculated the sky spectra with geo- and meteo data.

In our work the new approach (figure 1) of camera spectral sensitivity calibration was suggested. It based on consistency estimation averaged image color and received spectra data from spectrometer. In this work we imply that FOV of camera and spectrophotometer are coincides. Our work is the first step in creation of the sensor with the real-time auto – spectral calibration system.

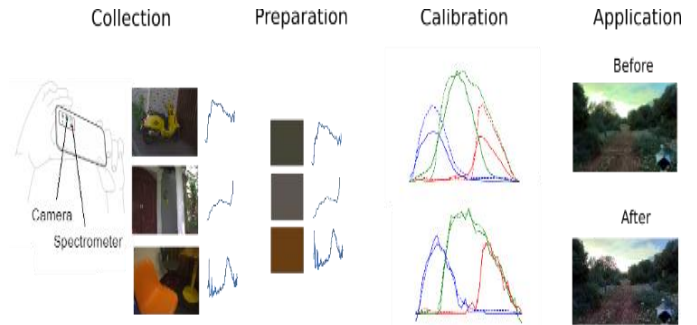


Fig. 1. The illustration of stages of the process of dynamic camera spectral sensitivity correction. Second one is their preparation. Final stage is calibration

2. RECONSTRUCTION PROBLEM

Let the dataset includes m pairs (image, averaged radiance $\mathbf{r} \in \mathbb{R}^n$ over scene), where $n = 431$ – is the wavelengths number. Let's write image linear formation model for all channels in the following form:

$$\mathbf{c} = \mathbf{r}^T X \quad (1)$$

where it is assumed that $\Delta\lambda$ incorporated in \mathbf{r}, \mathbf{c} – is three-dimensional tristimulus vector, $X \in \mathbb{R}^{n \times 3}$ – is the matrix of spectral sensitivities $\chi_i \in \mathbb{R}^n$ in the columns, $i = \overline{1,3}$. For m pairs (1) can be written in matrix form:

$$C = RX, \quad (2)$$

where $C \in \mathbb{R}^{m \times 3}$ – is the tristimulus matrix, $R \in \mathbb{R}^{m \times n}$ – is the reflectance matrix.

In practice, to reduce the number of parameters, χ_i is expressed through a linear combination of a certain basis functions set B_i :

$$\chi_i = B_i^T \mathbf{x}_i, \quad (3)$$

where $\mathbf{x}_i \in \mathbb{R}^{k_i}$ – is the coefficient vector, $B_i \in \mathbb{R}^{k_i \times n}$ is the matrix composed of basis functions (k_i – the number of basis functions for i -th channel). In this case, the tristimulus component \mathbf{c}_i for all images:

$$\mathbf{c}_i = R B_i^T \mathbf{x}_i, \quad (4)$$

where $\mathbf{c}_i \in \mathbb{R}^m$.

According to introduced notation and paper [1] spectral sensitivity estimation of i -th channel can be written in the following form:

$$\hat{\mathbf{x}}_i = \underset{\mathbf{x}_i}{\operatorname{argmin}} (||\mathbf{c}_i - R B_i^T \mathbf{x}_i ||_2^2 + \gamma_i \cdot r(\mathbf{x}_i)), \quad (5)$$

where γ_i – regularization parameter; $r(x_i)$ – regularization term.

For example, in case of Tikhonov regularization:

$$r_i(x_i) = \|L_i x_i\|_2^2, \quad (6)$$

In a similar manner to [1], we applied the singular value decomposition (SVD) method to extract the basis functions from the golden set of known sensitivities. We used best performed optimization methods from scikit-learn to solve (5).

For shape comparison of estimated spectral sensitivity with ground truth (GT) sensitivity, we introduced normalized spectral recovery error:

$$NSE = \frac{1}{3} \sum_{i=1}^3 \frac{\|x_i / \max(X) - \hat{x}_i / \max(\hat{X})\|_2}{\|x_i / \max(X)\|_2} \cdot 100\% \quad (7)$$

where \hat{X} is the vector matrix of estimated sensitivities, $\max(X)$ and $\max(\hat{X})$ are the highest sensitivity values in these vectors over the entire wavelengths grid. This error gives the general quality measure of sensitivity recovery for all channels on an equal scale.

3. EXPERIMENTS AND RESULTS

Here we present the results of a series of experiments performed with singular value decomposition (SVD) on synthetic data of images and spectra for sensitivity estimation according to (5). Synthetic data were calculated based on the 450 public hyperspectral images which were collected as part of the NTIRE2020 workshops [3]. They guarantee the alignment of FOV and Canon noise parameters (assuming the low noise of the hyperspectral data). The spectral sensitivities of 9 cameras Canon EOS 600D, Canon 500D, Canon 300D, Canon 60D, Canon 50D, Canon 40D, Canon 20D, Canon 5D Mark II, Canon 1D Mark III were used as a golden set [5]. In the first experiment the golden set includes the camera that spectral sensitivity will be evaluated. In the second one we exclude estimated sensitivity from the set. According to (5), we use different regularization types of $r(x_i)$ and vary their parameters γ to find the best ones. Both experiments showed that Tikhonov Regularization and Tikhonov Regularization based on Derivatives [1] do not increase accuracy using SVD. For this reason, it was proposed to use Tikhonov Regularization without the first component and L1 regularization (table 1), which give a significant increase in accuracy (1.5 times).

Таблица I. AVERAGED NSE (%) ERRORS FOR CANON CAMERAS BASED ON SYNTHETIC NOISED DATA WHEN THE GOLDEN SET INCLUDES ESTIMATED SENSITIVITY

Basis	The number of basis functions		
	1	2	3
SVD	9.52± 3.57	10.94± 3.42	13.54± 1.26
SVD + L2 regularization without first	9.52± 3.57	8.66± 3.88	8.27±2
SVD + L1 regularization	9.78± 3.76	9.51± 3.19	8.79± 1.27

Tikhonov Regularization without the first component means that matrix L_i in (6) has zero first column.

When estimated sensitivity is not in the golden set, SVD shows lower accuracy. Averaged NSE (%) errors of recovery are given in table 2.

Таблица II. AVERAGED NSE (%) ERRORS FOR CANON CAMERAS BASED ON SYNTHETIC NOISED DATA WHEN THE GOLDEN SET DOES NOT INCLUDE ESTIMATED SENSITIVITY

Basis	The number of basis functions		
	1	2	3
SVD	10.25± 4.25	14.5± 6.52	15.22± 3.78
SVD + L2 regularization without first	10.25± 4.25	10.0± 5.5	9.87± 4.24
SVD + L1 regularization	10.46± 4.47	10.44± 5.09	9.62± 4.7

In the third experiment for each camera from the golden set we found the closest one among others in terms of NSE error, namely, chose for every i -th golden set's sensitivity χ_i such another sensitivity χ_j that $NSE(\chi_i, \chi_j)$ is minimum. We name this operation as *selection of the closest from the set (SCS)*. The average NSE (%) error of SCS over all cameras from the golden set is 10.3 % NSE. The averaged recovery error with SVD from the previous experiment is 9.62 % NSE. Thus, we can conclude that the considered method not only allows to increase the estimation accuracy working with noisy data, but it is better to use a linear mixture of the set's sensitivities.

4. CONCLUSION

The paper considers a new approach to spectral sensitivity estimation of device camera in operation. The results of the work show a high potential for the applicability of this approach. Our research has several restrictions: despite the added noise we use only synthetic data, and it is assumed that camera and spectrometer are aligned by field of view. Nevertheless, this is a necessary first step in the development of the dynamic calibration approach.

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