Calibrating Color Cameras using Metameric Blacks

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Abstract

Spectral calibration of digital cameras based on the spectral data of commercially available calibration charts is an ill-conditioned problem which has an infinite number of solutions. To improve upon the estimate, different constraints are commonly employed. Traditionally such constraints include: non-negativity, smoothness, uni-modality and that the estimated sensors results in as good as possible response fit.

In this paper, we introduce a novel method to solve a general ill-conditioned linear system with special focus on the solution of spectral calibration. We introduce a new approach based on metamerism. We observe that the difference between two metamers (spectra that integrate to the same sensor response) is in the null-space of the sensor. These metamers are used to robustly estimate the sensor's null-space. Based on this null-space, we derive projection operators to solve for the range of the unknown sensor. Our new approach has a number of advantages over standard techniques: It involves no minimization which means that the solution is robust to outliers and is not dominated by larger response values. It also offers the ability to evaluate the goodness of the solution where it is possible to show that the solution is optimal, given the data, if the calculated range is one dimensional.

When comparing the new algorithm with the truncated singular value decomposition and Tikhonov regularization we found that the new method performs slightly better for the training set with noticeable improvements for the test data.

Introduction

Camera sensor calibration is the problem of estimating the device's spectral sensitivities from its responses to a number of spectrally different surfaces. Generally, there are two approaches to solving the spectral calibration problem: one based on physical measurements and one based on a theoretical model. The physical approach, using a monochromater gives an accurate estimate of the spectral sensitivities but it is expensive and time consuming to use. The model-based approach is cheaper and provides insight into the characteristics of the camera system. It is based on solving a linear equation system of the form:

$$\mathbf{Y}_\Upsilon = \mathbf{Y} - \Upsilon = \mathbf{A}\mathbf{X} \tag{1}$$

Let L be the number of sensor sensitivity functions of the camera, M the number of surfaces used and N the dimension of the spectral data. Typical values are; $N = 31$, corresponding to a $10nm$ sampling of the wavelength range $400nm$ to $700nm$ and $L = 3$ for an RGB-camera. For the matrices involved we have: $\mathbf{A}$ is the $M \times N$ matrix of measured color signals, $\mathbf{X}$ is a $N \times L$ dimensional matrix whose elements are the spectral sensitivities, $\mathbf{Y}$ is of size $M \times L$ and contains the measured camera responses and Υ is the acquisition noise matrix. The color signals are the point-wise products of the illumination spectrum and the reflectance spectra. The goodness of the solution for the spectral sensitivities

based on Equations (1) depends on two main factors: the noise level in the response data (Υ) and the statistical properties of the spectral data available from the calibration chart (the matrix $\mathbf{A}$). Estimation of $\mathbf{X}$ from the *rgb* measurements $\mathbf{Y}_\Upsilon$ and $\mathbf{A}$ is a typical inverse problem and standard methods from linear algebra are often used to solve it. From the general theory it is however also known that the quality of the estimation can be substantially improved by usage of additional constraints. The findings in [1] indicate that the uncertainty surrounding spectral recovery is proportional to the size of the recovered set and governed by factors such as: the noise level, the dimensionality of the spectral data, and the constraints imposed on the solution space. In [2] the authors constrained the sensors to be positive, smooth, and to predict the responses within an acceptable noise bound. In [3] the authors added a constraint on the number of peaks allowed in the recovered sensor, while the authors in [4, 5, 6] constrained the sensor's magnitude to be small. All these methods [4, 5, 6, 3, 2] require that the recovered sensor should minimize the difference between the measured and estimated responses.

In this paper we introduce a new approach based on the observation that the space of color signals is convex and compact. The novel contribution of this paper is to use metamerism to construct new color signals that are metameric blacks. These metameric black color signals are then used to construct projection operators that characterize, fully or partially, the null-space of the camera. This knowledge about the properties of the null-space of the camera is then used to reduce the noise sensitivity of the estimator. Different from standard methods, the proposed algorithm is based on estimating the space of the sensor without resorting to minimisation. Said differently, our method does not require that the estimated sensor results in the best data fit between the measured and estimated response values. This property results in a method which is robust to outliers; and is not driven by large response values.

In the experimental part we test the proposed method by calibrating two digital cameras: namely the *Nikon D70* and *MegaVision*. We compare the result obtained by the proposed methods with standard estimation methods like the truncated singular value decomposition and Tikhonov Regularization.

Projection operators for calibration

We consider first the role of the calibration chips, ie. the properties of the matrix $\mathbf{A}$. The least squares estimate of the solution of Equation ([**?**]) can be written as $\mathbf{X} = \left(\mathbf{A}^{\mathbf{T}}\mathbf{A}\right)^{-1}\mathbf{A}^T\mathbf{Y}_\Upsilon$. Often, $(\mathbf{A}^{\mathbf{T}}\mathbf{A})^{-1}$ does not exist. Thus, we can find an orthogonal matrix $\mathbf{U}$ such that

$$\mathbf{A}\mathbf{U}^{\mathbf{T}} = \begin{pmatrix} \mathbf{A}_1 & \mathbf{0} \end{pmatrix} \tag{2}$$

and $\mathbf{A}\mathbf{X} = (\mathbf{A}\mathbf{U}^{\mathbf{T}})(\mathbf{U}\mathbf{X}) = \begin{pmatrix} \mathbf{A}_1 & \mathbf{0} \end{pmatrix} \begin{pmatrix} \mathbf{X}_1 \\ \mathbf{X}_2 \end{pmatrix} = \mathbf{A}_1\mathbf{X}_1.$

We can therefore find a projection operator $\mathbf{Q}$ defined as the projection operator that maps $\mathbf{X}$ to $\mathbf{X}_1 = \mathbf{Q}\mathbf{X}$ where $\mathbf{X}_1$ is defined

as above. Replacing $\mathbf{A}$ by $\mathbf{A_1}$ we can work in the subspace of the original space where we can assume that $\mathbf{A}$ has a pseudo-inverse $\mathbf{A}^\dagger = \left(\mathbf{A^T A}\right)^{-1}\mathbf{A}^T$.

We now investigate the properties of the camera and start with the following observation: Assume that we can split the color signals from the calibration chart into two components with one of them in the null space of the camera. This gives a decomposition of $\mathbf{A}$ into $\mathbf{A} = \mathbf{A_0} + \mathbf{A_\perp}$. Corresponding to this split we introduce projection operators $\mathbf{P_0}, \mathbf{P_\perp}$ such that $\mathbf{A_0} = \mathbf{AP_0}$, $\mathbf{A_\perp} = \mathbf{AP_\perp}$ and $\mathbf{A_0 X} = \mathbf{AP_0 X} = \mathbf{0}$. We can see the knowledge of the operator $\mathbf{P_0}$ as a type of extra knowledge and we see also that the mapping $\mathbf{A} \mapsto \mathbf{AP_\perp} = \mathbf{A_\perp}$ reduces the rank of the matrix $\mathbf{A}$. We can use the same reduction procedure as before when we investigated the role of the calibration chips. We will then show that the knowledge of such projection operators leads to reduced noise levels in the estimated camera response curves.

Metamers and projection operators

We now apply the following procedure to construct projection operators to the null-space of the camera:

- Collect the color-signal measurement pairs (a_m, y_m) where a_m is the color-signal and y_m is the camera output belonging to the m-th surface: $y_m = a_m x$. The calculation is carried out on the individual channels.
- For the response value y_m, $0 \le y_m \le 1$, in the set of camera output vector, find two points $y^{(v)}, y^{(\mu)}$ such that $y_m = \gamma y^{(v)} + (1-\gamma)y^{(\mu)}$ where $0 < \gamma < 1$.
- The three output vectors $y^{(v)}, y^{(\mu)}, y$ define three color-signals through the pairs

$$\left(a^{(v)}, y^{(v)}\right), \left(a^{(\mu)}, y^{(\mu)}\right) \text{ and } (a_m, y_m)$$

  The color signal a_m and the "numerical" color signal $z = \gamma a^{(v)} + (1-\gamma)a^{(\mu)}$ are metameric resulting in the same camera output. For a three dimensional case, this procedure is discussed in details in [7].
- Depending on the number of surfaces available for the calibration, a number of metameric surfaces z can be calculated for the same response value y_m by simply using different points $y^{(v)}, y^{(\mu)}$.
- By definition we know that two metameric surfaces z^i and z^j result in the same camera response y_m, i.e. $z^i x = z^j x = y_m$. Thus is follows $z^i x - z^j x = 0$. In other words the difference between two metamers is in the null space of the sensor x.
- Thus if we collect all the numerical metamers for a single camera response y_m in a matrix $\mathbf{Z}$ and subtract the mean of the set from each surface then the result is a matrix $\mathbf{Z_n}$ where $\mathbf{Z_n} x = 0$. The mean is subtracted from the data to define the vectors in a plane. In theory, any metamer can be used instead of the mean point but we choose the mean as it is, statistically, the most representative vector.

From the construction of $\mathbf{Z_n}$ we know that the dot product of any vector in $\mathbf{Z_n}$ with the sensor x is zero. Further, we know that the the points in $\mathbf{Z_n}$ define a hyperplane in the space of the colour signal data in $\mathbf{A}$. The planes associated with different response values y have to be parallel to each other and intersect the sensor x at a point y. A three dimensional example is shown in Figure 1. Where we notice that for a number of responses we have calculated the associated black planes defined as $\mathbf{Z_n}$ and that they are all orthogonal to a single vector.
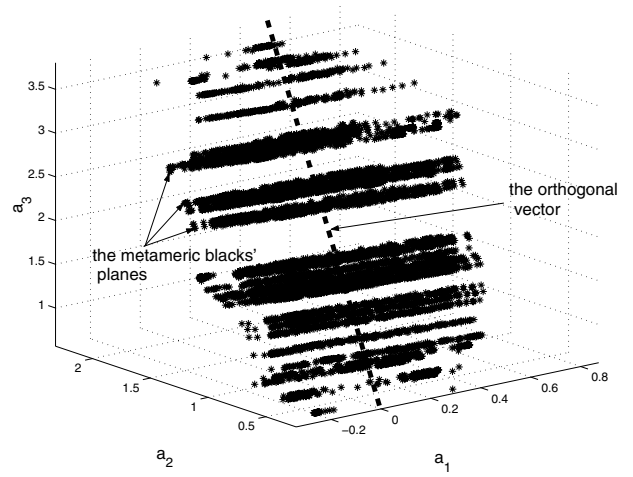

Figure 1. *A 3-d example of the metameric black planes which are shown to be orthogonal to a single vector. The axes, a_1, a_2 and a_3 are the three dimensional axes of the input data.*

Estimating the sensor from the black metamers

Thus far, we have shown that for each response value y_m from a colour filter, x it is possible to solve for a set of metameric surfaces, $\mathbf{Z}$ and calculate their orthogonal elements on the sensor, i.e. the black metamers $\mathbf{Z_n}$. The sensor is defined as the component orthogonal to $\mathbf{Z_n}$. Further, theoretically it is sufficient to calculate a single black plane to use in the sensor estimation, however, our experiments show that calculating a number of planes improves upon the robustness of the estimate.

Consider the case of a 31 dimensional vector space where all the colour signals are defined. Further, let us assume that the colour signals available from a calibration target span the whole space. In this case the calculation of the metameric black outlined previously, amounts to calculating a 30 dimensional subspace where the sensor is the orthogonal complement. It is, however, known that the dimensionality available from natural surfaces including those compromising calibration targets is adequately represented by $3-11$ basis vectors. Furthermore, the dimensions of the metameric black planes can at most be in the range of the actual dimensionality of the target (3-11). Thus to estimate the sensor we first define the singular value decomposition of $\mathbf{Z_n}$ as:

$$\mathbf{Z_n} = \mathbf{U_{Z_n} D_{Z_n} V_{Z_n}^T} \tag{3}$$

Since $\mathbf{U_{Z_n}}$ is orthonormal we define the projection onto the black hyperplane as:

$$\mathbf{P_0} = \mathbf{U_{Z_n} U_{Z_n}^T} \tag{4}$$

Here, we note that consideration must be given to the dimensionality of the original data; and thus only a limited number of basis vectors can be included in the calculation of $\mathbf{P_0}$ (in the experiments we used 7-9 basis vectors). Note that: while $\mathbf{U_{Z_n}^T U_{Z_n}}$ is the identity, $\mathbf{U_{Z_n} U_{Z_n}^T}$ defines a projection onto the null space of the sensor and is not equal to the identity matrix.

The definition of the projection matrix $\mathbf{P_0}$ in Equation (4) allows us to determine the portion on the colour signals which are in the direction of the sensor x. This is defined as:

$$\mathbf{A_\perp} = \mathbf{A} - \mathbf{AP_0} \tag{5}$$

In this paper, we define a sensor as the first principal vector of $\mathbf{A}_\perp$. If the decomposition defined in Equation (5) is exact, which is the case for noise free data, then the vector is $\mathbf{A}_\perp$ will be perfectly parallel to each other. Thus choosing the first principal vector is only necessary when $\mathbf{A}_\perp$ has higher dimensions than one. Figure 2 shows an example based on the red sensor of the *Nikon D70* calibrated in the experiments section. We notice that the result improves, i.e. the vectors in the range become increasingly parallel to each other by adding and increasing number of black basis vectors $1b - 7b$ but then worsens, i.e. the vectors diverge from the shape of a real sensor $8b - 9b$.

Measuring the goodness of the estimate

Thus far, we have divided the spectral space into two components, $\mathbf{A}_\perp$ and $\mathbf{A_0}$. Theoretically, given that the original data has dimension n we wish to divide the space such that $\mathbf{A}_\perp$ has dimension 1 and $\mathbf{A_0}$ has dimension $n - 1$. If such a decomposition is achieved then we have calibrated the sensor. However, in the general case, when noise is present in the calibration data, it is not possible to estimate the black planes perfectly. Thus there will be no unique orthogonal, sensor, but rather a number of possible vectors. One of the novel features of the proposed algorithm is that it allows us to clearly estimate the goodness of the recovery in the spectral space. This is different to the goodness estimation used for other methods where goodness is normally defined in the least squares sense between the measured and estimated responses.

We have stated that the sensor is perfectly calibrated if the dimensionality of the colour signals in matrix $\mathbf{A}_\perp$ is one. Thus we propose a goodness measure which is based on the rank of $\mathbf{A}_\perp$. Such a measure can be defined by considering the singular value decomposition of $\mathbf{A}_\perp$:

$$\mathbf{A}_\perp = \mathbf{U_{A_\perp}} \mathbf{D_{A_\perp}} \mathbf{V_{A_\perp}^T} \tag{6}$$

It is known that in the case where the vectors in $\mathbf{A}_\perp$ are parallel; the first element is the only non zero element on the diagonal of $\mathbf{D_{A_\perp}}$. It is further understood that the dimensionality of $\mathbf{A}_\perp$ can be estimated by studying the ratio:

$$g = \frac{d_{A_\perp}^1}{\sum_{i=1}^n d_{A_\perp}} \times 100 \tag{7}$$

where the vector $d_{A_\perp}$ is the diagonal of $\mathbf{D_{A_\perp}}$ and contains the singular values of $\mathbf{A}_\perp$ and $d_{A_\perp}^1$ is the first diagonal element. Clearly, the closer the goodness measure, g is to 100% the more accurate the sensor estimate.

Experiments and Results

To test the performance of the proposed algorithm and compare it with standard methods we spectrally calibrated a *Nikon D70* digital camera and a MegaVision camera. For the *Nikon D70* the actual sensitivities were not available while for the *MegaVision* the sensor curves were measured using a monochrometer.

In the first experiment, two calibration charts were used: the Esser chart with 282 colored patches and the 24 patches of the Macbeth Color Checker. For both charts, the spectral data was measured using a Minolta CS-1000 spectroradiometer under the daylight simulator of the Macbeth Verda viewing booth. The camera responses were captured in the Nikon raw image format; and the response data was checked for linearity and the dark noise was subtracted.

For numerical data comparison we used the absolute error between the estimated and measured responses. This is defined

as:

$$AE = |\mathbf{A}\widetilde{x} - y| \tag{8}$$

where $\widetilde{x}$ is the estimated sensor. To allow meaningful comparison in terms of the absolute error metric; the data in y and $\mathbf{A}\widetilde{x}$, for all channels, were normalized such that the maximum value was set to 100. Thus a difference of one is equivalent to 1% error.

In the second experiment, *MegaVision*, the spectral data was that of the Macbeth color checker measured under a daylight simulator. Further, because the actual sensitivities were available it was possible to compare the estimate with the measured sensitivities in the spectral space.

Nikon D70

In the first part of this experiment we performed a spectral calibration of the *Nikon D70* based on the camera's responses to the spectral data of the Esser calibration chart. The validity of the sensors estimate was checked by calculating the responses to the spectral data of the Macbeth Color Checker. When calculating the sensitivities using the proposed method, only a subsection of the Esser data was used. This subset was chosen such that the data points were the extremes of three dimensional *rgb* space. For the Nikon data we got 38 out of the 282 data points. Further, for comparison we calculated the sensitivities using the truncated singular value decomposition **TSVD** and Tikhonov regularization **TR**. For both the training data was the whole of the Esser chart. We chose these two methods because they are known to result in better data fit compared to the constrained optimisation techniques [5].

The results of the comparison based on the Esser data are tabulated in Table 1; and those based on the Macbeth Color Checker, test set, are tabulated in Table 2. Further, the spectral sensitivities obtained with the new method, the **TSVD** and **TR** are plotted in Figures 3, 4 and 5 respectively. Here we point out that the sensitivities obtained with the new method are sharper than those of achieved with the **TSVD** and **TR**.

The value of the proposed goodness measure is also tabulated in Table 1, where we find that the red channel achieves the value of 81.4%, for the green channel we get 81.6% and for the blue 79.8%. Our experiments with different sensor sets concludes that adding an increasing number of basis vectors to the black space gradually improves the results until a maximum value is obtained. For the red sensor the effect of adding an increasing number of basis vectors, to the black space, on the recovery and the goodness measure is demonstrated in Figure 2. As we see beyond the maximum value obtained at $7b$ the goodness measure drops. This property means that the proposed goodness measure can be used to automate the choice of number of basis vectors included in the calibration. Indeed for the purpose of this paper we used to optimal values reported in Table 1. When calculating the goodness measure, for data used in the experiment, using an increasing number of black basis vectors we obtained the values plotted in Figure 6. As we see those values increase almost linearly until a maximum value is achieved.

From Table 1 we note that the new metamer based **MB** algorithm performs slightly better than the truncated singular decomposition. Here, we remind the reader that the metamer based method is not aimed at minimizing the difference between the measured and estimated responses. Thus the fact that the results outperforms those achieved with minimization based approaches such as the truncated singular value decomposition and Tikhonov regularization is clearly significant. Finally, when the estimated sensors from the three methods were used to predict the camera's

method	Abs-Error		
TSVD	red	green	blue
mean	1.34	1.00	0.96
median	0.94	0.62	0.75
max	8.40	8.08	6.61
TR	red	green	blue
mean	1.82	1.26	1.53
median	1.35	0.83	1.07
max	8.92	5.75	6.13
MB	red	green	blue
GM	0.816	0.834	0.798
mean	1.298	1.025	1.036
median	0.789	0.704	0.738
max	8.918	8.059	5.592

The absolute error between the measured and estimated responses for the red, green and blue channels of the *Nikon D70*. The results are based on the truncated singular value decomposition TSVD, Tikhonov Regularization TR and the metamer based MB methods. The calibration data was that of the Esser calibration chart.

method	Abs-Error		
TSVD	red	green	blue
mean	2.64	2.58	2.74
median	1.66	2.34	2.04
max	9.21	8.34	8.84
TR	red	green	blue
mean	2.07	2.49	2.80
median	1.54	1.45	1.77
max	8.09	8.61	10.49
MB	red	green	blue
mean	1.736	2.00	1.173
median	0.871	1.589	0.776
max	9.192	6.216	7.106

The absolute error between the measured and estimated responses for the red, green and blue channels of the *Nikon D70*. The results are based on the truncated singular value decomposition TSVD, Tikhonov Regularization TR and the metamer based MB methods. The calibration data was that of the Macbeth Color Checker.

responses to the spectral data of the Macbeth Color Checker, which was used as a test set, the metamer based method showed clear advantage over both the truncated singular value decomposition and Tikhonov regularization. These results are tabulated in Table 2, where we find that similar to the results achieved for the training set, Table 1, the error between the estimated and measured responses are within 1%.

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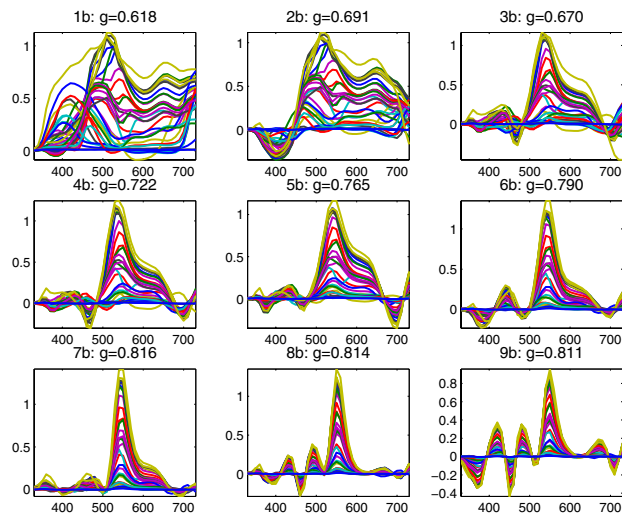[4] Bob Dyas. Robust sensor response characterization. *IS& T/SID*

Figure 2. *The effect of adding an increasing number of basis vectors (in the null space) on the recovery and the goodness measure. The horizontal axis shows the wavelength, 330-730 nm. As is seen the recovery improves by adding an increasing number of basis vectors until a maximum values is achieved (7 basis vectors in this case).*

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MegaVision

In this experiment, we estimated the spectral sensitivities of the *MegaVision* camera using the Macbeth Color Checker. Measurements of the camera's spectral sensitivities using a monochrometer were available to us. The estimated sensitivities are plotted in Figure 7. To estimate the similarity between the two sets we used the Vora value [8] which is a measure between the norm of the sensor set in its original space to the norm of its projection onto the space of the second sensor. A Vora value of one indicates that the sensors are within a linear transform of each other while a value of 0 means that the sensors are orthogonal. For the estimates shown in Figure 7 we found that the Vora value is 0.96, which indicates a very close fit. When the estimated sensitivities were used to estimate the responses we found that the results are comparable to those achieved with the measured filters. These results are tabulated in Table 3. In Table 3 we note that the goodness measure is higher for the red and blue channel than that achieved for the *Nikon D70* camera, however, we would like to point out that the goodness measure is dependent on the number of calibration surfaces used, where using one surface is guaranteed to result in a goodness value of one while including more surfaces would only result in a value of unity if all the vectors in the range are perfectly parallel to each other.
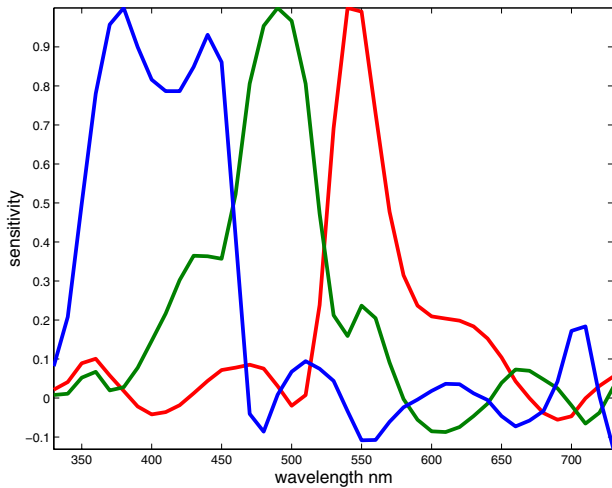
Figure 3. *The estimated spectral sensitivities of the Nikon D70 as a function of wavelength* $380 - 750$ *nm. The estimation method used is the proposed metameric blacks.*
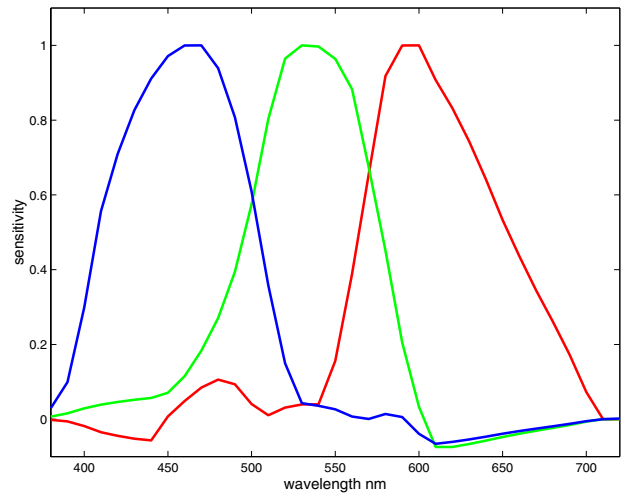

Figure 5. *The estimated spectral sensitivities of the Nikon D70 as a function of wavelength* $380 - 750$ *nm. The estimation method used is Tikhonov regularization.*
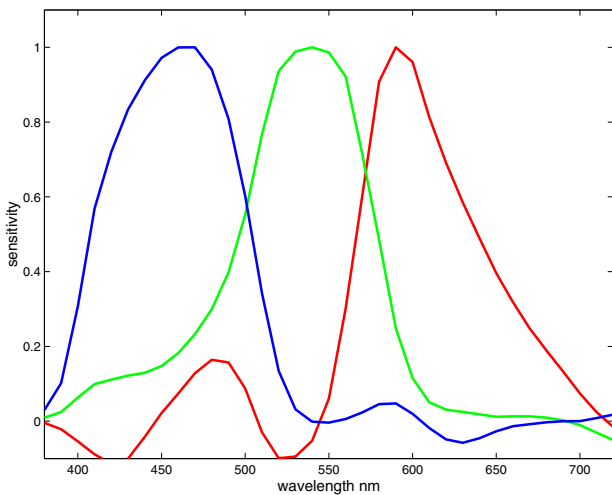

Figure 4. *The estimated spectral sensitivities of the Nikon D70 as a function of wavelength* $380 - 750$ *nm. The estimation method used is the truncated singular value decomposition.*
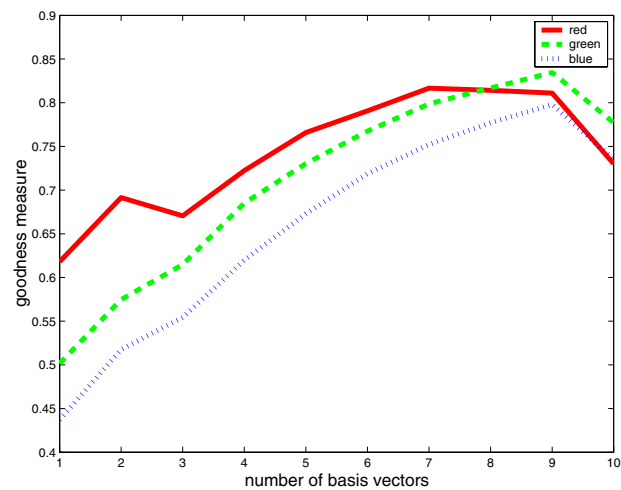

Figure 6. *The measure for the estimates of the red, solid line, green, dashed line, and blue, dotted line.*

Conclusion

In this paper, we introduced a novel method to estimate the color sensitivity curves of a camera. The methods is based on the observations that for a given illumination the space of color signals is convex and that the difference between two metameric spectra lies in the black space of the sensor. In the first step of the estimation we use selected triples of calibration colors to construct numerical spectral distributions that are in the black space of the sensor. After constructing a set of metameric blacks the sensor sensitivity function is found in the second step as the orthogonal complement of the black space. This construction is based on the construction of subspaces of the color signal space only.

We tested the basic properties of the new algorithm by spectrally calibrating a Nikon-D70 and a MegaVision camera. In the case of the Nikon-D70 we evaluated the performance with the help of the estimation errors between the measured and the estimated RGB vectors. For the MegaVision camera measurements of the sensitivity curves were available and we could therefore

compare these measured curves with the curves obtained by the new calibration method.

Our first implementation of the method showed that for the training set the results were comparable to those obtained by standard techniques (truncated SVD and Tikhonov regularization). For colors patches that were not used in the calibration the performance of the new method was clearly better than the performance of the truncated SVD and Tikhonov regularization.

The experiments described in this paper are only a first test of the properties of the new estimation method. Further improvements can be obtained by a more detailed evaluation of the noise characteristics.

Author Biography

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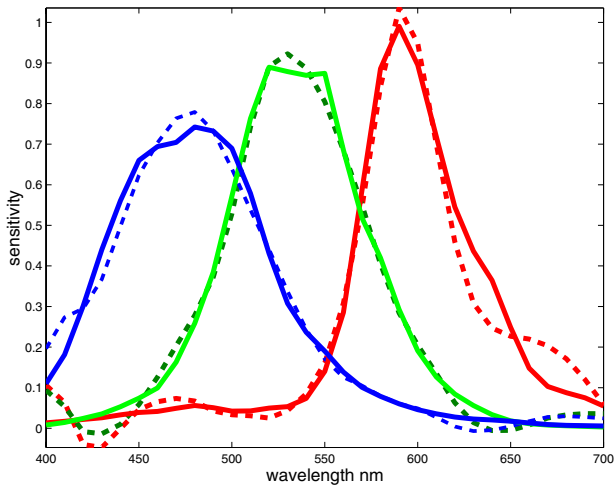
Figure 7. *The estimated spectral sensitivities, dotted lines, of the MegaVision as a function of wavelength $400 - 700$ nm. The actual sensitivities are shown as the solid lines.*

method	Abs-Error		
Measured	**red**	**green**	**blue**
mean	0.73	0.62	0.67
median	0.63	0.44	0.65
max	1.58	1.72	1.64
MB	**red**	**green**	**blue**
GM	0.82	0.87	0.95
mean	0.50	0.50	0.42
median	0.47	0.37	0.37
max	1.01	1.89	1.22

The absolute error between the measured and estimated responses for the red, green and blue channels of the *MegaVision* camera. The results are based on the metamer based MB method and the actual sensitivities. The calibration data was that of the Macbeth Color Checker.

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