Journal of Imaging Science and Technology® 53(1): 010501–010501-10, 2009.

Adaptive Statistical Methods for Optimal Color Selection and Spectral Characterization of Color Scanners and Cameras

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Abstract. *The aim of the study was to create an improved colorimetric and broadband spectral characterization for scanners and cameras. In such characterization, selecting an adequate number of color samples of known reflection spectra is necessary. And though countless sample data sets are available, the properties required of a data set for such optimal characterization remain elusive. Therefore a new methodology was required to address the characterization task. Such a characterization method is introduced in this article and is based on statistical classification of the colorimetric and broadband spectral properties of color sample sets. It introduces and effectively utilizes both the reflectance spectrum of the color sample and the spectral power distribution of the source. However it is shown that characterization methods based on a regression model can be used only if the conditions of the regression model are satisfied and that most statistical estimation errors are caused by conditions of the regression model not being satisfied (for instance heteroscedasticity, autocorrelation, multicollinearity). Nevertheless, the method introduced selects optimal representative color samples, so that with these samples the spectral responsivity of the detector can be estimated more precisely. The selection method is self-adaptive. If the reflectance spectra of the color samples and the spectral power distribution of the source are known, the optimal number of color samples, the number of principal eigenvectors, etc., are automatically set up according to the given a priori information, and the responsivity curves are determined where, the given z target function [see Eq. (5)] is minimal. The study has shown that the estimation error of broadband characterization can be decreased significantly if an optimal set of color samples is selected using these statistical methods. If there is more a priori information (for instance the spectral power distribution of the source of the scanner) the estimation error can be further decreased. © 2009 Society for Imaging Science and Technology.*
[DOI: 10.2352/J.ImagingSci.Technol.(2009)53:1(010501)]

INTRODUCTION

Determining the sensitivity of a scanner or camera can be performed using two methods. The spectral responsivity of the detector can be determined directly using a monochromator or interference filters.[1,2] This will be called the direct or narrowband method. The responsivities of the detectors can also be determined indirectly using reflecting color samples.[3,4] This method will be called the broadband or indirect characterization method. There are two different types of the broadband method: the spectral[5] and the colorimetric characterization.[6] The applicability of these methods is highly dependent on the reflectance spectra of the selected color samples.[7,8] Using the broadband method, color samples of known reflectance spectra are scanned. One would expect that the characterization of the responsivity of the detector would be very simple using a regression method.[9] Using more reflectance spectra in the regression model should improve the estimation of the detector responsivity determination. Using earlier published methods[5–8] experiments have shown that with some samples one could improve the estimation, but with other color samples this was not possible. For example, there are many redundant color samples in the Munsell, or the Natural Color System (NCS) atlases.[7,8] The use of these violates, in the regression methods, the condition of independent variables (avoiding correlation) of the characterization process.

The colorimetric characterization method handles the input device as a "black box." In this method we do not examine the functioning of the different parts of the device (it is not necessary to determine the spectral power distribution of the source, the spectral transmission of the color filters, and the spectral responsivity of the detectors). Only the input and the output values are known, the transformation function between device dependent RGB and device independent CIE XYZ or CIELAB color space has to be determined with linear or polynomial regression.[6,10] In the colorimetric characterization it is very relevant to question the nature of the optimal color sample set.[8] Vien Chung and Stephen Westland created a selection method in which the Euclidean distance $D_{i,j}=\|\beta_i(\lambda),\beta_j(\lambda)\|_2$ between the reflectance spectra of the test samples should be as high as possible for any $(\beta_1(\lambda),\ \beta_2(\lambda),\ldots\beta_n(\lambda))$ color sample pairs. However in the broadband characterization it is practical to select color samples with spectra which have a wide range (the range is defined as $\max(\beta(\lambda))-\min(\beta(\lambda))=R\in[0,1]$), or high relative spectral deviation [see Eq. (3)], because color samples with a narrow range, or low chroma, provide very little information in the course of the characterization

Received Mar. 24, 2008; accepted for publication Dec. 6, 2008; published online Feb. 4, 2009.
1062-3701/2009/53(1)/010501/10/$20.00.

process. The next section will show that the distance function between two different reflectance spectra should be based on the correlation function [see Eq. (4)], instead of the Euclidean distance, if the primary goal is improvement of the condition of the regression method.

In the case of the spectral characterization, the spectral responsivity function must be determined.[5] In this case the following model-equations can be used:[4]

$$r_{i,j} = \sum_{\Lambda} S(\lambda)\beta_j(\lambda)s_i(\lambda)\Delta\lambda \rightarrow \hat{s}_i(\lambda)\Delta\lambda, \tag{1}$$

$$\sum_{\Lambda} S(\lambda)\beta_j(\lambda)\hat{s}_i(\lambda)\Delta\lambda = \hat{r}_{i,j} \approx y = \mathbf{X}\cdot b + u, \tag{2}$$

where $i=1,2,3$ (for the R,G,B measuring channels); $j=1,\ldots,n$ is the number of color samples. $r_{i,j}$ is the response of the detector i for measuring sample j, $S(\lambda)$ is the spectral power distribution of the source, $\beta_j(\lambda)$ is the reflectance spectrum of the j-th color sample, and, $s_i(\lambda)$ is the spectral responsivity of ith detector, and the ˆ sign is used to show the estimate.

In the case of broadband characterization, the detector responsivity cannot be determined directly but can be estimated using mathematical or statistical methods.[5] Equation (2) can be transformed into the $y=\mathbf{X}b+u$ regression equation, where y is the response of the detector, $\mathbf{X}$ is the product of the spectral power distribution of the source and of the reflectance spectrum of a color sample, and b describes the responsivity of the detector which has to be estimated. One possibility is to estimate the detector responsivity $b=s_i(\lambda)$ as a linear regression using the least squares method.[11] However, the conditions of linear regression are not always satisfied, therefore this method is very sensitive to noise. Thus the errors of estimation may be very high.[12]

Nevertheless, a possibility exists to decrease noise sensitivity by using only the singular vectors and singular values for the approach. This method is the principal eigenvector method (PE).[7] In spite of the fact that this method has lower noise sensitivity than the least squares method, the application of this method has some limitation. For accurate modeling, some *a priori* information is needed and this method ignores this information, e.g., the restriction that the color sensitivity functions must be smooth functions. If the spectral power distribution of the scanner's source has sharp peaks, then after using the PE method, sharp peaks (local maxima) will be observed in the responsivity functions.

In summary, one can see that there are a number of characterization methods which are different from each other in their detector responsivity error estimation and demands on computation and cost. However, most broadband characterization methods (both spectral and colorimetric) use a regression calculation scheme. The question is whether the conditions of the regression methods are satisfied or not satisfied.

SPECTRAL CHARACTERIZATION OF DETECTOR RESPONSIVITY

Regression Methods for Characterizing Detector Responsivity

In the regression model, the response depends on the spectral power distribution of the source, the reflectance spectrum of the color sample, and the detector spectral responsivity. In this case an overdetermined equation system is received, where the equations are highly correlated. Unfortunately the least squares or quadratic programming methods, or any other similar methods, will supply satisfactory results only if some conditions are fulfilled, otherwise the estimation could be unreliable. First, it has to be assumed that there is no systematic error in the measurement. If a linear regression method is used, some systematic errors (for instance the dark current) can be corrected by adding the dark current component to the model and the systematic error can be handled in a very simple way. However, there are further problems that cannot be handled in such a simple way. Such problems are caused by the correlation among the reflectance spectra of the color samples. On the one hand, the low number of base color pigments, from which the color samples are mixed, produces correlations. This causes autocorrelations (errors of the estimation are not independent from each other) and the inner correlation causes multicollinearity. On the other hand the reflectance spectra of the different color samples have different slopes. (For instance the reflectance spectrum of a neutral sample has a lower slope compared to the reflectance spectra of samples with high chroma.) Thus the variances of the errors will not be the same. This symptom is called heteroscedasticity. If the variances of the errors is not homoscedous then the estimation will not be distorted, but the estimation will be inefficient (estimation of variances will increase). The received responsivity curves will show high oscillations. This situation can be explained as follows: The $\mathbf{X}$ matrix of the regression model contains the products of the reflectance spectra of the samples, the spectral power distribution of the source(s), and the responsivity spectra of the detectors. This causes the heteroscedasticity to be lower if the source has a continuous spectral power distribution (like CIE illuminant A), but becomes large for fluorescent lamps with band-plus-line spectra.

The oscillation effect can also be caused by the overdetermined regression model. The redundant reflectance samples are correlated with each other, therefore the estimation error can increase. This effect is the (stochastic) multicollinearity, where the reflectance of sample x_i from a sample database $\mathbf{X}$ depends from other reflectance sample(s). [If the reflectance spectrum of the color sample x_i can be constructed using the reflectance spectra of other samples, (for instance, $x_i=ax_j+bx_k$) then there is a deterministic multicollinearity. (x_i correlates with x_j and x_k, and their correlation value is unity)]. Autocorrelation (estimation errors correlate) and stochastic multicollinearity (correlation of the independendent variables) are not the same effect. However if there is multicollinearity (caused by overdetermined regression models) and there is heteroscedasticity (errors of estimation are not identical, for instance, they depend on the independent variables) that can cause autocorrelation. {x_i correlates with x_j [there is a (stochastic) muticollinearity], u_i correlates with x_i, and u_j correlates x_j (there is a heteroscedasticity), then u_i can correlate with u_j (can also cause autocorrelation)}. Autocorrelation causes the estimation to be distorted. If there is multicollinearity and there are measurement errors, then even if the reflectance spectra of the samples are measured accurately, high estimation errors may be caused. One cannot assume that the independent variables are deterministic, because they are the result of measurements that also have some uncertainties.

Evaluation Methods for Characterizing Color Scanners and Cameras

We have tested many methods, from least squares regression (LSQR),[11] quadratic programming (QPROG),[3] principal eigenvector method (PE),[7,12] projection onto convex set (POCS),[12] and some other ones. Tests have shown that the functioning of the different methods was highly influenced by how well the method fulfilled the requirements of the model. It was observed that the PE model is one of the best estimation methods, because it uses a lower number of equations, which are more significant, and therefore the uncertainty of estimation will be lower. If too few principal eigenvectors are used, the estimation will be distorted. If too many principal eigenvectors are used, the estimation will be inefficient (variance of estimation will increase), similar to a least squares regression calculation.

Least squares regression and quadratic programming methods are forms of regression methods. Therefore these methods have the same requirements as regression methods. Fulfillment of assumptions of the regression methods can be tested with hypothesis tests. We have tested fulfillment of assumptions by these tests and methods. (Null hypothesis: there is no autocorrelation). This was investigated by the Durbin Watson test and the general LM test. Homoscedasticity can be tested by the Ramsey test, Goldfield Quandt test, Breusch Pagan test, etc. Multicollinearity can be measured by the variance inflation factor (VIF), or condition number. Normality of estimation error can be measured by One-sample Kolmogorov–Smirnov test or χ^2 test.

POCS method determines convex sets, but the partition cannot be determined if the color samples are highly correlated. Since PE vectors are uncorrelated vectors, there is no multicollinearity (principal vectors are independent from each other).

In spite of the fact that the principle eigenvector method produces the best estimate—because this method uses few orthogonal principal eigenvectors, and this way decreases the effect of autocorrelation—it is also very sensitive to the source and the reflecting samples. Principal eignenvectors are noncorrelated vectors, but the error of estimation is not necessarily identical for all eigenvectors. If the PE method is modified using a smoothing function, the oscillations produced by heteroscedasticity can be reduced, see Figure 1.

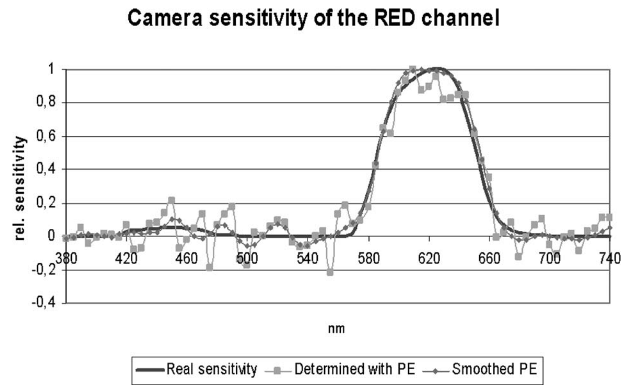

Figure 1. Results of a camera channel (*R*) determination using PE and adapted PE (PE and smoothing function), where the smoothing parameters and the number of principal eigenvectors are automatically set up.

If this modification is used, where the postsmoothing parameters are automatically set up for the given target function, the correlation between the real and the estimated sensitivity curves can be increased, and the CIELAB color differences between the real and estimated responsivities can be decreased at the same time. (This method is called the adapted principal Eigenvector method.) Decreasing the color differences becomes more significant if the source of the scanner is also considered, since the oscillation effect produced by heteroscedasticity (and multicollinearity) are more significant in the case of fluorescent lamp irradiation. While the oscillation effect of heteroscedasticity can be decreased by using the smoothing parameters, the effect of heteroscedasticity itself is not eliminated.

Introducing Selection Methods—Decreasing the Number of the Reflecting Samples

The previous section shows that if the color samples are not selected properly, heteroscedasticity will occur. For spectral characterization, the statistical distribution of the color samples is also important, as the mapping is from low-dimensional device response space to high-dimensional spectral reflectance space. If the proper method is used to select the samples, the requirements of the detector responsivity estimation method can more easily be satisfied. The following method shows how optimal selection of color samples can be achieved.

In the new method introduced here, color samples are separated into two batches: The first group, classified as so-called *representative color samples*; the second group will serve as test color samples. Sensitivity curves can be estimated with the representative color samples, but the color differences will be calculated using all color samples. This statistical clustering method for reflectances and sources method (SCRS) has three steps.

The first step is the initial filtering. For this we have to define a deviation function and a scatter coefficient. (The deviation function describes the slope of the spectral reflectance functions.)

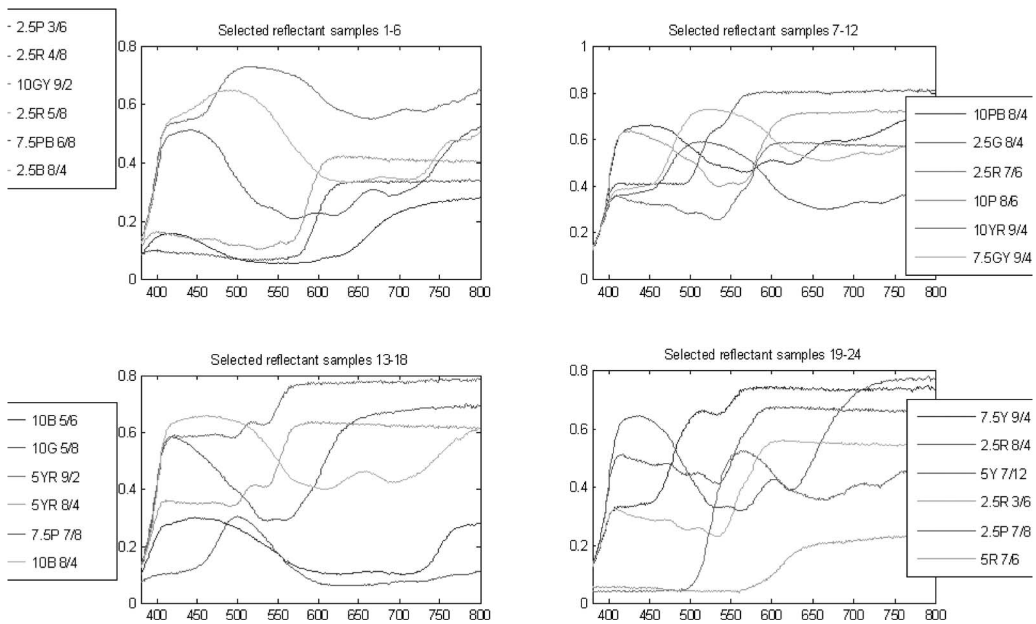

Figure 2. Selecting 24 color samples from Munsell atlas with the SCRS method.

In this initial filtering, the color samples, which have no additional information for the characterization, must be put into the test color samples set. These samples are the neutral (gray) samples (with low chroma). Their spectra are typically similar over the 400 to 700 nm wavelength range. To group the samples into these two groups, their dispersion has to be measured. There are two common measures of dispersion, the range and the relative deviation. The range is simply the highest value minus the lowest value of the reflectance of a given jth color sample. (It is represented as R (range): $\{\max[\beta_j(\lambda)]-\min[\beta_j(\lambda)]\}=R_j\in[0,1]$, $j=1,2,\ldots,n$. The other possible measure is the relative spectral deviation of a given color sample defined as:

$$R_D=\sqrt{\int_\Lambda(\beta(\lambda)-\bar{\beta})^2\mathrm{d}\lambda}\Big/\bar{\beta}, \tag{3}$$

where $\bar{\beta}=E(\beta(\lambda))$ and $\beta(\lambda)$ is the spectral reflectance of the color sample, $\bar{\beta}$ is a constant, independent of wavelength.

The advantage of both indicators is that the results are fractions. Both indicators show the spectral dispersion of a reflectance spectrum. These values are low in the case of neutral samples and high in the case of color samples with high chroma. One can set a minimal value (a scatter coefficient): If for a sample, the value of the relative spectral deviation (or the range) is lower than the given scatter coefficient, the sample will not be included in the representative color sample base (e.g., gray samples), and will be put into the test sample set. With this step the heteroscedasticity can be avoided.

The second step is clustering. For this, a distance function has to be defined. Cheung and Westland[8] used the Euclidean distance between two reflectance spectra in their method. For the distance function, we use the correlation between two reflectance spectra in the following form:

$$\begin{aligned} d(\beta_i(\lambda),\beta_j(\lambda)) &= 1-r(\beta_i(\lambda),\beta_j(\lambda)) \\ &= 1-\frac{\mathrm{cov}(\beta_i(\lambda),\beta_j(\lambda))}{\sqrt{\mathrm{var}\beta_i(\lambda)}\sqrt{\mathrm{var}\beta_j(\lambda)}} \\ 0 \leqslant d(\beta_i(\lambda),&\beta_j(\lambda)) \leqslant 1, \end{aligned} \tag{4}$$

where $r(\beta_i(\lambda),\beta_j(\lambda))$ is the correlation between ith and jth reflectance spectra. If the correlation between two reflectance spectra is high then the value of distance function is low. If there is no correlation between two reflectance spectra, then the value of the distance function is unity. If there is negative correlation between the two spectra, then the value of the distance function can increase to two.

If correlation functions are used for clustering, one can get significant clusters where the inner elements (color samples) of a cluster are highly correlated, but the correlation between two chosen clusters is below a given threshold; thus autocorrelation can be avoided. Thus samples from different clusters have to be selected into the group of representative samples. It is practical to choose the color sample from each cluster with the highest value of the relative spectral deviation (R_D).

After performing this selection we have k representative color samples, where the reflectance spectra of these samples exhibit low correlation and there is low heteroscedasticity. If the reflectance spectra of these samples are multiplied by the spectral power distribution of the source, a unique color stimuli is received for the given source. Figure 2 shows the results of a selection process.

For the broadband spectral characterization, the main problem is whether the assumptions of the regression method are satisfied or not satisfied. This is the case irrespective of which version of the regression method is used. In the overdetermined regression models, the main problems are the multicollinearity, heteroscedasticity, and the autocorrelation. If we manually select some reflectance samples of different hues, we can decrease the variance of estimation in the regression model,[8] because correlations among reflectance samples are decreased. In this way the effect of multicollinearity (independent variables are correlated) can be decreased, and if there is heteroscedasticity, the effect of autocorrelation can also be decreased [multicollinearity and heteroscedasticity can also cause autocorrelation (see below)]. The Cheung and Westland method can also decrease the multicollinearity because their optimal selection method selects reflectance samples, where the Euclidean distance between every two reflectance spectra is maximal. In spite of the fact that this method can decrease multicollinearity directly, and the autocorrelation indirectly, this method does not consider the heteroscedasticity. Our proposed method improves all assumptions of the regression methods directly. The estimation error can be decreased significantly if the assumptions of the regression methods are satisfied. One way of improving the regression methods is to fulfill the assumptions of the regression formulas. The following example compares some selection methods in the case of a real flatbed scanner characterization.

Real Flatbed Scanner Characterization

Characterizing real flatbed scanners is a more difficult task because there is no *a priori* information on detector responsivities. Because the real and the estimated responsivity curves cannot be compared, selecting an optimal number of color samples is accordingly more difficult.

First, after scanning color samples there are $j=1,2,\ldots,n$ responses for $i=1,2,3$ channels, and if the spectral power distribution of the lamp and the reflecting spectra of the samples are known, then the spectral responsivity curves can be estimated by a linear regression calculation.

In the target function, the color differences and the standard deviations of the color differences between the real and the estimated responsivities must decrease simultaneously.

$$z = E(\Delta E^{*}_{a,b}(r_{i,j},\hat{r}_{i,j})) + \kappa \cdot u_c((\Delta E^{*}_{a,b}(r_{i,j},\hat{r}_{i,j}))) \rightarrow \min, \tag{5}$$

where z is a target function, $E(\Delta E^{*}_{a,b}(r_{i,j},\hat{r}_{i,j}))$ is the mean value, and $u_c((\Delta E^{*}_{a,b}(r_{i,j},\hat{r}_{i,j})))$ is the combined standard uncertainty of the color difference between the real and the estimated responsivities. κ is a constant which usually can be set between 2 and 3, taking into consideration the significance levels and the distribution of errors of color differences. (For instance, $\kappa=2$, if the significance level is 95, 45% of the color difference errors have a normal distribution.)

If one uses the spectral power distribution of the lamp in the scanner as *a priori* information, a source-dependent selection of the color samples can be made for estimating the detector responsivities. In this way the effect of heteroscedasticity and the autocorrelation can be diminished to an insignificant level. After selection, the responsivity curves must be estimated using the above target.

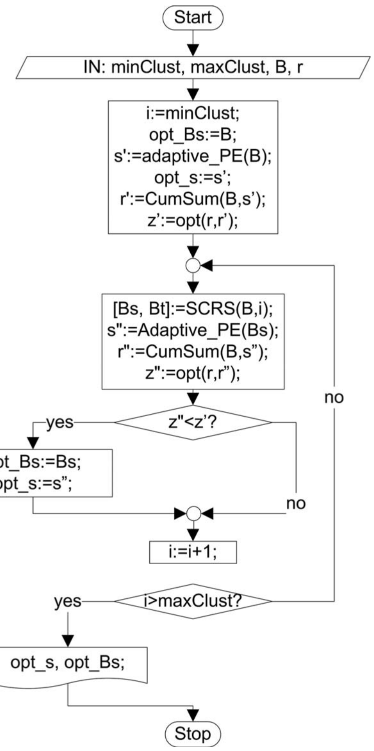

Figure 3. Flowchart of adaptive statistical classification method for selecting color samples (adaptive SCRS).

Using an adaptive selection method, as described in the previous section, the optimal number of color samples can be determined. Figure 3 shows a flow chart of the procedure.

1st step (initialization): Input, determine the minimal and maximal number of clusters (minimal number of clusters can be the relevant principal components of reflecting samples, maximal number of clusters can be the number of reflectance samples of a given database B). Estimate the s' sensitivity curve and r' responses for the full reflecting sample database with adaptive PE algorithm, which has already been mentioned above. The z' is the value of the target function in case of using Eq. (5); B can be the spectral reflectance of the samples or the array multiplication of reflectances and the spectral power distribution of the sources. In the first case $r'=\mathrm{CumSum}(B,S,s')$, where S is a spectral power distribution of the source and B is the spectral reflectance of the samples. In the second case $r'=\mathrm{CumSum}(B,s')$, where B is an array multiplication of the spectral reflectance of the samples and the spectral power distribution of the source. In this way, this selection method can take into consideration the spectral power distribution of the sources during the selection process.

2nd step (iterations): Let i be the actual number of clusters [minClust (minimal number of clusters) $<=i<=$maxClust (maximum number of clusters)]. Separate the full set of reflecting samples (B) into the selected (B_s) and the test (B_t) sample base with the SCRS method. Determine the sensitivity s'' of the detector based on the measured reflecting sample base, but determine the target

Table I. Results of comparison.

Sensitivities	Sources	Color differences	All color samples	36 selected reflecting color samples (with random selection)	36 selected reflecting color samples (with Cheung and Westland's method)	36 selected reflecting color samples (with adaptive SCRS method)
Sensitivity = CIE $\bar{x}(\lambda)$ function	CIE-A	$E(\Delta E^*_{a,b})$	1.3815	0.9816	0.1904	0.0889
		$D(\Delta E^*_{a,b})$	0.4134	0.2752	0.1622	0.0597
	CIE D65	$E(\Delta E^*_{a,b})$	0.9312	0.6711	0.1415	0.0397
		$D(\Delta E^*_{a,b})$	0.3451	0.2715	0.0505	0.0212
	AGFA STUDIOSCAN II	$E(\Delta E^*_{a,b})$	1.9561	1.6578	0.7309	0.2315
		$D(\Delta E^*_{a,b})$	0.9311	0.8562	0.4043	0.1105
	HP SCANNER 3300C	$E(\Delta E^*_{a,b})$	1.9312	1.3452	0.3511	0.1207
		$E(\Delta E^*_{a,b})$	1.5152	1.1236	0.1612	0.0714
	HP SCANNER 5470C	$E(\Delta E^*_{a,b})$	2.1512	2.0230	0.5153	0.1224
		$D(\Delta E^*_{a,b})$	1.3341	1.1250	0.4602	0.0540
	DEXXA SCANNER	$E(\Delta E^*_{a,b})$	1.5134	1.0244	0.2583	0.1381
		$D(\Delta E^*_{a,b})$	0.9334	0.8044	0.1673	0.0606

function and the responsivity r'' based on the full sample base. The z'' is the value of the target function used in Eq. (5). If z'' is lower than the z' the optimal sensitivity curve (opt-s), and the selected samples (opt-B_s) are saved.

3rd step (printing): Print the optimal number of clusters, the optimal estimated sensitivity curve s'', and the estimated responsivity r''.

RESULTS

In order to test the selection method, an ideal responsivity of the detector and ideal spectral power distribution of the source was assumed. If the model Eqs. (1) and (2) are assumed, and a different source and detector, as well as reflecting samples' spectra are known or can be simulated, different methods (adapted PE with or without selection method) can be used for restoring the given detector responsivity and one can estimate how different the responsivity of the detector is from the responsivity of the restored detector.

We have determined, for a number of sources, the color differences between the evaluated and the restored responsivities, $E(\Delta E^*_{a,b})$, as well as their standard deviations, $D(\Delta E^*_{a,b})$. The following test was performed.

A virtual scanner was assumed, where the responsivities of its detectors corresponded to the CIE $\bar{x}(\lambda), \bar{y}(\lambda), \bar{z}(\lambda)$ color matching functions (CMFs). The sources adopted were CIE A, CIE D65, and sources of four flatbed scanners (three with fluorescent lamps and one LED scanner). The test samples used were the 1269 color samples of our Munsell atlas, 205 photographic samples, 2008 color samples of our NCS atlas, and 24 color samples of the Machbeth Color Checker Chart. Using Eq. (1) the detector responses could be determined. The aim was to restore the spectral responsivities with target function, Eq. (5). Assuming that the target responsivities, reflectance spectra, and the spectral power distribution of the source are known, the real and restored responsivities could be compared. The results achieved with the new method have been compared with those of the Cheung and Westland method and a random selection method, where the color samples have been selected randomly. Data are shown in Table I.

Figure 4, shows the target CIE $\bar{x}(\lambda)$ function and the reconstructed responsivity curves using PE method with and without different selection methods.

As shown in Table I, the mean and the standard deviation of color differences between the responses can be significantly decreased with optimal sample selection. The characterization can be further improved if the spectral power distribution of the source is taken into consideration. In this case, instead of distance function (4) a modified distance function can be defined:

$$d(S(\lambda)\beta_i(\lambda), S(\lambda)\beta_j(\lambda)) = 1 - r(S(\lambda)\beta_i(\lambda), S(\lambda)\beta_j(\lambda)). \tag{6}$$

In this way, a source-dependent selection method can be established. The source-dependent selection method is especially effective in the case of the fluorescent sources. Table II compares the results of using the source-dependent and source-independent methods.

Cheung and Westland's method does not take into consideration the spectral power distribution of the light source. However in the scanner regression model, the sum of product of the detector sensitivity of the spectral power distribution of the source and of the spectral reflectance of the samples is used [see Eq. (1)]. Especially in the case of fluorescent sources, the spectral power distribution of the source can improve the estimation, because the lack of multicollinearity assumption must be satisfied in matrix **X** of Eq. (2),

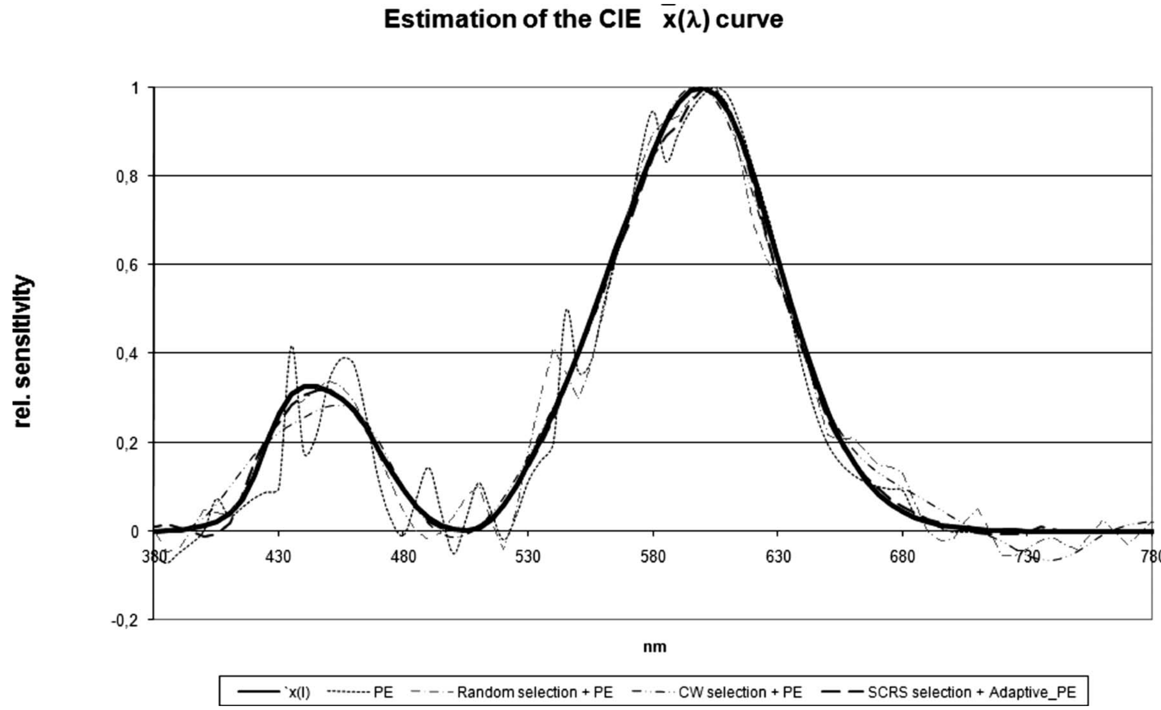

Figure 4. Comparison of estimates of the CIE $\bar{x}(\lambda)$ function with general PE method, and using PE method after an optimal selection.

which is the array multiplication of the spectral reflectance of the samples and of the spectral power distribution of the source.

The results obtained show very low color differences, but the assumed responsivities were the theoretical CIE CMFs: $\bar{x}(\lambda), \bar{y}(\lambda), \bar{z}(\lambda)$ and the spectral responsivities of a color camera are near to a linear transformation of CIE CMFs. Unfortunately spectral responsivities of flatbed scanners usually are very different from the theoretical CIE CMFs.

Next, in order to act as an example, a real HP 5470C scanner was characterized using the adapted PE method with and without selection. The responsivities of the scanner detectors were measured with an independent spectral measurement and these data were used as target spectra. In the first case, the color samples were the 1269 samples of the Munsell atlas. In the second case, the 24 color samples of the Macbeth Color Checker Chart plus 205 photographic samples, and 2008 color samples of NCS atlas were added to this database. In both cases, without selection, the color differences between the real scanned (target) and the estimated responsivities was higher than $5\Delta E^*_{a,b}$. In this case, the best estimator method, the adapted PE method, was used. As discussed in the Introduction, without selecting color samples the determined responsivity curves show oscillations around the mean values. This is due to heteroscedasticity. Autocorrelation and multicollinearity distort the estimation. If the adaptive selection method is used, the effects of autocorrelation, multicollinearity, and heteroscedasticity can be decreased. The responsivity curves have to be estimated using the selected (representative) color samples, but the color differences have to be calculated for the all-color sample base (using the procedure shown in Fig. 3). The necessary parameters (number of eigenvectors, smoothing parameters, the number of clusters/selected color samples) can be automatically setup with this procedure. A comparison is made of cases when all the 1269 Munsell samples are used in determining the spectral responsivities—if 36 samples are selected randomly, or by using Cheung and Westland's method, or by using the SCRS selection method—can be seen in Table III. The sensitivity curves have been estimated using a 36 color sample.

Characterization using color samples only from the Munsell atlas can be performed with a lower estimation error than published earlier (see Refs. 5–8, 13, and 14). The characterization method can be further improved if samples from more color sample bases are used, and selection can be made from a united big color sample set. In this way, the effect of multicollinearity can be reduced significantly. In this study the samples of the Munsell atlas, the 24 element Macbeth color checker chart, 205 photographic samples, and the 2008 samples form the NCS atlas were united. To characterize a real HP SCANJET 5470C flatbed scanner, nine color samples have been selected from the Munsell atlas, 13 from NCS atlas, eight photographic samples, and six color samples from the Macbeth color checker chart, using the earlier adaptive selection method. The results are shown in Table IV. The relative spectral sensitivity of the scanner can be seen in Figure 5.

The characterization method cannot be significantly further improved because the standard deviation of the DAC values of the responsivities are in the order of one to three for each color sample. This produces a mean error of the scanning process of about $0.8\Delta E^*_{a,b}$ for all color samples.

Table II. Table II. Comparison of source-dependent and source-independent SCRS selecting methods with the Cheung and Westland method and randomly selected reflectance samples. (Sample database = 1269 reflectance samples from Munsell atlas + 205 photographic samples + 2008 reflectance samples from NCS atlas + 24 color samples from Macbeth color checker chart. (The number of selected samples is 36.)

			Sources									
Sensitivities	Selection methods	Color differences	CIE A	CIE D65	Mean of CIE F1–F12	Mean of CIE F3.1–F3.15	Mean of CIE HP 1–HP5	AGFA STUDIO SCAN II	HP SCANJET 3300C	HP SCANJET 5470C	DEXXA FLATBED SCANNER	Average
Sensitivity = CIE XYZ	LSQR method	$E(\Delta E^*_{a,b})$	6.3416	5.2351	8.4587	9.4362	8.9456	11.4612	10.4629	11.5744	7.4772	8.956
		$D(\Delta E^*_{a,b})$	3.8767	2.3425	6.4223	6.4789	5.8932	5.1788	4.8832	7.4663	3.4652	6.0771
	Random selection	$E(\Delta E^*_{a,b})$	0.9616	0.6311	1.3851	1.4104	1.9048	1.5623	1.2991	1.421	0.9921	1.4255
		$D(\Delta E^*_{a,b})$	0.2452	0.2672	0.7823	0.7542	0.983	0.8032	1.0312	1.0422	0.7631	0.7834
	Cheung and Westland's method	$E(\Delta E^*_{a,b})$	0.189	0.1407	0.214	0.2152	0.5012	0.7032	0.3412	0.4972	0.2455	0.2742
		$D(\Delta E^*_{a,b})$	0.1561	0.0499	0.1469	0.151	0.329	0.3904	0.1576	0.4515	0.1655	0.1854
	Source-independent selection	$E(\Delta E^*_{a,b})$	0.0568	0.0334	0.1403	0.1767	0.1944	0.1703	0.1023	0.0805	0.1395	0.155
		$D(\Delta E^*_{a,b})$	0.0319	0.0201	0.0876	0.1164	0.1481	0.0924	0.0586	0.0451	0.0831	0.1018
	Source-dependent selection	$E(\Delta E^*_{a,b})$	0.0557	0.0331	0.0841	0.0898	0.103	0.121	0.0699	0.0699	0.0924	0.0872
		$D(\Delta E^*_{a,b})$	0.0398	0.0184	0.0394	0.0476	0.0696	0.0831	0.0863	0.0534	0.088	0.0501
Sensitivity = Camera RGB	LSQR method	$E(\Delta E^*_{a,b})$	6.7427	5.4262	8.7326	9.7351	9.1643	11.7413	10.6288	11.824	7.8117	9.2319
		$D(\Delta E^*_{a,b})$	3.9426	3.1348	6.3381	6.3728	4.9162	4.4161	5.721	6.1787	3.7811	5.8791
	Random selection	$E(\Delta E^*_{a,b})$	0.9816	0.6711	1.4512	1.4104	1.9731	1.6578	1.3452	2.023	1.0244	1.4773
		$D(\Delta E^*_{a,b})$	0.2752	0.2715	0.8341	0.7542	1.0401	0.8562	1.1236	1.125	0.8044	0.8152
	Cheung and Westland's method	$E(\Delta E^*_{a,b})$	0.1904	0.1415	0.2452	0.2152	0.512	0.7309	0.3511	0.5153	0.2583	0.2873
		$D(\Delta E^*_{a,b})$	0.1622	0.0505	0.1501	0.151	0.3402	0.4043	0.1612	0.4602	0.1673	0.1888
	Source-independent selection	$E(\Delta E^*_{a,b})$	0.0889	0.0397	0.1414	0.1401	0.2139	0.2315	0.1207	0.1224	0.1381	0.1476
		$D(\Delta E^*_{a,b})$	0.0597	0.0212	0.0771	0.098	0.149	0.1105	0.0714	0.054	0.0606	0.0925
	Source-dependent selection	$E(\Delta E^*_{a,b})$	0.088	0.0391	0.1047	0.1191	0.1747	0.1401	0.0817	0.0999	0.1042	0.1176
		$D(\Delta E^*_{a,b})$	0.0502	0.021	0.0631	0.0666	0.1027	0.1048	0.0511	0.0661	0.0783	0.0695
Weights/Number of sources			1	1	12	15	5	1	1	1	1	

Table III. Expected values, $E(\Delta E^*_{a,b})$ and standard deviations, $D(\Delta E^*_{a,b})$ of color differences between the real scanned and the determined responses of the scanner for the 1269 samples of the Munsell atlas (applied characterization method is adaptive PE method) for four methods of selecting the characterizing samples (see text).

Munsell color samples	$E(\Delta E^*_{a,b})$	$D(\Delta E^*_{a,b})$
All samples 1269 samples of Munsell atlas without selection:	6.77	5.52
Random selected samples (36):	5.19	4.37
Selected samples with Cheung and Westland's method (36):	2.90	2.40
Selected samples with SCRS (36):	1.65	1.04

Table IV. Expected values, $E(\Delta E^*_{a,b})$ and standard deviations, $D(\Delta E^*_{a,b})$ of color differences between the real responsivities and the estimated responsivities. (Applied characterization method is adaptive PE method, see text.)

Color samples	$E(\Delta E^*_{a,b})$	$D(\Delta E^*_{a,b})$
All samples without selection:	7.17	5.41
Random selected samples (for 36 selected samples):	6.02	4.19
Selected samples with Cheung and Westland's method (for 36 selectedsamples):	2.86	2.33
Selected samples with SCRS (for 36 selected samples):	1.19	0.91

In order to verify our results, it is not enough to calculate the responsivity curves and the color differences between the scanned and the estimated responsivities, because the value of the target function z [see Eq. (6)] might have a low value, and the color differences between the scanned and the estimated responsivities might be very low, but using the estimated responsivity curves in another color sample base [using Eq. (1)], one might get different results. Therefore to be sure of the effectiveness of the introduced method, scanner detector responsivities have been determined using interference filters (the narrowband spectral characterization method). For this, the source of the scanner was switched off and an external CIE-A standard lamp was used. With interference filters, the detector responsivity and the

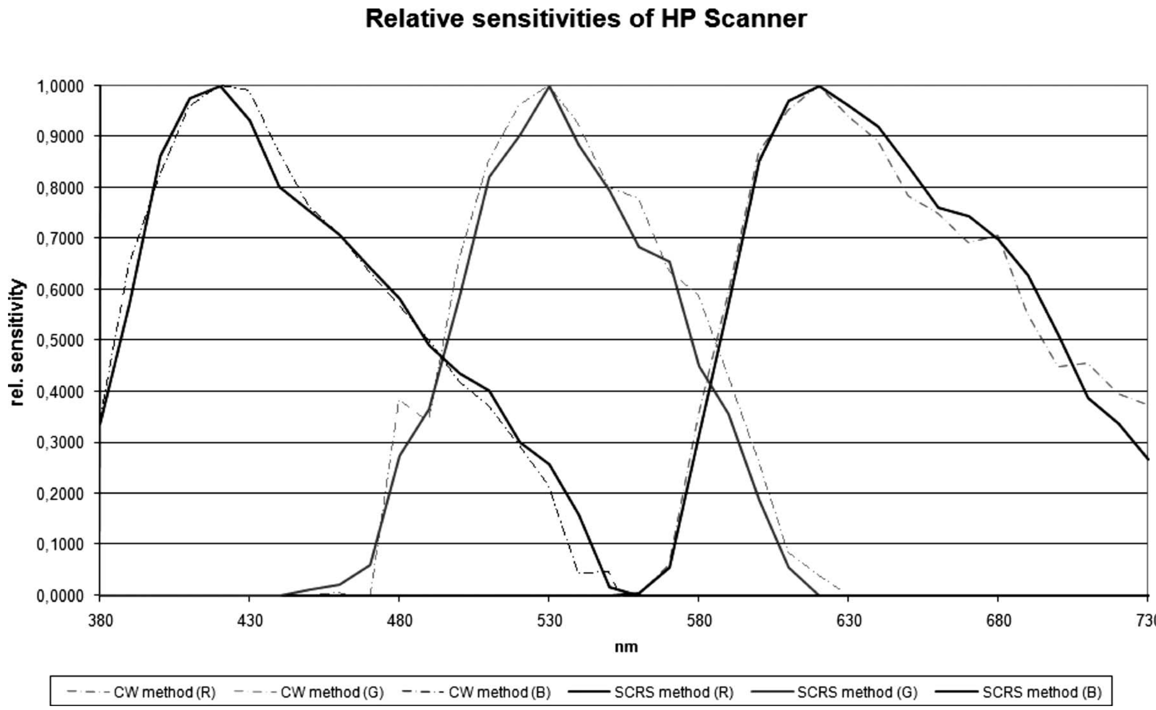

Figure 5. Relative spectral responsivities determined with broadband adaptive SCRS method and Cheung and Westland's method.

nonsystematic (measurement) errors can be determine directly, with ISO GUM[15] and Monte-Carlo simulation. The results can be seen in Figure 6. The detector responsivity functions obtained by the new method, by the Cheung and Westland method (see Fig. 5), and by the narrowband method (see Fig. 6), are very close to each other.

In Fig. 6 mean responsivities and their combined standard uncertainties can be seen in both the case of the narrowband spectral characterization method and the new method, determined on an HP 5470C scanner. Using these values, together with the estimated uncertainties, the spectral method was compared with the broadband method. Table V compares the two determination methods.

Comparing the results of Tables IV and V one can see that despite the fact that the responsivity curves using the direct (spectral) and the indirect (broadband) methods are

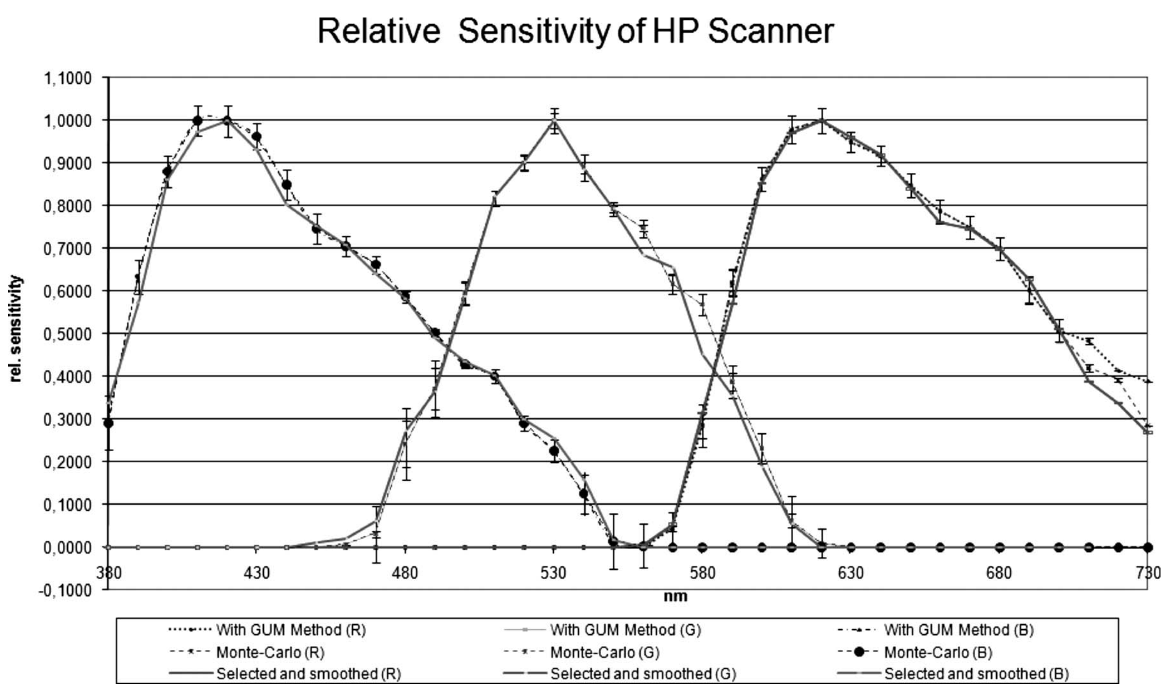

Figure 6. Relative spectral responsivities determined using the broadband (adaptive SCRS) and narrowband method (with interference filters).

Table V. Expected values, $E(\Delta E^*_{a,b})$ and standard deviations, $D(\Delta E^*_{a,b})$ of color differences using the narrowband spectral method and the adaptive SCRS method.

Color samples for all color selected samples (3506).		
GUM method for all samples	$E(\Delta E^*_{a,b})$	2.87
	$D(\Delta E^*_{a,b})$	2.16
Monte-Carlo simulation for all samples	$E(\Delta E^*_{a,b})$	2.78
	$D(\Delta E^*_{a,b})$	2.07
Adaptive SCRS for all samples	$E(\Delta E^*_{a,b})$	1.19
	$D(\Delta E^*_{a,b})$	0.91

nearly the same, the color differences are lower if we use the indirect (broadband) method with the statistical classification selection method. Theoretically, lower uncertainty could be achieved if instead of the quasimonochromatic light of the incandescent lamp filtered with interference filters, tunable lasers would be used, but these were not at our disposal. Actually the narrowband method to determine the spectral responsivities was only used to control our measurement data, and we have not dealt with this method in detail.

CONCLUSIONS

The conditions of the regression model using broadband characterization for scanners and cameras were investigated. If these conditions are not satisfied, the estimation of detector responsivity would be distorted and/or the determination would be inefficient.

The importance of optimal color sample selection was emphasized. Selection methods which improve the condition of the characterization method are judged to be effective. The selection method, based on statistical classification, introduced in this article improves all broadband characterization methods based on a regression analysis. In this case, the error of estimation can be decreased very significantly because the conditions of the regression models are improved. The selection method can be used for any arbitrary color sample set. The selection methods improve the assumptions of the characterization method directly. In this way, the error of the estimation of sensitivity curves can be very significantly decreased. In the case of characterization using regression models, other selecting methods that increase the effect of multicollinearity and autocorrelation indirectly can also be very useful. However, better results can be achieved if the assumptions of the characterization method are investigated and one selects samples for the characterization where the assumptions are satisfied.

In case of flatbed scanners, where the illuminant is a fluorescent source, the selection method should also take into consideration the spectral power distribution of the source, because the assumptions of the regression method must be fulfilled and can only be investigated in this way.

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