

# The Impact of UCR on Scanner Calibration

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## Abstract

Most present day color scanners, with red, green, and blue filters, are non-colorimetric. This means that their outputs cannot be linearly transformed into CIE tristimulus values for arbitrary input materials. On the other hand, by restricting oneself to a single class of inputs such as photographic, lithographic, or xerographic materials, very accurate scanner calibrations are possible. In this paper, we conjecture that such accurate calibrations can be achieved if the input document is made with only "three colorants", i.e., has only three independent degrees of freedom. The validity of the above conjecture is tested experimentally using a CMYK (four colorant) printer. Usually in CMYK printing, there are only three fundamental degrees of freedom. Even though four colorants are used, the amounts of these colorants are inter-related through the method used for undercolor removal (UCR). The fourth degree of freedom is re-introduced when the method of undercolor removal is varied. To test the above conjecture concerning "degrees of freedom", we evaluated the impact of different UCR methods on scanner calibration accuracy. The paper also proposes an analytic similarity measure for comparing color spectra from different media, which is shown to be in fair agreement with the experimental results.

## Media Dependence of Scanner Calibration

Color scanner calibration is important for obtaining device independent color. The calibration transformation converts the scanner RGB values into corresponding measured color values, expressed as CIE XYZ tristimuli or derivatives thereof. If the scanner spectral sensitivities can be linearly transformed into the CIE XYZ color matching functions, the same linear transformation converts scanner measurements to CIE XYZ tristimuli and can therefore be used for calibration<sup>1,2</sup>. Sensitivities of actual scanners deviate significantly from this ideal "colorimetric" requirement and therefore, an empirical approach is more common in scanner calibration. Typically, a calibration target with several color patches is scanned and a transformation is determined that (approximately) converts the scanner RGB values into corresponding color values for each patch (which are measured independently with a spectrophotometer/colorimeter). Several calibration transformations have been reported in literature including 3x3 linear matrices, higher-order polynomials, look-up tables, and Neural-Network based methods<sup>3-7</sup>.

The calibration transformation is applied to scanned images to obtain device independent color representations of these images. Usually, the calibration transformation is most accurate for input images on a medium (e.g., photographic, lithographic, xerographic, inkjet, etc.) identical to the target material and the performance over other materials (cross-tests) with different spectral characteristics is poorer. This is especially true of the non-linear calibration transformations that often give excellent color accuracy for a single input material but do not perform significantly better than linear transformations in cross-tests<sup>3</sup>. An example of this dependence is shown in Table 1 for a Neural Network based scanner calibration scheme. For obtaining the data in this table, the scanner was calibrated using three IT8.7 targets<sup>8</sup> produced by different means: 1) a photographic target, 2) a lithographic target, and 3) a Xerographic target. Each row of the table corresponds to a different target used in the calibration and each column corresponds to a different target used for testing the calibration. The first column of each row lists the corresponding calibration target and the first row of each column lists the corresponding test target. The numbers in the table are average CIELAB  $\Delta E^*_{ab}$  color errors that are obtained in scanner calibration when the calibration target listed in that row is used for training the Neural Network and the calibration is tested on the test target listed in that column. Thus the diagonal entries represent self-tests and the off diagonal entries represent cross-tests.

Calibration Medium	Test Medium		
	Photographic	Lithographic	Xerographic
Photographic	0.95	4.14	3.83
Lithographic	4.32	0.78	1.90
Xerographic	3.97	1.82	1.11

*Table 1: Self and Cross Test Calibration Errors for a typical scanner.*

Note that in Table 1, the off-diagonal entries are significantly larger than the diagonal entries, indicating that the scanner calibrations produce significantly larger errors across media than in a single medium.

In this paper, we hypothesize that the non-linear transformation schemes for a single medium perform well because these media are color reproductions with only three degrees of freedom in the input, corresponding to the three (subtractive) primaries used in the reproduction.

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This conjecture is experimentally tested using a four colorant (CMYK) printer. Typically, even though CMYK printers have four colorants, the amounts of these colorants are determined from virtual amounts of CMY through undercolor removal (UCR), thus yielding only three independent degrees of freedom. However, the fourth degree of freedom is re-introduced if the UCR method is allowed to vary. Therefore, the impact of different UCR methods on scanner calibration accuracy can be used to estimate the validity of the conjecture.

## Impact of UCR on Scanner Calibration

For all experiments described here, a UMAX 24-bit (30bit internal) color scanner was used. Calibration and test targets used were spectrally measured using a Gretag spectrophotometer and CIELAB values under CIE D50 standard illumination were computed from these measurements. For each calibration target chosen, the scanner was calibrated by scanning in the calibration target and training a Neural Network to map from scanner red, green, and blue (RGB) signals to CIELAB over corresponding uniform patches in the target. In all cases, the structure of the Neural Network was kept simple to prevent it from representing the noise in the data.

A xerographic printer was used to assess the impact of different UCR methods on scanner calibration accuracy. In the first experiment, two scanner calibration targets were generated by sampling the CMY cube on a 6x6x6 uniform grid and printing the resulting patches with two different UCR methods. The first method used 0% UCR, i.e., printed with only the CMY colorants and the second used a 100% UCR that replaces the minimum of CMY with K and subtracts the corresponding amounts from CMY. The two printed targets were then used to train two independent Neural Networks for scanner calibration. The resulting calibration transformation from the Neural Networks were then applied to the scanned data from both targets to obtain scanner (calibrated) CIELAB values. Thus for each Neural Network, two sets of Lab values were obtained: one corresponding to the target that was used in training the network (self-test) and the second corresponding to other target (cross-test). The self/cross test scanner CIELAB values were compared against the original measured values (for the corresponding targets) by computing CIELAB  $\Delta E_{ab}^*$  color differences. The results of these self and cross tests are shown in Table 2.

Calibration Target	Avg. $\Delta E_{ab}^*$ /Max. $\Delta E_{ab}^*$	
	Test Target	
	0% UCR	100% UCR
0% UCR	1.18/3.48	3.78/10.53
100% UCR	3.46/13.81	1.22/4.35

Table 2: Self and Cross Calibration Errors for the 0 and

## 100 percent UCR Targets generated by sampling CMY cube

Note that, just as in Table 1, the cross-calibration errors in Table 2 are significantly larger than the self-calibration errors. This suggests that if the scanner is color-calibrated for scanning prints from a given CMYK printer, the scanner calibration depends significantly on the UCR method used in the printer. Thus color-calibrated scans of prints could have large color errors if they used a different UCR strategy from that used in printing the calibration target. Also a single calibration will not be very accurate for scanning the output of a CMYK printer if the UCR strategy is allowed to vary. If we compare the magnitude of the numbers in Table 2 with those in Table 1, we can see that the cross-test errors are comparable. Thus the change in the UCR method could result in errors comparable to those encountered with change in the medium.

A further analysis of the data shows that as the amount of black (K) colorant or toner increases, the color differences due to cross scanner calibration increase. The results of such a comparison are shown in Table 3, where the results of Table 2 are partitioned into a number of different cases based on the amount of black (K) colorant used. It can be seen that for self calibration, the average errors remain around 1  $\Delta E_{ab}^*$  with increasing amounts of black colorant. But with the cross calibration, the average errors increase with increasing amount of black colorant. From this we can deduce that as the UCR is changed the amount of black changes thereby producing the difference in calibration. From Table 3, comparing only the average errors produced in the cross calibration, it can be seen that with 0 digital counts of black, these errors are of the same magnitude as self calibration errors, but with higher amounts of black the cross calibration errors increase significantly in relation to the self calibration errors.

Train/Test UCR	K Amount				
	0	43	51	86	100
0/0	1.15	0.98	1.17	0.95	1.39
100/100	1.28	1.20	1.05	0.98	1.31
0/100	1.31	2.65	5.78	5.19	7.77
100/0	1.52	2.47	4.22	4.08	7.33

Table 3: The average  $\Delta E_{ab}^*$  errors for all the four tests (self and cross calibration) for varying amounts of black colorant

The experiment described above began with a sampling of the device color space and considered the two extremes of UCR (0 and 100 percent). In order to have a more realistic estimate, the experiment was repeated with two changes. Instead of generating the calibration targets by sampling the CMY cube, the standard IT8.7 scanner calibration target was used and instead of the 100% UCR removal case we used a UCR strategy similar to lithographic printing that smoothly replaces CMY with K as one gets closer to neutral axis. The IT8.7 target was printed using the two different UCR methods and the self and cross tests were repeated. Once again, the calibration errors for the self and cross tests were determined in CIELAB  $\Delta E_{ab}^*$  units. These numbers are

tabulated in Table 4. The errors follow the same trend as those in Table 2, with the cross-tests yielding much higher errors than the self tests and the magnitudes of the numbers are consistent with Table 2.

Calibration Target	Avg. $\Delta E^*$ /Max. $\Delta E^*$	
	Test Target	
	0% UCR	Typical UCR
0% UCR	1.05/3.41	4.51/19.13
Typical UCR	3.92/11.53	1.16/2.93

Table 4: Self and Cross Calibration Errors for the 0 and typical UCR IT8.7 Targets

## Spectral Similarity Measure

Different input media require different calibration transformations because of their differing spectral characteristics. Hence, a quantitative measure of "spectral similarity" between different media is useful for assessing the differences between different media types and its potential impact on scanner metamerism. One such measure that has been proposed earlier is the correlation coefficient between spectra of the corresponding colorants<sup>3</sup>. Here, we extend this to a more general measure that directly measures the similarity of spectral data-sets, without requiring that the colorants be equal in number and of similar type. The mathematical development of such a measure is given in the appendix. In this section, we consider the use of such a measure in comparing different media and discuss its limitations.

To test the usefulness of the spectral similarity measure, the measure was computed for the targets used in generating Table 1. The resulting similarity measures are given in Table 5, in the same format as Table 1. Note that these spectral similarity measures are in good agreement with the average errors listed in Table 1. The spectral similarity measures suggest that the lithographic and xerographic test targets are most similar and among the two, the xerographic target is closer to the photographic than the lithographic. The same conclusions can be drawn from Table 1.

Medium I	Medium II		
	Photographic	Lithographic	Xerographic
Photographic	1.0000	0.9750	0.9820
Lithographic	0.9750	1.0000	0.9886
Xerographic	0.9820	0.9886	1.0000

Table 5: Spectral Similarity measures ( $\rho$ ) corresponding to Table 1.

Note that the spectral similarity measure considers the similarity of the complete spectral characteristics and therefore only hints at potential problems. For instance, for a completely colorimetric scanner, the errors in Table 1, would all be negligible with diagonal and off-diagonal terms

having similar magnitude. Nonetheless, the spectral similarity measure is useful in comparing different materials in the absence of any knowledge of the scanners spectral characteristics.

The similarity measure was also applied to the evaluation of similarity of reflectance spectra from targets using different UCR methods. The data from the first experiment of the last section was used. In order to observe any impact on the similarity of spectra with the introduction of black colorant, the data from the 100% UCR target was partitioned into separate sets based on the amount of black (K), just as in Table 3. The similarity  $\rho$  between the different spectral datasets corresponding to the third row of table 3, was then calculated. The resulting values of  $\rho$  were 0.9997, 0.9899, 0.9579, 0.9938, and 0.9814. While these values are not in perfect correlation with those in table 3, they are in rough agreement with those values and follow a similar trend.

## Conclusion

Since most present day scanners are non-colorimetric, one would inherently expect them to produce large color errors. That one does not get large color errors is due to the lack of "richness" of input, i.e., common scanner inputs have similar spectral characteristics. In the limiting case, when input is itself a color reproduction with only three independent degrees of freedom, extremely accurate calibration is feasible. However, such a calibration is sensitive to variation in the spectral characteristics of input materials.

In this paper, we demonstrate that a significant increase in scanner color-calibration error is possible if the input is not constrained to having only three degrees of freedom. The experiment focussed on using a four colorant CMYK printer for generating the scanner input and varying the method used for undercolor removal (UCR). The results indicate that if a scanner is calibrated for scanning prints from a CMYK printer, a simple change in the UCR method can lead to a substantial increase in calibration errors. Similar results can probably be anticipated for the scanning of output from hi-fi printers.

The paper also proposes a numerical measure for evaluating the spectral similarity of different media. The similarity measure is shown to have fair agreement with the cross-media calibration error for a typical (non-colorimetric) scanner. Note that the conclusions in this paper would not apply to a truly colorimetric scanner, which would have no dependency what-so-ever on the input medium.

## Appendix: A Spectral Similarity Measure

Let  $\mathbf{R}^1 = [\mathbf{r}_1^1, \mathbf{r}_2^1, \dots, \mathbf{r}_N^1]$  and  $\mathbf{R}^2 = [\mathbf{r}_1^2, \mathbf{r}_2^2, \dots, \mathbf{r}_N^2]$  represent data-sets of reflectance vectors (with the columns of these

matrices representing different color spectra). Let the SVD's of these matrices be given by,

$$\mathbf{R}^1 = \mathbf{U}_1 \Sigma_1 \mathbf{V}_1^T \text{ and } \mathbf{R}^2 = \mathbf{U}_2 \Sigma_2 \mathbf{V}_2^T,$$

where  $\mathbf{U}_1, \mathbf{U}_2, \mathbf{V}_1, \mathbf{V}_2$  are matrices with orthonormal columns and  $\Sigma_1$  and  $\Sigma_2$  are square diagonal matrices with their diagonal entries in decreasing order. Then the columns of  $\mathbf{U}_1$  represent an orthonormal basis set for the reflectances in  $\mathbf{R}^1$  with their relative energies in the diagonal elements of  $\Sigma_1$  and the columns of  $\mathbf{U}_2$  represent an orthonormal basis set for the reflectances in  $\mathbf{R}^2$  with their relative energies in the diagonal elements of  $\Sigma_2$ . The columns of  $\mathbf{U}_1$  are the "principal components" of  $\mathbf{R}^1$  in decreasing order of significance and the columns of  $\mathbf{U}_2$  are the "principal components" of  $\mathbf{R}^2$  in decreasing order of significance.

A similarity measure between the media may be defined by considering "how similar" the first few principal components are. Since the similarity of the media does not change drastically if their significant principal components are re-ordered the energy that is common between spaces spanned by the significant principal components is a

reasonable measure of the similarity. If  $\tilde{\mathbf{U}}_1$  and  $\tilde{\mathbf{U}}_2$  denote these significant principal components, the energy common to the sub-spaces spanned by them is

$\left\| \tilde{\mathbf{U}}_1^T \tilde{\mathbf{U}}_2 \right\|_F^2$ , where  $\|\bullet\|_F$  denotes the Frobenius norm.

The limitation of such a measure based on just the "significant" principal components is that the definition of what constitutes significant is arbitrary. A better alternative is to weight the energy according to the strength of the principal components and to use all principal components. Introducing this weighting, we get a measure of similarity

$$\left\| \Sigma_1^{(1/2)} (\mathbf{U}_1^T \mathbf{U}_2) \Sigma_2^{(1/2)} \right\|_F^2 = \left\| (\mathbf{U}_1 \Sigma_1^{(1/2)})^T (\mathbf{U}_2 \Sigma_2^{(1/2)}) \right\|_F^2$$

. Normalizing this appropriately, a measure of the similarity for spectral data sets can be obtained as

$$\rho = \frac{\left\| (\mathbf{U}_1 \Sigma_1^{(1/2)})^T (\mathbf{U}_2 \Sigma_2^{(1/2)}) \right\|_F^2}{\left\| \Sigma_1^{(1/2)} \Sigma_2^{(1/2)} \right\|_F^2}$$

It can be shown that the above measure is bounded between 0 and 1 with 1 indicating that the data-sets are close and 0 that they are very different (orthogonal)<sup>9</sup>.

## References

1. B.K.P. Horn, Exact Reproduction of Colored Images, *Comput. Vision Graphics and Image Processing*, **26**, 135-167 (1984).
2. G. Sharma and H. J. Trussell, Digital Color Imaging, *IEEE Trans. Image Proc.*, **6** (7), 901-932 (1997).
3. H. Haneishi, T. Hirao, A. Shimazu and Y. Miyake, Colorimetric Precision in Scanner Calibration Using Matrices, in *Proc. IS&T/SID 1995 Color Imaging Conf.*, 106-108.
4. P. G. Roetling, J. E. Stinehour, and M. S. Maltz, Color Characterization of a Scanner, in *Proc. IS&T 7<sup>th</sup> Intl. Congress on Non-impact Printing*, 443-451 (1991).
5. P. Hung, Colorimetric Calibration of Scanners and Media, in *Proc. SPIE Cameras and Input Scanner Systems*, vol. 1448, 164-174 (1991).
6. H. Kang, Color Scanner Calibration, *Jnl. of Imaging Sci. & Tech.*, **36** (2), 162-170 (1992).
7. H. Kang and P. G. Anderson, Neural Network Applications to the Color Scanner and Printer Calibrations, *Jnl. of Electronic Imaging*, **1** (2), 125-135 (1992).
8. M. Nier and M. E. Courtot, Ed., *Proc. SPIE Standards for Electronic Imaging Systems*, vol. CR37, 1991.
9. R. A. Horn and C. R. Johnson, *Topics in Matrix Analysis*, Cambridge Univ. Press, New York, (1991), pp. 183.