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Methods for Optimal Color Selection

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Abstract. *The color characterization of digital cameras often requires the use of standard charts containing a fixed number of color samples. The exact choice of such characterization charts—how many (and which) known samples to include—is known to affect characterization performance. This study describes methods to select optimum color samples from a set of 1269 Munsell surface colors. The effect of sample selection on characterization performance is evaluated and compared with performance using the standard GretagMacbeth ColorChecker and GretagMacbeth ColorChecker DC colors. The work confirms that the standard charts appear to have been well selected. However, we show that it is possible to select 24 samples from the Munsell set that outperform the GretagMacbeth ColorChecker and that this selection can be efficiently derived using an algorithm called* MAXMINC. *It is proposed that this algorithm may have general applicability; for example, to the optimal selection of samples constrained to be a subspace Munsell color solid.* © *2006 Society for Imaging Science and Technology.* [DOI: 10.2352/J.ImagingSci.Technol.(2006)50:5(481)]

INTRODUCTION

Digital cameras can, to some extent, be used as tristimulus colorimeters if they are properly characterized.[1–5] The characterization process involves developing a transform between the camera *RGB* values and CIE color coordinates. Often, a nonlinear transform between *RGB* and CIE *XYZ* is developed although some researchers have suggested that linear transforms are more appropriate.[6] Irrespective of whether a linear or a nonlinear transform is used, the coefficients of any characterization model are normally determined based upon the camera responses of some known samples that are conveniently arranged in a chart (e.g., the GretagMacbeth ColorChecker chart). This approach, where the coefficients of the transform are determined empirically to give optimal performance for a set of data, is sometimes referred to as data-based characterization. Other approaches to characterization are also possible; for example, an analytical approach which involves measuring—or estimating—the spectral sensitivities of the imaging device. A common practical consideration for any data-based characterization is the choice of the characterization target; that is, how many (and which) known samples to choose from which to construct the chart. The GretagMacbeth ColorChecker and GretagMacbeth ColorChecker DC charts are widely used as targets for color characterization tasks.[7–10]

Characterization charts such as the GretagMacbeth ColorChecker, the GretagMacbeth ColorChecker DC and the ANSI IT8 charts are designed to be used in a color-management process with the aim to allow a system to reproduce colors with acceptable tolerance. These charts are typically checkerboard array targets containing a number of carefully selected and prepared squares or chips in a wide range of achromatic and chromatic colors. Many of these square patches represent the color of certain natural objects of special interest, such as human skin, foliage, and blue sky.[11,12] Primary colors for both additive and subtractive color mixing are also commonly included. A series of achromatic patches in the characterization charts provide a convenient grayscale that may be used for color balance and tone-reproduction purposes. Repeated white, midgray, and black patches around the outer edge of the chart (GretagMacbeth ColorChecker DC, for example) allow measurements for spatial uniformity of illumination. Special colors, such as glossy surface colors in the GretagMacbeth ColorChecker DC and optional vendor colors in the ANSI IT8 charts, can also be included.

A great deal of work has been carried out to address which characterization method gives the best performance[3,13–16] and some work has been carried out to investigate which characterization target is optimum for the characterization process.[17,18] Recently, there has also been an interest in using these charts to determine the spectral sensitivity of imaging systems[13,19,20] and, in one study, an emissive chart has been developed for use with cameras that allows the user greater control over the color and spectral properties of the chart.[21] This study describes methods to select samples from a set of 1269 Munsell surface colors[22] specifically to optimize the colorimetric characterization of camera systems. The effect of sample selection on characterization performance is evaluated and compared with performance using the standard GretagMacbeth ColorChecker and GretagMacbeth ColorChecker DC charts.

Hardeberg proposed a method to select a set of samples of known reflectance that would be most suitable for spectral sensitivity estimation.[13] This work was concerned with the estimation of the spectral sensitivity of the *RGB* channels of a camera using samples whose spectral reflectance factors were known. The approach adopted by Hardeberg was to select spectra from a large set of Munsell samples such that each selected spectrum was as different as possible (in reflectance space) from the other already selected spectra. This optimal selection method was compared with a heuristic method (whereby samples with the highest chroma were

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selected for each hue) and with 20 samples from the GretagMacbeth ColorChecker. It was found that performance (in terms of accuracy of estimation of the camera spectral sensitivities) using 20 optimally selected spectra was almost as good as it was using the full set of 1269 Munsell spectra. The implication is that the 1269 Munsell spectra include a lot of redundancy and that the choice of samples used in the spectral estimation technique is important.

Although Hardeberg's work was concerned with spectral sensitivity estimation rather than with colorimetric characterization, it seems clear that the selection of samples for a color chart might also be expected to have a substantial effect on the usefulness of charts for camera characterization. In this work, methods for the selection of samples for a characterization chart have been considered; the general strategy that underlies all of the methods is to aim, as in Hardeberg's work, to select samples that are as different as possible from each other. However, this still allows for various strategies. For example, it is possible to develop algorithms that operate in the multidimensional space of spectral reflectance or in 3-dimensional colorimetric space. Algorithms that operate in both of these spaces are explored in this study.

EXPERIMENTAL

Two basic algorithms, called here MAXSUMS and MAXMINS, were developed and investigated. The algorithms define rules for selecting samples based on samples that are already selected but do not include a rule for selecting the first sample. One approach would be to select the first sample at random. However, in this study two candidates were considered for the first sample; either the sample with the greatest variance in its spectral reflectance factors or the sample with the minimum variance. It was hypothesized that the use of the sample with the greatest variance as the first sample (this being likely to be a highly chromatic sample) would subsequently lead to the greatest variance in the subsequently selected samples.

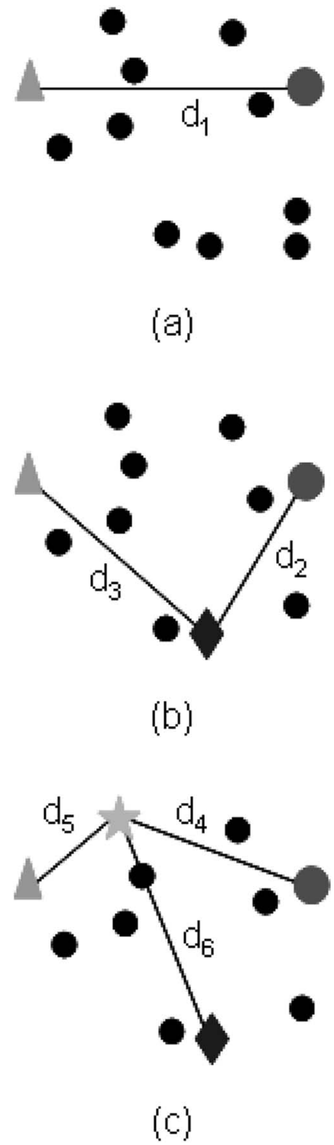

Figure 1. Illustration of the MAXSUMS method with the first selected sample (large circle) and (a) the second selected sample (triangle) chosen such that it is maximally distant from the first; (b) the third selected sample (diamond) chosen such that the sum of the distances ($\sqrt{d2}+\sqrt{d3}$) from the selected samples is maximum; and (c) the fourth selected sample (star) chosen such that the sum of the distances ($\sqrt{d4}+\sqrt{d5}+\sqrt{d6}$) from the selected samples is maximum.

In the MAXSUMS method, following the selection of the first sample, subsequent samples are selected in turn (without replacement) from the pool of samples such that each new sample selected is as different as possible from the samples already selected. Imagine that from a pool of N samples we have already selected m samples leaving N-m samples in the pool. The metric Q_j is computed for each of the N-m samples thus

$$Q_j = \sum_{i=1}^{m} \Delta D_{j,i}{}^{1/2}, \tag{1}$$

where $\Delta D_{j,i}$ represents the Euclidean distance (in 31-dimensional reflectance space) between the jth sample ($j \in \{1,2,\ldots,N\text{-}m\}$) in the pool and the ith sample ($i \in \{1,2,\ldots,m\}$) from those samples already selected. The sample that is selected is that for which Q_j is smallest (Fig. 1). The square-root exponent is included to penalize small spectral differences and the reason for this is evident from the following example: For the selection of the third sample, if one candidate has Euclidean distances of 2 and 6 from the two already selected samples and a second candidate has Euclidean distances of 3 and 5 from these samples, the second candidate would be selected (the sum of the Euclidean distances is the same but the sum of the square-roots of these distances is not).

In the MAXMINS method, following the selection of the first sample, subsequent samples are selected in turn (without replacement) from the pool of samples such that the Euclidean distance between its closest neighbor in the set of samples already selected is maximized. Again, imagine that from a pool of N samples we have already selected m

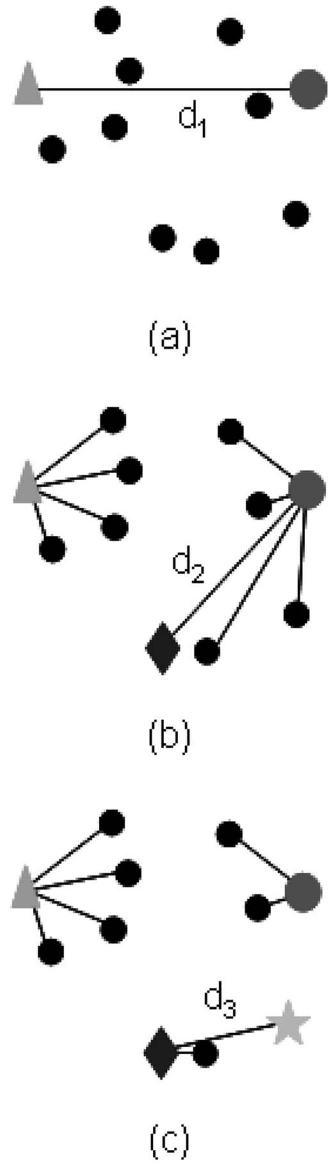

Figure 2. Illustration of the MAXMINS method with the first selected sample (large circle) and (a) the second selected sample (triangle) chosen such that it is maximally distant from its closest neighbor in the selected samples; (b) the third selected sample (diamond) chosen such it is maximally distant from its closest neighbor in the selected samples; and (c) the fourth selected sample (star).

samples leaving N-m samples in the pool. The metric P_j is computed for each of the N-m samples thus

$$P_j = \min_{i=1}^{j=1}\{\Delta D_{j,i}\}, \tag{2}$$

where, as before, $\Delta D_{j,i}$ represents the Euclidean distance (in 31-dimensional reflectance space) between the jth sample ($j \in \{1,2,\ldots,N\text{-}m\}$) in the pool and the ith sample ($i \in \{1,2,\ldots,m\}$) from those samples already selected. The sample that is selected is that for which P_j is largest (Fig. 2).

The main idea behind both methods is to generate a chart where the samples are as different to each other as possible. However, in the MAXSUMS method we find the sample that is on average as different as possible from the already selected samples in order to cover the largest color gamut; whereas in the MAXMINS method the sample whose closest neighbor (in the already selected samples) is as far away as possible is found.

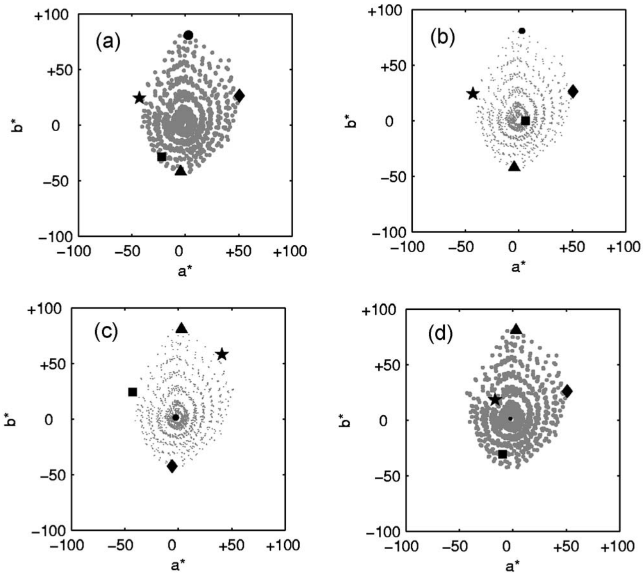

Figure 3. Diagrammatic representation of the selection sequence (in order, large circle, triangle, diamond, star, and square) for MAXSUMC [(a) and (c)] and MAXMINC [(b) and (d)] methods where the first sample was selected with greatest [(a) and (b)] or smallest [(c) and (d)] spectral variance.

The two methods, MAXSUMS and MAXMINS, were used to select samples that are maximally dissimilar from each other in 31-dimensional reflectance space. The same algorithms were also applied in 3-dimensional CIELAB space. To achieve this, the CIELAB coordinates of each of the samples were computed for illuminant D65 and for the CIE 1964 (10 deg) standard observer. The Euclidean distances in Equations (1) and (2) were computed in the 3-dimensional CIELAB space rather than in the 31-dimensional reflectance space. These two additional methods are referred to as MAXSUMC and MAXMINC where the final letter of the name denotes Euclidean distance is computed in colorimetric rather than spectral space. The rationale for this approach is that the selection of samples in the approximately visually uniform CIELAB space may give rise to samples that are better distributed than when the selection is carried out in reflectance space.

The samples were selected from a set of 1269 Munsell samples.[22] Figure 3 illustrates how the two main types of algorithm operate using the selection in colorimetric space as an example.

The subfigures in the upper row of Fig. 3 show that for both methods the selection of the first sample (in this case, the sample with greatest spectral variance represented by the large red circle) is, of course, the same. The selection of the second (triangle), third (diamond), and fourth (star) is also the same for both methods. However, the fifth and subsequent samples are selected differently depending upon the method. The MAXSUMC method continues to select samples that are highly chromatic whereas the fifth sample (square) for the MAXMINC method is a very unsaturated sample that is not close to any one of the already selected samples. The subfigures in the lower row of Fig. 3 show the selection of samples where the first sample was selected on the basis of the least spectral variance. Note that, given that the selection of the first sample is the same, the two methods are guaranteed to produce the same second sample.

For comparison, a "straw man" method was also adopted whereby 24 samples were randomly selected from the set of 1269 Munsell samples. This random method was repeated ten times, with a different randomly selected set of 24 spectra each time. The performance of the random set that performs best is said to be the "best random" result. Similarly, the performance of the random set that performs worst is said to be the "worst random" result. The average performance of the ten randomly chosen sets is referred to as the "average random" performance the significance of which is that it is an estimate of the performance that would be obtained if a random-selection method was used. Finally, the performance of all methods was also compared with the performance of the 24 samples from the GretagMacbeth ColorChecker chart.

In order to assess performance, the 24 colors selected by each of the methods were used to construct virtual characterization charts. A linear camera model [Eq. (3)] with known camera channel sensitivities and a known illuminant was used to compute the camera RGB values for each of the samples in the virtual charts, thus

$$R = \sum E(\lambda) S_R(\lambda) P(\lambda),$$

$$G = \sum E(\lambda) S_G(\lambda) P(\lambda),$$

$$B = \sum E(\lambda) S_B(\lambda) P(\lambda), \tag{3}$$

where $E(\lambda)$ is the spectral power distribution of the D65 illuminant, $S_R(\lambda)$, $S_G(\lambda)$, and $S_B(\lambda)$ are channel spectral sensitivities of the camera system, and $P(\lambda)$ is the spectral reflectance of the sample. The spectral sensitivities of the camera were those estimated for the Agfa StudioCam camera system (Fig. 4) and were approximately Gaussian-shaped functions with peak sensitivities at 460, 540, and 630 nm.[23]

The coefficients of a nonlinear transform were determined to provide the least-square mapping between sample camera responses RGB and tristimulus values XYZ. Equation (4) shows an example of a set of polynomial transforms

$$X = a + bR + cG + dB + eR^2 + fG^2 + gB^2 + hRGB,$$

$$Y = i + jR + kG + lB + mR^2 + nG^2 + oB^2 + pRGB,$$

$$Z = q + rR + sG + tB + uR^2 + vG^2 + wB^2 + xRGB. \tag{4}$$

A more efficient representation is provided by Eq. (5),

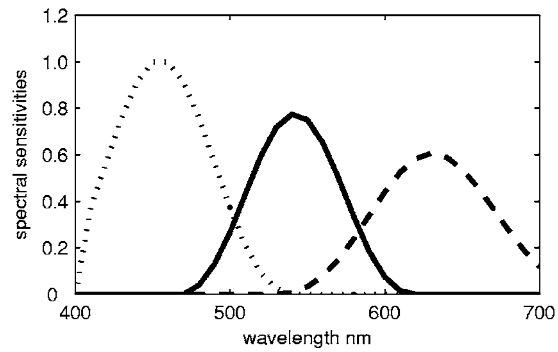

Figure 4. Estimated camera spectral sensitivities (blue channel, dotted line; green channel, solid line; red channel, dashed line) of an Agfa StudioCam: estimation by Chen *et al.* (see Ref. 23).

$$\mathbf{t} = \mathbf{M}\mathbf{r}, \tag{5}$$

where $\mathbf{t}$ is a 3×1 matrix of tristimulus values, $\mathbf{M}$ is a 3×8 system matrix, and $\mathbf{r}$ is a 8×1 matrix of augmented camera responses containing the terms $[1\ R\ G\ B\ R^2\ G^2\ B^2\ RGB]$. A third-order transform was actually used in this study. The choice of transform was somewhat arbitrary but a third-order transform was used because it has been found to be effective in some other studies.[13,24,25] The specific 3×20 third-order transform that was used included the following terms:

$$[R\ G\ B\ RG\ RB\ GB\ R^2\ G^2\ B^2\ RGB\ R^2G\ R^2B\ G^2R\ G^2B\ B^2R\ B^2G\ R^3\ G^3\ B^3\ 1],$$

to provide a mapping from RGB to XYZ.

The 24 samples selected using each of the methods were used as training sets to determine the coefficients of the transform and then characterization performance was evaluated for three test sets: 1269 Munsell samples, 50 selected Natural Color System samples and 494 natural surfaces[26] including leaves, petals, grasses, and barks. Figure 5 illustrates the CIELAB L^*, a^*, and b^* distributions of the test sets. The 24 samples were always selected from the 1269 Munsell set and the use of the 1269 Munsell set alone to test the performance of our charts may introduce a bias. It is for this reason that we also used a set of samples from the Natural Color System and a set of natural spectra as test sets.

Performance of the methods was assessed in terms of CIELAB color difference between the actual XYZ values and the XYZ values predicted from the camera responses by the third-order transform.

RESULTS

Tables I–III show the CIELAB color differences (illuminant D65, 1964 CIE observer) that were obtained using the various testing sets. It is evident that the test performance of the best random selection is quite good. This is not unexpected (because as the number of repeats increases the best random selection will tend towards the optimum selection) but, of course, the average random selection performs poorly compared with the GretagMacbeth ColorChecker.

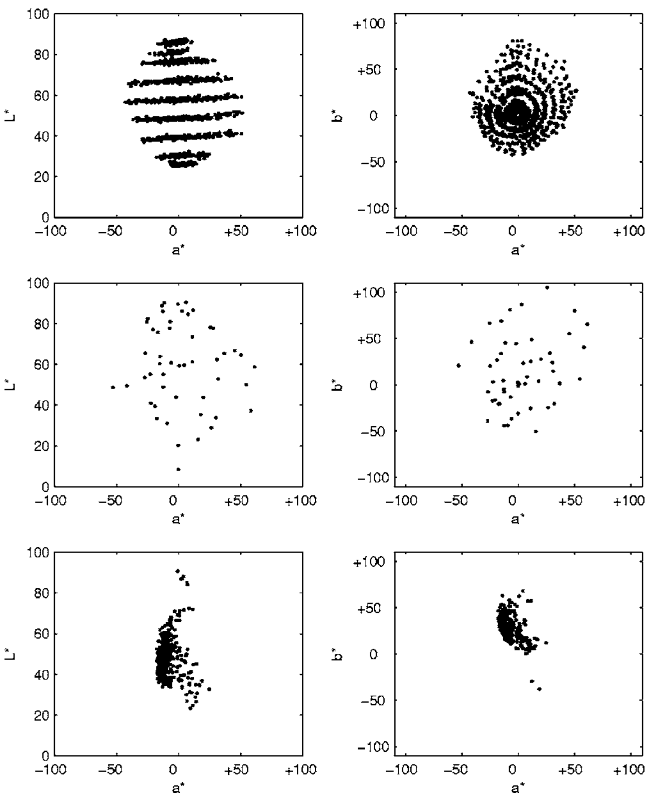

Figure 5. CIELAB coordinates under illuminant D65 of 1269 Munsell (top), 50 selected Natural Color System (middle), and 494 natural (bottom) samples plotted in L^* vs a^* (left) and b^* vs a^* (right) diagrams.

Table I. Testing performance (3×20 polynomial transform) on 1269 Munsell samples using different methods (the figures shown in parentheses are for the case where the first sample was selected with minimal spectral variance).

	CIELAB color difference			
Methods	Median	Mean	Min	Max
GretagMacbeth ColorChecker	2.64	3.15	0.09	15.60
MAXSUMS	2.31(2.90)	5.26(5.36)	0.03(0.05)	44.75(40.16)
MAXMINS	5.21(2.51)	5.73(3.09)	0.07(0.07)	57.57(24.13)
MAXSUMC	7.70(4.89)	11.25(6.49)	0.04(0.01)	45.05(34.27)
MAXMINC	1.62(1.70)	2.04(2.17)	0.02(0.04)	12.79(13.38)
Best random	2.01	3.51	0.03	22.69
Worst random	3.08	5.86	0.00	103.08
Average random	2.92	5.44	0.01	88.09

The results indicate that the selection of samples using the spectral methods (MAXSUMS and MAXMINS) generally give poor characterization performance. The MAXSUMS method gave median ΔE values of 2.31 (2.90), 4.34 (9.15), and 7.54 (10.57) for the 1269 Munsell samples, the 50 Natural Color System samples, and the 494 natural samples, respectively, where the values in parentheses refer to the case where the first sample was selected with minimal spectral variance. The MAXMINS method was no better with median ΔE values of 5.21 (2.51), 6.93 (4.66), and 7.59 (3.50). The transform derived from the GretagMacbeth ColorChecker was statistically better than both spectral methods for all three testing sets ($p<0.05$).

Table II. Testing performance (3×20 polynomial transform) on 50 Natural Color System samples using methods (the figures shown in parentheses are for the case where the first sample was selected with minimal spectral variance).

	CIELAB color difference			
Methods	Median	Mean	Min	Max
GretagMacbeth ColorChecker	5.10	6.79	0.40	35.94
MAXSUMS	4.34(9.15)	11.63(20.47)	0.24(0.18)	58.97(81.60)
MAXMINS	6.93(4.66)	13.26(9.73)	0.66(0.81)	155.80(113.75)
MAXSUMC	10.69(7.38)	15.39(12.65)	1.63(0.81)	148.62(65.32)
MAXMINC	4.93(4.61)	7.42(9.88)	0.20(0.54)	37.03(61.22)
Best random	7.88	14.56	0.45	80.20
Worst random	14.16	33.47	0.58	211.97
Average random	13.17	30.63	0.05	150.78

Table III. Testing performance (3×20 polynomial transform) on 494 natural samples using different methods (the figures shown in parentheses are for the case where the first sample was selected with minimal spectral variance).

	CIELAB color difference			
Methods	Median	Mean	Min	Max
GretagMacbeth ColorChecker	2.31	3.20	0.12	14.24
MAXSUMS	7.54(10.57)	8.08(11.57)	0.03(0.20)	39.15(40.67)
MAXMINS	7.59(3.50)	12.62(5.07)	0.40(0.13)	74.31(24.55)
MAXSUMC	7.91(3.00)	11.20(12.07)	0.54(1.55)	54.25(36.35)
MAXMINC	1.17(2.16)	1.56(2.28)	0.08(0.11)	7.78(10.16)
Best random	2.28	3.13	0.18	15.68
Worst random	4.61	5.31	0.38	123.06
Average random	4.29	5.74	0.15	37.04

The MAXSUMC method gave median color difference values of 7.70 (4.89), 10.69 (7.38), and 7.91 (1.17) for the 1269 Munsell samples, the 50 Natural Color System samples, and the 494 natural samples, respectively, and was consid-

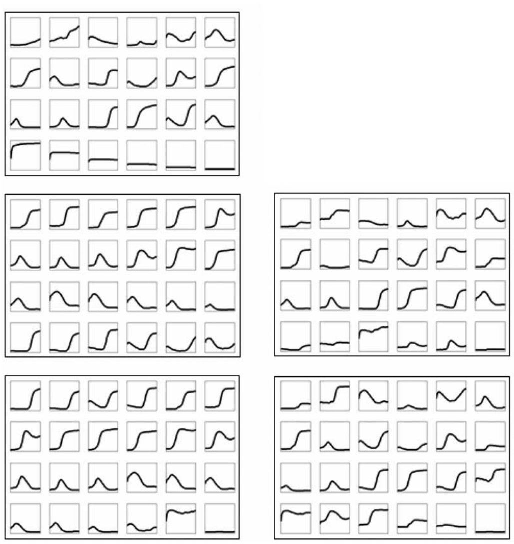

Figure 6. Spectral reflectance curve vs wavelength (400–700 nm) plots of the GretagMacbeth ColorChecker (first row), the MAXSUMC-selected (left) and MAXMINC-selected (right) charts where the first sample was selected with maximum spectral variance (second row), and the MAXSUMC-selected (left) and MAXMINC-selected (right) charts where the first sample was selected with minimal spectral variance (third row).

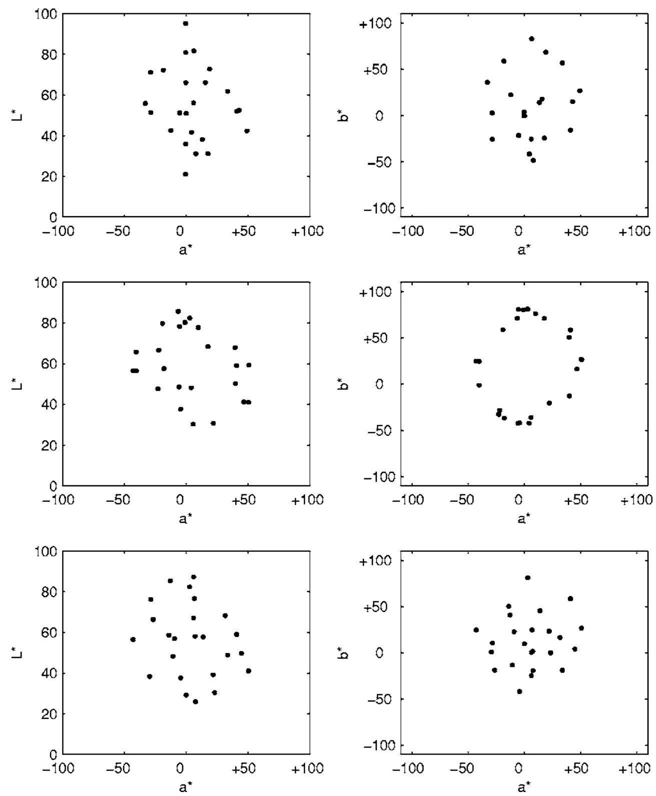

Figure 7. CIELAB coordinates under illuminant D65 of the 24 ColorChecker (first row), MAXSUMC (second row), and MAXMINC (third row) samples (for the case where the first sample was selected with maximal spectral variance) plotted in L^* vs a^* (left) and b^* vs a^* (right) diagrams.

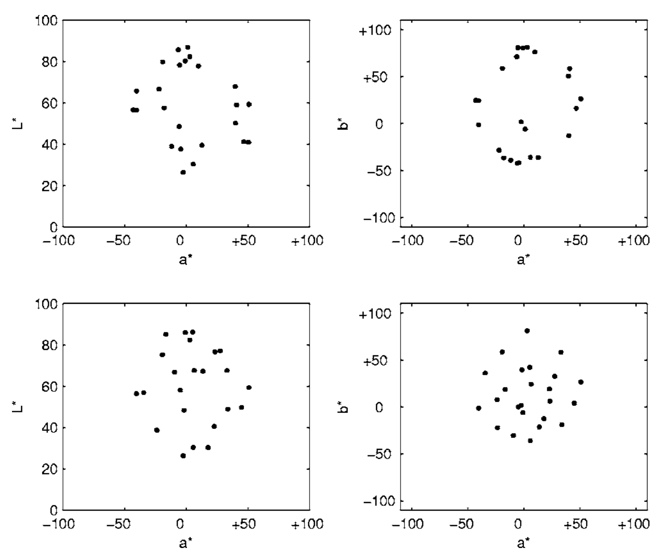

Figure 8. CIELAB coordinates under illuminant D65 of the 24 MAXSUMC (upper row) and MAXMINC (bottom row) samples (for the case where the first sample was selected with minimal spectral variance) plotted in L^* vs a^* (left) and b^* vs a^* (right) diagrams.

ered to be the worst method. In Hardeberg's work the heuristic method of selecting samples of high chroma also performed quite poorly.[13] However, the best performance came from the MAXMINC method (with first sample selected with maximum spectral variance) with median color difference values of 1.62 (1.70), 4.93 (4.61), and 1.17 (2.16). The results also show that the MAXMINC method generally is more robust to the choice of the first sample than the other methods. The MAXMINC scores were statistically identical to those from the GretagMacbeth ColorChecker for the Natural Color System testing set ($p > 0.10$) but performed significantly better than the GretagMacbeth ColorChecker using the larger Munsell ($p < 0.05$) and natural samples ($p < 0.05$) testing sets. (In order to test the robustness of the results we replicated the entire experiment using the CIEDE2000 color-difference formula to assess the performance of the various algorithms since there are some known problems with the CIELAB formula. Although, on average, the use of the CIEDE2000 formula generated smaller color difference values, the relative performances of the algorithms remained broadly the same and supported the same conclusions as those reached using the CIELAB formula.)

Figure 6 illustrates the spectral reflectance curves (between 400 and 700 nm) for the colors of selections.

Figures 7 and 8 illustrate the CIELAB L^*, a^*, and b^* distributions of the 24 colors of GretagMacbeth ColorChecker, and those selected using MAXSUMC and MAXMINC methods.

Since the MAXMINC method appeared to be successful in designing a color chart for characterization a further test was conducted by using this method to select 166 samples and comparing the performance of camera characterization using this chart with the performance obtained using 166 samples from the GretagMacbeth ColorChecker DC chart. (The full chart contains 240 samples but this collection excludes the repeated grayscale colors and those having very glossy surfaces.). Tables IV–VI summarize the performance

Table IV. Testing performance (3×20 polynomial transform) on 1269 Munsell samples using different methods (the figures shown in parentheses are for the case where the first sample was selected with minimal spectral variance).

	CIELAB color difference			
Methods	Median	Mean	Min	Max
GretagMacbeth ColorChecker DC	1.21	1.53	0.08	8.54
MAXMINC	1.11(1.14)	1.39(1.42)	0.04(0.09)	8.52(9.25)

Table V. Testing performance (3×20 polynomial transform) on 50 Natural Color System samples using different methods (the figures shown in parentheses are for the case where the first sample was selected with minimal spectral variance).

	CIELAB color difference			
Methods	Median	Mean	Min	Max
GretagMacbeth ColorChecker DC	1.72	2.81	0.03	17.13
MAXMINC	2.04(2.21)	3.71(4.30)	0.26(0.22)	21.78(22.14)

of the MAXMINC method against the 166 samples from the GretagMacbeth ColorChecker DC chart.

The GretagMacbeth ColorChecker DC chart samples gave statistically better performance ($p<0.05$) using the 50 Natural Color System testing samples but the opposite results were found using the other two testing sets where the MAXMINC method performed better ($p<0.05$). The MATLAB function *maxminc* presents the implementation of the MAXMINC algorithm. (Appendix available as Supplemental Material on the IS&T website, www.imaging.org).

DISCUSSION

One of the findings from this work is that the original samples of the GretagMacbeth ColorChecker chart appear to have been well selected and it is not easy to find an equivalent number of samples from the pool of samples that was used in this work that will give substantially better performance. However, the finding that 24 samples from the Munsell set can be selected, using the MAXMINC method, to provide a color chart that outperforms the GretagMacbeth ColorChecker chart is interesting. It is important to note, however, that six of the samples in the GretagMacbeth ColorChecker chart are achromatic to enable linearization of the imaging device whereas our new method was not subject to this constraint. The intended application of this work, however, was not to explicitly design a new 24-patch GretagMacbeth ColorChecker chart. Comparison with the GretagMacbeth Colorchecker was only carried out as a useful benchmark of performance to demonstrate that the method works. Charts such as the GretagMacbeth ColorChecker are intended for general use. For many applications it is useful to characterize a camera that is very accurate in some parts

Table VI. Testing performance (3×20 polynomial transform) on 494 Natural samples using different methods (the figures shown in parentheses are for the case where the first sample was selected with minimal spectral variance).

	CIELAB color difference			
Methods	Median	Mean	Min	Max
GretagMacbeth ColorChecker DC	2.20	2.43	0.10	7.73
MAXMINC	1.57(1.86)	1.69(2.01)	0.26(0.19)	5.21(5.94)

of color space and less so in other parts that are less relevant. For example, if we wish to develop a camera system to measure the color of bananas or teeth it would be sensible to select a characterization set containing many yellow or white samples respectively.[27,28] The new method, MAXMINC, would allow an optimum selection of a fixed number of chips from a set of samples in one particular part of color space.

Not only does the MAXMINC method perform better than the GretagMacbeth ColorChecker but it also performs better than the GretagMacbeth ColorChecker DC chart for two out of three test sets. The fact that the GretagMacbeth ColorChecker DC performs better for the small set of Natural Color System chips may indicate that the evaluation of characterization charts (and even the evaluation of characterization methods) may require substantially larger test sets if robust and meaningful results are to be obtained. However, some further work is required before it is possible to conclude without doubt that the improvement in performance afforded by the samples selected using the MAXMINC method are real and of practical interest. This work has been carried out using a virtual camera system that was both linear and noiseless. Further experiments with more sophisticated cameras models—or even with real camera systems—are required. Although the use of a different characterization transform (such as a second-order polynomial or a linear transform) would likely have given different characterization results we believe that it is likely that the relative performances of the various algorithms tested here would have remained unchanged but it would be interesting to confirm this experimentally.

Note, however, that in this study the selection methods were all used to select from a relatively small number of Munsell reflectances. It may be that better performance can be obtained if the number of samples from which the methods select is increased and, more importantly, if the gamut of these samples is increased. There are many numerical ways to simulate spectral reflectances.[29,30] One possible approach is to use a linear model of basis functions rather than a limited pool of samples so that the characterization charts could contain samples that are highly saturated and yet are physically reproducible. Such linear models are efficient but are derived from the statistical properties of reflectance data sets so that consequently the representation of a spectrum in the model does not provide any explicit information about the physical processes involving the causes of the reflectance spectrum. Linear models have other drawbacks[24,31] such as the existence of metamers and the possibility that certain generated spectra would be unreasonable (with reflectance factors that are negative, for example).

Alternatively, a physical (rather than statistical) model of reflectance spectra, based on the fact that the colors themselves are derived from a variety of physical and chemical properties[32–34] can be considered, and this model could be used to generate synthetic, but physically reasonable, spectra. Gaussian distributions, for example, can be considered as a preliminary framework to model the absorbance properties of objects since they closely approximate the physical processes involved in electronic transition absorptions.[35,36] Each absorption process can be represented by three parameters (amplitude, bandwidth, and the location of the peak wavelength of the Gaussian distributions). The absorption profile of a sample can be considered to be the linear sum of a small number of individual absorption processes.[37]

In summary, a color selection algorithm MAXMINC has been introduced that can be used to select samples for a color characterization chart. In this study, the algorithm was used to select 24 samples from a large set of Munsell samples and our computational modeling was used to show that the characterization performance of a chart constructed from these 24 samples outperformed the GretagMacbeth ColorChecker. The idea of the MAXMINC algorithm is to select samples that are as different (in CIELAB space) to each other as possible, and the sample whose closest neighbor (in the already selected samples) is as far away as possible is found. It is proposed that this algorithm may have general applicability; for example, to the optimal selection of samples constrained to be a subspace Munsell color solid.

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