Representative Data Selection for Standard Object Colour Spectra Database (SOCS)

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Abstract

'Standard Object Colour Spectra Database for Colour Reproduction Evaluation (SOCS)', which contains about 50,000 object color reflectances/transmittances, was published as a Japanese Industrial Standard Technical Report (JIS-TR) in 19981. To promote, widen and standardize usage of SOCS, we selected representative data sets, including both typical sets and difference sets. Typical set samples have average characteristics of whole data in an object group, and difference set samples have metameric characteristics to corresponding typical set samples, respectively. This paper describes concepts, purposes and algorithms by which they were selected from many spectral data samples.

A total of 365 representative data samples (235 samples for typical sets and 130 samples for difference sets) were selected and evaluated to determine whether they meet the purposes for the sets. An experiment verified that they are very useful in the following applications.

(a) Determination of simple color correction matrix using typical sets.
(b) Easy evaluation of color reproduction quality for color sensors by a combinatorial use of typical and difference sets.

ISO/TC130/WG2 is discussing SOCS as a new ISO technical report. The above-mentioned representative data sets will be the principal part of the technical report.

Introduction

'Standard Object Colour Spectra Database for Colour Reproduction Evaluation (SOCS)' was prepared and published as a Japanese Industrial Standard Technical Report (JIS-TR) in 19981. SOCS includes 49,672 object spectral reflectance/transmittance data, which were classified according to object categories. After the publication, data for other categories were added, and the current number of collected data is summarized in Table 1. Each data is 31-dimensional spectral reflectance or transmittance.

Though they are very valuable data even in the current form, the number of data is very large, and their distribution is biased toward some categories. Though many data are desirable to statistically evaluate the quality of color image input devices, careful data arrangement is necessary for meaningful use, and a smaller data set for easily evaluating the quality of color image input devices was hoped. We therefore decided to select only several hundreds of representative spectral data for use instead of the full data set. This paper describes the selection procedure and usefulness of the selected data. The selected data will be the principal part of an ISO technical report to be published in the near future.

Table 1. Number of Spectral Data Collected for SOCS.

Category	No. of sub-categories	No. of colors
Photographic materials (Transparencies/Reflection prints):	8	2,304
Graphic printing (Offset/Gravure)	33	30,624
Color computer printers	21	7,856
Paint (for exterior/interior objects)		336
Paints (for art)	4	229
Textiles	6	2,832
Flowers		148
Leaves		92
Human skin		8,570
Krinov data (natural objects)		370
Total		53,361

Typical Sets and Difference Sets

Color device developers can simulate color reproduction of image input devices using SOCS, when they have knowledge on spectral properties of optical components used in the device. Such simulation has two important roles.

(a) To ascertain necessary color correction for input color values.
(b) To analyze residual errors which remain even after the above color correction is applied.

As a typical example of color correction, a linear model is assumed in this paper. In the model, equation (1) is applied to obtain optimal tristimulus values X, Y and Z from sensor outputs R, G and B, where the matrix elements a_{ij}'s are determined so that the sum of squared error is minimized. Eq. (2) shows an example for determining a_{21}, a_{22} and a_{23}.

$$\begin{pmatrix} X \\ Y \\ Z \end{pmatrix} = \begin{pmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{pmatrix} \begin{pmatrix} R \\ G \\ B \end{pmatrix} \equiv A \cdot \begin{pmatrix} R \\ G \\ B \end{pmatrix} \tag{1}$$

$$E_y = \sum_{n=1}^{N} \left(Y_{0n} - a_{21} R_n - a_{22} G_n - a_{23} B_n\right)^2 \tag{2}$$

where $a_{21} + a_{22} + a_{23} = 1$.

If a small number of data can be used for this minimization instead of whole data, the data set can be considered as a 'typical set' for the whole data. The typical set is one of the representative data sets. In practical applications, color difference in a uniform color space is often minimized, and such minimization may be applied for this typical set evaluation. However, as the objective of this work is to evaluate whether the typical data set has a characteristic similar to that of whole data set, and it is not important to obtain the best correction matrix, we used the simple linear model. The differences in this linear space also relates to differences in the spectral space, which is described in the next section.

Metamers are a set of colors which look the same under an illumination condition, but have different spectral reflectances. If a set of colors sensors satisfies the Luther condition, sensor outputs for all metamers are equal. If the sensor spectral sensitivity does not satisfy the Luther condition and the quality of the sensors is low, they may look different even under the same illumination condition. Hence, output signal variation for metamers should be analyzed for quality evaluation. Though we can imagine an infinite variety of spectral reflectances, it is pointless to evaluate sensor outputs for extremely complicated metamers that do not exist in the real world; i.e., evaluation should be made based on real metamers. For the evaluation, we selected a difference set in which a member's color is very similar to that of a typical set member, but whose member's spectral characteristic is maximally different from that of a typical set member. The difference set is the other representative data set.

Data were selected for both typical and difference sets. Table 2 shows data groups and numbers of spectral data in each group in these sets. For every group, a typical set was selected. Difference sets were selected mainly from artificial color groups.

Typical Set Selection

Artificial Color Groups

Printers usually reproduce many colors, mixing three or four primary inks. Groups such as printers are called 'artificial color groups' in this paper. For each group, a typical device was determined, and three achromatic colors and twelve chromatic colors produced by the device were selected in predetermined hue directions.

Table 2. Numbers of Data Selected for Typical Sets and Difference Sets.

	Groups	Typical sets	Difference sets
Artificial Colour Groups	Photo (transparency)	15	15
	Photo (reflection print)	15	15
	Offset prints	15	15
	Dye sublimation printer	15	15
	Electrostatic printer	15	15
	Ink-jet printer	15	15
	Textiles (synthetic dyes)	15	15
Natural Colour Groups	Flowers/grasses/leaves (incl. Krinov's grasses and leaves)	25	25
	Paint (not for art)	15	-
	Oil paints	15	-
	Water colours	15	-
	Textiles (plant)	15	-
	Non-grass/leaf Krinov	15	-
	Bare North Asian skin	5	-
	FD-applied North Asian skin	5	-
	Bare South Asian skin	5	-
	FD-applied South Asian skin	5	-
	Bare Caucasian skin	5	-
	Bare Negroid skin	5	-
Total		**365**	

As the first step, fifteen basic colors whose L*a*b* values under the D65 illuminant were determined (Table 3). We determined twelve chromatic colors from the common color gamut of seven artificial color groups, regularly sampling hue angles.

Next, a typical device is defined in a group. The typical device is the device that has average properties among multiple devices in the group. Typical set samples are extracted from the typical device.

It is known that the optimal color correction matrix A_{opt} is equal to the product of the color matching function matrix χ and a spectrum restoration matrix (Eq.(3)), when color correction is carried out based on Eq.(1).[2]

$$A_{opt} = \chi^t \cdot S^- \quad \text{where} \quad \chi = (\bar{x}\ \bar{y}\ \bar{z}) \ \text{and} \ S^- = K_{\beta R} K_{RR}^{-1}. \tag{3}$$

K_{β_R}: mutual correlation matrix between spectral reflectance/transmittance and R, G and B.
K_{RR}: auto-correlation matrix relevant to R, G and B.

If there are N devices, N matrices (A_1, $\cdots$, A_N) are obtained based on $(S_1^-, \cdots, S_N^-)$, respectively. It is obvious that S_k^- would be the optimal spectrum restoration matrix for spectra of colors that are output from the k-th device. However, the matrix is not necessarily appropriate for restoring spectra of colors that are output from other devices. The typical device *kt* is defined so that spectral reflectances in the group can be restored with the least squared errors, when $S_{k_t}^-$ is applied.

A sample that shows the nearest L*, a* and b* values to a basic color among the typical device outputs under D65 illuminant, is selected as a member of the typical set.

Table 3. Fifteen Basic Colors.

	L*	H*	C*
1	20	-	0
2	50	-	0
3	80	-	0
4	40	0	30
5	45	30	35
6	50	60	37
7	60	90	45
8	60	120	30
9	45	150	30
10	45	180	23
11	45	210	22
12	45	240	20
13	40	270	20
14	35	300	27
15	40	330	30

Skin Color Groups

It is known that variations in skin color mainly depend on melanin and hemoglobin quantities.[3,4] As an example, Table 4 shows the principal component analysis result for North-Asian skin color distribution in the L*a*b* space under D65. In most groups, the first principal component lies in the white – black (brown) direction, and the second lies in the yellow – blue or green – magenta direction. The former seems to correspond to the melanin quantity, and the latter seems to correspond to the hemoglobin quantity. The distribution is shown in Fig. 1. Based on the distribution, five typical set samples C0, C1, $\cdots$, C4 were selected by the following procedure.

Table 4. North-Asian Skin Color Distribution Under D65

	Mean	1st principal component	2nd principal component	3rd principal component
L*	64.7	0.895	0.017	0.445
a*	10.1	-0.353	-0.584	0.731
b*	18.7	-0.273	0.812	0.516
Variance		13.97	5.71	1.31

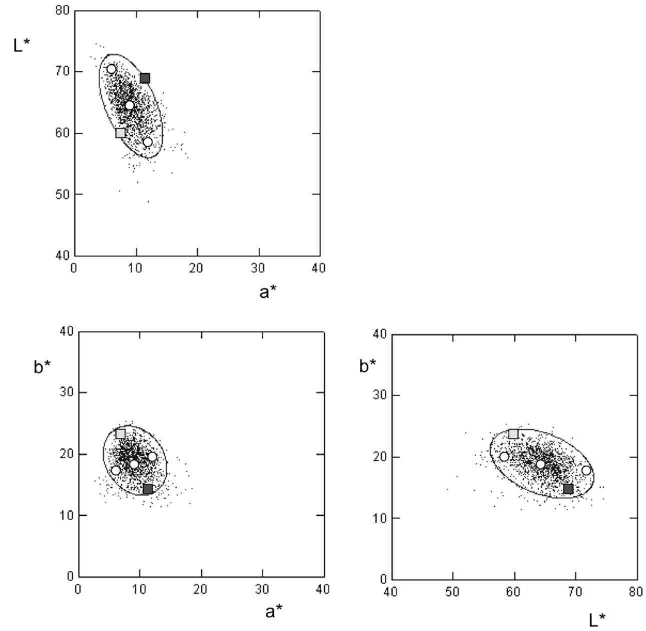


Figure 1. North-Asian skin color distribution.

(a) The mean color:

$$C_0 = \begin{pmatrix} \overline{L} * \\ \overline{a} * \\ \overline{b} * \end{pmatrix} \tag{4}$$

(b) Two extreme colors along the first principal axis.

$$\begin{aligned} C_1 &= C_0 + 2\sigma_1 \cdot \lambda_1 \\ C_2 &= C_0 + 2\sigma_1 \cdot \lambda \end{aligned} \tag{5}$$

(c) Two colors which lie in the perpendicular direction to C_1 and C_2 on the chromaticity plane with respect to the mean color, and have lightness differences with respect to other selected colors.

$$\begin{aligned} C_3 &= C_0 - (2\sigma_2 \cdot \lambda_2 - 2\sigma_3 \cdot \lambda_3) + \sigma_1 \cdot \lambda_1 \\ C_4 &= C_0 - (2\sigma_2 \cdot \lambda_2 - 2\sigma_3 \cdot \lambda_3) - \sigma_1 \cdot \lambda_1 \end{aligned} \tag{6}$$

Natural Color Groups

It is difficult to select typical color samples in natural color groups, since colors are not distributed in all hues and there are no rules for the distribution. Hence, we selected typical samples from the viewpoint that the data are distributed in the spectral vector space. Each sample data is a 31-dimensional vector, whose components are spectral reflectance values at 400nm, 410nm, …, 700nm. We assume a regular 31-dimensional hyper-cubic lattice. Each data sample is contained in a hyper-cube. In this situation, we can count hyper-cubes that contain one or more data samples. If we would like 15 typical samples, the hyper-lattice is resized so that exactly 15 hyper-cubes contain all data samples. This process is depicted in Fig. 2, where a two-dimensional vector space is used for simplicity, and eight hyper-cubes contain sample data. If multiple data samples are contained in a hyper-cube, the sample nearest to the cube center is selected as a typical set sample.

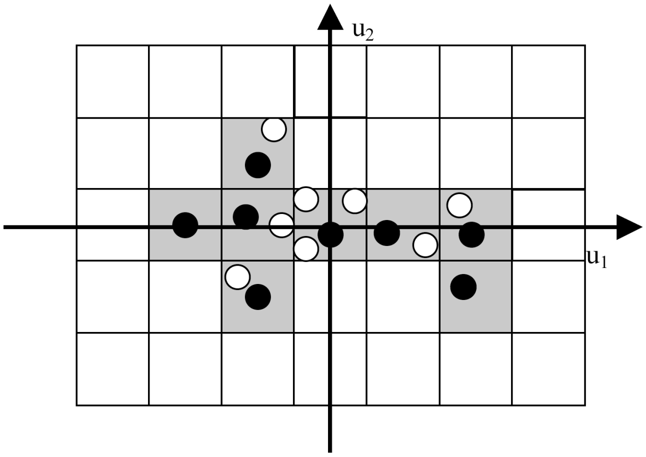


Figure 2. Typical sample selection for natural color groups.

Difference Set Selection

We wish to obtain a metamer corresponding to each typical sample as a difference set sample. However, as it is selected from measured spectral data in SOCS, no data sample can be found which has exactly the same L*, a* and b* values as the typical sample under, say, D65. Hence, we adopt data samples whose color differences from the typical sample are less than 5, with a small number of exceptions. Difference set samples are, therefore, pseudo-metamers. Selection steps are as follows.

(a) Data samples whose color differences from the typical sample are less than 5 are extracted in the L*a*b* space.

(b) A data sample i whose spectral difference *D* (Eq.(7)) from the typical sample is largest is selected as a difference set sample.

$$D = \sqrt{\sum_{\lambda=400}^{700} (\beta_{i\lambda} - \beta_{t\lambda})^2} \tag{7}$$

where $\beta_{i\lambda}$ is spectral reflectance/transmittance at a wavelength ë of the i-th data sample, and $\beta_{t\lambda}$ is that of the typical data sample.

Evaluation of Selected Representative Colors

We evaluated the selected representative spectral data sets, based on the linear color correction model described in Eq.(1). Though non-linear color correction is often applied in practical cases, it is hard to select one typical method. In addition, a typical set or a difference set includes only about 15 samples, and more samples are required for non-linear correction in many cases. It is well known that linear color correction is sufficient in many practical cases, too.

Color reproduction error in a color image input device is calculated by Eq.(8), after X, Y and Z values are obtained from sensed R, G and B values using the linear color correction (Eq.(1)).

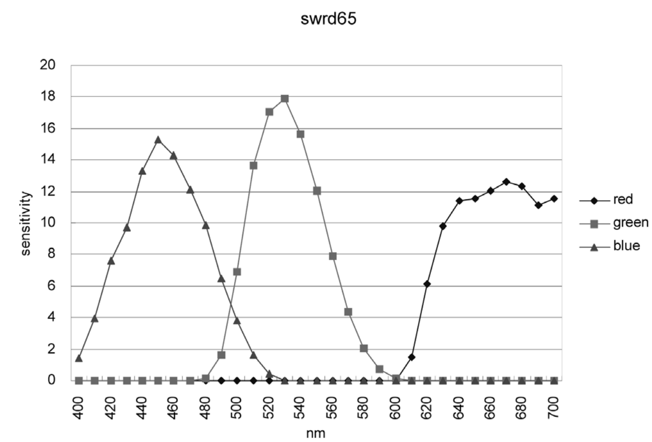
$$E = \sqrt{\sum_i \left\{ (X_i - X_{i0})^2 + (Y_i - Y_{i0})^2 + (Z_i - Z_{i0})^2 \right\}} \tag{8}$$

In this study, the following two sets of example sensors were used with D65 illuminant.

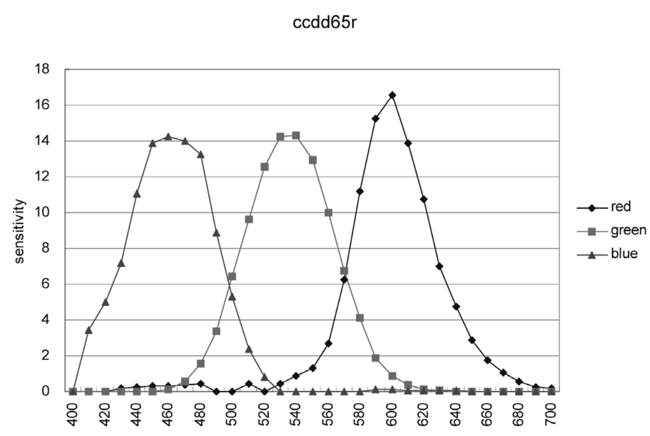
(a) swrd65: Spectral transmittances of Kodak Wratten filters (No.29(Red), No.61(Green), No.47(Blue)) are integrated with spectral sensitivity of silicon photo-diode. These filters were formerly used widely as color separation filters. This sensor is an example of a modest quality sensor,

(b) ccdd65r: Spectral sensitivities of a digital camera CCD (RGB type). This is an example of a good quality sensor.

Their integrated spectral sensitivities are shown in Fig. 3. Discussions on quality of these sensor sets can be found in the reference.[2]



(a) swrd65



(b) ccdd65r

Figure 3. Spectral sensitivities of sensors used for the experiment.

Evaluation of Typical Sets

For each group in Table 2, we optimized two color correction matrices for swrd65, using (1) typical samples and (2) all samples, and applied the optimized matrices to all samples. Residual rms errors were calculated and are de picted in Fig.4. In most groups, the residual errors are about the same for both matrices, and this shows that typical set samples can generate a color correction matrix similar to that generated using all samples. As examples, matrices for photo (transparency) and skin are shown below. A' is the matrix based on the typical samples, and A_0 is the matrix based on all samples. In this example, 30 typical set samples in six skin groups are used to generate a color correction matrix in comparison with all skin spectral samples.

• Photo(transparency)

$$A' = \begin{pmatrix} 38.0 & 48.0 & 8.9 \\ 19.7 & 83.0 & -2.6 \\ -0.8 & -1.0 & 110.5 \end{pmatrix} \quad A_0 = \begin{pmatrix} 37.9 & 44.7 & 12.4 \\ 19.9 & 80.5 & -0.4 \\ -0.6 & -1.8 & 111.1 \end{pmatrix}$$

• Skin

$$A' = \begin{pmatrix} 29.6 & 59.3 & 6.0 \\ 12.9 & 96.1 & -8.9 \\ 0.0 & 1.4 & 107.3 \end{pmatrix} \quad A_0 = \begin{pmatrix} 27.2 & 68.4 & -0.7 \\ 11.9 & 100.3 & 12.2 \\ 0.0 & 1.6 & 107.1 \end{pmatrix}$$

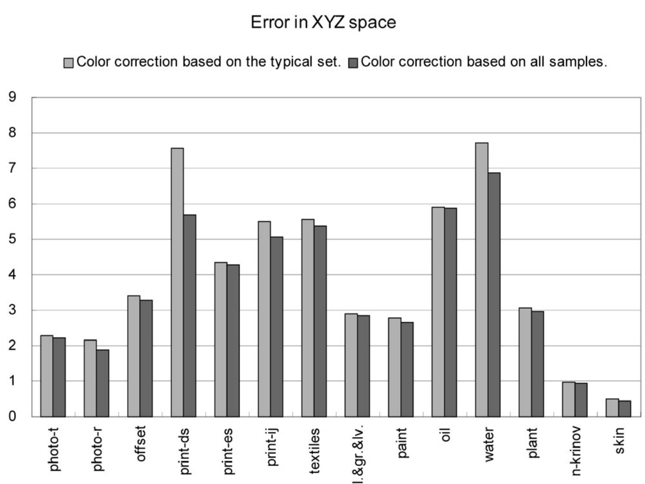


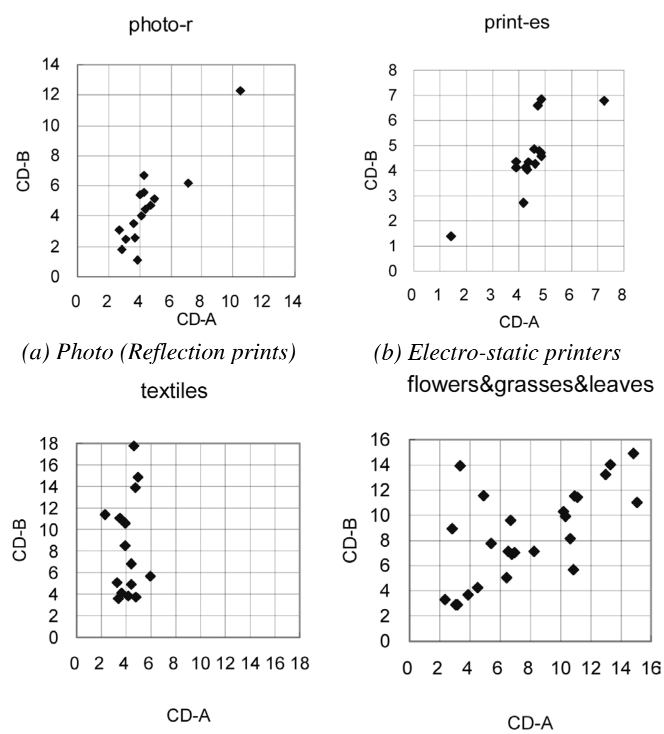
Figure 4. Residual rms errors after the linear color correction. (a) Photo (Reflection prints) (b) Electro-static printer (c) Textiles (d) Flowers, grasses & leaves

Evaluation of Difference Sets

As mentioned above, difference set samples are pseudometamers. They are used to evaluate the practical range of color reproduction errors caused by low-quality sensors that do not satisfy the Luther condition. The color of a difference set sample should be similar to that of its corresponding typical set sample. However, if the color is input by low-quality sensors, a large color difference can be anticipated. The framework of the evaluation is as follows.

(1) Color difference in L*a*b* space between a typical set and its corresponding difference set is calculated under D65. The color difference is called 'CD-A'.
(2) RGB values sensed by a sensor set for typical set samples and difference set samples under D65 are calculated.
(3) The RGB values are converted by a color correction matrix obtained based on the typical set, and color difference in L*a*b* space between a typical set and its corresponding difference set is calculated. The color difference is called 'CD-B'.
(4) If CD-A is about the same as CD-B, the sensor set is good. The larger the difference is, the worse the sensor quality is.

We first applied the sensor set swrd65 to this evaluation, and analyzed the relation between CD-A and CD-B for each sample. Figure 5(a) shows the relation for photo (reflection prints), 5(b) for electro-static printer outputs, 5(c) for textiles, and 5(d) for flowers & grasses & leaves. We obtained a very interesting result in this experiment, i.e. the correlation between color differences was high in Figs. 5(a) and (b), but low in Figs. 5(c) and (d). In the case of textiles, several CD-Bs are three or four times larger than CD-A. However, we applied the sensor set ccdd65 to the evaluation, high correlation was obtained for textiles and for flowers & grasses & leaves as well (see Figs.6(a) and (b)). These results clearly show that when a high-quality sensor is used, CD-B behaves like CD-A.



(a) Photo (Reflection prints) *(b) Electro-static printers*

(c) Textiles *(d) Flowers, grasses & leaves*

Figure 5. Relation between CD-A and CD-B (swrd65)

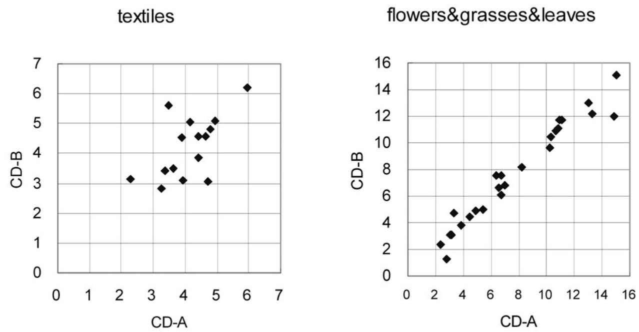


Figure 6. Relation between CD-A and CD-B (ccdd65)

This experiment shows that difference sets are very useful tools for sensor quality evaluation. The shown color differences are especially useful, since the samples are spectral reflectances/transmittances measured in the real world.

Conclusion

Representative sample sets–typical sets and difference sets– were defined in SOCS. This paper describes methods of selecting these sets, which contain only a small number of samples. Using such small-sample sets makes it possible to easily evaluate color reproduction for color image input devices. Usefulness of the sample sets was verified and confirmed as follows.

(a) Typical sets represent properties of all spectral data in the groups, and the optimal color correction matrices can be easily estimated through the use of typical set samples. Color reproduction errors for individual samples can easily be investigated, since the number of colors is small.

(b) Difference set samples may be used as pseudo metamers for corresponding typical set samples. Sensor set quality can be evaluated by comparing color differences between typical set sample colors and difference set sample colors input by the sensor set, with those sensed by the human visual system.

These results meet the purpose of SOCS very well. In an ISO technical report to be published in the near future, the principal part of SOCS will be the spectral data of representative sample sets followed by all collected spectral data. The authors hope that this paper will help users to use the technical report efficiently.

Acknowledgements

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Biographies

Johji Tajima graduated from the Faculty of Science, the University of Tokyo, in 1971 and received a doctorate in 1990. Since he joined NEC Corporation in 1971, he has been engaged in research on image processing and pattern analysis, especially color image processing and 3D vision. He is a research fellow in Multimedia Research Laboratories, NEC Corporation. Dr. Tajima is a member of the IEICE, IIEEJ, the Information Processing Society of Japan (IPSJ), and the Japanese Society of Printing Science and Technology. He is a fellow of IAPR.

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