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MASTER THESIS WORK

QUALITY METRICS FOR SPECTRAL ESTIMATION

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Quality metrics for spectral estimation

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Abstract. The quantitative assessment of the spectral estimation quality in multispectral imaging systems is an active field of research. The design and optimization of multispectral imaging systems are very dependent on how the cost function is selected. Several spectral estimation metrics have been used depending on the attribute it is intended to measure: visual matching, correlation of spectral curves or reduction of metamerism. The purpose of this project is to analyze various metrics that have been used for spectral matches and to show the appropriateness and weakness of each metric.

Keywords: Metrics, multispectral imaging systems, comparative, spectral match.

1. Introduction

The use of multispectral systems (Fig**.** 1) has become more generalized in the last years.[1,2] These systems allow the spectral characterization of the scene (reflectance, radiance, transmittance etc.) through several acquisition channels with different spectral features. The number of bands involved in a multispectral system for an accurate spectral reconstruction may vary depending on the application but according to some analyses, less than 10 channels are normally needed[3] due to the relatively smooth spectral properties of most surfaces.[4]

Multispectral systems often consist of a conventional light source, such as a daylight discharge lamp or a halogen lamp, and a set of narrowband filters, commonly interference or liquid crystal tunable filters.[1,2,5] Multispectral systems are also linked to a high spatial resolution since they normally use a digital camera as a sensor. Therefore, they are capable of providing instant information on a full spectrum of each pixel in the image of the captured scene, by means of several mathematical algorithms.[2,6]

Thanks to all these features, multispectral systems can be used for developing low-cost devices for the industry since they allow overcoming some of the drawbacks that conventional spectroradiometric and spectrophotometric devices have, such as their high price due to the use of diffracting grating components, and the fact that they only provide a single spot spectral measurement with a relative large area.

The quantitative assessment of the spectral estimation quality in multispectral imaging systems is an active field of research. The design and optimization of such systems are very dependent on how the cost function is selected. Several spectral estimation metrics that compare the real and reconstructed spectra have been used depending on the attribute it is intended to measure with the multispectral system used: visual matching, correlation of spectral curves or reduction of metamerism. The purpose of this project is to analyze various metrics that have been already used for analyzing spectral matches in multispectral systems, comparing the information that they provide. The final goal is to develop in the future a new strategy for multi-dimensional visualization of spectral estimation quality taking into account simultaneously different metrics.

2 Experimental setup

Two different configurations of a multispectral system were used in this study to reconstruct the reflectance spectra of the analyzed scene pixel by pixel. Both configurations had already been previously developed and characterized at the Center for Sensors, Instruments, and Systems Development (CD6), and consisted of a 12 bits cooled monochrome CCD camera (QImaging

QICAM Fast1394 12 bit cooled), a zoom lens (Nikon AF Nikkor 28 – 105 mm), and two different sets of filters one for each configuration .[7] Firstly, an RGB liquid crystal tunable filter was used in the 3-channel configuration. Secondly, a set of seven interference filters with a full width half maximum of approximately 40 nm, covering the whole visible range of the spectrum and fitted in a motorized filter wheel, were used in the 7-channel configuration (Fig. 2).

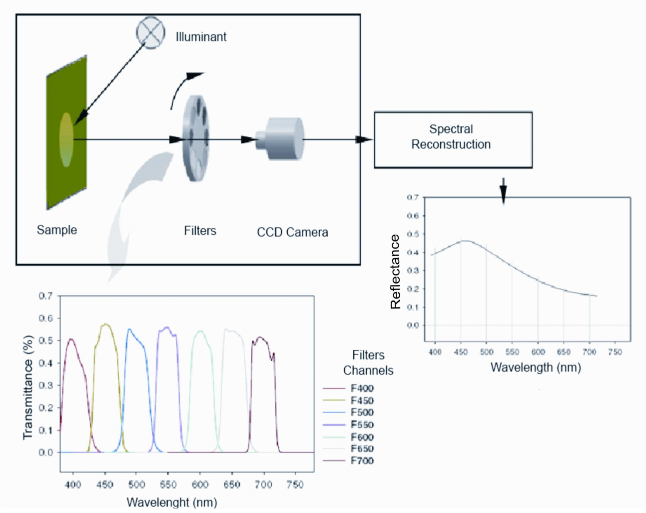

Figure 1. Example of a multispectral imaging system.

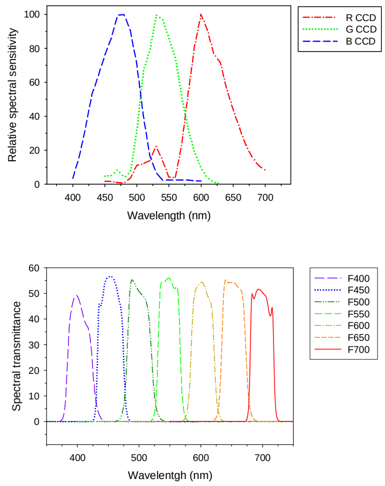

Figure 2. Sensitivities of the 3 and 7 channels of the two configurations used.

With the two different configurations described, multispectral images of the GretagMacbeth ColorChecker DC chart (CCDC) placed inside a special light booth (63cm x 64cm x 52cm) with a daylight D65 simulator, which provided a diffused and rather uniform illumination over the chart with a geometry of D/0 (illumination/observation), were acquired. The CCDC chart is a standardized chart with 180 different colour patches (Fig. 3). Five minutes were used for warming up and stabilizing the illumination system. The acquisitions were repeated 20 times and the averaged digital levels corresponding to a circular area of approximately 1 cm in diameter for each patch were calculated. Furthermore, the same areas of the colour patches were also characterized by means of a tele-spectra-colorimeter (PhotoResearch PR-655 with the MS-75 zoom lens), which provided the spectral reflectances in the visible range of the electromagnetic spectrum, with exactly the same measurement geometry used with the multispectral system.

Figure 3. CCDC chart placed inside the light booth. The tele-spectra-colorimeter used is also shown.

3.1. Reconstruction algorithms

The former multispectral system was trained to reconstruct[8] the reflectance spectra from the camera's digital levels of the two configurations of the system, that is, 3 and 7 channels respectively, using two different mathematical algorithms commonly used in the literature: the pseudoinverse method (PSE)[2] and the matrix R method.[6]

The PSE method uses a direct transformation that relates both sets of values (i. e. the reflectance spectra and the digital levels) by means of a matrix computed using the Moore-Penrose pseudo-inverse technique. This technique allows minimizing the existing "distance" between the real and reconstructed spectra using a least-squares regression. However, it does not take into account the existing colour difference between both the real and reconstructed data, and therefore, it might be large for certain pairs of spectra.

On the other hand, the method called Matrix R allows accurately reconstructing spectral reflectances while simultaneously achieving high colorimetric performance (visual match) for a defined illuminant and observer. The method reconstructs reflectance spectra by combining the fundamental stimulus from the predicted tristimulus values with the metameric black from the estimated spectral reflectance, based on the Wyszecki hypothesis.[9] This hypothesis states that any stimulus can be decomposed into a fundamental stimulus with identical tristimulus values and a residual metameric black.[10] The matrix [***R***], which is used in this method to compute the reflectance spectra from the camera's digital levels, can be calculated from the matrix ***A*** of weights for the reference illuminant and observer as shown in equation (1).

$$[\boldsymbol{R}] = A \cdot inv(At \cdot A) \cdot At \qquad (1)$$

where t denotes transposed of the matrix and ***A*** is a $n \times 3$ matrix (n being the number of wavelengths considered) calculated as the product of the spectral power distribution (SPD) of the standard illuminant and the color matching function of the reference observer used (A[λ]=SPD[λ]*CMF[λ]).

For both reconstruction algorithms, in this study the transformation matrices were calculated taking into account the mean digital levels of each patch from the 20 acquisitions and the corresponding true spectral reflectances measured with the tele-spectra-colorimeter.

3.2. Tested metrics for spectral comparison

From the literature, many metrics for spectral comparison can be found. These metrics allow evaluating the performance of any multispectral system in terms of differences between the real spectral reflectance of the measured sample and that reconstructed from the images acquired by the multispectral system. In general, metrics for spectral matching quality tend to fall within the following categories:[11]

3.2.1. Colour differences

Psychophysical experiments have shown that the human eye's sensitivity to light is not linear. The RGB and also the XYZ color spaces defined by the CIE (International Commission on Illumination) are linearly related to the spectral power distribution of the coloured light. When changing the tristimulus values XYZ (or RGB) of a colour stimulus, the observer will perceive a difference in colour only after a certain amount, equal to the Just Noticeable Difference (JND). In both RGB and XYZ spaces the JND depends on the location in the colour spaces. To remedy this, the CIE proposed in 1976 a uniform colour space, denoted CIELAB,[9] defined by the quantities L*, a* and b*:

$$L^* = \left(\frac{Y}{Y_w}\right)^{\left(\frac{1}{a}\right)} = 16 \qquad (2)$$

$$a^* = 500\left[\left(\frac{X}{X_w}\right)^{\left(\frac{1}{3}\right)} - \left(\frac{Y}{Y_w}\right)^{\left(\frac{1}{3}\right)}\right] \qquad (3)$$

$$b^* = 200\left[\left(\frac{Y}{Y_w}\right)^{\left(\frac{1}{3}\right)} - \left(\frac{Z}{Z_w}\right)^{\left(\frac{1}{3}\right)}\right] \qquad (4)$$

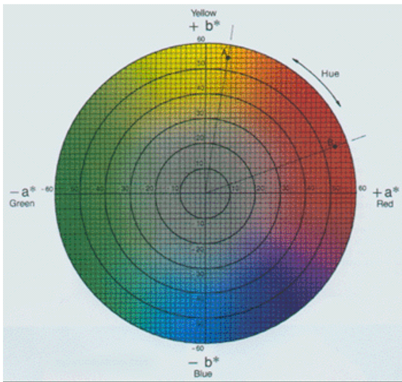

Figure 4. Two-dimensional (a*, b*) diagram.

where X_W, Y_W, Z_W are the tristimulus values of the reference white, L* is the lightness of a colour and its scale goes from 0 (black) to 100 (white).

The chromaticity of a colour can be represented in a two-dimensional (a*,b*) diagram, a* representing the degree of red versus green, and b* the degree of yellow versus blue (Fig. 4). Taking into account this, different metrics have been defined to assess visual colour differences.

<u>ΔE: CIELAB colour difference</u>[9]When comparing two colours, specified by [L^*_1, a^*_1, b^*_1] and [L^*_2, a^*_2, b^*_2], one widely used measure of the colour difference is the CIE 1976 CIELAB

colour difference which is simply calculated as the Euclidean distance in the CIELAB space as follows:

$$\Delta E = \sqrt{\Delta L^2 + \Delta a^2 + \Delta b^2} \text{ or } \Delta E = \sqrt{\Delta L^2 + \Delta C^2 + \Delta H^2} \qquad (5)$$

where C is the chroma, h (in degrees) the hue angle, and ΔH is calculated as follows:

$$C = \left(a^2 + b^2\right)^{\left(\frac{1}{2}\right)} \qquad (6)$$

$$h = arctg\left(\frac{b}{a}\right) \qquad (7)$$

$$\Delta H = 2 \cdot \sqrt{C_1 \cdot C_2}\,\sin\left(\frac{\Delta h}{2}\right) \qquad (8)$$

It is normally assumed that colour differences of $\Delta E < 3$ are hardly perceptible, from 3 to 6 are perceptible, but acceptable, and above 6 are not acceptable.[12,13] However, the evaluation of quality and acceptability is highly subjective and depends on the application.

ΔE_{94}: 1994 CIELAB colour difference[14]

Many modifications of the former equation have been carried out, trying to improve the correlation found between predicted and perceived colour differences. The CIE defined the ΔE_{94} as a new colour difference equation to be applied under certain specific reference conditions (homogeneous specimens, ΔE smaller than 5, placed in direct edge contact, specimen subtends and angle of 4 degrees or more, illuminated at 1000 lux with a D65 illuminant):

$$\Delta E_{94} = \sqrt{\left(\frac{\Delta L}{k_L \cdot S_L}\right)^2 + \left(\frac{\Delta C}{k_c \cdot S_c}\right)^2 + \left(\frac{\Delta H}{k_H \cdot S_H}\right)^2} \qquad (9)$$

The weighting functions S_L, S_C, and S_H vary with the chroma of the specimen C:

$S_L=1$, $S_C=1+0.045\cdot C$ and $S_H=1+0.015\cdot C$ (10)

The variables k_L, k_C, and k_H are called the parametric factors and are included in the formula to allow for adjustments to be made independently to each colour difference term to account for deviations from the reference viewing conditions. Under reference conditions they are set to 1.

CIEDE2000: 2000 CIELAB colour difference[15]

The last recommended CIE colour difference formula is the CIEDE2000, which include new terms to improve the predicted colour differences in the blue region (R_T) and for neutral colours, for pairs of samples with small to moderate colour differences:

$$CIEDE2000 = \sqrt{\left(\frac{\Delta L^*}{k_L \cdot S_L}\right)^2 + \left(\frac{\Delta C^*}{k_c \cdot S_c}\right)^2 + \left(\frac{\Delta H^*}{k_H \cdot S_H}\right)^2 + R_T\left(\frac{\Delta C^*}{k_c \cdot S_c}\right)\left(\frac{\Delta H^*}{k_H \cdot S_H}\right)} \qquad (11)$$

3.2.2. Spectral curves difference metrics

Another approach to comparing spectral curves is based on computation of spectral curve differences.

RMSE: Root Mean Square Error

This is a very simple metric that has been used for spectral estimation evaluation in many studies[5]:

$$RMSE = \sqrt{\frac{1}{n}\sum_{\lambda}\left(r(\lambda) - r_{rec}(\lambda)\right)^2} \qquad (12)$$

where $r(\lambda)$ are the spectral reflectance components of the real curves, $r_{rec}(\lambda)$ are the reconstructed values and n is the number of wavelengths tested.

GFC: Goodness-of-fit Coefficient[16]

To test the reconstruction's accuracy, one can use this coefficient based on the inequality of Schwartz. In fact, the GFC is the multiple correlation coefficient, the square root of $r_{rec}(\lambda)$'s spectral variance with respect to the original $r(\lambda)$. The GFC ranges from 0 to 1, with 1 corresponding to an exact duplicate of $r(\lambda)$. Hernández-Andrés[16] et al. suggested that colorimetrically accurate $r_{rec}(\lambda)$ require a GFC > 0.995; a ‘‘good’’ spectral fit requires a GFC > 0.999, and GFC > 0.9999 is necessary for an ‘‘excellent’’ fit.

$$GFC = \frac{\sum_{\lambda} r(\lambda) r_{rec}(\lambda_j)}{\sqrt{\sum_{\lambda} [r(\lambda_j)]^2} \sqrt{\sum_{\lambda} [r_{rec}(\lambda_j)]^2}} \qquad (13)$$

<u>ΔR: Average fractional deviation[16,17]</u>

This metric is similar to RMSE but uses absolute values. It calculates the difference in area between the real and reconstructed profile:

$$\Delta R = \frac{\sum_{\lambda} |r(\lambda) - r_{rec}(\lambda)| \cdot \Delta\lambda}{\sum_{\lambda} r(\lambda) \cdot \Delta\lambda} \qquad (14)$$

3.2.3. Weighted RMSE metrics

It is possible to weight spectral reflectance RMSE error between real and reconstructed curves in a way that consider some properties of the human visual system. The general weighted RMSE equation is shown as follows:

$$WRMSE = \frac{\sqrt{\sum_{\lambda=1}^{n} \left(\sqrt{w(\lambda)\Delta\beta(\lambda)}\right)^2}}{n} \qquad (15)$$

where $w(\lambda)$ is the weight, and $\Delta\beta(\lambda)$ is the difference between the two spectra.

In this study two different weights have been applied: WRMSE_R and WRMSE_inv.

<u>WRMSE_R: Weighted RMSE based on Matrix R method.[11]</u>

This metric uses the diagonal of the matrix [***R***] method as the weighting function for the RMSE calculation:

$$w(\lambda) = diag([R]) \quad (16)$$

It follows that there is one set of weights for each combination of illumination and observer. In this study, the D65 illuminant and 2-degree observer have been used (Fig. 5). It can be seen that this metric biases the RMSE calculation in a fashion that gives more importance to the wavelengths that correspond to higher sensitivity in the human visual response for a specific combination of illuminant and observer.

<u>WRMSE_inv: Weighted RMSE based on the inverse of the real spectra[11]</u>

Weigthed RMSE considering that it is more important to weight spectral data with small magnitude, since the visual system is more sensitive to mismatches in dark colors than light colors. The inverse relationship is:

$$w(\lambda) = \frac{1}{r(\lambda)} \qquad (17)$$

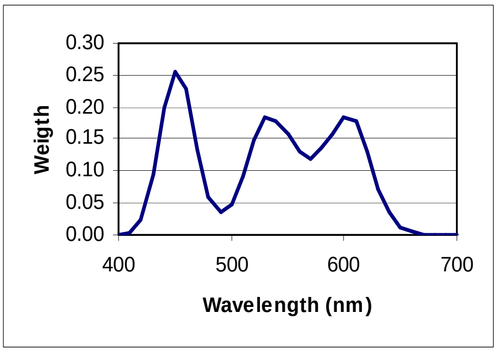

Figure 5. Weighting functions calculated from matrix [R] for D65 and 2º observer.

3.2.4. Metamerism indices

One can also assess the performance of a multispectral system in terms of an index of metamerism, which is a measure of the degree to which two samples that match one another become different when the illuminant or the observer is changed. In this work two different indices have been tested:

<u>FI: Fairman index[10]</u>

Fairman proposed a mesmerism index using a parametric decomposition. The metameric index is a CIE colour difference equation (ΔE_{94}) for a test illuminant and observer. In this method, the test spectrum is corrected spectrally until an exact tristimulus equality is achieved under a reference condition (in this study D65 illuminant and 2-degree observer). Then, the colour difference is calculated under the test condition (in this study A illuminant and 2-degree observer). The CIE refers to this type of index as a "special index of metamerism."

VI: Viggiano index[18,19]

This is a perception reference method that compares reflectance ratio spectra. It is computed as shown bellow:

$$VI = \sum_{\lambda} w(\lambda)|\Delta\beta(\lambda)| \qquad (18)$$

where $w(\lambda)$ are the weights computed as follows:

$$w(\lambda) = \sqrt{\left(\frac{dL^*}{d\beta(\lambda)}\right)^2 + \left(\frac{da}{d\beta(\lambda)}\right)^2 + \left(\frac{db^*}{d\beta(\lambda)}\right)^2} \qquad (19)$$

This index is a refinement of a spectral-based metameric index based on a weighted sum of the absolute differences between two spectra proposed by Nimeroff and Yukov.[19] The CIE refers to this type of index as a “general index of metamerism”.

3.2.5. Combined metrics

Finally, the former metrics can be used simultaneously to account for spectral match quality. The only metrics found in the literature of this type is the following:

CSCM: Colorimetric and Spectral Combined Metric[16]

This metrics gives the same weight to GFC, ΔE, and ΔR(%) metrics. This metric should approach zero for near-perfect matches. Its chief advantage is that it quantifies spectral mismatches among metamers.

$$CSCM = \log\left(1 + 1000^*(1 - GFC)\right) + \Delta E + \Delta R(\%) \qquad (20)$$

This combined metric is a good candidate for developing a multispectral system optimized for both visual and spectral matches since it takes into account these different metrics.

In order to analyze the similarities and differences among metrics, in this study all of them have been implemented using MATLAB software. They have been used to analyze the results (differences between real and reconstructed spectra) provided by the two configurations of the multispectral system tested (3 and 7 channels) and also the two mathematical reconstruction algorithms (PSE and Matrix R).

4. Results

The results of the reconstructions achieved by means of the two configurations of the multispectral system (3 and 7 channels) are shown in tables 1 and 2, for the PSE and Matrix R methods, respectively. In these tables, the statistics (mean, standard deviation [SD], maximum and minimum) for each analyzed metric of the results obtained for the 180 colour patches of the CCDC chart are detailed. As the tables show, both methods provide rather good reconstruction results. It can be seen that better mean results are achieved when more spectral bands, or equivalently acquisition channels, are used in the multispectral system. In this context, the 7-channel configuration provides much better results than that with 3 channels, independently of the reconstruction algorithm used (PSE or Matrix R method). This was already expected, since with more channels, a larger amount of spectral information is recollected from the acquired scene, thus allowing a better performance of the reconstructions.

On the other hand, it can be also seen that the Matrix R method gives slightly better mean results than the PSE method in terms of all analyzed metrics. In this context, the colour differences are slightly smaller, as well as the spectral curves difference metrics, the weighted ones, the metamerism indices, and the combined metric CSCM. Even though the PSE tries to minimize the existing spectral differences between the real and reconstructed spectra, meanwhile the goal of Matrix R method is to simultaneously achieve the best reconstruction in terms of colour difference and spectral difference (which could compromise and limit the results obtained in terms of spectral differences), it seems from the results of all considered metrics that the Matrix R method is a most robust tool to perform the reconstructions of the CCDC chart.

From the results obtained, it can be seen that using 7 channels the mean colour differences can be considered perceptible ($3<\Delta E<6$), meanwhile using 3 channels, these values tend to increase above 6, differences that are considered in general unacceptable in terms of visual colour match (colour differences are good metrics when metamerism is not an issue).

Table 1. Statistics for the metrics tested obtained when the PSE algorithm is used.

	ΔE	ΔE_{94}	CIEDE2000	RMSE	GFC	ΔR	WRMSE_R	WRMSE_inv	FI	VI	CSCM
3 channels											
Mean	6.67	4.97	4.52	0.058	0.9866	0.217	0.016	0.123	1.3	26.3	26.515
±SD	4.70	2.67	2.57	0.020	0.0207	0.178	0.007	0.080	1.0	18.4	19.916
max	38.44	14.99	14.62	0.141	1.0000	1.216	0.042	0.701	5.8	154.0	137.872
min	0.00	0.00	0.00	0.000	0.8411	0.000	0.000	0.000	0.0	0.0	2.924
7 channels											
Mean	3.86	3.10	2.80	0.032	0.9970	0.148	0.009	0.073	0.7	16.7	19.823
±SD	3.49	2.60	2.23	0.014	0.0114	0.187	0.004	0.077	0.8	17.0	22.070
max	32.73	22.49	18.07	0.095	1.0000	1.412	0.029	0.895	5.8	148.3	175.916
min	0.00	0.00	0.00	0.000	0.8522	0.000	0.000	0.000	0.0	0.0	2.038

Table 2. Statistics for the metrics tested obtained when the Matrix R algorithm is used.

	ΔE	ΔE_{94}	CIEDE2000	RMSE	GFC	ΔR	WRMSE_R	WRMSE_inv	FI	VI	CSCM
3 channels											
Mean	5.72	3.76	3.63	0.036	0.9890	0.169	0.013	0.097	1.2	19.7	20.169
±SD	4.62	2.41	2.29	0.021	0.0207	0.162	0.006	0.077	1.0	16.8	17.513
max	38.23	13.58	13.62	0.144	0.9998	1.079	0.037	0.670	5.5	142.9	122.766
min	0.60	0.27	0.26	0.007	0.8258	0.022	0.003	0.021	0.0	3.5	3.885
7 channels											
Mean	3.37	2.54	2.30	0.026	0.9974	0.122	0.008	0.062	0.6	14.7	15.519
±SD	3.56	2.50	2.15	0.013	0.0107	0.173	0.004	0.073	0.7	15.7	20.981
max	31.81	21.71	17.40	0.090	0.9999	1.333	0.028	0.849	5.3	140.1	170.067
min	0.46	0.34	0.28	0.005	0.8615	0.011	0.002	0.008	0.0	1.9	1.160

In the case of GFC, the coefficients are closer to 0.997 when 7 channels are used, which can be considered colorimetrically accurate. This is not true for three spectral bands, for which the results are worse. The spectral difference metrics such as RMSE, GFC, and the ΔR are easy to calculate but do not consider aspects of human vision. Therefore they are suitable for comparing mismatches of physical stimuli, but not to analyze perceived differences.

The weighted RMSE parameters have different behaviours: on one hand, the WRMSE_R, which considers the illuminant used as well as the cone sensitivities, provides smaller results than the conventional RMSE metrics. However, the WRMSE_inv, which puts more weight on darker colors than light colors, gives larger (worse) results of reconstruction.

The two indices of metamerism provide results that are not comparable between them. The Fairman index is a very useful metric to compare two spectra under two different illuminants but it is not a general metric in the sense that illuminants need to be specified (it only provides the degree of metamerism under specific conditions). Furthermore, it is intuitive since it gives colour difference units (i.e. ΔE_{94}), which can be easily interpreted. Differently, this is not the case with the Viggiano index, which provides larger results and in terms of not familiar units. This metric presents both properties of different weights for differences in lightness and consideration of the human cone sensitivities, and does not need any specific conditions of illumination to be calculated.

The same happens with the CSCM coefficient (0 for a perfect match), which although takes into account different aspects (colour differences and spectral difference metrics), it is difficult to interpret due to the fact that we are not used to its scale.

In order to perform a better comparison among the analyzed metrics, linear regressions between them were performed taking into account the results for all the colour patches as well as the different filter configurations (3 and 7 channels) and the two reconstruction algorithms (PSE and Matrix R method). The correlation coefficients (r^2) when using the Matrix R method are listed in table 3 (the results for the PSE method have been omitted for the large existing similarity). In this table, we use colours to distinguish among very good correlations ($0.9<r^2<1.0$, in green), good correlations ($0.8< r^2 \leq 0.9$, in yellow) and moderate correlations ($0.7< r^2 \leq 0.8$, in red).

Table 3. r^2 coefficients for the metrics tested obtained when the Matrix R algorithm is used.

3channels	ΔE	ΔE_{94}	CIEDE2000	RMSE	GFC	ΔR	WRMSE_R	WRMSE_inv	FI	VI	CSCM
ΔE	1.000	0.640	0.700	0.130	0.540	0.440	0.290	0.540	0.440	0.638	0.360
ΔE_{94}		1.000	0.950	0.070	0.400	0.730	0.230	0.560	0.610	0.763	0.650
CIEDE2000			1.000	0.070	0.400	0.630	0.210	0.530	0.550	0.727	0.550
RMSE				1.000	0.220	0.050	0.470	0.440	0.090	0.194	0.000
GCF					1.000	0.470	0.170	0.620	0.370	0.455	0.290
ΔR						1.000	0.100	0.570	0.670	0.738	0.900
WRMSE_R							1.000	0.410	0.120	0.329	0.030
WRMSE_inv								1.000	0.470	0.846	0.350
FI									1.000	0.584	0.560
VI										1.000	0.553
CSCM											1.000
7channels											
ΔE	1.000	0.790	0.820	0.320	0.540	0.630	0.360	0.820	0.510	0.817	0.720
ΔE_{94}		1.000	0.980	0.440	0.380	0.630	0.480	0.820	0.790	0.965	0.940
CIEDE2000			1.000	0.410	0.420	0.830	0.460	0.790	0.730	0.993	0.890
RMSE				1.000	0.200	0.320	0.870	0.430	0.360	0.400	0.350
GCF					1.000	0.390	0.200	0.770	0.380	0.489	0.430
ΔR						1.000	0.340	0.710	0.840	0.908	0.990
WRMSE_R							1.000	0.440	0.360	0.443	0.370
WRMSE_inv								1.000	0.650	0.872	0.770
FI									1.000	0.798	0.830
VI										1.000	0.948
CSCM											1.000

When analyzing the results obtained with 3 channels, it can be observed that in terms of colour differences, a very good correlation is found between ΔE_{94} and CIEDE2000 (Fig. 6), meanwhile the rest of comparisons between colour differences formulae (i.e. the former two and ΔE) generally show moderate correlations, too. This can be better understood if one has in mind that all these metrics try to account about the same phenomenon (perceived colour differences). The newer metrics (ΔE_{94} and CIEDE2000) are improved versions of the eldest and conventional one, and have appeared with the aim of obtaining a better correlation with the experimental observations. However, the essence of all them is the same. Another very good correlation to highlight is the one found between the CSCM and ΔR metrics (Fig. 7). This fact means that ΔR metric has an important role (or weight) in the CSCM metric.

The analysis of the correlations between tested metrics when 7 channels are used provides more “good” correlations. This is the case between the VI index and colour differences ΔE_{94} and CIEDE2000, which could be partially explained because the VI metrics considers the human vision (cone sensitivities and differences between light and dark colours) and colour difference also does. A very good correlation between VI and ΔR can also be found. This can be explained by the fact that VI is a perception reference method that compares reflectance ratio spectra, and ΔR also does (although this last one does not consider human vision aspects). Finally, other marked correlations can be found between the CSCM and the ΔE_{94}. This was not expected since the CSCM metric does not use ΔE_{94} in its computation, but it takes into account the ΔE conventional colour difference.

Another surprising result is that the best correlations are not found within metrics of the same category, meaning that each metric provide a very different information of the existing difference between the real and reconstructed spectra.

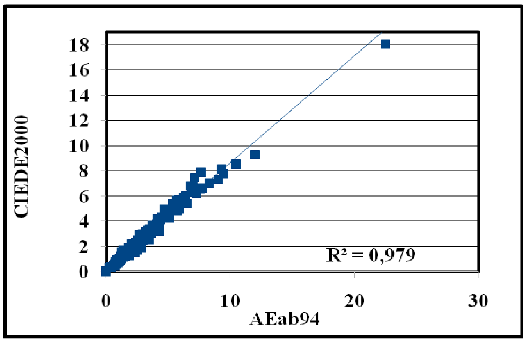

Figure 6. Correlation between ΔE and CIEDE2000 for 7 channels and the PSE method.

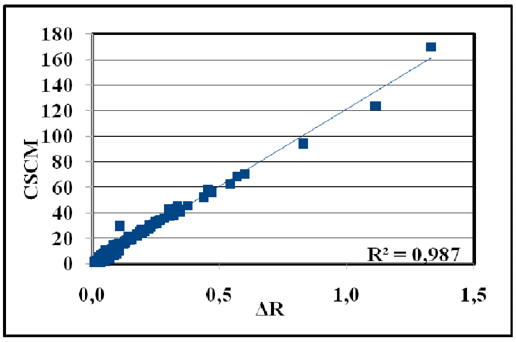

Figure 7. Correlation between CSCM and ΔR for 7 channels and the matrix [R] method.

Finally, figure 8 shows real and reconstructed reflectance spectra for some specific samples. Table 4 details the obtained metrics for each of them. For sample 167, both colour differences and spectral curves difference metrics are high. We observe large differences between real and reconstructed spectra in the mid-long wavelength range. For sample 107, the colour difference is low, while the RMSE is high; Differences between spectra are concentrated in the red-near infrared zone, where the human eye is not much sensitive and for this reason perceived references are not important in this case. Sample 112 shows high colour differences and the RMSE is low. This can be explained since the mismatches are located at the green region, where the human eye is more sensitive. Sample 172 has an almost perfect reconstruction over the whole visible region, with small colour differences and spectral curves difference metrics.

Table 4. Comparison of the spectral fit metrics for various reflectance pairs shown in figure 8.

Metric	Sample 167	Sample 107	Sample 112	Sample 172
ΔE	9.08	1.95	20.18	0.79
DE_{94}	8.12	1.82	12.47	0.46
CIEDE2000	7.80	1.28	12.07	0.50
RMSE	0.102	0.076	0.051	0.009
GFC	0.9666	0.9931	0.9437	0.9997
ΔR	0.268	0.119	0.391	0.019
WRMSE_R	0.030	0.013	0.022	0.003
WRMSE_inv	0.231	0.120	0.187	0.016
FI	0.9	1.7	3.7	0.3
VI	37.0	11.1	42.7	5.1
CSCM	13.712	13.392	51.473	1.729

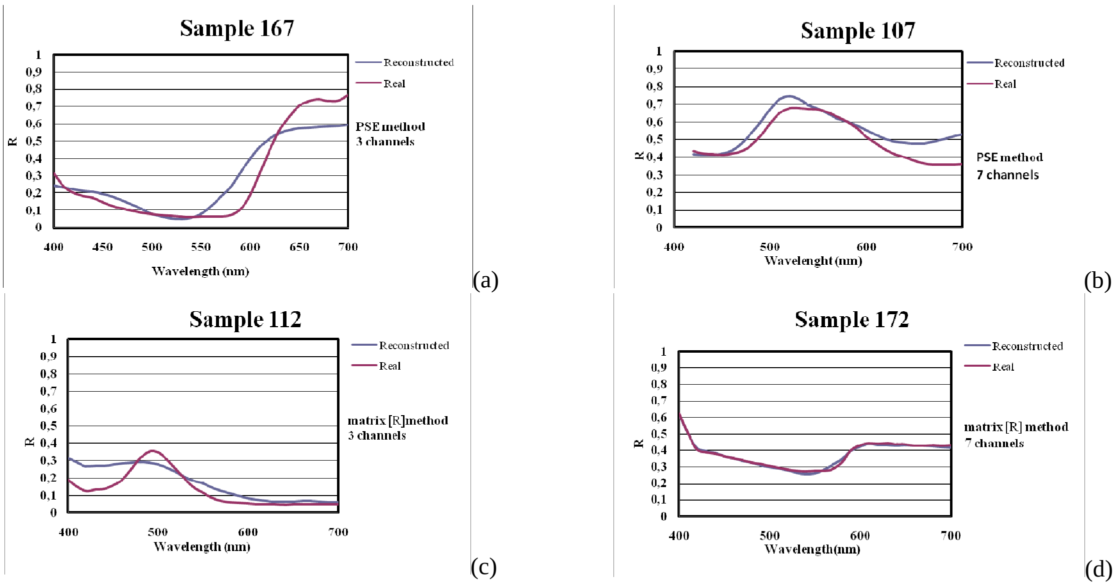

Figure 8. Real and reconstructed spectra for samples 167, 107, 112 and 172.

5. Conclusions

In this study we evaluated two different configurations with 3 and 7 channels of a multispectral system used to reconstruct the reflectance spectra in the visible range. The digital levels of the 180 colour patches of the CCDC chart were obtained with this system as well as with a conventional tele-spectra-colorimeter, which provided the real spectral reflectances to be compared later with the reconstructed ones. Two different algorithms were used to reconstruct the reflectance spectra: the PSE and Matrix R methods. Statistical results have shown that the 7-channel configuration and the Matrix R method are the best options to reconstruct the spectral information of a scene. Even though some good correlations between metrics have been found, especially between colour difference formulae, most of them give not regular information. Therefore, depending on the feature that we want to optimize in the reconstruction process they are more or less advisable (i.e. if one want to obtain the best colour difference, spectral curve difference, etc.). To have a better evaluation, it would be necessary to develop a new multi-dimensional metric which included several metrics with minimum correlation among them in it. Future work is oriented in this direction.

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