Spectral Colour Differences through Interpolation

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Abstract. The existing spectral colour difference metrics are not similar to CIEDE2000. The goal in this study was to implement a system to calculate the difference of spectral colours so that the calculated differences are similar to CIEDE2000 colour differences. The developed system is based on a priori calculated differences between known spectra and the calculus parameters derived from them. With the current system one can calculate spectral differences between a limited set of spectra which are derived by mixing the known spectra. The computation of calculus parameters for the system is a demanding process, and therefore, the calculations were distributed to a cluster of computers. The proposed spectral difference metric is very similar to CIEDE2000 for most of the test spectra. In addition, the metric shows non-zero differences for metameric spectra although CIEDE2000 colour difference metric results in zero differences. This indicates more correct operation of the spectral difference than the operation of CIEDE2000 colour difference.

1 Introduction

Spectral differences are needed in many scientific areas, e.g. in colour science [12], remote sensing [5], and in recording cultural heritage [1]. The applications of spectral information vary from clustering and classification to spectral reconstruction and to application of regression analysis [10].

The current approaches for computing spectral differences are emphasizing low computational complexity, and applications may be built based on the Euclidean distance even though it might not fully match with the requirements. In remote sensing, Spectral Angle Mapper (SAM) [2] has gained significant popularity. Spectral information is used also in computing the vegetation index. Now only some bands from the spectrum are used in the calculation [3], [5]. For the classification task, support vector machines have been introduced [7]. In general, the classification task does not require exact differences, but only a measure to construct the hyperplanes that separate the groups of objects from each other.

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The motivation for a new spectral difference metric originates from applications and cases where the CIEDE2000 difference (ΔE_{00}) is zero even though the two spectra are different. ΔE_{00} is computed using inner products between the spectra and the colour matching functions, and these inner products are exactly the reason that the spectral differences are concealed. Two metameric spectra act similarly and the illuminant removes the colour difference even though the actual values for the two spectra are different. Yet another example is the spectral reconstruction (e.g., multiple regression analysis, MRA) [10] where a high-dimensional spectrum is estimated from the original colour. If the original spectrum is available, one can quantify the quality of the estimation process with the spectral differences [10].

Our goal is to develop a general approach to calculate the difference for any two spectra. The difference can then be used in various applications. The basic requirement for the approach is that the differences should match the ΔE_{00} colour difference values which, in this study, is considered as a model for the human visual system. This constraint implies that the approach in its current form is usable only in the human visual range.

The structure of the paper is as follows. In Section 2, we show the traditional approaches how to calculate the colour and spectral differences. In Section 3, we introduce the proposal for the calculation of the spectral differences. Section 4 contains the experiments, and the discussion and conclusions are presented in Section 5.

2 Differences for 3D Colours and Spectral Colours

2.1 Colour Differences

The differences computed by the proposed approach are following the values from ΔE_{00} colour difference equation [8], [6]. This difference equation uses *Lab* colour space, and it is well designed to take into account also nonlinearities in the colour space. The equation for ΔE_{00} is

$$\Delta E_{00} = \sqrt{\left(\frac{\Delta L'}{k_L S_L}\right)^2 + \left(\frac{\Delta C'}{k_C S_C}\right)^2 + \left(\frac{\Delta H'}{k_H S_H}\right)^2 + R_T \left(\frac{\Delta C'}{k_C S_C}\right)\left(\frac{\Delta H'}{k_H S_H}\right)} \tag{1}$$

where the *Lab* values are transformed to LCH values (luminance, chroma, hue). The last term accounts for the special case in the blue region.

2.2 Spectral Differences

For spectral data, many practical solutions have been developed to calculate the spectral differences. Typically, they are simple to calculate and in many cases they are measuring the physical stimulus and not the response of the human visual system. Several approaches are compared in [11]. They found that the

Spectral Comparison Index (SCI) performed best for various levels of ΔE. SCI is defined as a sum of weighted differences M_v as

$$M_v = \sum_{\lambda} w(\lambda) * \parallel \Delta\beta(\lambda) \parallel, \tag{2}$$

where the weights $w(\lambda)$ are calculated as

$$w(\lambda) = \sqrt{\left(\frac{dL^*}{\Delta\beta(\lambda)}\right)^2 + \left(\frac{da^*}{\Delta\beta(\lambda)}\right)^2 + \left(\frac{db^*}{\Delta\beta(\lambda)}\right)^2}, \tag{3}$$

where $\Delta\beta(\lambda)$ contains the spectral differences and $dL^*/\Delta\beta(\lambda)$, $da^*/\Delta\beta(\lambda)$, and $db^*/\Delta\beta(\lambda)$ contain derivative values with respect to $\Delta\beta(\lambda)$ [11].

The Spectral Angle Mapper (SAM) measures the angle between the two spectra [2]

$$SAM(\mathbf{s}, \mathbf{t}) = \arccos\left(\frac{\mathbf{s} \cdot \mathbf{t}}{\parallel \mathbf{s} \parallel \parallel \mathbf{t} \parallel}\right). \tag{4}$$

with $\mathbf{s}$ and $\mathbf{t}$ as the two spectra and it is very popular in remote sensing applications [5].

When the two spectra are considered as random variables then an information theoretic approach proposes a measure between the two variables can be derived as SID [2]. First, the probabilities q_j in a spectrum y are computed as

$$q_j = \frac{y_j}{\sum_{l=1}^{L} y_l}, \tag{5}$$

and similarly to p_j from spectrum x, and then the dependency $D(\mathbf{x} \parallel \mathbf{y})$ is defined as

$$D(\mathbf{x} \parallel \mathbf{y}) = \sum_{l=1}^{L} p_l * log\left(\frac{p_l}{q_l}\right), \tag{6}$$

and finally SID is received as

$$SID(\mathbf{x} \parallel \mathbf{y}) = D(\mathbf{x} \parallel \mathbf{y}) + D(\mathbf{y} \parallel \mathbf{x}). \tag{7}$$

There are many positive properties with the above measures. The calculations are simple and they are not limited to spectral colours, but the measures can be used in any range which is important in remote sensing applications.

3 Interpolating Spectral Differences in Spectral Domain

Our proposal is based on interpolation: we interpolate between the known values which are the ΔE_{00} colour differences between the known spectra. These known values are precomputed as a separate task. As the set of known spectra we have been using the Munsell set of spectra [9].

A new spectrum sp_3 is interpolated from the two known spectra sp_1 and sp_2 as

$$sp_3 = (1 - a) * sp_1 + a * sp_2 \quad 0 \leq a \leq 1, \tag{8}$$

and the corresponding difference $\Delta E_{i_1}(sp_2, sp_3)$ between the two spectra sp_2 and sp_3 becomes

$$\Delta E_{i_1}(sp_2, sp_3) = k_1 * \Delta E_{00}(sp_1, sp_2). \tag{9}$$

Now the problem is to define the dependency between k_1 in Eq. 9 and a in Eq. 8. In our initial experiments we found that this dependency is not linear but parabolic, and now k_1 becomes

$$k_1 = f_1(a) = p_{1_2}a^2 + p_{1_1}a + p_{1_0}. \tag{10}$$

The coefficients p_{1_i} in Eq. 10 need to be computed, and for the parabolic equation, three additional known spectra between sp_1 and sp_2 are needed to determine the coefficients. When the coefficients are found then in Eq. 8 any value can be set for $a, 0 < a < 1$. Since these coefficients are static, they were precomputed and stored in a database.

The setting is shown in Fig. 1a where there are two known spectra, sp_1 and sp_2, the interpolated spectrum sp_3, and the spectral difference ΔE_{i_1} is computed between sp_2 and sp_3.

Next we are adding new neighbors for the interpolation, the various constellations are shown in Fig. 1b, ..., e. In case e, we show only the first group and the spectrum sp_{n1} in the tetrahedron. The second group has the similar construct and the second spectrum sp_{n2} exists in that tetrahedron. The difference ΔE_i is calculated between sp_{n1} and sp_{n2} as $\Delta E_i = \Delta E(sp_{n1}, sp_{n2})$. More known spectra can be added in a similar fashion, but the visualization of those higher-dimensional cases becomes more complicated.

For each case the corresponding equations for the spectral differences ΔE_i and for the multiplier k are as follows:

$$\begin{aligned}
b)\ & \Delta E_{i_2}(sp_3, sp_4) = k_2 * \Delta E(sp_2, sp_4) + (1 - k_2) * \Delta E(sp_1, sp_4) \\
& k_2 = f_2(a) = p_{2_4}a^4 + p_{2_3}a^3 + p_{2_2}a^2 + p_{2_1}a + p_{2_0} \\
c)\ & \Delta E_{i_4}(sp_3, sp_6) = k_4 * \Delta E(sp_3, sp_4) + (1 - k_4) * \Delta E(sp_3, sp_5) \\
& k_4 = f_4(a, b) = p_{4_4}b^4 + p_{4_3}b^3 + p_{4_2}b^2 + p_{4_1}b + p_{4_0} \\
d, e)\ & \Delta E_{i_5}(sp_{n1}, sp_{n2}) = k_5 * \Delta E(sp_{n1}, sp_{s2}) + (1 - k_5) * \Delta E(sp_{n1}, sp_{p2}) \\
& k_5 = f_5(p_{s1}, p_{s2}) = p_{6_4}p_{s2}^4 + p_{6_3}p_{s2}^3 + p_{6_2}p_{s2}^2 + p_{6_1}p_{s2} + p_{6_0}.
\end{aligned} \tag{11}$$

The solution of the coefficients p_i in cases b, ..., e becomes more complicated than for the basic case a, but in all the cases, the values for the multipliers were precomputed and they were stored in the database. Now we can freely set the values for the interpolation parameters, and compute the spectral differences between those two spectra.

If the two spectra are some known ones, e.g. from a specific application, then one can calculate the barycentric coordinates for those two spectra and then find the difference between them.

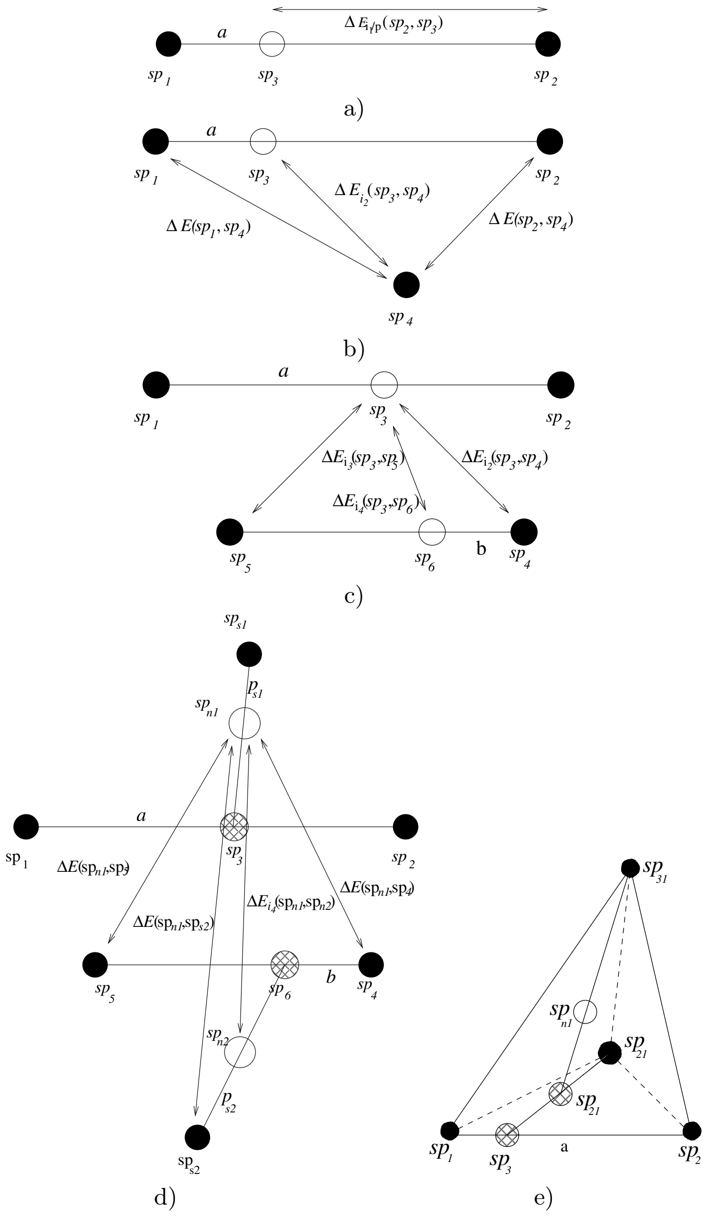

Fig. 1. Constellation of spectra. Black circles correspond to known spectra, hashed spectra correspond to interpolated spectra, and the difference is computed between the (interpolated) unfilled circles. a) sp_1, sp_2 and sp_3 and the difference is computed as $\Delta E(sp_2, sp_3)$, b) $\Delta E(sp_3, sp_4)$, c) $\Delta E(sp_3, sp_6)$, d) $\Delta E(sp_{n1}, sp_{n2})$. e) The first group is shown as a tetrahedron. Now the spectrum sp_{n1} is selected from this group and the similar spectrum sp_{n2} is selected from the second group. The difference is then $\Delta E(sp_{n1}, sp_{n2})$.

4 Experiments

In the experiments, we show how our interpolative system finds the spectral differences. The first experiment is comparing the spectral differences ΔE_i to ΔE_{00} colour differences. The second test works with the metameric spectra, and in the third experiment, the interpolative system is compared with the well-known metrics in calculating the spectral differences.

4.1 Spectral Differences ΔE_i vs. ΔE_{00} Colour Differences with Small Colour Differences

Many spectral and colour differences were calculated in various locations in *Lab*-space. For each (a, b) center, a set of differences between several spectra were calculated. The interest in this experiment was in the difference between the spectral difference and the colour difference, in principle in $||\Delta E_i - \Delta E_{00}||$. Fig. 2 illustrates the results. The mean of the absolute differences, standard deviation, and median are presented for all those sets of differences for many (a, b) centers.

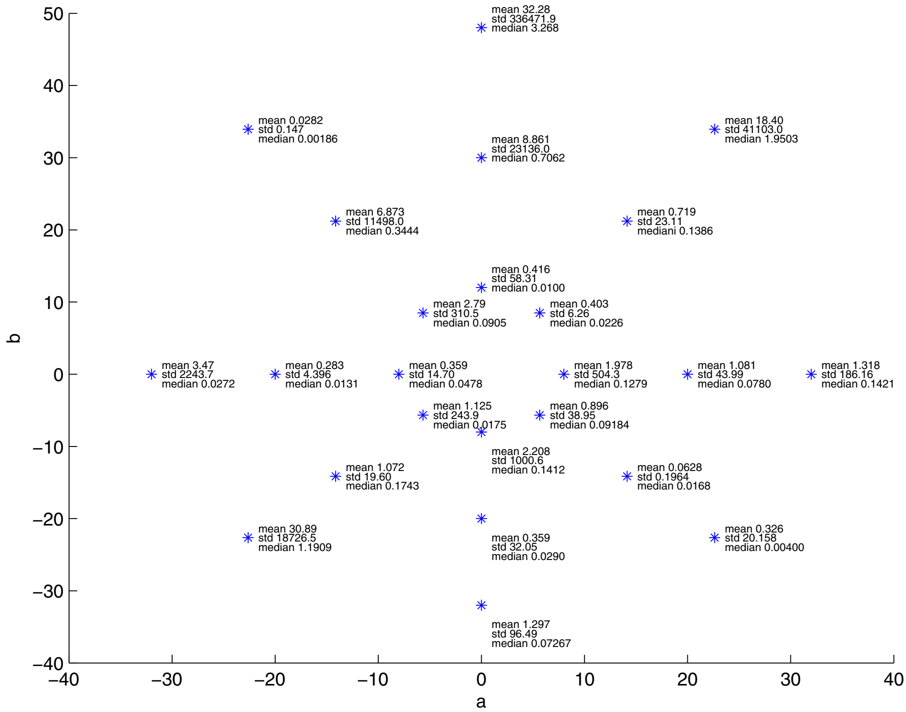

Fig. 2. ΔE_i spectral differences vs. ΔE_{00} colour differences in (a, b) space. $L = 50$

The experiment indicates that the proposed measure fulfills the requirement for matching with ΔE_{00}. The results in Fig. 2 support this conclusion. Large values for the mean and for the standard deviation show that the calculation of the differences have failed for some spectrum pairs. The median indicates the overall operation better than those values that include also outliers.

4.2 Spectral Differences ΔE_i vs. ΔE_{00} Colour Differences for Metameric Spectra

The colour difference between two metameric spectra disappears. One of the design goals for the proposed model was to find the difference also for the metameric spectra. This would reveal that the two basic spectra are different. We constructed six metameric pairs and the results for this experiment are in Table 1. The pairs were computed according to the model proposed in [11].

Table 1. Spectral difference ΔE_i vs. ΔE_{00} colour difference. The two last columns indicate how metameric the two spectra are. Small values in column $\Delta(\beta_{F_1}, \beta_{F_2})$ indicate the higher metamerims for the basic spectra. High values in column $\Delta(\beta_{B_1}, \beta_{B_2})$ indicate the distance to metameric black.

Pair	ΔE_{00}	ΔE_i	$\Delta(\beta_{F_1}, \beta_{F_2})$	$\Delta(\beta_{B_1}, \beta_{B_2})$
1	3.02	7.08	3.34e-02	1.34
2	3.05	6.56	3.92e-02	1.08
3	0.495	13.9	5.21e-17	1.51
4	0.237	19.1	6.86e-17	1.53
5	0.546	2.15	6.04e-03	1.10
6	0.678	19.8	3.00e-17	1.72

The results with metameric spectra show that the proposed measure is able to find the difference between the two spectra.

4.3 Spectral Differences ΔE_i vs. Differences from the Standard Metrics

Since the CIEDE2000 colour difference equation is designed for small colour differences then this experiment is also comparing only small differences, namely $0 < \Delta E_{00} < 10$. The results in Table 2 show the difference between the measure (either ΔE_i, RMS, Weighted RMS [4], SAM, SID, and SCI) and ΔE_{00}. Again, a large set of experiments were run using various *Lab* centers. Typical results, for one *Lab* center, are shown in Table 2.

Also the comparative results in Table 2 indicate the good correspondence with ΔE_{00}. In general, the proposed measure has better match with the human visual system than any of the well-known metrics, see Table 2. The large mean and the value for standard deviation for ΔE_i include again some outliers. The median reflects the general operation.

Table 2. Spectral differences vs. the differences from the well-known metrics. The test set was in *Lab* space close to location $(L, a, b) = (50; 4.84; -4.94)$.

Metric	Number of samples	Mean	Median	Std.
ΔE_i	2500	2.09e+00	8.35e-03	3.37e+03
RMS	2500	2.51e+00	2.33e+00	1.87e+00
WRMS	2500	2.50e+00	2.32e+00	1.85e+00
SAM	2500	2.47e+00	2.30e+00	1.82e+00
SID	2500	2.52e+00	2.34e+00	1.87e+00
SCI	2500	2.51e+00	2.33e+00	1.88e+00

5 Conclusions

The paper proposes a new approach to calculate spectral differences. The basic requirement in the design was that the spectral differences should be close to the ΔE_{00} values. As a consequence the measure also match with the differences seen by the human visual system. The reporting allows to show only a limited set of experimental results, but they indicate the operation quality of the proposed measure.

There are also some issues where new development steps would be needed. One consequence of the original requirements is that the measure is applicable only for the colour spectra. The extension would require some measure that would provide the learning set, as ΔE_{00} for the colour spectra. The computational complexity is also high, both in the pre-calculation of the k parameters in Eq. 11. There are also situations where the model breaks up in calculating k values. This can be seen in Fig. 2 as the value for standard deviation. In computations this was seen almost as a division by zero and the reason originates from the poor selection of the original spectra for the constellation, see Fig. 1.

These shortcomings are difficult to avoid and our future work will concentrate in non-linear modelling of the spectral space and the corresponding colour space and then finding the geodesics in those spaces.

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