Color Differences in a Spectral Space

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Abstract

In this study two measures for defining color differences in spectral space are defined using two spectral databases, Munsell Glossy and NCS. First of the measures is a N-dimensional Euclidean distance between two radiance spectra. Spectral differences of constant chroma, adjacent hues and adjacent values in Munsell and NCS-databases are evaluated and analyzed based on this measure.

Three-dimensional conical color-space with first three PCA-eigenvectors of NCS- and Munsell data as basis vectors is defined and analyzed. The second error measure is defined as the Euclidean distance in this space.

Similarities between eigenvectors and opponent signals proposed by Hurvich and Jameson are noticed. Smoothed eigenvectors of NCS are concluded to be better for creation of a uniform color-space than the Munsell eigenvectors. The projections of a radiance spectrum to the modified eigenvectors define the coordinate values of the color-space. It is noticed that by weighting the first and the second eigenvector by luminous efficiency curve the color-space will be more uniform. Finally the variables are modified so that the color-space would be as uniform as possible but still allowing the calculations be quite simple. Also simple chromatic adaptation terms are defined for this color-space to improve its performance. Hue angle differences between adjacent hues of Munsell value 6 are determined using standard color-spaces and modified 3-dimensional spectral eigenvector space. Also the chroma scales as a function of hue are evaluated. Chroma and hue differences in spectral space and in modified eigenvector space are compared to the most common color difference formulas (CIELAB E, CIE94 and CIEDE2000). Performance of defined color-space with Munsell Glossy spectra is compared to the CIELAB-space and the CIECAM97s-model.

Introduction

A majority of color difference formulas are based on the CIELAB-color-space. The original color difference formula in the CIELAB-space was defined as an euclidean distance in a 3D-space. Afterwards different kind of terms and parameters have been added to improve the performance of the color difference formula.[1, 2, 3]

Recently, many kinds of color appearance models have been constructed. These include ATD-models[4] and CIECAM97s-model, which is recommendation of CIE.[5] Although one claims, that CIECAM97s is uniform, it still hasn't been used much for color difference definitions. One reason may be its complexity. Furthermore, CIECAM97s-model has been revised many times since the original version was published, and a completely new version, CIECAM02s, has been published recently.[6-8] Also a new color difference formula based on CIELAB, CIEDE2000, was developed. CIEDE2000-color difference formula is also recommended by CIE.

The color difference formulas based on CIELAB cannot be explained physiologically. They are formulas, which improve mathematically the uniformity of the CIELAB-space. However, we can't define any logical coordinate system with those formulas. An ideal uniform colorspace should base on the physiology of human visual system. The lack of information about the human visual system makes it impossible to create an unarguable color appearance model on physiological basis.

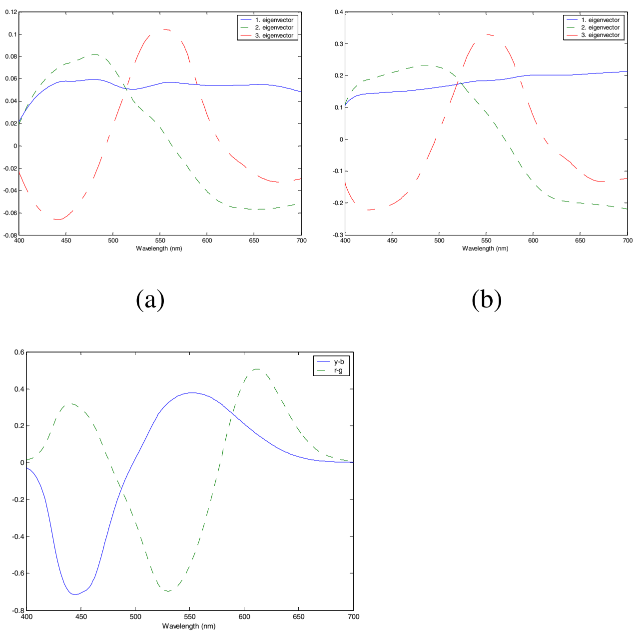
The second chance to create uniform color-space is to use statistical methods. We can create three-dimensional dataset by calculating the first three principal components for radiance spectra of the dataset.[9] Recently this kind of PCA-based spectral analysis has been done much in the field of spectral imaging.[9,10] By editing these eigenvectors we are able to define almost the same dimensions as the human color vision system has. Here one needs to point out that usually our databases are based on some physiological theory or model, for example in case of Munsell system that is the opponent theory model. It is well known that the first eigenvector of spectral dataset is proportional to the mean of the spectra and further to the intensities of the spectra.[10] The second and the third eigenvectors are quite similar to the opponent signals proposed by Hurvich and Jameson.[10-12]

Another way to create uniform colorspace statistically is to use optimizing methods which map spectra to the uniform color space defined by uniform dataset.[13]

Experimental

The coordinate systems were defined using two spectral datasets, Munsell Glossy data (1600 samples) and NCS-data. In case of Munsell Glossy dataset, reflectance spectra of colorpatches were measured by a spectrophotometer from wavelength 380 to 780 nm with 1 nm intervals. Radiance spectra were calculated using C-illumination, to which Munsell data is calibrated. In case of NCS data, reflectance spectra were measured between wavelengths 400-700 nm with 10 nm intervals. NCS-data was used with D65-illuminant.[12]

First, the eigenvectors of both datasets (from radiance spectra) were defined. The first three eigenvectors for both Munsell Glossy and NCS-data, and the opponent signals proposed by Hurvich and Jameson are shown in figure 1. The first three eigenvectors of NCS-data were interpolated to have intervals of 1 nm. The smoothed NCS eigenvectors proved to work slightly better as a basis of a novel color-space. At this point our color-space is simply a three-dimensional subspace of the original 301-dimensional spectral space.



(a) (b)

(c)

Figure 1. (a) First three Munsell Glossy eigenvectors (b) First three NCS eigenvectors (c) Opponent signals proposed by Hurvich and Jameson.[10]

It is known that the first eigenvector of spectral dataset is proportional to meanvector of the spectral data and further to intensity.[9] By multiplying the first eigenvector by the cone sensitivity (V( )-curve), we can get a value proportional to luminance by projecting a reflected spectra to this modified first eigenvector. Because cone sensitivity isn't linear, some nonlinear modification to the projection must be done. We used the same modification as CIELAB system does, i.e. cubic root of projection.[12]

It has been concluded that human visual system is conical.[10] In certain luminance plane the second and the third eigenvector coefficients (projections of spectra to the second and third eigenvector) define a cartesian plane, and with those cartesian coordinates we are able to define hue and chroma as usual.[7] In case of the color-space based on the first three Munsell eigenvectors it was noticed, that the gray-axis was a little bit slant to blue region, so the whitest sample had some chroma. However, as we note, the Munsell data is defined under C-illumination, and we also know, that C-illumination is little bit bluish. We conclude that this phenomenon is because of chromatic adaptation and this problem can be corrected by a simple adaptation term.[12]

It also follows from experiments made with Munsell data, that values of chroma predicted by the projections of spectra to the second and the third eigenvectors of constant chroma spectra appears to increase when brightness (or lightness) is increasing. The problem is solved by dividing the second and the third projections by squareroot of brightness value described above, and "chromarings" of various values match better to each other. When considering the chromarings of value 6 at this point, we could see that chromarings were slightly flattened on green area. So we conclude that we must weight also the second eigenvector by product of Judd's V( )-curve and the first eigenvector before calculating projections. However, the third eigenvector must not be weightened by Judd's V( )-curve, because that would bend the grayaxel to a very slant one. Figure 2 represents eigenvectors, of which the first and the second have been weighted by Judd's sensitivity curve.

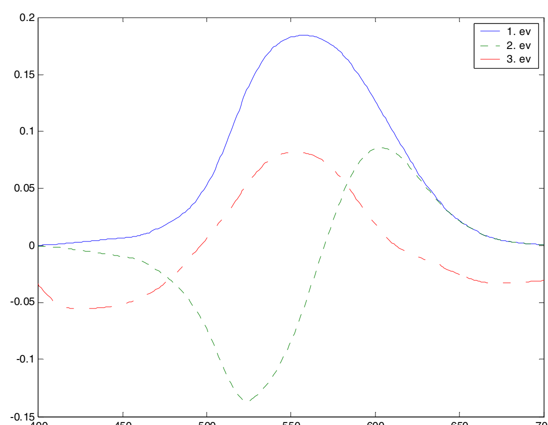


Figure 2. NCS-eigenvectors (the first and the second eigenvector weighted by Judd's sensitivity curve, and the third one scaled to have approximately the same magnitude as the second eigenvector).

Comparing Figs. 1 (c) and 2 we can see, that the opponent signals proposed by Hurvich and Jameson are very much like signals presented in Fig. 2, but still some differences exist.

Finally we weightened the projections so that the brightness and the chroma values matches as well as possible to the original Munsell values and chromas. The

final formulas to modified eigenvectorspace coefficients are as follows (using eigenvectors of NCS):
Brightness (B):

$$B = \left[V(\lambda)E_1(\lambda)\cdot R(\lambda)\right]^{1/3} \tag{1}$$

Blue-orange-value (b):

$$b = 16\frac{\left[(V(\lambda)E_1(\lambda)E_2(\lambda))\cdot R(\lambda)\right]}{B^2} - D_b \tag{2}$$

Purple-green-value (g):

$$g = 0.95\frac{E_3(\lambda)\cdot R(\lambda)}{B^2} - D_g\ , \tag{3}$$

where $E_1(\ )$, $E_2(\ )$ and $E_3(\ )$ are the first three eigenvectors of NCS-data (reflectance) weighted by radiance spectrum of illuminant D65, $R(\ )$ is radiance spectrum of the sample, and D_b and D_g are chromatic adaptation factors defined as follows:

$$D_b = 16 d_A B \frac{(V(\lambda)E_1(\lambda)E_2(\lambda))\cdot W_A(\lambda)}{{B_{W_A}}^3} \tag{4}$$

$$D_g = 0.95 d_A B \frac{E_3(\lambda)\cdot W_A(\lambda)}{{B_{W_A}}^3}\ , \tag{5}$$

where d_A is the degree of chromatic adaptation (0-1) and W_A is the radiance spectrum of adapted illumination which is C for the Munsell data and D65 for NCS-data. This chromatic adaptation model simply straightens the gray-axis if we choose d_A to be equal to one.

Finally, the brightness value B was normalized to W (Whiteness) to correspond better Munsell value:

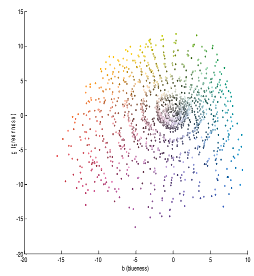
$$W = B - 2.6 \tag{6}$$

Spectral data of Munsell and NCS was also converted to CIELAB and CIECAM97s-spaces. With CIECAM97s we used Qab-space, where Q corresponds brightness and a and b defines a plane of chromaticity in the same manner as CIELAB does. It should be noticed that hue angles on bg-plane do not correspond to hue angle on a*b*-plane of CIELAB or hue angles on ab-plane of CIECAM97s.

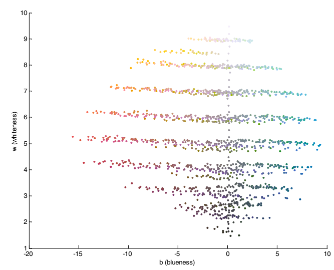
We also defined distance matrices in 301 (400-700 nm with intervals of 1 nm) dimensional space in the case of Munsell Glossy data and in 31-dimensional (400-700 nm with 10 nm intervals) space in the case of NCS-data. From this data we calculated chromadifferences with different chromas as a function of hue in a certain value plane (Fig 5 (d)).

Results

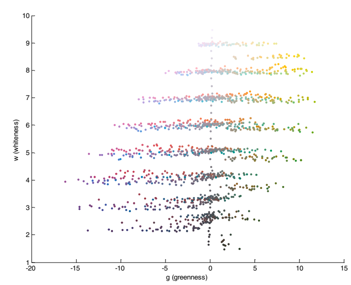
Munsell Glossy spectra in C illumination with full chromatic adaptation to C-illumination was plotted to the resultant 3D-colorspace, and the projections of that colorspace with Munsell spectra are shown in Fig 3 (a)-(c).



(a)



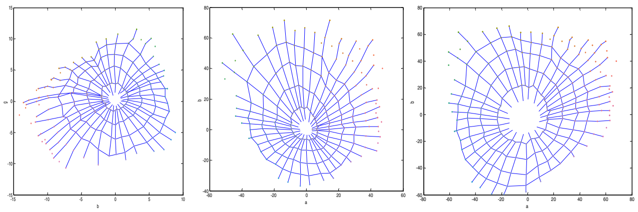
(b)



(c)

Figure 3. Munsell Glossy spectra plotted in 3D-colorspace based on the NCS-eigenvectors. (a) bg-plane. (b) Wb-plane. (c) Wg-plane.

The constant hue and constant chroma lines of Munsell Glossy value 6 in Wbg-space, CIELAB-space and CIECAM97s-space are shown in Fig 4 (a) –(c). This figure shows that CIECAM97s works slightly better than our novel wbg-colorspace in terms of smoothness of constant chromalines.



(a) *(b)* *(c)*

*Figure 4. Constant Hue and constant chroma lines (a) on bg-plane of Wbg-space, (b) on a*b*-plane of CIELAB-space and (c) on ab-plane of CIECAM97s-space.*

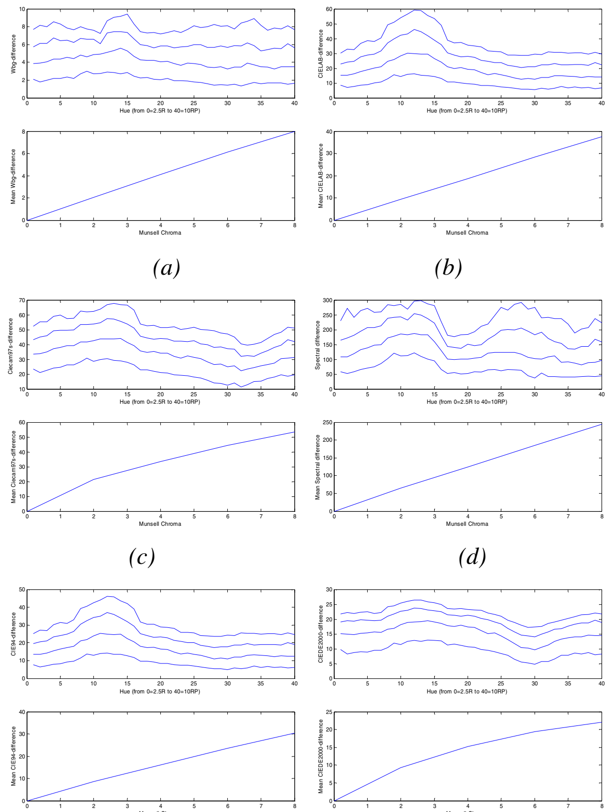
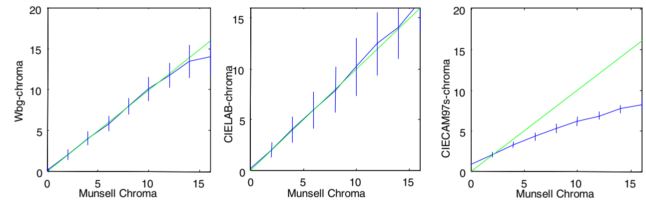


Figure 5. Constant chroma lines (chromas 2, 4, 6 and 8) of Munsell Glossy value 6 data as function of Hue and mean chromas as function of Munsell chroma (a) in Wbg-space, (b) in CIELAB-space, (c) in CIECAM97s-space, (d) in 301-dimensional euclidean spectral space, (e) defined by CIE94 color difference formula and (f) defined by CIEDE2000 color difference formula.

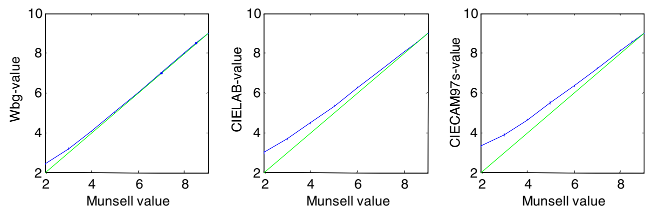
Figures 6-8 shows that the performance of the wbg-space is quite competent if we compare it to CIELAB- or CIECAM97s-model. While predicting Munsell chroma or value (Figs 6-7) we can see that Wgb-space works unarguably best. Prediction of Munsell Hue is quite similar in all three models.

The results with the NCS-data were very similar with Munsell data.



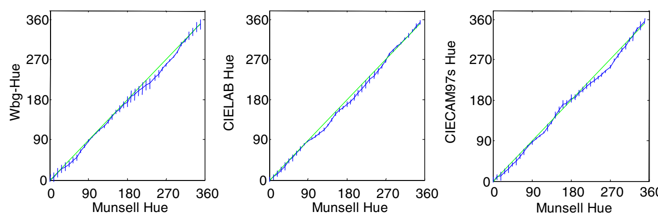
(a) *(b)* *(c)*

Figure 6. Mean (a) Wbg-chroma, (b) CIELAB-chroma, and (c) CIECAM97s-chroma vs. Munsell Chroma with their standard deviations. Chroma-scales have been normalized so that Munsell Chromas 2 have the right prediction of chroma.



(a) *(b)* *(c)*

Figure 7. Mean (a) Wbg-value, (b) CIELAB-value, and (c) CIECAM97s-value vs. Munsell Value with their standard deviations. Value-scales have been normalized so that Munsell Values 9 have the right prediction of value.



(a) *(b)* *(c)*

Figure 8. Mean (a) Wbg-hue, (b) CIELAB-hue, and (c) CIECAM97s-hue vs. Munsell Hue with their standard deviations. Hue-scales have been normalized so that Munsell Hues 0 (2.5 R) have the right prediction of hue.

Conclusions

The newest modifications of three dimensional color coordinates have a tendency to become rather complex. Our goal in this study was to find out a simple way to define a uniform three dimensional color coordinate system based directly on color spectra.

A very interesting question related to the novel colorspace based on eigenvectors of radiance spectras is that why the second and third eigenvector are so similar to those functions proposed by opponent color theory. We can find out the fact that the simplest solution to represent smooth natural spectra by three components is to use one constant function (intensity), sine-function and cosine-function. When considering for instance the opponent signals proposed by Hurvich and Jameson, it's easy to see that they are quite similar to sine- and cosine functions. However, evolution hasn't been able to match them perfectly to each other.

Another thing, which is increasing the similarity between opponent functions and the second and the third eigenvector, can be purely statistical; Munsell colorsystem is based on opponent colortheory.

When comparing opponent signals proposed by Hurvich and Jameson to three first eigenvectors, from which the first and the second are weighted by cone's spectral sensitivity, we can note that third eigenvector is quite different compared to yellow-blue-channel opponent signal. The biggest problem is in this case that the third eigenvector isn't zero in its ends. This property means that chroma is too large when brightness is small with purple spectra. Model also allows negative brigthness values. Also the chromatic adaptation model, which is included to the novel color-space is too simple and it is expected that it doesn't work properly enough. Also adaptation to different background luminance levels is ignored. That is also the reason why Wbg-model uses term brightness instead of lightness. Hence it's obvious that this novel spectral color-space should be developed further before it can be used as a uniform color-space.

However this novel colorspace works quite well at least with smooth spectra, e.g. with Munsell or NCS-data if we compare it to CIELAB or original CIECAM97s model. A topic for a new research is to clear out, if the model works also with spectra containing sharp peaks, such as with LCD and CRT spectra. It's obvious that with these spectra we can not use eigenvectors, which cover only wavelengths from 400 nm to 700 nm, because CRT's red phosphor has significant luminance also on wavelengths over 700 nm, for example.

In this research we also test the performance of a 301-dimensional euclidean spectral space. However, because the testing was done only with chromadifferences, we couldn't get a good general view of its performance. We realize that the ability of the 301-dimensional spectral space to predict chromadifferences is not yet satisfactory.

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Biographies

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