Color Differences in a Spectral Space

Diana Kalenova, Pekka Toivanen and Vladimir Botchko
Department of Information Technology, Lappeenranta University of Technology
Lappeenranta, Finland

Abstract

In this study, color similarity metrics in a spectral space are considered. The paper gives a brief overview of several existing measures and presents a novel approach based on kernel methods. New similarity measures for spectral images based upon kernel methods include polynomial, Gaussian radial basis function and sigmoid kernels. The performance of the methods is tested against the Munsell Matte spectral dataset. Kernel methods are compared to twelve well-known similarity metrics, i.e. Correlation Coefficient, Exponential Similarity, Maximum-Minimum methods, etc. Spectral differences of constant Hue, adjacent Values and Chromas have been evaluated using these metrics. The tests show that the proposed Gaussian radial basis function kernel metric performs significantly better, compared to the rest of the measures.

Introduction

In this paper, a novel kernel based approach to color similarity estimation problem is proposed. The methods used can be employed in a number of different applications, including image compression, electronic commerce, archiving etc.

One of the most popular color similarity metrics is Euclidean distance defined in the CIE L*a*b* color space.[1] It has an advantage of simplicity in understanding and realization, however the metric is not efficient. Euclidean distance calculates the difference between colors not taking into account the angle between color vectors, which produces a significant divergence for RGB image reproduction.

Another set of color similarity metrics was proposed in Refs. 2 and 3 The set contains twelve well-known color similarity measures, created upon the assumption that an optimal color similarity metric should take into account both the distance and the angle between color vectors. The measures are based upon popular distance functions, such as Mahalanobis or Hamming distances. All of the metrics have been tested in Ref. [4]. It has been shown that the absolute-value exponential method was the most effective in the task of color differencing.[4]

All of the above-mentioned measures have been applied to standard RGB or CIE L*a*b* color spaces. They can be extended to incorporate spectral data. An approach to spectral color differencing has been proposed in Ref. [11]. The measures are, in this case: N-dimensional Euclidean distance between two radiance spectra and Euclidean distance in this space. These measures are defined based on two spectral databases: Munsell Glossy[8] and NCS.[11]

This measure has been applied to spectral differences of constant chroma, adjacent hues and adjacent values in Munsell and NCS-databases. Then a three-dimensional conical color-space with first three PCA-eigenvectors of NCS- and Munsell data as basis vectors has been defined and analyzed. The Euclidean distance has been computed in this color space. The metric performed significantly better than standard CIE L*a*b* DeltaE, CIE94 and CIEDE2000 formulae. However, as most of the measures built upon Euclidean distance, it suffers from a serious drawback of neglecting the angle between color vectors, which carries significant information in itself.[11]

In this paper, a novel approach of color difference estimation, incorporating spectral data, is proposed. The color similarity metrics introduced are based on a well-known pattern recognition technique – kernel methods.[5] A kernel can be considered an extension of a canonical dot product, which in turn, is one of the techniques described in Refs. [2] and [3]. Kernel methods applied in this study include: polynomial, Gaussian radial basis function (RBF) and sigmoid kernels.

Spectral differences between colors have been measured using a Munsell Matte Collection spectral dataset,[6] against constant Hues and adjacent values of Chromas and Values. The results of the measurements produced using the kernel-based methods[5] have been compared to twelve well-known color metrics[2,3] extended to incorporate spectral data.

Color Similarity Measures

Color similarity measures generally take two spectral vectors as an input and produce an output on a 0 to 1 scale. Where 0 means that the colors are "not similar at all" and 1 means "identical".[7]

In this paper, a kernel-based approach to color similarity is proposed. The performance of these measures is compared with the performance of twelve widely known metrics.[2,3] Kernels can be assumed to be dot products of vectors in a certain feature space, meaning that if we have two vectors x_i and x_j in the input domain X, we can produce a mapping:

$$\begin{aligned} &\Phi : \mathrm{X} \to \mathrm{H} \\ &x \mapsto x := \Phi(x) \end{aligned} \tag{1}$$

So the dot product is computed in thus induced feature space.[5] The kernel similarity measures considered in this paper include polynomial, Gaussian radial basis function and sigmoid kernels.

Polynomial kernel similarity measure can be presented as follows:

$$S_{polynomial} = (x_i, x_j)^d \tag{2}$$

where d is the parameter of the sensitivity of the measure, x_i and x_j are input p-dimensional color vectors. The similarity functions have a general form of $S(x_i,x_j)$, the arguments are skipped for simplicity in the formulae shown in this paper.

The Gaussian radial basis function kernel has the following form:

$$S_{Gaussian} = \exp\left(-\frac{\|x_i - x_j\|^2}{2\sigma^2}\right) \quad (3)$$

where $\sigma > 0$, σ is the parameter of the sensitivity of the function.

And the sigmoid kernel based similarity metric can be presented as follows:

$$S_{sigmoid} = \tanh(k*(x_i, x_j) + \vartheta) \quad (4)$$

where k an ϑ are variable parameters.

The twelve other metrics are as follows[7]:

Metric 1

$$S_1 = \frac{x_i x_j^t}{|x_i||x_j|} = \cos(\theta) \quad (5)$$

where θ is the angle between vectors x_i and x_j

Metric 2

$$S_2 = \left(\frac{x_i x_j^t}{|x_i||x_j|}\right)\left(1 - \frac{\left||x_i| - |x_j|\right|}{\max(|x_i|, |x_j|)}\right) \quad (6)$$

Metric 3

$$S_3 = \frac{|x_i|\cos(\theta) + |x_j|\cos(\theta)}{\left(|x_i|^2 + |x_j|^2 + 2|x_i||x_j|\cos(\theta)\right)^{\frac{1}{2}}} \quad (7)$$

Metric 4

$$S_4 = \frac{\cos(\theta)\left(|x_i|^2 + |x_j|^2 + 2|x_i||x_j|\cos(\theta)\right)^{\frac{1}{2}}}{|x_i| + |x_j|} \quad (8)$$

Metric 5

$$S_5 = 1 - \frac{\left(|x_i|^2 + |x_j|^2 - 2|x_i||x_j|\cos(\theta)\right)^{\frac{1}{2}}}{\left(|x_i|^2 + |x_j|^2 + 2|x_i||x_j|\cos(\theta)\right)^{\frac{1}{2}}} \quad (9)$$

Metric 6: Correlation Coefficient Method

$$S_6 = \frac{\sum_{k=1}^{p} |x_{ik} - \bar{x}_i||x_{jk} - \bar{x}_j|}{\left(\sum_{k=1}^{p}(x_{ik} - \bar{x}_i)^2\right)^{1/2}\left(\sum_{k=1}^{p}(x_{jk} - \bar{x}_j)^2\right)^{1/2}} \quad (10)$$

where $\bar{x}_i = \frac{1}{p}\sum_{k=1}^{p} x_{ik}$

Metric 7: Exponential Similarity Method

$$S_7 = \frac{1}{p}\sum_{k=1}^{p}\exp\left(-\frac{3}{4} * \frac{(x_{ik} - x_{jk})^2}{\beta_k^2}\right) \quad (11)$$

where $\beta_k^2 > 0$ is a parameter that is determined experimentally.

Metric 8: Absolute-Value Exponent Method

$$S_8 = \exp\left(-\beta\sum_{k=1}^{p}|x_{ik} - x_{jk}|\right) \quad (12)$$

where $\beta > 0$.

Metric 9: Absolute-Value Reciprocal Method

$$S_9 = 1 - \beta\sum_{k=1}^{p}|x_{ik} - x_{jk}| \quad (13)$$

β is determined empirically.

Metric 10: Maximum-Minimum Method

$$S_{10} = \frac{\sum_{k=1}^{p}\min(x_{ik}, x_{jk})}{\sum_{k=1}^{p}\max(x_{ik}, x_{jk})} \quad (14)$$

Metric 11:Arithmetic-Mean Minimum Method

$$S_{11} = \frac{\sum_{k=1}^{p}\min(x_{ik}, x_{jk})}{\frac{1}{2}\sum_{k=1}^{p}(x_{ik} + x_{jk})} \quad (15)$$

Metric 12: Geometric-Mean Minimum Method

$$S_{12} = \frac{\sum_{k=1}^{p}\min(x_{ik}, x_{jk})}{\sum_{k=1}^{p}(x_{ik}x_{jk})^{1/2}} \quad (16)$$

Experiment

The tests of the viability of color similarity metrics were performed on Munsell Colors Matte dataset[6] (1269 matt Munsell color chips). The reflectance spectra had been measured by a Perkin-Elmer lambda 9 UV/VIS/NIR spectrophotometer in the 380 nm - 800 nm interval with 1 nm wavelength resolution.[8]

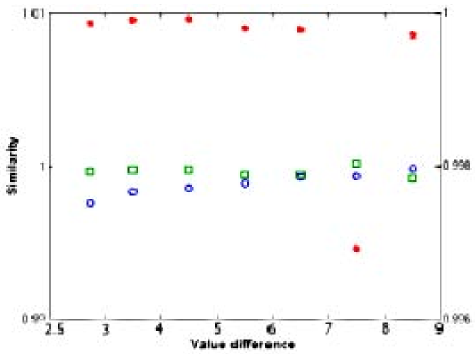
The purpose of the experiment was to choose a metric that would give comparable values of differences for perceptually equally disparate colors, and at the same time would account for the changes in Hue, Value and Chroma with the whole range of values. Another requirement imposed on the measures was the possibility of adjustment of the sensitivity of similarity measurements.

The first set of experiments concerned the possibility of color discrimination based on spectral information of Munsell colors with constant values of Hue and Chroma and adjacent values of Value. The set was chosen so that it covers the entire range of Values. Hue was selected to be 5R, 5B and 5G, Chroma equal to 1, and Values ranging from 2.5 to 9.

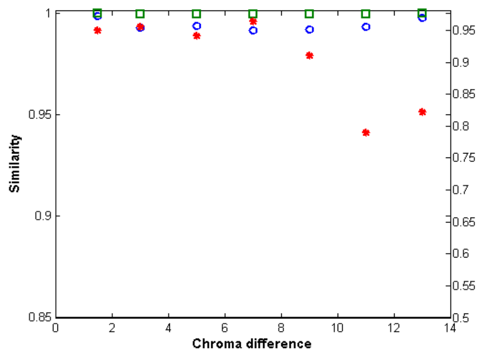
The second set of tests was similar to the previous one, except that the Values and Hues remained constant, while Chroma was varied. Thus, Hue was set to 5R, 5B and 5G, Value to 6, and Chroma ranged from 1 to 14.

In order to account for the visual uniformity of the Munsell color dataset, the input data was multiplied by Spectral Luminous Efficiency Function for photopic vision[9] and illumination factor.[10]

Considering the purpose of the whole experiment, the results obtained can be divided into several categories. First, would come the metrics that gave comparable values of differences for perceptually equally disparate colors. For that purpose, based upon the experimental settings described above, diagrams of the functional relations between similarity measures, Value and Chroma have been obtained (see Fig. 1). The diagrams show the three best metrics from the point of view of the linearity of the response given to the inputs. Meaning that the measures gave close to linear (to a certain extent) responses to the changes in Value and Chroma. The metrics that gave the smoothest responses are Metric 1, Metric 8 and Gaussian radial basis function, presented in Fig. 1.



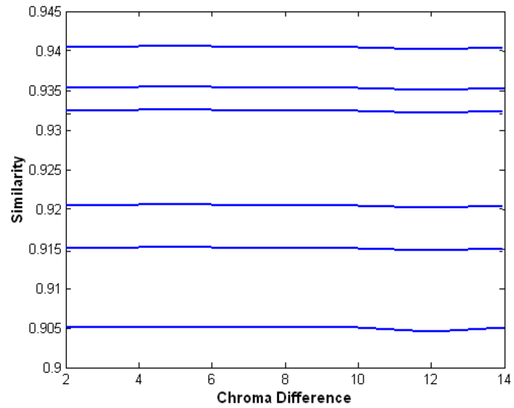
(a)



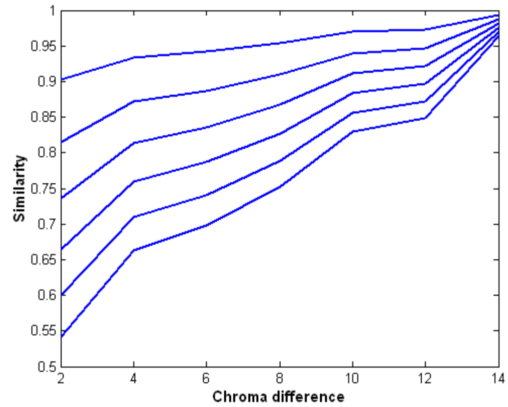
(b)

Figure 1. (a) Similarity vs. Value, (b) Similarity vs. Chroma (Metric 1 – red asterisk (second scale); Metric 8 – Absolute-Value Reciprocal Method blue circles, RBF – green squares) for 5R Hue

The second requirement set upon the metrics has been the possibility of adjustment of the sensitivity of similarity measurements. Looking back at the Eq. 2-16, it can be stated that the kernel methods (polynomial, Gaussian RBF and sigmoid), exponential similarity, absolute-value exponential, absolute-value reciprocal methods poses similarity terms, which allow adjustment of the measurements. However, the kernel methods provide a significantly better control over the whole equation. The results of testing of the sensitivity parameters in the measures for Gaussian RBF and Metric 8 (absolute-value exponent) are presented in Fig. 2.



(a)



(b)

Figure 2. Sensitivity of (a) Gaussian RBF (b) Metric8 (absolute-value exponent) for 5R Hue, Value 6

A functional relation between the similarity values of Gaussian RBF and Metric 8 for different sensitivity are shown in Fig. 2, where both β and σ have been varied in the range of 0.005 and 0.03. The resulting graphs show that the sensitivity of the measures can be varied through the use of the special terms in a certain range. However, the absolute value exponential method tends to produce non-linearities with the growth of the sensitivity value. The choice of the Gaussian RBF and Metric 8 functions for testing is not accidental. Both of these metrics have shown the best results for the smoothness of the response of the sensitivity function requirement, thus it would seem reasonable to continue comparing them.

And the final requirement upon the similarity measures that has been set is the possibility of accounting for the changes in Hue, Value and Chroma with the whole range of values. This requirement implies that the sensitivity of the metric should be such that it would account for the just noticeable by a human eye differences in the color. The best results have been produced by kernel metrics, Metric 7 (exponential similarity) and Metric 8 (absolute-value exponential).

Considering the results obtained, several metrics could be considered as the most promising. The best results have been obtained using the Gaussian RBF and absolute-value exponential metrics. Both of these measures have produced approximately linear responses to perceptually uniformly distributed values of Value and Chroma (with Gaussian RBF producing the smoothest response (see Fig. 1)), at the same time, accounting for the change of color vectors with the whole range of values. The sensitivity of the function could be adjusted. However control over the sensitivity in the Gaussian RBF metric is significantly better due to a special term σ introduced into the formula. All of that brought us to a conclusion of the efficiency of the Gaussian RBF measure in the task of color discrimination.

Another result obtained from the experiments performed, is that the response of the similarity functions became smoother with the introduction of the efficiency curve[9] and the illumination factor.[10]

Conclusion

In this paper, color similarity metrics in spectral space have been considered. The measures include twelve well-known metrics created upon well-known distance functions, such as Mahalanobis or Hamming distances, and a set of novel kernel-based color similarity measures. The performance of all of these measures has been tested against Munsell Matte spectral dataset.[8] The purpose of the experiments has been to find a metric that gives comparable values of differences for equally disparate color, at the same time accounting for the values of change in Hue, Chroma and Value with the whole range of values. Based on the results presented above, it can be concluded that the kernel-based approach to color differencing in spectral space is efficient. The performance of the kernel-based metrics gave results comparable with the traditional color similarity measures. Moreover, Gaussian radial basis function kernel performed more effectively considering the traditional color similarity methods. The response of the measure was smoother in the case of both the Value and the Chroma change, and the sensitivity of the function was greater and could be varied in a more efficient way (through the use of a special sensitivity term). Furthermore, weighting the input data by the efficiency curve[9] and illumination factor[10] produced a smoother output of the similarity functions.

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Biographies

Diana Kalenova received the engineer degree in Information Technology in Economics from St. Petersburg State University of Telecommunications in 2001 and M.Sc. in Information Technology at Lappeenranta University of Technology, Finland, in 2003. Since 2003 she has been working at Lappeenranta University of Technology, Finland, as an assistant. Her work is primarily focused on spectral image analysis, color appearance models, statistical characteristics of images and image quality issues. Ms. Kalenova is a member of Pattern Recognition Society of Finland. diana.kalenova@lut.fi

Professor, Doctor of Technology Pekka Toivanen has graduated from Helsinki University of Technology in 1989. Since 1991 he has been working at the Lappeenranta University of Technology, at the Department of Information Technology. He is at the moment a head of the laboratory of Information Processing of the Department of Information Technology at Lappeenranta University of Technology. Pekka Toivanen is a member in SPIE and IEEE. His main research interests are multispectral image processing, color, and distance transforms. pekka.toivanen@lut.fi

Vladimir Botchko is a senior assistant in the Information Technology Department at Lappeenranta University of Technology. Dr. Botchko received his Master's degree at the Electrotechnical Telecommuni-cation University of St. Petersburg, and Ph.D degree at Electrotechnical University of St. Petersburg. His interests lie in the field of computer vision, computer graphics, pattern recognition, spectral and color image analysis. Dr. Botchko is a member of Finnish Pattern Recognition Society. vladimir.botchko@lut.fi