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SPECTRAL RECONSTRUCTION IN CASE OF DIFFERENT ILLUMINANTS

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ABSTACT: Finding the spectral features of color sample sets is a main issue of colorimetry. It is widespread to apply Principal Component Analysis in these researches. Several studies were written about the reconstruction of samples with known spectra using principal components, and some works dealt with approximate reconstruction from tristimulus values. Our study examines how spectral reconstruction done with genetic optimization works in case of different illuminants. The authors have taken only the tristimulus values of the color samples given. Also, they examine the reconstruction in case of illuminants that have unknown spectral power distributions, then they give the solution for these cases in brief.
Keywords: Spectral reconstruction, tristimulus values, principal component analysis, genetic optimization, illuminants

1. INTRODUCTION

It is a basic thesis of colorimetry that any color stimulus can unequivocally be given by three numbers. These numbers can be the CIE X,Y,Z tristimulus values or the coordinates of any other suitable color space ($Y,x,y;L^*,a^*,b^*;L^*,u^*,v^*$ etc.). However, the description of self-luminous objects (light sources) and surfaces (secondary light sources) is often given with spectral features, in other words with spectra. This type of description provides much more information about the observed object, it needs, therefore, more than three parameters. The researchers in colorimetry started examining how they can determine or give approximately the reflection spectra of surfaces with only a few numbers. Principal Component Analysis (PCA), which is based on elements of mathematical statistics and linear algebra, has appeared to be an especially strong and interesting tool.

Several studies deal with the usage of Principal Component Analysis in colorimetry, therefore its mathematical presentation is not the subject of the present article. Publications [1]-[7] provide a general view how it works. In order to apply this method effectively, it is necessary to have a set with a large number of known spectra. Principal Component Analysis produces the eigenvectors belonging to the sample set. The linear combination of these eigenvectors helps to reconstruct the spectrum. The above mentioned studies present reconstruction of samples that have known and measured spectra. The question is whether it is possible to say anything about the spectrum of color samples that have unknown reflectance functions if we only know their tristimulus values X,Y,Z. In some of the studies focusing on this problem [8], [9], the spectral reconstruction is done with an algorithm using pseudo invers matrix operations.

However, Principal Component Analysis or weighed Principal Component Analysis has been used in other studies. Corresponding to the tristimulus values, the three eigenvectors, whose eigenvalues are the greatest ones, are enough to get the same X,Y,Z values as the result of reconstruction [10], [11]. More accurate results can be reached with more components, but they lead to undetermined

equation systems, as the tristimulus values can be given in many ways from more than three components. Because of this critical statement, three vectors have been considered to be satisfactory in most cases.

Publication [12] describes the authors' method that deals with this problem. They used the first five eigenvectors instead of the first three vectors and the features of the reflection functions of real color samples for generic optimization. It was considered that the reflection functions of the real samples are smooth, without strong oscillation and they are non-negative. This method provides a much more accurate reconstruction than the earlier ones. (Figure 1) The set of 2 832 textile samples with known reflectance functions were used. Furthermore, 148 flower samples, 565 paint samples and 8

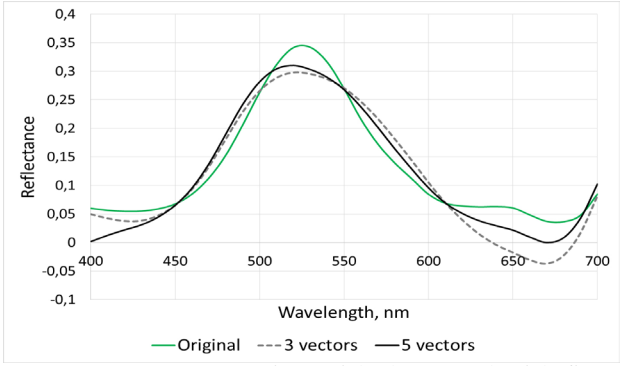

Figure 1. Reconstruction with three and with five eigenvectors

formalism of optimization is to be shown in brief. More details can be read in publication [12].

2. THE FORMALISM OF OPTIMIZATION

During calculation, the authors work with spectra (reflectance functions) whose resolution is given, therefore, finite-dimensional vectors are used instead of continuous functions. Let N denote the dimension number of these vectors. For example, if a spectrum is with a range of 400 nm - 700 nm and with an equidistant-wavelength step of at 10 nm, $N = 31$.

The eigenvalues of the PCA method arranged in decreasing order are denoted by $\tau_1 \geq \tau_2 \cdots \tau_N \geq 0$, the eigenvectors relating to the eigenvalues are denoted by $v_1, v_2, \cdots, v_N$, and the mean vector by m. The linear combination of M eigenvectors and the principal components $c_1, c_2, \cdots, c_M$ provides the following spectrum.

$$f(c_1, c_2, \cdots, c_M) = \sum_{i=1}^{M} c_i \cdot v_i + m \tag{1}$$

$f(c_1, c_2, \cdots, c_M)$ is also an N-dimensional vector.

Having M fixed, variables $c_1, c_2, \cdots, c_M$ determine the spectrum of the reconstructed f according to equation (1). As a next step, a function is to be created that measures the difference between this type of spectrum and the ideal spectrum. The difference is small for smooth and non-negative metamers, and it is greater and greater, if the tristimulus values deviate from the stipulated ones or if the function oscillates strongly or it takes up negative values. It is easy to calculate the tristimulus values of the spectrum by the application of color-matching functions.

$$X_0 = \sum_{i=1}^{N} f_i \cdot S_i \cdot \bar{x}_i, Y_0 = \sum_{i=1}^{N} f_i \cdot S_i \cdot \bar{y}_i, Z_0 = \sum_{i=1}^{N} f_i \cdot S_i \cdot \bar{z}_i \tag{2}$$

In Eq. 2, $\bar{x}_i, \bar{y}_i, \bar{z}_i$ denote the discrete versions of the CIE color-matching functions which have the same resolution as that of the spectra, S_i. is the discrete spectral power distribution of the illuminant. Obviously, the values of X_0, Y_0, Z_0 depend on the coefficients c_i, but this dependenceis not emphasized for the sake of briefness.

It is possible to calculate the squared sum of the differences to show how much the values X_0, Y_0, Z_0 deviate from the predefined values X, Y, Z

$$d_0(c_1, c_2, \cdots, c_M) = (X - X_0)^2 + (Y - Y_0)^2 + (Z - Z_0)^2 \tag{3}$$

This d_0 value is non-negative and it is equal to 0 when a metamer complies with the definition. If $M = 3$, the equation system of the metamer has a single solution. A lot of earlier studies which used PCA ended with giving this solution. If $M > 3$, it has an infinite number of solutions, and the most realistic one can be chosen with the use of constraints on negativity and strong oscillation.

It is possible to describe the negativity of the function bythe integral of the negative and the positive part, or with the ratio of their sums in the discrete case. Denote:

$$f_i^+ = \max(f_i, 0); \; f_i^- = \min(f_i, 0) \tag{4}\text{-}(5)$$

$$F^{+}=\sum_{i=1}^{N} f_i^{+}\ ;\ F^{-}=-\sum_{i=1}^{N} f_i^{-} \qquad (6)\text{-}(7)$$

Definitions (4) and (5) resemble the terms of lower and upper covering functions used in analysis. The penalty term on negativity is:

$$P_n=\frac{F^{-}}{\left(F^{+}+F^{-}\right)}\cdot W_n \qquad (8)$$

W_n is the weight factor which is used to set the relative weight of this term within the optimization function. It is obvious that $P_n=0$ if the function has only non-negative values and $W_n=1$, and the more negative parts, f contains the greater positive values P_n has got. It is 1 in extreme cases.
The oscillation of the function is defined by the squared sum of the deviation between the neighboring terms:

$$V=\sum_{i=1}^{N-1}\left(f_{i+1}-f_i\right)^2 \qquad (9)$$

The penalty term on oscillation is

$$P_v=\sqrt{\frac{V}{(N-1)}}\cdot W_v \qquad (10)$$

The cost function whose minimum is assumed to determine the metamer with the best qualitative features is the following.

$$d\left(c_1,c_2,\cdots,c_M\right)=d_0+P_n+P_v \qquad (11)$$

It is possible to get d_0 from (3), P_n from (8) and P_v from (10). The weights W_n and W_v show the importance of one or the other penalty terms. According to the pre-calculation we have already made, the useful values are $W_n=100, W_1=1$. A little change in them will not influence the final result.
All in all, d is a non-linear function with M variables, whose minimum corresponds to the best function for the researchers, in other words, vector $\left(c_1,c_2,\cdots,c_M\right)$ which gives the location of the extreme values, contains the optimal weight of the eigenvectors used in the reconstruction.
In order to find the minimum point of function d, which has been given in equation (11) above, we use our own genetic optimization program. The genetic algorithm was chosen because d has a lot of local minima (mainly because of the oscillation term) and the gradient-based methods generally cannot find the global minimum in these cases.
Our genetic algorithm uses the standard genetic operators, e.g. mutation and crossing, and in order to accelerate the search for local maxima, it uses hill-climbing steps. The authors had already applied this code to solve more industrial optimization problems [13].

Values describing the accuracy of the reconstruction

It is possible to describe the accuracy of the reconstruction by several measuring numbers in a quantitative way. Also, it is possible to measure the color difference between the examined sample and the reconstructed sample, the spectral deviation and accuracy between the original and the reconstructed reflection function.
The color difference can be given as it follows. As the first step, the tristimulus values X,Y,Z of the samples have to be transformed into values L^{*},a^{*},b^{*} (12), where X_n,Y_n,Z_n are the tristimulus values of the reference white tristimulus values under a given illuminant.

$$L^{*}=116\cdot f\left(\frac{Y}{Y_n}\right)-16,\ a^{*}=500\cdot\left(f\left(\frac{X}{X_n}\right)-f\left(\frac{Y}{Y_n}\right)\right),\ b^{*}=200\cdot\left(f\left(\frac{Y}{Y_n}\right)-f\left(\frac{Z}{Z_n}\right)\right)$$

$$f(t)=\begin{cases} t^{\frac{1}{3}}, t>\left(\frac{6}{29}\right)^3 \\ \frac{1}{3}\cdot\left(\frac{29}{6}\right)^2\cdot t+\frac{4}{29}, t\le\left(\frac{6}{29}\right)^3 \end{cases} \qquad (12)$$

In case of all the used samples, the condition $t>\left(\frac{6}{29}\right)^3$ is met. The X_n,Y_n,Z_n values of the reference white tristimulus under the illuminant with $S(\lambda)$ spectral power distribution are given by equation (13).

$$X_n = k_\varphi \cdot \int_{400}^{700} S(\lambda)\cdot \bar{x}_\omega(\lambda)d\lambda, Y_n = 100, Z_n = k_\varphi \cdot \int_{400}^{700} S(\lambda)\cdot \bar{z}_\omega(\lambda)d\lambda \quad (13)$$

$$k_\varphi = \frac{100}{\int_{400}^{700} S(\lambda)\cdot \bar{y}_\omega(\lambda)d\lambda} \quad (14)$$

The normalisation coefficient is denoted by k_φ and $\bar{x}_\omega(\lambda), \bar{y}_\omega(\lambda), \bar{z}_\omega(\lambda)$ are the CIE color matching functions. The values of the comparable color samples are L_1^*, a_1^*, b_1^*, and L_2^*, a_2^*, b_2^*. Knowing these, the CIE Lab ΔE_{ab}^* color difference can be determined (15).

$$\Delta E_{ab}^* = \sqrt{(L_2^* - L_1^*)^2 + (a_2^* - a_1^*)^2 + (b_2^* - b_1^*)^2} \quad (15)$$

If $\Delta E_{ab}^* = 0$, the test samples are the same. If $\Delta E_{ab}^* = 1$, it gives the just perceptible difference under a given illuminant.

Two different values are given for the spectral accuracy by the publications. One of them is a numerical value, GFC (goodness of fit coefficient) (16).

$$GFC = \frac{\sum_{i=1}^{31} \varphi(\lambda_i)\cdot \varphi_r(\lambda_i)}{\sqrt{\sum_{i=1}^{31} \varphi(\lambda_i)^2}\cdot\sqrt{\sum_{i=1}^{31} \varphi_r(\lambda_i)^2}} \quad (16)$$

$\varphi(\lambda_i)$ denotes the sample reflection function at wavelength λ_i. $\varphi_r(\lambda_i)$ denotes the reconstructed spectrum at λ_i. If GFC = 1, the reconstructed function is perfectly identical with the original one. Therefore, the closer *GFC* gets to 1, the more accurate the spectral reconstruction is. The formula in (16) corresponds to the cosine value of the angle of two abstract vectors.

The other accuracy specifying value is *RMS* (root mean square), which gives the reconstruction error according to the differences between the original and the reconstructed spectra (17).

$$RMS = \sqrt{\frac{1}{31}\cdot\sum_{i=1}^{31}(\varphi(\lambda_i) - \varphi_r(\lambda_i))^2} \quad (17)$$

The notations in equation (17) are the same as the notations in equation (16). The smaller the value is, the smaller the spectral error is and the greater the reconstruction accuracy is.

The illuminants used in the test

The authors used only one well-known illuminant, the CIE E, i.e. the equienergetic illuminant in their former publication [12]. This illuminant was used for the reconstruction of textile samples, flower samples, skin samples and,- paint samples. Now the question is how the spectral reconstruction will work in cases of different illuminants with familiar spectral power distributions. Moreover, the second question is what happens if the spectral components of the illuminant are unknown. The illuminants are as it follows.

CIE D65 standard illuminant, which corresponds to the daylight distribution with 6 504K correlated color temperature. (Figure 2)

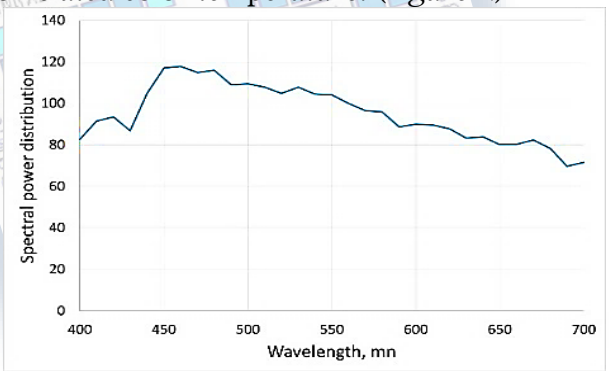

Figure 2. The spectal power distribution of CIE D65 illuminant

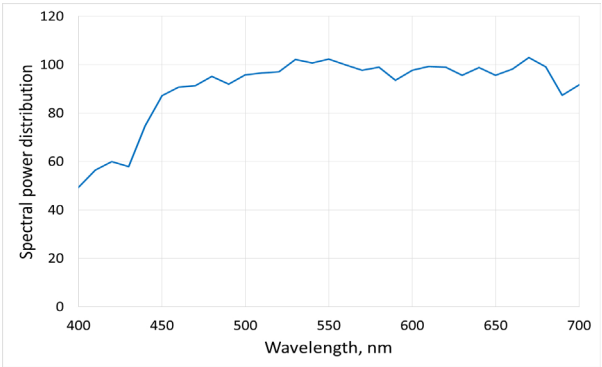

Figure 3. The spectral power distribution of CIE D50 illuminant

CIE D50 standard illuminant represents the daylight with a correlated color temperature of 5 003 K. (Figure 3) CIE A standard illuminant is intended to represent tungsten-filament lighting. Its

spectral power distribution corresponds to that of a Planckian radiator with a temperature of 2 856 K(Figure 4).

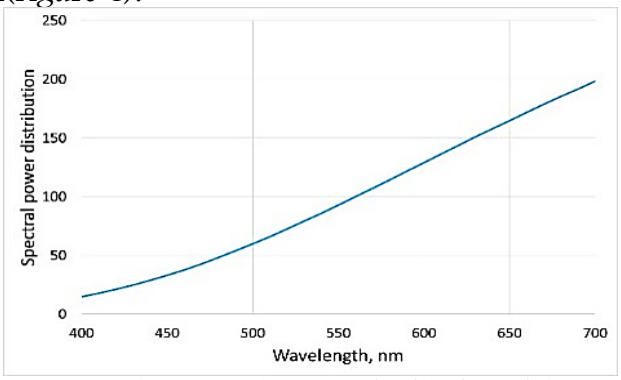

Figure 4. The spectral power distribution of theCIE A illuminant

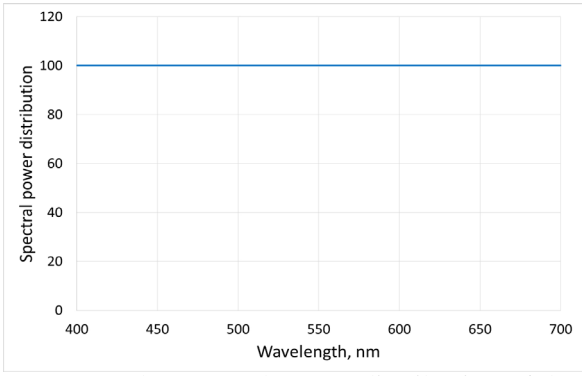

Figure 5. The spectral power distribution of the CIE E illuminant

CIE E equienergetic illuminant. This illuminant has constant spectral power distribution. This theoretical radiator renders equivalent weight to each wavelength. (Figure 5) CIE F11 standard illuminant. Its spectral power distributions correspond to the power distributions of narrow-band fluorescent lamp with 4 000K correlated color temperature (Figure 6).

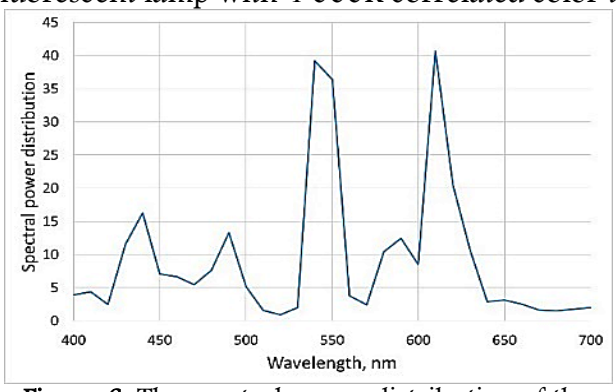

Figure 6. The spectral power distribution of the CIE F11 illuminant

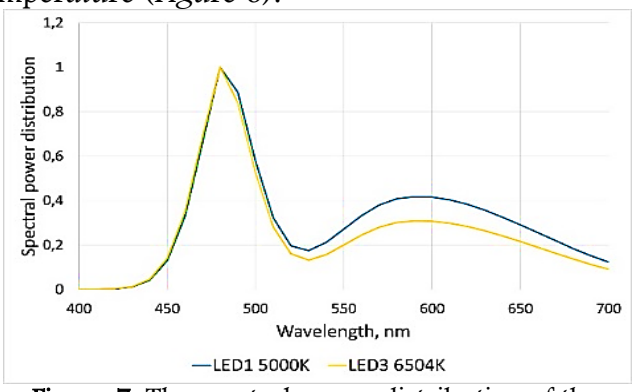

Figure 7. The spectral power distribution of the white LEDs with phosphor

White LEDs with phosphor and three-band white LEDs with 5 000K and 6 504K correlated color temperature arealso applied. The white LED with phosphor with 5 000K is named as LED1, the three-band white LED with 5 000K is named as LED2, the white LED with phosphor with 6 505K is named as LED3 and the three-band LED with 6 504K is named as LED4. Figure 7 shows the spectral power distributions of the white LEDs with phosphor, Figure 8 shows the spectral power distributions of the three-band, white LEDs. Figure 9 shows the spectral power distribution of the Planck radiator whose color temperature is 6 504 K and which is also used in this research.

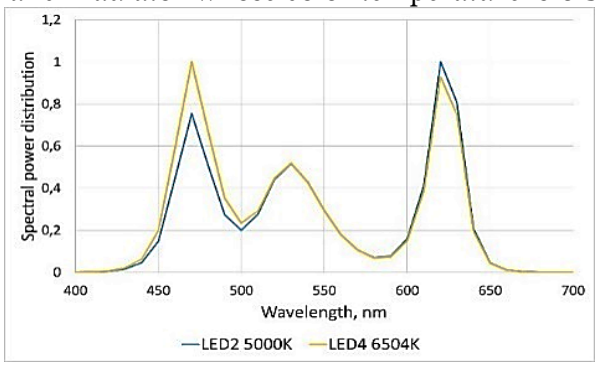

Figure 8. The spectral power distribution of the three-band LEDs

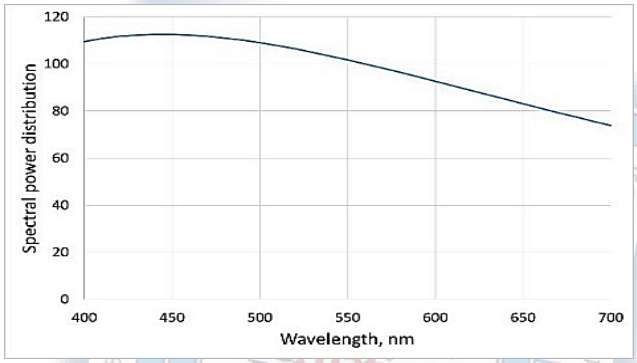

Figure 9. The spectral power distribution of the Planck radiator at the color temperature of 6504 K

The reconstruction of color samples under illuminants with known spectral power distributions

The reconstruction of the reflectance functions of the depicted textile samples has been done by the help of genetic optimization on the basis of the tristimulus values X,Y,Z. The first five eigenvectors given by the PCA and complemented with restrictive conditions on the reflectance functions of real samples were used. Each sample has been reconstructed under the above mentioned illuminants. Figure 10 shows the reconstruction for some samples.

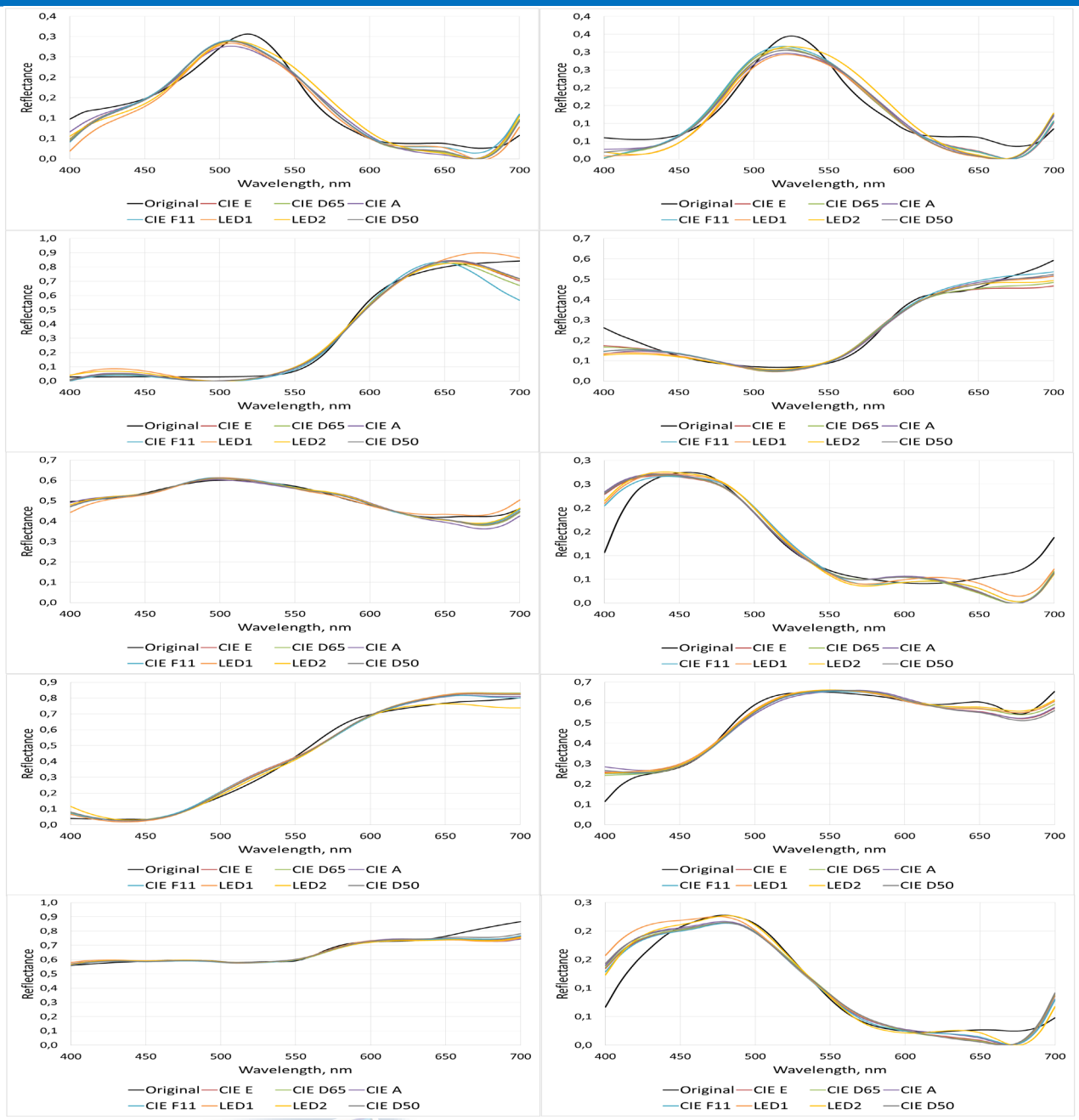

Figure 10. The reconstruction of color samples supposing different illuminants

The values $\Delta E^*_{ab}, RMS, GFC$ giving the reconstruction accuracy have been determined for each sample in case of each resource. The numeric values are given with the use of the original reflectance function which is presumed unknown and the reflectance function gained after optimization under the given illuminants. Table 1 shows the average of the values $\Delta E^*_{ab}, RMS, GFC$ for the tested samples.

As for comparison, Table 2 shows the mean values *RMS* for the reconstructions of other textile samples indicated in publication [10]. The first three eigenvectors are used by the help of PCA and wPCA.

Table 1. The mean values of ΔE^*_{ab}, RMS, GFC in case of different illuminants with genetic optimization and with the use of five eigenvectors.

	RMS	GFC	ΔE^*_{ab}
CIE E	0.0300	0.9926	0.0100
CIE D65	0.0307	0.9918	0.0105
CIE D50	0.0294	0.9914	0.0133
CIE A	0.0316	0.9914	0.0134
CIE F11	0.0308	0.9922	0.0128
LED1	0.0312	0.9915	0.0135
LED2	0.0300	0.9919	0.0137

Table 2. The mean values of *RMS* with methods of PCA and wPCA and using three eigenvectors.

PCA:	wPCA:
0.073	0.059

The tables show that our method of reconstruction which uses five eigenvectors and considers the restrictions on the forms of real samples provides much better results than the classical PCA and wPCA with the three eigenvectors.

Figure 10 and Table 1 prove that our method does not depend on the type of the known illuminant. This method provides the reflectance function of one of the metamers of the color sample with great accuracy in case of any illuminants with known spectral power distribution.

Illuminant with unknown spectral power distribution

Is is natural demand to know what the reconstruction will be like if the spectral power distributions of the illuminants were not known. First, we supposed that we did not have any information about the illuminants. Then it is supposed that the white points X_n, Y_n, Z_n of the illuminants are known (see next chapter).

A color sample is depicted and the reconstruction is done as it follows. It is supposed that the spectral power distribution of the real illuminant is unknown. Certainly, it has to be taken into account for the sake of the numerical formulation and the comparison but *not for reconstruction*. Then the authors use the seven above mentioned illuminants as the real, unknown illuminants of the samples, and the reconstructions are done with all the seven illuminants. That means 7·7 cases altogether. Certainly, the illuminant that is used in reality is among the seven illuminants. The reconstruction is as accurate as in the former cases. When the illuminant is different from the real one, the reconstruction is generally quite weak.

Figure 11 shows the reconstruction of one sample as it is described above. The title of the graph refers to the real but surpassingly unknown illuminant. The solid black line indicates the original sample in each case. The colorful lines indicate the reconstructed spectra under the supposed illuminants. Only few of the cases are shown because of immensity.

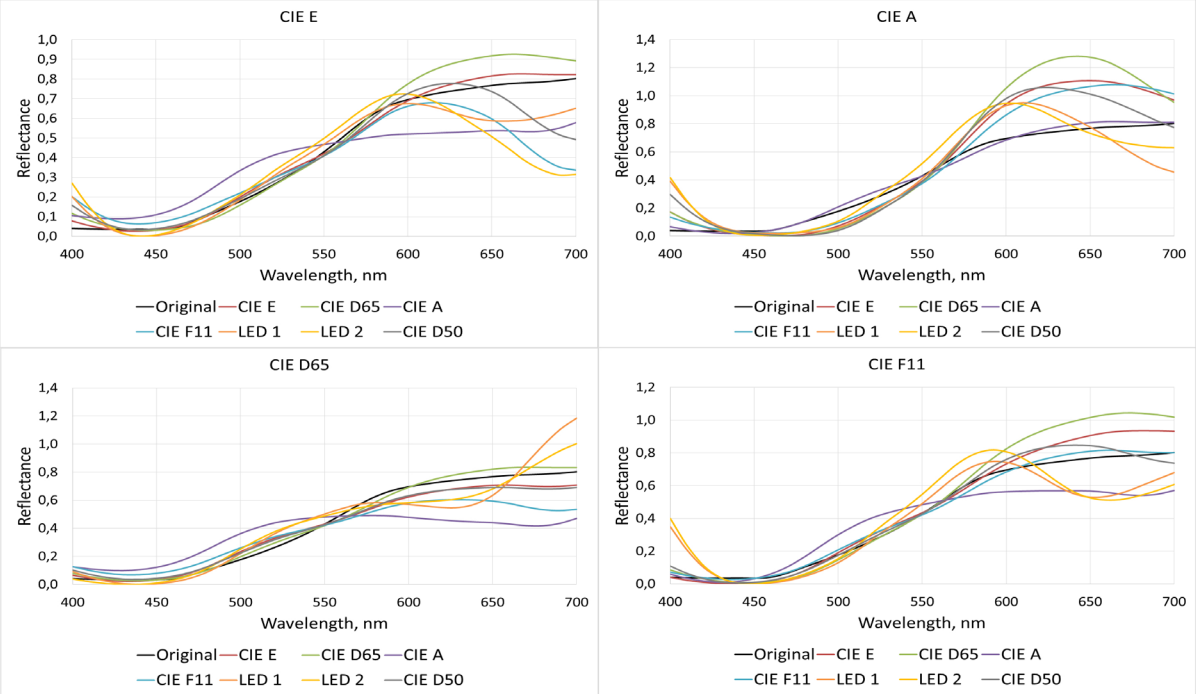

Figure 11. The reconstruction in case of an unknown illuminant

Table 3 shows the averages of the numerical values describing the reconstruction considering the combination of all illuminants, the combination without the real illuminant and the original, actual illuminant.

Table 3. The mean values of ΔE^*_{ab}, RMS, GFC for different combinations of illuminants

	The combination of all illuminants	The combination without the actual real illuminant	The original, actual real illuminant
RMS	0.1018	0.1144	0.0266
GFC	0.9848	0.9828	0.9990
ΔE^*_{ab}	11.6112	13.5457	0.0041

All the graphs show what the tables show: the reconstruction is not accurate if the spectral power distribution of the illuminant is unknown.

Illuminant with known white point but without known spectral power distribution

As a next step, they examine the reconstruction when the spectral power distribution is unknown but there is some information about the illuminant and its white point is known.

In this case, we modify the cost function (11) of the genetic reconstruction. Instead of the tristimulus values X, Y, Z, we use the values L^*, a^*, b^* for optimization (18), (19).

$$d(c_1, c_2, \cdots, c_M) = d_0' + P_n + P_v \tag{18}$$

Unlike equation (3), here d_0' does not contain the tristimulus values of the sample, but the values L^*, a^*, b^* (12) derived from the tristimulus values. They are used because the CIE Lab system considers the adaptation of white.

$$d_0'(c_1, c_2, \cdots, c_M) = (L^* - L_0^*)^2 + (a^* - a_0^*)^2 + (b^* - b_0^*)^2 \tag{19}$$

The values L_0^*, a_0^*, b_0^* in the equation are the original values of the sample under an illuminant without known spectral distribution but with known white point. The values L^*, a^*, b^* can be calculated from the reconstructed spectrum. During calculation, the white point of the chosen illuminant is used. The principal components are determined with the genetic optimization algorithm.

The method of reconstruction is similar to the former ones. They use a real illuminant without known spectral distribution but known white point and the reconstruction is done with seven known illuminants. It means $7 \cdot 7$ cases altogether. Figure 12 shows the reconstruction of a depicted sample. The title of the graph contains the name of the illuminant surpassingly without spectral power distribution but with known white point. Only few cases are shown because of immensity.

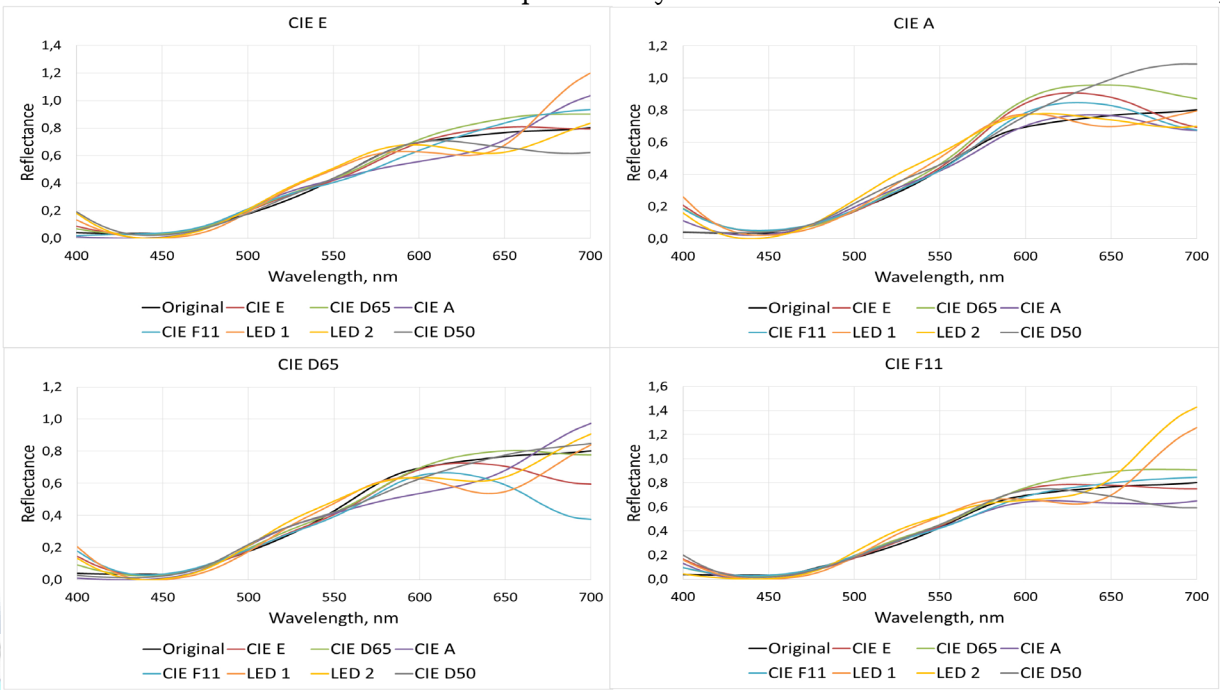

Figure 12. The reconstruction for an illuminant whose spectral power distribution is unknown but the white point is known

Table 4 shows the average value of ΔE_{ab}^*, RMS, GFC for all possible combinations, even if the real, original illuminant is left out when the average values are determined. Moreover, the values are examined when the real illuminant is considered.

Table 4. The mean values of ΔE_{ab}^*, RMS, GFC for different combinations of illuminants

	The combination of all illuminants	The combination without the actual real illuminant	The original, actual real illuminant
RMS	0.0759	0.0835	0.0302
GFC	0.9915	0.9903	0.9984
ΔE_{ab}^*	0.0090	0.0102	0.0016

According to Figure 12 and Table 4, they can state that the reconstruction for an illuminant with unknown spectral distribution is more accurate if there is some information about it, in other words, the white point of it is known. However, the value *RMS*, which gives the reconstruction error, is still great.

Illuminant with known white point and with correlated color temperature but without known spectral power distribution

It is supposed that the results of the reconstruction will be better if they use illuminants with known spectral power distributions whose correlated color temperature values are the same as that of the actual real illuminants which have unknown spectral power distributions but their white points are known. They determined the spectrum for samples chosen randomly according to the description in the chapter mentioned above. The reconstruction is done with illuminants whose spectral power distribution is known instead of the actual real illuminant whose white point, correlated color temperature is only known but its spectral power distribution is unknown. The illuminants have the same correlated color temperature as the real one does.

The principal components are provided by the genetic optimisation program. The following four illuminants are used in all four cases: CIE D65, white LED with phosphor (or LED3), three-band, white LED (or LED4) and the Planckian radiator. Figure 13 shows just a few cases of reconstruction. The title of the graph contains the name of the actual real illuminant that is supposed to be unknown.

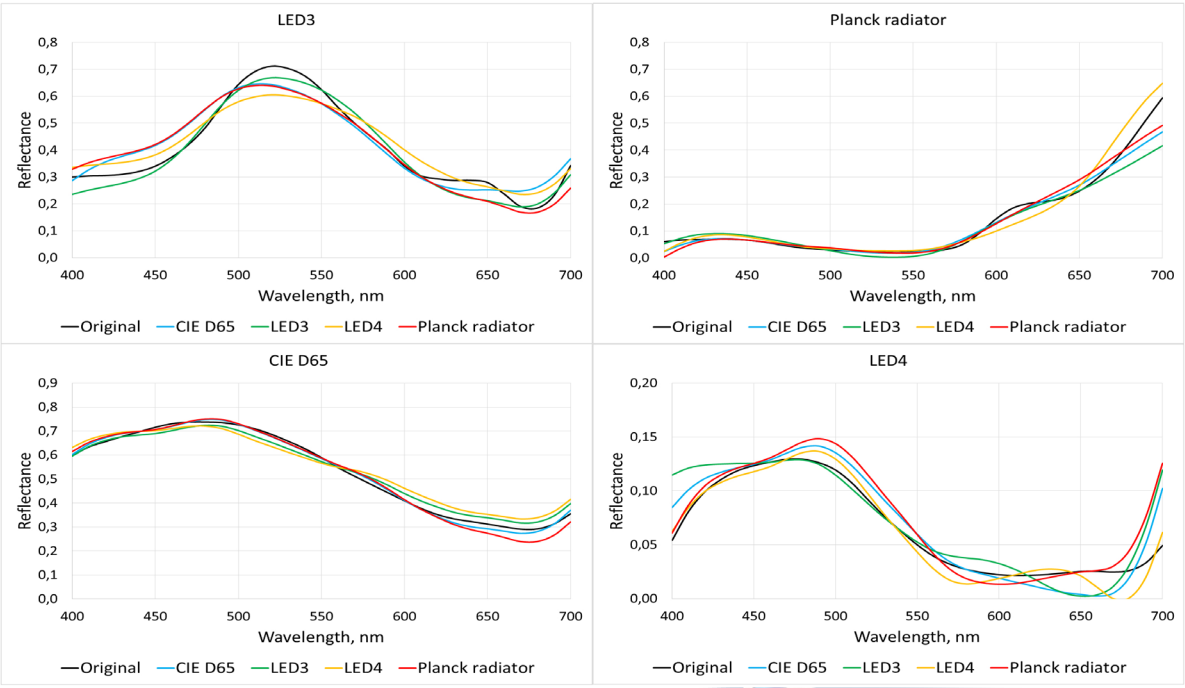

Figure 13. The reconstruction for illuminants whose spectral power distributions are unknown, but which have a known white point and a correlated colour temperature

Table 5. The mean values of ΔE^*_{ab}, RMS, GFC for different combinations of illuminants

	The combination of all illuminants	The combination without the actual real illuminant	The original, actual real illuminant
RMS	0.0389	0.0433	0.0258
GFC	0.9921	0.9909	0.9959
ΔE^*_{ab}	0.0069	0.0082	0.0029

The authors determine all the combinations and the average values of ΔE^*_{ab}, RMS, GFC, when they do not calculate with the original illuminant and when they calculated with only that one. The values are shown by Table 5.

Figure 13 and Table 5 show that the reconstruction is effective for an illuminant without known spectral power distribution but with a white point and correlated color temperature if the correlated color temperature of the illuminant is the same as the correlated color temperature of the original illuminant with unknown spectral power distribution.

The Table 6 shows the summary of former cases.

Table 6. The summary of former cases

	Illuminant above the color samples, S1	Illuminant used in the reconstruction, S2 (spectrum always known)
Chapter 5	spectrum known	$S_1 = S_2$
	cost function's basis: CIE XYZ	
Chapter 6	spectrum unknown	-
	cost function's basis: CIE XYZ	
Chapter 7	spectrum unknown , white point known	$L^*_1 = L^*_2 = 100, a^*_1 = a^*_2 = 0, b^*_1 = b^*_2 = 0$
	cost function's basis: CIE Lab	
Chapter 8	spectrum unknown white point known ⇒ correlated color temperature known	$L^*_1 = L^*_2 = 100, a^*_1 = a^*_2 = 0, b^*_1 = b^*_2 = 0$ $T_{cp}(S_2) = T_{cp}(S_1)$
	cost function's basis: CIE Lab	

3. CONCLUSION

Present study shows a genetic optimisation process that helps to reconstruct the reflectance function of colorful samples on the basis of their tristimulus values. During reconstruction the authors use the first five eigenvectors provided by the PCA together with restrictive terms for the shape of the reflectance functions of the real samples. It gives the opportunity to choose those metamers from their infinite set in such a way that the reflectance function corresponds with the reflectance functions of the real samples.

This study examines how the above mentioned method works in case of 7 different illuminants whose spectral power distribution is known. It can be found that the genetic optimization provides the reflectance function accurately if the spectral power distribution of the illuminant is known and it does not depend on the type of the illuminant.

Finally, the reconstruction is effective for an illuminant that has unknown spectral power distribution but known white point and a correlated color temperature when they use such an illuminant whose correlated color temperature is the same as that of the original one.

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