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# Representing Spectral Data Using Lab PQR Color Space in Comparison with PCA Method 

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#### Abstract

In many applications of color technology such as spectral color reproduction, it is of interest to represent the spectral data with lower dimensions than spectral space dimensions. It is more than half of a century that Principal Component Analysis (PCA) method has been applied to find the number of independent basis vectors of spectral dataset and representing spectral reflectance with lower dimensions. Recently, a new Interim Connection Space (ICS) named LabPQR was introduced, which contains three colorimetric dimensions and additional black metamer space. In the present study, the performance of PCA method in comparison to LabPQR was investigated for representation of spectral reflectance. For this end, different color data sets including Munsell, Glossy Munsell, GretagMacbethColorChecker, Esser test chart and two printing datasets were evaluated. The results show that, the performance of PCA and LabPQR, depends on the applied dataset. Based on spectral metrics such as RMS and GFC values, PCA has better results than LabPQR. Considering color difference errors, LabPQR is a better space than PCA even based on the color difference under second illuminant. Moreover, the dataset used for obtaining PQR vectors affects the representation results. For some datasets, the PQR components of the other sets perform better. However, obtaining PQR bases from the same data source, gives better results. It was found that Cohen and Kappauf-based methods performs better for all the datasets compared with unconstrained LabPQR method. Prog. Color Colorants Coat. 4(2011), 95-106. © Institute for Color Science and Technology.


## 1. Introduction

Spectral reflectance data is the most important and valuable information from a color sample. It is possible to achieve the color characteristics of the sample under any viewing conditions using spectral data. Spectral data
is usually expressed with 31 dimensions in the range of 400 nm to 700 nm with intervals of 10 nm , which is difficult to use in many applications such as color reproduction, color gamut mapping and, etc. In such cases, colorimetric features are usually considered which constrain metamerism effect. Therefore, it is always of

[^0]interest to reduce the dimensions of spectral data with the least error. During the last 50 years, Principal component analysis (PCA) has been considered as a useful mathematical tool for dimensionality reduction and recovery of spectral data. In 1964, Cohen published the first three principal components or basis vectors of a subset of 150 out of 433 Munsell chips reflectance spectra [1]. He concluded that the spectral data of these 150 color chips depend only on three components, which account for $99.18 \%$ of the variance. However, no evaluation of spectral reconstruction from these 3 basis vectors was applied. Following Cohen, several researches have been done on applying PCA method for extracting the suitable number of basis vectors for different spectral datasets [2-18]. Maloney investigated 462 Munsell spectral reflectances and a set of natural spectra. He mentioned that the first 5 to 7 basis vectors of Munsell dataset are appropriate for representing Munsell as well as other datasets. Jaaskelainen et al. extracted the principal vectors of Munsell chips and a set of 218 natural spectral reflectances. They found that the basis determined using the Munsell spectra can be used for representing the natural spectra. In addition, it was concluded that more basis vectors of Munsell dataset are needed to represent the natural spectra with the same accuracy [2]. Parkkinen et al. investigated the number of PC vectors which is needed to represent a set of 1257 reflectance spectra of the Munsell chips. They reported that as many as eight eigenvectors were necessary, for acceptable results, which were more than the number proposed by Cohen and also Maloney [3]. Dannemiller investigated a suitable number of basis vectors which are needed for representation of natural objects using 337 samples. Ideal-observer analysis was used to determine the number of basis functions necessary for representing the spectral reflectances of natural samples. He reported that three eigenvectors are necessary and probably sufficient for representing the spectral reflectance of natural objects [4]. Vrhel et al. performed principal component analysis on a set of 354 spectral reflectances including 64 Munsell chips, 120 Du Pont paint chips, and 170 reflectance spectra from various natural and manmade objects. They reported the reconstruction error of PCA method using 3 to 7 basis vectors. The errors were measured as average and maximum CIELAB color difference as well as square spectral error. They noted that even with seven basis functions, the maximum color difference was 5.05 . Moreover, as many as 16 basis vectors have to be taken into account if $99 \%$ of the
information content is to be preserved. [5]. Eem et al. computed the basis vectors of the reflectance spectra of 1,565 glossy Munsell color chips by using the PCA method. They found that the first four principal vectors of the Glossy Munsell dataset can be accurately used for reconstruction of Macbeth Color Checker spectral data. It was shown that with the first three characteristic vectors, however, color differences between the measured and reconstructed spectra were not negligible. [6]. Lenz et al. investigated the properties of basis vectors of three datasets included the Munsell colours of Parkkinen et al, 1269 Munsell chips and a set of 1513 NCS spectra. They reported that the first few eigenvectors of these datasets are highly correlated. No conclusion is drawn on the number of basis spectra needed, but 6 were used as an example, giving a reconstruction error of about 4\%. [7]. Garcia et al. applied PCA method for representing the reflectances of a group of 5574 acrylic paint on paper. They stated that the first 7 basis vectors were sufficient for more adequate mathematical representation of the spectral-reflectance curves. In addition, they investigated the effect of sample hue on the performance of PCA method by hue grouping the samples. They showed that representing the spectral data using hue categorized bases, reduces 1 or 2 of the vectors needed to attain the same accuracy of the overall basis [8].

Continuously during the last half century, different approaches such as recovery of spectral reflectance and device color characterization have been introduced applying PCA method on spectral data [9-15]. Connah et al. described the development of a mathematical model of a multispectral imaging system that takes into account imaging parameters and noise. Their reconstruction method was based on the fact that the vast majority of reflectance spectra for natural and man-made surfaces are smooth functions of wavelength. They applied PCA method for obtaining basis vectors for spectral recovery from camera responses. The number of basis functions used in the recovery process was always equal to the number of sensor channels [9]. Ramanath et al carried out a study to compare the color spaces with spectral spaces derived by a variety of dimensionality reduction techniques such as PCA. They showed that in terms of interval scales, there are large differences between color and spectral spaces. They pointed out that spectral spaces suffer from lack of specific relationship to human color vision and so the term "color space" should not be used for them [10]. Fairman et al reviewed the method of calculation and presented tables of the principal
components of a very large collection of object color samples that was derived by combining the specimens in the Munsell Book of Color with those in the Swedish Natural Color System and adding the samples of the OSA-UCS atlas. The total number of the specimens and the spectra was 3,534 . They described two kinds of principal-component coordinates of a measured reflectance spectrum; one obtained by least-square best fit and the other by tristimulus match under one or more specified lights. Moreover, they proposed some possible new uses for principal-component analysis of reflectances [11]. Cheung et al. studied same methods for the recovery of reflectance spectra from the responses of trichromatic camera systems. They suggested a new method for reflectance recovery that finds the smoothest spectrum consistent with both the colorimetric data and a linear model (based on PCA technique) of reflectance. Their proposed method gave the lowest maximum colorimetric error in terms of camera characterization with test data that were independent of the training data. However, they reported that none of the evaluated recovery techniques could outperform most of standard polynomial techniques [12]. Mansouri et al introduced an algorithm that makes PCA adaptive in the framework of reflectance recovery from tri-stimuli (color camera). They proposed the adaption of the PCA basis derivation by selecting more relevant elements for each sample from the training set elements. The adaptivity criterion is achieved by a likelihood measurement. The spectral reflectance estimation results were evaluated with the commonly used goodness-of-fit coefficient and color difference. The results prove the effectiveness of this algorithm [13]. Tzang et al reported a valuable review paper on the application of PCA method for color technology [14]. In recent years to be able to spectral reproduction of color images, Derhak \& Rosen proposed a new interim connection space named LabPQR which included three colorimetric components ( $L^{*}, a^{*}$ and $b^{*}$ ) and three metameric blacks [15]. Tsutsumi et al. also investigated the LabPQR about how to derive a metameric black and the number of dimensions to include [16].

The present study introduces a new application for LabPQR as a method for dimensionality reduction of spectral space compared to PCA. To this end, the performance of LabPQR color space as a semi spectral color space with 6 dimensions is investigated for express different datasets with lower dimensions. In addition, the traditional PCA method is applied with the same
dimensions and the performance of PC space (which is also a spectral space) is compared with LabPQR.

## 2. Experimental

### 2.1. Principal component analysis (PCA)

The purpose of PCA is to identify the dependence features of a dataset and reduce the dimensionality of it while preserving as much information as possible [1718]. The basis vectors of a dataset are the eigenvectors of its covariance matrix.

If $R$ is an $m \times n$ matrix with $m$ spectral samples along n wavelengths, the reconstruction spectral with p limited dimensions can be computed using equation 1 . In this equation, FV is an $m \times p$ matrix consists of the first $p$ eigenvectors of the covariance matrix of R , and $\hat{R}$ is the represented spectra with p dimensions.
$X_{(m \times p)}=F V_{(m \times n)}^{\prime} \cdot R_{(n \times p)}$

The original data can be estimated by equation (2). The estimation error is related to the number of PC basis vectors used. Obviously, the accuracy increases by the number of basis vectors.

$$
\begin{equation*}
\hat{R}_{(n \times p)}=F V_{(n \times m)} \cdot X_{(m \times p)} \tag{2}
\end{equation*}
$$

### 2.2. Lab PQR method [15-16]

In LabPQR method, it was proposed that the spectral reflectance vector is converted to $L^{*}, a^{*}, b^{*}$ and $P Q R$. In this regard, $L^{*} \mathrm{a}^{*} \mathrm{~b}^{*}$ represents the three colorimetric values (CIELAB) of the sample and PQR describes a stimulus metameric black, a spectral difference between the actual spectrum and a spectrum derived based on the CIELAB components. Two methods have been discussed to obtain PQR components, named unconstrained LabPQR and Cohen-Kappauf based (CK-based) LabPQR. In unconstrained LabPQR, metameric blacks are derived after applying a statistical analysis of a specific device's metamer space and for CK-based LabPQR, Cohen and Kappauf's spectral decomposition is applied.

In Cohen and Kappauf decomposition method, any spectral reflectance (R) can be decomposed to two main parts including fundamental $\left(\mathrm{N}^{*}\right)$ and black metamers
(B). Fundamental metamer can be obtained from the tristimulus values by the following equation:

$$
\begin{equation*}
N^{*}=A\left(A^{\prime} A\right)^{-1} N_{c} \tag{3}
\end{equation*}
$$

If $A\left(A^{\prime} A\right)^{-1}$ is shown by $T_{C K}$, then equation 3 can be rewritten as follows:

$$
\begin{align*}
& N^{*}=T_{c k} N_{c} \\
& T_{c k}=A\left(A^{\prime} A\right)^{-1} \tag{4}
\end{align*}
$$

where $N_{C}$ is a 3 by 1 tristimulus vector and A represents the illuminant and observer pair according to equation 4.

$$
\begin{equation*}
A=e \times S^{\prime} \tag{5}
\end{equation*}
$$

where $e$ stands for the spectral power distribution of the illuminant and $S$ is the spectral sensitivity of the standard observer. The black is computed from the difference between the original spectral data and $\mathrm{N}^{*}$ as follows.
$B=R-N^{*}$

Based on LabPQR space, again any spectral data is reconstructed from two main parts including tristimulus values and an additional part as follows:
$\widehat{R}=T N_{c}+V N_{p}$
where $N_{p}$ is a 3 by 1 vector of PQR values, V is a n by 3 matrix describing $P Q R$ bases and $T$ is a $n$ by 3 transformation matrix with n samples. T can be $T_{c k}$ based on Cohen and Kappauf's metameric black. For unconstrained metameric black approach, T is determined by a matrix calculation using least square analysis and applying tristimulus vectors. The computation is done by equation 8 .
$T_{u}=R N_{c}^{\prime}\left(N_{c} N_{c}^{\prime}\right)^{-1}$

PQR bases $V$ were derived using principal component analysis method on a set of metameric blacks which is defined as:
$B=R-T N_{c}$

The first three principle vectors of $\mathrm{B}\left(V_{P Q R}\right)$ are computed using PCA method to estimate the metameric blacks. If the first two eigenvectors are applied, V is expressed as Vpq and for only one vector it defined as Vp.

### 2.3. Methodology

In this study, the accuracy of LabPQR space was evaluated in comparison with standard PCA method for representation of spectral data with lower dimensions and applying different color sample sets. To this end, six different datasets including 1269 Matt Munsell set, 1600 Glossy Munsell set, Gretag Macbeth Color Checker (24 chips), IT8.7/2 chart and two printing charts including a set of 2250 samples and a 2500 color chart, were used.

The reason for choosing these color charts is that they are standard color sets, which almost have acceptable color gamuts and are generally used in similar researches. Therefore, to be able to compare the obtained results with the previous ones and give the opportunity to readers to do the same computational procedure, similar charts have been applied in this research.

About the printed patches, it is because one of the most important applications for LabPQR is spectral color management, which is usually utilized for printers. Therefore, it is important to check the applicatin of this method for different printers. In one of the earliest researches which proposed this method [16], a Canon i9900 dye-based inkjet printer some other standard tests were applied. In the present study, the method is tested for two other inkjet printers. The first printed colors were produced by an Hp Photosmart Pro B8850 photo printer. This printer had eight ink sets including cyan, yellow, magenta, light cyan, light magenta, gray, and both a matte black and photo black. The other printed set, consisted of 2500 samples were printed by a four-ink Hp Deskjet 1220c printer containing cyan, yellow, magenta and black inks. Both two color charts were printed on Premium Silky Photo Paper.

The spectral reflectances of the printed colors were measured using a GretagMacneth Eye-One spectrophotometer in the range between 380 nm and 730 nm . For all the samples and experiments, the applied data was between 400 nm and 700 nm . The color characteristics of the samples were calculated under D50 illuminant and the 1931 CIE standard observer.


Figure 1: The color distribution of the used color datasets in $C I E a^{*} b^{*}$ color space.

D50 standard illuminant represents warm daylight and is usually used in the graphic arts and printing industries. Considering that PCA and LabPQR methods are generally applied for multispectral imaging and color management, D50 is almost applied in related researches as a standard illuminant. Because of the small size of the samples of the color charts, the viewing condition should be according to $1931 \mathrm{CIE}\left(2^{\circ}\right)$ standard observer. Figure

1 shows the color coordinates of the samples in CIEa ${ }^{*} b^{*}$ color space.

Traditional PCA method by 6, 5, 4 and 3 PC components and LabPQR method by applying three, two and one black vectors (LabPQR, LabPQ and LabP) was employed for spectral representation of the mentioned color datasets.


Figure 2: The first six PC vectors of different datasets.

Reconstruction error has been reported based on the average color difference values using CIEDE2000 (1:1:1) [19], Root Mean Square Error (RMSE) of spectral reflectance and Goodness-of- Fit Coefficient
(GFC) [20].
GFC metric is calculated by the following equation, where $R$ and $\hat{R}$ are the original and reconstructed spectral reflectance, respectively. The values of the

GFC range from 0 to 1 , where 1 indicates a perfect reconstruction. The goodness of GFC value is evaluated as follows:
If $\mathrm{GFC}>0.99$, the reconstruction is acceptable, If the GFC $>0.999$, the reconstruction is very good, If it was $>0.9999$, the reconstruction is mathematically almost exact
$G F C=\frac{\left|\sum_{\lambda} R_{\lambda} \hat{R}_{\lambda}\right|}{\sqrt{\left|\sum_{\lambda} R_{\lambda}^{2}\right|} \sqrt{\left|\sum_{\lambda} \hat{R}_{\lambda}^{2}\right|}}$


Figure 3: Metameric blacks of different datasets computed by C-K decomposition method.

In addition, the CK-based PQR vectors of each set are shown in Figure 4. It can be seen that although the $P Q R$ vectors are dependent on the dataset, there are some similarities between them.

### 3.2. The results of representing spectral data using PCA and LabPQR methods

The results of applying PCA and CK-based LabPQR methods for spectral reflectance representation with 6 to 3 dimensions (using from 6 to 3 principle bases
determined by PCA or 3 to 1 metameric blacks determined by LabPQR) based on RMS, GFC and color differences under first and second illuminant are given in Tables 1, 2, and 3, respectively. As illustrated in Table 1, according to RMS and also GFC terms (Table 2), for all the color sets, representation of spectral reflectance by PCA method causes a lower spectral error than CK-based LabPQR with the same dimensions (for instance, 6PCA in comparison with LabPQR or 5PCA compared to LabPQ).


Figure 4: PQR bases of CK-based Lab PQR for different datasets.

Table 1: The mean of RMS values for representation of each dataset by applying PCA and CK-based Lab PQR.

|  | PCA |  |  |  | Lab |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | 6 PCs | 5 PCs | 4 PCs | 3 PCs | PQR | PQ | P |
| Munsell | 0.0076 | 0.0094 | 0.0130 | 0.0192 | 0.0088 | 0.0163 | 0.0356 |
| GlossyMunsell | 0.0086 | 0.0109 | 0.0147 | 0.0213 | 0.0107 | 0.0167 | 0.0405 |
| Macbeth | 0.0109 | 0.0150 | 0.0201 | 0.0298 | 0.0144 | 0.0217 | 0.0491 |
| IT8.7/2 | 0.0051 | 0.0083 | 0.0094 | 0.0137 | 0.0072 | 0.0097 | 0.0265 |
| Printed colors1 | 0.0035 | 0.0047 | 0.0074 | 0.0159 | 0.0066 | 0.0144 | 0.0348 |
| Printed colors2 | 0.0040 | 0.0058 | 0.0093 | 0.0208 | 0.0089 | 0.0167 | 0.0358 |

Table 2: The mean of GFC values of representation of each dataset by applying PCA and CK-based Lab PQR.

|  | PCA |  |  |  | Lab |  |  |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- |
|  | 6 PCs | 5 PCs | 4 PCs | 3 PCs | PQR | PQ | P |
| Munsell | 0.9991 | 0.9987 | 0.9974 | 0.9949 | 0.9990 | 0.9965 | 0.9867 |
| Glossy Munsell | 0.9991 | 0.9986 | 0.9972 | 0.9951 | 0.9988 | 0.9970 | 0.9857 |
| Macbeth | 0.9974 | 0.9964 | 0.9935 | 0.9883 | 0.9968 | 0.9942 | 0.9771 |
| IT8.7/2 | 0.9994 | 0.9987 | 0.9985 | 0.9971 | 0.9991 | 0.9983 | 0.9921 |
| Printed colors1 | 0.9913 | 0.9910 | 0.9906 | 0.9625 | 0.9952 | 0.9726 | 0.9566 |
| Printed colors2 | 0.9991 | 0.9989 | 0.9980 | 0.9801 | 0.9984 | 0.9930 | 0.9744 |

Table 3: The mean color difference under illuminant D50 and illuminant $A$ as the reference and the second illuminants, respectively (according to $2^{\circ} \mathrm{CIE}$ standard observer).

|  | D50 illuminant |  |  |  | A illuminant |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | PCA |  |  |  | PCA |  |  |  | Lab |  |  |
|  | 6 PCs | 5 PCs | 4 PCs | 3 PCs | 6 PCs | 5 PCs | 4 PCs | 3 PCs | PQR | PQ | P |
| Munsell | 0.5828 | 0.5904 | 1.3347 | 1.9942 | 0.4867 | 0.5436 | 1.3618 | 1.7117 | 0.1695 | 0.6376 | 0.8857 |
| GlossyMunsell | 0.5431 | 0.5835 | 1.1367 | 2.3057 | 0.4600 | 0.5444 | 1.2092 | 1.7041 | 0.1429 | 0.5859 | 0.8719 |
| Macbeth | 0.6690 | 0.7671 | 1.5052 | 4.8594 | 0.7440 | 0.8156 | 1.8747 | 4.1904 | 0.1903 | 0.7446 | 1.1615 |
| IT8.7/2 | 0.2715 | 0.5186 | 0.6308 | 1.8655 | 0.3144 | 0.6256 | 0.6815 | 1.4713 | 0.1675 | 0.3419 | 0.8151 |
| Printed colors 1 | 0.6332 | 0.7614 | 1.0249 | 3.8904 | 0.8095 | 0.9976 | 1.1540 | 3.5088 | 0.2052 | 1.0460 | 1.3523 |
| Printed colors2 | 0.3088 | 0.3696 | 0.9048 | 3.6271 | 0.4042 | 0.4871 | 1.0165 | 3.0503 | 0.2313 | 0.7791 | 1.4788 |

As expected, reducing the number of vectors of PC and similarly PQR makes increasing the RMS and decreasing the GFC values.

By comparing different datasets, it can be seen that, based on RMS values, the best performance of PCA method is obtained for Printed colors 1 followed by Printed colors 2 and IT8.7/2; for LabPQR method, Printed colors 1 and IT8.7/2 show the least error. However, based on GFC values, and for PCA method,

IT8.7/2 shows the best performance followed by Munsell, Glossy Munsell and Printed colors 2; for LabPQR the best GFC was again obtained for IT8.7/2 followed by Munsell. In addition, for both PCA and LabPQR methods, Printed colors 1 performed the worst which is unexpected according to RMSE results. Generally, the printed colors 2 can be represented with the lowest error because this chart is almost a complete and compact chart including patches which properly
cover the printed gamut so the PC vectors of this chart would be adequate to represent each printed sample. Consequently, PCA method is a better choice as a lower dimensional color space based on spectral criteria such as RMS and GFC values.

The average color difference values of representation of spectral data by the PCA and CK-based methods are given in Table 3. Using LabPQR method the color difference under reference illuminant is zero so it is not shown here. As mentioned above, the minimum color difference under illuminant D50 is obtained for Printed color sets by applying PCA method with 6 PC bases. Totally, the mean color difference values under reference illuminant is varied from about 0.30 to 0.63 units of CIEDE2000 (1:1:1) by applying 6 PC vectors. The values of color difference increases by eliminating more PC bases. Moreover, it is dependent on the applied
dataset. Considering the color difference values under illuminant A, CK-based LabPQR method gives a better result for all the sets. The results of Table 3 show that, considering colorimetric criteria, LabPQR is a better choice.

In general, it was shown that like previous studies, spectral data can be preciously expressed with only six PC or LabPQR vectors. Moreover, LabPQR would be a more powerful technique if it is important to preserve the exact colorimetric values of the sample.

### 3.3. The effect of the source of metameric blacks (PQR) on the performance of LabPQR

Each dataset was represented by applying the PQR other bases ; the obtained results are reported in Table 4.

Table 4: Reconstruction results for each dataset using other metameric blacks for CK-based Lab PQR method.


Table 5: Spectral representation results for different datasets using unconstrained Lab PQR (for each dataset the metameric blacks of itself are applied).

|  | RMSE |  | GFC |  |  |  |  |  |  |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- |
|  | LabPQR | LabPQ | LabP | LabPQR | LabPQ | LabP | LabPQR | LabPQ | LabP |
| Munsell | 0.0288 | 0.0440 | 0.0501 | 0.9835 | 0.9679 | 0.9628 | 0.4499 | 0.4809 | 1.0639 |
| GlossyMunsell | 0.0430 | 0.0495 | 0.0557 | 0.9711 | 0.9682 | 0.9637 | 0.4599 | 0.5094 | 1.1451 |
| Macbeth | 0.0458 | 0.0480 | 0.0518 | 0.9754 | 0.9743 | 0.9714 | 1.0778 | 1.1007 | 1.1783 |
| IT8.7/2 | 0.0365 | 0.0396 | 0.0444 | 0.9717 | 0.9702 | 0.9676 | 0.5583 | 0.8571 | 0.8595 |
| Printed colors1 | 0.0374 | 0.0438 | 0.0568 | 0.9413 | 0.9380 | 0.9249 | 1.0212 | 1.3458 | 2.4466 |
| Printed colors2 | 0.0424 | 0.0471 | 0.0611 | 0.9541 | 0.9505 | 0.9336 | 1.0801 | 1.3177 | 2.5205 |

The best result of each row is underlined. Based on RMS values, each dataset resulted in the best by applying PQR bases of it. Only for GlossyMunsell, PQR of the Munsell gives almost a little better result. The maximum GFC value for GlossyMunsell is obtained using PQR of the Munsell dataset however it is close to GlossyMunsell. For the Macbeth set, the PQR of Glossy Munsell gives the best GFC result and for the other sets, the highest GFC values are obtained using their PQR. Considering the color difference under illuminant A, except IT8.7/2 and Printed colors1, the other data sets give their minimum color difference using the PQR of GlossyMunsell. For IT8.7/2 and Printed colors1, the best result is obtained applying its own PQRs bases. Consequently, considering all the three criteria it seems that using the metameric blacks of the same dataset would have a better result.

### 3.4. Comparing CK-based and unconstrained LabPQRs methods

The results of unconstrained LabPQRs are shown in Table 5. Comparing these results with the previous tables (Table 1 to 3 ) shows that based on all the three metrics (RMS, GFC and color difference under A illuminant), CK-based LabPQR performs better for all the datasets.

## 4. Conclusions

PCA is a well known mathematical tool for spectral representation with a lower dimensional space. Recently, a new interim connection space called LabPQR was introduced. In this paper, different datasets including Munsell, GlossyMunsell, Macbeth, Esser test chart and two printed charts were applied and the performance of PCA and LabPQR methods for representation of spectral data in a lower dimensional space were compared with different metrics consisted of spectral and colorimetric criteria. Moreover, the effect of dataset on the accuracy of two methods was evaluated. The experimental results showed that the performance of PCA and LabPQR methods is completely depended on the applied dataset. Considering spectral metrics such as RMS and GFC values, PCA method generally shows more accuracy for all the datasets. According to the colorimetric results, CK-based LabPQR can be a better choice, and is more appropriate to use the same dataset for obtaining PQR vectors. Comparison between CK-based and unconstrained LabPQR shows that the former clearly has better results.

Consequently, it seems that both the first PC vectors of PCA method and LabPQR can be applied to represent spectral data in a lower dimension. However, while spectral properties are more important, PCA method is more applied, and LabPQR is preferred for preserving colorimetric properties.

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