Multispectral Image Acquisition and Simulation of Illuminant Changes

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1 Introduction

In this chapter we describe a system for the acquisition of multispectral images using a CCD camera with carefully selected optical filters. We further present an application where the acquired multispectral images are used to simulate the image of a scene as it would have appeared under a given illuminant. For this application, the use of multispectral images is found to yield a much higher accuracy compared to traditional methods using only three-channel colour images.

A multispectral image is an image where each pixel contains information about the spectral reflectance of the imaged scene. Multispectral images carry information about a number of spectral bands: from three components per pixel for colour images to several hundreds of bands for hyperspectral images. Multispectral imaging is relevant to several domains of application, such as remote sensing [1], astronomy [2], physics, analysis of museological objects [3, 4], cosmetics, medicine [5], high-accuracy colour printing [6, 7], or computer graphics [8]. Hyperspectral image acquisition systems are complex and expensive, limiting their current use mainly to remote sensing applications. Multispectral scanners are mostly based on a point-scan scheme [9-11], and are thus too slow for our applications.

We use a low-cost approach based on digital imaging techniques in which a set of chromatic filters are used with a CCD camera. It is well known that with 3 well-chosen filters, it is possible to obtain a fairly good reconstruction of the colour tristimulus values of the reference human observer as defined in colorimetry. Our aim is to reconstruct the spectral reflectance curve using more than three filters. We propose in Section 2 a solution where the filters to be used are chosen sequentially from a set of readily available filters [3]. This choice is optimized, taking into account the statistical spectral properties of the objects that are to be imaged, the spectral characteristics [12] of the camera, and the spectral radiance of the lighting used for the acquisition.
We present in Section 3 an application where the acquired multispectral images are used to predict changes in colour due to changes in the viewing illuminant. Applied to fine arts paintings, museological objects, jewelry, textiles, etc., such simulations could be of particular interest as a multimedia application. It is well known that the appearance of an object or a scene may change considerably when the illuminant changes, due to physical and psychophysical effects. These effects are taken into account in most colour appearance models in a somewhat heuristic manner. However, such models can not predict correctly changes for arbitrary illuminants, one important reason for this being metamerism. To be able to predict quantitatively the physical phenomena involved when the illuminant is changed, a more complete spectral description of the illuminant radiances and the scene reflectances is needed. The multispectral imaging approach provides us with such information in each image pixel. We compare the results obtained with this approach to the results using CIELAB space as a colour appearance model. The proposed method of illuminant simulation is found to be very accurate, and working on a wide range of illuminants having very different spectral properties.

2 Multispectral image acquisition

The system for a multispectral image acquisition system we describe here is inherently device independent, in that we seek to record data representing the spectral reflectance of the surface imaged in each pixel of the scene, independently of the spectral characteristics of the acquisition system and of the illuminant. We will suppose that the spectral radiance of the illuminant used for the acquisition is known, either by direct measurement, or indirectly by estimation of the spectral characteristics of the acquisition system. We will thus not discuss here issues such as computational colour constancy [13-18], that is, the automatic determination of the colour image of a scene as it would have been seen under a standard illuminant, from the camera responses obtained under an arbitrary unknown illuminant.

To obtain device independent measurements of high quality, it is important to know the spectral characteristics of the components involved in the image acquisition process. We thus proceed, in the next section, to a brief description of methods for the estimation of the spectral characteristics of the acquisition system, followed in Section 2.2 by a discussion on how the spectral reflectances of actual surfaces may be estimated from the camera responses. Then, in Section 2.3, we discuss how to choose an optimal set of colour filters to be used with the camera. Finally, in Section 2.4, we perform an evaluation of the quality of the entire multispectral image acquisition system.

2.1 Spectral characterisation of the acquisition system

The main components involved in the image acquisition process are depicted in Figure 1. We denote the spectral radiance of the illuminant by \( I_R(\lambda) \), the spectral reflectance of the object surface imaged in a pixel by \( r(\lambda) \), the spectral transmittance of the optical systems in front of the detector array by \( o(\lambda) \), and the spectral sensitivity of the CCD array by \( a(\lambda) \). In this section we consider only an unfiltered monochrome camera and we thus omit the spectral transmittance of an optical colour filter \( \phi_k(\lambda) \) in the calculations.

Supposing a linear optoelectronic transfer function of the acquisition system, the camera
response $c$ to an image pixel is then equal to

$$c = \int_{\lambda_{\min}}^{\lambda_{\max}} l_R(\lambda) r(\lambda) o(\lambda) a(\lambda) \, d\lambda = \int_{\lambda_{\min}}^{\lambda_{\max}} r(\lambda) \omega(\lambda) \, d\lambda$$

where $\omega(\lambda) = l_R(\lambda) o(\lambda) a(\lambda)$ denotes the system unknowns. The assumption of system linearity is founded on the fact that the CCD sensor is inherently a linear device. However, for real acquisition systems this assumption may not hold, due for example to electronic amplification non-linearities or stray light in the camera [19, 3]. Then, appropriate nonlinear corrections may be necessary [3].

By uniformly sampling the spectra at $N$ wavelength intervals, we can rewrite Equation (1) as a scalar product in matrix notation as

$$c = r^T \omega,$$

where $\omega = [\omega(\lambda_1) \omega(\lambda_2) \ldots \omega(\lambda_N)]^T$ and $r = [r(\lambda_1) r(\lambda_2) \ldots r(\lambda_N)]^T$ are the vectors containing the spectral sensitivity of the acquisition system and the sampled spectral reflectance, respectively.

Let us now consider the vector $\omega$ describing the system unknowns. Two classes of methods exist for the estimation of this vector. The first class of methods is based on direct spectral measurements, requiring quite expensive equipment, in particular a device emitting monochromatic
light. The camera characteristics is determined by individually evaluating the camera responses to monochromatic light from each sample wavelength of the visible spectrum [20-22].

The second type of approach is based on the acquisition of a number of samples with known reflectance or transmittance spectra. By observing the camera output to known input, we may estimate the camera sensitivity. Several researchers have reported the use of such methods, i.e. Pratt and Mancill [23], Sharma and Trussell [24, 25], Farrell and Wandell [19], Sherman et al. [26-29], Hardeberg et al. [3, 12]. We adopt this second approach.

To perform an estimation of \( \omega \), the camera responses \( c_p, p = 1 \ldots P \), corresponding to a selection of \( P \) colour patches with known reflectances \( r_p \) are measured. Denoting the sampled spectral reflectances of all the patches as the matrix \( \mathbf{R} = [r_1r_2 \ldots r_P] \), the camera response \( c_p = [c_1c_2 \ldots c_P]^t \) to these \( P \) samples is then given by

\[
\mathbf{c}_p = \mathbf{R}^t \omega.
\]  

When the reflectance spectra of the \( P \) target patches and the corresponding camera responses \( \mathbf{c}_p \) are known, Equation (3) can be used as a basis for the estimation \( \tilde{\omega} \) of the camera characteristics \( \omega \).

Several methods for this estimation are presented in [12]. A first method is based on a simple system inversion using a pseudo-inverse approach as follows:

\[
\tilde{\omega} = (\mathbf{R}\mathbf{R}^t)^{-1} \mathbf{Rc}_p = (\mathbf{R}^t)^{-1} \mathbf{c}_p,
\]  

where \((\mathbf{R}^t)^{-1}\) denotes the Moore-Penrose pseudo-inverse [30] of \( \mathbf{R}^t \). In the presence of acquisition noise, this method yields very large errors, and is thus not suitable. Instead, the Principal Eigenvector method [24, 25, 28, 19, 12] should be used. With this method the noise sensitivity of the system inversion is reduced by only taking into account the singular vectors corresponding to the most significant singular values. A Singular Value Decomposition [31, 32] (SVD) is then applied to the matrix \( \mathbf{R}^t \) of the spectral reflectances of the observed patches.

We recall that for any \((P \times N)\) matrix \( \mathbf{X} \) of rank \( R \), there exist a \((P \times P)\) unitary matrix \( \mathbf{U} \) and an \((N \times N)\) unitary matrix \( \mathbf{V} \) for which

\[
\mathbf{X} = \mathbf{U}\mathbf{W}\mathbf{V}^t,
\]  

where \( \mathbf{W} \) is a \((P\times N)\) matrix with general diagonal entry \( w_{ii}, i = 1 \ldots R \), called a singular value of \( \mathbf{X} \), all the other entries of \( \mathbf{W} \) being zero. The columns of the unitary matrix \( \mathbf{U} \) are composed of the eigenvectors \( \mathbf{u}_i, i = 1 \ldots P \), of the symmetric matrix \( \mathbf{XX}^t \). Similarly the columns of the unitary matrix \( \mathbf{V} \) are composed of the eigenvectors \( \mathbf{v}_j, j = 1 \ldots N \) of the symmetric matrix \( \mathbf{X}^t\mathbf{X} \). Since \( \mathbf{U} \) and \( \mathbf{V} \) are unitary matrices, it can easily be verified that when \( \mathbf{X} = \mathbf{U}\mathbf{W}\mathbf{V}^t \), \( \mathbf{X}^t = \mathbf{V}\mathbf{W}^{-1}\mathbf{U}^t \), where \( \mathbf{W}^{-1} \) has a general diagonal entry equal to \( w_{ii}^{-1}, i = 1 \ldots R \), and zeros elsewhere.

It has been found by several studies [33-36] that the singular values of a matrix of spectral reflectances such as \( \mathbf{R}^t \) are strongly decreasing, and by consequence that reflectance spectra can be described accurately by a quite small number of parameters. It has thus been proposed to only take into account the first \( r < R \) singular values in the system inversion. The spectral sensitivity may thus be estimated by

\[
\tilde{\omega} = \mathbf{V}\mathbf{W}^{(r)-1}\mathbf{U}^t\mathbf{c}_p,
\]
where $W^{(r)}$ has a general diagonal entry equal to $w_i^{-1}$, $i = 1 \ldots r$, $(r < R)$, and zeros elsewhere.

The optimal number $r$ of principal eigenvectors that should be used has been evaluated in [12] and found to depend on the level of noise. Furthermore, it has been shown that the choice of samples is of great importance for the quality of the characterisation, and an algorithm for an optimised selection of a reduced number of samples has been presented.

### 2.2 Spectral reflectance estimation from camera responses

The spectral characteristics $\omega(\lambda)$ of the image acquisition system being determined, we may now model the camera responses $c_k$, $k = 1 \ldots K$ to an unknown reflectance $r(\lambda)$, using a set of $K$ chromatic filters with known spectral transmittances $\phi_k(\lambda)$. Analogously to Equation (1), the response $c_k$ obtained with the $k$th filter is given by

$$c_k = \int_{\lambda_{\text{min}}}^{\lambda_{\text{max}}} r(\lambda)\phi_k(\lambda)\omega(\lambda) d\lambda. \quad (7)$$

The vector $c_K = [c_1c_2 \ldots c_K]^T$ representing the response to all $K$ filters may be described using matrix notation as

$$c_K = \Theta^T r, \quad (8)$$

where $\Theta$ is the known $N$-line, $K$-column matrix of filter transmittances multiplied by the camera characteristics, that is $\Theta = [\theta_k]$ = $[\phi_k(\lambda_n)\omega(\lambda_n)]$.

We now address the problem of how to retrieve radiometric and spectrophotometric information from these camera responses. A first approach is to define a direct colorimetric transformation from the camera responses $c_K$ into for example the CIELAB space [37] under a given illuminant, minimising typically the root mean square error in a way similar to what is often done for conventional three-channel image acquisition devices [38]. Given an appropriate regression model, this is found to give quite satisfactory results in terms of colorimetric errors [20]. However, for our applications we are concerned not only with the colorimetry of the imaged scene, but also with the inherent surface spectral reflectance of the viewed objects.

In existing multispectral acquisition systems, the filters often have similar and rather narrow bandpass shape and are located at approximatively equal wavelength intervals. For the reconstruction of the spectral reflectance, it has been proposed to apply interpolation methods such as spline interpolation or Modified Discrete Sine Transformation (MDST) [39, 40]. Such methods are not well adapted to filters having more complex wide-band responses, and suffer from quite severe aliasing errors [20, 41].

We will formulate the problem of the estimation of a spectral reflectance $\tilde{r}$ from the camera responses $c_K$ as finding a matrix $Q$ that reconstructs the spectrum from the $K$ measurements as follows

$$\tilde{r} = Qc_K. \quad (9)$$

Our goal will thus be to determine a matrix $Q$ that minimises a distance $d(r, \tilde{r})$, given an appropriate error measure $d$. Some solutions to this problems are presented and discussed in this section.
An immediate solution for estimating the spectral reflectance consists in simply inverting Equation (8) by using a pseudo-inverse approach, which provides us with the following minimum norm solution [30]

$$\hat{r} = (\Theta^t)^{-1}\Theta c_K = (\Theta^t)^{-1}c_K.$$  \hspace{1cm} (10)

The pseudo-inverse reconstruction operator denoted $Q_0$ is thus given by

$$Q_0 = (\Theta^t)^{-1}.$$ \hspace{1cm} (11)

If the matrix $\Theta$ were of full rank $N$, and if we assume noiseless recordings, this method of reconstruction would be perfect. However it is not very well adapted in practical situations. First, in order to achieve that the rank of $\Theta$ equals $N$, the number of colour filters $K$ should be at least equal to the number of spectral sampling points $N$. Furthermore this representation is very sensitive to signal noise. In fact, by this solution we minimise the Euclidian distance $d_E(\Theta^t r, c_K)$ in the camera response domain. A small distance does not guarantee the spectra $r$ and $\hat{r}$ to be close. Nevertheless, this approach is used by Tominaga [16, 17] to recover the spectral distribution of the illuminant from a six-channel acquisition. However, he applies a nested regression analysis to choose the proper number of components in order to better describe the spectrum and to increase the spectral-fit quality.

We now define another reconstruction operator $Q_1$ that minimises the Euclidian distance $d_E(r, \hat{r})$ between the original spectrum $r$ and the reconstructed spectrum $\hat{r} = Q_1 c_K$. To achieve this minimisation, we take advantage of apriori knowledges on the spectral reflectances that are to be imaged. We know that the spectral reflectances of typical objects are smooth. We present this by assuming that the reflectance in each pixel is a linear combination of a set of smooth reflectance functions known apriori. Denoting these reference spectral reflectances as $R = [r_1 r_2 \ldots r_P]$, our assumption implies that, for any observed reflectance $r$, a vector of coefficients $a = [a_1 a_2 \ldots a_P]^t$ exists such that any reflectance $r$ may be expressed as

$$r = Ra.$$ \hspace{1cm} (12)

Hence, we obtain $\hat{r}$ from $a$ by using Equations (9), (8), and (12):

$$\hat{r} = Q_1 c_K = Q_1 \Theta^t r = Q_1 \Theta^t Ra.$$ \hspace{1cm} (13)

With Equations (12) and (13) the ideal expression $r = \hat{r}$ becomes

$$Q_1 \Theta^t Ra = Ra.$$ \hspace{1cm} (14)

Assuming that $R$ is a good representation of the reflectances that will be encountered, Equation (14) should be true for any $a$, and hence

$$Q_1 \Theta^t R = R.$$ \hspace{1cm} (15)

This gives then the reconstruction operator minimising the RMS spectral error by a pseudo-inverse approach as

$$Q_1 = R R^t (\Theta^t R R^t \Theta)^{-1}.$$ \hspace{1cm} (16)
The choice of the spectral reflectances in $R$ should be well representative of the spectral reflectances encountered in the applications. In our experiments on paintings we used a set of 64 spectral reflectances of pure pigments used in oil painting and provided to us by the National Gallery in London [3]. For other applications, sets that are supposed to be representative of general reflectances could be used, such as the object colours of Vrhel et al. [36] or the natural colours of Jaaskelainen et al. [42].

Note that slightly different methods exist for the estimation of a spectral reflectance from the camera responses, such as the Wiener estimation method [41, 43, 4] based on the autocorrelation matrix of $R$, and a principal component analysis method where the principal components of the spectral reflectance are estimated by a least mean square approach from the camera responses [20].

The colorimetric and spectral sampling methods being not adapted to our applications, we have performed a rapid evaluation of the two reconstruction operators presented in this section. The experimental results shown in Figure 2 indicate clearly that the reconstruction operator $Q_1$ is superior to $Q_0$, as expected.

Figure 2: Reconstruction of the spectral reflectance of the cadmium orange (left) and the manganese blue (right) pigments from the camera responses using seven filters. We note the clear superiority of method $Q_1$ compared to method $Q_0$. Method $Q_1$ takes into account a-priori knowledge on the spectral reflectances encountered in oil painting.

### 2.3 Choice of the filters

The quality of the spectral reflectance reconstruction depends not only on the reconstruction operator, but also heavily on the spectral characteristics of the acquisition system: illuminant, camera and filters. The design of optimal filters given an optimisation criterion has been proposed by several authors, for example Trussell and coworkers [43,45-48], Lenz et al. [48, 49], and Wang et al. [50]. A drawback with such methods is the production cost of the optimised filters. Another approach encountered in most existing multispectral scanner systems is to use a set of heuristically chosen colour filters which are typically equi-spaced over the visible spectrum [20,39,40,52-54]. For example, the VASARI scanner implemented at the National Gallery in London uses seven broad-band nearly-Gaussian filters covering the visible spectrum [52]. Al-
though promising results are reported using such systems, the choice of filters seems to remain rather heuristic and likely sub-optimal.

We use an intermediate solution, where the camera filters are chosen from a set of readily available filters [3, 44, 45]. This choice is optimised, taking into account the statistical spectral properties of the objects that are to be imaged, as well as the spectral transmittances of the filters, the spectral characteristics of the camera, and the spectral radiance of the illuminant [12]. The main idea of this method is to choose the filters so that, when multiplied with the illuminant and camera characteristics, they span the same vector space as the reflectances that are to be acquired in this particular application [54, 55]. The filters are selected sequentially to maximise their degree of orthogonality after projection into the vector space spanned by the most significant eigenvectors [3]. Although this approach remains suboptimal, it avoids the heavy computation cost required for an exhaustive search, such as used for example by Vora et al. [44, 45].

2.4 Evaluation of the acquisition system

We have performed a simulation to evaluate the complete multispectral image acquisition system. We used D65 as the scanning illuminant, the Eikonix CCD camera spectral characteristics, filters chosen from a set of 37 Wratten, Hoffman, and Schott filters, and the spectral reflectances of a colour chart of 64 pure pigments used in oil painting. The resulting spectral sensitivities of the camera channels are shown in Figure 3 (right) for the case of a selection of seven filters with transmittances shown in Figure 3 (left). We note that, as expected, the peak sensitivities of the camera channels are distributed over the entire wavelength interval, however, they are not equally spaced. We resume in Figure 4 the complete chain of a multi-channel image acquisition system with the final spectral reconstruction step.

Figure 3: The spectral transmittance of seven filters chosen according to the method described in [3] (left). The corresponding spectral sensitivities of the seven camera channels including the spectral characteristics of the Eikonix camera, the spectral radiance of the illuminant D65, and the spectral transmittance of the filters (right). The numbers denote the sequence in which the filters are chosen.
When evaluating the quality of an image acquisition system, it is of great importance to define appropriate quality measures [56-60]. Depending on the intent, these may be based on colorimetric or spectral properties, on mean or maximal errors in a data set, or alternatively on critical samples for which the reconstruction quality is particularly important for a specific application.

We have chosen to use the mean and maximum RMS spectral reconstruction errors, that is, the Euclidian distance between original and reconstructed spectral reflectances, as a quality measure. This presents the advantage to be simple and general. In Table 1, the RMS spectral reconstruction errors using different number of filters are reported. As expected, we see that the mean reconstruction error decreases when an increasing number of filters are used. The maximum error shows some exceptions to this, however it follows the same decreasing trend. In Figure 5 we show some examples of spectral reflectance reconstruction, along with the corresponding RMS errors.

Table 1: Comparison of the RMS spectral reconstruction error for varying number of filters using the reconstruction operator $Q_1$ (cf. Section 2.2).

<table>
<thead>
<tr>
<th>Number of filters</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
<th>12</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean RMS error ($\times 100$)</td>
<td>3.57</td>
<td>2.39</td>
<td>1.78</td>
<td>1.32</td>
<td>1.11</td>
<td>0.87</td>
<td>0.57</td>
<td>0.56</td>
<td>0.36</td>
<td>0.30</td>
</tr>
<tr>
<td>Max RMS error ($\times 100$)</td>
<td>8.79</td>
<td>6.77</td>
<td>5.38</td>
<td>4.93</td>
<td>6.16</td>
<td>3.23</td>
<td>1.74</td>
<td>1.84</td>
<td>1.22</td>
<td>1.05</td>
</tr>
</tbody>
</table>

3 Multimedia application: Illuminant simulation

In the previous section we have presented different aspects of the acquisition of a multispectral image. This multispectral image may be used for many purposes: object recognition, colour constancy, high-quality reproduction, etc. We present here a particular application which is the simulation of the original scene as it would have appeared when viewed under different illuminants. Applied to fine arts paintings, museological objects, jewelry, textiles, etc., such simulations displayed on a colour calibrated computer monitor could be of particular interest in i) a high-end multimedia application for the open market, the user himself choosing his preferred light source, or ii) a computer aided tool for specialists, for example a curator having to decide the appropriate light sources for an art exhibition.

It is well known that the appearance of an object or a scene may change considerably when the illuminant changes, due to physical and psychophysical effects. These effects are taken into
account in most colour appearance models in a somewhat heuristic manner. However, such models cannot predict correctly changes for arbitrary illuminants, one important reason for this being metamerism. To be able to predict precisely the physical phenomena involved in a change between any illuminants, a complete spectral description of the illuminants and the scene reflectances is required.

We will here present two methods for the simulation of objects viewed under different illuminants. First, a classical method based on the CIELAB space is described in Section 3.1. Then, we describe in Section 3.2 the method applying multispectral imaging techniques. In Section 3.3 we compare the two methods using $\Delta E_{04}^*$ under the simulated illuminant as an error measure.

### 3.1 Illuminant simulation using CIELAB space

It is found by several studies [60, 61] that the CIELAB space [37] performs well in simulating a change in illuminant, and that it can be compared to more complicated colour appearance models such as RLAB [62] or the Hunt model [63]. It is clear, however, that CIELAB does not make an attempt to take into account parameters such as ambient light, surround, etc.

To evaluate the ability of CIELAB space to account for changes in viewing illuminant, we first define an ideal colorimetric image capture device having as spectral sensitivities the colour matching functions of the CIE XYZ-1931 standard observer, and for which we use D65 as illuminant. The three channels of this ideal camera provide us directly with the tristimulus values of the surface imaged in each pixel,

$$[X_{D65}, Y_{D65}, Z_{D65}]^T = A^t L_{D65} r,$$

where $A = [XYZ]$ represents the colour matching functions, and $L_{D65}$ is a diagonal matrix containing the D65 spectral radiance.
The key point in the way CIELAB treats the illuminant is that when converting from XYZ to CIELAB, the XYZ values are taken relative to the XYZ values of the illuminant. Thus,

\[
\begin{bmatrix}
L^*_{\text{D65}}, a^*_{\text{D65}}, b^*_{\text{D65}}
\end{bmatrix} = \begin{bmatrix}
g(X_{\text{D65}}/X_{W,\text{D65}}, Y_{\text{D65}}/Y_{W,\text{D65}}, Z_{\text{D65}}/Z_{W,\text{D65}}),
\end{bmatrix}
\]

(18)

\(g(\cdot)\) being defined by well-known functions given in [37], and \([X_{W,\text{D65}}, Y_{W,\text{D65}}, Z_{W,\text{D65}}]\) being the tristimulus values of a perfect diffuser under D65 lighting. Since we assume an ideal image capture device, these CIELAB values are colorimetrically exact for illuminant D65.

When using CIELAB as a colour appearance model, we assume that the CIELAB values of a given surface colour are constant and independent of illuminant changes. The estimation of the CIELAB values of this colour under a simulated illuminant \(L_{\text{sim}}\) are thus given by

\[
\begin{bmatrix}
\hat{L}^*_{\text{sim}}, \hat{a}^*_{\text{sim}}, \hat{b}^*_{\text{sim}}
\end{bmatrix} = \begin{bmatrix}
L^*_{\text{D65}}, a^*_{\text{D65}}, b^*_{\text{D65}}
\end{bmatrix}.
\]

(19)

By applying the inverse transformation \(g^{-1}(\cdot)\) we obtain the following relation

\[
\begin{bmatrix}
\hat{X}_{\text{sim}}, \hat{Y}_{\text{sim}}, \hat{Z}_{\text{sim}}
\end{bmatrix} = \begin{bmatrix}
\begin{bmatrix}
X_{\text{D65}}/X_{W,\text{D65}}, Y_{\text{D65}}/Y_{W,\text{D65}}, Z_{\text{D65}}/Z_{W,\text{D65}}
\end{bmatrix},
\end{bmatrix}
\]

(20)

where \([\hat{X}_{\text{sim}}, \hat{Y}_{\text{sim}}, \hat{Z}_{\text{sim}}]\) and \([X_{W,\text{sim}}, Y_{W,\text{sim}}, Z_{W,\text{sim}}]\) are the tristimulus values of the surface and of the perfect diffuser, respectively, under the illuminant \(L_{\text{sim}}\). We see from Equation (20) that the CIELAB space takes into account the effects of chromatic adaptation by applying a Von Kries [64] transform in the XYZ space.

### 3.2 Illuminant simulation using multispectral images

We consider now the simulation of spectral changes in lighting if multispectral images are available. Such images may be acquired as described in Section 2 or by other means, the essential being that they contain, in each pixel, information about the spectral reflectance imaged on it.

To simulate the scene as it would have appeared when lit by a given illuminant \(L_{\text{sim}}\), the multispectral image provides us with a straightforward approach: the reconstructed spectra \(\hat{\mathbf{e}}\) in each pixel is first reconstructed from its multispectral coordinates \(\mathbf{e}_k\) using Equation (9), \(\hat{\mathbf{e}} = \mathbf{Q}_k \mathbf{e}_k\). We then calculate colorimetrically the XYZ tristimulus values of the surface imaged in this pixel and lit by illuminant \(L_{\text{sim}}\) as in Equation (17),

\[
\begin{bmatrix}
\hat{X}_{\text{sim}}, \hat{Y}_{\text{sim}}, \hat{Z}_{\text{sim}}
\end{bmatrix} = \mathbf{A}^t \mathbf{L}_{\text{sim}} \hat{\mathbf{r}},
\]

(21)

where \(\mathbf{L}_{\text{sim}}\) is the diagonal matrix corresponding to the spectral radiance of the simulated illuminant. These values are then used to estimate the CIELAB values under this particular illuminant,

\[
\begin{bmatrix}
\hat{L}^*_{\text{sim}}, \hat{a}^*_{\text{sim}}, \hat{b}^*_{\text{sim}}
\end{bmatrix} = \begin{bmatrix}
g(\hat{X}_{\text{sim}}/X_{W,\text{sim}}, \hat{Y}_{\text{sim}}/Y_{W,\text{sim}}, \hat{Z}_{\text{sim}}/Z_{W,\text{sim}})
\end{bmatrix}.
\]

(22)

### 3.3 Evaluation of the two illuminant simulation methods

When evaluating the ability of different methods to take into account a change in illuminant, psychophysical tests using real observers should be applied [60, 61]. However, a numerical
criterion for this evaluation may also be of great interest because of its simplicity and rapidity. We have chosen to perform an analysis based on the CIE \( \Delta E_{94}^{ab} \) colour difference formula [65]. For a simulated illuminant \( L_{\text{sim}} \), the exact CIELAB values under this illuminant are calculated as follows

\[
[X_{\text{sim}}, Y_{\text{sim}}, Z_{\text{sim}}] = A_{\text{sim}} L_{\text{sim}},
\]

\[
[L_{\text{sim}}^*, a_{\text{sim}}^*, b_{\text{sim}}^*] = g(X_{\text{sim}}/X_{W_{\text{sim}}}, Y_{\text{sim}}/Y_{W_{\text{sim}}}, Z_{\text{sim}}/Z_{W_{\text{sim}}}).
\]

These values are then compared to the estimated values by the CIELAB model, \( [L_{\text{sim}}^*, a_{\text{sim}}^*, b_{\text{sim}}^*] \) (cf. Equation (19)), and to those estimated by the multispectral image approach \( [L_{\text{sim}}^*, a_{\text{sim}}^*, b_{\text{sim}}^*] \) (cf. Equation (22)).

We have performed an analysis of the illuminant-simulation quality for i) the multispectral image approach with 5, 7 and 10 channels, and for ii) the CIELAB space as a colour appearance model with D65 as starting reference. The methods are evaluated using five illuminants, the CIE daylight illuminants D65 and D50, the CIE standard illuminant A (representative of a typical tungsten lighting with a colour temperature of 2856K), a normal fluorescent lamp F2, and a low-pressure sodium lamp (LPS) widely used in street lighting, see Figure 6. The spectral reflectances used for evaluation are those of the 64 oil pigments previously introduced in Section 2.3.

![Figure 6: The relative spectral radiances of the five illuminants used in the experiment.](image)

The results in terms of mean and maximal \( \Delta E_{94}^{ab} \) errors are listed in Table 2, the error histograms are given in Figure 7, and a graphical representation of the results for the case of a seven-channel acquisition system is given in Figure 8. The obtained results are found to be comparable to those obtained in previous research, i.e. by Vrhel et al. [66, 43].

We note that at the evident exception of D65 which serves as reference for the CIELAB model, the multispectral approach performs generally significantly better than the CIELAB model. The CIELAB model performs reasonably well for the D50 case. This was expected since D65 and D50 have similar spectra, the change from D65 to D50 introducing only limited
Table 2: Mean and maximal $\Delta E_{94}^{*}$ errors obtained for four illuminant simulations using the CIELAB space as a colour appearance model, and the multispectral approach using 5, 7 and 10 filters.

<table>
<thead>
<tr>
<th>Simulated illuminant</th>
<th>CIELAB</th>
<th>Multispectral (5)</th>
<th>Multispectral (7)</th>
<th>Multispectral (10)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Max</td>
<td>Mean</td>
<td>Max</td>
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<td></td>
<td>Mean</td>
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<td></td>
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<td>Max</td>
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<tr>
<td></td>
<td>Mean</td>
<td>Max</td>
<td>Mean</td>
<td>Max</td>
</tr>
<tr>
<td>D65</td>
<td>0.00</td>
<td>0.00</td>
<td>1.58</td>
<td>10.53</td>
</tr>
<tr>
<td>A</td>
<td>4.94</td>
<td>11.33</td>
<td>1.92</td>
<td>15.51</td>
</tr>
<tr>
<td>F2</td>
<td>3.63</td>
<td>7.67</td>
<td>2.15</td>
<td>14.31</td>
</tr>
<tr>
<td>D50</td>
<td>1.56</td>
<td>4.27</td>
<td>1.71</td>
<td>12.23</td>
</tr>
<tr>
<td>LPS</td>
<td>20.10</td>
<td>52.68</td>
<td>1.40</td>
<td>10.06</td>
</tr>
</tbody>
</table>

Figure 7: Histograms of $\Delta E_{94}^{*}$ simulation errors for the CIELAB method and the multispectral methods using 5, 7, and 10 filters. The models’ performance is compared to direct spectral calculation of CIELAB under the simulated illuminant.

metameric problems. The D50 illuminant simulation using the CIELAB model is even better than the multispectral approach when using only 5 filters, the spectral reconstruction errors
Figure 8: Simulation results with the illuminants A, F2, D50 and a low-pressure sodium lamp. The models’ performance is compared to direct spectral calculation of CIELAB under the simulated illuminant. The results are projected in the a*-b*-plane of the CIELAB space. The reference CIELAB values under the simulated illuminant are marked with circles (⊙), the values predicted by the CIELAB model by asterisks (⋆), and those predicted by the multispectral image approach by crosses (×). We note a clear superiority of the simulation obtained by using the multispectral image approach.

becoming greater than the errors induced by the CIELAB model. Almost complete failure, with a mean $\Delta E_{94}^* \approx 20.10$, is found for the CIELAB model in the case of low-pressure sodium lamp. This was also expected, since its spectral power distribution consists almost entirely of two spectral lines at 589.0 and 589.6 nm [67].

4 Conclusion

We have described a system for the acquisition of multispectral images in which a set of chromatic filters are used with a CCD camera. We have proposed an efficient method for the reconstruction of the spectral reflectance of the object surface imaged in each pixel of the scene, from
the camera responses obtained with the set of filters. This reconstruction as well as the choice of filters are optimised by taking into account the statistical spectral properties of the objects that are to be imaged, as well as the spectral characteristics of the camera and the spectral radiance of the illuminant that is used for the acquisition.

In order to reveal the modifications in the colour appearance of an object or a scene when the illuminant is changed, a colorimetric simulation can be of particular interest in multimedia applications, especially in the museum field. We have investigated two methods for such an illuminant simulation, a classical method using the CIELAB colour space as a colour appearance model, and a method using multispectral images. The multispectral image approach is found to be very performant, even when applied to illuminants that are particularly difficult to handle with conventional methods.

References


