ABSTRACT

Predicting a surface color under different lights is an easy task if the surface reflectance function is available. However, often only colorimetric information is available, and the tristimulus values of a color that undergoes an illuminant change are estimated using transforms inspired by the von Kries coefficient rule model. We propose a new method, based on the reconstruction of multispectral data, for modeling illuminant change. It assumes that the problem is specific for a domain of colors, and that this domain can be modeled in a three dimensional Gaussian space. The performance of our method is compared with that of the simple von Kries diagonal transform, and the results are reported for three sets of data.

Keywords: color prediction, von Kries transform, reflectance function recovery.

1. INTRODUCTION

Many color and image processing applications share the problem of modeling a change in lighting in order to predict the appearance of a given color, under an illuminant that differs from the specified one. If multispectral information about surface reflectance is available, calculation of the tristimulus values under illuminants of specified Spectral Power Distribution (SPD) is straightforward. When the colorimetric information is known, the change in lighting can be computed by applying transforms based on the Von Kries scaling model. Unfortunately, the scaling model, based on ideal sharp and non-overlapping sensors, may not accurately predict the change of illuminant. Recently other methods for predicting the color of a surface under a different illuminant have been proposed, and the feasibility of exploiting multispectral data has been attested.

We propose here a new method for modeling illuminant change based on the estimation of a reflectance function, given the tristimulus values and the corresponding illuminant SPD. The method assumes that the problem is specific for a domain of colors, and that this domain can be modeled in a three dimensional Gaussian space. Given the Gaussian space domain, colors may be represented by synthesized reflectance spectra, and their tristimulus values under the target illuminant directly computed. The Gaussian space is defined by a set of three Gaussian functions, estimated from a “training” data set. In our experiments, we have computed the Gaussian bases for three datasets: the Munsell Atlas, the Macbeth Color Checker, and the Vrhel dataset of natural reflectances.

To assess the feasibility of this method, we have compared its performance with that of the von Kries coefficient rule method.
2. METHOD

Reflectance functions of real surfaces are smooth, and may be represented as a linear combination of a few basis functions. We assume that the reflectance functions can be represented as a linear combination of three Gaussian functions, plus an offset term.

If we indicate with \( \mathbf{R} \) the reflectance vector; with \( \mathbf{G}_1, \mathbf{G}_2, \) and \( \mathbf{G}_3 \) the Gaussian function vectors; and with \( \mathbf{M} \) a mean term; then the linear model representation is:

\[
\mathbf{R} = a_1 \mathbf{G}_1 + a_2 \mathbf{G}_2 + a_3 \mathbf{G}_3 + \mathbf{M}
\]

where the mean term vector is a constant and each Gaussian function is defined as follows:

\[
G_{j,\lambda} = \exp \left( -\frac{4 \ln 2 \left( \frac{\lambda - \lambda_j}{N_\lambda} \right)^2}{w_j^2} \right) \quad M_\lambda = m
\]

In equation 2, \( \lambda \) is the index of wavelength, \( N_j \) is the number of wavelength samples, \( \lambda_j \) is the wavelength index at the function maximum, and \( w_j \) is the width of the function at half of its maximum.

Given the reflectance function expressed with equation 1, tristimulus values are computed as:

\[
X = K \sum_{\lambda=1}^{N} \left( \sum_{j=1}^{3} a_j G_{j,\lambda} + m_\lambda \right) I_{\lambda} \bar{x}_{\Delta \lambda}
\]

\[
Y = K \sum_{\lambda=1}^{N} \left( \sum_{j=1}^{3} a_j G_{j,\lambda} + m_\lambda \right) I_{\lambda} \bar{y}_{\Delta \lambda}
\]

\[
Z = K \sum_{\lambda=1}^{N} \left( \sum_{j=1}^{3} a_j G_{j,\lambda} + m_\lambda \right) I_{\lambda} \bar{z}_{\Delta \lambda}
\]

where \( K \) is a normalization factor, \( I \) is the illuminant’s SPD, and \( \bar{x}, \bar{y}, \bar{z} \) are the standard CIE 2-degree observer color matching functions. Denoting with \( \mathbf{S} \) the column vector of tristimulus values, \( \bar{\mathbf{s}} \) is the matrix having as columns the observer sensitivities; \( \mathbf{I} \), the matrix having the illuminant’s spectral power distribution in the diagonal and zero elsewhere; \( \mathbf{G} \), the matrix having as columns the basis vectors; \( \mathbf{a} \), the weights column vector; and \( \mathbf{M} \), the column vector representing the linear model mean term, then the equation for the calculus of tristimulus values can be written as:

\[
\mathbf{S} = K \bar{\mathbf{s}}^T \mathbf{I} (\mathbf{Ga} + \mathbf{M}) \Delta \lambda
\]

Equation 4 is a linear system of three equations and three unknowns, \( a_1, a_2, a_3 \). Given a triplet of tristimulus values and its corresponding illuminant, the solution of equation 4 supplies the weights in the Gaussian linear model of equation 1. Once the reflectance spectrum has been obtained, calculation of tristimulus values under the target illuminant is straightforward. A diagram of the illuminant change transform is reported in Figure 1.
Figure 1. Flowchart illustrating conversion of the tristimulus values from illuminant $I_1$ to illuminant $I_2$.

The key point of the method is the definition of the Gaussian basis. The basis components are computed on a training set of reflectances. We estimate the Gaussian basis set that best represents the training dataset in the reflectance function synthesis from the tristimulus values, proceeding as follows:

STEP 1. Given an input set of $N$ reflectance spectra, compute the corresponding set of input tristimulus values;

STEP 2. Define a random set of parameters that initializes the Gaussian functions and the offset term;

STEP 3. For each sample in the dataset,
compute a reflectance function on the XYZ triplet, inverting the linear model in equation 4;
compute a spectral-mismatch error between the input spectrum and the computed reflectance function;

STEP 4. Sum all the $N$ spectral-mismatch errors.

Step 4 defines the problem’s cost function. For its optimization, we employ a genetic algorithm, setting fitness minimization as the optimization criteria, and defining fitness as:
fitness = \frac{1}{N} \sum_{n} \left[ \left( 1 + \frac{\sum_{\lambda} \left( R_{n,\lambda} - R_{\text{input},\lambda} \right)^2}{N_{\lambda}} \right)^{1/2} + \delta_1(R_{n,\lambda}) + \delta_2(R_{n,\lambda}) \right] \tag{5}

where \( \delta_1(R_{\lambda}) = \max_{\lambda}(R_{\lambda}) - 100 \) iff \( \max_{\lambda}(R_{\lambda}) > 100 \), else \( \delta_1(R_{\lambda}) = 0 \) and \( \delta_2(R_{\lambda}) = -\min_{\lambda}(R_{\lambda}) \) iff \( \min_{\lambda}(R_{\lambda}) < 0 \), else \( \delta_2(R_{\lambda}) = 0 \).

Each individual in the genetic algorithm’s population is a vector of seven real values corresponding to the Gaussian basis parameters \( \lambda_1, w_1, \lambda_2, w_2, \lambda_3, w_3, \) and \( m \). In Step 1, the tristimulus values are computed considering a standard CIE 2-degree observer. In order to avoid the dependence of the estimated Gaussian basis on the illuminant used to compute tristimulus values, we take a perfect white illuminant, having a constant value in the range of the wavelengths of visible light.

3. EXPERIMENTS AND RESULTS

To assess the effectiveness of our procedure, designed to implement an illumination change transform by means of reflectance function estimation, we have compared our results with those obtained using the von Kries coefficient rule method. A detailed diagram of the comparison procedure is given in Figure 2.

**Figure 2.** Diagram of the method’s evaluation procedure. I\(_1\) is the reference illuminant and I\(_2\) is the target illuminant.
We performed two tests. The first test, applying the procedure shown in Figure 2, took the D50 illuminant as the reference illuminant $I_1$ and the A illuminant as the target illuminant $I_2$. The results are reported in Table 1. The second test was conducted taking the D65 illuminant as the reference illuminant $I_1$ and the D50 illuminant as the target illuminant $I_2$. The results are reported in Table 2.

Both tests were performed using Gaussian basis sets computed on each of the three datasets considered: the Munsell Atlas, the Macbeth Color Checker, and the Vrhel dataset. The illuminant change transform was performed for all possible combinations of input datasets and Gaussian bases.

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Von Kries (*)</th>
<th>Munsell G. Basis (***)</th>
<th>Macbeth G. Basis (***)</th>
<th>Vrhel G. Basis (***)</th>
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<tr>
<td></td>
<td>Mean</td>
<td>Max</td>
<td>Std</td>
<td>Mean</td>
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<td>1.82</td>
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**Table 1.** Statistics of the DeltaE errors computed on the procedure described in Figure 2. Three basis sets, computed on the three data sets considered, have been used (see first column); (*) and (***) refer the reader to Figure 2. D50 is the reference illuminant and A is the target illuminant.

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Von Kries (*)</th>
<th>Munsell G. Basis (***)</th>
<th>Macbeth G. Basis (***)</th>
<th>Vrhel G. Basis (***)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
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**Table 2.** Statistics of the DeltaE errors computed on the procedure described in Figure 2. Three basis sets, computed on the three data sets considered, have been used (see first column); (*) and (***) refer the reader to Figure 2. D65 is the reference illuminant and D50 is the target illuminant.

In Figure 3 we report the mean values of the deltaE errors in Table 1 and Table 2 for a visual comparison. As the average results show, the method proposed here outperforms the von Kries model. As expected, the performance improves when the Gaussian basis employed is that of the input dataset. But the results are better than those of the von Kries method even when the Gaussian basis is calculated on a different dataset.
Figure 3. Plot of the average deltaE errors in Table 1 and Table 2. The performance of the von Kries model is compared with that of the method, for the three Gaussian bases estimated.

4. CONCLUSION

We have proposed a method for modeling illuminant change based on the reconstruction of multispectral data. The results of a comparison with the von Kries model confirm that exploiting synthesized reflectance is an effective strategy for implementing an illuminant change transform.

REFERENCES