COLOR IMAGE NORMALIZATION THROUGH ILLUMINANT RECOVERY

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ABSTRACT

The information in a color image is always a function of the illuminating source, the geometry, the reflectance properties of the object and the characteristic of the camera. Separating the influence of the spectral distribution of the illumination and the reflectance properties of the object is known as the color constancy problem. Successful separation is important for vision and pattern recognition tasks, quality control in the graphic arts and image database applications. We describe an approach to the color constancy problem which is based on statistical assumptions about the distribution of colors. It uses the eigenvector system of the logarithmic spectra in a large database of color samples and employs methods from robust statistics to recover the illumination spectrum. We illustrate the performance of the algorithm with a simulation in which the effect of the illumination by the standard A-source is eliminated.

1. INTRODUCTION

One of the most remarkable properties of the human visual system is its ability to compensate the influence of changing illumination conditions, a phenomenon known as color constancy. The problem is actively pursued in computer vision, but a satisfactory solution for real world conditions is yet to be found (see [6, 3]). Color is an important indexing parameter in today's query by image content systems, e.g. [4]. The query may fail, however, if the colors in a scene are significantly modified due to illumination changes.

In this paper we present an algorithm which normalizes images of a scene taken under different illuminations to the same reference image. The illumination does not have to be the same across the scene since the algorithm requires only a small number (of differently colored) pixels. In spite of very simplistic assumptions about color image formation the technique produces reliable results.

All the possible colors in the image taken as reference are assumed to be adequately described by a database of spectral data. We used the Munsell system and the NCS system but other, similar systems exist and are described in [2]. The database used in our experiments consisted of 1269 colors from the Munsell system and 1513 samples from the NCS system. For the Munsell system the spectra were measured from 380nm to 800nm at 1nm steps. The NCS spectra were sampled at 5nm intervals. These spectra can be represented by a few coefficients of the Karhunen-Loève expansion (see [8] for a detailed discussion and [5] for investigations of the properties of the different databases used here).

In the following we denote by λ the wavelength variable and we assume that the spectral distribution $M(\lambda, \mathbf{x})$, measured at location $\mathbf{x}$ can be written as $M(\lambda, \mathbf{x}) = R(\lambda, \mathbf{x}) \cdot L(\lambda)$, where $R(\lambda, \mathbf{x})$ is the reflectance function at that location. Taking the logarithm a linear relation, $m(\lambda, \mathbf{x}) = r(\lambda, \mathbf{x}) + l(\lambda)$, is obtained, where the lower case represents the logarithm of the upper case symbol, i.e. $\log(R(\lambda, \mathbf{x})) = r(\lambda, \mathbf{x})$. Experiments show that also the logarithmic spectra can be described by only a few coefficients in an eigenvector expansion of the log-database spectra. If the k-th eigenvector of the log-database is $b_k(\lambda)$ then the expansions of the functions m, r and l are

$$m(\lambda, x) = \textstyle\sum_k \mu_k(x) b_k(\lambda), \quad r(\lambda, x) = \sum_k \rho_k(x) b_k(\lambda)$$

and

$$l(\lambda, x) = \sum_k \alpha_k b_k(\lambda).$$

Thus, for a given k we obtain $\mu_k(\mathbf{x}) = \rho_k(\mathbf{x}) + \alpha_k$, i.e., the effect of the illuminant on the k-th expansion coefficient of the log-reflectance function is a location independent (constant) shift.

2. THE ALGORITHM

In practice only the measured spectrum $M(\lambda, \mathbf{x})$, and therefore the coefficients $\mu_k(\mathbf{x})$ are available. The proposed algorithm is based on the following assumption.

It is possible to find a representative set of locations $\mathbf{x}$ *for which the most probable value of the* $\rho_k(\mathbf{x})$ *distribution is the same as the corresponding value computed for the log-database spectra.*

Since the latter can be determined a priori, the global shift parameters α_k, and thus the illuminant spectrum can now be recovered.

As can be seen in Figure 1, the distribution of the log-database spectra expansion coefficients is very diverse. To estimate the most probable value for each coefficient, a robust mode estimator has to be employed. In a Bayesian framework, the mode is a MAP estimator which minimizes the uniform error cost function [7, page 210]. In robust statistics several mode estimators were developed, and we have used the *least trimmed squares (LTS)* estimators which has better efficiency properties [9, page 170]. Once all the data is ordered in an ascending sequence, the mode must correspond to the densest region. The LTS estimator locates this region with a sliding window always containing half the data points. The center of the window yielding the smallest residual power (relative to the window mean), is the mode estimate. These estimates are marked on the abscissa of Figure 1, and show the robustness of the procedure.

The same mode estimator is used to find the most probable value of the measurement coefficients $\mu_k(\mathbf{x})$. Then α_k is given by the the difference between the two modes.

The quality of the illuminant recovery depends on how well the (unknown) log-reflectance coefficients $\rho_k(\mathbf{x})$, corresponding to the available log-measurements $\mu_k(\mathbf{x})$, subsample the distribution of the log-database coefficients. A priori knowledge about the relation between these two sets can also be employed. It is not possible to recover intensity changes of the illumination since for a large range of constants γ it is true that $M(\lambda, x) = \left(\frac{R(\lambda,x)}{\gamma}\right) \cdot (\gamma \cdot L(\lambda))$. Usually we apply a global post-processing step to the computed spectra which ensures that the intensity values in the final image use the available dynamical range of the output device optimally. How this is done is described in the following section.

3. EXPERIMENTS

In the first experiment we simulated the underlying image formation model. In this experiment we used only the spectral distributions in the Munsell database within the range from 400nm to 700nm and 5nm sampling. Given an RGB image, for every pixel the closest (by L_1 norm in the RGB space) Munsell spectrum was determined. Using a linear interpolation among several neighbors does not seem to yield significant improvements. This multispectral Munsell image is the reference image, which we try to recover under different illuminations.

As illumination spectra we used the standard sources A and D65, random members of the database, and illuminations described by the color temperature (see [10, 1] for details). Pixelwise multiplication of the reference image and the illumination source spectra provided the measured (simulated) multispectral images.

From the measured image a small number of pixels (around 250) were randomly selected and the modes of the coefficients in the eigenvector expansion of the logarithmic image $m(\lambda, \mathbf{x})$ were computed. The differences between these modes and the precomputed modes of the corresponding distributions from the database give the estimated values of the illumination source expansion coefficients α_k. From these coefficients the spectral distribution of the illumination source can be estimated up to a multiplicative constant.

The spectral distributions of the pixels in the recovered reference image are obtained by pointwise division of the measured image spectrum by the estimated illumination spectrum. From these spectra the recovered RGB values can be computed.

In lack of a priori information about the luminance of the recovered reference image pixel we usually have to use some normalization procedure. In figures 2 and 3 we norm the spectra to unit length to illustrate the different spec-

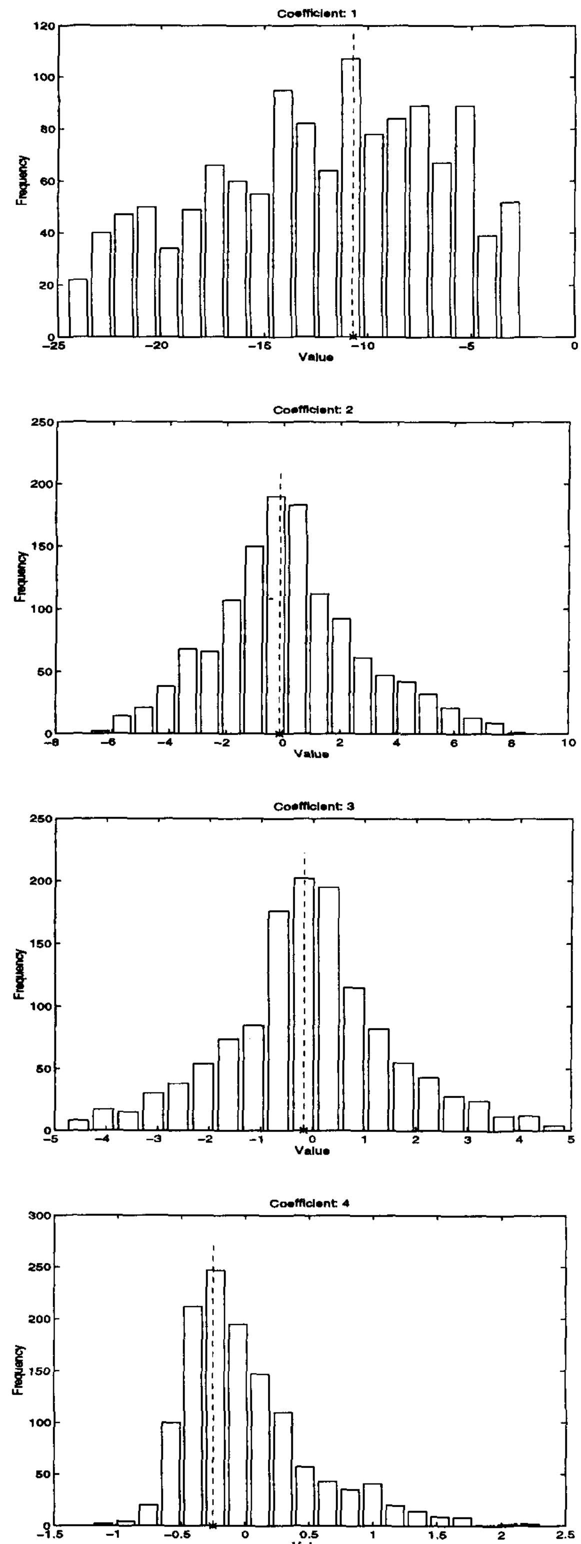

Figure 1. Histograms of coefficients for log-database

tral characteristics. In the images in Figures 4-5 we used a global normalization process. Here we computed first the mean intensity of the spectra in the three different images. Then we normalized two of them by multiplication with a global factor so that after the normalization all images had the same mean intensity. These normalized images are shown in the figure.

The figures 2-6 show the results of a typical experiment where the CIE-Source A was used. This source represents the spectral distribution of a tungsten lamp ([1]). In this experiment we used 3 basis functions and 256 points for the estimation of the light source.

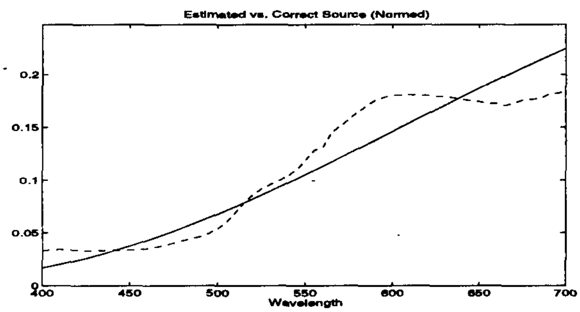

Figure 2. Original illuminant (solid) and estimated (dashed)

Figure 2 shows the spectrum of the standard source A (solid) and the recovered spectrum (dashed). Figure 3 shows the spectrum in the original image, the measured and the recovered spectrum at the same points in the image.

The Figures 4, 5 and 6 show a reference image, the measured image and the recovered image. Note that while the displayed images are RGB images all the computations are done with multispectral data. The images should therefore only be used as a visual illustration of the results obtained. (The color images are included in the electronic version of the paper).

The results show that the algorithm could reliably recover the spectral characteristics of the illumination source. In other experiments we tested the algorithm with different images ranging from paintings to photographs and with different parameter settings. In a series of experiments we varied the number of coefficients used in the eigenvector expansion from 3 to 15 and found that 3 to 5 coefficients are enough for visual purposes. We also saw that around 250 pixels are usually enough to estimate the coefficients of expansion of the light-source, given that they are spread across the entire database.

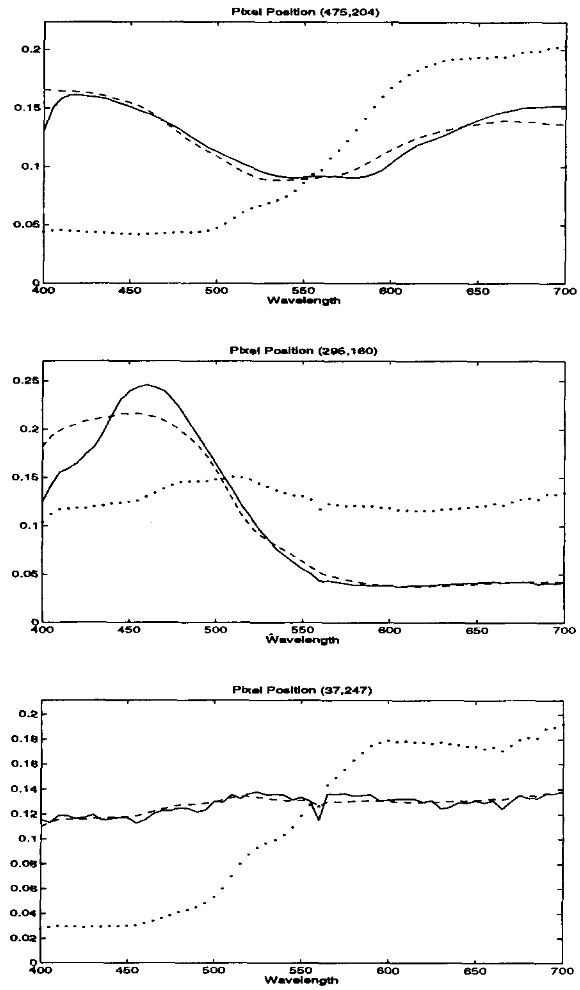

Figure 3. Reference (solid), Estimated (dashed) and Measured Spectra (dotted) at different positions.

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The spectra in the Munsell database were measured at the Department Physics, Joensuu University, Finland and are available from the Department Information Technology, Lappeenranta University of Technology, Lappeenranta, Finland. We also used some of the software that is available at the same site.

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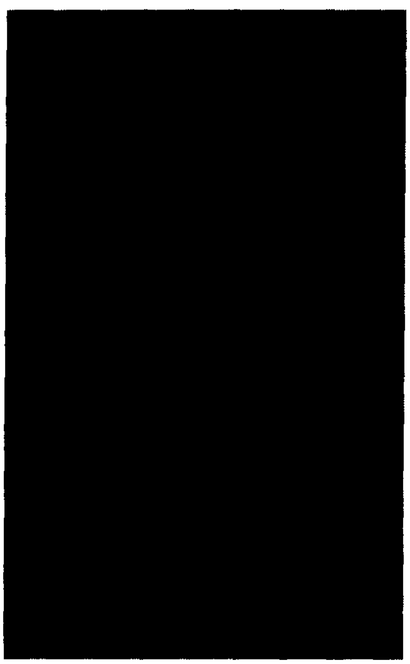

Figure 4. Reference image

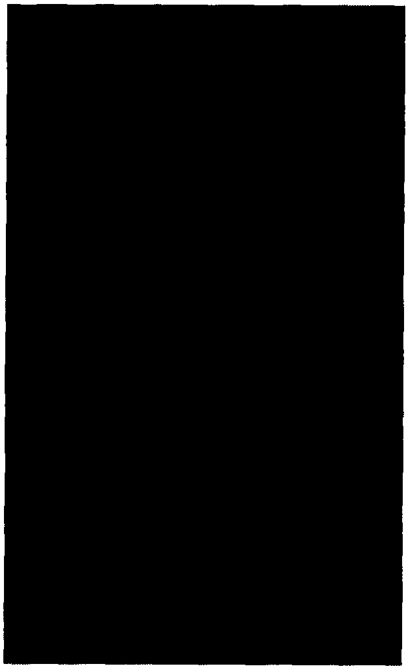

Figure 5. Measured image

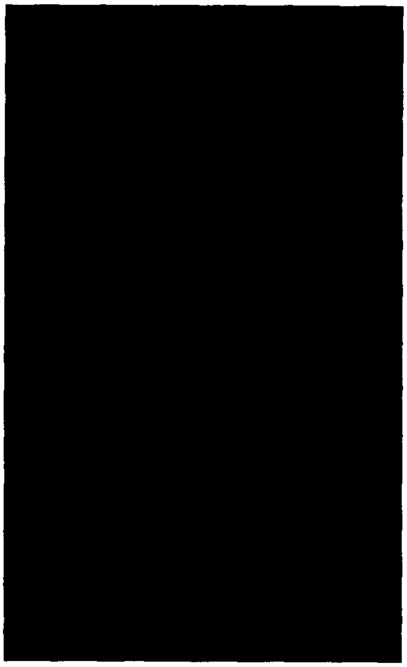

Figure 6. Recovered image