Spectral Images and the Retinex Model

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Abstract

*Human color vision models have been used as a basis for color image processing. One of the well known models is the Retinex model. The Retinex algorithm has mainly been applied to grayscale or RGB images, which brings discrepancy with real visual system even before the Retinex processing. In this paper we consider different ways of applying Retinex color appearance model to spectral images. We suggest processing of each spectral channel of the image separately. We also consider some other approaches, e.g. converting the spectral images to LMS responses or to different color spaces (XYZ, L*a*b*). We compare the results gained using spectral images as starting point with the results obtained by applying the Retinex to RGB images. In addition, we consider Retinex model in color constancy problem by using spectral images. In this paper The Retinex processing is done using the MATLAB™ implementation of the Retinex algorithm.*

Introduction

The Retinex theory for color computation was first introduced by Land in 1964 and was further published in the Journal of the Optical Society of America [7]. It was the first attempt to model one of the fundamental features of human color vision, *color constancy*.

Color constancy can be described as a feature of human visual system that helps to maintain the color of an object despite the variations in the illumination conditions and despite the variations in the color of the nearby objects. Although the human visual system reveals the color constancy property only to some extent, it still outperforms most of the existing artificial simulations of the visual system.

The Retinex model for color constancy has been previously used mainly with the RGB or grayscale images [4, 8]. This can serve as one of the reasons for possible inaccuracies in the output. In this paper we consider different ways of using the Retinex algorithm with the accurate color information, represented by spectral images. We analyze the obtained results in the context of color constancy of human vision. Finally, we compare our results with the results of applying Retinex to the RGB images.

The Retinex algorithm

The model proposed by Land was aimed to explain the following experimental fact. The color of an arbitrary area of the observed object can not be obtained exclusively from the product of the illumination and the reflectance of that isolated area (although it seems to be the only information reaching the eye). In reality, the visual system gets information from the entire visible scene. That information is used to eliminate the effect of the unknown and not uniform illumination.

Land suggested processing the spatial information from the visible scene with several independent systems. Originally the name “Retinex” came from the combination of the words “retina” and “cortex”. This illustrates Land’s suggestion about three retinal-cortical systems. Each system forms a separate image of the world; the images are not mixed but are rather compared. Each system discovers independently, in spite the variation and unknown properties of the illumination, the reflectance for the band of wavelengths to which that system responds [7]. The systems were assumed to be sensitive to the short-, middle- and long-wavelengths.

In the original algorithm the input data represented an array of short-, middle- and long-wavelength sensitive photoreceptor responses for each pixel of an image. Algorithm calculated the so-called lightness values (an estimate of the reflectance values) for each pixel of the image and each photoreceptor class by a scheme described below.

The main concept of the algorithm is the comparison of pixels in the image. This is done by accumulating lightness values along the paths of pixels. Each path starts with the pixel, whose lightness value is considered to be the maximum along the path. The values obtained from different paths are combined to estimate the output lightness value.

Each of the iterations of the Retinex algorithm represents a combination of four steps: *ratio*, *product*, *reset* and *average**. *Ratio* is used to compare nearby pixels. For two pixels the ratio of the radiance of the second pixel and the estimated reflectance (lightness) of the first pixel is calculated to estimate the lightness value of the second pixel. *Product* of ratios is used for long-distance interaction and is calculated for each path. Calculation starts with the current lightness value at one pixel and multiplies the value by the ratio of comparison pixel (next pixel in the path) and starting pixel; the new product is the current lightness value of the comparison pixel.

Reset step is used to find the pixel with the highest reflectance (lightness) along the path. In the beginning, the first pixel of the path is assumed to have the highest reflectance value. Then we move through the path and calculate the sequential product. Whenever we meet a pixel, for which the sequential product becomes greater than 1, it means that the pixel reflectance is higher than first pixel's reflectance. Thus this new pixel is assumed to have the highest reflectance and the path starts afresh from that pixel.

* The original algorithm also included a so-called *threshold* step, which was omitted in the further modifications of the algorithm, as no psychophysical support was found for it [8].

Finally, at the *average* step the average of all calculated sequential products for all considered paths ending in a single pixel is taken to obtain the lightness of that pixel.

In the algorithm the length of the path and number of paths for each pixel is an important parameter and must be carefully selected [5].

Modeling

One of the considered approaches of applying the Retinex to the spectral images arises from the original idea of Land and McCann to process separately the luminance information obtained by the three types of photoreceptors, sensitive to long-, middle- and short-wavelengths (as an analogy to the cone photoreceptors in the retina of human eye) [7]. Spectral images provide the accurate color information. By combining it with the information about the light source and the photoreceptor sensitivities (see Formulas (1) and (2)), we obtained the accurate photoreceptor responses for each pixel of considered images.

The other approach we used is the separate Retinex processing of each spectral channel. It is a modification of the previous case in the sense, that here the amount of photoreceptors increases from 3 to the number of spectral channels in the image.

In our experiments we tested how the output of the Retinex algorithm changes for an image when it is examined under different illuminations. To obtain the radiance values $R^x(\lambda_n)$ of wavelength λ_n for each pixel *x* under each illumination we multiplied the surface reflectance values $S^x(\lambda_n)$ by $E(\lambda_n)$ - the spectral power distribution of the ambient light:

$$R^x(\lambda_n) = S^x(\lambda_n)E(\lambda_n) \quad (1)$$

As the sources of ambient light, standard illuminants with fixed power distribution were used (Fig.2).

By Formula (2) we obtained the responses $\rho^x{}_k$ of long-, middle- and short-wavelength sensitive photoreceptors to the radiance values using spectral absorption curves of the photoreceptors (see Fig. 1).

$$\rho^{x}{}_{k} = \sum_{n=1}^{N} C_k(\lambda_n) R^{x}(\lambda_n) \qquad (2)$$

In the previous formulas, the wavelength λ_n is taken within the visible spectrum. $C_k(\lambda_n)$ is the spectral sensitivity of k^{th} photoreceptor class, where $k = L, M, S$ [2]. The spectral sensitivities were obtained from the Stockman and Sharpe (2000) 2-deg cone fundamentals [9, 10] (Fig. 1).

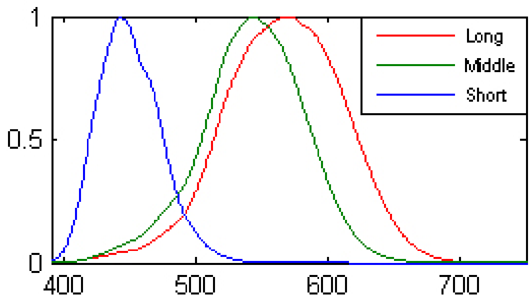

Figure 1. Spectral sensitivities of long-, middle- and short-wavelength sensitive cones.

For comparison, we also obtained *L*, *M* and *S* values using a transformation from the original spectra through the *CIE XYZ* color space given in [11]:

$$\begin{bmatrix} L \\ M \\ S \end{bmatrix} = \begin{bmatrix} 0.38971 & 0.68898 & 0.07868 \\ -0.22981 & 1.18340 & 0.04641 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \end{bmatrix}$$

In addition, we transferred the spectral image to the sRGB and CIELAB spaces [1, 11]. The Retinex processing was performed independently on the channel of these color spaces.

There are several published versions of the Retinex algorithm. We used one of the most popular variations of the Retinex algorithm, suggested by Frankel and McCann [3] and further implemented in MATLAB™ [4]. The variations between the algorithms are mainly aimed to improve computational efficiency, rather than the model itself. Further when talking about the Retinex algorithm we will bear in mind the selected implementation.

In order to compare the outputs of applying Retinex to different color representations, we converted the outputs for each representation to the sRGB space using corresponding transformations that can be found in literature [1, 11]. To display the results with reasonable brightness, the converted images were postprocessed taking into the account the response of the output device. The proper modification was obtained experimentally for each image.

As one of the performance measures we used the *median angular distance* in RGB space. It is a slight modification of commonly used measure for color constancy, when the angle between the RGB of the actual illumination and the RGB of illumination estimate is used [6]. For our purposes we considered the same image under different illuminations and compared the Retinex outputs for D65 illumination with outputs for other considered illuminations. We calculated the angles between the 3-dimensional vectors (in sRGB space) for every pixel of all tested images and then accepted as a measure the median of all angles for each pair of considered illuminations.

Experiments

The comparison of the stated approaches has been done based on two following aspects. First: how well the modeled output preserves the colors of the scene, when varying the spectral power distribution of the ambient light? Second: how the changes in the visible scene affect the color of a specific area of the scene?

Varying the Illumination

For the illumination variation experiment 10 different spectral images were used. They were selected to be of different size and wavelength properties. The images were considered under 4 different standard illuminants A, B, C and D65 (Fig. 2).

Retinex was applied to each considered representation:

- spectra
- L channel of the L*a*b*
- LMS
- sRGB.

All outputs were normalized to interval [0, 1]. The results for all representations were converted to the sRGB space to compare the performance in each case. We calculated the *median angular distance* between the outputs for D65 illuminant and for three other illuminants. To summarize the results, we calculated the median and maximum of angular distance for all cases.

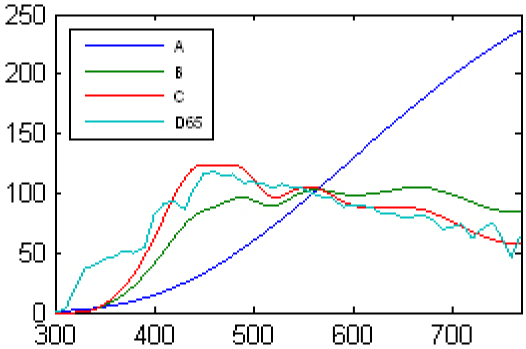

Figure 2. Spectral power distribution of 4 standard illuminants: A, B, C and D65.

Scene Changes

For the second part of the evaluation the following vision phenomenon was used. Let as compare the images from Fig. 3.

Figure 3. sRGB representation of the original spectral image (on the left) and the same image with a cyan filter placed over the yellow square (on the right). As a result the yellow square appears green.

Left image is the sRGB representation of the original spectral image under the D65 illumination. On the right image a cyan filter is placed over the yellow square of the same image. As a result it appears green. Now let us apply the same cyan filter to the entire image (Fig. 4). Although the actual values for the "yellow" square are exactly the same, as on the right image from Fig. 3 (when the filter was placed on the yellow square only and appeared green), we again can recognize the color of the selected square as yellow (although the colors of the whole scene have slightly changed).

Figure 4. A cyan filter is applied to the entire image.

For performing this experiment we modeled the effect of placing a cyan filter over a spectral image (or its part) by eliminating the red component from the spectral power distribution of the ambient light (D65). As in previous experiment, Retinex was applied to each considered representation (spectra, L channel of the L*a*b*, LMS, sRGB) of the "filtered" image. The outputs were converted to the sRGB space to display (after proper normalization to [0, 1]). The desired result after processing would be such that the actual color values of the "yellow" square would shift to green or back to yellow area, depending on whether the filter was applied to the square, or to the whole image.

Results

Varying the Illumination

Median and maximum values of the angular difference in sRGB space were calculated for each image (outputs of all representations were converted to sRGB values). Table 1 represents the average of those values among 10 tested images (the maximum values represent the maximum over all images).

Table 1. Retinex performance for different color representations

Illuminants	**A to D65**		**B to D65**		**C to D65**	
	Med	Max	Med	Max	Med	Max
RGB	6,94	177,3	0,79	168,1	0,19	143,6
L*a*b*	1,10	90	0,48	90	0,13	83,7
LMS	1,51	166,3	0,41	141,0	0,15	62,1
LMS_{XYZ}	4,83	164,4	1,24	144,9	0,34	88,6
Spectra	0,00	6,1	0,00	1,5	0,00	0,22

From Table 1 we can see that median values for the spectral approach are close to 0.

Although the real reflectance and reflectance estimation of Retinex are not equal, there are considerable similarities between them. We tried to illustrate that in Figure 6. Left half of it represents the radiance spectra for different illuminants (reflectance multiplied by the light source spectra) for a pixel in one of the tested images. In the right half of the figure we plotted the real reflectance spectra (magenta curve) for the same pixel and the reflectance estimates retrieved with Retinex processing (the same black curve for all illuminants). It can be seen, that the shapes of the curves are quite similar.

It also can be seen from the Table 1 that differences between results got using L*a*b* values for Retinex input are quite small. This is mostly due to the specifics of the L*a*b* representation itself.

Almost in all cases the results for the RGB are the highest (i.e. the median of 6.94 versus 1.51 for LMS).

In the case of LMS space the values are quite small for the median, but the maximum values can be significant. In this case a proper postprocessing is essential.

Scene Changes

For this part of the experiments the color checker image under the D65 illumination was considered (see Fig. 3 and Fig. 4). For comparison the sRGB values of the yellow square are plotted in the sRGB space. In Fig. 5 the values for sRGB, L*a*b*, LMS, LMS_{XYZ} and spectra are represented with the filter applied to the yellow square only and to the entire image.

It can be seen, that for L*a*b* and LMS Retinex tends to remove all the illumination without taking into the account the real color appearance. The values for the "yellow" square remain mostly the same and are close to yellow (note the differences in scaling of the plots).

In the case of spectra and sRGB the values notably differ and in first case tend to be green, while in the second case (when the filter is applied to the entire image) the values are in the yellow range.

Discussion and Future Work

In this study we considered different approaches in applying the Retinex algorithm to the spectral images. We compared different approaches in the context of human color constancy. The two experiments, described in this article, were performed to evaluate the performance of the Retinex algorithm for spectral images and different color representations.

First experiment considered the behavior of the Retinex output with changes in the illumination. We saw that for different color representations the results differ significantly (Table 1). It can also be interesting to study the behavior of the algorithm when there are gradual changes of the illumination.

We noticed in the experimental part that when we apply Retinex to spectral images, the output of the algorithm is in practice always the same independent of the illuminant used for multiplying the original reflectance spectra. To explain this behavior is an interesting topic for our future more detailed research.

In the case of applying Retinex for each spectral channel separately, the algorithm seems to be able to take into account the light source constant by which the reflectance values of each spectral channel are multiplied.

It should be noted that even though in Figure 6 the shape of Retinex output and the original reflectance spectrum seems to be quite similar, it's not the case for all spectra in images we have tested. This means that there probably doesn't exist a straightforward way (like scaling by a constant) to map Retinex output directly to reflectance spectra. The postprocessing for spectral Retinex output used in our experiments was just a linear scaling to full [0, 1] range. Because the postprocessing step seems to have quite a large effect on the results, next thing to do is to compare this simple approach with other possibilities for postprocessing.

In general, the output of the Retinex for all color spaces requires a careful selection of the postprocessing method (different for different spaces), which can be a subject of a separate study. The idea of such post Retinex processing can be found in [5].

In the second experiment we saw, that Retinex applied to the spectra and RGB space supports one of the phenomena of human color vision (see Fig. 3 and Fig. 4). Although, as it was stated above, the spectral approach needs more complicated postprocessing, the results for it, in the context of this experiment, are closer to human color appearance perception.

Other possible matters for further study are the results of changes in the length of the path and number of paths in the Retinex algorithm.

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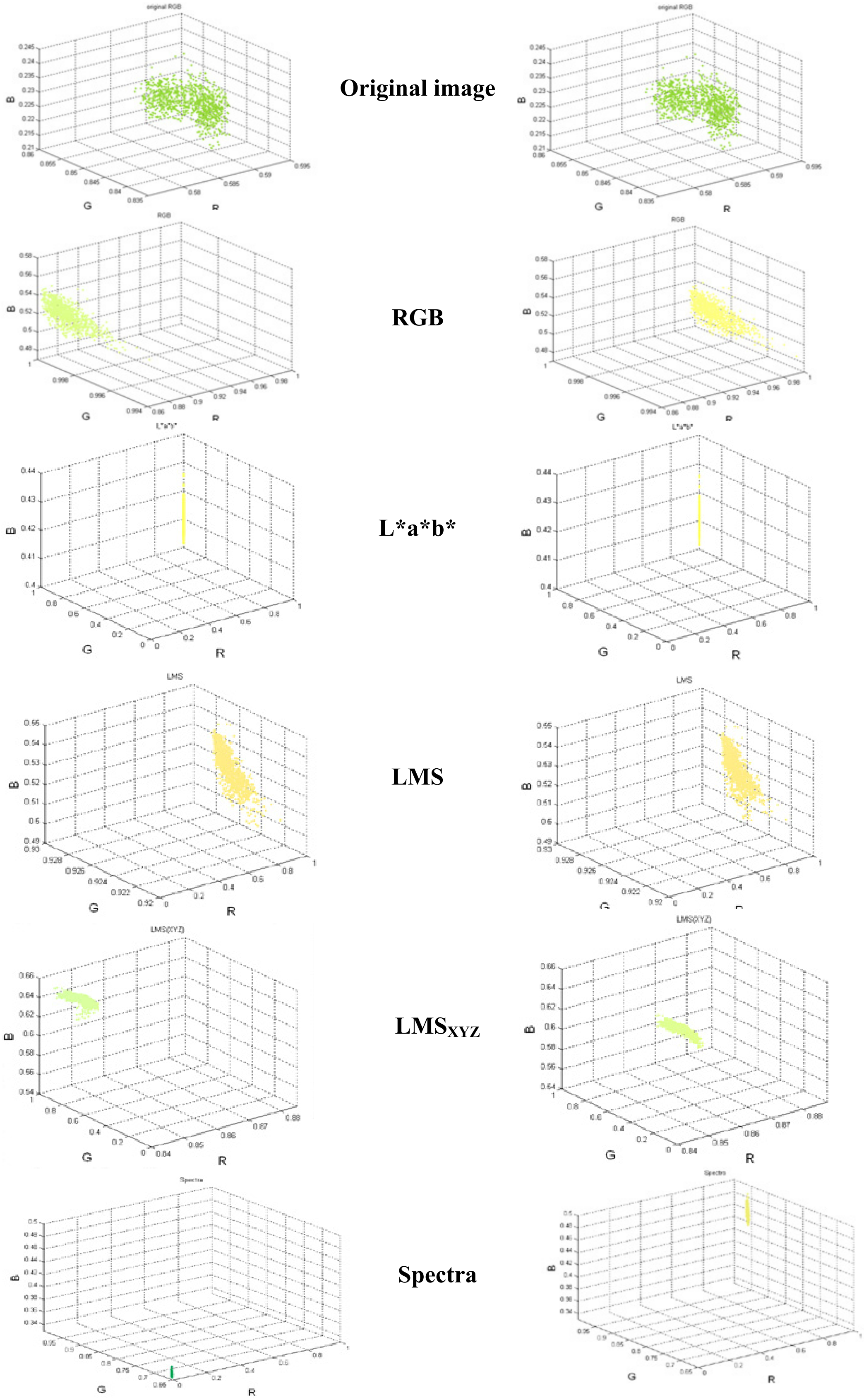

Figure 5. The values of the yellow square in the sRGB space. In the left column are the values, when the filter is applied to the square only. In the right column are the values, when the filter is applied to the entire image. Note the scaling differences.

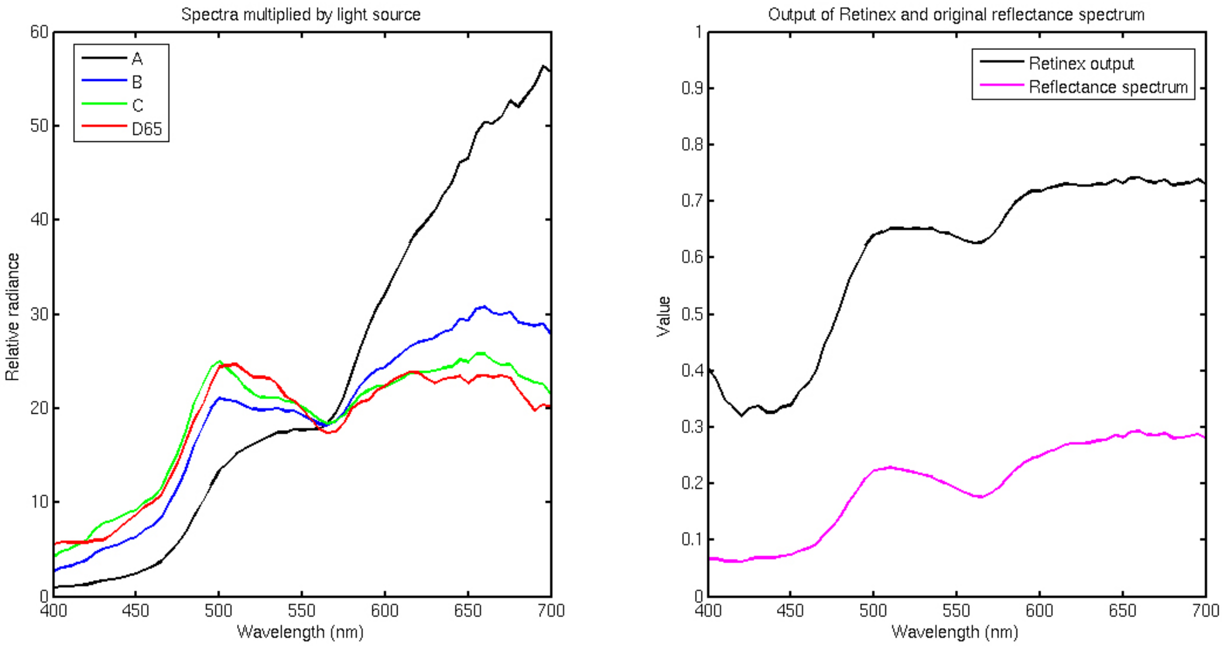

Figure 6. The radiance spectra for 4 different illuminations for a randomly selected pixel from one of the tested images (on the left) and the original reflectance spectra vs. the estimated by Retinex reflectance of the same pixel (on the right).