Testing Spectral Sensitivity of Sensors for Color Invariant at a Pixel

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Abstract

Marchant and Onyango (J. Opt. Soc. Am. A 17, 1952, 2000) and Finlayson and Hordley (.J. Opt. Soc. Am. A 18, 253, 2001) proposed the definition of an invariant parameter that can be applied to each pixel of a colored image in such a way that this image can be changed into a grey-scale one, in which color constancy is obtained with complete precision whenever the illuminant is Planckian-type and the three sensors which capture the image have Dirac's delta spectral sensitivities. In this work we look more closely at one of the points touched upon in the above-mentioned papers, which still needs to be studied in more detail: the optimal position of their spectral sensitivity maximums when we have real daylight illumination. We used an exhaustive search method, finding the best behaviour for the sets of spectral maximums: (645, 675 and 595 nm) and (550, 610 and 400 nm). Next, we extend our study to more realistic sensors considering for them a gaussian-type spectral sensitivity with 30nm half-bandwidth and maximum sensitivity at the wavelength of the two above mentioned triads. We compared the results obtained with these sensors with those obtained for real sensors, like commercial CCD cameras sensors. The performance of our sensors improves that obtained for the rest of sensors, also those employed by other authors. We have applied these results to natural scenes with the aim of classifying different kinds of vegetation.

Introduction

One of the ways of obtaining artificial vision systems which satisfies color constancy has been to define invariant descriptors to the possible changes in the illumination over an scene. Marchant and Onyango[1] and Finlayson and Hordley[2] proposed the definition of an invariant parameter that can be applied to each pixel of a colored image in such a way that this image can be changed into a grey-scale one, which will remain the same whatever the illumination of the scene in question. With the aid of this invariant parameter, color constancy is obtained with complete precision whenever the illuminant is Planckian-type and the three sensors which capture the image have Dirac's delta spectral sensitivities. Marchant and Onyango[3-4] have extended their proposed invariant to encompass daylight. Their method is based on the possibility of expressing the logarithm of the spectral power distribution (SPD) of daylight in terms of a linear model with only one free parameter.

In this work we look more closely at one of the points touched upon in the above-mentioned papers, which still needs to be studied in more detail: the possibility of using sensors with non-monochromatic spectral sensitivity and, simultaneously, the optimal position of their spectral sensitivity maximums.

Method

With three sensors of Dirac's delta spectral sensitivity at wavelengths λ_1, λ_2 and λ_n, the invariant is defined as

$$F_{12} = y_{\lambda_1} / y_{\lambda_2}^{A_{12}} \tag{1}$$

where

$$y_{\lambda_1} = C_{\lambda_1} / C_{\lambda_n} \ ; \ y_{\lambda_2} = C_{\lambda_2} / C_{\lambda_n} \tag{2}$$

$C_\lambda = g\rho(\lambda)E(\lambda)$ being the response of the sensor in question to the spectral radiance generated by the reflectance object $\rho(\lambda)$ illuminated by the SPD $E(\lambda)$. The term g includes the gain-factor and geometric components. The expression of exponent A_{12} will depend upon the mathematical representation made of the illuminants. Also the value of A_{12} can be determined experimentally.

The validity of the invariant will depends on whether the spectral representation of daylight is accurate enough and whether the hypothesis of very narrow-band sensors can be applied. Whatever the case, if the sensors are either broad-band or real, the validity of the invariant can be studied by representing for any group of objects and illuminants the logarithm of $y_{\lambda 2}$ versus that of $y_{\lambda 1}$, taking the values of C_λ as the response of the sensors, the sensitivities of which are maximum at the corresponding wavelength. If the invariant is valid for a set of sensors this representation will generate for each object under whatever illuminant, points over a straight line, the slope of which, $1/A_{12}$, must be the same for all the objects involved.

We took as our objects 24 samples from ColorChecker and 64 SPD's of daylight measured on days with different atmospheric conditions and times of day ranging from midday to morning and evening twilight hours[5].

Results

First we tested monochromatic sensors in order to obtain the best three wavelengths along the visible spectrum which optimize the correlation coefficient and the uniformity of the slope in the representation of the logarithm of $y_{\lambda 2}$ versus that of $y_{\lambda 1}$ for the different objects. For that we used an exhaustive search method, finding the best behaviour for the sets (λ_1= 645, λ_2= 675 and λ_n=595 nm) and (λ_1= 550, λ_2= 610 and λ_n=400 nm). For this second triad we fixed a minimum interval of separation between maximum sensitivities of sensors of 50 nm, in order to cover more visible spectrum.

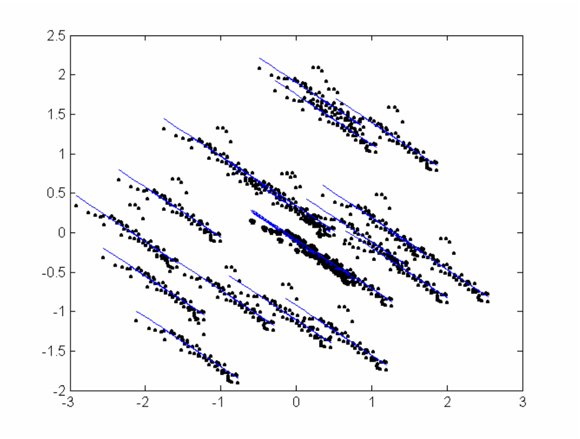

Figure 1: (log $y_{\lambda 2}$) versus (log $y_{\lambda 1}$) for 24 objects and 64 daylight SPDs. Monochromatic sensors (λ_1= 450, λ_2= 610 and λ_n=540 nm)

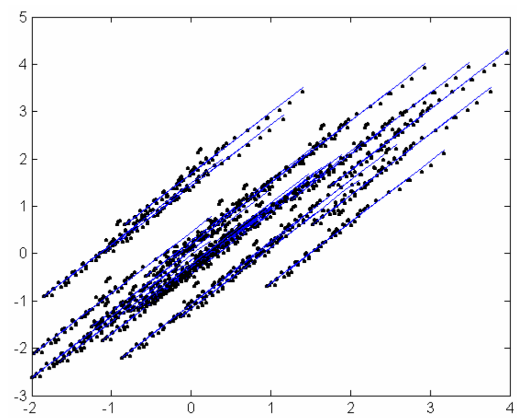

Figure 2: (log $y_{\lambda 2}$) versus (log $y_{\lambda 1}$) for 24 objects and 64 daylight SPDs. Monochromatic sensors (λ_1= 550, λ_2= 610 and λ_n=400 nm)

The performance of these sensors improves that obtained for the sensors employed by Marchant and Onyango[1] (λ_1= 605, λ_2=530 and λ_n=440 nm) and Finlayson and Hordley[2] (λ_1= 450, λ_2= 610 and λ_n=540 nm). In figures 1-2 we show two examples of the representations of (log $y_{\lambda 2}$) versus (log $y_{\lambda 1}$).

In table 1 we show the results for different sets of monochromatic sensors, where we can observe how the average correlation coefficient varies for the different sets. For this kind of sensors, the variation in the value of the slope for the different objects is nearly null.

Table 1: Values of average slope and correlation coefficient obtained for representations like Figs. 1 and 2 using monochromatic sensors with maximum sensitivities at λ_1, λ_2 and λ_n..

λ_1 λ_2, λ_n	Average slope	Average correlation coefficient	A_{12}
645 nm, 675 nm 595 nm	1.596	0.999	0.627
550 nm 610 nm 400 nm	1.295	0.989	0.772
450 nm 610nm 540 nm	-0.634	0.887	-1.578
605 nm 530 nm 440 nm	0.562	0.977	1.778

Table 2: Values of average slope and correlation coefficient obtained for representations like Figs. 1 and 2 using sensors with maximum sensitivities at λ_1, λ_2 and λ_n and 30nm bandwidth.

λ_1 λ_2, λ_n	Average slope	Average correlation coefficient	A_{12}
645 nm, 675 nm 595 nm	1.539 (σ=0.026)	0.999	0.650
550 nm 610 nm 400 nm	1.320 (σ=0.017)	0.989	0.758
450 nm 610nm 540 nm	-0.617 (σ=0.037)	0.892	-1.617
605 nm 530 nm 440 nm	0.563 (σ=0.017)	0.978	1.776
CCD	0.467 (σ=0.059)	0.964	2.135

Next, we extend our study to more realistic sensors assuming a gaussian-type spectral sensitivity with 30nm half-bandwidth and maximum sensitivity at the wavelength of the two above mentioned triads. We compared our results with those obtained for commercial CCD camera sensors. In table 2 the values of the average slope, its standard deviation and the average correlation coefficients are shown. Again best results are obtained for sensors with maximum sensitivity at (λ_1= 645, λ_2= 675 and λ_n=595 nm). In figure 3 we show the representations of (log $y_{\lambda 2}$) versus (log $y_{\lambda 1}$) for these non-monochromatic sensors.

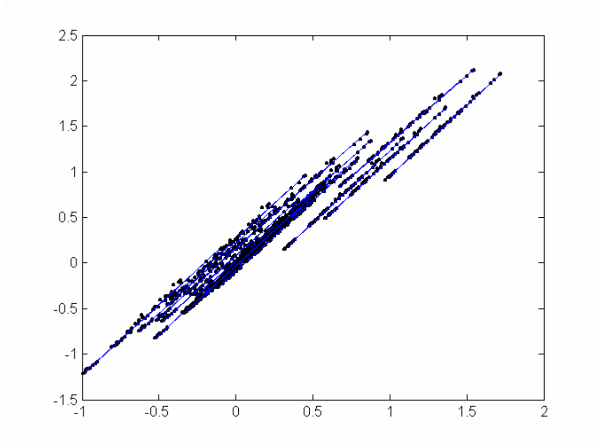

Figure 3. (log $y_{\lambda 2}$) versus (log $y_{\lambda 1}$) for 24 objects and 64 daylight SPDs. Gaussian-type sensors (30nm half-bandwidth) and (λ_1= 645, λ_2= 675 and λ_n=595 nm).

We tested our best results for the spectral sensitivity of the sensors by applying the invariant to natural scenes provided by Nascimento et al.[6] in order to recognize flowers in vegetation. In figure 4 we show the grey-scale image obtained by applying the invariant definition with the Gaussian-type sensors (30nm half-bandwidth) and (λ_1= 645, λ_2= 675 and λ_n=595 nm).

Figure 4. Invariant image of one of the natural scenes of Nascimento et al[6]. Gaussian-type sensors (30nm half-bandwidth) and (λ_1= 645, λ_2= 675 and λ_n=595 nm).

For this scene we know the spectral reflectance values of the objects involved and simulated different natural scenes with the different daylight SPDs previously tested. For each daylight and non-monochromatic sensors sets we obtained invariant histograms which show bi-modal distributions. When different daylight SPDs are employed the histograms obtained with the gaussian-type sensors with 30nm half-bandwidth and (λ_1= 645, λ_2= 675 and λ_n=595 nm) superimposed nearly perfectly, figure 5. For the other sensors studied, the histograms are shifted for the different daylight and recognition of objects is difficult. Thus, in figures 6-9 we can have difficulties to fixed invariant values intervals where the recognition of objects can be made invariant to illumination conditions.

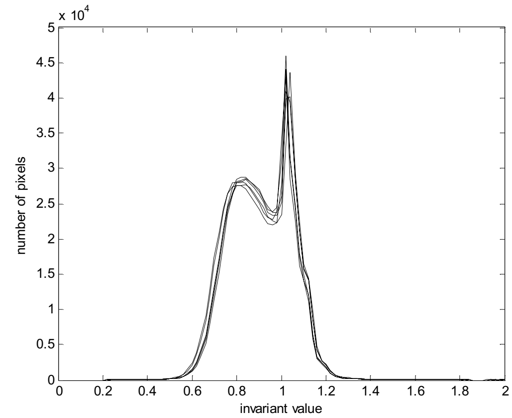

Figure 5. Histograms for grey-scale images of the scene represented in figure 4 when different daylight SPDs are simulated. The definition of the invariant is applied with non-monochromatic gaussian-type sensors of maximum sensitivities (λ_1= 645, λ_2= 675 and λ_n=595 nm). The color temperatures for the daylight SPDs are: 3757, 4425, 5555, 9091, 12449 and 32753 K.

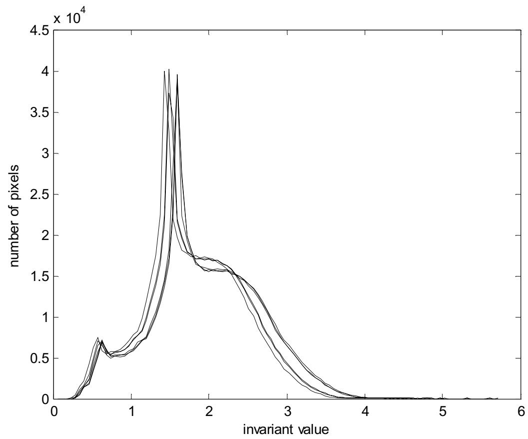

Figure 6. The same as figure 5 for non-monochromatic gaussian-type sensors of maximum sensitivities sensors (λ_1= 550, λ_2= 610 and λ_n=400 nm).

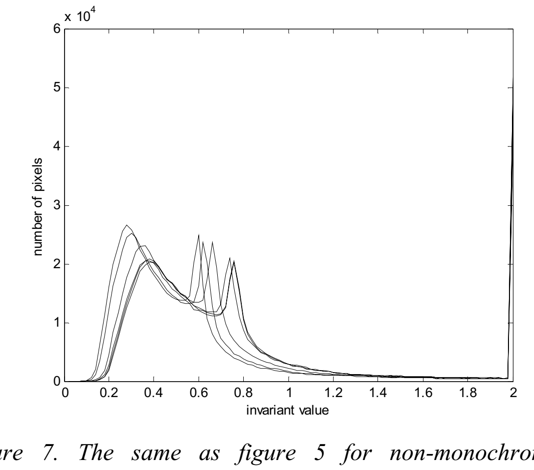

Figure 7. The same as figure 5 for non-monochromatic gaussian-type sensors of maximum sensitivities sensors (λ_1= 605, λ_2=530 and λ_n=440 nm).

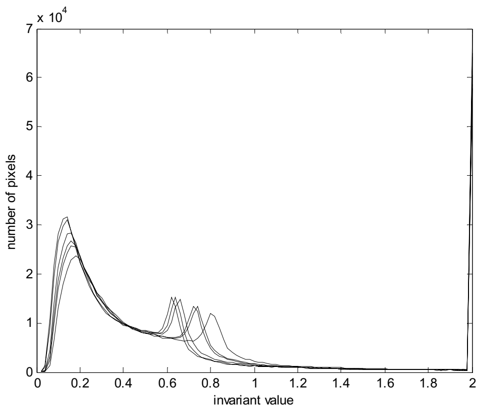

Figure 8. The same as figure 5 for non-monochromatic gaussian-type sensors of maximum sensitivities sensors (λ_1= 450, λ_2= 610 and λ_n=540 nm)

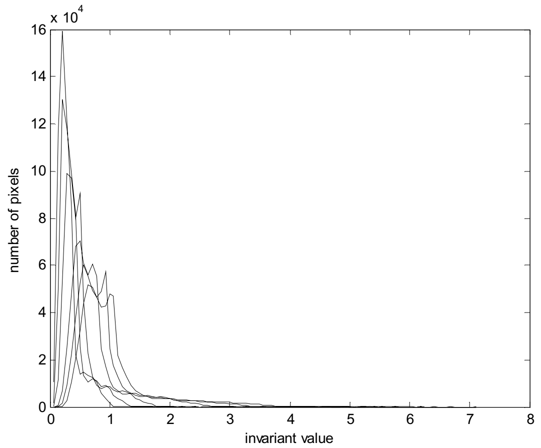

Figure 9. The same as figure 5 for commercial CCD camera sensors.

Conclusions

This work has served us to present the good results generated for real measurements of daylight using the invariant parameter defined in the form expressed in Equation (1). We have not employed other techniques to improve the performance of the sensors[7-9], such as spectral sharpening, which will be investigated further. In our case, given a natural scene in which we know the value in each pixel of the response to this type of sensor, we can reliably find a parameter that does not vary according to changes in daylight illumination. That is to say, we can move to a scene described in a scale of greys in which shadows are eradicated and the objects can be selected according to the value of F_{12}. Object-recognition experiments based on this value have been made in previous studies, Marchant and Onyango[1] and Finlayson and Hordley[2], with satisfactory results when the elimination of shadows to distinguish ground vegetation is called for, or to recognise different types of objects. In our case we have applied these results to natural scenes with the aim of classifying different kinds of vegetation.

References

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Biography

Javier Romero is full professor in the Department of Optics of the University of Granada, Spain. He has been working in colour vision, applied colorimetry, colour constancy and linear models for spectral reflectances and spectral power distributions of light. More recently, his interest is centred in the spatio-chromatic analysis and processing of natural colour images.