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ORIGINAL PAPER

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Estimation of a fluorescent lamp spectral distribution for color image in machine vision

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Abstract We present a technique to quickly estimate the Illumination Spectral Distribution (ISD) in an image illuminated by a fluorescent lamp. It is assumed that the object colors are a set of colors for which spectral reflectances are available (in our experiments we use spectral measurements of 12 colors checker chart), the sensitivities of the camera sensors are known and the camera response is linear. Thus, the ISD can be approximated by a finite linear combinations of a small number of basis functions.

Keywords Machine vision · Illumination spectral distribution · Quadratic programming · Constrained least square

1 Introduction

A color image is always the result of a complex interaction between three different components: the physical content of the scene, the illumination incident on the scene, and the characteristics of the camera. Estimating the influence of these three factors on the measured signals is one of the main goals of color image analysis. The influence of the sensors is usually known and the remaining problem is to separate the effects of the scene properties and the influence of the illumination. The human visual system can nearly solve this problem, a phenomenon known as color constancy.

In many studies, the Spectral Power Distribution (SPD) of illuminants and the reflectance of objects are separately subjected to the Principal Component Analysis (PCA) to obtain the basis functions from which only the first few ones are used in order to reduce complexity and to compress the data. It has been shown that these basis functions can be applied for color constancy purposes either in a direct way as in the Maloney's algorithm [1] or indirectly as in the spectral sharpening [2]. They are also used in a color correction based on illumination estimation, where typically seven basis functions are used for the illumination estimation [1, 3].

In this paper we present an approach to Illumination ISD, formulating the problem as one of constrained regression. Rather than relying on making accurate measurements of the ISD, our approach requires only the response of the device to a number of objects of known surface reflectance (for example a Macbeth color checker chart) under known sensitivities; it can then approximate the ISD by a finite linear combination of a small number of basis functions obtained with the PCA.

As we show, a simple regression leads to very poor estimates of the ISD. To overcome this problem, we incorporate into the problem formulation a number of natural constraints. We then estimate the ISD by a constrained regression. Coleman in [4] and R. Conn in [5] present methods to solve constrained optimization problems like this but in our case we used Matlab the "*quadprog*" function to solve it.

In order to present the formulation for the mathematical model and constrains mentioned above, we first, in Sect. 2, describe the machine vision system components. In Sect. 3 we present the basic mathematical model used to formulate the problem of ISD estimation as a quadratic programming problem and also show that an unconstrained regression leads to poor estimates. Furthermore, we present in Sect. 4 the correction factor to compensate for unwanted effects presented in out machine vision system. The method for constraining the regression and its formulation in Sect. 5. The results in Sect. 6 show that in all cases the recovered ISD are close to those measured by the spectoradiometer. Finally, we summarize this work and draw some conclusions from it in Sect. 7.

2 Machine vision system description

Our machine vision system is an automated planar surface visual inspection system made up basically of a color line camera, frame grabber and an illumination device.

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The intensity level of the illumination is controlled by a feedback control but, it does not satisfy chromaticity constancy over a long period of time. Moreover, the acquired images have a high signal to noise ratio in order to make the system sensitive enough to discern subtle variations in color. And the camera sensors response is affected by temperature effects despite its isolation inside chamber.

In the following lines we describe all the components of the system to present the characteristics that we have to take into the account in the formulation of the mathematical model of the system.

2.1 Color line camera

The colour line scan camera is MSC-1024RGB12 manufactured by TVI. It captures successive lines of the image as the piece moves along. This colour camera contains three CCD line arrays, one for each RGB channel. Each of the CCD line array has 1024 pixels. Each pixel value is digitised already in the camera by using a 12 bit A/D converter and the Correlated Double Sampling method (CDS). Its maximum line rate is 2000 lines/s.

The response of the camera sensors is highly dependant on the temperature and it is not linear for low values of the camera response.

2.2 Lens

The lens attached to the camera is a Nikon Nikkor 28/1.4. Its focal distance is 28 mm, so if we place the lens at a distance of approximately 1.5 meters above the piece, the spatial resolution is 1.6 pixels/mm, giving the camera a Field Of View (FOV) of 640 mm.

The aperture, focal length and sensor position in the focal plane affect the camera response and it is necessary to take them into account in order to estimate ISD correctly.

2.3 Fame grabber

The frame grabber is a Road Runner RUN-PCI.12 manufactured by Bitflow. The frame grabber captures the camera lines and, at the same rate, the host CPU moves them, through the PCI bus, from the memory board to the PC RAM memory.

This device does not have an influence on the camera response.

2.4 Illumination device

The light sources are two fluorescent lamps FA48T12/CW/VHO/RCD/30 manufactured by LCD Lighting Inc., frequently used in automated planar surfaces visual inspection systems. They are placed on both sides of the FOV and are parallel to it.

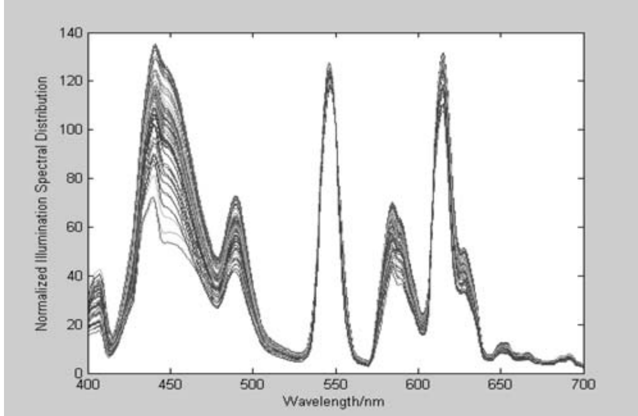

Fig. 1 All possible normalized ISDs of the illumination device (the value at 550 nm isset to 100)

These light sources are controlled by an intensity feedback control, which ensures the brightness stability over the time. During the live of the fluorescent lamp the ISD changes, affecting each color of the captured image independently.

In order to present this chromaticity change, we have measured the ISD of different fluorescent lamps at different times in their utile live, at different positions of the lamp, with different controlled intensities, and normalized them to eliminate the brightness effect, which is controlled by the hardware.

The signals used in this study were measured by a spectoradiometer and normalized to $E(550) = 100$, where E is the illumination spectral distribution.

Figure 1 represents a wide possible normalized ISD of the illumination device. It is clear that a change in the intensity, time and position in the image is not only a brightness change. There is also a chromaticity change, so it is necessary to estimate the ISD to have a good constancy in the color measures.

As explain in Sect. 5, the illumination exhibits a number of features, which are likely to be common in the majority of the ISD of our device. The ISD values and its smoothness are limited and the modality of the curve is always the same.

In the next section we present the basic model used in this study to formulate the problem of ISD estimation as a quadratic programming problem.

3 Basic mathematical model

In general [6], the ith channel's linearized response ρ_i^j of the image capture system to a light signal $E(\lambda)$, associated with a given surface reflectance can by modeled by:

$$\rho_i^j = \int_w E(\lambda) S_j(\lambda) R_i(\lambda) d\lambda \quad i = r, g, b \tag{1}$$

where $E(\lambda)$ is the ISD of the scene illuminant, $S_j(\lambda)$ is the surface reflectance imaged at pixel or region of pixels j,

$R_i(\lambda)$is the spectral sensitivity of the ith sensor, the integral is taken over the visible spectrum w, and r,g,b are the RGB channels of the camera . In this formulation $R_i(\lambda)$ absorb the contributions due to the aperture, focal length, sensor position in the focal plane, and temperature effects.

For practical purposes, it is sufficient to approximate the various continuous spectra by their value at a number of discrete sample points. Typically, 31 or more sample points, between 400 nm and 700 nm are used adopting these approximations [13], the integral is replaced by a summation and Eq. (1) becomes:

$$\rho_i^j = \sum_{\lambda=1}^{n} E(\lambda)S_j(\lambda)R_i(\lambda) \quad i = r, g, b. \tag{2}$$

This model has been verified as being adequate for computer vision over a wide variety of systems. This model is also used for the human visual system, and forms the basis for the CIE colorimetry standard [7].

It is common to ignore the brightness information in the sensor response and focus only on the changes in the chromaticity. In our case this is done by correcting the three dimensional RGB responses of n color samples according to the black and white levels using the following Eq. [8, 9]:

$$\rho_i(n) = \frac{\tau_i(n) - \tau_i(b)}{\tau_i(w) - \tau_i(b)} \times 1000 \quad i = r, g, b \tag{3}$$

where $\tau_i(b)$ and $\tau_i(w)$ are the black and white levels of the each camera channel, respectively and $\tau_i(n)$ are the responses of the channel i for the n color patches.

In this paper, we focus on the normalized ISD. Therefore, we apply the PCA directly to a collection of normalized, real ISD to obtain the basis functions. The signals used in this study were measured directly by a spectoradiometer and normalized to $E(550) = 100$ (Fig. 1).

If a set of spectra is well approximated by p basis functions, then this set will be referred to as p-dimensional set and $E(\lambda)$ can be represented by a linear combination of a fixed set of basis functions:

$$E(\lambda) = \sum_{k=1}^{p} a_k E_k(\lambda) \tag{4}$$

a_k is the characteristic parameter representing the spectral properties of the illumination,, $E_k(\lambda)$ is the basis function, which best characterize the device ISD.

Taking into account the assumption mentioned above, Eq. (2) can be rewritten in the form:

$$\rho_i^j = \sum_{k=1}^{p} a_k \sum_{\lambda=1}^{31} E_k(\lambda)S_j(\lambda)R_i(\lambda) \quad i = r, g, b \tag{5}$$

Or, rewriting Eq. (2) in the form:

$$\rho_i^j = \sum_{k=1}^{p} C_{ik}^j a_k \quad i = r, g, b \tag{6}$$

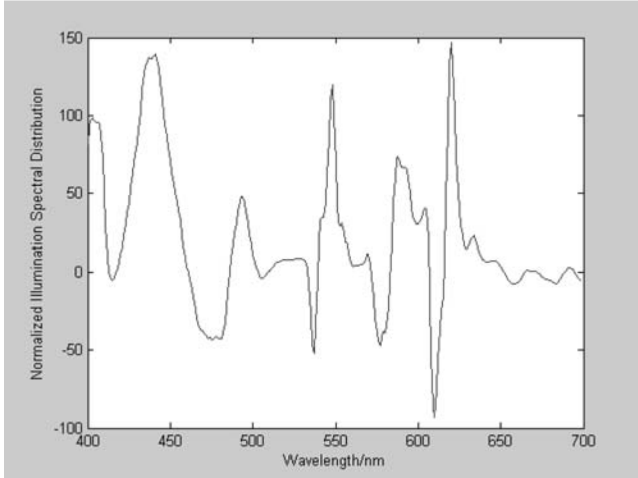

Fig. 2 Recovered ISD using a least squared regression

where

$$C_{ik}^j = \sum_{\lambda=1}^{31} E_k(\lambda)S_j(\lambda)R_i(\lambda).$$

Now suppose we capture an image of j objects of known reflectance under unknown illumination conditions. WE use 12 patches of our color checker chart, which represent a range of naturally occurring reflectance spectra. Averaging the recorded sensor values for each patch results in 12×3 equations in the form of Eq. (6). Multiplying both sides of the equation system by its pseudo-inverse can solve this equation system. However, this does not work very well.

The results obtained using this method are very sensitive to noise, the resulting estimation tends to have numerous large spikes, and an abundance of non-negligible negative values (see Fig. 2).

4 Compensation for unwanted effects

The objective of this paper is to present a method to estimate quickly and accurately the ISD in a color image illuminated with a fluorescent lamp used in a real industrial aplication [10]. In the previous section we have established the model used in computer vision. This model is in general applicable to all machine vision system but in our case we have to made more assumptions to bring the theorical model closer to our real model.

The signal of our camera is affected by geometric and temperature effects as we move around the image and with time respectively. It is possible to reduce these effects by introducing the correction factor α_i Eq. (6) as follow:

$$\alpha_i \rho_i^j = \sum_{k=1}^{p} C_{ik}^j a_k \quad i = r, g, b \tag{7}$$

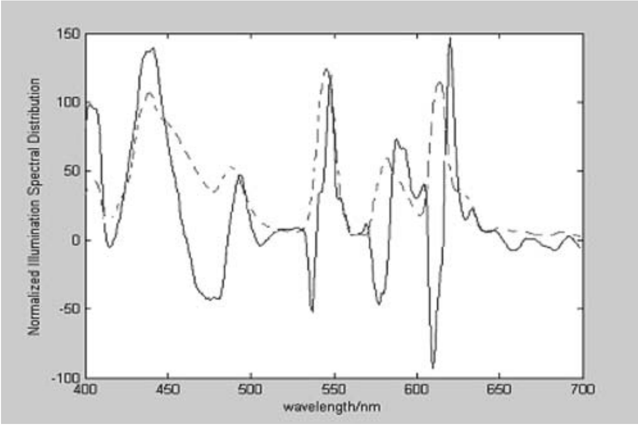

Fig. 3 Measured ISD (dashed line) together with the estimation without constrains (solid line). Each curve is normalized

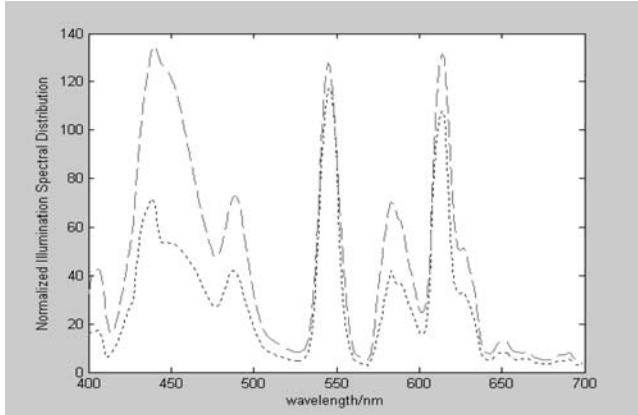

Fig. 4 Constraints of the normalized ISD

α_i tries to compensate the deviation in the ith channel response produced by the temperature, position change and other unknown effects.

Our objective is to obtain α_i and α_k parameters which minimize the Residual Squared Error (RSE), for the three channels (ρ_i^j) of the n colors of the color chart (Eq. (8)), and to ensure that the estimated signal and the measured data by the spectraradiometer are similar.

$$RSE = \sum_{j=1}^{n} \sum_{i} \left[\sum_{k=1}^{p} C_{ik}^{j} a_k - \alpha_i \rho_i^j \right]^2 \quad i = r, g, b \tag{8}$$

Figure 3 shows the result of recovering the illuminant of our 3-band *RGB* digital camera using a least-squares regression; clearly a very poor estimate of the illuminant. This method minimizes the error, but takes nothing else into account. The obtained results are clearly incorrect (see Fig. 3), and if they are used on different data the error will be very large. Thus, it is necessary to constrain the problem to obtain an accurate solution.

5 Constrained regression

The normalized ISD curves of our device, shown in Fig. 1, represent a very wide range of possible illuminants $EP(I,\lambda)$ with varying intensities of our light source (I), from the maximum to the minimum possible intensity of the light source. Fig. 1 exhibits a number of features, which are likely to be common to the majority of ISD of our device.

First, our system illumination device tries to control the illumination at 75% from the maximum intensity of the illumination device, so the ISD is going to be controlled somewhere between the two curves shown in Fig. 4. These two curves represent the extreme normalized illuminations, where the fluorescent can operate.

Second, the curves are everywhere positive, and finally, all the curves in Fig. 1 have the same number of main peaks at the same position. It is clear that it is possible to constrain the smoothness and modality of the estimation. We claim that by incorporating these natural constraints into the regression formulation, we can constrain the problem enough to overcome the noise sensitivity problem and thus obtain accurate estimates of the illumination.

As well as being intuitive, all of the constraints we introduced here can also be written as simple linear inequalities. This linearity allows us to formulate the regression as a quadratic programming problem and solve the problem by minimizing the quadratic objective function subject to a set of linear constraints:

$$\min \left(\sum_{j=1}^{n} \sum_{i} \left[\sum_{k=1}^{p} C_{ik}^{j} a_K - \alpha_i \rho_i^j \right]^2 \right) \quad i = r, g, b \tag{9}$$

Quadratic programming is exactly the same as linear programming except for the quadratic objective function. Like linear programming there is always a unique global optimum and it is always found. When the regression is presented in this form it can easily be solved using standard mathematical software e.g. Matlab, and moreover, the simplicity of the method allows one to search for many different combinations of constraints to find the best estimates of the sensors. We now consider the constraints in more detail, showing that they can be formulated as sets of linear inequalities:

5.1 Positivity

The constraint that our spectra is positive is written as:

$$E(\lambda) = \sum_{k=1}^{p} a_k E_k(\lambda) \geq 0 \tag{10}$$

To find the illumination curve we must find a_k i that satisfies Eq. (9), where the constraint in this equation is the constraint in Eq. (10).

5.2 Smoothness and modality

The ISD is always going to be between the two curves shown in Fig. 4 and it will have the same number of main peaks at the same position. Therefore, we can constrain the modality and smoothness of the estimated ISD by limiting the illumination spectral distribution values and its first derivative. These constraints are written as:

$$\min(EP(I,\lambda)) \leq E(\lambda) = \sum_{k=1}^{p} a_k E_k(\lambda) \leq \max(EP(I,\lambda)) \tag{11}$$

$$\begin{aligned} \min\left(\frac{\partial(EP(I,\lambda))}{\partial\lambda}\right) &\leq \frac{\partial(E(\lambda))}{\partial\lambda} \\ &= \sum_{k=1}^{p} a_k \frac{\partial(E_k(\lambda))}{\partial\lambda} \qquad (12) \\ &\leq \max\left(\frac{\partial(EP(I,\lambda))}{\partial\lambda}\right) \end{aligned}$$

$EP(I,\lambda)$ is the population of ISD used to calculate the basis functions. With the second equation we are constraining the smoothness of the estimation, and stabilizing the modality of ISD

In this case the entire fitting procedure is a least squares minimization problem with linear constraints, or equivalently, it can be viewed as a quadratic programming problem. Such problems can be solved with standard numerical techniques for which software is readily available. We use Matlab's routine "quadprog" [11].

6 Results

We tested this recovery method as a part of a color constancy algorithm applied to planar surface color sorter system illuminated with a florescent lamp and found it to perform well in all cases. We present results for recovering ISD of two different intensities.

Due to the characteristics of our machine vision system the brightness can be known in every moment, but not the changes in the chromaticity, so it is necessary to estimate the normalized ISD to ensure good enough color constancy.

The first stage in the recovery procedure is to obtain the linearized response of the device to a number of objects of known surface reflectance, under unknown illuminant. The second stage is to normalize the response according to the black and white levels as given in Sect 3. Finally, to recover the illuminant we simply have to solve the quadratic programming problem described above.

In these experiments we used 12 patches of the color checker chart and seven basis functions. The spectral reflectance data was measured using a spectrophotometer, or can be generated synthetically from published data [6] if the color chart is a normalized one. The camera manufacturer supplied the camera response but, it is possible to estimate it with very simple and flexible methods. The 400–700 nm range, in which the regression is performed, is defined by the camera's spectral response. Our camera does not a significant response outside the 400–700 nm range, thus, extending this range does not improve results.

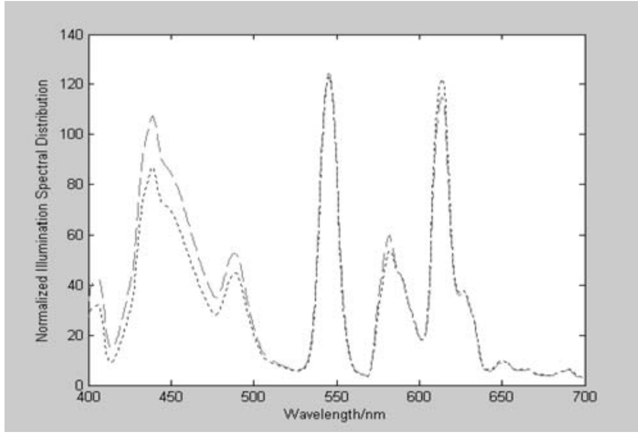

Fig. 5 Measured ISD (pointed line) together with an estimation with constraints (dashed line) at 75% of the maximum intensity of the light source

It is possible to reduce the residual squared error Eq. (8) by working with more than 7 basis functions, but the error does not decrease sufficiently to compensate for the increase in processing time.

For the purpose of this paper we tried to reconstruct the normalized ISD for two different intensities of the light source.

Figure 5 shows the measured illumination curve at 75% of the maximum intensity of the light source and the reconstructed one. It is clear from this image that the reconstruction exhibits the features, which are common to the majority of device's ISDs and match with the measured ISD very closely.

Finally, the Fig. 6 shows the results after we apply the constrained regression to obtain an estimate of the illuminant at the minimum intensity of the light source. At this

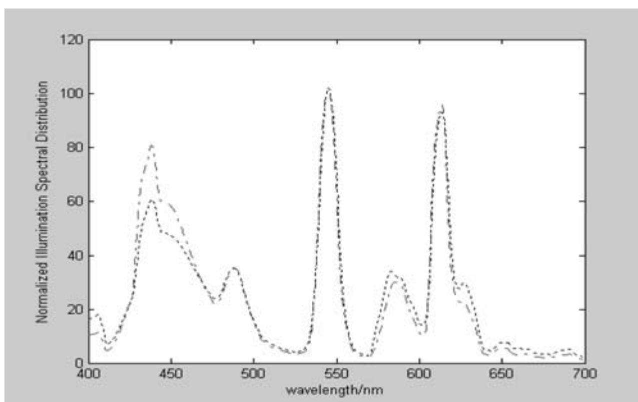

Fig. 6 Measured ISD (pointed line) together with an estimation with constrains (dashed line) at the minimum intensity of the light source

position the conditions are extreme. The camera linearity is not ensured for very dark values and the noise ratio is very high and even in this case the ISD estimation is close to the real one.

All estimated illuminants, at different intensities of the light source, match the normalized real ISD, measured using a spectoradiometer, closely.

In order to measure mathematically the accuracy of the proposed method we used the linear correlation coefficient, used in statistics and in the color shade algorithm to measure the similarity between two distributions.

In all cases, the linear correlation coefficient is over 0.98 even when the RGB values captured by the camera are very low, where the linearity of the sensors is not ensured and the noise ratio is very high.

7 Conclusion

In this paper we modeled a real machine vision system to estimate the ISD from a color image, composed of a reference set of colors illuminated by a fluorescent lamp, and diminished or removed the effect of the illumination. Therefore, we "see" the physical scene more precisely.

The basic idea of our method is to minimize the squared error subject to linear constraints, which enforce range of the result. The method can be easily implemented, as an example of a quadratic programming problem, for which there are many software solutions available. In this paper we provide the results using this method to calculate the ISD in a real industrial application [10].

Our method can be viewed as an improvement of the algorithms given in [8, 12], where the ISD is also calculated as a part of these methods. But in our case, due to the characteristics of our illumination, these methods lead to fairly poor estimation of the ISD (Fig. 2). To overcome this problem, we incorporate into our problem formulation a number of natural constraints, which are characteristic for our illumination.

The assumptions we have imposed on this algorithm allow us to quickly estimate the ISD by only capturing a reference set of colors. This allows easy and fast calibration of the machine vision system to ensure the repeatability of the color measures [8, 3] and quality of the fluorescent lamps illumination.

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