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A Parallel Algorithm for Color Constancy

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Abstract

Objects retain their color in spite of changes in the wavelength and energy composition of the light they reflect. This phenomenon is called color constancy and plays an important role in computer vision research. We have devised a parallel algorithm for color constancy. The algorithm runs on a two dimensional grid of processors each of which can exchange information with its four neighboring processors. Each processor estimates the average light illuminating the scene. This information is then used to estimate the reflectances of the object. The algorithm was tested on several images of everyday objects.

1 Introduction

The human visual system is able to correctly perceive the color of objects irrespective of the light which illuminates the scene. That is, the leaves of a tree still look green to a human observer even if the tree is illuminated with red light and the leaves actually reflect more red than green light. The task of computing color constant descriptors for an image is known as the problem of color constancy. One is able to somehow discount the illuminant and extract a measure of the object's reflectance properties [28]. The same ability would also be useful for a robot which has to work under different lighting conditions. To date, the lighting still has to be carefully controlled such that the algorithms continue to work. The problem of color constancy is also of particular importance for the task of object recognition [12, 15].

Numerous solutions to the problem of color constancy have been proposed, i.e. Land's retinex theory [23], variants of the retinex theory [4, 5, 17, 22], gamut-constraint methods [2, 13, 14], the gray world assumption [6, 19], recovery of basis function coefficients [18, 21, 25], mechanisms of light adaptation coupled with eye movements [10], neural networks [8, 9, 16, 20, 26], minimization of an energy function [27], comprehensive color normalization [12], committee-based methods which combine the output of several different color constancy algorithms [7] or use of genetic programming [11]. We now summarize some background on color image formation and discuss the two most widely known algorithms for color constancy: white-patch and the gray world assumption.

2 Color image formation

The response of a sensor at position $\mathbf{x}_s$ measuring the light reflected from a Lambertian surface at position $\mathbf{x}_o$ is given by

$$\mathbf{I}(\mathbf{x}_s) = \mathbf{n}_l \cdot \mathbf{n}_o \int_\lambda R(\lambda, \mathbf{x}_o) L(\lambda) \mathbf{S}(\lambda) d\lambda$$

where $\mathbf{I}(\mathbf{x}_s)$ is a vector of sensor responses, $\mathbf{n}_l$ is the unit vector pointing in the direction of the light source, $\mathbf{n}_o$ is the unit vector corresponding to the surface normal, $R(\lambda, \mathbf{x}_o)$ specifies the percentage of light with wavelength λ reflected by the surface at position $\mathbf{x}_o$, $L(\lambda)$ is the intensity of light hitting the surface and $\mathbf{S}(\lambda)$ specifies the sensor's response functions [12]. The integration is over all wavelengths to which the sensors respond. Assuming ideal sensors for red, green and blue light $(S_i = \delta(\lambda - \lambda_i))$ with $i \in \{r, g, b\}$ and a light source which illuminates the surface at a right angle the equation simplifies to

$$I_i(\mathbf{x}_s) = R(\lambda_i, \mathbf{x}_o) L(\lambda_i)$$

where $I_i(\mathbf{x}_s)$ denotes the i-th component of the vector $\mathbf{I}(\mathbf{x}_s)$.

In this case the light illuminating the scene simply scales the reflectances. If there exists at least one pixel for each band which reflects all light for this particular band, one could simply rescale all color bands to the range $[0, 1]$.

$$R(\lambda_i, \mathbf{x}_o) = \frac{I_i(\mathbf{x}_s)}{L_{\max}(\lambda_i)}$$

with $L_{\max}(\lambda_i) = \max_{\mathbf{x}}\{I_i(\mathbf{x})\}$. This algorithm is called the white-patch retinex algorithm [15].

Another possibility would be to calculate space average color of the image and use this information to estimate the intensities of the light illuminating the scene. If one assumes that the reflectances of the surface are uniformly distributed over the interval $[0,1]$, one gets

$$\begin{aligned}
\frac{1}{N}\sum_{\mathbf{x}}^{N} I_i(\mathbf{x}) &= \frac{1}{N}\sum_{\mathbf{x}}^{N} R(\lambda_i,\mathbf{x})L(\lambda_i) \\
&= L(\lambda_i)\frac{1}{N}\sum_{\mathbf{x}}^{N} R(\lambda_i,\mathbf{x}) \\
&= L(\lambda_i)\frac{1}{2}
\end{aligned}$$

This is the so called gray world assumption. Thus, for a sufficiently complex image one can estimate the intensities of the light illuminating the scene as twice the space average color.

$$L(\lambda_i) = \frac{2}{N}\sum_{\mathbf{x}}^{N} I_i(\mathbf{x})$$

With this information the reflectances can be calculated as follows.

$$R(\lambda_i,\mathbf{x}_o) = \frac{I_i(\mathbf{x}_s)}{L_(\lambda_i)}$$

Both cues, space-average scene color as well as the color of the highest luminance patch are used by the human visual system to estimate the color of the light illuminating the scene [24].

3 A parallel algorithm for color constancy

We have devised a parallel algorithm for the problem of color constancy. The algorithm assumes a two-dimensional mesh of processing elements [1]. It is constrained to obtain and exchange information only locally but not globally. This property is very important in order for the algorithm to be scalable to arbitrary sizes. Each processing element is able to exchange information with its 4 neighboring elements as shown in Figure 1. The elements receive an image as input and their task is to compute the reflectances of the objects shown in the image.

Each element consists of three sub-elements, one for each color band. We assume that we have three different color bands red, green and blue (Figure 2). Colors are adjusted for each band independently. Each sub-element has access to 4 data paths (left, right, up and down) to and from neighboring elements, one temporary storage (tmp), and to the intensity value of the current pixel for its color band (pixel). The algorithm basically calculates the average scene color. The element's estimate of the average scene color is distributed to the neighboring elements. The data received from the neighboring elements is used to update the current estimate. Each sub-element runs the following algorithm:

$$1.)\qquad \text{avg} = (\text{left} + \text{right} + \text{up} + \text{down})/4.0$$

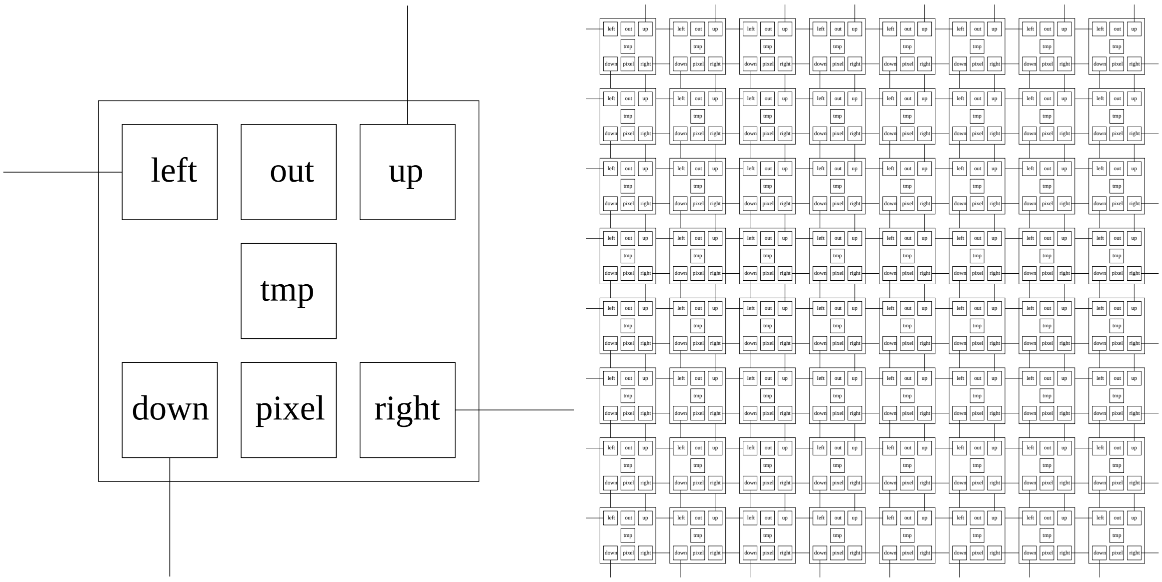

Figure 1: A single processing element is shown on the left. The current average of pixel values is stored inside the element (tmp) and is also distributed to the left, right, up and down. This knowledge is continually updated. Each element has access to the red, green and blue intensities of the viewed image (pixel). Using its knowledge about average pixel values, each element calculates the reflectances of its pixel (out). Each element only exchanges information locally, thus the individual elements may be combined easily to form a large $n \times n$ array (shown on the right).

$$
\begin{array}{ll}
2.) & \text{tmp} = \text{pixel} \cdot p + \text{avg} \cdot (1 - p) \\
3.) & \text{tmp} \rightarrow \text{left}, \text{right}, \text{up}, \text{down} \\
4.) & \text{out} = \text{pixel}/(2 \cdot \text{tmp})
\end{array}
$$

where out is the output of the sub-element. The output of each sub-element as well as the estimate of the intensities of the ambient light are restricted to the range $[0, 1]$. The percentage p was set to 0.0005 for the experiments which are described below. Step 1 of the algorithm averages the data received from the neighboring elements. Step 2 adds a small percentage p from the current pixel intensity. Step 3 distributes the new average pixel value to neighboring elements. And finally step 4 calculates the output intensity. Steps 1 through 4 are iterated indefinitely. The algorithm has a very simple structure and as such can be realized easily in hardware. All that is needed is to give one element access to the temporary storage of neighboring elements.

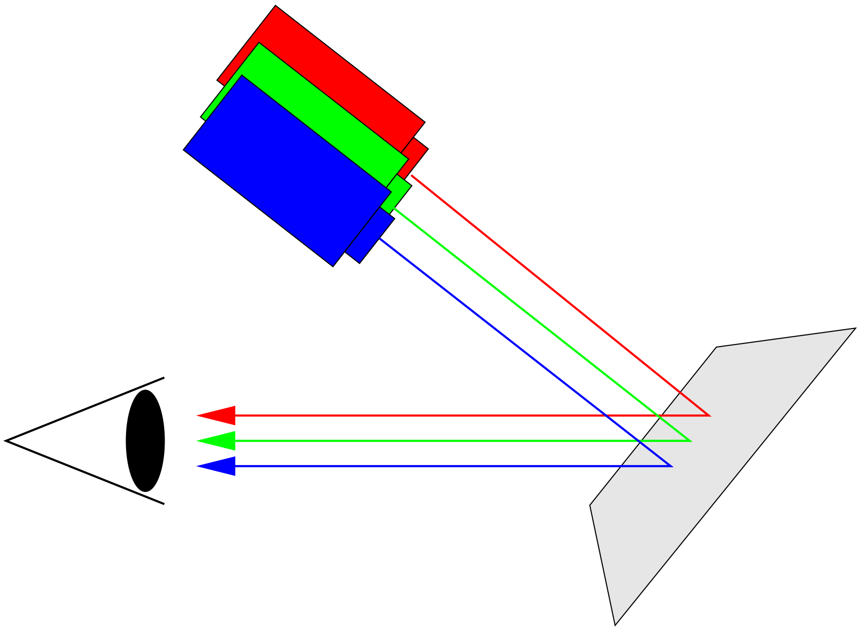

Figure 2: Our algorithm assumes that we have three independent color bands red, green and blue.

Figure 3: A bouquet of flowers shown under five different illuminants: Sylvania 75W halogen bulb, Sylvania Cool White fluorescent tube. Philips Ultralume fluorescent, Macbeth 5000K fluorescent, Macbeth 5000K fluorescent with a Roscolux 3202 full blue filter. The input images were taken from a library which was created by Funt et al. [15, 3] to test color constancy algorithms. The bottom row shows the output of the algorithm.

4 Results

We tested our algorithm on a set of images [1] created by Barnard et al. [3] to test color constancy algorithms. From the available data sets we have used the one which was also used in the paper

[1] http://www.cs.sfu.ca/∼colour/data/index.html

Figure 4: The images show the output image after 1000, 2000, 3000, 4000, and 5000 iterations of the update rule. One can clearly see how the algorithm continually refines its estimate of the average pixel values and improves its output image.

by Funt et al. [15] [2]. This data set has the advantage that all objects are upright and not rotated. The newer data sets are especially suited for object recognition. Figure 3 shows an image of a flower bouquet taken from the data set viewed under different illuminants. The top row shows the images which were used as input for our algorithm. The images are very dark because they were purposely under-exposed such that the number of clipped pixels was small (usually zero). The bottom row of images shows the output images of our algorithm.

Figure 4 shows how the algorithm iteratively refines its estimate of the average pixel values. Results for additional objects from the same data set are shown in Figure 5. Note that the algorithm is based on the gray world assumption and works only if this assumption is valid. The assumption is valid as long as the scene is sufficiently complex which is the case for most of the images tested. All images shown in this article can be viewed in color on the authors web page[3].

5 Conclusion

We have developed a parallel algorithm to solve the problem of color constancy. The algorithm was designed such that information is only exchanged locally, not globally. The algorithm is thus scalable to arbitrary sizes. The algorithm was tested on several images taken from a publicly available database to test color constancy algorithms.

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[3] http://www2.informatik.uni-wuerzburg.de/staff/ebner/research/colorConstancy/colorConstancy.html

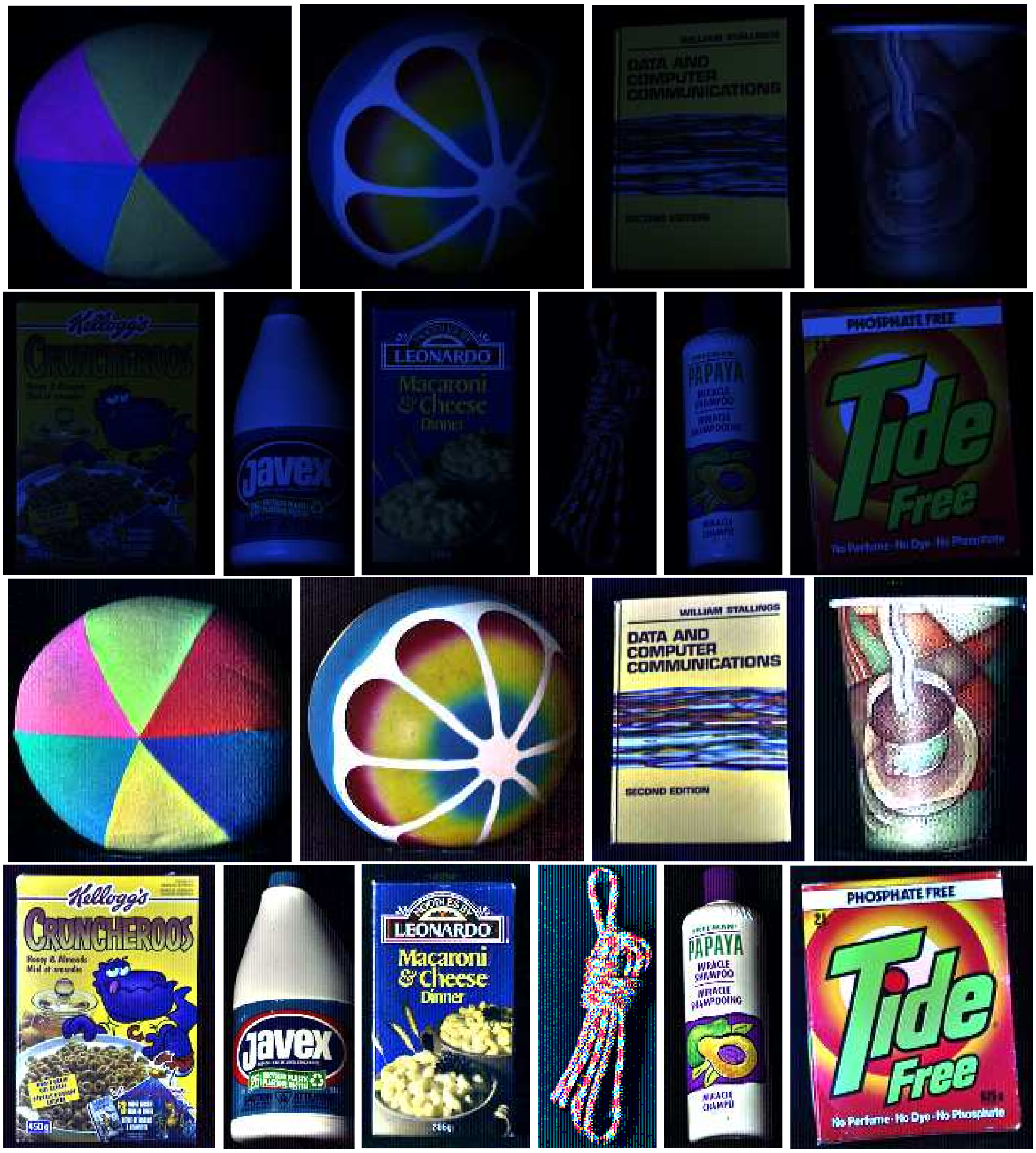

Figure 5: Results for 10 additional objects taken from a library created by Funt et al. [15, 3] which is used to test color constancy algorithms. The illuminant is a Macbeth 5000K fluorescent with a Roscolux 3202 full blue filter. The top row shows the input images. The resulting images are shown in the bottom row.

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