Computational Color Constancy

Simone Bianco
Università degli Studi di Milano-Bicocca, Italy

Raimondo Schettini
Università degli Studi di Milano-Bicocca, Italy

INTRODUCTION

Computational color constancy aims to estimate the actual color in an acquired scene disregarding its illuminant. Several strategies have been proposed in the last few years. In general these require some information about the camera being used, or exploit the statistical properties of the expected illuminants and surface reflectances. From a computational perspective, once the illuminant has been estimated, the image colors can be corrected on the basis of this estimate. The correction generates a new image of the scene as if it was taken under a known canonical illuminant.

In this article we briefly review state of the art methods and illustrate recent research on classification-based color constancy, where automatically extracted image features are used to drive the selection and application of the best algorithm for each image.

Finally, we highlight research trends in this field.

BACKGROUND

A generic image acquired by a digital camera is mainly characterized by three physical factors: the illuminant spectral power distribution $I(\lambda)$, the surface spectral reflectance $S(\lambda)$ and the spectral sensitivities $\mathbf{C}(\lambda)$ of the sensor. Using this notation, the sensor responses at the spatial point with coordinates (x,y) can be then described as:

$$\boldsymbol{\rho}(x,y) = \int_{\omega} I(\lambda) S(x,y,\lambda) C(\lambda) d\lambda \tag{1}$$

where ω is the wavelength range of the visible spectrum, $\boldsymbol{\rho}$ and $\mathbf{C}(\lambda)$ are three-component vectors (Figure 1). Since the three spectral sensitivities of the sensor $\mathbf{C}(\lambda)$ are usually respectively more sensitive to low, medium and high wavelengths, the three-component vector of the sensor response $\boldsymbol{\rho} = (\rho_1, \rho_2, \rho_3)$is also referred to as the sensor or camera raw $\mathbf{RGB} = (R, G, B)$ triplet.

Assuming that the color $\mathbf{I}$ of the illuminant in the scene observed by the camera only depends on the illuminant spectral power distribution $I(\lambda)$ and on the spectral sensitivities $\mathbf{C}(\lambda)$ of the sensor, color constancy is equivalent to the estimation of $\mathbf{I}$ by:

$$\mathbf{I} = \int_{\omega} I(\lambda) \mathbf{C}(\lambda) \mathrm{d}\lambda \tag{2}$$

given only the sensor responses $\boldsymbol{\rho}(x,y)$ across the image. This is an under-determined problem and therefore cannot be solved without further assumptions and/or knowledge, such as some information about the camera being used, and/or assumptions about the statistical properties of the expected illuminants and surface reflectances. From a computational perspective, once the illuminant has been estimated, the image colors can be corrected on the basis of this estimate. The correction generates a new image of the scene as if it was taken under a known canonical illuminant (see Figure 2). The estimation of the color of the illuminant could be performed if an achromatic patch is present in the image. This is because the spectral reflectance $S(\lambda)$ of an achromatic surface is approximately constant over a wide range of wavelengths, and thus the sensor response $\boldsymbol{\rho}$ is proportional to $\mathbf{I}$, i.e. the R**GB** of the achromatic patch is proportional to that of the incident light.

To reduce the dimensionality of the problem, one common method is to not estimate the whole **RGB** triplet of the illuminant color, but a 2D projection of it in a chromaticity space. The color correction is usually based on a diagonal model of illumination change derived from the von Kries hypothesis (von Kries,

DOI: 10.4018/978-1-4666-5888-2.ch581

Figure 1. The image formation process

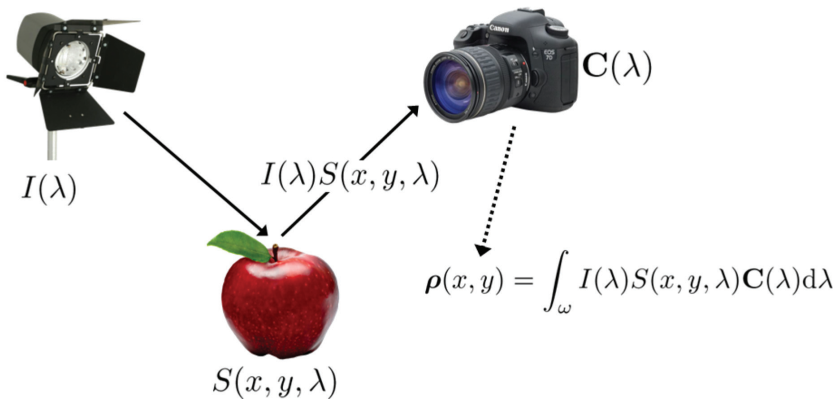
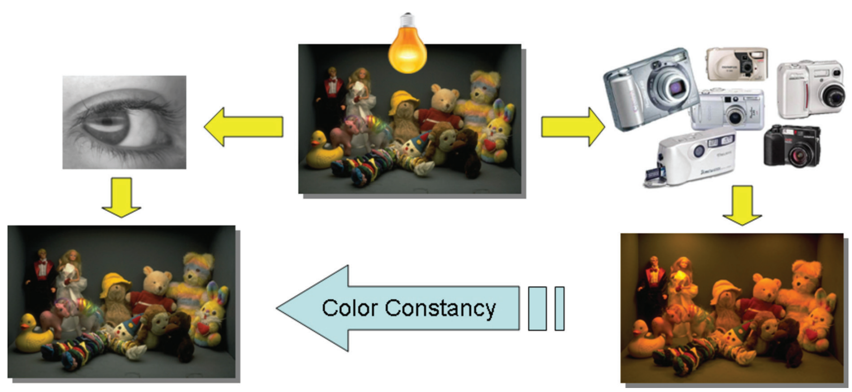


Figure 2. Computational color constancy aims at generating a new image of the scene as if it was taken under a known canonical illuminant by automatically estimating the scene illuminant



1902). This model assumes that two acquisitions of the same scene with the same imaging device but under different illuminants are related by an independent gain regulation of the three imaging channels as shown by Finlayson et al. (1994).

We need to specify an error measure. Since in estimating the scene illuminant it is more important to estimate its color than its overall intensity, an intensity independent error measure is commonly used. Hordley and Finlayson (2004) suggest to use the angle between the **RGB** triplets of the illuminant color ($\boldsymbol{\rho}_w$) and the algorithm's estimate of it ($\hat{\boldsymbol{\rho}}_w$):

$$e_{Ang} = \arccos\left(\frac{\boldsymbol{\rho}_w^t \hat{\boldsymbol{\rho}}_w}{\left\|\boldsymbol{\rho}_w\right\|\left\|\hat{\boldsymbol{\rho}}_w\right\|}\right) \qquad (3)$$

MAIN FOCUS OF THE ARTICLE

Since the only information available are the camera responses across the image, color constancy in as under-determined problem (Funt et al., 1998), and thus further assumptions and/or knowledge are needed to solve it. Typically, some information about the camera being used is exploited, and/or assumptions about the statistical properties of the expected illuminants and surface reflectances.

The Gray World algorithm assumes that given an image of sufficiently varied colors, the average surface color in a scene is gray (Buchsbaum, 1980). This means that the shift from gray of the measured averages on the three channels corresponds to the color of the illuminant.

Related Content