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# Color Constancy Techniques

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**Abstract:** ***Color constancy is the ability to estimate the color of light source. The color of light source may impact the appearance of object in the scene. Human has the natural tendency to recognize the actual color of object despite variations in the color of the light source. However, it is not easy for computer vision systems to discover the actual color of objects in the scenes. Several algorithms have been proposed to estimate the effect of color of light source on a digital image. A review of the color constancy techniques is presented in the paper. Also, the comparative analysis of various color constancy techniques is discussed***

**Keywords:** Color Constancy, Illumination, Computer Vision, Survey

## 1. Introduction

Color constancy refers to computational approaches to recover the actual color of surface objects independent of the color of light source. Color is important in many applications such as human computer interaction, color feature extraction and color appearance models. The color of light source significantly affect on the color of object in the scene. As a result, the same object, taken by the same camera but under different illumination, may vary in its measured color values. This color variation may introduce undesirable effects in digital images. Human has the ability to recognize the actual color of object despite variations in the color of the light source. However, it is not easy for computer vision systems to discover the actual color of objects in the scenes. Color constancy helps to identify objects notwithstanding large differences in illumination. The goal of computational color constancy is to estimate the actual color of object in an acquired scene disregarding its illuminant.

The paper is organized as follows: in section 2 color constancy problem is explained. Section 3 contains motivation behind solving color constancy problem is discussed. Previous work is discussed in section 4. Section 5 contains comparative analysis of the methods. Finally, the paper is concluded in section 6.

## 2. Color Constancy

Color constancy processing involves estimating the color of the illuminant and then to correct the image to a canonical illumination using the diagonal model. Diagonal Model [33] called Von Kries Model is used to correct the image in recent research. The color of objects in the scene consists of the actual color of surface, the color of illuminant and the camera characteristic. Hence it is essential to remove the color of illuminant, to recover the actual surface color. Image color for a Lambertian surface [14] at location can be modeled as,

$$f(\mathrm{x}) = \int_{\omega} e(\lambda)\rho k(\lambda)s(\mathrm{x},\lambda)d\lambda, \quad (1)$$

Where, $e(\lambda)$ is the color of the light source, $s(\mathrm{x},\lambda)$ is de surface reflectance and $\rho k(\lambda)$ is the camera sensitivity function ($k \in \{R,G,B\}$). $\omega$ *is* the visible spectrum, x is the spatial coordinates and $\lambda$ is the wavelength of the light.

## 3. Motivation

Many color constancy algorithms have been proposed by researchers. However, none of the proposed methods is both computationally inexpensive and sufficiently high-performing. Many color constancy algorithms are based on some assumptions that are not necessarily true in all cases, hence generates some failure cases [1]-[2]. Also, these methods do not perform well enough compared to recent more complex methods [3]. Complex color constancy methods are developed from a learning model based on training data sets. These methods are not suitable for real-time application as they are computationally expensive. Some of the color constancy algorithms assume that the spectral distribution of light source is spatially uniform in the image and that the color of the illuminant is constant across the whole image. But this assumption is violated in real images, e.g. images captured under daytime skylight from windows together with additional indoor light; or two different light sources in an indoor room. This situation is called the case of multiple illuminants, which is a common failure for current color constancy methods [3]-[4]. Therefore, color constancy in such situations is still an open problem despite much research for the uniform illuminant situation [4].

## 4. Color Constancy Techniques

The term illumination estimation refers to estimate the geometry or direction of light [5]-[6], or to estimate the color of light, or to estimate the full spectral power distribution of light. The different nomenclatures of categorizing methods that estimate the color of the illuminant are: supervised methods vs. unsupervised methods; static methods vs. learning-based methods; and physics-based methods vs. non-physics-based methods. The illumination estimation methods falls into following categories (1) statistical methods estimates the illuminant for each image based on its statistical properties, (2) physics-based methods estimates the illuminant using physical models of image formation, (3) learning-based methods estimates illuminants by a model that is learned from training images, and (4) gamut based methods compares a canonical gamut and image gamut to estimate the illuminant.

### 4.1 Statistical Color Constancy

The Retinex Algorithm [7] is one of the first color constancy methods. It works on assumption that an abrupt change in chromaticity is caused by a change in reflectance properties. This implies that the illuminant smoothly varies across the image and does not change between adjacent or nearby locations. This algorithm partially addresses the issue of varying illumination. The White-Patch or Max-RGB is the foundational color constancy method, based on retinex theory. This method estimates the illuminant color from the maximum response of the three color channels. The White-Patch method typically deals with the single brightest pixel in the image for each channel; hence it could be noisy and non-robust. A few methods [8]-[9] try to identify these white-patches or generally grey surfaces in the image. If there is a grey surface in the image which can be correctly identified then the color of that surface is a good estimate of the color of the light source since it should be unchanged after reflection. The Grey-World hypothesis [10] is another color constancy method. It assumes that the average reflectance in the scene is achromatic. It estimates the illumination color as the average color of all pixels in the image. The alternative for Grey-World hypothesis is to segment the image and then compute the average color of all segments of the image [11]. Using segments as surfaces in the image instead of pixels usually improves the result since large colored segments can dominate the estimates. Finlayson and Trezzi [12] introduced the Shades of Grey method that uses the Minkowski p-norm instead of averaging. The Grey-Edge method is another version of the Grey-World hypothesis. It states that the average of reflectance differences in a scene is achromatic [13]. Therefore, the estimated illuminant is the average over gradients of an image instead of its RGB values themselves. The Grey-Edge method has been extended by considering different kinds of edges such as shadow, specular, color shadow and inter-reflection edges. The statistical methods are simple and their speed is good. But accuracy of these methods is less.

### 4.2 Physics Based Color Constancy

Physics based color constancy is another type of static algorithms. These methods use general dichromatic reflection model instead of Lambertian reflectance model. The difference between static method and physics based method is a specular component, which is used to model the reflectance in the viewing direction. These methods use information about the physical interaction between the light source and the objects in a scene. The underlying assumption of most methods is that all pixels of one surface fall on a plane in *RGB* color space. Multiple of such surfaces result in multiple planes, so the intersection between the planes can be used to compute the color of the light source. The first attempt is made by Lee [15]. He used specularity to compute illumination. In the CIE chromaticity diagram [16] the coordinates of the colors from different locations on the same surface will fall on a straight line connecting the illuminant point and the surface color point. He used the fact that. And so if there are more surfaces of different colors in the scene then more lines can be determined, and the intersection of these lines is the illuminant chromaticity result. Finding the lines in chromaticity space is difficult for real images. Theoretically this algorithm makes good use of a segmented image for finding each straight line, but for real textured surfaces the segmentation itself is a difficult task. Several extensions have been proposed to Lee's algorithm [15]. One of the methods is Color Line Search proposed by Lehmann and Palm [17], which uses dichromatic regions of different colored surfaces. This method estimates the color of a single illuminant for noisy and microtextured images. The assumption is that the surface color is uniform, in each highlight region. Therefore, the technique fails when dealing with complex textured surfaces, which usually have more than one surface color in their highlight regions. Another extension to Lee's algorithm is defining constraints on the colors of illumination. It makes estimation more robust. Finlayson and Schaefer [18] proposed imposing a constraint on the colors of illumination in 2D chromaticity pace. This constraint is based on the statistics of natural illumination colors, and it improves stability in obtaining the intersection. Further, they suggested the use of the Planckian locus as a constraint to accomplish illumination estimation from uniformly colored surfaces [19]. This Planckian constraint on the illumination chromaticity makes the estimation more robust, especially for natural scene images. Tan et al. [20] uses a color space called "Inverse-intensity Chromaticity Space" to recover specularities. These highlights are subsequently used to recover the color of light source.

### 4.3 Learning Based Color Constancy

Learning based methods estimate the illuminant using a model which is learned on training data. One of the first attempts using machine learning techniques used neural networks [21]-[22]. In this a multilayer neural network system with two hidden layers was designed for the purpose of estimating the [r; g] chromaticity of light. In the neural network approach a binarized 2D chromaticity space histograms was used as input and two dimensional illuminant chromaticities was the output. Another learning-based approach to illumination estimation problem is the Bayesian approach [23]-[24]. In this, the variability of reflectance of illuminant is modeled as independent random variables. These methods estimate illuminant color from the posterior distribution condition learned from training images. Bianco et al. [25] proposed a two-level learning method to find illumination. In this method a classifier is learned to determine if an image is in indoor, outdoor or unsure classes and then a different model is learned for estimating illuminant for each classifier. Therefore for any test image it is first classified into one of the classes and then its illumination is estimated using the model learned for that class. According to A. Gijsenij [26], many learning-based color constancy methods that try to find the best or combination of algorithms for each image using extracted features go through a similar procedure. Learning based technique extract texture, shape or color features from sets of training images, and estimate the color of illuminant for each of these images using several statistical illumination estimation algorithms. Then a model is learned based on extracted features as well as the error of these estimates to ground truth, which is known. An extension to Grey World hypothesis [27] suggests that the average reflectance of semantic classes in an image is equal to a constant color, rather than being just grey. The illuminant is computed for each of the semantic classes present in an image. The illuminant is used to transform the pixels assigned to that class into the average reflectance color of that semantic class in the training images. In this method, semantic classes are assigned to each 20 × 20 patch of an image based on models learned in the training phase. This is a top-down approach.

### 4.4 Gamut-Based color constancy

The gamut mapping algorithm and its extensions can also be considered as one of learning based constancy methods. But because of its own strength they are placed in a separate category. Gamut mapping algorithm presented by Forsyth's [29] is one of the most successful color constancy algorithms. This was first method that estimates the illuminant by a model. The model is learned on training images. This algorithm is limited to the use of pixel values to estimate the illuminant. Additional information that is present in higher-order structures is ignored, because the focus is only on pixel values. The assumption is that in real-world images, under a given light source, only a limited number of colors are observed. Therefore, any variations in the colors of an image are due to variation in the color of the light. The 2D version of gamut mapping is used by Finlayson and Hordley [30]-[31]. It finds feasible sets of mappings and then transforms feasible mappings back to 3 dimensions to select the best mapping which improves performance while reducing the complexity by the use of the 2D version. The gamut mapping algorithm fails when there is no feasible mapping to map the input gamut to the canonical gamut. In this case the algorithm generates no result. In another approach the size of canonical gamut is increased uniformly in all directions [34]. An improvement over the 2D gamut mapping is Color by Correlation [32]-[33]. It suggests replacement of canonical gamut with a correlation matrix which describes the extent to which proposed illuminants are comparable with the occurrence of image chromaticity. In its first version matrix entries were Boolean. Color by correlation was simply a different version of implementation of a discrete version of 2D gamut mapping.

## 5. COMPARATIVE ANALYSIS OF METHODS

An overview of often used techniques of illuminant estimation together with recent developments is presented. The comparative analysis of the discussed techniques is presented in table **1.**

**Table 1:** Comparative Analysis of the Methods

| Color Constancy Techniques | Advantages | Disadvantages |
|---|---|---|
| Statistical Color Constancy | * Simple to implement<br>* Fast execution<br>* Accurate for adequate parameters | * Opaque parameter selection<br>* Inaccurate for inferior parameters<br>* Limited success on real images |
| Physics Based Color Constancy | * No training phase<br>* Few parameters<br>* Fast execution | * Mediocre performance<br>* Difficult to implement |
| Learning Based Color Constancy | * They are simple to implement<br>* Tunable for specific data set<br>* Potentially high accuracy<br>* Incorporates semantic | * Requires training data<br>* Slow execution<br>* Difficult to implement |
| Gamut Based Color Constancy | * Straightforward computation<br>* Good performance<br>* Potentially high accuracy | * Requires training data<br>* Difficult to implement<br>* Proper preprocessing is required |

## 6. Conclusion

An overview of techniques to estimate an illumination is presented here. The main concern of all techniques is to estimate the scene illuminant which can help to remove the effect of it on color images. Though Color constancy is a quite difficult problem, many solutions are available for it. Some of the algorithms are capable of working with true real images. The accuracy of the estimation, the computational runtime of the method, and the complexity of the implementation are important factors for color constancy algorithms. Statistical methods estimates the illuminant for each image based on its statistical properties. These methods are not dependent on training data. Physics based methods estimates the illuminant using physical models of image formation. Some of the physics based methods adopt the dichromatic reflection model of image formation. Whereas, learning based methods estimate illuminants by a learning model obtained from training images. And the gamut based methods compare a canonical gamut and image gamut to estimate the illuminant. Advantages and disadvantages of the above methods are also discussed. In spite of the large variety of available methods, none of the color constancy methods can be considered as universal.

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