INVARIANCE OF COLOR CONSTANCY MODELS TO COMPLEX LIGHTING CONDITIONS

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ABSTRACT

Color constancy is the ability of human vision to recognize a stable color in objects under varying lighting conditions. When it comes to computer vision, color constancy is not as accurate as in human vision. Computer vision aims at "seeing" and "understanding" visual data in order to provide decision-support for many applications. It is a multi-disciplinary approach which seeks to get closer to human visual perception and understanding in order to automate tasks that the human visual system can do. In this quest, colour constancy is a prevalent issue in every discipline associated with computer vision. The results of computer vision models deeply depend on the point of view and lighting conditions. The task of computational color constancy is to estimate the scene illumination and then perform the chromatic adaptation in order to remove the influence of the illumination and the camera sensor on the colors of the objects in the scene. Removing the influence of the illuminants, of the camera sensor, and of the optical effects is of primordial importance in computer vision to make sense of digital videos and images. This is how, for example, most digital cameras use color constancy methods in their camera Image Signal Processing (ISP) Pipeline. In this paper we will survey the most recent models/methods dealing with color constancy and will discuss the following research questions: - how might we make computer vision more robust against complex illumination/viewing conditions? - how to make materials/colors appearance, optical/photonics models consistent with human perception when using new image sensors (e.g. multispectral sensors) and display devices (e.g. AR/XR)? - how might we improve the deployment of smartphones and low-cost sensors in professional uses? We will also discuss some areas of improvements using machine learning methods.

Keywords: Color Constancy, Illumination Estimation, Color Correction, Multi-Views, Multi-Illuminants

INTRODUCTION

Color constancy is the ability of human vision to recognize a stable color in objects under varying lighting conditions. Usually, when we look at some objects the Human Visual System (HVS) [1, 2] unconsciously removes the influence of the lightning, then the color of the objects is perceived as if they were illuminated by a neutral white light. In computer vision, we can mimic this complex human system with different approaches that try to solve these under-constrained challenges related to the color constancy problem, and the solutions can be used in multiple fields like object recognition, tracking, color calibration, pattern recognition, etc.

Generally this problem is solved with a function ρ(x,y) depending on three important factors [3]: illuminant distribution I(x, y, λ), surface reflectance R(x, y, λ), and the camera sensitivity S(λ), where (x, y) is the pixel position and λ is the wavelength. See Figure 1. We can express this function for each RGB channel as, i.e., (Eq. 1):

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

If we assume that the scene is illuminated by a single light source and that the lighting field is uniform on the surface of the object, and that the surface is Lambertian and flat (i.e. R(λ) is constant whatever the pixel location), then the goal of color constancy is to estimate the light source color I(λ) independently of the pixel position. See Figure 2. In real world the lighting conditions are various, especially in indoor environment, so conventional approaches based on single illumination assumption cannot apply, see Figure 3.

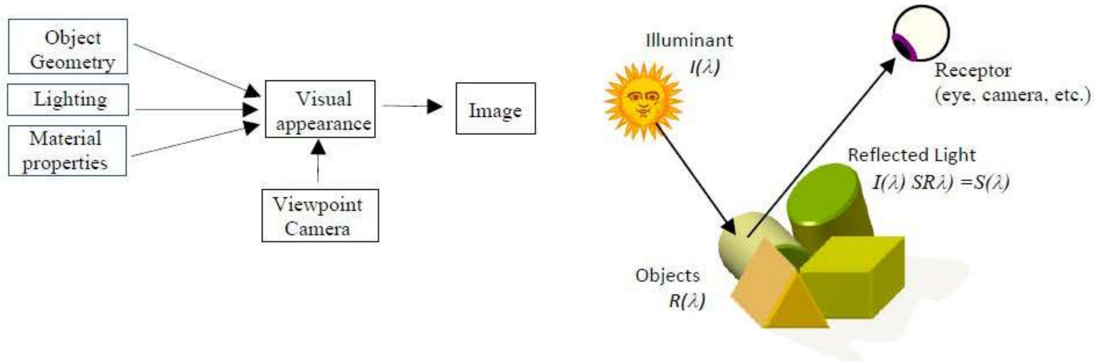

Figure 1: Visual appearance depends on geometry, materials reflectance, lights

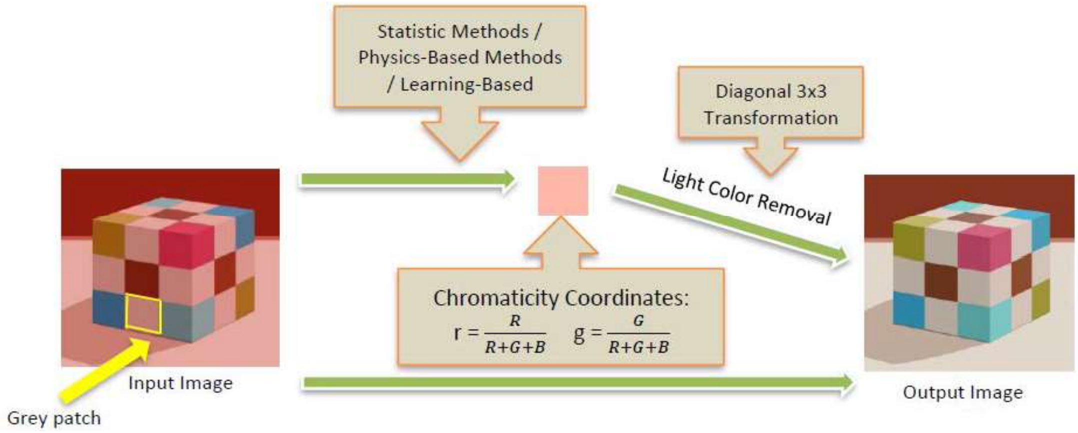

Figure 2: White balance of a scene lighted by a single illuminant based on the average grey computation. One solution consists to extract a grey patch, next to perform white balance from the color of this patch. Another solution consists to use a color chart, next to perform white balance from the colors of this chart.

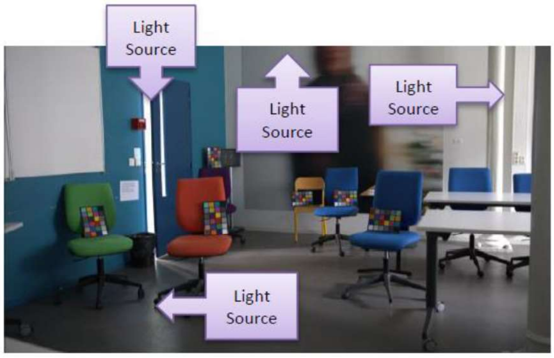

Figure 3: Example of scene lighted by various light sources (direct & indirect illumination). Six color charts are located in different areas (depths, orientations).

SHORT SURVEY OF THE STATE OF THE ART

Color constancy methods are generally classified into three main categories [3]: statistic-based, physics-based, and learning-based methods. The first group of solutions uses different low-level image statistics and empirical assumptions to achieve the color estimation, all of them can be unified with the framework proposed by van de Weijer et al. [4] as i.e., (Eq. 2):

$$\left(\int \left|\frac{\partial^n \mathbf{f}^\sigma(\mathbf{x})}{\partial \mathbf{x}^n}\right|^p d\mathbf{x}\right)^{\frac{1}{p}} = k\mathbf{e}^{n,p,\sigma} \tag{2}$$

where: n is the parameter (the order of the image structure) determining if the method is a Grey-World or a Grey-Edge algorithm; p (the Minkowski norm) determines the relative weights of the multiple measurements from which the final illuminant color is estimated. A high Minkowski norm emphasizes larger measurements whereas a low Minkowski norm equally distributes weights among the measurements; σ determines the scale of the local measurements. For first or higher order estimation, this local scale is combined with the differentiation operation computed with the Gaussian derivative.

Most of the grey patch -based methods do the assumption that to estimate the scene illumination, it is only required to extract one grey patch from the surface reference. However, in [5] it was proven that the prediction of a set of 19 patches (18 color and 1 grey among the 6 grey-level patches of the MacBeth color checker) from a reference surface is much more accurate in terms of light estimation and color correction. Considering that the illumination fields are not equally distributed in a scene (as example see Figure 4) and that they depend on multiple factors, we suggest to predict locally the color of these 19 patches in the scene using a deep learning -based approach, as if the color checker would have been there during the acquisition. Predicting multiple color checkers captured in the same image would enable to train a model able to predict illumination conditions, and to insert a synthetic color checker at any image location in order to prove that color pixel values change when we change color chart position.

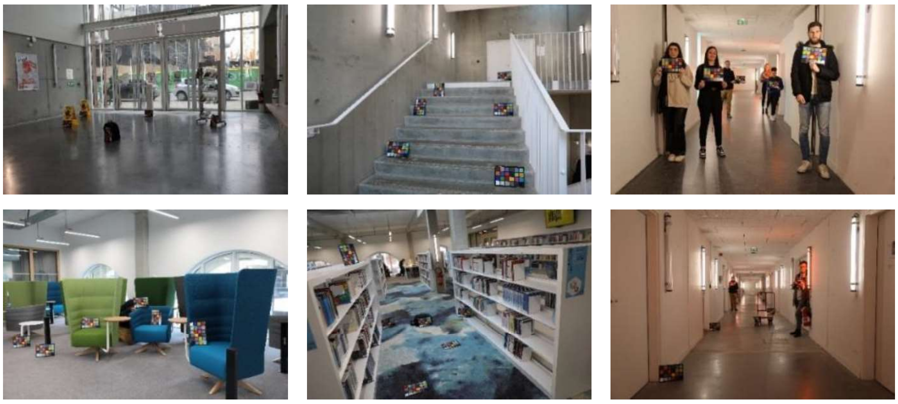

Figure 4: Examples of indoor images captured with the same Canon camera, taken under multi-illuminant conditions. In each image six color charts were put in various positions.

The second group of solutions exploits the dichromatic reflections principle and they require to detect grey surfaces, specularities, or segments from the image. As example, a segmentation-based method for mixed-illuminant scene images was proposed in [6]. On the other hand, a dichromatic reflection -based method for multiple illumination estimation was proposed in [7]. This method is based on a grayness index.

Lastly, the third group of solutions focuses on learning algorithm methods based on gamut mapping, patch-based approaches, or deep learning frameworks to model illumination estimation and related problems. One of the first paper addressing the problem of multiple illumination estimation was proposed in [8]. This paper is based on the concept of exemplar-based learning. It consists, first to apply a mean-shift segmentation of the input image (with unknown illuminant), next to generate surface models for each surface, then to find the nearest neighbour surface model in training surface models (from a dataset of images with known illuminants), and lastly for each nearest neighbour surface model to estimate the illuminant. Until recently most of state-of-the-art methods rely on single illuminant, complex features, and have long evaluation and training times. However, the paper proposed in [9] suggests a learning-based method based on four simple color features (average color chromaticity, brightness color chromaticity, dominant color chromaticity, and palette chromaticity mode), and an ensemble of regression trees (based on basic decision rules) to estimate the illumination. This method only works for a single illuminant but was extended to two illuminants in [10]. On the other hand, the CNN-based estimator, followed by a local-to-global regressor, approach proposed in [11] works for multiple illuminants. A multiple illuminant detector is used to determine whether or not the local estimates of the network must be aggregated into a single estimate. The GAN-based approach proposed in [12] incorporates a discriminator loss and a conventional color constancy loss. This method requires ground truth illumination data which may not be available in a common case. It does not need to estimate an illumination color map, as it is based on an image-to-image transformation. Another GAN-based approach was proposed in [13]. Using an image-to-image domain translation (domain transfer) learning approach this method estimates a multi-illumination probability map. The most relevant illumination estimation methods are based on pixel-wise approaches. Very recently, several pixel-wise / patch-by-patch approaches have been proposed in the literature, such as [14, 15, 16, 17]. Pixel-wise approaches are more efficient than patch-based methods to estimate illuminant conditions when multiple light sources illuminate the scene.

Another approach consists to "colorize" color images, as in [18], or to "white balance" color images, as in [19]. The colorization method proposed in [18] is based on training a deep neural network to learn the connection between the colors in an "improperly balanced" image and those in a "properly balanced" one. This method does not explicitly estimate the chromaticity of the illumination, however it handles spatially varying illumination conditions. The Automatic White Balance (AWB) method proposed in [19] is based on a camera imaging pipeline dealing with a small set of predefined white-balance settings. Given a set of rendered images, this method learns to estimate weighting maps to generate the final corrected image. This method does not require illuminant estimation. It generates spatially varying weighting maps that allows to correct for mixed lighting conditions in the captured scene.

To evaluate the accuracy of a color constancy method various standard metrics may be used [20, 21]: the Misclassification Rate, the Average or Median Angular Error (MAE), the Peak-Signal-to-Noise-Ratio (PSNR), the Root Mean Square Error (RMSE), etc.

ILLUMINATION ESTIMATION IN THE FIELD OF VR/AR/XR

Very few papers investigated chromatic characterization issues in VR, and color reproduction and calibration issues with VR. The first experiment done with a VR head mounted display (HMD), reported in [22, 23], consists of an indoor scene (office environment) rendered by the Unreal Engine (a gaming engine software). The office room contains matte and glossy objects, and two light sources: one on the ceiling, and a dimmer one at the back of the room. This study demonstrated that colour constancy performance in an immersive realistic VR environment is similar to what is reported for natural scenes. More investigations are necessary to extend the promising results obtained in the color vision domain with VR to the computer vision domain (to more realistic real-world scenarios) with AR and XR (as example see [24]).

Very recently, few image editing solutions based on Neural Rendering and Relighting (NeRF) have been proposed in the literature to estimate light sources and their direction in each pixel using implicit radiance fields, as for example in [25, 26, 27, 28]. With these solutions, it is now possible to insert virtual objects in an indoor or outdoor scene from a single color image and also to add or remove light sources. To the best on our knowledge till now none of these papers used explicitly these solutions for color constancy, but this would make sense.

COLOR CONSTANCY IN SPECTRAL IMAGING

Very few papers investigated the influence of camera spectral sensitivities (with varying spectral resolutions) and number of channels on color constancy. Some promising results were obtained in [29, 30]; in [30] the authors claimed that the spectral dimension is more important than the spatial dimension for estimating the illuminant white points. However, to the best on our knowledge, till now, spectral color constancy models were only developed for single illuminant case.

SHORT SURVEY OF COLOR CONSTANCY DATASETS

Very few real-world images datasets with multiple light sources have been proposed in the state of the art. One of the first datasets with real world images was introduced in [20]. It only contains 68 images (59 were taken in laboratory environments and 9 were real-world images) but it also contains their corresponding illuminations. The one proposed in [31] contains 197 images of faces taken with a varying number of color charts (most of images contains only one color chart) and captured with 4 different cameras. The MIMO public dataset introduced in [32] contains 58 indoor images (10 scenes, with complex scenes with multiple reflectances and specularities, lighted by 2 lights) and 20 outdoor images (with shadow, sun light, and in some cases with additional direct light); it provides pixel-level illumination images (for each light the illumination map is provided; images are taken with and without a color chart). This dataset was extended in [33] with high-resolution multi-view images (5 scenes acquired with 6 cameras) of complex multi-illuminant scenes (4 single-illuminant, 11 multi-illuminant, and 5 specular multi-illuminant) with precise reflectance and shading ground-truth. However, these data sets are both small and mainly consist of images of quite constrained single-object scenes [34].

The Cube++ illumination estimation dataset contains 4890 real world images (indoor and outdoor) with known illumination colors as well as with additional semantic data [35]. A Spyder cube color target (with white faces, grey faces, black patch and chrome ball) provides for every image two ground-truth illumination records covering different directions. In the dataset proposed in [36], the illumination for each scene was determined at once at many different points using a flying drone (carrying a grey ball); it contains multiple images (indoor and outdoor) taken from multi-view taken during the flight (150 images per scene, 30 scenes). According the authors "expanding the dataset further to include many more scenes would make it more useful for training machine learning methods; the range of illumination chromaticities could also be increased by recording scenes at sunrise/sunset, during different seasons, and different parts of the world". The two equipment used to build these datasets are less convenient than the use of color charts; the use of only one Spyder cube can be insufficient to estimate complex illumination fields; the use of a flying drone can be too low to estimate rapid illumination changes.

The large-scale multi-illuminant (LMSI) dataset is the biggest dataset publicly available; it contains 7,486 raw format images of realistic scenes, captured with three different cameras (on more than 2,700 scenes), captured under two or three illuminants (natural light, indoor light) [37]. It provides the ground truth illumination map from multiple images of the same scene taken under different combination of the lights. For each scene, 3 Macbeth color charts were arranged in places that are well affected by each light source in the scene. Even though the LSMI dataset contains a variety of images with various lighting settings, the diversity is still limited compared to real-world lighting conditions. To evaluate the relevance of a deep learning architecture trained and tested, we suggest to use the LMSI dataset (as it is the biggest one) and to train the network from a subset of images (e.g. images acquired with the Sony camera) and to test the network from another subset of images (e.g. images acquired with the Samsung Galaxy camera), independently from the training step; we also suggest to use 3-fold cross-validation separating both training and testing sets by the number of unique scenes that we have in total.

The NUS-8 dataset contains 1736 outdoor and indoor images taken with 8 different high-end consumer cameras (approximately 250 images per camera) [38]. For each image, the coordinates of the color-checker put inside the image are provided, as well as small region masks for every color patch. The ground truth illuminants provided were obtained from the difference of the two brightest achromatic patches. Despite having only one color checker in the scene, this dataset can be used to compare the performance of illumination estimation methods with past approaches for predicting one single color estimation per scene. As with the LMSI dataset, we suggest to train single illuminant estimation networks from a subset of images (acquired with only one camera) and to test the network from another subset of images (acquired with another camera), independently from the training step; we also suggest to use 3-fold cross-validation separating both training and testing sets.

CONCLUSION

Traditional color constancy algorithms consist of two steps: light color estimation and color correction. Till recently, most of papers in the state-of-the-art proposed solutions to estimate the lightning condition under a single illuminant. Since few years, several papers (mainly based on machine learning methods) proposed solutions to face multi-lighting conditions. Some of these methods outperform others, but there is still a room for improvement. Firstly, the training process should be improved from a large and well-balanced images dataset. Secondly, a good trade-off should be found between the efficiency of a method and its computational cost (e.g. if we want to embark it on a camera ISP hardware). Lastly, a good trade-off should be found between the efficiency and the relevance of a global/local estimation method and a pixel-wise estimation method; this could be managed using additional loss functions.

There is still a lack of relevant color constancy datasets with pixel-wise ground-truth. Datasets with more realistic scenarios (including linear mixtures of light sources; shadows and specularities; mixing ambient, direct light and natural light; no fully controlled lighting conditions) and a higher number of images (including multi-view of the same scene, multi-images from various cameras, multi-illuminant) are still needed to train and test color constancy methods. More reliable ground-truth (i.e. accurate estimation of the illumination map, not a estimation from a grey sphere, color chart, chrome ball, uniform diffuse grey spray paint) is still needed, for outdoor images taken under daylight condition only, for images of indoor scenes captured under multi-illuminant, for outdoor images combining natural light and light sources. We assume that using several color charts could improve the local illumination estimation (depending on their location in a scene); it could also improve grey-patch -based methods and single color chart -based methods when dealing with multi-illuminant. The first experiments we did confirmed this assumption; we created a new dataset satisfying the conditions above (as examples see images shown in Figures 4 and 5) in order to perform our evaluations. As future work, we will increase the number of real-world images (of acquisitions from various cameras and viewing directions) in this dataset before making it publicly available.

Figure 5: Outdoor images captured with the same Canon camera, taken under multi-illuminant conditions (eg. shadows, daylight shifts, etc.). In each image six color charts were put in various positions and distances to the camera.

In computer vision, in some study cases, color changes induced by shadows and illumination fields (as illustration see Figure 6) can impact object detection and tracking in videos, 3D scene analysis and understanding, 3D pose trajectories estimation of moving objects, etc. However, thanks to the progress made in the computer vision domain after the start of the deep learning area, many computer vision tasks (such as human body pose detection in complex lighting environments) are nowadays robust to illumination changes, shadows, object's reflectance, etc. Color constancy and illumination estimation are nowadays less problematic for computer vision tasks, up to complex situations involving multi-views and multi-illuminations.

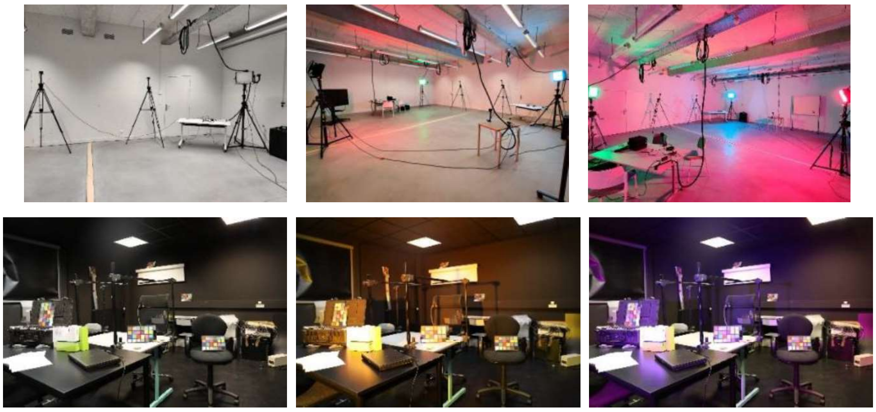

Figure 6: (top images) Indoor images of the same scene captured from various points of view using a set of GoPro cameras, (bottom images) Indoor images of the same scene captured from the same point of view. From left to right different light sources have been used to make the multi-illumination estimation (resp. object detection) more challenging.

ACKNOWLEDGEMENT

This work was partially supported by HORIZON-CL2-2021-HERITAGE-01-04 grant. Project: 101061303 — PREMIERE.

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