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Multiple illuminant estimation from the covariance of colors ☆

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ABSTRACT

In this paper we present a single and a multiple illuminant estimation physics-based algorithm. Both algorithms are based on the mean projections maximization assumption and un-centered component analysis. The proposed assumption is validated for a large collection of images and later used to estimate the illuminant color. The multiple illuminant estimator assumes that the spectral power distribution of the light source is not the same for the whole scene, which is the case for a wide range of images. In such cases, our new multiple illuminant estimator recovers an accurate illuminants estimates map for each input image while maintaining speed. The evaluation of the proposed algorithms on different real image datasets is realized. The experimental results are satisfying; our algorithms maximize the trade-off between accuracy (illuminant estimation error) and computational complexity.

1. Introduction

Illuminant estimation from image data is a key step for many computer vision applications. A well-known application is the accurate reproduction of the scene colors when acquiring the image. This is an inherent ability of the human visual system called color constancy [1]. Scene illuminant estimation from image content is also used in photography [2], printing technologies, industry [3], design and even in environments and ecosystems [4].

In image processing, the illuminant is the light acquired by the camera, originating from one or several sources that illuminate a scene. In the literature, much work has been devoted to the estimation of the illuminant. Some of the proposed methods are based on image statistics [5–8], on physics [9–14], on image structure [15–20], or even on a fusion of existing methods [21,22]. All of them are based on some prior knowledge and hypothesis. Scene illuminant estimation is considered as an under-constrained problem. Therefore, the dichromatic model, the lambertian model, the Grey world or other independent assumptions can be used to resolve this problem. In our case, we employ the hypothesis introduced in [23] based on the dichromatic model. We assume that the illuminant is the vector that maximizes specular pixels projections on it. This assumption is checked for the case of 3D embedded color space. We show that the illuminant is the eigenvector of the matrix of selected colors' inner product. A selection criterion for the colors involved in the estimation of the product matrix is proposed. The resulting algorithm recovers a single illuminant per image. However, in real images, several light sources can be used, as the case with indoor scenes lighted by both indoor and outdoor illumination. Based on the same assumption, we propose a multiple illuminants estimator.

The paper is organized as follows. In Section 2, some illuminant estimation methods are analyzed. In Section 3, we check the maximal projections mean assumption for 3D color space and we present our new algorithms based on the 3D hypothesis. In the same section, the problem of color selection is addressed, while Section 4 is devoted to accuracy evaluation of the two new algorithms on different image collections.

2. Related works

A scene illuminant estimation algorithm can be characterized by underlying assumptions, required prior knowledge, the color space used and its performance. The performance of an illuminant estimation algorithm is evaluated using angular error; that is, the angle between the estimated and the true illuminant vector. This means that the lower the angular error, the better the algorithm estimates the illuminant. In Table 1, we provide a summary of

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Table 1
Description of some existing algorithms with their accuracy scores in terms of median and mean angular errors, respectively, between brackets. Note that best scores are reported for each algorithm.

Algo	Data, prior knowledge	Color space	Strategy	Performance evaluation	Class
CbyC [24]	Single light source, lambertian reflectance, image chromaticities, equiprobable illuminant chromaticities	$\left(\sqrt[3]{\frac{R}{G}}, \sqrt[3]{\frac{B}{G}}\right)$	Correlation and probabilities	SFU Lab (3.2°, 6.6°) [25]	Learning
SG [7]	Single light source, lambertian reflectance	RGB	Weighted averaging of pixel values using the Minkowsky norm	Color Checker (5.3°, 7.0°), Grey Ball (5.3°, 6.1°), SFU Lab (3.7°, 6.4°)	Static
GE [26]	Single light source, lambertian reflectance, image derivatives	RGB	Weighted averaging of image derivative using the Minkowsky norm	Color Checker (5.2°, 7.0°), Grey Ball (4.7°, 5.9°), SFU Lab (3.2°, 5.6°)	Static
NN [27]	Single light source, lambertian reflectance, sampled image chromaticity space	(r,g)	Neuronal Network	SFU Lab (7.8°, 9.2°) [25]	Learning
FACE [28]	Multiple light source, lambertian reflectance, skin regions, uniform illumination on faces	RGB	Gamut mapping on skin pixels	Cambridge Portrait (1.8°, 2.3°), Milan portrait (2.0°, 2.6°) [28]	Learning
NIS soft-cv-EDC [18]	Single light source, lambertian reflectance, 3D scene geometry models	RGB	Selection of the color constancy algorithm among four existing algorithms using the learned 3D geometry	Linear Color Checker (2.2°, 2.8°), Grey Ball (2.6°, 3.9°) [18]	Learning, combination
3D HT [12]	Single light source, dichromatic reflectance	RGB	Dichromatic planes intersection using 3D Hough transform	SFU Lab (1.7°, –) [12]	Static
Exemplar [29]	Multiple light source, lambertian reflectance, image regions	(r,g)	Selection from training surfaces ground truth	Color Checker (3.7°, 5.2°), Grey Ball (3.3°, 4.4°) [29]	Learning
Zeta [14]	Single light source, dichromatic reflectance	(r,g)	Selection of the geometric mean of specular pixels	Color Checker, Grey Ball, SFU Lab (1.9°, 4.3°) [14]	Static
GM [30]	Single light source, lambertian reflectance, canonical gamut	RGB	Selection of mapping bringing the input gamut into the canonical gamut	Color Checker (4.9°, 6.9°), Grey Ball (5.8°, 7.1°), SFU Lab (2.6°, 4.3°) [31]	Learning
Proposed	Multiple light source, dichromatic reflectance, maximal projections mean assumption, refined gamut	RGB	Selection of the eigenvector corresponding to the maximum eigenvalue of the image colors product matrix	Color Checker (4.9°, 6.3°), Grey Ball (6.1°, 5.1°), SFU Lab (2.4°, 5.8°)	Static

some approaches for illuminant estimation. For each approach, prior knowledge, color space used, the basic idea, datasets and corresponding angular errors are given. Scores are obtained either by running programs or referring to papers referenced in Table 1. In this table, we observe that the algorithms can use 3D or 2D color spaces and are evaluated on common datasets. They differ, however, by the prior knowledge needed and the strategy adopted. Prior knowledge may include assumptions made about reflection models and color distribution and/or data pre-processing. Based on required prior knowledge, we divided the existing algorithms into two major categories: dichromatic model-based methods and lambertian model-based methods. Depending on the strategy used, the lambertian algorithms can be subdivided into two categories: static methods and learning methods.

Note that a basic assumption used by algorithms is the number of illuminants lighting the scene. The majority of illuminant estimation approaches [5,6,14,7,26,30,16] assumes that the spectral power distribution of the light source is identical over the whole scene. However, some approaches [28,29,17,32] take into account the fact that the spectral power distribution of the light source is not the same for the whole scene. They do not use reflectance models that consider multiple light sources; they just divide images into patches and estimate the illuminant color for each patch. Considering the reflectance models used and the strategy adopted, we discuss only a selected set of methods. Extensive surveys can be found in [25,33].

2.1. Lambertian model-based approaches

Lambertian model algorithms consider perfect diffuse surfaces, i.e. lambertian surfaces [34]. Within the static scheme category, lambertian algorithms with fixed parameters [5–8,35] make further assumptions about pixel distribution in the image to resolve the illuminant estimation problem. Some of these algorithms [5–7] were later integrated in a more general framework [26] that includes higher order assumptions like the gray edge hypothesis.

The learning-based algorithms were previously introduced as gamut learning by Forsyth [30]. He defines the canonical gamut as a set of all possible colors that can appear under a white light source as learned from the training set. The colors observed under the unknown light source are called the input gamut. Given the canonical gamut and the input gamut, he defines a set of all possible mappings that will bring the input gamut completely within the canonical gamut, referred to as the feasible mappings set. The estimation of the light color is then achieved by selecting the mapping that produces the gamut with the largest volume [30] or by selecting a weighted average of the feasible set [36]. Other extensions of the gamut mapping method [31] used image derivatives or even face pixels [28] rather than simply using pixel intensity to compute the canonical gamut. Neural networks [27,37], color by correlation [24], support vector regression [38], linear regression [39] and bayesian inference [40,41],[42] are also learning algorithms for illuminant estimation. Another alternative is learning the illuminant color directly using ground truth information [29].

In fact, there are many works that propose a combination of existing algorithms rather than the use of independent algorithms [43,21,22,15–19]. This is a legitimate choice for enhancing the performance of estimation, knowing that none of the existing algorithms can provide satisfactory accuracy with all types of images. Combination takes place either by combining outputs of different algorithms (linear and non-linear combination [21], or by combining statistics-based and physics-based algorithms [22]). It is also possible to combine adequate algorithms after image characterization [15–18] or 3D geometry classification [19,20,18] or even train a decision forest to identify the best algorithms for each image [43].

2.2. Dichromatic model-based approaches

The basic idea behind early dichromatic approaches [10] is the use of image highlights to estimate the illuminant color. However,