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Correcting color and hyperspectral images with identification of distortion model☆

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This paper presents a novel identification-based image correction method using a bi-illuminant dichromatic reflection model. Image patches with uniform properties over distorted and distortion-free images or image parts are used as a prior knowledge for identification. We identify the distortion correction function on a set of these patches, called spectrum shape elements, with the Hausdorff metric. The main issue during prior knowledge representation is for each distorted spectrum shape element to find a corresponding distortion-free element. A necessary condition to find a matching spectrum shape element is presented and theoretically proved. Identification problem was solved using a RANSAC-based optimization with this necessary condition as an optimization constraint. The method works well both for color and hyperspectral images. The proposed image correction procedure was tested on a set of color images and AVIRIS hyperspectral remote sensing data and proved to provide the quality superior to the results obtained with Retinex correction.

1. Introduction

With proliferation of the computer vision, aerial photography and large-scale image warehouses, automatic correction of color and hyperspectral images is increasingly becoming an important area of research. Even small quality improvements in the image correction quality can have a substantial impact on the usability of images.

In this work we apply a dichromatic reflection model to correct image distortions. By making adjustments to the model requirements combined with the prior knowledge about the image, we developed a high fidelity correction identification technique that shows good results for both color and hyperspectral images.

Image distortions can have different sources, and a variety of models to address specific scenarios has been developed. Since it has been proven that the human color perception system utilizes a special type of averaging [18], a similar approach was used for computer color correction, such as Retinex [19] and other color constancy methods [13], accurate enough for many computer vision and pattern recognition tasks. However, certain applications call for a higher precision of the color correction. A number of heuristic [21] and theoretical methods improve color correction quality by calculating a white point, memory colors, etc. An idea of using a priori knowledge for image correction is not new: [2,11]. In [25], image fragments selected by an operator are used for the unsupervised color segmentation, showing good results for color correction [2], and for the restoration of remote sensing images using IIR filter [11].

Many color correction methods need modifications for multichannel or hyperspectral images, because these correction methods rely on the human tristimulus color perception, while hyperspectral data has artificial coloring with no equivalent optics properties. For example, memory color methods [36] and heuristic color correction techniques of a human operator [21] are all based on the human color perception.

One of the distinctive features of a human visual system is the phenomenon of color constancy, an ability to perceive stable colors of objects under variable illumination conditions [23]. The Retinex technique implements this color constancy with a simplified but effective model of a human visual system [18]. Following its definition, the Retinex theory relies on a human color vision model. Citing [18] — “A retina-and-cortex system (Retinex) may treat a color as a code for a three-part report from the retina, independent of the flux of radiant energy but correlated with the reflectance of

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Fig. 1. Comparison of Retinex with proposed technique.

objects”. In this paper we will use a more general physical model to deal with multi- and hyperspectral images.

Several authors analyzed the dichromatic reflection model, initially proposed by Shafer [31] as a candidate for a more general, unified approach in image processing. Initially it was proposed to separate highlights and shading from the source illuminant [1,30]. It later became useful in many other cases of color and hyperspectral image processing. Spectral reflection properties and the illumination of color and hyperspectral images have been thoroughly studied in [14]; several authors analyzed the dichromatic model with additional constraints [11,16,34]. Despite its popularity, the original dichromatic model includes only a single illuminant, an oversimplification of realistic lighting scenarios. A bi-illuminant dichromatic reflection model introduced by Maxwell [22] is an improvement, but its usefulness is severely limited due to the cumbersome ambient light term and the difficulty of its analysis [29].

We propose a generalized approach that uses a priori data to identify distortions and the correction function using a bi-illuminant dichromatic reflection model. Paper [2] describes an image correction technique based on the color correction function identification that includes three steps: a detection of the color distortion, an identification of the correction function, and a pixel-by-pixel correction. We will concentrate only on the identification of the correction function. Our main contribution is a generalized and refined approach, originally described in our previous work [2]. We propose a model for prior knowledge representation and formally prove the necessary conditions for the correction function to exist. The model is equally effective for color and hyperspectral cases, verified on both image types and compared with an open implementation of Retinex image correction [19]. The comparison with Retinex was performed on a classic example from [6], and as shown in Fig. 1, our proposed technique shows better visual quality. In Section 7 we will apply quality measure to perform a quantitative comparison of these two methods.

For our correction procedure, we will use a prior knowledge about small image patches of the uniform material and orientation. The specific features of the bi-illuminant dichromatic reflection model applied to these small patches, both for color and hyperspectral images, are described in Section 2. In Section 3, we show how these patches, called spectrum-shape elements, can be automatically detected. Distortion correction function identification, based on the spectrum-shape elements prior along with the necessary condition as an optimization constraint, is discussed in Section 4. Section 5 describes a numerical procedure to identify correction function. Experimental results and our concluding remarks are given in Sections 6 and 7, respectively.

2. Image formation based on the reflection model

This paper considers multichannel images. A retina or a sensor usually collect K measurements, which depend on the spectral reflectance of the observed scene surfaces as well as on the spectral irradiance reaching the scene.

We define the K-dimensional vector of measurements accumulated in each pixel as a finite integral:

$$\mathbf{p}(\mathbf{x}) = \left[p^1(\mathbf{x}), \ldots, p^K(\mathbf{x})\right]^T = \int L(\lambda, \mathbf{x})\mathbf{T}(\lambda)d\lambda, \quad (1)$$

where L is $R \times Z_2 \to [0, 1]$ function of wavelength λ describing the radiance reaching each scene point and arriving at the image sensor. $\mathbf{T}(\lambda) = [T^{\{1\}}(\lambda), \ldots, T^{\{K\}}(\lambda)]^T$ is the spectral transmittance distribution of the color sensor. We will call vector $\mathbf{p}(\mathbf{x})$ a spectral intensity vector for hyperspectral images and a color vector for color images.

To simplify our notation we will omit the index k when referencing a component $\mathbf{p}$ of the vector p, and will assume that the domain of integration in (1) is always a full range of the wavelength radiance.

The color space with points $\mathbf{p}(\mathbf{x})$ is normalized using L_2 norm or unicontrast norm CIE Lab [15]. In hyperspectral case we have a SAM measure; other distances can also be used [5]. For the correction, as well as for the color segmentation step, we can use a $K+2$ dimensional space Y, which combines color and spatial spaces [8]:

$$[\mathbf{x}, \mathbf{p}(\mathbf{x})] \in \Upsilon = Z_2 \oplus R_K. \quad (2)$$

The metric of this space is defined as:

$$\left\| [\mathbf{x}, \mathbf{p}(\mathbf{x})]^T, [\mathbf{y}, \mathbf{p}(\mathbf{y})]^T \right\| = \|\mathbf{x}, \mathbf{y}\| + \|\mathbf{p}(\mathbf{x}), \mathbf{p}(\mathbf{y})\|. \quad (3)$$

Image correction can be defined as the removal of the non-isoplanatic deviation in illumination and restoring an image with the given illumination:

$$\mathbf{p}(\mathbf{x}) = \int L(\lambda, \mathbf{x})\mathbf{T}(\lambda, \mathbf{x})d\lambda \to \mathbf{p}_0(\mathbf{x}) = \int L_0(\lambda, \mathbf{x})\mathbf{T}(\lambda)d\lambda. \quad (4)$$

The problem (4) is ill posed, and the only way to solve it is to use some *a priori* knowledge. Most color correction techniques such as “grey world” and Retinex approaches [13,19], convert an image to an illuminant-invariant representation. These techniques transform the image color to the value that corresponds to an invariant illuminant rather than to the original scene illumination.

This invariant representation is acceptable for a wide range of image analysis or machine learning applications, but it is not accurate enough for the high fidelity image correction because the assumption of the invariant illumination does not hold in most real images. It is therefore important to be able to correct non-isoplanatic deviation in illumination and to restore the image with the real illumination.

The color invariant methods use “grey world” or “grey edges” assumptions [13,16] as a prior. We propose that we use prior color information about small image patches the same way the color correction is performed by a specialist. We will then be able to restore the image under the real illuminant with this prior. Note that not all techniques used for color image processing, such as memory colors and image representation based on specialized color spaces (unicontrast Lab/Luv spaces or perceptual relevant HSL), are directly applicable for hyperspectral images.

We will use a general reflection model to describe image distortions, based on the dichromatic model proposed by Shafer [31] in 1985 and its refined version by Maxwell [22] in 2008 as a bi-illuminant dichromatic model.

The original dichromatic model assumes that a single point light source uniformly illuminates the scene. So, the radiance L is a linear combination of the specular and the diffuse reflection:

$$L(\lambda, \mathbf{i}(\mathbf{x}), \mathbf{v}(\mathbf{x})) = L_B(\lambda, \mathbf{i}(\mathbf{x}), \mathbf{v}(\mathbf{x})) + L_S(\lambda, \mathbf{i}(\mathbf{x}), \mathbf{v}(\mathbf{x})), \quad (5)$$

where $\mathbf{i}(\mathbf{x})$ is the vector of the angles between the surface normal and incident light direction, and $\mathbf{v}(\mathbf{x})$ is the vector of the angles between the surface normal and the viewing direction. L_S is the

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