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Multi-objective optimization based color constancy

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ABSTRACT

This paper presents a new combining approach for color constancy, the problem of finding the true color of objects independent of the light illuminating the scene. There are various combining methods in the literature that all of them use weighting approach with either pre-determined static weights for all images or dynamically computed weights for each image. The problem with weighting approach is that due to the inherent characteristics of color constancy methods, finding suitable weights for combination is a difficult and error-prone task. In this paper, a new optimization based combining method is proposed which does not need explicit weight assignment. The proposed method has two phases: first, the best group of color constancy algorithms for the given image is determined and then, some of the algorithms in this group are combined using multi-objective optimization methods. To the best of our knowledge, this is the first time that optimization methods are used in color constancy problem. The proposed method has been evaluated using two benchmark datasets and the experimental results were satisfactory in compare with state of the art algorithms.

1. Introduction

The color of real world objects depends on physical characteristics of objects plus the color of light source illuminating the scene containing the objects. Therefore, a blue object under an illuminant appears differently if the color of illuminant changes. But, thanks to the human visual system, a human can recognize same color of an object even if the scene illuminant largely changes. This ability which is called color constancy is based on removing the influence of the scene illuminant on the color of objects.

There are three groups of color constancy algorithms in the literature; see [1] for a complete review. The first group contains algorithms that have a learning phase and use the information gained in this phase to estimate the scene illuminant. The methods of the second group are based on the low-level image features and algorithms that try to reach better results by combining other algorithms or selecting the best algorithm for a given image are placed in the third group. Our previous works [2–4] and also other neural network based approaches [5–7] are instances of the first group. In general, these methods extract some features from a dataset of images and train a neural network using these features and the real scene illuminant as the inputs and targets, respectively. The network is then used to estimate the scene illuminant of an unseen image. For example, Cardei et al. used color histogram of images in rg-chromaticity space to train a multilayer perceptron (MLP) neural network for color constancy [6]. However, the proposed network architecture is complex; it consists of 3600 input nodes, 400 neurons in the hidden layer, 40 neurons in the second hidden layer and 2 output neurons. Another drawback of this approach is that using rg-chromaticity space discards all intensity information while intensity information can help in estimating the illuminant [6]. Other neural network based approaches for color constancy [5,7] also used the color histogram of images in rg-chromaticity space and therefore, they all suffer from the mentioned drawbacks. Gamut based methods [8,9], genetic based algorithms [10], and also probabilistic methods (color by correlation) [11] are subsets of the first group. Examples of the second group are Gray-World [12,13], White-Patch [14], Shades of Grays [15] and Gray-Edge [16] algorithms. The NIS (Natural Image Statistics) [17] and CAS (Classification-based Algorithm Selection) [18] algorithms are two new algorithms of the third group. NIS [17] is based on the fact that the distribution of edge responses of an image can be modeled using two parameters Weibull distribution as follows [19]:

$$w(s_x) = \frac{\gamma}{\beta}\left(\frac{s_x}{\beta}\right)^{\gamma-1} e^{-(s_x/\beta)^{\gamma}} \quad (1)$$

where s_x is the edge responses in a single color channel, $\beta > 0$ is the scale parameter of the distribution and $\gamma > 0$ is the shape parameter. These parameters are representative for the statistics of the scene when Weibull distribution is fitted on edge responses of an image. The parameter β represents the contrast of the image, and the parameter γ indicates the grain size. Therefore, a higher value for β shows more contrast, whereas a higher value for γ indicates

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a smaller grain size (more fine textures). In NIS paper, it is also showed that the Weibull parameters of images are useful for determining the best algorithm for the images. In other word, for a group of images that one algorithm is the best, the Weibull parameters can be clustered together. Therefore, in NIS algorithm, a classifier is learned using Weibull parameters of a dataset of images to predict the best algorithm for new images. CAS [18] is another method that uses decision trees to detect the best algorithm for a given image. The structure of the decision tree in this approach is such that a color constancy algorithm is placed in each leaf and every intermediate node contains a criterion based on an image feature which is determined in the training phase. For a given image, the traversal of tree begins from the root; then in each node, the feature corresponding to that node will be extracted from image and the next node will be selected by comparing the extracted feature and the node criterion. This process continues till reaching a leaf node which contains an algorithm that is expected to be the best algorithm for the given image. The CAS and NIS algorithms also provide a way for combining multiple algorithms. The classifier used in NIS and the decision tree of CAS assign a weight to each pre-selected algorithm and the combination can be done by weighted averaging the output of algorithms.

The problem with the second group of color constancy methods is that all of them are based on specific assumptions. This limits their use to conditions that satisfy the assumptions. For example, Gray-World algorithm assumes that, *on average, the world is gray*. This assumption is correct only when there is enough large number of different colors in the image. If this is not the case, then the Gray-World algorithm will not work correctly [20]. Algorithms in the third group solve this problem to some extent. But these algorithms are all based on a weighting approach. They use either pre-determined static weights or dynamically computed weights combining multiple algorithms. The problem with weighting approach is that due to the inherent characteristics of color constancy methods (every algorithm is based on a specific assumption and no algorithm can be thought as universally better than the others), finding suitable weights for combination is a difficult and error prone task. Also, it should be considered that while combining multiple algorithms for a given image, the result is not as good as expected if a good algorithm is combined with a bad one. In other word, it is important to combine the algorithms that have good performance on the input image. Current algorithms of the third group (e.g. CAS and NIS) do not take this into account. They only assign a weight to each pre-defined algorithm and combine all of them. Although the algorithm may assign a near zero weight to bad algorithms, a too bad algorithm with a near zero weight still may decrease the accuracy of the combination output. Also, considering the bad algorithms in the process of determining combination weights increases the complexity of this process and as a result, the algorithm may not be able to determine the weights precisely.

In this paper, a new combining approach for color constancy algorithms is proposed which does not need explicit computation of weights and also always tries to combine those algorithms that have good performance on the given image. For a given image, the method consists of two steps. In the first step, the best group of color constancy algorithms for that image is determined using a classifier based on image features and in the second step, some of the algorithms in this group are combined by a multi-objective optimization method to estimate the scene illuminant. In this way, the proposed method always tries to combine good algorithms for the input image and as a result, the overall performance increases.

The rest of paper organized as follows: Section 2 describes color constancy and reflection model. Proposed approach is discussed in Section 3 and finally, in Section 4, the proposed approach is evaluated using two benchmark color constancy datasets.

2. Color constancy

An image taken by a digital camera under the assumption of Lambertian reflectance can be seen as function f depending on three physical factors: the spectral power distribution of scene illumination $e(\lambda)$, the surface spectral reflectance $s(\lambda)$ and the camera sensitivity function $\rho(\lambda)$. The sensor responses at pixel with coordinate (x, y) with this notation can be formulated as the following [17]:

$$f(x,y)=\int_{\omega} e(\lambda)s(x,y,\lambda)\rho(\lambda)d\lambda \tag{2}$$

Here ω is the visible spectrum. The color constancy is equivalent to estimate $\vec{e}$ (the observed color of the light source) using the following equation [17]:

$$\vec{e}=\begin{pmatrix} e_R \\ e_G \\ e_B \end{pmatrix}^T=\int_{\omega} e(\lambda)\rho(\lambda)d\lambda \tag{3}$$

After estimating the color of the light source, the image colors can be corrected using this estimate to produce a new image of the scene as if it was taken under a perfect white light (i.e. $(1/\sqrt{3}, 1/\sqrt{3}, 1/\sqrt{3})$). Under the assumption of diagonal model [8], the correction is simple; first, the image values are divided by $\vec{e}$ and then, the white light is multiplied to the image. This procedure corrects the image colors but its intensity may differ from the original intensity. Therefore, some methods have been proposed in order to preserve the original image intensity such as proposed method in [21].

In general, both values of $e(\lambda)$ and $\rho(\lambda)$ are unknown and therefore, the problem of color constancy is an under-constrained problem and it is not possible to solve this problem without further assumptions. Hence, most color constancy algorithms assume that an hypothesis is met while trying to estimate $\vec{e}$. As an example, a popular color constancy algorithm named Gary-World [12] is based on the assumption that *the average reflectance in a scene is achromatic*. The following equation shows the formal representation of this assumption:

$$\frac{\int s(\lambda,x)dx}{\int dx}=k \tag{4}$$

Using this assumption, the color of light source can be computed as follows:

$$\frac{\int f(x)dx}{\int dx}=\frac{1}{\int dx}\int\int_{\omega} e(\lambda)s(\lambda,x)\rho(\lambda)d\lambda dx \tag{5}$$

$$=\int_{\omega} e\lambda\left(\frac{\int s(\lambda,x)dx}{\int dx}\right)\rho(\lambda)d\lambda \tag{6}$$

$$=k\int_{\omega} e(\lambda)\rho(\lambda)d\lambda=k.\vec{e} \tag{7}$$

where k is a constant that is chosen such that the illuminant color $\vec{e}$ has unit length.

White-Patch [14] is another common color constancy algorithm which assumes that *the surface in the scene with highest luminance (white patch) reflects maximally and uniformly over the spectrum*. With this assumption, the color of light source can be approximated by the color of brightest patch in the image [20].

It is shown in the reference [15] that the Gray-World and White-Patch algorithms are two different instantiations of a more general color constancy algorithm based on Minkowski norm. This