Efficient Illuminant Estimation for Color Constancy Using Grey Pixels

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Efficiently removing the color cast triggered by light source, i.e., color constancy, is necessary for color feature extraction in both computer vision systems and biological visual systems [4, 5]. The majority of the existing color constancy models are generally realized by first estimating the color of light source from the given color-biased image and then transforming the color-biased image to a canonical image rendered under the white light source through the process of chromatic adaption [5].

In this work, we propose a simple color constancy model based on another simple hypothesis. We argue that there are some grey (or approximately grey) pixels widely appearing in natural scenes, which can be utilized to reliably estimate the illuminant. After comprehensively validating this hypothesis, we then develop a simple framework to detect the grey pixels from the color-biased images and then estimate the illuminant using these pixels. In addition, we further extend our method to the situation of multiple illuminants by a simple yet efficient strategy.

Hypothesis. The captured image values $I^i(x,y)$ with $i \in \{r,g,b\}$ can be normally expressed as the product of the illuminant $C(x,y)$ and surface reflectance $R(x,y)$[3, 6]

$$I^i(x,y) = C^i(x,y) \cdot R^i(x,y), \;\; i \in \{r,g,b\} \tag{1}$$

With logarithmic transform, we have

$$\log(I^i(x,y)) = \log(C^i(x,y)) + \log(R^i(x,y)) \tag{2}$$

We reasonably assume that the illuminant $C(x,y)$ is uniform within small local patches (at least with a size of 3×3 pixels). Thus, it is obvious that in logarithmic space, any measure defined as the difference between neighboring pixels is independent of illuminant, and they can be used in the both situations of uniform and non-uniform illuminant.

We denote the local *illuminant-invariant measure (IIM)* in three channels as $\Delta I^i_{\log}$ with $i \in \{r,g,b\}$, and then $\Delta I_{\log}$ should be equal to each other for each pixel within a local patch that is grey. Therefore, we finally identify a pixel as grey when it meets

$$\Delta I^r_{\log}(x,y) = \Delta I^g_{\log}(x,y) = \Delta I^b_{\log}(x,y) \neq 0 \tag{3}$$

Once we find these grey pixels, we can easily extract the illuminant of a color-biased image from them. However, it is worthy to note that Equation 3 is just a necessary condition for pixel (x,y) being grey.

Validation. In order to verify whether most of the natural images contain more or less grey pixels, we evaluate the possibility of detectable grey pixels in ground-truth images provided in the benchmark datasets [1, 2, 7] and two irrelevant natural datasets collected for other applications, e.g., saliency region detection. More than 95% of images in each dataset contain detectable grey pixels with *Grey Index (GI)* lower than 0.02 and almost all images contain detectable grey pixels with GI lower than 0.1. Note that GI is defined to measure how close a pixel approximates to grey.

Algorithm. For an input color-biased image $I(x,y)$, we first transform the color channels into logarithmic space. Then the IIM defined by local contrast (standard deviation) within the patch of $\eta \times \eta$ pixels, denoted by SD^r_η, SD^g_η, and SD^b_η, are computed for each pixels. In the work we always set $\eta = 3$. Finally, the relative standard deviation of local contrasts in three channels are computed as

$$P(x,y) = \sqrt{\frac{1}{3}\sum_{i\in\{r,g,b\}} \frac{\left(SD^i_\eta(x,y) - \overline{SD}_\eta(x,y)\right)^2}{\overline{SD}_\eta(x,y)}} \tag{4}$$

where $\overline{SD}_\eta(x,y) = \frac{1}{3}\left(SD^r_\eta + SD^g_\eta + SD^b_\eta\right)(x,y)$.

This is an extended abstract. The full paper is available at the Computer Vision Foundation webpage.

Figure 1: The **top row** lists (from left to right) the original color-biased image under single illuminant, the ground-truth image, and the corrected image by the proposed method. The **bottom row** shows an example of multi-illuminant estimation; from left to right: original image, ground-truth illuminants, and the estiamted illuminants in this paper.

We further exclude some undesired points that usually are of low luminance (e.g., dark pixels) or are isolated in spatial locations. Therefore, we weaken the influence of these dark or isolated pixels by

$$GI^*(x,y) = AF\left\{\frac{P(x,y)}{L(x,y)}\right\} \tag{5}$$

where $L = (I^r + I^g + I^b)/3$ denotes the luminance of each pixel in the input image. $AF\{\}$ indicates a averaging filter that is applied within the local neighborhood of 7×7 pixels. Finally, we choose the top n% pixels with the lowest GIs as the final grey pixels retrieved for illuminant estimation. An example of results on a single-illuminant image is shown in Fig.1 (top row).

For multi-illuminant situation, we first detect the grey pixels with the same steps as the situation of single illuminant, then cluster these retrieved grey pixels into M groups using a simple *K-means* based on their spatial locations. Next, the illuminant for each group is computed using the corresponding grey pixels. An example of multi-illuminant estimation is shown in Fig.1 (bottom row).

Our conclusion is that most natural images contain grey pixels that can be used to accurately estimate single or multiple illuminants in a scene. In this paper, a simple but effective approach is also proposed for color constancy via illuminant estimation.

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