Edge Classification for Color Constancy

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Abstract

The goal of color constancy is to measure image colors despite differences in the color of the light source. Traditionally, the computational method of obtaining this ability is by using pixel values only. Recently, methods using edges instead of pixel values have been proposed. However, different edge types exist, such as material, shadow and specular edges. Therefore, in this paper, the main goal is to analyze the influence of different edge types on the performance of edge-based color constancy. It is shown that, on generated data without color clipping, specular edges deliver near-perfect color constancy and that shadow edges are more valuable than material edges. However, with color clipping, the performance using the specular edges decreases significantly, while the performance using the material or shadow edges is less affected.

Introduction

Differences in illumination cause measurements of object colors to be biased towards the color of the light source. Color constancy is the ability to maintain invariance with respect to these differences. The ability of color constancy facilitates many computer vision related tasks like color feature extraction [10] and color appearance models [7].

Even though many algorithms for illuminant estimation have been proposed, see [13] for an overview, most of these methods use the pixel values. Examples of such methods include approaches based on low-level features [5, 15] and gamut-based algorithms [9]. Only recently, attempts to use transitions (i.e. edges) or even higher-order statistics have been proposed [6, 12, 17].

Edges can be categorized into several types like shadow, specular and material edges [11, 16]. The contribution of this paper is to analyze which edge types contain the most valuable information for estimation of the illuminant. It is known that highlights contain important information [1, 3]. However, in real-world images, pixels with high intensity are often clipped some certain maximum value (like 255), causing the information about the illuminant to be less reliable.

Using zeroth-order statistics, it was shown that a varying illumination can aid the estimation of the illuminant, if surfaces are accurately identified under different light sources [2, 8]. In this paper, the goal is to analyze the performance of color constancy methods using first-order statistics (i.e. edges), with respect to the type of edges that occur in images. For this purpose, edge data is generated under controlled circumstances, and the performance of edge-based color constancy is measured for different edge types.

Color Constancy

The image values $\mathbf{f}$ for a Lambertian surface depend on the color of the light source $e(\lambda)$, the surface reflectance $s(\mathbf{x},\lambda)$ and the camera sensitivity function $\mathbf{c}(\lambda)$:

$$\mathbf{f}(\mathbf{x}) = \int_{\omega} e(\lambda)\mathbf{c}(\lambda)s(\mathbf{x},\lambda)d\lambda, \tag{1}$$

where ω is the visible spectrum, λ is the wavelength of the light and $\mathbf{x}$ is the spatial coordinate. Assuming that the scene is illuminated by one light source and that the observed color of the light source $\mathbf{e}$ depends on the color of the light source $e(\lambda)$ as well as the camera sensitivity function $\mathbf{c}(\lambda)$, then color constancy is equivalent to the estimation of $\mathbf{e} = \int_{\omega} e(\lambda)\mathbf{c}(\lambda)d\lambda$, given the image values of $\mathbf{f}$, since both $e(\lambda)$ and $\mathbf{c}(\lambda)$ are, in general, unknown. This is an under-constrained problem and therefore it can not be solved without further assumptions.

Pixel-based Color Constancy

Two well-known and often used algorithms are based on the Retinex Theory proposed by Land [15]. The White-Patch algorithm is based on the White-Patch assumption, i.e. the assumption that *the maximum response in the RGB-channels in caused by a white patch*. The second algorithm, the Grey-World algorithm [5] is based on the Grey-World assumption, i.e. *the average reflectance in a scene is achromatic*. Another type of algorithm are gamut-based methods, originally proposed by Forsyth [9]. Gamut-based algorithms use more advanced statistical information about the image, and are based on the assumption, that *in real-world images, one observes, under a given illuminant, only a limited number of different colors*. Even though the White-Patch, Grey-World and gamut mapping are completely different algorithms, they all have in common that they estimate the illuminant using only the pixel values in an image.

Edge-based Color Constancy

Recently, pixel-based methods are extended to incorporate derivative information (i.e. edges) and higher-order statistics, resulting in the Grey-Edge [17] and the derivative-based gamut mapping [12].

The Grey-Edge actually comprises a framework that incorporates zeroth-order methods (e.g. the Grey-World and the White-Patch algorithms), first-order methods (e.g. the Grey-Edge), as well as higher-order methods (e.g. 2^{nd}-order Grey-Edge). Many different algorithms can be created by varying the three parameters:

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

where n is the order of the derivative, p is the Minkowski-norm and $\mathbf{f}^\sigma(\mathbf{x}) = \mathbf{f} \otimes \mathbf{G}^\sigma$ is the convolution of the image with a Gaussian filter with scale parameter σ. Good results are obtained by using instantiation $e_{1,1,\sigma}$, i.e. a simple average of the edges at scale σ also called the Grey-Edge method [17].

Another extension of pixel-based methods to incorporate derivative information involves the gamut mapping. This method has been extended to include not only pixel values, but also linear combinations of pixel values, e.g. image derivatives. The use of image derivatives has some advantages over using pixel values directly as certain effects that cause a failure of the diagonal model, like scattered light, have little effects on the derivative of an image. It is shown that the derivative-based gamut mapping suffers less from these degrading conditions [12]. For simplicity, however, in this paper the focus will be on the Grey-Edge algorithm.

Edge Types

The aim is to analyze which edge types have the most influence on the accuracy of the illuminant estimation. To this end, a spectral data set is used [4], consisting of 1995 surface reflectance spectra and 287 illuminant spectra. These two different kinds of spectra were gathered from different sources and the whole data set contains a wide variety of colors and illuminants. Each surface reflectance can be combined with every illuminant, hence a large set of surfaces (i.e. *RGB*-values) can be created for the experimental analysis. A transition is generated with real spectra by taking the difference between two surfaces. For these experiments, the following surfaces are created:

- Material surface $\mathbf{m}_i$:
$$\mathbf{m}_i = \int_\omega e_i(\lambda)\mathbf{c}(\lambda)s_i(\mathbf{x},\lambda)d\lambda. \quad (3)$$
- Shadow surface $\mathbf{p}_i$:
$$\mathbf{p}_i = \int_\omega \frac{e_i(\lambda)}{\phi}\mathbf{c}(\lambda)s_i(\mathbf{x},\lambda)d\lambda. \quad (4)$$
- Specular surface $\mathbf{h}_i$:
$$\mathbf{h}_i = \mathbf{m}_i + \gamma\int_\omega e_i(\lambda)\mathbf{c}(\lambda)d\lambda, \quad (5)$$

where ϕ and γ are random variables uniformly distributed between 1 and 4. Since the focus is on edge-based color constancy, three different edge types are analyzed in this paper: material edges, shadow edges and specular edges. A material edge is generated by a transition between two different surfaces from one surface to another. A shadow edge is computed by an intensity-difference: the difference between a normal, bright, surface and the same surface with a lower intensity is taken as shadow transition. A specular edge is computed by taking the difference between the regular, bright surface and the specular surface:

- Material edge: $\mathbf{m}_i - \mathbf{m}_j$.
- Shadow edge: $\mathbf{m}_i - \mathbf{p}_i$.
- Specular edge: $\mathbf{m}_i - \mathbf{h}_i$.

Note that these edges can be considered to be step edges. In real-world scenes, transitions are likely to be more gradual. However, for the purpose of this analysis, these edges are used to give a best-case assessment of algorithm performance.

In the first experiment, the performance of the Grey-Edge algorithm is analyzed with respect to different edge types. Using the spectral data set, a number of random surfaces are created, including n material surfaces, n shadow surfaces and n specular surfaces , resulting in a total of $3n$ surfaces. Note that to create these surfaces, the same illuminant is used. Using these surfaces, n material edges, n shadow edges and n specular edges are created. The Grey-Edge algorithm is evaluated by gradually increasing the number of edges. For each value of n ($n = \{4, 8, 16, 32, 64, 128, 256, 512, 1024\}$), the experiment is repeated 1000 times. When a combination of different edge types is used for the estimation of the illuminant, then all generated edges of these types are used.

The second experiment involves color clipping. Would a real-world image be created using the generated *RGB*-values, then the pixel values are often bound to a maximum. This effect is called color clipping. Since the specular surfaces have the highest *RGB*-values, these surfaces (and consequently the specular edges) risk to be affected by color clipping. To analyze this effect, an experiment is performed using the same surface reflectance and illuminant spectra. The setup of this experiment is similar to the first experiment, i.e. n material surfaces are created, n intensity shadow surfaces and n specular surfaces. After that, the generated *RGB*-values are color clipped at a gradually decreasing value. The clipping value is set such that $c\%$ of the total number of surfaces (i.e. $3n$) are clipped, where $c = \{0, 10, 20, 30, 40\}$.

Results

To evaluate the performance of color constancy algorithms, the angular error ε is widely used [14]. This measure is defined as the angular distance between the actual color of the light source $\mathbf{e}_l$ and the estimated color $\mathbf{e}_e$:

$$\varepsilon = \cos^{-1}(\hat{\mathbf{e}}_l \cdot \hat{\mathbf{e}}_e), \quad (6)$$

where $\hat{\mathbf{e}}_l \cdot \hat{\mathbf{e}}_e$ is the dot product of the two normalized vectors representing the true color of the light source $\mathbf{e}_l$ and the estimated color of the light source $\mathbf{e}_e$. Since the illuminant spectrum that is used to create the surfaces is known, the correct color of the light source $\mathbf{e}_l$ can be determined.

Different number of edges

The results of the first experiment are shown in figure 1. As expected, using specular edges results in a close to ideal performance. Less expected, however, is the fact that using shadow edges results in a lower angular error than when using material edges. A combination of both material edges and shadow edges results in an intermediate performance.

To study the observation why using specular edges result in a close to ideal performance, and why shadow edges result in a better performance than when using material edges, the distribution of different edge types is considered. For the ease of illustration of the physical properties of edge types, the edges are converted to the opponent color space:

$$o1_x = \frac{R_x - G_x}{\sqrt{2}} \quad (7)$$
$$o2_x = \frac{R_x + G_x - 2B_x}{\sqrt{6}} \quad (8)$$
$$o3_x = \frac{R_x + G_x + B_x}{\sqrt{3}} \quad (9)$$

where R_x, G_x and B_x and derivatives of the R, G and B channels, respectively.

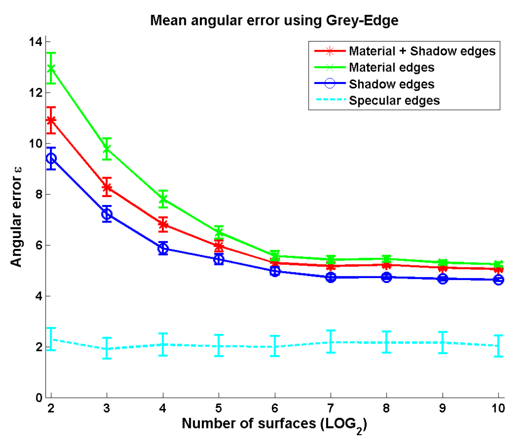
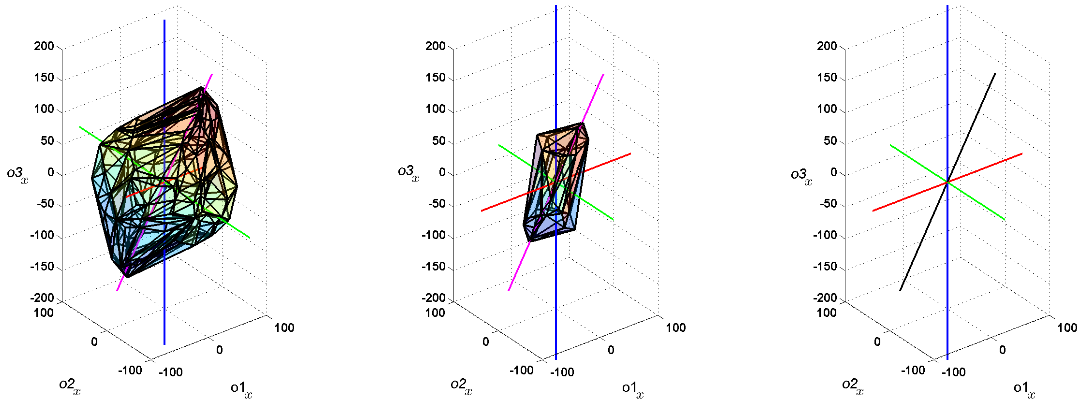
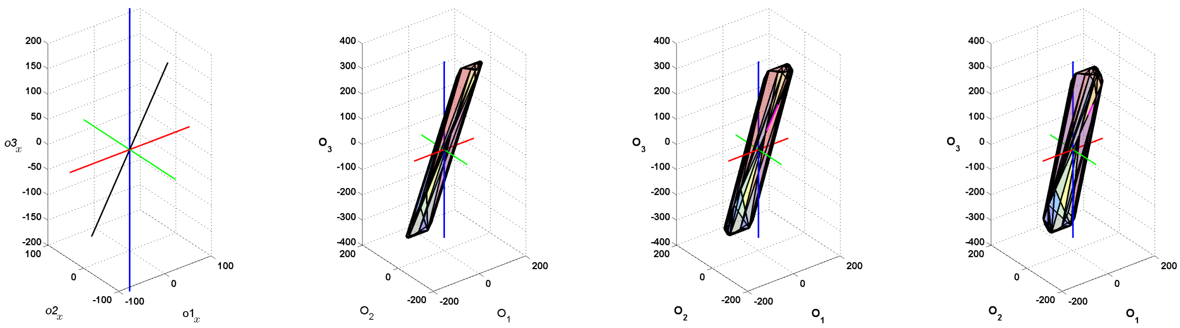


Figure 1. Mean angular error using the grey-edge, on different edge types, plotted with a 95% confidence interval.



(a) (b) (c)

Figure 2. *Gamut in opponent color space of material edges, figure (a), shadow edges, figure (b) and specular edges, figure (c), put under one illuminant, which is specified by the fourth axis. In figures (d)-(f), it is shown what happens with the gamut of the specular edges for decreasing clipping values. Figures (d), (e) and (f) have* 10%*,* 20% *and* 30% *of the pixels clipped, respectively.*



(a) (b) (c) (d)

Figure 3. *The effects of clipping on the gamut of the specular edges. In figures (a)-(d),* 0%*,* 10%*,* 20% *and* 30% *of the total number of pixels is clipped, respectively.*

The distribution of edges in opponent color spaces is shown in figure 2. From these graphs, it can be seen that the specular edges align perfectly with the diagonal representing the color of the light source (shown by the fourth axis) . Further, the shadow edges contain less variation in color than the material edges, and the shadows are more directed towards the color of the light source.

These graphs show that it is beneficial to use edges that are aligned with the color of the light source. The specular edges are all distributed on the diagonal representing the color of the light source, and near-perfect color constancy can be obtained using these edges. This observation is in accordance to pixel-based highlight analysis, where highlights contain valuable information about the color of the light source [1, 3]. Shadow edges are distributed denser around the color of the light source than material edges, resulting in a higher performance.

Color clipping

In practice, pixel values are often bound to a certain maximum value. This effect is called color clipping. To analyze this effect, a second experiment is performed using the same surface reflectance and illuminant spectra. The results of this experiment are shown in figure 4. The accuracy of the estimation using the specular edges immediately starts to decrease significantly when clipping is applied. The performance using the material and shadow edges is less affected; the angular error does not significantly increase until 40% of the total number of surfaces are clipped.

The effects of color clipping on the gamuts of the specular edges are shown in figure 3. These plots display the gamuts of the specular edges after clipping 0%, 10%, 20% and 30% of the total number of pixels. The gamuts of the specular edges slowly shift towards the intensity axis ($O3_x$). This causes the estimate of the illuminant to bo biased towards white, and the effect increases as more pixels are clipped. Since color clipping cannot be prevented in practice, specular edges are less valuable.

Conclusion

In this paper, the performance of edge-based color constancy was analyzed with respect to different edge types that occurs in images. The experiments have been performed on a spectral data set. The results show that, in theory, specular edges contain a valuable clue in estimating the color of the light source. However, because of color clipping, these edges can not be used in real-world images.

The experiment further showed that a shadow edge in the form of an intensity change is a more valuable clue than material edges for color constancy. More experiments need to be performed on real-world data to confirm these results. However, preliminary results reveal that shadow edges can indeed improve the performance of edge-based color constancy.

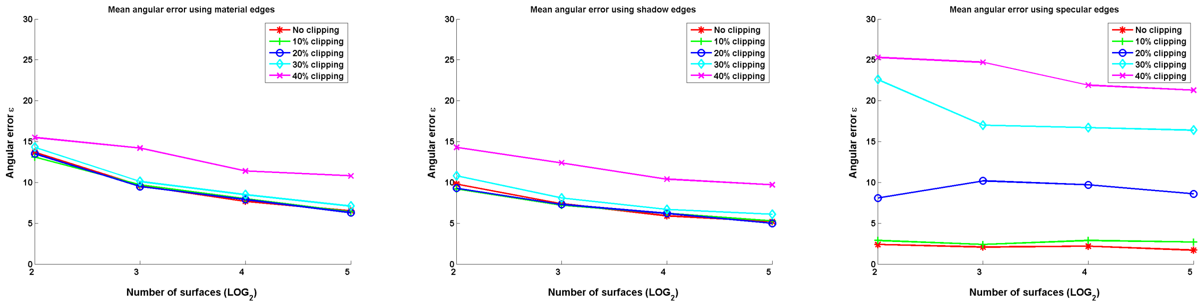


Figure 4. *Mean angular error using material edges, shadow edges and specular edges, for different clipping values.*

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