Edge-driven color constancy
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Citation for published version (APA):
Gijsenij, A. (2010). Edge-driven color constancy

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Chapter 4

Improving Color Constancy Using Photometric Edge Classification*

4.1 Introduction

Changes in illumination cause the 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 changes. The ability of color constancy facilitates many computer vision related tasks like color feature extraction [59] and color appearance models [32].

Many computational color constancy algorithms have been proposed, see [67, 30] for overviews. Traditionally, color constancy methods use pixel values of an image to estimate the illuminant. Examples of such methods include approaches based on low-level features [16, 42, 73], gamut-based algorithms [37, 40, 44], and other methods that use knowledge acquired in a learning phase [14, 28]. Only recently, methods that use derivatives (i.e. edges) and even higher-order statistics have been proposed [20, 64, 91].

From earlier studies on pixel-based color constancy, it is known that highlights (under the assumption of the neutral interface reflection) contain important information about the color of the light source [5, 7]. Other work shows that, using pixel values, a varying illumination can aid the estimation of the illuminant, if surfaces are accurately identified under different light source [6, 35]. However, as it is hard to classify pixels automatically into e.g. material and highlight pixels, prior knowledge about the scene is needed [5, 7, 6, 35]. Therefore, in this chapter, the focus will be on edge-based color constancy, as edges can automatically be classified into different photometric types.

For the classification of edges, different schemes have been proposed that categorize edges based on their photometric characteristics [38, 56, 60, 90]. For example, edges can be classified into material edges (e.g. edges between objects), shadow/shading edges (e.g. edges caused by the geometry of an object) and specular edges (e.g. highlights). Edge-based color constancy algorithms make use of image derivatives to estimate the illuminant, and consequently, different edge types may provide a different impact on the performance of the illuminant estimation. Although edge-based color constancy show promising results [91], an analysis of different edge types on the performance of color constancy algorithms has not been studied.

Therefore, in this chapter, an analysis is provided of the physical nature of different edge types on the performance of edge-based color constancy methods. Further, the results of this analysis are used to improve edge-based color constancy algorithms. To this end, first, an edge-based taxonomy is presented classifying edge types based on their reflectance properties (e.g. material, shadow-geometry and highlights). Then, a performance evaluation of edge-based color constancy using these different edge types is performed using hyperspectral data. From this performance evaluation, it is derived that highlights and shadow edges are more valuable than

*Submitted to Transactions on Pattern Analysis and Machine Intelligence
other edges (e.g. material edges) for the estimation of the illuminant. Then, an edge-weighting scheme to extend edge-based color constancy algorithms like the Grey-Edge and the Derivative-based Gamut mapping algorithm are extended to incorporate this information. The proposed methods are evaluated on a data set containing over 11,000 images and compared to pixel-based methods and unweighted edge-based methods.

This chapter is organized as follows. In section 4.2, color constancy is discussed followed by a categorization of edges into several types in section 4.3. In section 4.4, the performance of edge-based color constancy is analyzed with respect to different edge types. Then, in section 4.5, the observed results are applied to two edge-based color constancy algorithms. Finally, in sections 4.6 and 4.7, the results are discussed and conclusions are drawn, respectively.

4.2 Color Constancy

The image values $f = (f_R, f_G, f_B)^T$ for a Lambertian surface depend on the color of the light source $I(\lambda)$, the surface reflectance $S(x, \lambda)$ and the camera sensitivity function $\rho(\lambda)$ which is given by the tuple $(\rho_R(\lambda), \rho_G(\lambda), \rho_B(\lambda))^T$, where $\lambda$ is the wavelength of the light and $x$ is the spatial coordinate (e.g. [67, 44, 57]):

$$f_c(x) = m(x) \int_\omega I(\lambda) \rho_c(\lambda) S(x, \lambda) d\lambda,$$

where $\omega$ is the visible spectrum, $m(x)$ is Lambertian shading and $c = \{R, G, B\}$. It is assumed that the scene is illuminated by one light source and that the observed color of the light source $e$ depends on the color of the light source $I(\lambda)$ as well as the camera sensitivity function $\rho(\lambda)$:

$$e = \begin{pmatrix} e_R \\ e_G \\ e_B \end{pmatrix} = \int_\omega I(\lambda) \rho(\lambda) d\lambda.$$

Color constancy can be achieved by estimating the color of the light source $e$, given the image values of $f$, followed by a transformation of the original image values using this illuminant estimate. This transformation will leave the intensity of every pixel unaltered, as the proposed method will only correct for the chromaticity of the light source. Since both $I(\lambda)$ and $\rho(\lambda)$ are, in general, unknown, the estimation of $e$ is an under-constrained problem that cannot be solved without further assumptions.

4.2.1 Pixel-based Color Constancy

Two well-known and often used algorithms are based on the Retinex Theory proposed by Land [73]: the White-Patch and the Grey-World algorithm. The White-Patch algorithm is based on the White-Patch assumption, i.e. the assumption that the maximum response in the RGB-channels is caused by a white patch. The second algorithm, the Grey-World algorithm [16] is based on the Grey-World assumption, i.e. the average reflectance in a scene is achromatic. Another type of algorithms are gamut-based methods, originally proposed by Forsyth [44]. 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.

4.2.2 Edge-based Color Constancy

Extending pixel-based methods to incorporate derivative information, i.e. edges and higher-order statistics, resulted in the Grey-Edge [91] and the derivative-based Gamut mapping [65].

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. 2nd-order Grey-Edge). Many different algorithms can be created by varying the three parameters:

\[
\left( \int \left| \frac{\partial^n f_{c, \sigma}(x)}{\partial x^n} \right|^p dx \right)^{\frac{1}{p}} = k e^{n,p,\sigma},
\]

where \( \cdot \) indicates the Frobenius norm, \( c = \{R, G, B\} \), \( n \) is the order of the derivative and \( p \) is the Minkowski-norm. Further, the derivative is defined as the convolution of the image with the derivative of a Gaussian filter with scale parameter \( \sigma \) [48]:

\[
\frac{\partial^{s+t} f_{c, \sigma}}{\partial x^s \partial y^t} = f_c \ast \frac{\partial^{s+t} G_\sigma}{\partial x^s \partial y^t}
\]

where \( \ast \) denotes the convolution and \( s + t = n \). Good results are obtained by using instantiation \( e_{1,1,\sigma} \), i.e. a simple average of the edges at scale \( \sigma \) also called the Grey-Edge method [91].

Another extension of pixel-based methods to incorporate derivative information involves the Gamut mapping algorithm. This method has been extended to include not only pixel values, but also linear combinations of pixel values, e.g. image derivatives or \( n \)-jet. The use of image derivatives has the advantages over using pixel values directly, that certain effects that cause a deviation 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 [65]. Therefore, in this chapter, in addition to the Grey-Edge method the derivative-based Gamut mapping method is used as a different type of color constancy method to assess the influence of different edge types.

4.3 Photometric Edge Types

Edges can be categorized into several types based on their photometric properties such as material edges, shadow or shading edges, and specular edges [38, 56, 60, 90]. Material edges are transitions between two different surfaces or objects. Shading edges are transitions that are caused by the geometry of an object, for instance by a change in surface orientation with respect to the illumination. Shadow edges are cast shadows, caused by an object that (partially) blocks the light source. Specular edges are edges that are caused by highlights. Besides these main edge types, i.e. material, shadow/shading and specular edges, two more edge types, colored shadow edges and interreflection edges, are used in this chapter.

A colored shadow edge is an instantiation of a shadow edge. A shadow edge can be either a sudden change of intensity, e.g. caused by the geometry of an object, or it can be somewhat differently colored. When the latter is the case, then the sudden gradient is not only an intensity gradient but it also contains a faint color gradient at the same time. Hence, a shadow edge can be separated into an intensity shadow edge and a colored shadow edge. When we refer to shadow edges in general, the union of these two edge types is implied. Furthermore, in real-world images, interreflection is an important aspect. Interreflection is the effect of light reflected from one surface onto a second surface. This effect changes the overall illumination that is received by the second surface, and hence the color of this surface. This results in the following set of edge types:

- material edges,
- intensity shadow edges,
- colored shadow edges,
- specular edges,
- interreflection edges.

The aim is to analyze to what extent these edge types influence the accuracy of the illuminant estimation.
4.3.1 Reflectance-based Edge Classification

Classification of edges into different types can be done using a set of photometric variants and quasi-invariants [90]. To this end, the derivative of an image, $f_x = (f_{R,x}, f_{G,x}, f_{B,x})^T$, is projected on three directions called variant directions. By removing the variance from the derivative of the image, a complementary set of derivatives is constructed called quasi-invariants.

The projection of the derivative on the shadow-shading direction is called the shadow-shading variant and is defined as:

$$S_x = \left( f_x \cdot \hat{f} \right) \hat{f},$$

(4.5)

where $\hat{f} = \frac{1}{\sqrt{R^2 + G^2 + B^2}} (R, G, B)^T$ indicates the direction of the variant and the dot indicates the vector inner product. The shadow-shading variant is that part of the derivative which could be caused by shadow or shading. What remains after subtraction of the variant from the derivative is called the shadow-shading quasi-invariant:

$$S^t_x = f_x - S_x.$$  

(4.6)

The quasi-invariant $S^t_x$ is insensitive to shadow-shading edges, hence contains only specular and material edges.

Using the same reasoning, a specular variant and quasi-invariant is obtained:

$$O_x = \left( f_x \cdot \hat{c} \right) \hat{c},$$

(4.7)

$$O^t_x = f_x - O_x,$$

(4.8)

where $\hat{c}$ is the specular direction. The specular quasi-invariant is insensitive to highlight edges.

Finally, the shadow-shading-specular variant and quasi-invariant can be constructed by projecting the derivative on the hue direction:

$$H_x = \left( f_x \cdot \hat{b} \right) \hat{b},$$

(4.9)

$$H^t_x = f_x - H_x,$$

(4.10)

where $\hat{b}$ is the hue direction. $H^t_x$ does not contain specular or shadow-shading edges.

These quasi-invariants can be used for edge classification [90] as follows. If little of the energy of an edge is directed towards the shadow-shading-specular direction, then this edge is classified as a material edge. An edge is classified as shadow edge if more energy is directed towards the shadow-shading direction than towards the specular direction. Finally, if more energy is in the specular direction than in the shadow-shading direction, then this edge is classified as specular edge.

4.4 Performance using Different Edge Types

In this section, 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 first to generate different edges types under controlled circumstances. On this data set, the two different edge-based color constancy algorithms are evaluated i.e. the Grey-Edge and the derivative-based Gamut mapping approach. Then, the quasi-invariants are used to classify edges in real-world images into material and shadow edges, extending the experiments from a controlled setting to real-world scenarios.

To evaluate the performance of color constancy algorithms, the angular error $\epsilon$ is widely used [68]. This measure is defined as the angular distance between the actual color of the light source $\mathbf{e}_l$ and the estimated color $\mathbf{e}_e$:

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

(4.11)

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 $\mathbf{e}_e$. To measure the performance of an algorithm on a whole data set, the median angular error is reported.
4.4. PERFORMANCE USING DIFFERENT EDGE TYPES

4.4.1 Spectral data

The first experiments are performed using the spectral data set introduced by Barnard et al. [9]. This set consists of 1995 surface reflectance spectra and 287 illuminant spectra, from which an extensive range of surfaces (i.e. RGB-values) can be generated using eq. (4.1). As discussed before, for these experiments, the following types of surfaces are created:

- Material surface \( m_i \):
  \[
  m_{ik} = \int \omega e_k(\lambda) c(\lambda) s_i(x, \lambda) d\lambda. 
  \]  
  \( (4.12) \)

- Intensity shadow surface \( p_i \):
  \[
  p_{ik} = \int \omega \frac{e_k(\lambda)}{\phi} c(\lambda) s_i(x, \lambda) d\lambda. 
  \]  
  \( (4.13) \)

- Colored shadow surface \( q_i \):
  \[
  q_{i(k)} = p_{ik} + \eta \int \omega e_k'(\lambda) c(\lambda) s_i(x, \lambda) d\lambda, 
  \]  
  \( (4.14) \)

- Specular surface \( h_i \):
  \[
  h_{ik} = m_{ik} + \gamma \int \omega e_k(\lambda) c(\lambda) d\lambda, 
  \]  
  \( (4.15) \)

- Interreflection surface \( r_{ijk} \):
  \[
  r_{ijk} = m_{jk} + \theta m_{ik}, 
  \]  
  \( (4.16) \)

where the subscript \( i \) and \( j \) denote different surface reflectance spectra and \( k \) and \( k' \) denote different illuminant spectra. Further, \( \phi \) and \( \gamma \) are random variables uniformly distributed between 1 and 4, and \( \eta \) and \( \theta \) are random variables uniformly distributed between 0 and 0.25.

Since the focus is on edge-based color constancy, the following transitions (i.e. edges) between surfaces are generated:

- Material edge: \( m_{ik} - m_{jk} \).
- Intensity shadow edge: \( m_{ik} - p_{ik} \).
- Colored shadow edge: \( m_{ik} - q_{i(k)} \).
- Specular edge: \( m_{ik} - h_{ik} \).
- Interreflection edge: \( m_{ik} - r_{ijk} \).

A material edge is generated by taking the difference between two different material surfaces, \( m_i - m_j \). The difference between a material surface \( m_i \) and the same surface under a weaker light source results in an intensity shadow edge, \( m_i - p_i \). A colored shadow edge is defined as the difference between a material surface \( m_i \) and a colored shadow surface, \( m_i - q_i \). A specular edge is defined as the difference between a material surface \( m_i \) and the bright version of the same material, \( m_i - h_i \). Finally, an interreflection edge is defined as the difference between a material surface \( m_i \) and an interreflection surface \( r_{ij} \) where surface \( m_i \) interreflects onto a second surface \( m_j \), hence \( m_i - r_{ij} \). 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 relative assessment of algorithm performance, comparing the different edge types under the same conditions.
4.4.2 Different number of edges

In the first experiment, the performance of two edge-based color constancy algorithms is analyzed with respect to different edge types. Using the synthetic data set, a number of random surfaces are created, including \( n \) material surfaces, \( n \) intensity shadow surfaces, \( n \) colored shadow surfaces, \( n \) specular surfaces and \( n \) interreflection surfaces, resulting in a total of \( 5n \) surfaces. Note that to create these surfaces, the same illuminant is used. Using these surfaces, \( n \) material edges, \( n \) intensity shadow edges, \( n \) colored shadow edges, \( n \) specular edges and \( n \) interreflection edges are created. Two edge-based color constancy algorithms are evaluated (the Grey-Edge algorithm and the Derivative-based gamut mapping) 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.

In figure 4.1(a), the median angular error for the Grey-Edge algorithm is shown differentiated by the five edge types. Remarkably, the angular error when using intensity shadow edges is significantly lower than when using material edges. As expected, color constancy based on specular edges results in a close to ideal performance. Further, the performance using the colored shadow edges and the interreflection edges is similar to the performance when using the material edges. The performance of the Derivative-based gamut mapping, see figure 4.1(b), shows a similar trend. Using specular edges results in near-perfect color constancy, and intensity shadow edges are more favorable than the other types of edges.

4.4.3 Gamuts of different edge types

To study the observation why using shadow edges results in a better performance than when using material and other types of 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:

\[
\begin{align*}
o_1 &= \frac{R_x - G_x}{\sqrt{2}}, & o_2 &= \frac{R_x + G_x - 2B_x}{\sqrt{6}}, & o_3 &= \frac{R_x + G_x + B_x}{\sqrt{3}}
\end{align*}
\]  

(4.17)

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

The distribution of edge responses in the opponent color space is shown in figure 4.2. From these graphs, it can be derived that the variation in edge color is much higher for the material edges, figure 4.2(a), than for shadow edges, figures 4.2(b) and (c). Further, the intensity shadow edges are more directed towards the color of the light source (shown by the fourth axis) than the colored shadow edges. The shape of the gamut of the color shadow edges, which appears to be less directed towards the color of the light source than other edge types, can be explained by the influence of the second light source. The gamut of interreflection edges, figure 4.2(e), is similar to the material edges. Finally, specular edges, figure 4.2(e), all align perfectly with the color of the light source (shown by the fourth axis).

![Figure 4.1: Median angular error of the Grey-Edge, figure (a), and the Derivative-based Gamut Mapping, figure (b), including a 95% confidence interval, using several different edge types.](image)
4.5. WEIGHTED EDGE-BASED COLOR CONSTANCY

Figure 4.2: Gamut in opponent color space of several edge types put under one illuminant which is specified by the fourth axis. Shown are material edges in figure (a); intensity shadow edges in figure (b); colored shadow edges in figure (c); specular edges in figure (d); interreflection edges in figure (e).

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 [5, 7]. Shadow edges are distributed denser around the color of the light source than material edges and interreflection edges, resulting in a higher performance.

4.4.4 Color clipping

In practice, pixel values are often bound to a certain maximum value. 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, a second experiment is performed where the generated RGB-values are color clipped at a gradually decreasing value. The results of this experiment for the Grey-Edge algorithm are shown in figure 4.3. The derivative-based Gamut mapping reveals a similar trend (not shown here). The performance using the specular edges immediately starts to decrease significantly. The performance using the material and the 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 cause the gamuts of the specular edges to shift towards the intensity axis ($Oz_3$), hence the estimate of the illuminant will be biased towards white. Color clipping is an often occurring phenomena and cannot be prevented in practice.

To conclude, from an analytical approach, it can be derived that using specular edges for edge-based color constancy results in a close to ideal performance, because the specular edges align with the color of the light source. However, in practice, color clipping may eliminate the advantages of specular edges and cause a decrease in performance. Shadow edges contain more variation than specular edges but are still aligned with the color of the light source. Consequently, the performance of edge-based color constancy using shadow edges degrades only slightly with respect to using highlights. However, as material edges vary even more, their performance degrades even more. Although interreflection edges vary less than material edges, they are not aligned with the color of the light and hence their performance is the worst.

4.5 Weighted Edge-based Color Constancy

In section 4.4, it was shown that using specular edges can result in near-perfect color constancy. Further, it was shown that shadow edges results in a more accurate performance than material edges. This section is concerned with extending this analysis to real-world images.
Improving Color Constancy Using Photometric Edge Classification

4.5.1 Weighted Grey-Edge Algorithm

In this section, the weighted Grey-Edge algorithm is proposed based on physics principles. For now, assume the original edge-based framework of eq. (4.3) to be reduced to the first-order Grey-Edge with a Minkowski-norm of 1, leading to a simplified version of eq. (4.3):

$$\int |f_{c,x}(x)| dx = k e_c,$$

(4.18)

where \( f_{c,x}(x) \) is the derivative of color channel \( c \in \{R,G,B\} \) of image \( f \) at a certain scale. Then, the weighted Grey-Edge algorithm is given by:

$$\int |w(f)\kappa f_{c,x}(x)| dx = k e_c,$$

(4.19)

where \( w(f)\kappa \) is a weighting function that assigns a weight to every value of \( f \). The power \( \kappa \) can be used to enforce the differences between high weights and medium weights. For now, we take \( \kappa = 1 \). Alternative values can be used depending on the data set.

**Weighting schemes** In these experiments a real-world data set is used [22], denoted by SFU-set. This data set consists of 15 clips with a total of 11,346 images and is widely used for evaluation of color constancy algorithms. For all images, the ground truth is known from a grey sphere that was mounted on top of the camera, and this sphere was masked during the experiments, see figure 4.5(a) for some example images of this data set.

First, several weighting schemes are proposed, based on the photometric edge types discussed in section 4.3. Using these quasi-invariants, an edge is classified as shadow edge if there is more energy in the shadow-shading variant \( S_x \) than in the specular variant \( O_x \). However, since the shadow-shading variant \( S_x \) measures the amount of energy that is directed towards the shadow-shading direction, this variant can also be used directly to assign higher weights to shadow edges. If all derivative-energy is in the shadow-shading direction, then this indicates that there is a high probability that the current edge is in fact a shadow edge. On the other hand, if no energy is in this direction, then the current edge is likely to be a different type of edge. Hence, the ratio of the energy in the shadow-shading direction versus the total amount of energy can directly be used as a weighting scheme to weight shadow edges more than other types of edges:

$$w_{s,\text{shadow}}(f_x) = \frac{|S_x|}{|f_x|},$$

(4.20)

where \( S_x \) is the shadow-shading variant, \( |S_x| \) is the absolute value of \( S_x \) and \( ||f_x|| \) is the Euclidean norm of \( f_x \):

$$\sqrt{f_{R,x}^2 + f_{G,x}^2 + f_{B,x}^2}.$$

Using the shadow-shading invariant would result in higher weights for specular and material edges, and consequently lower weights for shadow edges:

$$w_{s,\text{spec.+mat.}}(f_x) = \frac{|S_x'|}{|f_x|},$$

(4.21)
4.5. WEIGHTED EDGE-BASED COLOR CONSTANCY

<table>
<thead>
<tr>
<th>Weighting scheme</th>
<th>Median $\epsilon$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$w_s; shadow$</td>
<td>4.5° - 2%</td>
</tr>
<tr>
<td>$w_s; shadow, \kappa = 10$</td>
<td><strong>4.2° - 9%</strong></td>
</tr>
<tr>
<td>$w_s; spec.+mat.$</td>
<td>5.8° + 26%</td>
</tr>
<tr>
<td>$w_s; specular$</td>
<td>4.4° - 4%</td>
</tr>
<tr>
<td>$w_s; shad.+mat.$</td>
<td>5.3° + 15%</td>
</tr>
<tr>
<td>$w_s; material$</td>
<td>5.4° + 17%</td>
</tr>
<tr>
<td>$w_s; shad.+spec.$</td>
<td>4.5° - 2%</td>
</tr>
</tbody>
</table>

(a) Several soft weighting schemes

<table>
<thead>
<tr>
<th>Method</th>
<th>Median $\epsilon$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Grey-World</td>
<td>7.0°</td>
</tr>
<tr>
<td>White-Patch</td>
<td>5.3°</td>
</tr>
<tr>
<td>Shades-of-Grey</td>
<td>5.3°</td>
</tr>
<tr>
<td>Grey-Edge</td>
<td><strong>4.6°</strong></td>
</tr>
<tr>
<td>2nd-order Grey-Edge</td>
<td>4.9°</td>
</tr>
<tr>
<td>Gamut mapping</td>
<td>4.8°</td>
</tr>
</tbody>
</table>

(b) Comparison to state-of-the-art

Table 4.1: Median angular errors on the real-world set containing 11346 images, using several soft weighting schemes in table (a). The relative performance is with respect to the regular Grey-Edge. In the different weighting schemes, $\kappa = 1$ is used unless stated otherwise. A comparison to state-of-the-art methods is shown in table (b). The soft weighting scheme using the shadow-shading variant $w_s; shadow$ with $\kappa = 10$ outperforms all methods on this set.

where $S^t_x$ is the shadow-shading invariant.

Instead of using the shadow-shading variant and quasi-invariant, the other variants and quasi-invariants can be used. For instance, if the specular variant is used, then specular edges are assigned higher weights. By using the specular quasi-invariant more emphasis is put on the shadow and material edges:

$$w_s; specular(f_x) = \frac{|O_x|}{|f_x|}$$

$$w_s; shad.+mat.(f_x) = \frac{|O^t_x|}{|f_x|}$$

where $O_x$ and $O^t_x$ are the specular variant and quasi-invariant, respectively. The material edges can be emphasized by using the shadow-shading-specular variant and invariant:

$$w_s; shad.+spec.(f_x) = \frac{|H_x|}{|f_x|}$$

$$w_s; material(f_x) = \frac{|H^t_x|}{|f_x|}$$

where $H_x$ and $H^t_x$ are the shadow-shading-specular variant and quasi-invariant, respectively.

Results. The proposed weighting schemes are evaluated on the complete SFU-set of 11,346 real-world images [22]. Results of the different weighting schemes, using $\kappa = 1$, are shown in table 4.1(a). Differences between using shadow-shading weighting scheme $w_s; shadow$ or the specular weighting scheme $w_s; specular$ are small. However, assigning higher weights to material edges (i.e. using $w_s; material$) results in a considerably worse performance.

Influence of $\kappa$. Using the weighting schemes with a value of $\kappa = 1$ already shows that shadow edges are more valuable than material edges. However, by increasing the value of $\kappa$, more weight is assigned to certain edges, effectively enforcing the differences between high and low weights. The effects of $\kappa$ on the different weighting schemes are shown in figure 4.4. It can be observed that the shadow-shading weighting scheme benefits, while the performance of the other weighting schemes degrades. An optimal performance is obtained for $\kappa = 10$, resulting in a median angular error of 4.2°.

Discussion. Compared to current state-of-the-art, the weighted Grey-Edge using shadow edges ($w_s; shadow$, with $\kappa = 10$) performs better than all other methods, see table 4.1. The Wilcoxon Sign Test [68] has been computed and shows that this improvement is significant with a 99% confidence level.
The best-performing pixel-based method is the Grey-Edge ($e_{1,1,1}$) with a median angular error of $4.6^\circ$. For the original Gamut mapping algorithm, the same implementation as in [5] is used (which is different from the implementation used in the next section 4.5.4). This implementation comes with tunable segmentation parameters that can significantly influence results (reported results are for optimal parameter settings for the current data set). In figure 4.5, some example results of the proposed method are shown. Note the reduction in angular error for the images where shadows are present.

Oddly, the results on real-world images are not entirely consistent with the analysis in section 4.4. On the hyperspectral data, it was shown that using specular edges can result in near-perfect performance, while specular edges that are detected in real-world images do not contribute to more accurate estimates. One possible explanation for this discrepancy is the lack of specular edges in the real-world images; if specular edges are not present, then it is impossible to use specular information for the estimation of the illuminant. However, the images shown in figure 4.5 refute this possibility, and manual screening of the data set reveals quite some images with specular edges. Two other explanations are discussed in the next subsections. The first possibility is the non-linearity of the images in the SFU-set: they lack gamma-correction and are therefore not linear, while linearity is an assumption of the used color constancy algorithm as well as the quasi-invariants. This possibility is analyzed in section 4.5.2. The second possibility that is examined is the failing assumption of the quasi-invariants of the white light source, which is addressed in section 4.5.3.

### 4.5.2 Gamma-correction

The SFU-set that is used in the experiments until now has many advantages, like the large variety and the size of the data set, but one disadvantage is that the images are non-linear, i.e. they are not gamma-corrected. Since the camera settings for this data set are unknown, this can not be undone. Unfortunately, the lack of gamma-correction causes specularities to lose its information about the color of the light source, i.e. the direction of a highlight is distorted for non-linear images. This is illustrated by the following example. Consider a simple 2-dimensional case, where the color of the surface and the color of the light source is kept fixed, and a highlight is simulated that reflects the color of the light as well as the color of the surface. If the generated image is linear, then the direction of the highlight is identical to the direction of the color of the light source, see figure 4.6(a). However, gamma compression transforms the direction of lines depending on their position in the $\mathbf{RGB}$-cube. Only values on a line which go through the origin, as is the case for varying surface color reflectances, remain on a line after compression. Lines which do not pass through the origin, as is generally the case for highlights, are transformed into curves.

![Figure 4.4: Median angular error of the weighted Grey-Edge using different values for the power $\kappa$. Note the change in scale on the y-axis for errors higher than 5, because of the large difference in range of error when using the weights based on material edges.](image)
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Figure 4.5: Some results of color constancy. In figure (a), the original image is shown, and in figure (b) the result of correction with the true, ground truth, illuminant is shown. In figure (c), the result of the proposed weighted Grey-Edge is shown. In figure (d) and (e), the regular Grey-Edge and Grey-World are shown, respectively.

Figure 4.6: A simple illustration to demonstrate the effect of gamma-correction on highlights. For linear images, the direction of a highlight coincides with the color of the light source, but for non-linear images this is not the case.

Consequently their derivatives point in directions deviating from the illuminant color direction, see Figure 7(b). Hence, for linear images, the highlights can perfectly be used to estimate the illuminant, but for non-linear images, this information is mostly lost.

To experimentally validate this rationale, an additional experiment is performed on a subset of the SFU-set, consisting of 150 image (10 images for every video clip are randomly selected). This time, however, gamma-correction is applied to the images and the ground truth is recomputed from these linear images. The estimated illuminants on the linear images are in general more chromatic than the once computed from the non-corrected images. As a consequence the angular errors tend to increase. Since the actual value for gamma is unknown, for this experiment we use $\gamma = 2.2$ which roughly corresponds to the sRGB color model. This RGB working space is widely used in many applications.

The weighted Grey-Edge algorithm is applied on the gamma-corrected images, using the shadow-shading, specular and material weight maps. Results, shown in table 4.2(a), indicate that the detected specular edges, indeed, contain more information about the color of the light source in the linear images. An increase in performance of 14% with respect to the regular Grey-Edge is obtained when specular edges are emphasized. Note that these results are obtained under the
Table 4.2: Median angular errors on a subset of 150 gamma-corrected images of the SFU-set. Since the actual value of gamma is unknown, for this experiment it is assumed that the images are recorded in the sRGB color model, roughly corresponding to \( \gamma = 2.2 \). Figure (a) denotes the realistic scenario where the weighting schemes are computed using the original images. Figure (b) denotes the theoretical scenario where the weighting schemes are computed using the images that are corrected for the color of the light source (using the ground truth).

4.5.3 White Light Assumption

The quasi-invariants are based on the assumption that the scene is viewed under a white light source [90], an assumption that is obviously not met for the images in the used data sets. To analyze the influence of failure of this assumption, an additional experiment is performed on the same subset of 150 linear images as was used in the previous section. For the images in this data set, the ground truth is known, which can be used to correct the images so that they appear to be taken under a white light source. These corrected images are used to compute the different weighting schemes using the quasi-invariants, as for these corrected images the assumption of the white light source is valid. After that, the weighting schemes are applied to the original uncorrected images to estimate the color of the light source using the weighted Grey-Edge algorithm. The results of this experiment, denoted by theoretical scenario, are shown in table 4.2(b).

This experiment shows that the detection of specular edges is sensitive to the color of the light source: in the realistic scenario, an improvement of 14% is obtained using specular edges, while the improvement in the theoretical scenario is nearly 25%. These results, again, confirm that specular edges are well suited for the estimation of the light source, if detected accurately. Further, the results of the shadow-shading weighting scheme are not dependent on the color of the light source; the performance of the weighted Grey-Edge using shadow edges is similar for both the theoretical and the realistic scenario.

4.5.4 Validation

Until now, all experiments on real-world images are performed on the same data set, i.e. the SFU-set, using the same algorithm, i.e. the Grey-Edge. To validate the results that are obtained so far, additional experiments are performed using a different edge-based color constancy algorithm, i.e. the derivative-based gamut mapping [65], and using a different data set. This additional data set is proposed by [95] and consists of 83 images (some examples are shown in figure 4.7). This data set, denoted by Barcelona-set, is much smaller and contains less variation that the SFU-set, but the advantage is that the images are available in XYZ-values. Hence, the influence of gamma-correction on the performance of the edge-weighted color constancy algorithms can be evaluated, as the linear and non-linear RGB-images can be computed.

**Weighted Derivative-based Gamut Mapping.** Similar to the Grey-Edge, the derivative-based Gamut mapping makes use of edge information too. However, this algorithm is more complex than the Grey-Edge method and weights can not naturally be incorporated. To still take advantage of the information that is obtained from the analysis is section 4.4, a threshold is used...
4.5. WEIGHTED EDGE-BASED COLOR CONSTANCY

<table>
<thead>
<tr>
<th>Gradient-based gamut mapping:</th>
<th>Median $\epsilon$</th>
</tr>
</thead>
<tbody>
<tr>
<td>using all edges</td>
<td>5.7°</td>
</tr>
<tr>
<td>using shadow edges</td>
<td><strong>5.4°</strong> -5%</td>
</tr>
<tr>
<td>using specular edges</td>
<td>5.6° -2%</td>
</tr>
<tr>
<td>using material edges</td>
<td>8.3° +46%</td>
</tr>
</tbody>
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Table 4.3: Median angular errors on the original SFU-set containing 11346 non-linear images, using several soft weighting schemes applied to the Gamut mapping algorithm using edge information.

to filter out unwanted edges and only maintain edges with a high information content regarding the estimation of the color of the light source. For this purpose, the same weighting schemes as for the weighted Grey-Edge are adapted. This time, a threshold $t_w$ is used to discard edges with a weight smaller than $t_w$. This results in a smaller, but more reliable gamut of the input image. A threshold of $t_w = 0$ indicates that all edges will be used, while $t_w = 1$ corresponds to the situation where only edges of a specific type are considered, depending on the scheme that is used.

For the experiments in this section, the Gamut mapping using gradient information is used. Results of using different weighting schemes are shown in table 4.3 (note that the performance that is reported is obtained without optimizing for possible segmentation parameters). The performance was obtained by setting the threshold slightly lower than 1, e.g. 0.98, to allow for some noise in the measurements. These results show that the derivative-based Gamut mapping, too, can be improved by considering only shadow edges, instead of all edges. Note that the performance for the other weighting schemes is optimal when the threshold $t_w$ is set to 0. This means that no performance improvement can be obtained for these weighting schemes.

**Barcelona-set.** To validate the results that are obtained on the SFU-set, the weighted Grey-Edge is applied to a second data set. This data set is available in XYZ-format, so linear and non-linear RGB-images can be created. First, the weighted Grey-Edge is applied to non-linear sRGB-images. This experiment is consistent with the setup of the experiment on the SFU-set in section 4.5.1. Results shown in table 4.4(a) show a similar trend as for the SFU-set: applying a higher weight to shadow edges improves the performance of edge-based color constancy with 14%, while applying a higher weight to specular edges only improves the performance with 7%. However, when the weighted Grey-Edge is applied to the linear RGB-images, it can be seen in table 4.4(b) that applying a higher weight to specular edges improves the performance as much as 41%. This improvement confirms the conclusions that are drawn from the experiments using spectral data in section 4.4, where it was shown that, in theory, specular edges can account for near-perfect color constancy. These results confirm the conclusions of the previous experiments, where it was shown that specular edge-weighted color constancy can improve edge-based color

Figure 4.7: Some examples of the data set proposed in [95]. The grey sphere, used to capture the ground truth illuminant, is masked during the experiments.
4.6 Discussion

In this chapter, the influence of different edge types on the performance of edge-based color constancy is analyzed. It is shown that weighted edge-based color constancy based on specular edges can significantly improve unweighted edge-based color constancy. Further, it is shown that shadow edges contain valuable information. The usefulness of shadow edges can be derived as follows. Shadow edges, as defined in section 4.3, are edges that are caused by a sudden change of intensity (or color) of the light source due to occlusions or object geometry changes. When considering a shadow edge on a plain surface, it can be observed that the color of this surface is bright on one side of the edge, and dark on the other side. Consequently, the hue and the saturation remain (approximately) the same, while only the intensity varies.

Let’s first consider edges that are completely unsaturated, when viewed under a white light source, i.e. achromatic edges. When the appearance of this edge is observed under a colored light source, the color of the edge is mainly caused by the color of the light source (by definition), and the saturation increases from 0 to the saturation of the light source. Consequently, these edges are well suited for estimating the color of the light source, as all properties of the light source are contained in this edge.

Colored edges, on the other hand, are edges that correspond to the transition from one surface (e.g. a red surface when viewed under a white light source) to another surface (e.g. a blue surface when viewed under a white light source). The saturation of this edge when viewed under a white light source can be an arbitrary value (e.g. red-to-blue). Moreover, when this edge is observed under a colored light source, the saturation and color will take on unpredictable values, from which it is extremely hard (if not impossible) to estimate the color of the light source. In general, the color of an edge is more affected by the color of the light source when the saturation of that edge under a white light source is lower. More formally, a negative correlation exists between $S_w$ and $d_{wu}$, where $S_w$ is the saturation of an edge under a white light source and $d_{wu}$ is the distance of that edge under a white light source $w$ to that same edge viewed under an unknown light source $u$.

From this, it can be derived that edges that are unsaturated under a white light source are good candidates for estimating the color of the light source. Specular and shadow edges are examples of such edges. However, specular edges are difficult to detect because of disturbances like a colored illumination and non-linearity of the input images. To conclude:

- For non-linear images, the preferred edges are shadow edges.
- For linear images, the most accurate illuminant estimates are obtained using specular edges.

Table 4.4: Results of the weighted Grey-Edge on 83 images from the Barcelona-set [95]. Results on both the $s$RGB-images and on linear RGB-images are shown, in table (a) and (b), respectively.

constancy significantly, if the specular edges are detected accurately.
4.7 Conclusion

In this chapter, the influence of different edge types on the performance of edge-based color constancy is analyzed.

It is shown that weighted edge-based color constancy based on specular edges can result in accurate illuminant estimates, but the accuracy of the detection of specular edges is severely degraded by failing assumptions of the quasi-invariants (like linear images and the assumption of a white light source). Weight maps that put more emphasis on shadow edges, on the other hand, result in slightly higher errors than using specular edges under perfect circumstances, but still improve unweighted edge-based color constancy. Further, the performance of using weight maps based on shadow edges is less affected by failing assumption of the quasi-invariants.

Two applications have been presented, where this information has been used to improve the performance of color constancy algorithms. Several weighting schemes have been evaluated using the weighted Grey-Edge and the derivative-based Gamut mapping. Using a soft weighting scheme based on the shadow-shading variant, i.e. assigning higher weights to edges with more energy in the shadow-shading direction, results in the best performance. When applying the derivative-based Gamut mapping only on a subset of the available edges (i.e. shadow-shading edges), the resulting illuminant estimates are more accurate than when using all edges. Further, all current state-of-the-art methods, including pixel-based and edge-based methods, are significantly outperformed by the proposed weighted Grey-Edge algorithm using shadow edges extracted from gamma-corrected images, resulting in an improvement of 9% with respect to the current best-performing algorithm. Moreover, when the weighted Grey-Edge algorithm is applied to linear RGB-images, specular edges will improve the performance even more, up to 14% to 41% with respect to the regular Grey-Edge algorithm.