Using High-Level Visual Information for Color Constancy

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Abstract

We propose to use high-level visual information to improve illuminant estimation. Several illuminant estimation approaches are applied to compute a set of possible illuminants. For each of them an illuminant color corrected image is evaluated on the likelihood of its semantic content: is the grass green, the road grey, and the sky blue, in correspondence with our prior knowledge of the world. The illuminant resulting in the most likely semantic composition of the image is selected as the illuminant color. To evaluate the likelihood of the semantic content, we apply probabilistic latent semantic analysis. The image is modelled as a mixture of semantic classes, such as sky, grass, road, and building. The class description is based on texture, position and color information. Experiments show that the use of high-level information improves illuminant estimation over a purely bottom-up approach. Furthermore, the proposed method is shown to significantly improve semantic class recognition performance.

1. Introduction

Light reflected by an object which enters the eye, or a camera, is a product of the object reflectance properties and the illuminant spectrum. The task of color constancy is to disentangle the two, allowing to recognize the colors of objects independent of the color of the illuminant. Computational color constancy is relevant for many computer vision tasks such as object recognition, tracking, and surveillance [3, 4, 11]. In addition, it allows for illuminant correction of images, with the aim to present images consistent with human perception of the world.

Computational color constancy research can be roughly divided in two approaches. One line of research focuses on illuminant invariant representations, which are primarily based on color differences between different patches in the image [14, 16, 17, 30]. The second, and more prominent line of color constancy research aims at estimating the color of the illuminant, after which the image can be corrected to how it would appear under a canonical, usually white, illuminant [4, 6, 9, 10, 13, 29]. This second line of color constancy research has the advantage that it allows for correcting the image for deviations from a canonical light source.

Several color constancy methods return a set of possible illuminants, from which one is to be selected [9, 13]. The subsequent selection procedures are often based on a heuristic, such as taking the average color of all possible illuminants [1]. Tous [28] considers the low-level image information, on which these color constancy methods are based, insufficient to select between a set of possible illuminants. Consequently, he proposes to return a set of solutions to the computer vision application, leaving the selection of the actual illuminant to the application. Another approach has been proposed by Gijsenij and Gevers [18], who use image statistics to decide on the most appropriate color constancy method given an image. All these methods are similar in that the illuminant estimation is based purely on bottom-up information, and high-level top-down information is disregarded. In this paper, we will explore the use of high-level visual information to select the most likely illuminant of a scene.

A motivation for the use of high-level visual information for color constancy can be found in recent human vision research. The mechanisms underlying human color constancy are still poorly understood. Most research uses collages of color patches in a 2D plane, so called Mondrian images, to infer mechanism of human color constancy [23]. Experiments on more real world like settings were performed by Kraft and Brainard [21], in which they proved that bottom-up clues, such as inter-reflections, specularities, and the range of colors present in a scene, all contribute to human color constancy. However, the scene still consisted of abstract objects, such as colored squares, and specular cylinders. Only recently research investigated the use of high-level visual information to obtain color constancy. Hansen et al. [19] illuminated fruit objects with an adjustable light source. They asked human observers to adjust the color of the light source such that the natural fruit objects appeared
achromatic. When the illuminant was adjusted to the point that the physical reflectance of the object was achromatic, observers still perceived a color sensation. The fruit objects only looked achromatic when the illuminant was shifted further away from the grey point in the direction opposite to the fruit color. This implies that high-level information of the objects color plays a role in human color constancy.

The first contribution of this article is the use of high-level visual information to select the best illuminant out of a set of possible illuminants. We achieve this by restating the problem in terms of semantic interpretability of the image. Which of the illuminants results in a likely image interpretation, i.e., an image where the sky is blue and in the top of the image, and the road is grey and in the bottom can be considered more likely than an image with purple grass surrounding a reddish cow. Several color constancy methods are applied to generate a set of illuminant hypotheses. For each illuminant hypothesis, we correct the image, and evaluate the likelihood of the semantic content of the corrected image. Finally, the most likely illuminant color is selected.

As a second contribution, we extend the set of illuminant hypotheses with a set of top-down hypotheses based on the assumption that the average reflectance of semantic classes in an image is equal to the average reflectance of the semantic topic in the database. For each of the semantic classes present in the image we compute the illuminant which transforms the pixels assigned to this class in such a way that the average reflectance is in accordance with the average color of the class in the database. For example, a patch of grass which turned reddish in the evening light, will correctly hypothesize a red illuminant, since such an illuminant will transform it to green under white light.

In contrast with existing work on color constancy, which uses a purely bottom-up approach, we investigate to what extent top-down color constancy can improve results. Both contributions, the selection mechanism based on the semantic likelihood and the generation of top-down illuminant hypotheses, are derived from the idea that high-level information plays an important role in color constancy.

2. Probabilistic Color Constancy

In this section, we state the illuminant estimation problem in a probabilistic manner and give an overview of our method.

Probabilistic approaches compute the probability of an illuminant given the image data \( P(\mathbf{c}|\mathbf{f}) \). The illuminant of a scene is that illuminant which is most likely given the image data

\[
\mathbf{c}_{\text{max}} = \arg \max_{\mathbf{c} \in C} \log (P(\mathbf{c}|\mathbf{f})) \tag{1}
\]

where \( \mathbf{f} = (R, G, B)^T \), and \( C \) is the set of possible illuminants \( \mathbf{c} \), which choice we will discuss later. Bold fonts are applied for vectors. Now assume that we have a function \( g \) which, if we know the illuminant of the scene, transforms the image as if it were taken under white light

\[
g(\mathbf{f}^\mathbf{c}, \mathbf{c}) = \mathbf{f}^w,
\]

where \( \mathbf{c} \) denotes the image’s illuminant and \( \mathbf{w} \) indicates the white illuminant. Then, the probability that the image \( \mathbf{f} \) is taken under illuminant \( \mathbf{c} \) is equal to the probability that the transformed image \( g(\mathbf{f}^\mathbf{c}, \mathbf{c}) \) is taken under a white illuminant:

\[
P(\mathbf{c} | \mathbf{f}) = P(\mathbf{w} | g(\mathbf{f}, \mathbf{c})). \tag{3}
\]

Applying this to Eq. 1 yields

\[
\mathbf{c}_{\text{max}} = \arg \max_{\mathbf{c} \in C} \log (P(\mathbf{w} | g(\mathbf{f}, \mathbf{c}))). \tag{4}
\]

This equation will be applied to select the illuminant color. This equation selects that illuminant \( \mathbf{c}_{\text{max}} \) which maximizes the probability that the color corrected image \( g(\mathbf{f}, \mathbf{c}_{\text{max}}) \) was taken under white lighting.

Probabilistic color constancy is based on choosing the most likely illuminant given the image data. Methods very close to the formulation in Eq. 4 have been proposed in literature [5, 10]. However, these methods interpret the probability in a purely bottom-up way. They are based on the probability of an \( RGB \) value to occur under a particular light source. Here we will propose an integrated bottom-up and top-down approach, where both the pixel values in the image and the semantic interpretation of the image as a whole influence the probability of the illuminant given the image data.

The success of color constancy as derived from Eq. 4 depends on two points. Firstly, how do we compute the chance that an image is taken under white light \( P(\mathbf{w} | \mathbf{f}) \), and how can we incorporate high-level information in this probability. Secondly, since it is unfeasible to evaluate Eq. 4 for all possible illuminants \( \mathbf{c} \), how do we select a plausible set of color illuminants for a scene. An overview of our approach is given in Fig. 1. For an input image a set of bottom-up and top-down illuminant hypotheses are computed (explained in Section 4). For each of these hypotheses the image is corrected and subsequently evaluated on the likelihood of its semantic content (explained in Section 3). The illuminant which results in the most probable image content is considered to be the illuminant of the input image. In the depicted case, the method estimates the illuminant to be reddish, since after correcting for this light source the image could be interpreted as green grass under a blue sky.

For the function \( g \), which transforms an image \( \mathbf{f}^\mathbf{c} \) taken under illuminant \( \mathbf{c} \) to an image \( \mathbf{f}^w \) taken under a white illuminant, we use a multiplication with a diagonal matrix:

\[
g(\mathbf{f}^\mathbf{c}, \mathbf{c}) = \mathbf{D}^\mathbf{c} \mathbf{f}^\mathbf{c} = \mathbf{f}^w \tag{5}
\]
illuminant hypotheses

compute semantic likelihood for all hypotheses, and computed from a data set which was taken under illuminant

Similar to the approach of Verbeek and Triggs [31], we as-

in an image

PLSA model the conditional probability of a visual word

is described by 64 words, each referring to one of the 64

words, and a color vocabulary of 1000 words. The position

is described by imposing a 8x8 grid of regular cells on the

image. Both the texture and color features are discretized

scriptor [24], 2. color, which is described by the Gaussian

modalities: 1. texture, which is described with the SIFT de-

patches which are extracted on a regular grid from the im-

proportional to

where \( v^T \), \( v^C \), \( v^P \), are successively the texture, color and position word. The distributions \( P(z|f) \) and the various \( P(v|z) \)'s are discrete, and can be estimated using an EM algorithm [20].

We set out to compute the chance that an image was taken under white light, which according to Bayes law is proportional to

\[
P(w|f) \propto P(f|w) P(w).
\]

If we assume a uniform distribution over the illuminants \( p(w) \), this can be rewritten using Eq. 7 to,

\[
P(w|f) \propto P(f|w) = \prod_{m=1}^{M} P(v_m|f, w)
\]

\[
= \prod_{m=1}^{M} \sum_{w \in Z^w} P(v_m|z^w) P(z^w|f),
\]

where \( P(v_m|z^w) \) means that the visual word topic distributions are learned from images taken under white light.

Let us consider what happens with Eq. 10 when we evaluate various illuminants. For the sake of simplicity we consider here that the texture descriptors do not change when varying the illuminant, although in the real implementation they are recomputed for each illuminant. By varying the illuminant color we change the color word \( v^C \) and via \( P(v^C|z) \) both \( P(v|z) \) and the topic distribution in the image \( P(z|f) \). The image will be more likely when
$P(v^C|z)$ corresponds with the combined distribution of $P(v^T|z)P(v^R|z)$. This means that illuminants become more likely when the color words they generate are in accordance with the texture and position information. Hence, color words representing green are more likely together with texture words describing grass, and a sky like texture in the top of the image is more likely to be blue.

The approach described here is related to the work of Manduchi [25], who uses the color similarity between a test image and labelled classes in one training image taken under white light to estimate the illuminant color. The classes are described by a Gaussian color distribution. Each pixel is assigned to a class and an illuminant to optimize the likelihood of the image. The method has the advantage that multiple illuminants are allowed within an image. However, the methods is only demonstrated to succeed when a single training image, similar to the test image, is available. This might be due to the limited discriminative power of the class description, in which multi-modality in color space, as well as texture and position information are disregarded.

### 4. Casting Illuminant Hypotheses

Evaluating Eq. 4 for all possible illuminants is not feasible. Instead, we propose to evaluate only a subset of color illuminants, which we call illuminant hypotheses. From these illuminant hypotheses the illuminant which is most likely given the image is selected. We propose two ways to generate hypotheses: a bottom-up approach and a top-down approach.

**Bottom-up hypotheses:** We can use existing color constancy algorithms to generate a set of possible illuminant colors for a scene. We call this approach bottom-up because these color constancy methods do not use any high-level visual information in the image. Here we choose to use a set of color constancy methods based on low-level features. Finlayson and Trezzi [12] unified two simple, broadly used, color constancy methods, by proving that the two methods are actually two instantiations of the Minkowski norm of an image:

$$
\left( \sum_{i=1}^{N} (f_i(x))^p \right)^{\frac{1}{p}} = kc
$$

where $i$ is counter over the $N$ pixels $f_i$, and $k$ is a constant which is chosen such that the illuminant color $c$ has unit length. The parameter $p$ is the Minkowski norm. For $p = 1$ the illuminant estimate is equal to color constancy derived from the Grey-World hypothesis, which assumes the average reflectance in a scene to be grey [6]. Using $p = \infty$ the illuminant estimate is equal to the max-RGB method [22] which assumes the maximum responses of the

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1. These classes are not semantically meaningful as in this paper and are labelled "class I", "class II", etc.
5.1. Illuminant Estimation

In this experiment we apply our method to estimate the illuminant color of a scene. For evaluation the angular error between the estimated light source $c_e$ and the actual light source $c_l$ is used:

$$\text{angular error} = \cos^{-1} (\hat{c}_l \cdot \hat{c}_e),$$  \hspace{1cm} (14)

where the (·) indicates a normalized vector.

**Data set:** We test our approach on a data set assembled by Ciurea and Funt [7]. The database contains 11,000 images extracted from 2 hours of digital video. Both indoor and outdoor scenes from a wide variety of locations are represented, see Fig. 3. A small grey sphere was mounted onto the video camera, appearing in all images in the right bottom corner. The sphere is used to estimate the illuminant color in the scene. This color illuminant estimation is available with the database and is used as a ground truth. The original images were extracted from 15 different film clips taken at different locations. Because of the high correlation between the images in the database, the experiments are performed on a subset of 600 images taken at equal spacings from the set. We divide the set in 320 indoor images, of which 160 training and 160 test images, and 280 outdoor images of which 140 training and 140 test images. The pixels in the right bottom corner, which contains the grey sphere, are excluded from color constancy computation.

**Training topic-word distribution:** For all the images in the training data set the ground truth of the illuminant is given. We correct the images in the training data set for their illuminant using Eq. 6, and obtain a set of images under white light. Subsequently we compute the distribution of visual words over the topics $P(v | z_w)$ on this set. For these images no labels of the semantic content are available, therefore we apply PLSA to discover the topics from the unlabelled data, similarly as in [27, 31]. We found that for topic discovery it proved beneficial to only use the texture modality. The assignments of patches to topics based on visual words over the topics $P(v | z_w)$ were then used to estimate the word-topic distributions for the other modalities $P(v | c_w)$ and $P(v | t_w)$. We used 20 topics for both the indoor and the outdoor set.

**Results:** The results for the indoor and the outdoor images are given in Table. 1. \(^2\) For both sets we give the results without applying color constancy (i.e. assuming the illuminant to be white), and for the worst and the best of the

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\(^2\)See also the erratum appended after the ICCV paper
Figure 3. From left to right. Input image, Grey-World approach and the most likely top-down illuminant hypothesis. The angular error is indicated in the right bottom corner.

Table 1. Mean angular error for several color constancy methods. From left to right: without applying color constancy, worst and best result of Eq. 12, select the best estimate for only the bottom-up (BU) hypotheses, only the top-down (TD) hypotheses, or the combination of bottom-up and top-down hypotheses. The last three columns use the methods proposed in this paper.

<table>
<thead>
<tr>
<th></th>
<th>standard color constancy</th>
<th>high-level selection using Eq.4</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>no cc</td>
<td>worst BU</td>
</tr>
<tr>
<td>indoor</td>
<td>10.2</td>
<td>8.6</td>
</tr>
<tr>
<td>outdoor</td>
<td>5.8</td>
<td>7.7</td>
</tr>
</tbody>
</table>

Combining the bottom-up approaches fails and the top-down approach finds a reasonable illuminant estimate. The bottom-up results are computed with the Grey-World algorithm. Assuming an average grey reflectance yields for both images an unsatisfying illuminant estimation. For example, the reddish sand image in the first row is turned grey by the bottom-up approach. The top-down method succeeds, because one of the topics describes brown sand-like structures, which resulted in a good top-down hypothesis with a high semantic likelihood.

In conclusion, the results show that selecting color constancy methods based on the likelihood that an image is generated by a mixture of topics learned under white lighting, improves color constancy results significantly for outdoor data. On indoor data, results are comparable to the best bottom-up approach.

5.2. Image Pixel Classification

In this experiment we will test the proposed approach on pixel classification. Pixels are to be classified as one of nine classes: building, grass, tree, cow, sheep, sky, water, face, and road. Because we already computed $P(v|m|f, w)$ for each illuminant, pixel classification is only one step away. It is simply obtained by taking the most likely topic for each visual word.

Data set: To learn the nine semantic classes we use the labelled images of the Microsoft Research Cambridge (MSRC) set [26]. We remove images which we consider to be taken under non-white light, and those which did not contain any of the nine semantic classes (resulting in 240 training images). To extend the variability of the training
In this paper we have presented a method to exploit high-level visual information for color constancy. Existing color constancy methods, as well as a new method based on prior knowledge of semantic classes in the world, are used to cast illuminant hypotheses. For each of the hypotheses we analyze the semantic likelihood based on a PLSA algorithm. The illuminant resulting in the most likely semantic composition of the image is selected as the illuminant color of the image. Results for both illuminant estimation and pixel classification into semantic classes demonstrate that using high-level image information improves results significantly.

### Table 2. Percentage of correctly classified pixels.

<table>
<thead>
<tr>
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</tr>
</thead>
<tbody>
<tr>
<td>no cc</td>
<td>worst BU</td>
<td>best BU</td>
</tr>
<tr>
<td>39.6</td>
<td>41.4</td>
<td>52.2</td>
</tr>
<tr>
<td>BU</td>
<td>53.4</td>
<td>59.5</td>
</tr>
<tr>
<td>BU &amp; TD</td>
<td>64.2</td>
<td></td>
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</tbody>
</table>

In conclusions, using the likelihood of images to select the best illuminant to use for pixel classification is proven to be beneficial. The proposed method significantly improved results over standard color constancy methods.

### References

Figure 4. Example of pixel classification. First row: input images. Second row: illuminant corrected images selected by our approach. All four are based on a top-down illuminant hypothesis. The hypotheses are based from left to right on the classes sky, face, grass, and tree. Third row: pixel classification results based on the images in the second row.

**Erratum (23 September 2008)**

A bug occurred in our implementation of experiment 5.1. For the bottom-up approaches we included the whole image in the illuminant calculation. The grey ball should have been excluded.

The correct results of the experiment are shown in Table 3. Selection of the color constancy method based on the semantic likelihood of the images is shown to improve results. For both indoor and outdoor the selected bottom-up approach outperforms the best hand-picked bottom-up approaches (obtained with $n = 0$ and $p = 2$ for indoor, and $n = 2$ and $p = 2$ for outdoor). Combining the bottom-up and top-down cues is shown to help in the case of outdoor images. In conclusion, using semantic likelihood to select the color constancy method obtains a improvement of 10% on the outdoor set and of 20% on the indoor set against the best *hand-picked* bottom-up approach.

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</tr>
</tbody>
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Table 3. Mean angular error for several color constancy methods. From left to right: without applying color constancy, worst and best result of Eq. 12, select the best estimate for only the bottom-up (BU) hypotheses, only the top-down (TD) hypotheses, or the combination of bottom-up and top-down hypotheses. The last three columns use the methods proposed in this paper.

We thank both Peter Gehler and Mark Everingham for bringing this error to our attention.