1. INTRODUCTION

With the fast development of photographic equipment, taking pictures has become the most convenient way to record a scene in our daily lives. The pixel values captured in an image may significantly vary under different illuminant colors, resulting in the so-called color deviation—the color difference between the image under the canonical light (i.e., white light) and the image under the colored (nonwhite) light. This situation not only degrades the image quality but also makes the subsequent applications, such as image retrieval, image segmentation, and object recognition more challenging.

To solve this problem, color constancy [1,2], an ability to reduce the influence of illuminant colors, has become an essential issue in both image processing and computer vision. Generally, there are two categories of methods to accomplish color constancy: One is to represent an image by illuminant invariant descriptors [3,4]; the other is to rectify the color deviation of an image, also called color correction [5–12]. Specifically, the resulting image after color correction will look as though it were pictured under the white light. In this paper, we mainly focus on this second category.

In the previous research on color correction, the illuminant color of an image is estimated first and then is used to calibrate the image color via the Von Kries model [1,13]. If the illuminant color is poorly estimated, the performance of color correction is also degraded. Therefore, how to accurately estimate the illuminant color has become the major concern in color correction [5–12].

Estimating the illuminant color is unfortunately an ill-posed problem [1], so the previous work [5–12] has simplified it by making assumptions on specific image properties, such as the color distribution, the restricted gamuts, or the possible light sources in an image. Land and McCann [5] introduced the white-patch assumption: The highlight patches of an image can totally reflect the RGB spectrum of the illuminant. Namely, the corresponding pixels in these patches can directly represent the illuminant color. Their proposed max-RGB algorithm [5], however, estimates the illuminant color only through pixels with the maximum R, G, B intensities of an image, which are susceptible to image noise as well as to the limited dynamic range of a camera [14], leading to poor color-correction results.

To make the estimated illuminant more robust, we claim that pixels around the maximum image intensity of each color channel should also be considered. That is, we average the R, G, B intensities of these pixels and the maximum intensity pixels—jointly named the representative pixels in our work—to be the illuminant color of an image. By applying the normalized accumulative color histogram, which records the percentage of pixels with intensities above an intensity bound, the representative pixels can be identified according to the bound of a certain percentage value. Now, the remaining problem is to select an appropriate percentage value to determine the representative pixels.

Inspired by the claim in Gasparini and Schettini [15]—the farther the chromaticity distribution is from the neutral point, the stronger the color deviation is—and our observations illustrated in Fig. 1, in which the chromaticity distribution of an image under the white light is nearly neutral, an iterative algorithm for percentage selection with the following two stages is proposed:

- Increasingly, pick up a percentage value (from 1 to 100%), determine the representative pixels, calculate the illuminant color, and then perform color calibration via the Von Kries model to get the color-corrected image.
Measure the closeness between the chromaticity distribution of (a), (b). Clearly, the change in color space). When the scene is achromatic, the gray-world mechanism is introduced to stop the iterative process. Finally, the estimated illuminant and the Von Kries model. Details are described in Section 3.

2. RELATED WORK

As mentioned in Section 1, algorithms of color correction generally consist of two stages: illuminant estimation and color calibration. Among all kinds of color calibration models, the Von Kries model [1,13] has become the standard in the literature. Therefore, the performance of color correction usually is evaluated by the accuracy of illuminant estimation. In the following, several illuminant estimation algorithms relevant to the proposed work are reviewed.

The max-RGB algorithm, a practical implementation of Land's white-patch assumption [5], takes the maximum intensities of the three color channels individually as the illuminant color components. Merely considering the pixels with the maximum intensities is susceptible not only to the image noise but also to the limited dynamic range of a camera [14], which usually leads to a poor illuminant color. Our method, by contrast, takes extra pixels around the highest intensities into account and hence makes the estimated illuminant more robust.

According to the assumption that the 1st-Minkowsky norm (i.e., L1 norm) of a scene is achromatic, the gray-world hypothesis [6] takes the normalized L1 norm (normalized by the pixel number) of each color channel as the illuminant color. Then, Finlayson and Trezzi [7] interpreted the max-RGB method and the gray-world hypothesis as the same illuminant estimation algorithm with different pth-Minkowsky norms: The max-RGB method exploits the L∞ norm, whereas the gray-world algorithm applies the L1 norm. They also suggested that the best color-correction result could be achieved with the L0 norm. This work was later improved in the general gray-world hypothesis [8] by further including a smoothing step on input images.

With the consideration of all the pixels in the illuminant estimation process, algorithms in Buchsbaum [6], Finlayson and Trezzi [7], and van de Weijer et al. [8] are more robust to both the image noise and the color clipping than the max-RGB method. Nevertheless, if an image contains a dominant color, these three methods incline to predict the illuminant color toward such dominant color, resulting in an unreliable illuminant color. Taking a picture full of green forests as an example, all of them will predict the illuminant color biasedly toward the green color. Conversely, our method averages only the pixel values higher than a certain bound, which provide more information about the illuminant color than the pixels with lower intensities [16]. Hence, the estimated illuminant color would not be dominated by the major color (e.g., the green forests) in an image.

Slightly different from the general gray-world hypothesis, the gray-edge hypothesis [8] suggests that the pth-Minkowsky norm of the first- or higher order image derivatives in a scene is achromatic; therefore, it takes the normalized pth-Minkowsky norm over all the derivative values with a specific order (computed in each channel) to be the illuminant color.
Like the (general) gray-world hypothesis, similar problems may occur in this method.

In the existing literature, the approaches mentioned thus far are categorized as the low-level statistics-based method [1]; the gamut-mapping method and its variants [2-11] form another popular category for illuminant estimation, which suggests that given an illuminant source, only a limited number of colors can be observed. Methods in this category attempt to map the input gamut into the canonical gamut, which requires a learning step with as many surface colors as possible. Because collecting varieties of surfaces is tedious, the quality of the estimated illuminant is easily degraded because of the poorly learned canonical gamut.

Unlike these categories, Tan et al. [12] estimated the illumination chromaticity by first finding the highlight pixels, projecting them to the inverse-intensity chromaticity space, and finally applying the Hough transform to estimate the illuminant chromaticity. Still suffering the limited dynamic range of a camera as well as the image noise, the highlight pixels are practically unreliable and hence result in inaccurate illuminant estimation.

3. PROPOSED COLOR CONSTANCY APPROACH

In this section, the proposed algorithm, including an illuminant estimation step and a percentage selection step as illustrated in Fig. 2, is described in more detail with three parts. First, the concept of representative pixels and how they contribute to the illuminant estimation step are introduced (in Subsection 3.A). Then, in the second part, the percentage selection method for determining the suitable set of representative pixels via chromaticity neutralization is presented (in Subsection 3.B). Finally, two early stopping criteria for efficiency and avoiding the overcorrection problem are discussed (in Subsection 3.C).

A. Illuminant Estimation with Representative Pixels

Inspired by the max-RGB algorithm [5], and considering the effect of the image noise as well as the limited dynamic range of a camera, we modify the original white-patch assumption [5] as follows: The pixels with intensities larger than a certain intensity bound in each color channel could jointly represent the illuminant color. More specifically, for illuminant estimation, we propose to consider not only the pixels with the maximum $R$, $G$, $B$ intensities but also the pixels with intensities around these maximum intensities, which are less vulnerable to the restricted dynamic range of a camera and the image noise. Through jointly considering all these pixels, named the representative pixels in our work, the estimated illuminant color could be more robust.

According to these modifications, the original illuminant estimation problem now can be converted into the exploration of the representative pixels. By applying the normalized accumulative color histogram in each color channel, which records the percentages of pixels with intensities above an intensity bound, the representative pixels are determined by selecting a suitable percentage $p$. This selected percentage $p$ simultaneously indicates the $R$, $G$, $B$ intensity bounds as illustrated in Fig. 3, and pixels with intensities above each bound are chosen to be the representative pixels of that color channel (the representative pixels of each channel could be different). The mechanism for selecting a suitable percentage will be described in Subsection 3.B.

After the representative pixels are identified, the illuminant color is estimated by averaging their intensities, and the color-corrected image can be acquired via the Von Kries model. The proposed illuminant estimation method is summarized in Table 1.

B. Percentage Selection by Chromaticity Neutralization

The proposed percentage selection method is inspired by the color-cast detection method in Gasparini and Schettini [15], which detects the color deviation (the color difference between the image under the white light and the image under the colored light) in the $L^*a^*b^*$ color space. According to the claim in Gasparini and Schettini [15]—that is, the farther the chromaticity distribution of image pixels is from the neutral point, the more serious the color deviation is—and our additional observations in Fig. 1, we found the following phenomena that facilitate the development of the percentage selection method: First, the illuminant color affects more on the chromaticity distribution than on the lightness. Second, the chromaticity distribution of an image under the white light is nearly neutral. In our work, the chromaticity distribution is defined on the $a^*b^*$ plane of the $L^*a^*b^*$ color space.

On the basis of these two phenomena, an appropriate percentage value should make the chromaticity distribution (from phenomenon 1) of the color-corrected image nearly neutral (from phenomenon 2). Because increasing the percentage value usually moves the chromaticity distribution of the corresponding color-corrected image toward the neutral point (at $a^* = 0$ and $b^* = 0$) as shown in Fig. 4, we could iteratively increase such value and then select the one that makes the resulting chromaticity distribution nearly neutral. To avoid confusion, the color-corrected image with the finally selected percentage is called the output-corrected image. In our method, the degree of neutralization is modeled as the closeness between the neutral point and a feature point that can represent the chromaticity distribution of the color-corrected image. By considering the efficiency and the robustness against outliers, the median values of $a^*$ and $b^*$ (called the median chromaticity) in the chromaticity distribution are selected as the feature point; the $L_2$ distance from the median...
chromaticity to the neutral point is denoted as the neutralization distance of the color-corrected image. The illustrations of these terms are provided in Fig. 4. Notice that the neutralization distance varies with the change in percentage values.

To execute the iterative process mentioned previously, named the chromaticity neutralization process in our work, we try the percentage values increasingly from 1% with a step size 1%. This execution guarantees that we can find the (integer) percentage with the minimum neutralization distance; however, trying all of the percentage values is tedious work and may degrade the efficiency of our color constancy approach. Furthermore, according to our experiments, a few test images are observed to suffer the so-called overcorrection problem during the chromaticity neutralization process; that is, after several iterations before reaching the percentage with the minimum neutralization distance (e.g., 45% in Fig. 4), the chromaticity distribution of the color-corrected images may shift away from the quadrant of the original color deviation, resulting in an opposite color deviation in the color-corrected image. Figure 4 illustrates this problem on an original greenish image, where the reddish deviation occurs during the iterative process.

C. Early Stopping Mechanism in Percentage Selection

To achieve efficiency and prevent the overcorrection problem (e.g., with 45% in Fig. 4), an early stopping mechanism of the chromaticity neutralization process is required. In our experiments, we found that almost all of the images having the following monotonic property: Before reaching the percentage with the minimum neutralization distance (e.g., 45% in Fig. 4), increasing the percentage values will monotonically decrease the resulting neutralization distance. On the basis of this finding, the first stopping criterion is designed as follows:

**Criterion 1:** In the chromaticity neutralization process, if the neutralization distance (as shown in Fig. 4) with the next percentage value is larger than the one with the current percentage value, the current percentage value is selected for final illuminant estimation.

Moreover, we observed that for images with the overcorrection problem, increasing the percentage value not only decreases the neutralization distance but also enlarges the gap between the maximum and the minimum color components of the $L_2$-normalized illuminant color (denoted as the component gap), as illustrated in Fig. 4. And when the component gap goes above a certain value, the resulting color-corrected

![Fig. 4. (Color online) $ab^*$ distribution (green circular dots) and the median chromaticities (red triangular dots) of a greenish input image and of subsequent corrected images at different percentage values. As shown, increasing the percentage value moves the median chromaticity toward the neutral point at $a^* = 0$ and $b^* = 0$; the neutralization distance, calculated by $L_2$ distance, also becomes smaller. In addition, when the gap between the maximum and the minimum components (illustrated with RGB bars) of the $L_2$-normalized illuminant color is larger than a certain threshold, the overcorrection problem occurs (as shown in the bottom-right example at $p = 45\%$). The reddish deviation can be obviously seen from the brightest intensity part in the red channel image, compared to the deviations of $p = 1\%$ and $p = 10\%$.](image-url)
image starts to be overcorrected (e.g., with 45% in Fig. 4). According to this phenomenon, the second criterion, for avoiding overcorrection, is defined as follows:

**Criterion 2:** If the component gap (as illustrated in Fig. 4) of the next normalized illuminant color (estimated by the next percentage) exceeds a certain threshold, the current percentage value is selected.

Rather than defining a constant threshold, setting an adaptive threshold for each image could better alleviate the overcorrection problem. Notice that the main goal of illuminant estimation is to predict the ground-truth illuminant color (of the input image); therefore, if the normalized ground-truth illuminant has a large component gap, the corresponding threshold theoretically should be high enough (i.e., higher than this ground-truth component gap) to prevent an incorrect early stoppage. It is, however, impossible to base the threshold directly on the ground-truth component gap, because the ground-truth illuminant color is unknown in real applications.

To reach this connection, the relationship between the component gap of the ground-truth illuminant and the color deviation of the input image offers a solution—that is, these two terms have a positive correlation. For example, the white light \( e = [1, 1, 1]^T / \sqrt{3} \), which results in no color deviation, has a zero component gap (the smallest); the pure blue light \( e = [0, 0, 1]^T \), on the other hand, has a component gap equal to 1 (the largest). Inspired by this fact, we model the threshold in Criterion 2 as a function of the input color deviation, and the larger the color deviation is, the higher the threshold is. The implementation details of the percentage selection algorithm with the early stopping mechanism are listed in Table 2. The two stopping criteria are combined in an “OR” fashion; that is, if one of them is reached, the iterative process is then terminated.

### 4. EXPERIMENTAL EVALUATION

The performance of the proposed color constancy algorithm is evaluated on the two benchmark databases: the gray-ball image set by Simon Fraser University (SFU-gray-ball [17]) and the color-checker image set by Microsoft Research Cambridge (MRC color-checker [18]), both of which are given the ground-truth illuminant colors. Additionally, several web images pictured under different light sources are also tested. To demonstrate the effectiveness of the proposed method, the following related work is compared: the max-RGB method [3]; the gray-world hypothesis [3] (denoted as GW); the shade of gray method [7] (denoted as SoG); the general gray-world algorithm [8] (denoted as GGW); the first, second-order gray-edge hypotheses [8] (denoted as GE1, GE2); pixel-, edge-, and

<table>
<thead>
<tr>
<th>Method</th>
<th>Median</th>
<th>Trimean</th>
<th>Mean</th>
<th>SD</th>
</tr>
</thead>
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<td>6.8</td>
<td>5.5</td>
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<td>5.4</td>
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<tr>
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<td>5.5</td>
<td>6.1</td>
<td>4.2</td>
</tr>
<tr>
<td>GGW [8]</td>
<td>5.3</td>
<td>5.5</td>
<td>6.1</td>
<td>4.2</td>
</tr>
<tr>
<td>GE1 [8]</td>
<td>4.7</td>
<td>5.1</td>
<td>5.9</td>
<td>4.2</td>
</tr>
<tr>
<td>GE2 [8]</td>
<td>4.9</td>
<td>5.3</td>
<td>6.1</td>
<td>4.4</td>
</tr>
<tr>
<td>PBGM [9]</td>
<td>5.8</td>
<td>6.1</td>
<td>7.1</td>
<td>5.3</td>
</tr>
<tr>
<td>EBGM [10]</td>
<td>5.8</td>
<td>6.0</td>
<td>6.8</td>
<td>4.8</td>
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<tr>
<td>IBGM [11]</td>
<td>5.8</td>
<td>6.1</td>
<td>6.9</td>
<td>5.0</td>
</tr>
<tr>
<td>UIICS [12]</td>
<td>5.6</td>
<td>5.8</td>
<td>6.6</td>
<td>5.1</td>
</tr>
<tr>
<td>Proposed</td>
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<td>4.9</td>
<td>5.8</td>
<td>4.6</td>
</tr>
</tbody>
</table>

### Table 2. Percentage Selection by Chromaticity Neutralization

**Presetting:**
- Set the starting percentage \( p = 1 \%), and the increasing step size \( \Delta p \) be 1%.
- The median chromaticity of the input image \( I \) is computed by converting \( I \) from the RGB color space to the \( L^*a^*b^* \) color space, dropping the pixels with \( L^* < 30 \) or \( L^* > 95 \), and finally computing the median values of \( a^* \) and \( b^* \) from the remaining pixels. The dropping operation is inspired by the fact that the chromaticities of too dark and too bright pixels are unreliable [19].
- Denote the neutralization distance at a percentage \( p \) as \( d_N(p) \), and set \( d_N(0) \) as the initial neutralization distance computed from the median chromaticity of \( I \).
- Denote the mapping function \( f \) from the color deviation of \( I \) to the overcorrection threshold \( T(I) \) as follows:
  \[
  T(I) = f(d_N(0)) = 1 + \exp(-s \times (d_N(0) - b)),
  \]
  where \( s \) and \( b \) are scalars controlling the slope and the translation of the sigmoid function \( f \) and will be defined in Section 4.

**Procedure:**
1. At percentage \( p \), perform the algorithm in Table 1 to get the estimated illuminant \( e_I(p) \), which is then used to calibrate the input image \( I \) via the Von Kries model. The corrected image is denoted as \( CI(p) \). 2. Convert \( CI(p) \) from the RGB color space to the \( L^*a^*b^* \) color space and drop the pixels with \( L^* < 30 \) or \( L^* > 95 \). The remaining pixels are then used to compute the median chromaticity \( m(p) \).
3. Compute the neutralization distance \( d_N(p) \) from \( m(p) \); compute the component gap \( G_C(p) \) from \( e_I(p) \).
4. Check the early stopping criteria:
   - Criterion 1: \( d_N(p) > d_N(p - \Delta p) \), for the efficiency concern
   - Criterion 2: \( G_C(p) > T(I) \), for avoiding overcorrection

**If none of the criteria is reached, set** \( p = p + \Delta p \), and **repeat the procedure from step 1 to step 4**.

**5. Output:** The percentage \( p - \Delta p \) is selected as the final percentage; the corresponding \( e_I(p - \Delta p) \) and \( CI(p - \Delta p) \) are the output illuminant color and the output-corrected image of the input image \( I \). If \( p - \Delta p = 0 \% \), no color correction is performed on \( I \); the illuminant color is the canonical light.
intersection-based gamut mappings (denoted as PBGM [9], EBGM [10], IBGM [11]); and inverse intensity chromaticity space [12] (denoted as UIICS). The gray balls or the color checkers in either of two image sets are masked during all experiments.

For an image, the performance of illuminant estimation is measured via the most popular criterion—that is, the angular error $\varepsilon_{\text{angle}}$ between the estimated illuminant $e_E$ and the ground-truth illuminant $e_G$ [1,13]:

$$
\varepsilon_{\text{angle}} = \cos^{-1} \left( \frac{e_E \cdot e_G}{\|e_E\| \|e_G\|} \right). \tag{3}
$$

Gijsenij et al. [19] proved that this error correlates reasonably well with the perceived quality of the output color-corrected images.

<table>
<thead>
<tr>
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<th>Mean</th>
<th>SD</th>
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<td>7.3</td>
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<td>GW [6]</td>
<td>7.4</td>
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<td>8.3</td>
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<tr>
<td>SoG [7]</td>
<td>5.3</td>
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<td>7.0</td>
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<td>GGW [8]</td>
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<td>7.0</td>
<td>6.4</td>
</tr>
<tr>
<td>GE1 [8]</td>
<td>5.2</td>
<td>5.5</td>
<td>7.0</td>
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<tr>
<td>GE2 [8]</td>
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<td>6.8</td>
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<td>UIICS [12]</td>
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<td>Proposed</td>
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<td>5.7</td>
<td>7.2</td>
<td>6.8</td>
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</table>

For an image database as a whole, we measure the performance of illuminant estimation by summarizing the angular errors of all images in the database. The mean value is a general choice of summarization, but not the best, because the distribution of the angular errors generally is nonuniform [1,19,20]. Two more appropriate summarizations suggested in Gijsenij et al. [19] and Hordley and Finlayson [20] are the median value, which can represent the majority error of an image set, and the trimean value, which considers both the majority and the extreme values of the angular error distribution. In our experiments, the three summarized angular errors as well as the standard deviation (SD) of the angular errors are computed; the results of the two databases are shown in Tables 3 and 4. In addition, the parameters $s$ and $b$ mentioned in Table 2 are set for the SFU and MRC databases, respectively, by the 15-fold and 3-fold cross validation [1].

A. Experiments on the SFU Real-World Image Set

The illuminant estimation results of the SFU database are shown in Table 3, where the median, trimean, mean, and SD values of angular errors for all compared work can be found in Gijsenij and Gevers [21]. It is clear in Table 3 that the proposed method outperforms other approaches in the summarized angular errors. The max-RGB algorithm, considering only the maximum intensities, performs similarly to SoG and GGW but performs worse than GE1 and GE2. UIICS and the three gamut-mapping methods (PBGM, EBGM, and IBGM) all perform poorly on this database, even though they are of elaborate formulations. In Fig. 5, two example images and the color-corrected results with all the compared illuminant estimation methods are illustrated; obviously, the results with our method are perceived to be the most similar to those with the ground-truth illuminant colors. Also from Fig. 5, GW leads
to the overcorrection problem, and other approaches cannot remove the original color deviation effectively for Input Image 1.

B. Experiments on the MRC Real-World Image Set

In Table 4, the summarized angular errors and the SD values of the MRC database are displayed; the angular errors of all the compared work can also be found in Gijsenij and Gevers [21]. As presented, our method is comparable to the gamut-mapping methods (PBGM, EBGM, IBGM) but slightly worse than the gray-edge methods (GE1, GE2). According to our observations, images in the MRC database generally have small or almost no color deviations compared with the SFU database; this phenomenon may restrict the power of our algorithm, which corrects images well with stronger color deviations.

To demonstrate this restriction, we select 200 images with larger color deviations from the 568 images of the MRC database and show the corresponding illuminant estimation results in Table 5. The magnitude of color deviations (for selecting images) is calculated by the angle between the white light \( e = [1, 1, 1] / \sqrt{3} \) and the ground-truth illuminant of images. As presented, the proposed method outperforms other algorithms on the 200 images with large color deviations; the overall performance on the 568 images is slightly degraded because of the rest of the images with smaller color deviations.

In Fig. 6, two example images from the MRC database and the color-corrected results with different illuminant estimation methods are presented. Clearly, the max-RGB algorithm cannot alleviate the color deviation for Input Image 1: The corresponding color-corrected image still looks quite yellowish. The performances of our approach and other algorithms on Input Image 1, except for GE1 and UIICS, are plausible. On Input Image 2, GW, SoG, GGW, and GE1, GE2 perform slightly better than our method; UIICS shows nearly no effect on the input image, producing the worst result.

C. Experiments on the Web Images

In this subsection, we take an additional step to see whether our approach can work on web images whose ground-truth illuminant colors usually are not available. In this condition, the performance of color correction is compared via the perceptual quality of the color-corrected images. Similar to Gijsenij et al. [19], we invite 14 subjects who have normal color vision and basic knowledge of color constancy to judge the quality of the color-corrected results. The judgment procedure includes a sequence of pairwise comparisons. That is, all of the subjects are shown three images at once (the original image and the corrected images of two color-correction algorithms) and then are asked to choose one (or both) of the corrected images that looks better: If both are chosen, they each get a score 0.5. Otherwise, the chosen one gets a score of 1; the other, a score of 0. The final performance of each color-correction algorithm is computed by summing up all scores of the 14 subjects. The parameters of our method (for the
The mapping function defined in Table 2 are computed from the SFU image set: This database contains images under various illuminant colors and hence is suitable for training the parameters for web images.

In Fig. 7, our color-corrected results on four web images are compared with the ones of max-RGB, GW, and GE1; the total scores from 14 subjects are also displayed (the highest score that an algorithm can get on each image is 42). The results of SoG, GGW, and GE2 are omitted because of the resemblance to those produced by GW and GE1, respectively. Besides, UIICS and the three gamut-mapping methods are not compared either because of the high computational complexity or because of the tedious-learning requirement. As presented, the proposed method achieves the best or the second-best color-correction results, according to the subjective scores. The max-RGB algorithm, on the other hand, is almost invalid for removing the color deviations, except on the “Lena” image; GW easily overcorrects the image, such as the “Lena” image and the “highway” image. In addition, for the “snow mountain” image with nearly no color deviation, the proposed method is the only algorithm that can retain the white color of the snow and the cloud in the original image, preventing incorrect color correction.

In Fig. 8, we further investigate the performance of the color-correction methods applied on the scenes in which the illuminant color and the object color are exchanged.

![Fig. 7. (Color online) Color-corrected results of web images (rendered under the reddish, greenish, bluish, and nearly neutral light source) with several low-level statistics-based approaches and the proposed method (annotated above the images). The numbers in () represent the total scores given by the 14 subjects for subjective performance judgment (the highest score that an algorithm can get on each image is 42).](image1)

![Fig. 8. (Color online) Color-corrected results of the red room illuminated by the white light (upper row) and the white room illuminated by the red light (bottom row): Several low-level statistics-based approaches and the proposed method (annotated above the images) are compared in this experiment.](image2)
The results of SoG, GGW, and GE2 are omitted again because of the resemblance to those produced by GW and GE1, respectively. As shown, the corrected result of the gray-world algorithm seems overcorrected in the case of the red room illuminated by the white light (the upper row) because of the dominant color in the scene; this problem can be alleviated in our method. With regard to the case of the white room illuminated by the red light (the bottom row), the result of our method is plausible and can be further improved by more suitable parameter settings in Table 2.

D. Discussion
The final selected percentage in our method average 6.67% on the SFU database, and 3.65% on MRC database, demonstrating the efficiency improvement achieved by the proposed early stopping mechanism. To summarize, the proposed approach can effectively estimate the illuminant color and leads to better color-correction results than the existing approaches on a variety of images.

5. CONCLUSION
In this paper, a robust illuminant estimation algorithm for color constancy is proposed. By applying the normalized accumulative color histogram, the proposed method iteratively explores the representative pixels with different percentage values in a color-deviated image for computing the illuminant colors, which are then used for color calibration via the Von Kries model. The percentage that makes the chromaticity distribution of the color-corrected image nearest to the neutral point is then selected as the best percentage. Further considering the efficiency of our method and the overcorrection problem, we present two criteria to stop the iterative process. When the best percentage value is reached, both the final estimated illuminant and the output color-corrected image are simultaneously obtained.

The experimental results show that our method outperforms other approaches in the SFU image set and has comparable performance with the gamut-mapping methods in the MRC image set, according to the three summarized angular errors. Furthermore, appealing color-corrected results on web images also demonstrate the effectiveness of the proposed approach.

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