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Hierarchical Integrated Color Matching in a Stereoscopic Image based on Image Decomposition

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Abstract. *Color discrepancies between the left and right image in a stereoscopic image cause many problems, including a reduction of the three-dimensional effect and increased visual fatigue. Thus, color matching in a stereoscopic image is very important for three-dimensional display systems. Therefore, a hierarchical integrated color matching method based on image decomposition is proposed for stereoscopic images. In the proposed method, global and local color discrepancies generated in a stereoscopic image are effectively reduced by histogram matching and illuminant estimation using image decomposition. The stereoscopic image is first decomposed into a base layer and several texture layers. Each decomposed layer is then matched using cumulative histogram matching and a multi-scale retinex algorithm. Lastly, inverse decomposition is applied to each layer to reconstruct the corrected stereoscopic image. Experimental results show that the proposed method has a better color matching performance in comparison with previous methods.*
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INTRODUCTION

With the recent development of 3D (three-dimensional) televisions and stereoscopic cameras, 3D imaging has become an important research focus. In 3D imaging systems, a left and right image captured by a stereoscopic camera are simultaneously represented in a 3D display, and then respectively perceived by the right and left eye to experience 3D perception. However, when the left and right images are acquired, color discrepancies are generated from different characteristics of the stereoscopic camera, such as the white balance, signal gain, and optics. The lighting conditions of a scene and differences in the reflectance of objects can also generate color discrepancies. Since these color discrepancies reduce the 3D effect and increase visual fatigue, color matching of stereoscopic images is important for 3D imaging.[1–3]

Color matching is also essential for a multi-view camera, which is an extended version of a stereoscopic camera. A multi-view camera captures a scene using several cameras located at different positions at the same time. Consequently, significant color discrepancies are generated in a multi-view image. Such color discrepancies deteriorate the virtual image at the specific viewing position generated by image-based rendering due to color shifts between the different views of the same scene.[3–6] This also degrades the coding efficiency in multi-view video coding (MVC). To efficiently compress the huge amount of data from a multi-view camera, the redundancy among the multi-view images has to be removed. However, color discrepancies between multi-view images induce incorrect disparity matching and degrade the coding efficiency. Therefore, to improve the compression performance in MVC, it is important to correct the color discrepancies between cameras.[7]

Various color matching methods have already been developed to reduce the color discrepancies with stereoscopic cameras and multi-view videos. Histogram matching which adjusts a histogram is the most popular color matching method. After selecting a reference image among the captured images, the histogram of a degraded image is modified to match the histogram of the reference image using a mapping function. The mapping function is derived from a weighted model or cumulative histogram. While histogram matching with a weight model defines a weight model reflecting environmental variations as a linear mapping function, cumulative histogram matching derives this mapping function based on a cumulative histogram[7–9]

Local region-based matching is another method. To consider a local statistical color distribution, corresponding local regions between the reference and the degraded images are determined using several matching methods, and the local mapping function is then derived from these regions.[5,10,11] In Ref. 5, after using a block matching method to find matching blocks in each image, a polynomial function is calculated using a least-squares regression, thereby matching the local statistical color distribution characteristics. In Ref. 10, RANSAC (RANdom SAmple Consensus) and a feature such as a corner or local invariant detector are used to find the corresponding features in stereoscopic images. The color discrepancies are then reduced by applying a color transform matrix. Corresponding segmented regions are also identified.[11] It is assumed that every pixel in a region segmented by a mean shift has the same color distortion characteristics. Therefore, individual color transformation is applied for identical segmented regions.

Recently, a hybrid color matching method was proposed for reducing global and local discrepancies simultaneously. Global color discrepancies are corrected using a modified histogram matching method, while local color discrepancies

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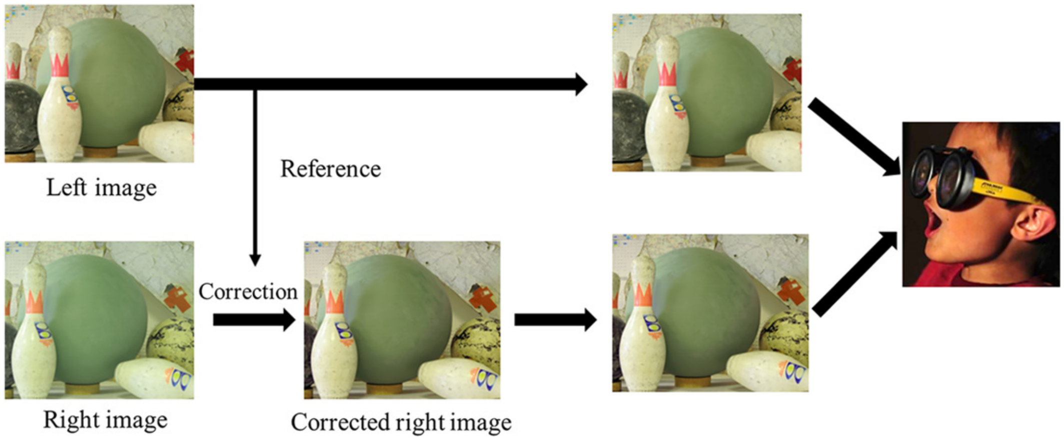

Figure 1. The basic procedure for color matching in a stereoscopic image.

are reduced by a weighted vector from feature matching between images.[12] However, this method can introduce local errors due to an inaccurate weighted vector. Therefore, modified hybrid color matching, called integrated color matching, has been proposed. It is presented using the 3D distance, which measures the reality distance between the current pixel and sample features which are the refined matching features. The algorithm first performs global matching using cumulative histogram matching. Local matching is then performed using a pixel-wise correction method considering a loop-up table of all the sample features.[13]

However, the weakness of these hybrid methods is that the accuracy of the color correction is dependent on the feature detectors, matching procedures, and color transform methods. Moreover, the determination of the feature points and matching procedure incurs a large computational cost. The histogram matching of these methods also induces a discontinuity in the bins of the histogram, thereby increasing the average color differences between images.

Accordingly, this article proposes a method that effectively reduces the local and global color discrepancies without a local region-based matching method. The proposed method uses image decomposition to match the stereoscopic images and the colors are matched at each decomposition level using cumulative histogram matching and a multi-scale retinex algorithm. As a result, local and global color discrepancies are both greatly reduced. The remainder of this article is organized as follows. The second section describes the proposed method, the third section presents experimental results, and the final conclusions are given in the fourth section.

THE PROPOSED METHOD

Concept of the Proposed Method

The basic procedure for color matching in a stereoscopic image is presented in Figure 1. Generally, one of the two images from a stereoscopic camera is selected as the reference image, and the colors in the second image are then matched to those in the reference image. After correcting the color discrepancies between the left and right images, each image is perceived using the left and right eyes.

The color discrepancies in a stereoscopic image can be divided into global and local color discrepancies. While global color discrepancies are represented as a uniform color difference across the whole image, local color discrepancies are represented as regional color differences. Thus, to reduce both types of discrepancy, this article introduces a novel color matching approach based on image decomposition.

The concept of the proposed color matching method is to correct color discrepancies based on histogram matching and illuminant estimation with image decomposition. A global color discrepancy is mainly generated due to the characteristics of the camera, so each channel of the degraded image undergoes a modification with respect to the reference image.[14] This modification affects the whole image and can be represented by a different shaped histogram. Thus, global color discrepancies can be corrected by applying histogram mapping to each channel, which means that each pixel count in the degraded image histogram is adjusted to make it similar to the reference image histogram.

In the proposed method, local color discrepancies are considered as the local illuminant difference. Thus, for local color matching, the local illuminants in the reference image and degraded image are estimated using the multi-scale retinex algorithm.[15–18] The estimated local illuminant in the degraded image is then compensated to match the estimated local illuminant in the reference image.

Color Matching Based on Image Decomposition

The flow of the proposed method is presented in Figure 2. Using the left image as the reference image, the stereoscopic image is decomposed on multiple levels. After decomposing the stereoscopic image, the local and global color matching is recursively performed at each decomposition level. The corrected right image is then reconstructed.

Image decomposition is the process of separating an image into different components. While a high level of decomposition contains the edge components, a low level contains the smooth components, all of which are common

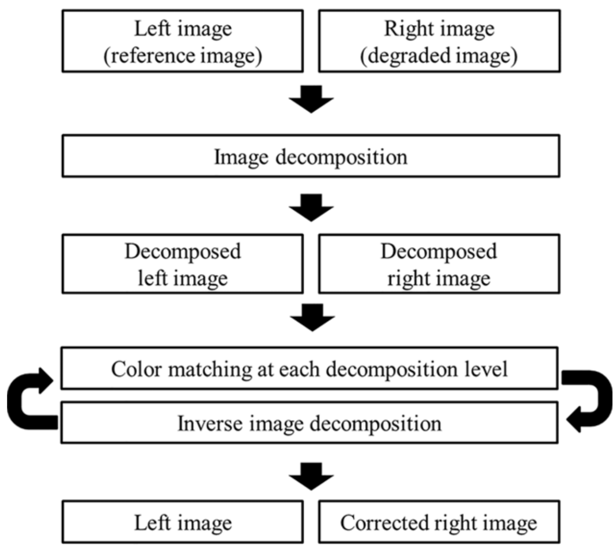

Figure 2. The flow of the proposed method.

components between the left and right stereoscopic images. In the proposed method, a Laplacian pyramid is used for the image decomposition. Laplacian pyramid decomposition is simple and efficient, and reflects the multiple processing levels in the human visual system.[19,20] When using Laplacian pyramid decomposition, an image $I(x, y)$ can be divided into hierarchical images that contain different frequency bands of the image:

$$I(x, y) = \sum_{l=1}^{k} L\{I(x, y)\}^{(l)}, \tag{1}$$

where k is the number of Laplacian pyramid decomposition levels and $L\{\cdot\}^{(l)}$ is the lth level of Laplacian pyramid decomposition. The first decomposition level represents the base layer of the image.

The colors in the stereoscopic images at each decomposition level are then matched using cumulative histogram matching and the multi-scale retinex algorithm. Cumulative histogram matching is used for global color matching. Here, $h^{(l)}$ is defined as the histogram of the lth level Laplacian pyramid decomposition, which is intended to obtain the cumulative histogram:

$$h^{(l)}(n) = \frac{1}{w \cdot h} \sum_{y=0}^{h-1} \sum_{x=0}^{w-1} \delta(n, I^{(l)}(x, y)),$$

$$\text{with } \delta(a, b) = \begin{cases} 1, & \text{if } a = b, \\ 0, & \text{else,} \end{cases} \tag{2}$$

$$c^{(l)}(n) = \sum_{n=0}^{255} h^{(l)}(n), \tag{3}$$

where $I^{(l)}(x, y)$ is the intensity of the lth level of Laplacian pyramid decomposition at position x, y, and w and h denote the width and the height of the image, respectively; $c^{(l)}(n)$ is the cumulative histogram of the lth level of Laplacian pyramid decomposition.

The mapping function for modifying the histogram is derived by comparing the cumulative histograms of the reference and degraded images. It adjusts the number of occurrences in the histogram. Thus, the shapes of the two histograms are matched. Here, $f^{(l)}(n)$, which is the mapping function in the lth level of Laplacian pyramid decomposition, is calculated as follows:

$$f^{(l)}(n) = p, \quad \text{with } c_r^{(l)}(p) < c_d^{(l)}(n) < c_r^{(l)}(p+1), \tag{4}$$

where the subscripts r and d denote the reference image and the degraded image, respectively. After deriving the mapping function from the lth level cumulative histograms for the reference image and degraded image, the shape of the histogram of the lth level of the degraded image can be modified. The globally corrected image of the lth level of Laplacian pyramid decomposition, $I_d^{\prime(l)}(x, y)$, is calculated as follows:

$$I_d^{\prime(l)}(x, y) = f^{(l)}(I_d^{(l)}(x, y)). \tag{5}$$

However, since global color matching is only based on whole statistical distributions and does not use the spatial information of the pixels, local color matching is also needed.

For local color matching, the proposed method uses the multi-scale retinex algorithm. The local color matching is considered as local illuminant matching. Thus, the local illuminants of the degraded image are matched with those of the reference image at the decomposition level. From the principle of retinex theory, an image $I(x, y)$ can be defined as follows:

$$I(x, y) = R(x, y) \cdot E(x, y), \tag{6}$$

where $E(x, y)$ represents the illumination and $R(x, y)$ represents the reflectance of an image. In the multi-scale retinex algorithm, a weighted average of the surrounding pixel values at each different scale is regarded as the estimated illumination and is used to compute the estimated reflectance. An image that has already been globally corrected is separated into illumination and reflectance using the multi-scale retinex algorithm, where a Gaussian-filtered image is regarded as the estimated local illuminant of the image, $E_d^{\prime(l)}(x, y)$. Three Gaussian filters, small, medium, and large scale, are generally used to estimate the local illuminant by adjusting σ_s:

$$E_d^{\prime(l)}(x, y) = \sum_{s=1}^{3} w_s \{F_s(x, y) * I_d^{\prime(l)}(x, y)\},$$

$$F_s(x, y) = K e^{-(x^2+y^2)/\sigma_s^2} \quad \text{and} \quad \int\int F_s(x, y) \mathrm{d}x\mathrm{d}y = 1, \tag{7}$$

where w_s represents the weight of the sth level of Gaussian filter, K is the normalized constant coefficient, and σ_s represents the standard deviation for the sth level of Gaussian filter.

The reflectance of the globally corrected image is calculated based on the division between the image and the

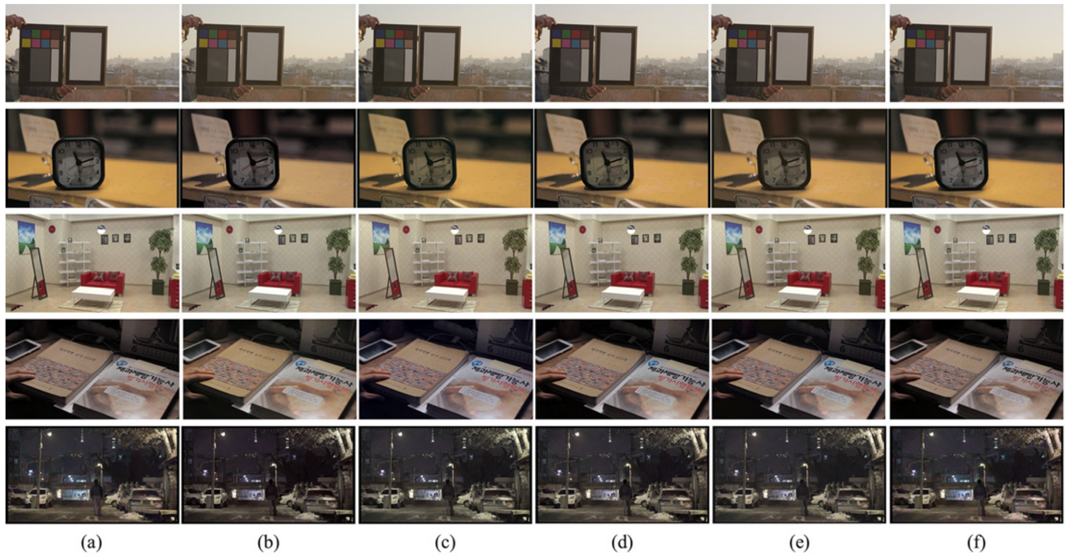

Figure 3. The experiments for color matching in a stereoscopic image: (a) left images (reference images), (b) right images, (c) color-matched right images by histogram matching with a weighted model, (d) color-matched right images by cumulative histogram matching, (e) color-matched right images by integrated color matching, and (f) color-matched right images by the proposed method.

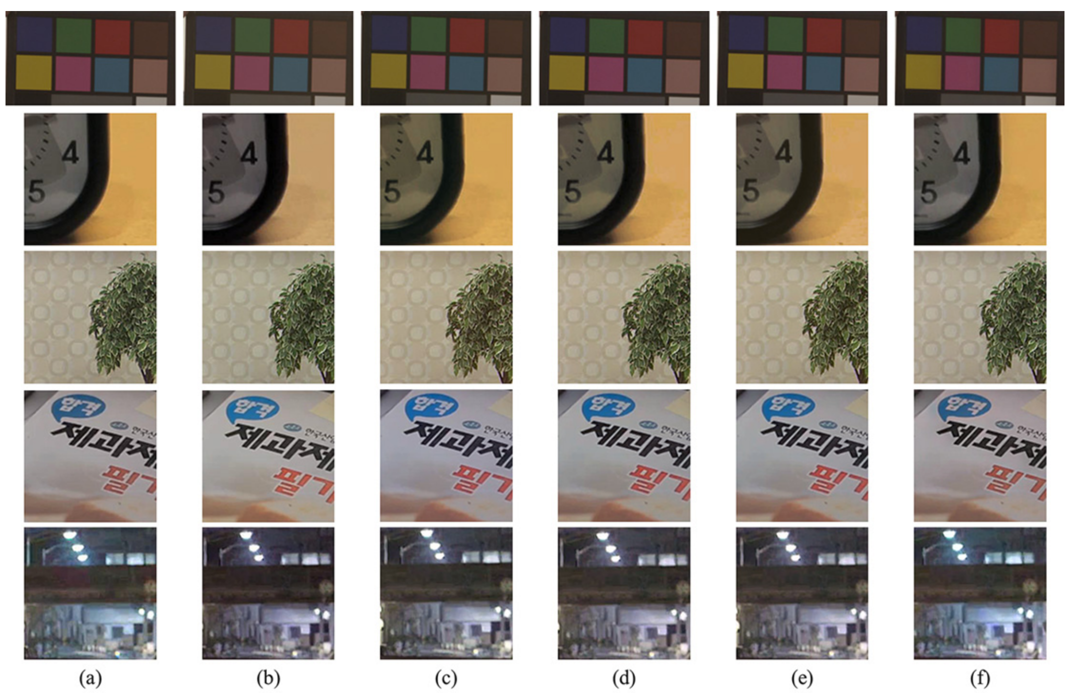

Figure 4. Enlargement of the images shown in Fig. 3: (a) left images (reference images), (b) right images, (c) color-matched right images by histogram matching with a weighted model, (d) color-matched right images by cumulative histogram matching, (e) color-matched right images by integrated color matching, and (f) color-matched right images by the proposed method.

Gaussian-filtered image. The local illuminant of the reference image can be acquired using Eq. (7) by substituting the reference image instead of the globally corrected image. The estimated local illuminant in the degraded image is then compensated by replacing it with the estimated local illuminant in the reference image. While the local illuminant of an image cannot be perfectly estimated using the multi-scale retinex algorithm, this does not have a significant effect on the color matching performance of the proposed method. The purpose of the proposed method is to reduce the difference between the estimated illuminants, which then allows local color matching, even though the estimated local illuminant may not be completely accurate. The globally and locally corrected intensity of the lth level of Laplacian pyramid decomposition, $I''^{(l)}_d(x,y)$, can be calculated as follows:

$$I''^{(l)}_d(x,y) = R'^{(l)}_d(x,y)\cdot E^{(l)}_r(x,y)$$
$$= R'^{(l)}_d(x,y)\cdot\left[\sum_{s=1}^{3} w_s\{F_s(x,y) * I^{(l)}_r(x,y)\}\right], \quad (8)$$

where $R'^{(l)}_d(x,y)$ denotes the reflectance of the globally corrected image of lth level of Laplacian pyramid decomposition.

After the local and global color matching are recursively performed at each decomposition level, inverse image decomposition is applied to reconstruct the left and right stereoscopic images. This recursive local color matching based on image decomposition in the proposed method does not need accurate image registration or a local region-based matching algorithm which has a high computational cost due to the feature detection and matching procedure. Since estimated local illuminant has smooth spatial transition and low level layer component of the right and the left images are mostly common, small displacements in a stereoscopic image have less affect on the recursive local color matching. Furthermore, the degree of color matching is adjustable depending on the number of decomposition levels and recursions for the color matching. The process of the inverse image decomposition is as follows:

$$\bar{I}^{(l+1)}_d(x,y) = I''^{(l)}_d(x,y) + L\{I_d(x,y)\}^{(l)}, \quad (9)$$

where $\bar{I}^{(l+1)}(x,y)$ is the intensity of the $(l+1)$th level of the corrected Laplacian pyramid decomposition at position x, y. Finally, local and global color matching are recursively performed until the last decomposition level. The corrected right image is then reconstructed.

EXPERIMENTAL RESULTS AND DISCUSSION

The color matching performance of the proposed method was evaluated, where the objective of the experiment was to match the colors of the right image with the colors of the left image. The test images were acquired using a vertical rig-type digital cinema camera, where the left and right images are captured using a beam splitter that reflects the scene into two perpendicularly placed cameras. Five test images were used for the experiments. The horizontal displacement of the test images was about four to five percent of the width, while the vertical displacement was almost nothing. Thus, image registration was not applied as a preprocessing step. The number of Laplacian pyramid decomposition levels was set to three, and the local color matching was applied once to the first level.

Figure 3 shows the resulting images from histogram matching with a weighted model, cumulative histogram matching, integrated color matching, and the proposed method. As shown in Figs. 3(a) and (b), the left and right images exhibited several color discrepancies around the color chart, wall, cover of a book,and table clock. However, after applying the color matching methods, the color-matched images showed fewer color discrepancies. Parts of the resulting images are also enlarged and presented in Figure 4 to clearly verify the color matching performance. The color-matched image using the proposed method generated fewer color discrepancies than the other color matching methods. In particular, when comparing parts of the book which has text and a bluish color in the lamp light of the third and fourth row images, respectively, the colors in Fig. 4(f) are the most similar to the colors in Fig. 4(a).

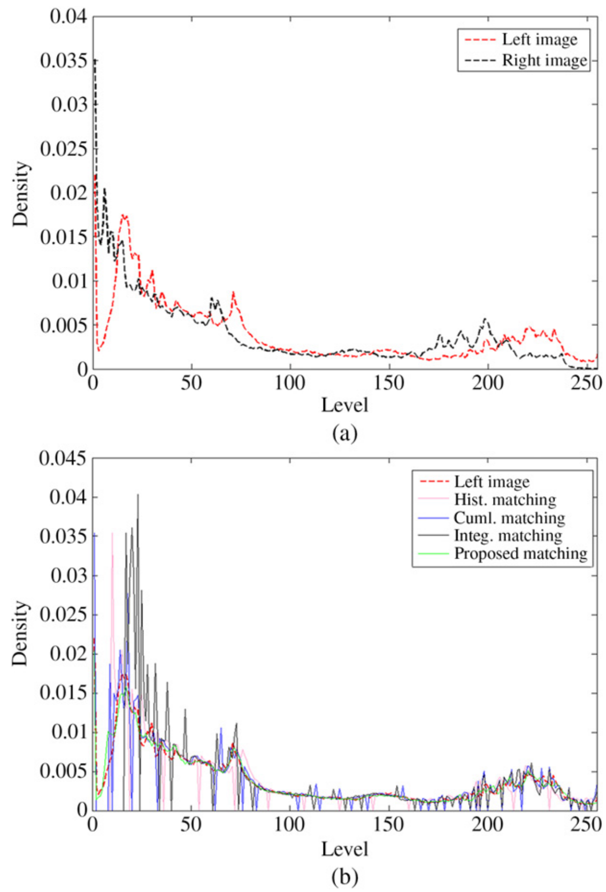

Figure 5. Comparisons of histograms of the image: (a) histograms of the left image and the right image and (b) histograms of the left image and color-matched right images from the different color matching methods.

To specifically evaluate the color matching performance, the shapes of the histograms and the color differences were also compared. The red channel histograms of the left and right images derived from one of the test images are presented in Figure 5(a). The distribution of the right image histogram tends slightly more to the low intensity level than the left image and the peaks of the histogram do not correspond to one another. These dissimilarities between the histograms characterize the global color discrepancies. The histogram of the right image is modified by several color matching methods to follow the histogram of the left image. In Fig. 5(b), histograms of color-matched right images are presented and are compared with the histogram of the left

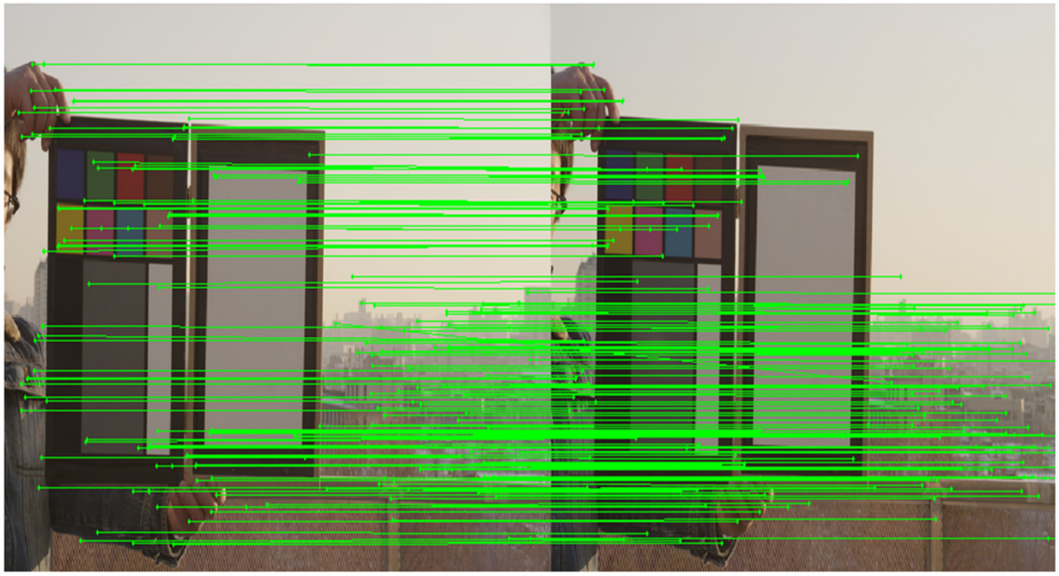

Figure 6. Matched regions of the left and right images for calculating ΔE_{ab}.

image, which is the reference image. The overall shapes of the color-matched right image histograms accord closely with that of the reference image.

However, the previous methods had discontinuity artifacts in the histogram. The modified histogram from histogram matching with a weighed model included equal discontinuity artifacts, while the modified histogram from cumulative histogram matching included non-equal discontinuity artifacts. These artifacts were caused by the linear function and cumulative histogram function used as the mapping functions for histogram modification by the histogram matching with the weighed model and cumulative histogram matching, respectively. In addition, the integrated color matching also showed discontinuity artifacts, where some parts were aggravated due to the local color matching process. In contrast, the histogram of the proposed method was more similar to the reference image and connected with continuity in the histogram. Since the color matching was recursively performed on each decomposition level, the discontinuity artifacts in the histogram were mostly reduced in the proposed method.

For a quantitative evaluation, ΔE_{ab}, representing the color difference between the matched regions in the left and right images, was calculated. Figure 6 shows corresponding feature points from the SIFT (scale-invariant feature transform) algorithm for calculating ΔE_{ab}. A nine by nine block centered on corresponding feature point is selected as a matched region and a total of twelve test images are used to calculate the average color difference.

Table I presents the average ΔE_{ab}. As shown in Table I, the proposed method has the smallest average color difference and represents a reduction of about ten percent when compared with the other methods.

Table I. Average color difference between matched regions.

	Histogram matching with weight model	Cumulative histogram matching	Integrated matching	Proposed method
ΔE_{ab}	5.473	5.471	5.465	5.016

CONCLUSIONS

Color discrepancies in a stereoscopic image reduce the perceived 3D effect and increase visual fatigue. Therefore, this article proposed hierarchical integrated color matching based on image decomposition to reduce such color discrepancies. While local color discrepancies are corrected by matching local illuminants estimated using the multi-scale retinex algorithm, global color discrepancies are corrected using a cumulative histogram matching method. After decomposing the left and right stereoscopic images, local and global color matching are recursively performed on each decomposition level. Experiments showed that the resulting images from the proposed method included fewer color differences when compared with other methods. In future work, the proposed method will be applied to color matching for a multi-view camera and image-based rendering.

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