A Novel Automatic White Balance Method for Color Constancy Under Different Color Temperatures

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ABSTRACT

The spectrum distribution of the light source between scenes is usually uniform in all scenes lit by a given light source per the color constancy assumption. Nonuniform spectrum distribution results in pictures with different color temperatures in different lighting conditions. With the conventional automated white balance method, the results under different degrees of color cast are inconsistent. To resolve this, a new automated white balance algorithm is proposed to achieve uniformity in images with color cast caused by color temperature variations. The proposed method features the selection of near-white points through automated regression and the dynamic adjustment of the color components’ weights. Finally, white balance is implemented according to the selected near-white points with various percentages. The proposed method can effectively select the appropriate white reference point of the image scene under different color temperatures, so that the adjusted results of the method under different color temperatures are close. The first major contribution of this study is the minimization of differences of continual color temperature images with different color temperatures and the achievement of favorable visual effects. The second contribution is the superior outcomes yielded by the proposed method in the visualization and quantification of data compared with those from the existing methods. The experimental results demonstrate that this method yields favorable results in the improvement of experiments with continual different color temperatures. The images at various color temperatures are adjusted to approach real-world color temperatures. In addition, this method provides superior color constancy preservation to other methods.

INDEX TERMS

Color constancy, color temperature, white balance, illumination estimation.

I. INTRODUCTION

When using different shooting equipment, different color temperature cards are used to adjust the color temperatures of images. Pictures shot at high color temperatures appear warm and reddish, whereas pictures shot at low color temperatures appear cold and bluish. White balance usually facilitates adjustment for the problems associated with these two color temperatures. To obtain the color components in one scene, the adjustment values required for white balance may be obtained with a gray card or with the ColorChecker Color Rendition Chart. In natural images, the wavelength of every color in the spectrum has its own attenuation rate. For example, the red wavelength usually attenuates after 5–6 m, orange after 7–8 m, yellow after 10–15 m, and green after 21 m [1]. Consequently, from observation, the attenuation and disappearance of a certain wavelength can result in the absence of one color channel in a scene. In daily life, sunlight is the easiest light source for which color changes may be visually detected. As shown in Figure 1, sunlight generates different light colors at different times of day. This also means that certain color channels sometimes cause color cast in natural scenes due to severe attenuation.

A simpler definition of the so-called “color temperature” is the color of light, and its unit of measurement is “K.” In everyday life, 3000 and 4000 K refer to the color of
the light, meaning color temperature. The current processing method for color temperature is adjustment with the automated white balance processing method. This algorithm usually has three steps. First, the color temperature is estimated, and the white point reference value in the image is identified. Thus, the characteristic quantity and average chromatic aberration value for this image are estimated. The second step of the algorithm is the gain calculation, and the red or blue correction factors of the image are identified. Finally, the RGB color channel values are multiplied by the corresponding correction factors to adjust the color channel gains. Thus, white balance is achieved.

Color constancy is the result of the automated white balance mechanism in the brain. As long as sufficient environmental information is provided, including the light source and the relative colors of surrounding objects, the brain automatically adjusts the colors, enabling the original colors of objects to be perceived. Various approaches exist for the study of color constancy: the image patch method of multiple light sources [2], the results of comparison and estimation experiments for three color constancy methods [3], key color constancy visual effects based on multiple light sources [4], and the perception of color constancy in light sources through human vision [5]. Multiple algorithms based on image processing methods were proposed for image restoration in color constancy [6]. They all restore the color constancy of images subject to some assumptions. In the experiment conducted for this study, the gray world method [7], the perfect reflector method [8], and dynamic threshold method [9] were compared, and the assumptions for each algorithm are introduced in the next section. These algorithms are all associated with some theoretical assumptions regarding the color distribution for specific images. [6] details various calculation methods on illumination estimation and color temperature estimation. For some algorithms, the white balance adjustment is influenced by the color ratios in the images, resulting in color cast toward blue or red. In other literature, the adjustment of images to obtain uniform color temperatures is rare.

Consequently, adjustments in such circumstances generate suboptimal results.

The method of this study was based on the dynamic threshold method [9], and similar processing concepts were adopted. The operation comprised two steps, namely the selection of reference white points and the image adjustment according to the reference white points. Specifically, as long as this method enables the range to include the central position of the color space, and the reference white point candidates pass the screening conditions, the adjustment of images in such situations is unlikely to be influenced by color temperatures and to cause color offset. The experiment was conducted for various color temperatures. Namely, the same scenes or pictures of people were shot with various illumination methods. The color cast was then adjusted using various white balance algorithms, and the colors were restored to the original real colors. The proposed method was compared with other existing methods in the CIE2000 color temperature difference test and yielded superior results for most color temperature comparison situations.

In summary, the main contributions of this paper are as follows:

1) The idea of color component offsetting in different color temperature situations was proposed to adjust each color temperature. Thus, the images with different color temperatures exhibited similar color temperatures visually after the adjustment.

2) A new automatic regression selection method in the color space was proposed. More white light source points located in the central locations of the color space were obtained through adjustment of the selection range.

The proposed method yielded superior results in the different continual color temperature experiment (including extremely low to extremely high color temperatures) compared with other methods. In addition, this method preserved the color constancy of the images.

II. RELATED WORK

In this section, the current image processing algorithms related to the experiment are introduced, and their advantages and disadvantages are presented for the various experiment groups in the experiment stage. The results of the study provide related detection experiments for solving the detection errors caused by the color cast images brought by color temperatures. Many approaches make effective adjustments to a single image due to their own assumptions, but it usually produce inconsistent results on multiple images with different color temperatures.

A. EXISTING AUTOMATIC WHITE BALANCE ALGORITHMS

The method classified as unsupervised unitary in [10] is introduced. This method conducts assumptions and provides the estimated illumination chromaticity based on the relationships between image colors and light sources. The respective assumptions are as follows:
The gray world algorithm is based on the assumption that, for the physical meaning, the average reflection value of light is represented by a fixed value in a natural scene. This value approximately represents “gray” [7]. Therefore, for an image with copious color changes, the average grayscale values for the three RGB components are approximately the same.

The perfect reflector algorithm is based on the assumption that the brightest point is the white point in the input image. That white point is used as the reference white point, and the R + G + B value of the reference white point is the maximum value [8]. This concept resembles the dynamic threshold detection of white points. However, in this study, the white point selection is conducted using the method of conforming to an area. The definitions of the brightest point therefore differ slightly.

The White Patch Retinex (WPR) algorithm is based on the assumption that, if a white patch is present in the scene of an image, this patch reflects the largest possible light of every wave band. That light is the color of the light source [11]. Thus, this algorithm relies on a white patch in the image to estimate the location of the light source. Although it relies on the white patch of a spot, the algorithm does not search for the patch but uses light intensity K as the estimated value for the light source. Thus, the percentage P% of all the pixel values larger than K among the total image pixels can be detected. Modified White Patch and Grey World Assumption [12] is proposed to adjust the images in L*a*b* space that improves the shortcomings of the original white Patch Retinex.

The weighted Grey-Edge (WGE) classification method is used for various types of edges. This classification method is based on the reflective characteristics of edge types (such as materials, geometric shapes of shades, and high illumination) [13] for the classification of edge types. From the performance of the color constancy method, it could be assessed that some edge types are more valuable for evaluating luminous bodies than are material edges. Therefore, this method, which was different from other Grey-Edge methods, was proposed to examine the edge types with more value for the light source estimation.

Hernandez-jurez et al. [14] found that the color constancy problem can be used as a framework for learning specific light source mapping, and proposed a Bayesian framework, which uses a variety of hypothetical strategies and can handle the color constancy problem. Afifi & Brown [15] proposed a method that preserves the linear characteristics of the original sensor RGB space and trains a single DNN model to be used on different camera sensors. This method uses two networks. The first network learns sensor independent, converts the RGB image into canonical color space and imports it into the second learning network to provide the predicted light source. It obtains superior results on multiple data sets. Bianco & Cusano [16] proposed a quasi-unsupervised learning framework based on CNN single image automatic white balance algorithm. To detect achromatic pixels in color images and convert them to grayscale. It does not require any light source information in the scene, and relies on weak assumptions, which can handle unbalanced images.

B. RELATED APPLICATIONS

Different color temperature conditions occur both indoors and outdoors. However, the colors of an image have valuable functions for the tracking and identification of portraits or objects in computer visual processing. When the color of light changes, the image color also changes, resulting in difficulties in image identification [17]. For outdoor images, image adjustment can be conducted for light attenuation by using image depth detection, or light color restoration can be performed with the illumination estimation model. For indoor situations, different light bulbs result in different illumination conditions. For shooting and research in such situations, the influence of light changes on experiments must be considered. For example, for skin color detection studies [18], [19], skin colors vary. Color temperature conditions affect skin color and background color. Consequently, when detection is conducted, background may be included in the estimated skin blocks, resulting in the problem of estimation errors. In one example, different reflection models were used to estimate the light colors from the lighter regions of the skin. However, when the pixel values in the more brightly lit regions are cut and removed from the expressible regions, the method fails to yield correct light color estimations [20]. In skin color detection research, skin health monitoring and diagnosis are also conducted [21]. This type of research requires more accurate light color calibration to avoid detection errors as a result of light colors’ influence on changes in image color temperatures. As a result, the image adjustment for color temperature is critical. In related research, the method in this study minimizes differences between continual color temperature, and the continual color temperature images from low to high exhibit almost identical light colors. Aside from the light color, the luminance is influential. Favorable light control illumination conditions generate favorable outcomes in facial feature detection experiments [22]. By contrast, insufficient illumination influences the images captured for traditional facial recognition software, causing unfavorable results.

C. COLOR SPACES

Color spaces are the method used for color organization. The fixed analog and digital display of colors can be obtained with color spaces and the tests of physical devices. A color model is an abstract mathematical model. Usually, the three primary colors generate other colors, and these colors define a color space. A three-dimensional space can be obtained by representing the three primary colors as x, y, and z axes. Every possible color can be represented by only one coordinate in this three-dimensional space. In computer vision, the most commonly used color spaces are RGB color spaces. These can usually be converted to other color spaces (such as YCrCb, CIELAB, and CIELUV) through linear or non-linear transformation [23]. The standards usually adopted for
officially defining a color space are the CIELAB or CIEXYZ color spaces because these two color spaces are designed to cover all colors that can be seen by humans with the naked eye. Hence, they are the most accurate color spaces, but they are too complicated for application in daily life. In the processing of various types of images, to effectively use color spaces, the chromatic aberration influenced by the space conversion formulas from the initial color spaces to color properties (lightness, saturation, and hue) must be understood [24]. Currently, models are adopted for the estimation of illumination values, and color spaces generated based on illumination are rare. A new color space was proposed in [25]; the reflectivity and illumination information were obtained from images for the conversion.

III. PROPOSED METHOD

To maintain the color constancy of images shot in different color temperatures, the proposed method uses the dynamic threshold [9] to detect the near-white regions in images for the proposed improvement method. The method has two main components: white point detection and white point image adjustment. However, the original images are converted from RGB to the YUV color space for more convenient acquisition of the chromatic components. This is because the YUV color model originates from the RGB model, the model enables lightness and chromaticity to be separated, so it is suitable for the image processing field. Therefore, according to the a priori knowledge of dynamic thresholds, the average value of $M_u$ and $M_v$, and the average absolute differences $D_u$ and $D_v$ are calculated. The formulas are as follows:

$$D_u = \frac{\sum_{x,y} |U (x, y) - M_u|}{N}$$

$$D_v = \frac{\sum_{x,y} |V (x, y) - M_v|}{N}$$

where $U (x, y)$ and $V (x, y)$ represent the $U$ and $V$ values of pixel position $(x, y)$ in the UV space, and $M_u$ and $M_v$ are the average values of pixel intensity in $U$ and $V$ channels, respectively.

A. AUTOMATIC RECURSION SELECTION OF NEAR-WHITE POINTS

Adjustment is conducted based on the original near-white region conditions. Candidates are adjusted based on weight value, and the proposed selection conditions after optimization are used. The near-white region condition formulas are as follows:

$$|U (x, y) - (M_u + D_u \times \text{sign} (M_u))| < W_r \times D_u$$

$$|V (x, y) - (M_v + D_v \times \text{sign} (M_v))| < W_r \times D_v$$

White candidates are selected from near-white regions. The numbers of white candidates differ according to the numbers of pixels and color temperatures of every image. The selection conditions for white candidates with different color temperatures are adjusted based on the different calculated points of every loop through the respective selection process. As shown in Figure 4, different from the range considered by the dynamic threshold [9], we extend the $W_r$ range from the center of the image, and adjust $W_r$ in a dynamic manner, which can be incorporated into the reference points of different color gamuts. The dynamic threshold [9] considers the addition of $D_u$ and $D_v$ because white is most affected by different color temperatures. In addition, the average values for images approaching 48–56 K are used as the reference for adjustment with different color temperatures. Thus, the optimal adjustment weights $W_p$ and $W_r$ for various color temperature conditions can be obtained.

B. ADJUSTMENT OF DYNAMIC COLOR COMPONENT OPTIMIZATION

Color temperature values influence the $U$ and $V$ components, which causes certain color components to be present in greater proportions when the RGB components are converted. Therefore, the adjustment of conversion rates associated with various color temperatures is assumed to influence the ratios of color components. To dynamically adjust to the optimal ratios through the algorithm, a new weight variable $W_r$ is proposed as the weight variable for the color temperatures and RGB conversion components:

$$W_r = \begin{cases} W_r + 0.1, & \text{if } Y_A > Y_B \\ W_r - 0.1, & \text{if } Y_A < Y_B \\ W_r, & \text{if } Y_A = Y_B \end{cases}$$

$W_r$ Y controls the outward expansion range from the chromaticity center of the UV color space. A is the target image after adjustment, and B is the reference target. $Y_A$ is the maximum value of $Y$ channel of $A$ image in the YUV space, while $Y_B$ is the maximum value of $Y$ channel of $B$ image in the YUV space. The initial values of $W_r$ is 1, and the range is between 0.5-1.5. The size of $W_r$ after every adjustment finally influences the color temperature direction and lightness of the adjustment for the entire image.

In the color gamut of YUV, when only the UV color space is considered, the white candidates closer to the center should be closer to the value of white light in the proposed method. Therefore, the frame of the near-white region is adjusted according to the weight values, so the center selected by the algorithm can include the near-white region in the YUV space center, even if it deviates toward R or B. This is different from the main idea of the fixed boundary for the dynamic threshold [9]. In Figures 2 and 3, all white points that conform to the color temperature conditions are shown. The larger the value of $W_r$ is, the more the range expands, and more points subsequently conform to the conditions. The total number of white points differs according to image size, so this number has no limit. However, a mechanism is required to filter these points because most of the white points are not truly white. The filter subsequently introduced is required to remove most of the fake white points from the candidate list, and only the white points that conform to the conditions in the range of
Different $W_r$ values are required for different color temperatures to lower the number of fake white points. In addition, the white points closer to the center of the color space must be filtered.

**C. OPTIMIZATION OF NEAR-WHITE POINT NUMBER**

Although the method of adjusting $W_r$ more effectively preserves the near-white candidates near the center of the color space, the method of dynamic adjustment of frame weights involves extremely large numbers of influence candidates. Therefore, the top P% values of the white candidates in the near-white region are decided by the scores before and after the adjustment:

$$W_p = \begin{cases} W_p + 0.1, & \text{if } S_A < S_B \\ W_p - 0.1, & \text{if } S_A > S_B \\ & \text{and } W_p \neq 0.1, \text{ if } S_A > S_B \text{ and } W_p = < 0.1 \end{cases}$$

(6)

$W_p$ is the parameter that controls the number of reference white points. $S_A$ is the image after adjustment, and $S_B$ is the reference image for adjustment. The initial values of $W_p$ is 0.1, and the range is between 0.4-0.001. $W_p$ has different values according to the size of the image, so in some cases the reference points can be filtered to less than 1%. The score calculation ($S_A$ and $S_B$) is for calculating the differences between color temperature images through CIE2000. The purpose is to minimize the color errors of the images. According to the experiment test process with various color temperatures from 28 to 65 K, setting the $W_r$ range at 0.5–1.5 according to color temperature enables effective filtering of the near-white points.

In Figure 5, the numbers of white candidates differ due to filter range differences. The original numbers are reduced to only 10% through the effect of $W_p$. The preserved white points are not random, and they are the white points with the top percentages among the white candidates. The white points also mostly represent white objects or white colors caused by reflection in the images. Therefore, effective control of
Algorithm 1 Algorithm for Automatic Recursive Filtering of White Points

**Input:** Original image $O$.
**Output:** Adjusted image $A$.

1) Obtain YUV from $O$.
2) Compute $M_u, D_u, M_v, D_v$ via Eq. (1) and (2).
3) Compute $B$, the average of low warm color temperature and low cold color temperature as the base score $S_B$.
4) Compute the maximum value of Y channel in the YUV space as $Y_B$ according to $B$.
5) initial $\text{Flag}=\text{false}, \text{Min}=100, W_r=1, W_p=0.1$.

**While** $\text{Flag}$ do

- Compute the white point candidates filtered by Eqs. (3) and (4).
- Compute A obtained via each $O$ by adjusting Eq. (5) and (6).
- Compute CIEDE2000 value between A and B as score $S_A$:
  - Calculate the maximum value of Y channel in the YUV space as $Y_A$ according to A
    - If $S_B > S_A$:
      - $S_B = S_A$.
      - Call function $W_r$ via Eq.(5)
        - If $(Y_B > Y_A)$ update $W_r + 0.1$;
        - Else If $(Y_B < Y_A)$ update $W_r - 0.1$;
        - Call function $W_p$ to update $W_p$ via Eq. (6);
        - $Y_B = Y_A$;
    - Else IF $S_B < S_A$:
      - Call function $W_r$ via Eq.(5)
        - If $(Y_B > Y_A)$ update $W_r + 0.1$;
        - Else If $(Y_B < Y_A)$ update $W_r - 0.1$;
        - Call function $W_p$ to update $W_p$ via Eq. (6);
  - Else:
    - $\text{Flag}=\text{true};$ Break;

End

$W_p$ can eliminate most of the fake white candidates in the filtering process. Even if numerous white points are present in the original image, which account for almost half of the entire image, the number can be reduced through adjustment of $W_p$, and the white points of the top percentages can be selected. The real white points preserved with this method are beneficial to the next image adjustment step. Thus, in the subsequent adjustment, color temperature deviation is unlikely to occur.

The dynamic process of the proposed method, as described in detail in Algorithm 1, is by dynamically adjusting the $W_r$ and $W_p$ parameters and comparing the $S_A$ and $S_B$ images. Next, the calculation process of the target image and the reference image is illustrated. A is the first calculation result image, and $A'$ is the next one. The A and B images are obtained through the initial value and the first iteration, and calculate their $Y_A, S_A, Y_B$, and $S_B$. If the score of A image is lower than that of B image, then assign the values of A image to B image and adjust the $W_r$ and $W_p$ parameters, and finally generate the new $A'$ result image according to new parameters. The process is repeated until the adjusted image with the smallest gap is found.

After the filtered white candidates were obtained, the YUV values were converted back to RGB values according to all the reference white points. In addition, the average values of different channels were used as the RGB channel gain values. The following formulas were used to adjust the RGB channels according to the diagonal models of the Von Kries model [26], [27]:

\[
R' = R \times R_{\text{gain}} \quad (7)
\]
\[
G' = G \times G_{\text{gain}} \quad (8)
\]
\[
B' = B \times B_{\text{gain}} \quad (9)
\]

R, G, and B are the pixel values of the original image, and $R', G',$ and $B'$ are the pixel values of the adjusted image. $R_{\text{gain}}$, $G_{\text{gain}}$, and $B_{\text{gain}}$ are obtained by dividing the maximum Y values, after conversion of the original image from RGB to YUV, by the average values of the reference white points. The images at different color temperatures are adjusted to similar color temperatures through this method to reduce the influence of the chromatic components exerted by color temperature. The pictures captured at various color temperatures are displayed in Section IV in order from low color temperature to high color temperature. In addition, the original images were adjusted to a uniform color temperature.
IV. EXPERIMENTAL RESULTS AND DISCUSSIONS

To verify the effectiveness of the proposed method, various experiment results were provided. The restoration of real-world colors for original images in various color temperature conditions was compared with that for other algorithms based on automatic white balance. All codes for the test algorithms were found on the Internet. A PC with 8GB Ram and Intel i7-7700 3.6 GHz in the MatlabR2019b environment and Anaconda Python environment was adopted for the test. The parameter initialization used in the experimental stage is introduced in Experimental Settings, and the selection of parameter placement is discussed.

A. EXPERIMENTAL SETTINGS

To validate the performance of the proposed method, indoor and outdoor datasets are used for comparison evaluation. Indoor test images are portraits of people with jaundice with various color temperatures (28, 32, 40, 48, 56, and 65 K). Two control groups (High Risk and Low Risk) were divided according to the standard jaundice value of 15. The test was conducted on the experiment images in the image dataset provided by the cooperating doctors. For outdoor test images, the TID2013 dataset [28] and NUS dataset [29] are used to artificially generate the images with different color temperatures through Photoshop for adjustment and comparison, as the outdoor test images in this study. The performance of the method was compared with the automatic white balance algorithms based on image processing, which are the gray world [7], perfect reflector [8], WPR [11], MWP [12], WGE [13], LSR [30] and dynamic threshold (DH) [9].

The concept of setting $W_r$ has been outlined in the third stage. This section describes the selection of the setting and its differences in more detail. Figures 7 and 8 show the two groups of estimated restored images with various color temperatures. According to (3), the images with the value of 0.5 that was finally selected in the first row of Figure 7 are gentler than the images with the value of 1.5. In addition, they exhibit no deviation toward high color temperature (blue) as in the left and right sides of the (c) images. The second row images exhibit partial overexposure effects in the chest positions, which influence the judgement of the detection system. Consequently, the exposure and fineness of the illumination require attention. The generated adjusted image in the first row (b) of Figure 8 exhibits superior detail adjustment (white line and exposure on the left side) than the image in (c) does.

B. QUALITATIVE COMPARISON IN DIFFERENT COLOR TEMPERATURE IMAGES

Next, the entire group of images with different color temperatures were adjusted to the same color temperature. The extreme color temperature values of 32 and 65 K cause large deviation of the original colors. Therefore, the reference color temperature was set to between 48 and 56 K, so the color component ranges circled by the near-white filters selected with different color temperatures in this method were closer. This created the visual effect whereby each image appears to exhibit the same color temperature after adjustment. Extreme color temperature images (deviated toward red or blue) are not generated.

The execution results of the proposed method are shown in Figures 9 and 10. The method demonstrates favorable
effects in the adjustment from low color temperature to high color temperature. The figures show that the method can minimize the influence of the chromatic components of different color temperatures. Thus, in the results, the images displayed at different color temperatures appear to exhibit similar color temperatures. No notable color cast is present after the adjustment with the proposed method. The gray world [7] and dynamic threshold [9] methods result in higher color temperatures, which cause the overall images to be deviated toward blue, as shown in Figure 13.

TABLE 1. The comparison between the High Risk dataset with the standard jaundice value of 15 and gray world [7], PRM [8], WPR [11], WGE [13], and dynamic threshold [9] methods. The red numbers are the smallest differences, and the blue numbers are the second smallest differences.

| Color Temperature | GW [7] | PRM [8] | WPR [11] | WGE [13] | DH [9] | Ours |
|-------------------|--------|---------|----------|----------|-------|------|
| 28K vs. 32K       | 3.09±1.64 | 3.69±1.77 | 4.01±1.52 | 3.53±1.58 | 4.47±3.82 | 3.67±1.8 |
| 28K vs. 40K       | 3.95±1.98 | 5.06±2.20 | 5.59±2.17 | 5.00±1.80 | 5.61±4.34 | 4.95±2.21 |
| 28K vs. 48K       | 4.49±2.59 | 6.28±2.68 | 7.22±2.69 | 6.12±2.27 | 5.91±3.58 | 5.52±2.3 |
| 28K vs. 56K       | 4.56±2.56 | 7.07±2.62 | 8.41±3.10 | 6.69±2.27 | 6.50±4.05 | 6.24±2.5 |
| 28K vs. 65K       | 4.84±2.83 | 7.14±2.65 | 8.42±2.46 | 6.59±1.86 | 6.94±3.95 | 6.27±2.5 |
| 32K vs. 40K       | 3.00±1.29 | 3.41±2.59 | 3.52±2.22 | 3.45±1.93 | 3.47±3.21 | 2.94±1.7 |
| 32K vs. 48K       | 3.75±1.67 | 4.78±2.06 | 5.24±1.58 | 4.48±1.79 | 3.69±1.58 | 3.93±1.5 |
| 32K vs. 56K       | 3.85±1.77 | 5.13±2.09 | 6.14±2.03 | 4.82±1.73 | 4.46±3.14 | 3.47±1.4 |
| 32K vs. 65K       | 3.87±2.19 | 5.12±2.14 | 6.00±2.12 | 4.82±1.47 | 4.67±2.94 | 4.52±1.9 |
| 40K vs. 48K       | 3.28±1.83 | 3.49±1.77 | 3.64±1.44 | 3.29±1.35 | 3.82±3.37 | 3.01±1.4 |
| 40K vs. 56K       | 3.41±2.46 | 3.88±2.41 | 4.57±1.94 | 3.50±1.94 | 4.78±3.75 | 3.23±1.5 |
| 40K vs. 65K       | 3.92±3.03 | 4.39±2.29 | 5.02±2.69 | 3.82±1.85 | 5.23±3.84 | 3.54±1.6 |
| 48K vs. 56K       | 2.46±1.50 | 2.76±1.44 | 2.93±1.45 | 2.55±1.29 | 3.51±2.80 | 2.48±1.2 |
| 48K vs. 65K       | 3.09±1.88 | 3.18±1.55 | 3.65±1.65 | 2.82±1.45 | 3.78±3.22 | 2.58±1.3 |
| 56K vs. 65K       | 3.12±2.08 | 3.87±1.72 | 2.86±1.74 | 2.53±1.62 | 2.44±1.19 | 2.68±1.5 |
| Mean              | 3.67±2.14 | 4.54±2.13 | 5.19±2.01 | 4.24±1.71 | 4.75±3.47 | 3.90±1.9 |
FIGURE 13. Adjustment results of different algorithms under different color temperatures for indoor images. The color temperatures are 28, 32, 40, 48, 56, and 65 K from left to right.

C. QUANTITATIVE COMPARISON
The color temperatures obtained with the proposed method were compared with color temperatures (28, 32, 40, 48, 56, and 65 K) obtained through other methods. If the adjusted images have the same color temperature, the calculated values for the distances in the color space are close. Therefore, CIE2000 was used to evaluate the distances of the chromatic components. CIE2000 is also used to evaluate the color fidelity of images. It can be used to accurately measure the overall chromatic components between two images and generate a value between 0 and 100. The smaller the value is, the better the color fidelity is. The comparison results of the proposed method and other methods are shown in Tables 1 and 2. The method in this study does not yield the smallest CIE2000 value after comparison with all of the other algorithms. However, according to one of the execution results, as shown in Figure 13, the proposed method has the visual effect of higher color fidelity compared with other automatic white balance algorithm with advantages in CIE2000.

In Tables 1 and 2, the proposed method does not yield the smallest value. However, the color temperature differences between the executed images are better than those obtained with the gray world method and are superior in
visual appearance. Figure 11 shows the difference between the proposed method and other methods in various color temperatures. CIE2000 was adopted as the evaluation method. For the continual color temperature images, the smaller the difference for every interval is, the smoother the entire curve is. The smaller the overall value is, the smaller the color cast between the images is. In addition, the color constancy of the images can be maintained. The figure shows that, for every method, small differences are observed in the interval from 48 to 65 K. This means that the methods exert favorable processing effects for white light color temperatures. However, from 28 to 40 K, obvious differences occur in the conversion of lower color temperatures. The grey world method can minimize the differences between color temperatures, but the adjusted images are all affected by color cast. Figure 12 depicts greater differences in the execution results. For the grey world method, most of the final adjusted images are deviated toward blue in different color temperatures. This provides unreliable data in Tables 1 and 2 because all color temperatures are deviated toward blue. Thus, the estimated differences in values are smaller between different images.

Figure 13 shows the results of the tests with five algorithms on a complete set of images with various color temperatures (32 K to 65 K). These pictures constitute one set of images randomly selected from the dataset provided by the cooperating doctors. The figure clearly shows that the results of the gray world [7] and dynamic threshold [9] methods have high overall color component values, resulting in images with poor image effects. The WPR [11] and WGE [13] methods yield acceptable overall effects, but the images are dark when the color temperatures are between 48 and 65 K. In particular, the images of 65 K have clearly different image lightness from the images of 32 and 40 K. The perfect reflector algorithm [8] yields visual effects with extremely consistent overall color temperature, but the white sheets in the images are affected by yellow deviation. In addition, the respective method exhibits similar problems in other images. However, the results of the proposed method maintain visual effects with almost consistent color temperatures. In addition, the white pixels feature no obvious yellow or blue deviation. The color constancy is better maintained.

Figure 14 shows a set of examples of artificially generated images with different color temperatures in the...
The adjustment results of different approaches under different color temperatures for images in NUS Dataset. From Top to down, the color temperature of the original image is high warm color (w1), medium warm color (w2), low warm color (w3), low cold color (c3), medium cold color (c2), and high cold color (c1).

The TID2013 dataset [28], and the angular error is used as the evaluation standard. The results can be found that when the images are severely affected by the color temperature, the results adjusted by different approaches are more prone to color shift. Among them, Modified White patch (MWP) and Weighted Grey-Edge (WGE) are more prone to color cast problems. The results of LSR [30] approach seem to effectively eliminate the chromatic aberration, but the overall image looks dark and the result image of lower color temperature is quite different from the result image of high color temperature. In summary, the results of most approaches have a relatively large gap between the maximum value and the minimum value. The proposed method is not the smallest among all, but the color temperature value adjusted under different color temperature is the smallest difference, which meet the purpose we mentioned. There are two similar ideas for screening white reference points, such as White Patch Retinex (WPR) and Modified White patch algorithm (MWP). Compared with the other two approaches, the proposed method can preserve the most important white areas of the image and use it as an adjustment basis in establishing the illuminant estimation map, and minimize the selection of white pixels with color casts, as shown in Figure 15.

Figure 16 shows a set of examples of artificially generated images with different color temperatures in NUS dataset [29], with angular error as the evaluation metric. From the results, it can be found that the state-of-the-art approaches perform poorly on this dataset, such as PRM, WPR, and MWP. These three white balance methods are all that define the light source in the image. WGE and LSR calculate the required light source estimation models according to different scenarios, and their results are relatively better than the first three. However, the results of the proposed method have better brightness than those of WGE and LSR. In addition, the adjustment results of six different color temperature images by our method are relatively closer than others. The average value of angular error for the six color temperatures after adjustment is listed in Table 3. The results indicate that the proposed method is better than the state-of-the-art approaches in both of that “between different color temperatures are closest” and “the difference between the maximum and the minimum values (R) is also the smallest”. Although the gap

| Dataset | NUS (NikonD40) |
|---------|----------------|
| Method  | w1  | w2  | w3  | c3  | c2  | c1  | R    |
| Original| 14.38| 11.05| 5.50| 3.17| 3.68| 6.50| 11.22|
| PRM     | 13.63| 10.17| 5.22| 3.52| 3.58| 5.83| 9.92 |
| WPR     | 14.62| 11.60| 5.42| 3.15| 3.67| 6.47| 11.17|
| MWP     | 13.65| 10.48| 5.60| 4.28| 4.18| 4.98| 9.47 |
| WGE     | 5.50 | 4.63 | 3.92| 3.48| 3.28| 3.63| 2.22 |
| LSR     | 4.62 | 3.72 | 2.85| 2.62| 2.58| 3.02| 2.03 |
| Ours    | 4.00 | 2.92 | 2.67| 2.53| 2.53| 3.85| 1.47 |

(w1: high warm color; w2: medium warm color; w3: low warm color; c3: low cold color; c2: medium cold color; c1: high cold color; R: max-min)
between images with severe color shifts (W1 and C1) has not been minimized, it may be necessary to consider the estimation model of the original color reproduction in the image under extremely high color temperature or extremely low color temperature.

V. CONCLUSION AND FUTURE WORK

In this study, the differences in color temperature and lightness were compared after the images shot in different color temperatures were adjusted with automatic white balance. Thus, a method that improved on the dynamic threshold method [9] was proposed. The color components of the images can be restored favorably by using the updated color component ratios of the weight parameters and changing the image pixel values for selected candidate percentages. The proposed method minimizes differences in color components at different color temperatures and reduces image exposure or the loss of detail. The experiment results demonstrate favorable adjustment effects achieved on a series of color temperature images through the use of this method, and the color constancy was effectively maintained. The proposed method is tested on indoor images at various color temperature (28K-65K) and outdoor images at various color temperature that are artificially generated. The proposed method works well except that the original scene color in the image has been discolored due to strong color cast. It cannot be restored correctly. Although a method was found for addressing the differences in the color components of images caused by differences in illumination, another problem remains. In natural images, the differences in distance, weather, and humidity result in different atmospheric scattering coefficients and illumination. Different color temperatures are thus generated visually. Consequently, in some circumstances, the color temperature values cannot be determined normally. Thus, the displacement of the color components in the images cannot be estimated easily or accurately, and a more flexible model is required. In future work, the standard color constancy data set (NUS data set and Gehler–Shi data set) will be used for color constancy experiments in other conditions, not at various color temperatures. To overcome this challenge, other advanced physical models can be considered. This problem requires additional research.

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