A Color Constancy Model for Non-uniform Illumination based on Correlation matrix

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***Abstract*—In this paper, we propose a novel color constancy model that works well even if illumination is not uniformly distributed. For this purpose, we introduce the positionally modified color correlation matrix. The color correlation matrix is a matrix that represents how different colors are correlated with one another. More concretely, the color correlation matrix is obtained as the spatial average of the product of two colors as $\langle I_i I_j \rangle$, and consequently, it is independent of position parameters. In addition to this correlation matrix, we define two position dependent correlation matrices as $\langle x I_i I_j \rangle$ and $\langle y I_i I_j \rangle$. We assume that the eigenvector of the correlation matrix corresponding to the largest eigenvalue presents the color gray when the illumination is parallel and white. Under this assumption, we can estimate the image when the illumination is parallel and white. The effectiveness of the proposed method is confirmed by simulation experiments using synthesized images and real images.**

Keywords-Color constancy; correlation matrix; non-uniform illumination; gray-world assumption; correlation between brightness and color.

I. INTRODUCTION

Color constancy is one of miracle abilities in human vision. Object colors are correctly perceived independent of the illumination color. This ability is called color constancy [1]. In the field of computer vision, color recognition is an important and basic task. In fact, color recognition has been used as preprocessing for various problems such as robot vision, object recognition, human behavior recognition, human interface and so on. For example, Kamada et al. [2] proposed a system that can count students' raising the color cards to accelerate communication between a teacher and many students in a classroom. In this system, it is very important to achieve accurate color recognition.

Several methods have been proposed for color constancy. Among these methods, the ones based on Gray-world assumption have been popular and they are considered the basis of arguing color constancy [3]-[6]. Gray-world assumption states that the average of the colors of the objects in the scene is gray, and the influence of the illumination is eliminated based on this assumption. This method would work well when sufficient colors exist in the scene. As an extension, a method based on local averaging was proposed by Gijsenij et al. [7]. Further, other methods have been proposed using image statistics such as correlation between the brightness and color [8]-[12]. Golz et al. [8] discussed human color constancy based on the correlation between luminance and redness and concluded that redness of the illumination could be correctly estimated using the mean redness of the image and the correlation between luminance and redness of the image. Inspired by the paper [8], we developed a computational method to estimate illumination color by replacing human eyes with a camera [11]. Previously [13], we proposed another method based on "Minimum Brightness Variance Assumption", in which it is assumed that variance of brightness is minimum when the illumination is white.

In another previous work [14], we proposed a color constancy model based on the color correlation matrix. More concretely, we proposed two methods for color constancy. Both are based on the correlation matrix on the three-dimensional space of colors, red, green and blue. In the first method, the eigenvector corresponding to the largest eigenvalue is assumed to be a good estimate of the illumination color. In the second method, it is assumed that the eigenvector corresponding to the largest eigenvalue presents the color gray when the illumination is white. The image under white illumination is predicted so as to satisfy the condition that the eigenvector corresponding to the largest eigenvalue presents the color gray.

In these methods, we assumed that illumination is parallel, and therefore it is uniform against position variation. In this paper, we extend the previous method so that it works well for non-uniform illumination. For this purpose, we introduce the positionally modified color correlation matrix. The effectiveness of the proposed method is confirmed by simulation experiments using synthesized images and real images.

This paper is organized as follows. In Section II, we outline of the previous method in which illumination is assumed to be parallel and be uniformly distributed spatially. In Section III, we extend this method in the case for non-uniform illumination. In Section IV, we show the experimental results which reveal the effectiveness of the proposed method.

II. OUTLINE OF THE PREVIOUS METHOD

Let $\mathbf{e}_1$, $\mathbf{e}_2$ and $\mathbf{e}_3$ be three unit vectors representing color orientations of red, green and blue in the three-dimensional color space. Then, the unit vector $\mathbf{e}^{(L)} = 1/\sqrt{3}(\mathbf{e}_1 + \mathbf{e}_2 + \mathbf{e}_3)$ represents the orientation of the white color. It is represented as $\mathbf{e}^{(L)} = 1/\sqrt{3}(1,1,1)^t$ in terms of components. Let $I_1(x,y)$, $I_2(x,y)$ and $I_3(x,y)$ be the color components red, green and blue of the input image at the point (x,y), respectively. This image can be represented as

$$\mathbf{I}(x,y) = I_1(x,y)\mathbf{e}_1 + I_2(x,y)\mathbf{e}_2 + I_3(x,y)\mathbf{e}_3, \quad (1)$$

in the three dimensional color space. We represent it simply as $\mathbf{I}(x,y) = (I_1(x,y), I_2(x,y), I_3(x,y))^t$. Then, 3 x 3 color correlation matrix K is defined as

$$K_{ij} = < I_i I_j > = \int_{-1/2}^{1/2}\int_{-1/2}^{1/2} I_i(x,y) I_j(x,y) dx dy. \quad (2)$$

where $< I_i I_j >$ is the spatial average of $I_i(x,y) I_j(x,y)$. We assume that the image is defined in the rectangle area of $-1/2 \le x, y \le 1/2$.

Let $\mathbf{S}(x,y) = (S_1(x,y), S_2(x,y), S_3(x,y))^t$ be object color and let $\mathbf{E} = (E_1, E_2, E_3)^t$ be illumination color. We assume that illumination is parallel, and therefore it is uniform against position variation. Then, the image $\mathbf{I}(x,y) = (I_1(x,y), I_2(x,y), I_3(x,y))^t$ is determined as

$$I_i(x,y) = E_i S_i(x,y). \quad (3)$$

We call it the image generation formula. From (2) the color correlation matrix K is obtained as

$$K_{ij} = < I_i I_j > = E_i E_j < S_i S_j >. \quad (4)$$

Using this relation, the illumination color $\mathbf{E} = (E_1, E_2, E_3)^t$ is determined so that the eigenvector corresponding to the largest eigenvalue of $< S_i S_j >$ is parallel to $\mathbf{e}_l = 1/\sqrt{3}(1 \quad 1 \quad 1)^t$ for the given $K_{ij} = < I_i I_j >$. Once $\mathbf{E}$ is determined, the image under white illumination is estimated as

$$\hat{I}_i(x,y) = c I_i(x,y) / E_i, \quad (5)$$

where c is a factor which is determined to keep the brightness invariant. In other words, $\hat{\mathbf{I}}(x,y)$ is considered to be an estimate of the object color $\mathbf{S}(x,y)$. In practice, $\hat{\mathbf{I}}(x,y)$ is obtained as follows.

First, let $\hat{\mathbf{I}}(x,y) = (\hat{I}_1(x,y), \hat{I}_2(x,y), \hat{I}_3(x,y))^t$ be the color components of the image to be estimated and let $\tilde{K}$ be the correlation matrix of these. $\tilde{K}$ is obtained as

$$\hat{K} = \frac{1}{N} \sum_{x,y} \hat{\mathbf{I}}(x,y) \hat{\mathbf{I}}^t(x,y). \quad (6)$$

Since we assume that the eigenvector of $\tilde{K}$ corresponding to the largest eigenvalue is parallel to the orientation of color gray, $\hat{\mathbf{I}}(x,y)$ is estimated so that $\mathbf{e}_l = 1/\sqrt{3}(1 \quad 1 \quad 1)^t$ is the eigenvector of $\hat{K}$ with the largest eigenvalue. More specifically, $\hat{\mathbf{I}}(x,y)$ is obtained by the following procedure. First, as an initialization, we set

$$\hat{\mathbf{I}}(x,y) = \mathbf{I}(x,y), \quad (7)$$

where $\mathbf{I}(x,y)$ is the input image. Second, calculate $\tilde{K}$ according to the equation (6), and obtain the eigenvector $\mathbf{u}$ of $\tilde{K}$ with the largest eigenvalue. Then, update $\hat{\mathbf{I}}(x,y)$ according to

$$\hat{I}_i(x,y) \leftarrow \alpha \frac{\beta u_i + 1}{2 u_i} \hat{I}_i(x,y), \quad (8)$$

where α is determined to keep the brightness invariant, and β is a factor to modulate the speed of the image change. The larger β is, the smaller the image change is. The above procedure should be terminated when the amount of image change according to (8) is less than a pre-determined value. The amount of image change is evaluated by the root-mean-square error (RMSE).

III. PROPSED METHOD

In the method outlined in the last section, the illumination is assumed to be parallel implicitly. Therefore it is uniform against position variation. In this section, we extend it in the case for non-uniform illumination. More specifically, we assume that position dependence of the illumination is linear and is represented as

$$E_i(x,y) = F_i(1 + \varepsilon_{x_i} x + \varepsilon_{y_i} y). \quad (9)$$

Then, (3) is modified as

$$I_i(x,y) = F_i(1+\varepsilon_{x_i}x+\varepsilon_{y_i}y)S_i(x,y). \tag{10}$$

and correspondingly the correlation matrix becomes

$$\begin{aligned} K_{ij} &= \langle I_i I_j \rangle = \\ &= F_i F_j \langle (1+\varepsilon_{x_i}x+\varepsilon_{y_i}y)S_i S_j(1+\varepsilon_{x_j}x+\varepsilon_{y_j}y) \rangle \\ &= F_i F_j \langle S_i S_j \rangle \\ &\quad + F_i F_j(\varepsilon_{x_i}\varepsilon_{x_j} \langle x^2 S_i S_j \rangle + \varepsilon_{y_i}\varepsilon_{y_i} \langle y^2 S_i S_j \rangle) \\ &= F_i F_j(1+\frac{1}{12}\varepsilon_{x_i}\varepsilon_{x_j}+\frac{1}{12}\varepsilon_{y_i}\varepsilon_{y_j}) \langle S_i S_j \rangle, \end{aligned} \tag{11}$$

where we assume that the image is defined in the rectangle area of $-1/2 \le x, y \le 1/2$ and that

$$\begin{aligned} &\langle xS_iS_i \rangle = 0, \langle yS_iS_i \rangle = 0, \langle xyS_iS_i \rangle = 0, \\ &\langle x^2 S_iS_i \rangle = \frac{1}{12} \langle S_iS_i \rangle, \langle y^2 S_iS_i \rangle = \frac{1}{12} \langle S_iS_i \rangle. \end{aligned} \tag{12}$$

Here, we introduce the positionally modified color correlation matrix as

$$\begin{aligned} K_{x_{ij}} &= \langle xI_iI_i \rangle \\ &= F_iF_j \langle x(1+\varepsilon_{x_i}x+\varepsilon_{y_i}y)S_iS_j(1+\varepsilon_{x_j}x+\varepsilon_{y_j}y) \rangle \\ &= F_iF_j(\varepsilon_{x_i}+\varepsilon_{x_j}) \langle x^2 S_iS_j \rangle \\ &= \frac{1}{12}F_iF_j(\varepsilon_{x_i}+\varepsilon_{x_j}) \langle S_iS_j \rangle \end{aligned} \tag{13}$$

and

$$\begin{aligned} K_{y_{ij}} &= \langle yI_iI_i \rangle \\ &= F_iF_j \langle y(1+\varepsilon_{x_i}x+\varepsilon_{y_i}y)S_iS_j(1+\varepsilon_{x_j}x+\varepsilon_{y_j}y) \rangle \\ &= F_iF_j(\varepsilon_{y_i}+\varepsilon_{y_j}) \langle y^2 S_iS_j \rangle \\ &= \frac{1}{12}F_iF_j(\varepsilon_{y_i}+\varepsilon_{y_j}) \langle S_iS_j \rangle \end{aligned} \tag{14}$$

From (11), (13) and (14) we obtain a system of equations for ε_{i_x} and ε_{i_y} as follows.

$$\begin{aligned} \frac{K_{x_{ij}}}{K_{ij}} &= \frac{\varepsilon_{x_i}+\varepsilon_{x_j}}{\varepsilon_{x_i}\varepsilon_{x_j}+\varepsilon_{y_i}\varepsilon_{y_j}+12}, \\ \frac{K_{y_{ij}}}{K_{ij}} &= \frac{\varepsilon_{y_i}+\varepsilon_{y_j}}{\varepsilon_{x_i}\varepsilon_{x_j}+\varepsilon_{y_i}\varepsilon_{y_j}+12}. \end{aligned} \tag{15}$$

This system of equations has 12 equations against 6 unknown parameters ε_{i_x} and ε_{i_y}. Among them we use only $i = j$ case (6 equations) for simplicity. Then, (15) becomes

$$\begin{aligned} T_{x_i} &= \frac{2\varepsilon_{x_i}}{\varepsilon_{x_i}{}^2+\varepsilon_{y_i}{}^2+12}, \\ T_{y_i} &= \frac{2\varepsilon_{y_i}}{\varepsilon_{x_i}{}^2+\varepsilon_{y_i}{}^2+12}, \end{aligned} \tag{16}$$

where $T_{x_i} = K_{x_{ii}}/K_{ii}$ and $T_{y_i} = K_{y_{ii}}/K_{ii}$. This system of six equations can be solved easily and we obtain

$$\begin{aligned} \varepsilon_{x_i} &= \frac{T_{x_i}\left(1-\sqrt{1-12(T_{x_i}{}^2+T_{y_i}{}^2)}\right)}{T_{x_i}{}^2+T_{y_i}{}^2}, \\ \varepsilon_{y_i} &= \frac{T_{y_i}\left(1-\sqrt{1-12(T_{x_i}{}^2+T_{y_i}{}^2)}\right)}{T_{x_i}{}^2+T_{y_i}{}^2}. \end{aligned} \tag{17}$$

As is described in (9), illumination is determined by parameters F_i, ε_{i_x} and ε_{i_y}. The remained problem is to obtain F_i. For this purpose, we notice that (10) can be rewritten as

$$\frac{I_i(x,y)}{1+\varepsilon_{x_i}x+\varepsilon_{y_i}y} = F_iS_i(x,y). \tag{18}$$

If we set

$$\tilde{I}_i(x,y) = \frac{I_i(x,y)}{1+\varepsilon_{x_i}x+\varepsilon_{y_i}y}. \tag{19}$$

Equation (18) becomes

$$\tilde{I}_i(x,y) = F_iS_i(x,y). \tag{20}$$

This equation has the same form as (3), which represents the image generation formula for the case when illumination is uniform. In view of this, the constant factor

$\mathbf{F}=(F_1,F_2,F_3)^t$ of the illumination color is determined so that the eigenvector corresponding to the largest eigenvalue of $<S_iS_j>$ is parallel to $\mathbf{e}_l = 1/\sqrt{3}(1 \quad 1 \quad 1)^t$ for the given $\tilde{K}_{ij} =< \tilde{I}_i \tilde{I}_j >$.

The algorithm of the proposed method is summarized as follows.

Step 1: Calculate the correlation matrixes as

$$K_{ij} =< I_i I_i >= \int_{-1/2}^{1/2}\int_{-1/2}^{1/2} I_i(x,y) I_j(x,y) dxdy,$$

$$K_{xij} =< x I_i I_i >= \int_{-1/2}^{1/2}\int_{-1/2}^{1/2} x I_i(x,y) I_j(x,y) dxdy$$

and

$$K_{y_{ij}} =< y I_i I_i >= \int_{-1/2}^{1/2}\int_{-1/2}^{1/2} x I_i(x,y) I_j(x,y) dxdy.$$

Step 2: Set

$$T_{x_i} = K_{x_{ii}} / K_{ii}$$

and

$$T_{y_i} = K_{y_{ii}} / K_{ii}.$$

Step 3: Get

$$\varepsilon_{x_i} = T_{x_i}\left(1-\sqrt{1-12({T_{x_i}}^2+{T_{y_i}}^2)}\right)\Big/\left({T_{x_i}}^2+{T_{y_i}}^2\right)$$

and

$$\varepsilon_{y_i} = T_{y_i}\left(1-\sqrt{1-12({T_{x_i}}^2+{T_{y_i}}^2)}\right)\Big/\left({T_{x_i}}^2+{T_{y_i}}^2\right).$$

Step 4:Calculate the modified correlation matrix as

$$\tilde{K}_{ij} =< \tilde{I}_i \tilde{I}_i > = \int_{-1/2}^{1/2}\int_{-1/2}^{1/2} \frac{I_i(x,y) I_j(x,y)}{(1+\varepsilon_{x_i}x+\varepsilon_{y_i}y)(1+\varepsilon_{x_j}x+\varepsilon_{y_j}y)} dxdy.$$

Step 5: Find $\mathbf{F}=(F_1,F_2,F_3)^t$ such that the eigenvector corresponding to the largest eigenvalue of the matrix $F_i^{-1}\tilde{K}_{ij}F_j^{-1}$ is parallel to $\mathbf{e}_l = 1/\sqrt{3}(1 \quad 1 \quad 1)^t$

Step 6: Obtain the image under white illumination as

$$\hat{I}_i(x,y) = c\tilde{I}_i(x,y)/G_i,$$

where c is a factor which is determined to keep the brightness invariant.

(a) (b) (c) (d) (e)

Figure 1. Examples of images: (a) an object color, (b) an input image, (c) a result by the Gray-world based method, (d) a result by the previous correlation based method and (e) a result by the proposed method.

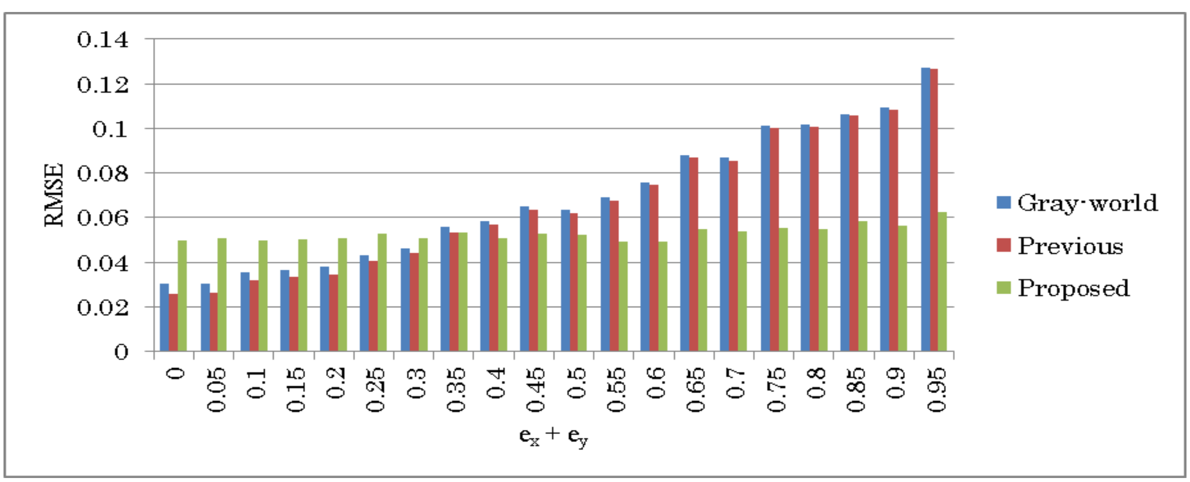


Figure 2. Root-mean-square error between the ideal image and the estimated image in the experiments using synthesized images.

IV. EXPERIMENTS

We conducted two types of simulation experiments to confirm the effectiveness of the proposed methods. In the first experiments we synthesized images with 512 × 512 size which represents the object color. The image has 8 × 8 = 64 blocks, and in each block the object colors are specified by $S_1(x,y)$, $S_2(x,y)$ and $S_3(x,y)$, which are determined at random and uniformly distributed from 0.0 to 1.0. In this manner, we prepared 100 samples of images representing object colors for each illumination condition mentioned below.

Figure 3.Input images under common room lighting.

An example of synthesized image is shown in Figure 1 (a).Next, we set F_1 , F_2 and F_3 to be 0.4, 0.7, 1.0 respectively as the constant factor of the color component red, green and blue (see equation (9)). Further, we set $\rho_1 = 0.0, \rho_2 = 0.05, \cdots, \rho_{20} = 0.95$, which represent the magnitude of $e_{x_i} + e_{y_i}$. Each e_{x_i} and e_{y_i} is determined randomly as follows. First, e_{x_i} is determined at random and uniformly distributed from 0.0 to ρ_m $(m = 1,2,\cdots 19)$. Then, e_{y_i} is determined as $e_{y_i} = \rho_m - e_{x_i}$. In consideration of origin symmetry, we restricted e_{x_i} and e_{y_i} to be zero or positive without loss of generality. The parameter ρ_m is considered to represent the amount of non-uniformity. Thus 20 kind illumination conditions are defined according to (9). Then, we generate 100 input images for each non-uniformity parameter according to (10) using randomly synthesized 100 sets of object colors $S_1(x,y)$, $S_2(x,y)$ and $S_3(x,y)$. In this way, we got 2000 (100 x 20) input images. An example of input image is shown in Figure 1 (b), where $e_{x_i} + e_{y_i}$ $(i = 1,2,3)$ are set to be 0.95.For these 2,000 images, we estimated images under white illumination based on the proposed method. We also estimated the images using the Gray-world based method and the previously proposed correlation based method for comparison. In Figure 2, the RMSE between the ideal image and the estimated images by the three methods are shown. Examples of estimated images by the three methods are shown in Figure 1 (c), (d) and (e). As can be seen in Figure 2, the proposed method has its own superiority when illumination non-uniformity is large. Inversely, when illumination is uniform, the previous method has rather better results.

Next, we conducted experiments using 9 groups of real images. Each group has 4 images, with one image taken under common room lighting. These are shown in Figure 3. The other three images in each group are taken under such illumination condition in which colored lamps (red, green and blue) are set from the upper right direction in addition to the common illumination. Figure 4 (a) shows an example of the input image under common room lighting. Figure 4 (b), (c) and (d) are examples of images taken under illumination condition where each of red, green and blue lamp is set.

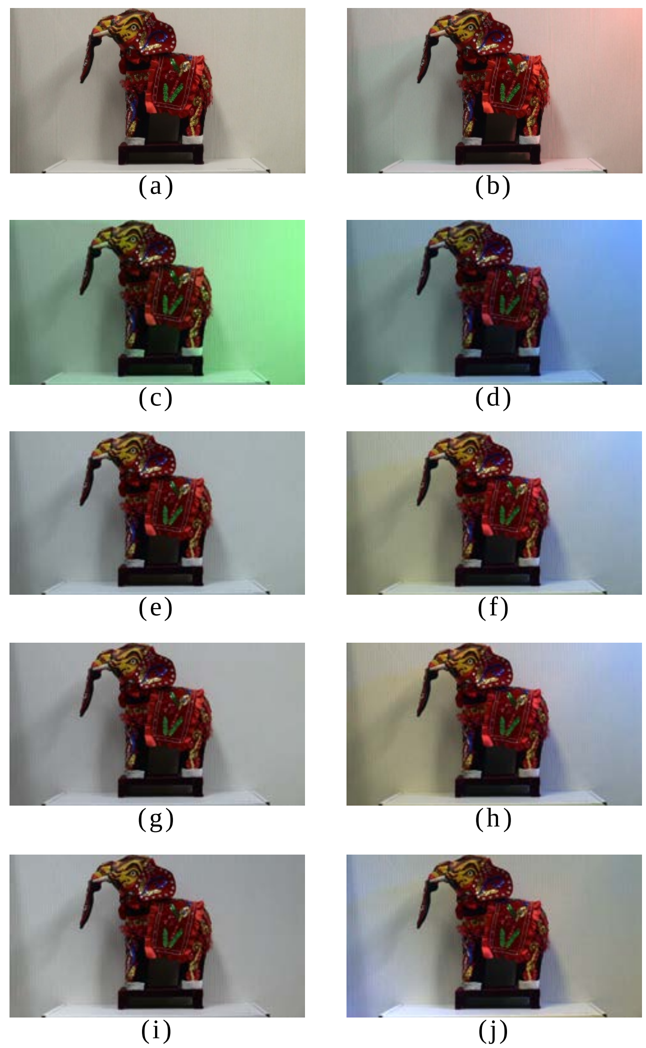


Figure 4. Examples of input images (a) – (d) and estimated images (e)- (j). (a) Common illumination is added. (b) Red illumination is added. (c) Green illumination is added. (d) Blue illumination is added. (e), (g) and (i) show the results for the case when the input image is (a). (f), (h) and (j) show the results in the case when the input image is (d)

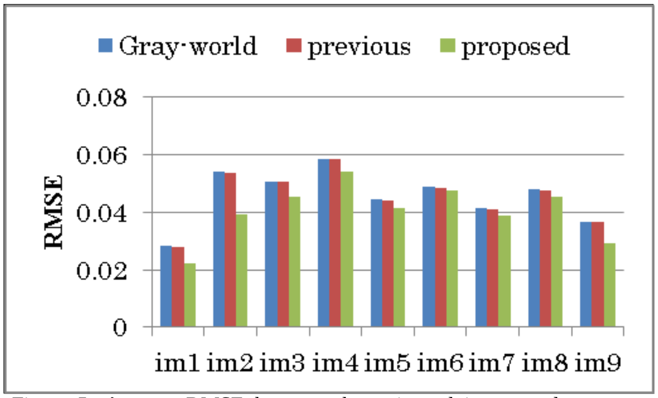


Figure 5. Average RMSE between the estimated image under common illumination and the estimated image under colored illumination.

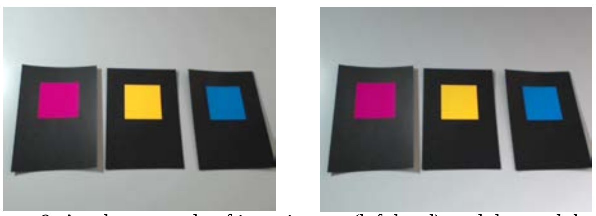


Figure 6. Another example of input images (left hand), and the result by the proposed method (right hand).

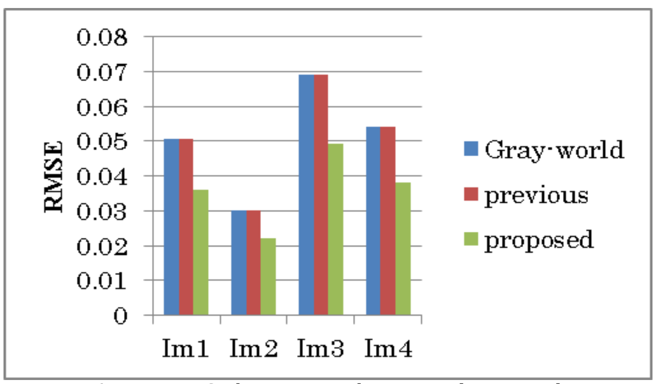
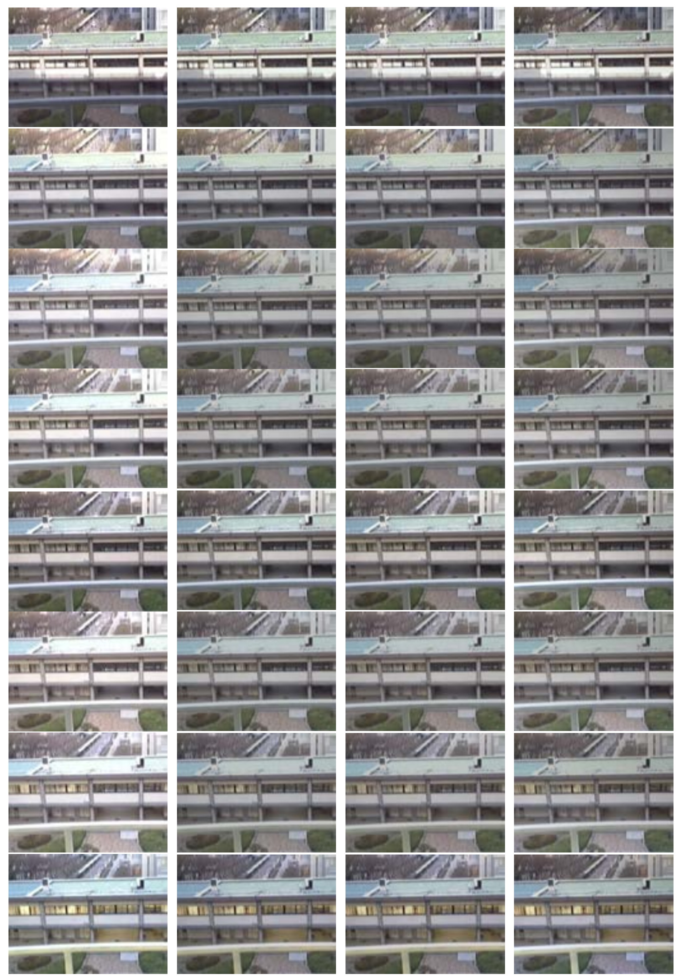


Figure 7. Average RMSE between two the estimated image under common illumination and the estimated image estimated under colored illumination.

Using these images, we conducted experiments to confirm the effectiveness of the proposed method. We compared three methods, Gray-world based method, the previously proposed correlation based method and the method proposed in this paper. To evaluate the effectiveness of each method, we calculate the RMSE between two estimated images. One is the image estimated from the image taken under common illumination. The other is the image estimated from the image taken under colored illumination. RMSEs for three illumination conditions are averaged. The results are summarized in Figure 5. As can be seen, proposed methods have smaller RMSE. It means that the proposed method is effective as a kind of a normalization tool of images to reduce image changes due to illumination changes. This method is not necessarily just a tool to obtain the image under white illumination. More specifically, the amount of change between two estimated images is less than the amount of change between the corresponding two input images with different illumination condition.

Figure 4 (e) – (j) shows examples of the estimated images. Among them (e), (g) and (i) show the results for the case when the input image is (a), the image taken under common room lighting. On the other hand, (f), (h) and (j) show the results in the case when the input image is (d), the image taken under blue illumination. The pairs (e)-(f), (g)-(h) and (i)-(j) correspond to the Gray-world based method, the previous correlation based method and the proposed method. Figure 5 shows average RMSE between two estimated images. One is the image estimated from the image taken under common illumination. The other is the image estimated from the image taken under colored illumination. RMSEs for three illumination conditions are averaged. From this figure, we can see that the RMSE between the image (i) and (j), which is in the proposed method, is about o.o4, which is significantly less than in the Gray-world based method and in the previous correlation based method.



(a) (b) (c) (d)

Figure 8 Sample images. (a) Original images. (b) Results by Gray-world based method. (c) Results by the previous method. (d) Results by the proposed method.

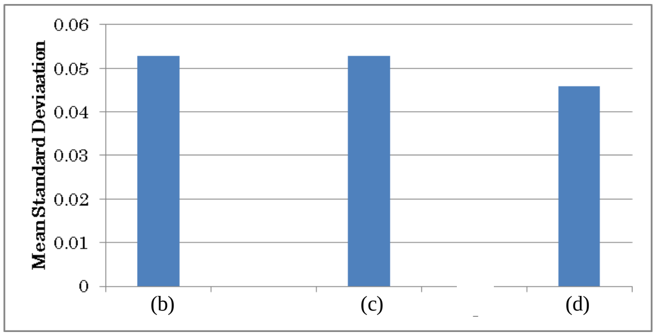


Figure 9 Mean standard deviation of pixel values.

We are planning to apply the proposed method to the system that can count students' raising the color cards to accelerate communication between a teacher and many students in a classroom [2]. An example of the color cards is shown in Figure 6 (a). The upper left part of the image is brighter than other parts. Figure 6 (b) is the result of the proposed method. Non-uniformity of the lighting effect is reduced. We prepared 4 groups of images like Figure 6 (a). Each group has 4 images with different illumination condition. One is taken under a common lighting, and the other three are taken under the common lighting added by another lamp with different strength. We evaluated the effectiveness of the proposed method in the same way as mentioned before, and we obtained the result shown in Figure 7. The proposed method has the lower RMSE. Figure 6 (a) is an image included in the group Im3.

We conducted other experiments to evaluate effectiveness of the proposed method in the case when illumination changes with setting of the sun. Figure 8 (a) shows 8 samples of original images taken in setting of the sun. We can see changes in these images caused by illumination change. These changes were eliminated by three color constancy models; the gray-world based method, the previous method and the proposed method. The results are shown in Figure 8 (a), (b) and (c). We calculated the standard deviation of pixel values over 8 images shown in Figure 8 (a), (b) and (c). Figure 9 shows the mean standard deviation. If this value is small, it means that effect of illumination change is effectively eliminated. From this figure, we can conclude that the proposed method is more effective than other two methods.

V. CONCLUSION

We extended the previous method [14] based on the color correlation matrix $K_{ij} = < I_i I_j >$ so that it works well for non-uniform illumination. In the proposed method, we introduce the modified correlation matrix. $K_{xij} = < xI_i I_j >$ and $K_{xij} = < xI_i I_j >$ to reduce the non-uniformity in the illumination. We conducted simulation experiments using synthesized image and confirmed that the proposed method has its own superiority when non-uniformity of the illumination is large. Inversely, when the illumination is uniform, the previous method has rather better results. We also confirmed that the proposed method is effective for real images too. In future work, we will address the problem that the proposed method does not have better result compared to the previous method when the illumination is uniform.

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