A Method of Estimating Non-parallel Illumination Based on Extended Gray-world Assumption

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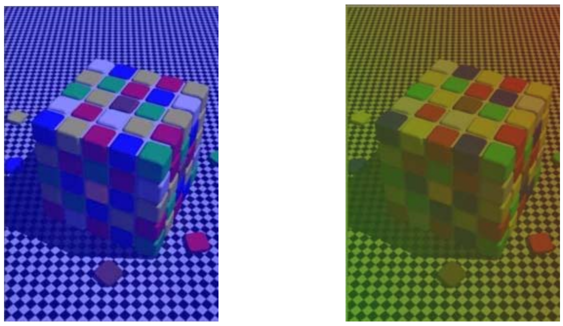
Summary
As a color constancy model, this paper proposes a novel method to eliminate illumination effect from images. This method is based on extended gray-world assumption. This assumption states that (1) illumination is not parallel and changes linearly according to positional coordinates, and (2) mean color of objects is gray and color is location unbiased. It is shown that under this assumption illumination can be effectively estimated even if illumination is not parallel; then illumination effect is not uniform in the image. Once illumination is estimated, we can estimate the image when white light is illuminated onto the object. Some experimental results are presented, and it is shown that the proposed method effectively eliminate illumination effect even for the case that illumination is not parallel.

Key words:
Color constancy, gray-world assumption, object recognition, non-parallel illumination, object color.



(a)Parallel illumination. (b)Non-parallel illumination.

Fig. 1. Images taken under parallel and non-parallel illuminations.

1. Introduction

Human being perceive an object color independent of illumination. This ability is called color constancy. This paper proposes a novel method to realize this ability on computer vision. As spectrum of light input to the camera is dependent of illumination, it is necessary to estimate illumination in order to detect object color. In this paper, we propose a method of estimating not only parallel illumination but also non-parallel illumination, and we show that object color is successfully obtained by compensating illumination effect.

As computational color constancy methods, there have been several methods as follows: In the papers [1, 2], the problem of color constancy was considered based on the relation between specula reflection and diffusion reflection. Retinex theory[3] was proposed, where color at each position in the image is estimated using a certain normalization process. As a related method, a method based using local averaging was proposed in the paper [4], and further, there was proposed a method using image statistics such as correlation between redness and luminance [5]. One simple method was proposed in the paper [6], where illumination was estimated based on an assumption that mean color of objects was gray; it was called gray-world model. This method works well for large situation, but it is assumed that illumination is parallel. It does not work well when illumination is non-parallel.

In this paper, we extend the gray-world assumption as follows: (1) illumination is not parallel and changes linearly according to positional coordinates, and (2) mean color of objects is gray and color is location unbiased. Under this assumption, we propose a novel method to estimate non-parallel illumination. Figure 1 shows an image obtained under parallel illumination and that under non-parallel illumination. The model based on gray-world assumption works well for the case of Figure 1 (a), but cannot cope with the case of Figure 1.(b) The proposed method work well for both cases of (a) and (b) of Figure 1.

In the next section, we formulate the extended gray-world assumption and propose a method to estimate effect of illumination. We also indicate that once illumination is estimated we can estimate the image when white light is illuminated onto the object. In the section 3, we show some experimental results, which show the proposed method effectively eliminate illumination effect even for the case that illumination is not parallel; it works well when the effect of illumination is not uniform on the image.

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2. Extended Gray-World Assumption

2.1 Low dimensional linear model

Let $I_1(x,y), I_2(x,y)$ and $I_3(x,y)$ be pixel values of red, green and blue, respectively at point (x,y) on the image plane. Then, $I_k(x,y)(k=1,2,3)$ is obtained in terms of reflectance of object surface $S(x,y;\lambda)$, spectral distribution of light $E(x,y;\lambda)$ and camera sensitivity function $R_k(\lambda);(k=R,G,B)$ as

$$I_k(x,y) = \int_{\lambda_1}^{\lambda_1} E(x,y;\lambda)S(x,y;\lambda)R_k(\lambda)d\lambda \ , \tag{1}$$

where λ is wave length, and we assume that $R_k(\lambda)$ is normalized as

$$\int_{\lambda_1}^{\lambda_1} R_k(\lambda)d\lambda = 1 \ . \tag{2}$$

In the equation (1), $I_k(x,y)$ and $R_k(\lambda)$ are known, and we have to solve unknown $S(x,y;\lambda)$ and $E(x,y;\lambda)$. It is ill posed because the number of unknown parameters is larger than the number of equations. To cope with this difficulty we reduce unknown parameters by assuming that $S(x,y;\lambda)$ and $E(x,y;\lambda)$ are low dimensional vector [7]. Specifically, we assume that $S(x,y;\lambda)$ and $E(x,y;\lambda)$ are represented as

$$S(x,y;\lambda) = \sum_{i=1}^{3} \sigma_i(x,y)S_i(\lambda) \ , \tag{3}$$

$$E(x,y;\lambda) = \sum_{i=1}^{3} \eta_i(x,y)E_i(\lambda) \tag{4}$$

These equations mean that $S(x,y;\lambda)$ and $E(x,y;\lambda)$ are represented as linear combinations of three basis functions of $S_1(\lambda), S_2(\lambda), S_3(\lambda)$ and $E_1(\lambda), E_2(\lambda), ES_3(\lambda)$, each of which corresponds to red, green and blue. Here, we require that

$$0 \le \sigma_i(x,y) \le 1 \ , \tag{5}$$

$$0 \le \eta_i(x,y) \le 1 \ . \tag{6}$$

without loss of generality. We notice that when both object color and illumination are white, the pixel should be white. This is guaranteed by assuming that

$$\sum_{i=1}^{3} S_i(\lambda) = 1 \ , \tag{7}$$

$$\sum_{i=1}^{3} E_i(\lambda) = 1 \ . \tag{8}$$

In fact, when both object color and illumination are white, $\sigma_i(x,y)=1$ and $\eta_i(x,y)=1$ for all i. Then, from (1-4), we get

$$I_k(x,y) = \int_{\lambda_1}^{\lambda_1} R_k(\lambda)d\lambda = 1 \ , \tag{9}$$

which means that

$$I_R(x,y) = I_G(x,y) = I_B(x,y) = 1 \ , \tag{10}$$

which is a desirable consequence. Under this assumption, equation (1) becomes

$$\begin{aligned} I_k&(x,y) \\ &= \int_{\lambda_1}^{\lambda_1} \left(\sum_{i=1}^{3} \eta_i)x,y)E_i(\lambda) \right) \left(\sum_{j=1}^{3} \sigma_j(x,y)S_j(\lambda) \right) R_k(\lambda)d\lambda \ . \\ &= \sum_{i=1}^{3}\sum_{j=1}^{3} \eta_i(x,y)\sigma_j(x,y) \int_{\lambda_1}^{\lambda_1} E_i(\lambda)S_i(\lambda)R_k(\lambda)d\lambda \end{aligned} \tag{11}$$

Since $S_i(\lambda)$, $E_i(\lambda)$ and $R_k(\lambda)$ is known, unknown parameters are reduced to six; $\sigma_1(x,y), \sigma_2(x,y), \sigma_3(x,y)$ and $\eta_1(x,y), \eta_2(x,y), \eta_3(x,y)$. However, the number of unknown parameters is still larger than the number of equations.

2.2 Gray-world assumption

One simple way to overcome the difficulty mentioned above is the method based on gray-world assumption. The gray-world assumption states that average of object color is gray, and illumination $E(x,y;\lambda)$ is position independent. From this assumption, the average of $S(x,y;\lambda)$ becomes independent of λ. Assume that $-1/2 \le x \le 1/2$ and that $-1/2 \le y \le 1/2$, we obtains

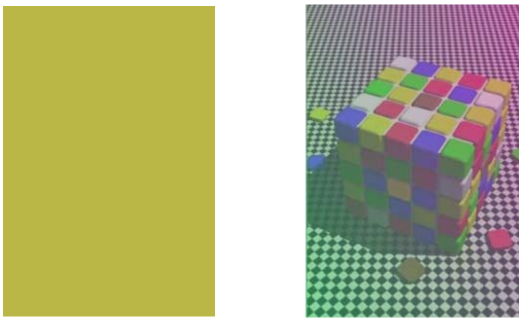
$$< S(x,y;\lambda) >= \int_{-1/2}^{1/2}\int_{-1/2}^{1/2} S(x,y;\lambda)dxdy = s \ , \tag{12}$$

where s is independent of λ, and represents mean luminance. Then, equation (1) becomes

$$\begin{aligned} < I_k(x,y) > &= \int_{-1/2}^{1/2}\int_{-1/2}^{1/2} I_k(x,y;\lambda)dxdy \\ &= \int_{\lambda_1}^{\lambda_1} E(\lambda) < S(\lambda) > R_k(\lambda)d\lambda \\ &= s\int_{\lambda_1}^{\lambda_1} E(\lambda)R_k(\lambda)d\lambda \\ &= s\sum_{i=1}^{3} \eta_i \int_{\lambda_1}^{\lambda_1} E_i(\lambda)R_k(\lambda)d\lambda \end{aligned} \ , \tag{13}$$

where we use the fact that illumination is parallel, that is,

$E(x,y;\lambda)$ is position independent, and hence η_i is also



(a). (b)

Fig. 2. An example where the method based on gray-world assumption does not work well. (a) Estimated illumination $E(x,y;\lambda)$. Estimated image $\hat{I}_k(x,y)$ when it is illuminated with white light.

constant.

Equation (13) can be regarded as a system of linear equations with three unknowns $s\eta_1$, $s\eta_2$ and $s\eta_3$. Once these parameters are obtained, object color $\hat{\sigma}_i(x,y)(i=1,2,3)$ at each point is estimated up to mean luminance s by solving Eq. (11) as a system of linear equations. In fact, Eq. (11) can be reformed as

$$I_k(x,y)=\sum_{i=1}^{3}\sum_{j=1}^{3}(s\hat{\eta}_i)(\sigma_j(x,y)/s)\int_{\lambda_1}^{\lambda_1}E_i(\lambda)S_i(\lambda)R_k(\lambda)d\lambda \cdot \tag{14}$$

Since $s\hat{\eta}_1$, $s\hat{\eta}_2$ and $s\hat{\eta}_3$ are already known, $\hat{\sigma}_1(x,y)/s$, $\hat{\sigma}_2(x,y)/s$ and $\hat{\sigma}_3(x,y)/s$ are obtained by solving the Eq. (14) as a system of linear equations. Then, the image under white illumination can be estimated up to the scale factor s as

$$\hat{I}_k(x,y)=\sum_{j=1}^{3}\hat{\sigma}_j(x,y)\int_{\lambda_1}^{\lambda_1}S_j(\lambda)R_k(\lambda)d\lambda . \tag{15}$$

Although the scale factor s is not determined in this method, it can be set by hand as any value such as 0.5, or it is fixed requiring some constraint such as

$$\int_{-1/2}^{1/2}\int_{-1/2}^{1/2}\hat{I}_k(x,y)dxdy=\int_{-1/2}^{1/2}\int_{-1/2}^{1/2}I_k(x,y)dxdy \ , \tag{16}$$

where $I_k(x,y)$ is the original image when the object is illuminated by colored light, and,. $\hat{I}_k(x,y)$ is the estimated image when the same object is illuminated by white light.

2.3 Extended gray-world assumption

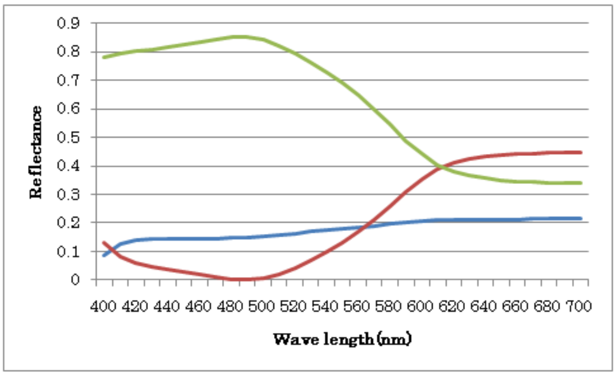


Fig. 3 Basis functions for object color.

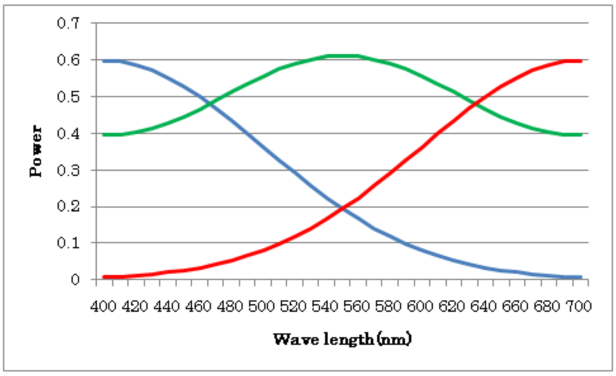


Fig. 4 Basis functions for illumination.

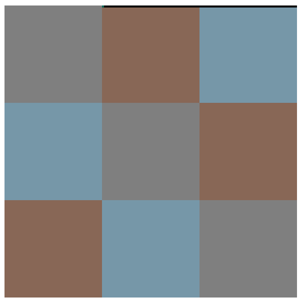


Fig. 5 An example of object color that satisfies extended gray world assumption.

The method based on gray-world assumption works well when illumination is parallel and equation (12) holds. However, when illumination is non-parallel, this method fails. An example is shown in Figure 2, where (a) shows the estimated illumination $E(x,y;\lambda)$, and (b) shows the estimated image when white light is illuminated. The result is not satisfactory; effect of illumination is still remaining. In this sub-section, we propose an extended gray-world assumption in order to cope with the case when illumination is non-parallel.

Extended gray-world assumption states as follows:

1. Let $E(x,y;\lambda)$ be spectral distribution of light at (x,y) on the image, then $E(x,y;\lambda)$ is a linear function of x and y as

$$E(x,y;\lambda)=\sum_{i=1}^{3}(\eta_{0i}+\eta_{xi}x+\eta_{yi}y)E_i(\lambda) \tag{17}$$

2. The average of object color $<S(x,y;\lambda)>$ is independent of λ as

$$<S(x,y;\lambda)>=\int_{-1/2}^{1/2}\int_{-1/2}^{1/2}S(x,y;\lambda)dxdy=s\,, \tag{18}$$

and $S(x,y;\lambda)$ is location unbiased as

$$<xS(x,y;\lambda)> =\int_{-1/2}^{1/2}\int_{-1/2}^{1/2}xS(x,y;\lambda)dxdy=0\,, \tag{19}$$

$$<yS(x,y;\lambda)> =\int_{-1/2}^{1/2}\int_{-1/2}^{1/2}yS(x,y;\lambda)dxdy=0\,, \tag{20}$$

$$<xyS(x,y;\lambda)> =\int_{-1/2}^{1/2}\int_{-1/2}^{1/2}xyS(x,y;\lambda)dxdy=0\,, \tag{21}$$

$$<x^2S(x,y;\lambda)> =\int_{-1/2}^{1/2}\int_{-1/2}^{1/2}x^2S(x,y;\lambda)dxdy=s/12\,, \tag{22}$$

$$<y^2S(x,y;\lambda)> =\int_{-1/2}^{1/2}\int_{-1/2}^{1/2}y^2S(x,y;\lambda)dxdy=s/12\,, \tag{23}$$

From Eq. (17), we obtain

$$\begin{aligned}I_k(x,y)&=\int_{\lambda_1}^{\lambda_1}E(x,y;\lambda)S(x,y;\lambda)R_k(\lambda)d\lambda\\ &=\int_{\lambda_1}^{\lambda_1}\sum_{i=1}^{3}(\eta_{0i}+\eta_{xi}x+\eta_{yi}y)E_i(\lambda)S(x,y;\lambda)R_k(\lambda)d\lambda\end{aligned}\ . \tag{24}$$

Using Eq. (19-23) we obtain

$$\begin{aligned}<I_k(x,y)>&=\int_{-1/2}^{1/2}\int_{-1/2}^{1/2}I_k(x,y;\lambda)dxdy\\ &=\sum_{i=1}^{3}s\eta_{0i}\int_{\lambda_1}^{\lambda_1}E_i(\lambda)R_k(\lambda)d\lambda\end{aligned}\ , \tag{25}$$

$$\begin{aligned}<xI_k(x,y)>&=\int_{-1/2}^{1/2}\int_{-1/2}^{1/2}xI_k(x,y;\lambda)dxdy\\ &=1/12\sum_{i=1}^{3}s\eta_{xi}\int_{\lambda_1}^{\lambda_1}E_i(\lambda)R_k(\lambda)d\lambda\end{aligned}\ , \tag{26}$$

$$\begin{aligned}<yI_k(x,y)>&=\int_{-1/2}^{1/2}\int_{-1/2}^{1/2}yI_k(x,y;\lambda)dxdy\\ &=1/12\sum_{i=1}^{3}s\eta_{yi}\int_{\lambda_1}^{\lambda_1}E_i(\lambda)R_k(\lambda)d\lambda\end{aligned}\ . \tag{27}$$

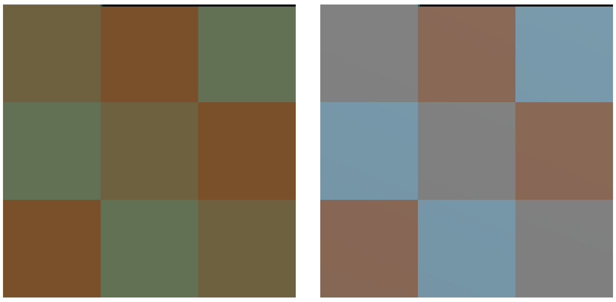
Each of Eq. (25-27) is a system of linear equation and $s\eta_{0i}$, $s\eta_{xi}$ or $s\eta_{yi}$ is obtained by solving it. In this way, illumination can be estimated even when it changes linearly according to position coordinates x and y. Once illumination is estimated, object color is obtained in the same way as in the case of the method based on gray-world assumption, and the image when white light is illuminated is estimated as in the last sub-section. Thus, it is shown that the method based on extended gray-world model is applicable to the case when illumination is non-parallel.

3. Experiments

3.1 Experiments using synthesized images

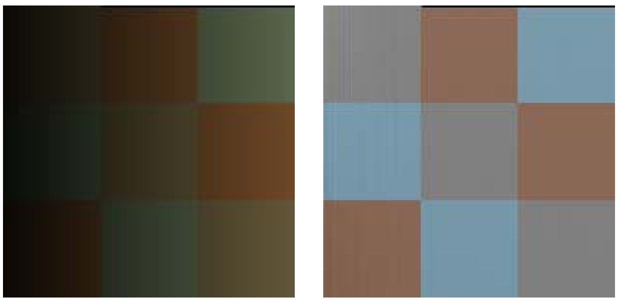
We conducted experiments to confirm effectiveness of the proposed method. In the first experiment we synthesized images based on the low dimensional linear model. We set the basis functions for object color as shown in Figure 3, which are constructed based on the result in [8], where principal component analysis was applied to 3534 objects. In Figure 3, reflectance distributions of red and green are principal bases obtained by the principal component analysis, and that of blue is derived using Eq. (7). As for spectrum distribution of light, we tentatively set the basis functions as in Figure 4. The basis functions of red and blue is assumed to be a certain Gaussian functions, and that of green is determined so as to satisfy the relation (8).

Figure 5 shows an example of the image when white parallel light is illuminated on to the object color that satisfies extended gray-world assumption. Figure 6 (a) shows the image obtained by illuminating the object with yellow parallel light. We applied the method based on the extended gray-world assumption to the image (a). The estimated image when white parallel light is illuminated is shown in Figure 6 (b). It is exactly the same as the image in Figure 5, which indicates the proposed method is effective. On the other hand, the case where non-parallel light is illuminated is shown in Figure 7 (a) that shows the original image illuminated by non-parallel light. The proposed method was applied to this image, and the estimated image when white light is illuminated is shown in (b). Exactly the same image as the image in Figure 5 is obtained in this case, too. These results show that the method based on extended gray-world assumption works well.



(a) (b)

Fig.6 .An example of the result of the experiment. (a)The image obtained by illuminating the image in Figure 5 with parallel illumination. (b)The Estimated object color by the proposed method.



(a) (b)

Fig. 7. An example of the result of the experiment. (a)The image when illuminated by non-parallel illumination.ion to the image in Figure 5. (b)The estimated object color by the proposed method.

To evaluate accuracy of estimated object color numerically, we prepared various illumination by changing $\eta_1(x,y)$, $\eta_2(x,y)$ and $\eta_3(x,y)$ in Eq. (3). We illuminated the object with these lights. Then, we estimated the images when white light was illuminated using the method based on gray-world assumption and extended gray-world assumption. The degree of accuracy was estimated as follows; we define estimation error as

$$error = \int_{-1/2}^{1/2}\int_{-1/2}^{1/2} \cos^{-1}(\sum_{k=1}^{3} I_k(x,y)\hat{I}_k(x,y))dxdy \, , \qquad (28)$$

where $I_k(x,y)$ is the true image when white light is illuminated on to the object, and $\hat{I}_k(x,y)$ is the estimated image by the method based on gray-world assumption or extended gray-world assumption.

Experiment 1. We set object color as in Figure 5. This image is considered to be the image when white light is illuminated onto the object, because white light does not change color. In this experiment, we assumed that illumination is parallel, and set $\eta_i(x,y)$ be constant value of 0.0, 0.2, 0.4, 0.6, 0.8, or 1.0, but we omitted the special case of $\eta_1(x,y)=\eta_2(x,y)=\eta_3(x,y)=0$. Thus, we prepared 6 x 6 x 6 – 1=215 kinds illumination, and the image in Figure 5 was illuminated by these lights. Then we estimated the images when white light was illuminated. The results are shown in Table 1. Amount of error is zero for both methods based on gray-world assumption and extended gray-world assumption. Amount of error when input images themselves are regarded estimated images is also shown in the table.

Table 1. The results of experiment 1.

	Gray-World	**Expended Gray-World**	**Without Processing**
Error	0	0	0.156758

Experiment 2. Object color is the same as Experiment 1. In this experiment, we used non-parallel illumination. We set η_{01}, η_{02} and η_{03} to be 0.5 respectively, η_{x1}, η_{x2} and η_{x3} to be -0.2, -0.1, 0.0, 0.1, or 0.2 independently, and η_{y1} , η_{y2} and η_{y3} to be 0.0 respectively. Thus we prepared 5 x 5 x 5 = 125 kinds non-parallel illumination, and estimated the images when white light was illuminated. The results are shown in Table 2. Amount of error is zero in the case of extended gray-world assumption, but it is not zero in the case of usual gray-world assumption.

Table 2. The results of experiment 2.

	Gray-World	**Expended Gray-World**	**Without Processing**
Error	0.052513	0	0.052598

Experiment 3. We synthesized object color randomly as is shown in Figure 8, which was considered to be the image when white parallel light was illuminated on it. This image does not necessarily satisfy extended gray-world assumption. In this experiment we prepared various parallel lights as in the case of Experiment 1, and estimated the images when white light was illuminated. The results are shown in Table 3. Amount of error is comparable between the case of extended gray-world assumption and the case of usual gray-world assumption.

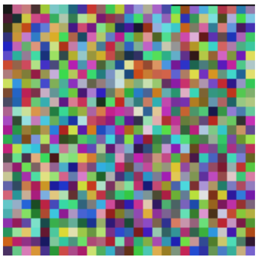
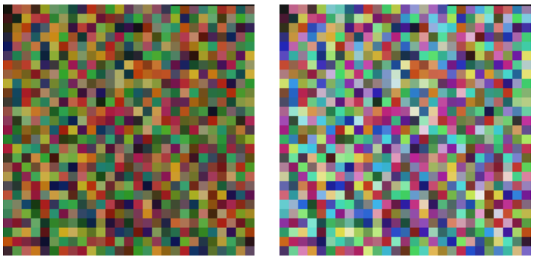
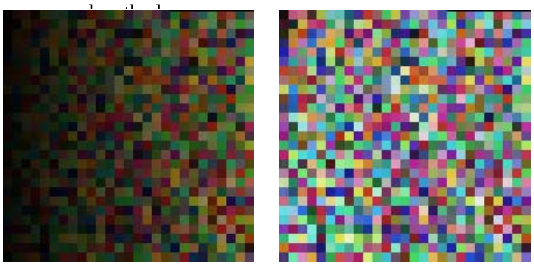


Fig. 8 An example of object color which does not satisfy extended gray world assumption.



(a) (b)

Fig.9 .An example of the result of the experiment. (a)The image obtained by illuminating the image in Figure 8 with parallel illumination. (b)The Estimated object color by the



(a) (b)

Fig.10 .An example of the result of the experiment. (a)The image obtained by illuminating the image in Figure 8 with non-parallel illumination. (b)The Estimated object color by the proposed method.

When nothing is processed, amount of error is significantly large. Figure 9 shows an example of the result of Experiment 3. (a) shows an example of input images which were illuminated with parallel colored light, and (b) is the estimated image when white light was illuminated using the proposed method.

Table 3. The results of experiment 3.

	Gray-World	**Expended Gray-World**	**Without Processing**
Error	0.025201	0.026456	0.128005

Experiment 4. In this experiment we prepared various non-parallel light as in the case of Experiment 2, and these were illuminated onto the image of Figure 8 in the same way as Experiment 3. We estimated the images when white light was illuminated. The results are shown in Table 4. In the case of usual gray-world assumption, amount of error is larger than the case without any processing, which indicates that the method based on the usual gray-world assumption sometimes produces undesirable side effect when non-parallel light is illuminated. On the other hand, proposed method, which is based on extended gray-world assumption, is seems to work well for this difficult situation. Figure 10 shows an example of the result of Experiment 4. (a) shows an example of input images which were illuminated with non-parallel light, and (b) is the estimated image using the proposed method.

	Gray-World	**Expended Gray-World**	**Without Processing**
Error	0.057556	0.027369	0.044359

3.2 Experiments using real images

In this sub-section, we show results of experiment using real images. We illuminated a real object by colored lights, and we got images by a camera. We used three colored lights shown in Figure 11 and a white fluorescent lamp.

Experiment 5. We printed out the image shown in Figure 5 as a real object. It was illuminated by the red light and the white fluorescent lamp. We illuminated the object by these light sources from far distance so that the illumination can be regarded as parallel light, and took the image by a camera, which were used as an input image. Figure 12 (a) shows the input image. (b) shows the estimated image based on gray-world assumption. (c) shows the estimated image based on extended gray-world assumption. We can see that both methods can eliminate effect of light as well.

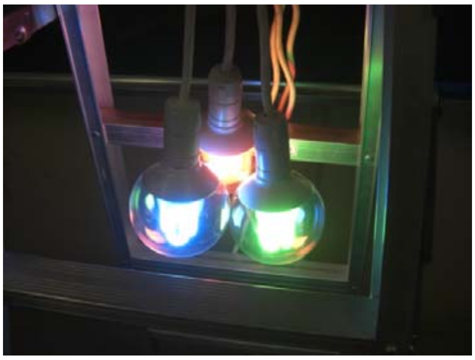
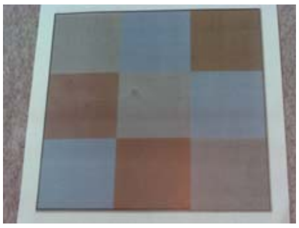


Fig.11 The colored lights used in the experiments.

(a)




(b) (c)

Fig. 12 .An example of the result of the experiment. (a)The image illuminated by a parallel light. (b) The estimated image based on gray world assumption. (c) The estimated image based on extended gray world assumption.

Experiment 6. In this experiment, non-parallel lights were illuminated onto the same object as Experiment 5. Figure 13 (a) shows the input image. (b) shows the estimated image based on gray-world assumption. (c) shows the estimated image based on extended gray-world assumption. We can see that the method based on extended gray -world assumption work better than the method based on the usual gray-world assumption.

(a
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(b
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(c
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Fig. 12 . An example of the result of the experiment. (a)The image illuminated by a non-parallel light. (b) The estimated image based on gray world assumption. (c) The estimated image based on extended gray world assumption.


(a
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(b
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Fig. 13 .An example of the result of the experiment. (a)The input image where color is location biased. (b)The Estimated object color by the proposed method.


(a
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(b
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Fig. 14 .An example of the result of the experiment. (a)The image obtained by illuminating the image in Figure 8 with parallel illumination. (b)The Estimated object color by the proposed method.

Experiment 7 We conducted experiment using other more realistic images. Figure 13 (a) shows an input image, where object color was location biased. (b) shows the estimated image using the proposed method based on extended gray-world assumption. The resultant image has red artifact around the up right corner. It seems that this is because the object color is location biased; in this image red paper is located around the down left corner.

Figure 14 (a) shows another input image where non-parallel light is illuminated from the left hand side. (b) shows the estimated image based on extended gray-world assumption. It seems that illumination effect is effectively eliminated, but not perfectly. The reason is considered to be that illumination does not necessarily change linearly.

3. Conclusion

In order to develop a computational color constancy model, we extended gray-world assumption so that it can cope with the case that illumination is not parallel. The extended assumption states that (1) illumination is not parallel and changes linearly according to positional coordinates, and (2) mean color of objects is gray and color is location unbiased. We showed that under this assumption illumination can be effectively estimated even if illumination is not parallel We also showed that once illumination is estimated we can estimate the image when white light is illuminated onto the object. We conducted various experiments, and showed that the proposed method can effectively eliminate illumination effect even for the case that illumination is not parallel.

The proposed method can cope with non-parallel illumination, but it is required that illumination changes linearly on the image according to position coordinate. It is a future work to extend the method so that it can cope with more general illumination change.

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