# A Method for Estimating Colors due to Fuzzy Reasoning 

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#### Abstract

It was well known that spectral reflectance information taken by using a CCD camera through $\mathrm{X}, \mathrm{Y}$ and Z filters was much related to both brilliance and illumination. Also color information in the groups that composed of five similar colors under the different lighting condition was examined; the groups were achromatic color, red, green and blue. However, the similar color groups of cyan, magenta and yellow, which are complementary colors of red, green and blue, were not examined. Therefore, this paper examines the color features for the above three groups, and proposes a method due to fuzzy reasoning for estimating colors from seven similar color groups. First, we estimate a color group to which an objective color belongs in seven groups. Secondly, the objective color is extracted from five similar ones in the estimated group. The reliability of the proposed method is demonstrated on an experiment using the data on thirty-five colors.


Key Words : color, similar color group, XYZ color space, fuzzy reasoning, image processing

## 1 INTRODUCTION

Color of objects is the surface spectral reflectance from the light sources. Color information is one of the important elements that characterize the object ${ }^{1)}$, and to distinguish colors is useful for object recognition. Our perception of surface colors is stable despite changes in illumination ${ }^{2}$. The illumination is rarely constant in color and intensity ${ }^{3}$, which influences on the digital number (DN) in image data ${ }^{4}$. The property will cause an error of automated color distinction in image processing.

In our previous study ${ }^{5}$, the relationship between the spectral reflectance information and the brilliance and illumination was analyzed. Color information in XYZ color space was adopted; the spectral reflectance was taken by using a monochrome Charge Coupled Device (CCD) camera through three interference filters: $\mathrm{X}, \mathrm{Y}$ and Z filters. We also estimated colors in color group, which was composed of five similar colors. The group number was four, i.e., achromatic color, red, green and blue. However, the similar color groups of cyan, magenta and yellow, which are complementary colors of red, green and blue, were not examined. Although the method in the previous study was able to distinguish colors in the same similar groups ${ }^{\text {s/ }}$, extraction of the difference of colors from the multiple color similar groups was not taken into account.
To improve color distinction accuracy under the different lighting condition, this paper examines the color features and proposes a method due to fuzzy reasoning for estimating colors from seven similar color groups. First, we estimate a color group to which an objective color belongs in seven similar color groups. Secondly, the objective color is extracted from five similar ones in the estimated group. This paper is concerned with thirty-five colors, and the reliability of the proposed algorithm is demonstrated in an experiment.

## 2 SAMPLE DATA

### 2.1 System to obtain the sample data

In order to obtain image data for colors, this study used a personal computer, a CCD camera and four white light sources. Distance between the camera and the sample data was $60(\mathrm{~cm})$ (Figure 1). The illumination ( lx ) in the position of sample data was measured and the brilliance ( $\mathrm{cd} / \mathrm{m}^{2}$ ) was also measured from the same position of the CCD camera.
This study focuses on seven kind of similar color groups; they are achromatic color, red, blue, green, cyan, magenta and yellow. Each group has five colors that belong to the same hue. In our color appearance, there are a large number of colors that classified as the same color ${ }^{6}$. The intensity and hue can grade colors for


Figure 1 System to obtain image data for colors.

Table 1 The details of sample data for thirty-five colors.

|  | Color | Red | Green | Blue | Hue | Saturation | Intensity |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| color group of achromatic. color | white | 255 | 255 | 255 |  | - | 255 |
|  | gray1 | 128 | 128 | 128 |  | $\square$ | 128 |
|  | gray2 | 192 | 192 | 192 |  | $\cdots$ | 192 |
|  | gray3 | 64 | 64 | 64 |  | - | 64 |
|  | black | 0 | 0 | 0 |  | - | 0 |
| color group of red | red1 | 255 | 0 | 0 | 0 | 255 | 128 |
|  | red2 | 255 | 128 | 128 | 0 | 255 | 192 |
|  | red3 | 128 | 0 | 0 | 0 | 255 | 64 |
|  | red4 | 255 | 64 | 64 | 0 | 255 | 160 |
|  | red5 | 192 | 0 | 0 | 0 | 255 | 96 |
| color group of green | green 1 | 0 | 255 | 0 | 120 | 255 | 128 |
|  | green2 | 128 | 255 | 128 | 120 | 255 | 192 |
|  | green 3 | 0 | 128 | 0 | 120 | 255 | 64 |
|  | green4 | 64 | 255 | 64 | 120 | 255 | 160 |
|  | green 5 | 0 | 192 | 0 | 120 | 255 | 96 |
| color group of blue | blue 1 | 0 | 0 | 255 | 240 | 255 | 128 |
|  | blue 2 | 128 | 128 | 255 | 240 | 255 | 192 |
|  | blue 3 | 0 | 0 | 128 | 240 | 255 | 64 |
|  | blue 4 | 64 | 64 | 255 | 240 | 255 | 160 |
|  | blue 5 | 0 | 0 | 192 | 240 | 255 | 96 |
| color group of cyan | cyan 1 | 0 | 255 | 255 | 180 | 255 | 128 |
|  | cyan2 | 128 | 255 | 255 | 180 | 255 | 192 |
|  | cyan 3 | 0 | 128 | 128 | 180 | 255 | 64 |
|  | cyan 4 | 64 | 255 | 255 | 180 | 255 | 160 |
|  | cyan 5 | 0 | 192 | 192 | 180 | 255 | 96 |
| color group of magenta | magental | 255 | 0 | 255 | 300 | 255 | 128 |
|  | magenta2 | 255 | 128 | 255 | 300 | 255 | 192 |
|  | magenta 3 | 128 | 0 | 128 | 300 | 255 | 64 |
|  | magenta4 | 255 | 64 | 255 | 300 | 255 | 160 |
|  | magenta5 | 192 | 0 | 192 | 300 | 255 | 96 |
| color group of yellow | yellow 1 | 255 | 255 | 0 | 60 | 255 | 128 |
|  | yellow2 | 255 | 255 | 128 | 60 | 255 | 192 |
|  | yellow3 | 128 | 128 | 0 | 60 | 255 | 64 |
|  | yellow4 | 255 | 255 | 64 | 60 | 255 | 160 |
|  | yellow5 | 192 | 192 | 0 | 60 | 255 | 96 |

their properties at regular intervals. The saturation is incapable of separating colors under the same rules because the division of the saturation depends on the intensity and hue. Therefore, we define five colors in each group by means of the difference of the intensity. Also the value of saturation in each color is fixed for 255 which shows the vivid color. Table 1 shows the details of sample data for thirty-five colors.
By using papers printed in each color, DN (0-255) in image data of each sample was taken by a CCD camera through $\mathrm{X}, \mathrm{Y}$ and Z filters on condition that the range of illumination is $1000(\mathrm{~lx})$ to 11000 (lx) at every 1000 (lx), and that a lens opening is eight types (f2.8-f32). Here, image data obtained by using an X filter is called X image data; Y and Z are as well as X .

### 2.2 Color features of sample data

In the previous study ${ }^{5}$, four color groups, i.e., achromatic color, red, green and blue were examined. As a result, it was clear that the DN in image data of each sample was much related to the brilliance and illumination. In addition, this study examines three color groups: cyan, magenta and yellow. Figure 2 shows examples of the resulting for three groups (f2.8). It is cleared that the DN is much concerned with the brilliance. It is also confirmed that all image data are related to the brilliance and illumination. Because of the property, the relationship between the DN in images and the brilliance and illumination is used as characteristics for color
distinction.

## 3 COLOR DISTINCTION ALGORITHM

Color information in image data is extracted from the printed material. Owing to color difference caused by the printing and lighting, the DN in image data, which shows the surface reflectance information from the light sources, involves obscurity.

Fuzzy set theory provides useful concepts and tools to deal with imprecise ${ }^{77}$. In order to consider the obscurity in the DN, this study assumes that the DN in XYZ color space is a fuzzy number. Also supervised data for membership function of colors assumes a fuzzy set. Namely, the DN in XYZ color space in proportion to the color is defined at the grade of membership, and the degree which belongs to the color is computed.

We propose a hierarchical approach for estimating colors in detail due to fuzzy reasoning. First, the fitness in each color is computed from the degree of belonging obtained in the membership function on $\mathrm{X}, \mathrm{Y}$ and Z image data. Secondly, color group is estimated by using the resulting. Thirdly, the objective color is extracted from five ones in the estimated group. Flowchart of the proposed approach is shown in Figure 3.

### 3.1 Preprocessing

3.1.1 Supervised data: The brilliance is used as the index element that shows the brightness of colors at data acquisition. By

(a) Color group of cyan in the X image data (f2.8).

(b) Color group of magenta in the X image data (f2.8).

(c) Color group of yellow in the Z image data (f2.8).

Figure 2 Examples of the relationship between the DN and the brilliance for three color group.
using the data on the relationship between the brilliance and the DN (0-255) in X, Y and Z image data, supervised data given in the membership function are extracted. To begin with, the measurements of average and variance of the component $i(i=X, Y, Z)$ in the color $C(C$ : color name) at each illumination (1000 ( 1 x ) to $11000(\mathrm{~lx})$ ) are coupled in the straight line, respectively. Next, an intersection point of the average line and the input brilliance $\alpha$ is used as the average for the membership function. Finally, an intersection point of the variance line and the input brilliance $\alpha$ is also computed, and then the difference between the intersection points on average and variance is used as the likelihood for the membership function of the component $i$ in the color $C$.
3.1.2 Membership function: Supposed that the DN for the supervised data has the normality, $f_{c}\left(x_{i}\right)$ is the probability density function, defined by
$f_{c i}\left(x_{i}\right)=\frac{1}{\sqrt{2 \pi \cdot v_{c i a}^{2}}} \exp \left\{-\frac{\left(x_{i}-m_{c i \alpha}\right)^{2}}{2 \cdot v_{c i \alpha}^{2}}\right\}$
where $X$ is a universal set in XYZ color space, $x_{i}$ is input variables to the membership function, $i=X, Y, Z, C$ is color (thirty-five colors), $m_{c i \alpha}$ indicates the DN and $v_{c i a}$ indicates the likelihood when the input brilliance is $\alpha$.

The maximum value of the probability density function is defined as $\max f_{c i}\left(x_{i}\right)$. Membership function $\mu_{c i}\left(x_{i}\right)$ can be written as

$$
\begin{align*}
\mu_{c i}\left(x_{i}\right) & =\frac{f_{c i}\left(x_{i}\right)}{\max f_{c i}\left(x_{i}\right)}  \tag{2}\\
& =\exp \left\{-\frac{\left(x_{i}-m_{c i a}\right)^{2}}{2 \cdot v_{c i a}^{2}}\right\} \tag{3}
\end{align*}
$$

Figure 4 shows an example of probability density and membership function; the probability density function for colors can be converted into the membership function.


Figure 3 Flowchart of the proposed method.

### 3.2 Computation of fitness $A$ and $B$

In order to estimate colors, the proposed method uses fitness $A$ and fitness B , which are computed by the degree of belonging that obtained from $\mu_{c i}\left(x_{i}\right)$.
3.2.1 Fitness $A$ : Define the fuzzy rule on color $C$ as
$R_{c i}$ : if $x_{i}$ is $A_{c i}$ then $b=w_{c i}$
where $A_{c i}$ is a fuzzy set of supervised data which has the membership function, $b$ is a set of weight coefficients for the estimated group, $w_{c i}$ is weight coefficient for color group.
$h_{1 c}$ is fitness A of color C, expressed by
$h_{1 C}=\frac{w_{C X} \cdot \mu_{C X}\left(x_{X}\right)+w_{C Y} \cdot \mu_{C Y}\left(x_{Y}\right)+w_{C Z} \cdot \mu_{C Z}\left(x_{Z}\right)}{w_{C X}+w_{C Y}+w_{C Z}}$
where $\mu_{c_{i}}\left(x_{i}\right)$ is degree of belonging of the component $i(i=X, Y$, $Z)$ in the color $C$.
3.2.2 Fithess $B$ : Define the fuzzy rule on color $C$ as
$R_{c}$ : if $x_{X}$ is $A_{C X}$ and $x_{Y}$ is $A_{C Y}$ and $x_{Z}$ is $A_{C Z}$ then Color is $C$
$h_{2 c}$ is fitness B of color C , the algebraic product of the degree of belonging for each component, obtained by
$h_{2 C}=\mu_{C X}\left(x_{X}\right) \cdot \mu_{C Y}\left(x_{Y}\right) \cdot \mu_{C Z}\left(x_{Z}\right)$

### 3.3 Estimation of color group

The algebraic sum of the fitness $B$ of the five colors in seven similar color groups is computed, respectively. As a result, the group with the largest value assumes the similar color one that the objective color attributes.

### 3.4 Estimation of objective color

The objective color is extracted from five ones in the estimated group by the fitness A and B. To begin with, the fitness A and B of each color in the estimated group are computed, respectively. When computing the fitness A , it is necessary to decide weight coefficient on the component of $\mathrm{X}, \mathrm{Y}$ and Z in each similar color group. As a result of the preparatory experiment, the weight coefficients are given in Table 2. Next, the color has the largest value of fitness $A$ and $B$ is classified as the objective one. If the values of fitness $A$ and $B$ are the largest in two different colors, the larger value of the algebraic product of them makes possible extraction of the color from two ones.

Table 2 Weight coefficients on the component of (X,Y,Z) in similar color group.

|  | $\mathrm{X}, \mathrm{Y}, \mathrm{Z}$ |  | $\mathrm{X}, \mathrm{Y}, \mathrm{Z}$ |
| :--- | :--- | :--- | :--- |
| achromatic color | $1,1,1$ | cyan | $1,1,1$ |
| red | $4,3,3$ | magenta | $3,2,3$ |
| green | $3,4,3$ | yellow | $1,1,1$ |
| blue | $3,3,14$ |  |  |

## 4 SIMULATION

### 4.1 Simulation data

Simulation on thirty-five colors is carried out; a hundred pixels extracted from $X, Y$ and $Z$ image data on the same condition serve as the simulation data. The extraction process is conducted for the data at each illumination (1000 (lx)-11000 (lx)) in all colors.

### 4.2 Estimation method for the comparison

In comparison with the results obtained with the proposed method, simulation was conducted with two methods under the same condition; one is a method using fitness A and the other is a method using max-min composition".
4.2.1 Use of fitness $A(\operatorname{method} A)$ : The similar color group, to which the color with the largest value of fitness A belongs, is estimated using a set of weight coefficients of $\left(w_{x}, w_{y}, w_{z}\right)=(1,1$, 1). And then, the color with the largest value of fitness $A$ is extracted from five ones in the estimated group. In the procedure, the fitness A is computed by using the weight coefficients set in the estimated group (See Table 2).
4.2.2 Use of max-min composition (method B): The smallest degree of belonging in component $\mathrm{X}, \mathrm{Y}$ and Z is used as fitness in each color. Next, the color with the largest value of the fitness is distinguished as the objective one.

## 5 RESULTS AND DISCUSSION

Distinction result with three methods ( $\mathrm{f} 2.8-\mathrm{f} 32$ ) is shown in Table 3. From the percentage of correctly classify the pixels, it is confirmed that the proposed method is much superior to the other methods for all simulation data, e.g., $96.2 \%$ is obtained in the case

(b) Membership function

(a) Probability density function

Figure 4 An example of probability density and membership function.

Table 3 Distinction result with three methods (f2.8-f32) (\%).

|  | $f 2.8$ | $f 4$ | $f 5.6$ | $f 8$ | $f 11$ | $f 16$ | $f 22$ | $f 32$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| proposed method | 96.2 | 95.8 | 91.7 | 82.3 | 67.3 | 47.5 | 28.2 | 13.9 |
| method $A$ | 89.8 | 89.6 | 84.4 | 74.7 | 59.9 | 41.1 | 24.7 | 12.7 |
| method B | 79.2 | 80.4 | 71.7 | 60.0 | 42.2 | 26.2 | 10.6 | 4.3 |

Table 4 Distinction result for thirty-five colors (f2.8) (\%).

| white | 100.0 | blue1 | 86.8 | yellow1 | 100.0 |
| :---: | ---: | :---: | ---: | :---: | :---: |
| gray1 | 100.0 | blue2 | 100.0 | yellow2 | 100.0 |
| gray2 | 99.3 | blue3 | 100.0 | yellow3 | 99.9 |
| gray3 | 99.6 | blue4 | 100.0 | yellow4 | 93.0 |
| black | 100.0 | blue5 | 86.2 | yellow5 | 82.2 |
| red1 | 100.0 | cyan1 | 75.5 | average | 96.2 |
| red2 | 100.0 | cyan2 | 100.0 |  |  |
| red3 | 99.7 | cyan3 | 97.5 |  |  |
| red4 | 100.0 | cyan4 | 88.0 |  |  |
| red5 | 99.3 | cyan5 | 100.0 |  |  |
| green1 | 90.5 | magenta1 | 94.0 |  |  |
| green2 | 99.8 | magenta2 | 100.0 |  |  |
| green3 | 99.6 | magenta3 | 99.9 |  |  |
| green4 | 83.6 | magenta4 | 96.0 |  |  |
| green5 | 95.0 | magenta5 | 100.0 |  |  |

of f 2.8 . There are two reasons for good accuracy of the proposed method. One is that fitness $B$ does not have to set the weight coefficients to estimate colors. While fitness A (method A) is also superior to max-min composition (method B), it needs weight coefficients and is unable to use the most suitable ones in the process of color group selection. The other is that the tendency of the distinction errors using fitness $A$ varies from that using fitness $B$. Compared to use of fitness $A$ or $B$, the proposed method that can effectively utilize both fitness $A$ and $B$ has the advantage of extraction of colors from unclear image information.

Distinction result of thirty-five colors using the data of $£ 2.8$ is summarized in Table 4. The proposed method enables fifteen colors to perfectly distinguish from the others. In seven similar


Figure 5 Relationship between the brilliance and the DN on cyanl and cyan4 in the $Y$ image data.
color groups, achromatic color and red have highly accuracy. On the other hand, the distinction result of three pairs of colors is low. They are cyan1 and cyan4, bluel and blue5, and greenl and green4. Figure 5 provides an example on cyanl and cyan 4 in the Y image data. The feature in two colors is very close to each other; the relationship between the brilliance and the DN is difficult to extract the difference of two colors through $Y$ image data as well as $X$ and $Z$ image data. The feature of each component in three pairs of colors is fairly obscure, which should give rise to the color distinction errors. However, $99.5 \%$ case in the distinction errors has rightly estimated the similar color group in the case of $\mathbf{f} 2.8$. The resulting is much better than that of the other methods. Therefore, it is concluded that the proposed method is effective for color distinction under the different illumination condition.

## 6 CONCLUSION

In order to distinguish colors of the object under the different lighting condition, this paper examined the color features and proposed a method for estimating colors due to fuzzy reasoning. The method estimated the color group, and then extracted the objective color from five ones in the estimated group. The DN in $\mathrm{X}, \mathrm{Y}$ and Z image data and the brilliance were used as the characteristics of colors, and the DN assumed a fuzzy number. As the simulation result for thirty-five colors, it was clarified that the proposed method was able to distinguish colors at the good accuracy.

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