Categorical Color Mapping Using Color Categorical Normalized Distance Transformation

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Abstract

◆ A new method for color appearance matching
  – Categorical color matching
    • Maintaining the relative color categorical relationship
    • Providing a mapping pair that has same color name
    • Setting a mapping point by referring to a categorical color matching criterion
    • Transforming a color categorical normalized distance
  – Comparing with CIECAM97s and RLAB
    • Ranked first in Z-score
Introduction

◆ Color appearance matching
  – Different viewing conditions
    • Different gamut
    • Matching destination color to source color exactly
  – Color appearance matching
    • Matching destination color to the source color exactly
  – Color reproduction
    • Matching to memory
  – Many color appearance models
    • Requiring optimized parameters
Proposed method

- Based on color categorical mapping
  - Deciding mapping point based on color name
- Suggesting a practical technique for realizing color appearance matching
- Using color categorical normalized distance transformation
Algorithm

◆ Categorical color matching
  – Objectives
    • Color name matching to maintain color categorical properties
    • Preserving the relative relationship between the points inside a given color categorical cluster
  – Designing step
    • Step 1 : Description of color name distribution in both the source space and the destination space (color categorical characterization)
    • Step 2 : Establishment of procedures to maintain the relative relationship between the points being inside a given color categorical cluster (color categorical correspondence)
– To realize Step 1

• Normalized sphere cluster

\[ D_i = \sqrt{(X - \mu_i)^t \sum_i^{-1} (X - \mu_i)} \]  \hspace{1cm} (1)

where \( \mu_i \) : an average vector
\( \sum_i^{-1} \) : a covariance matrix
\( X \) : the test color vector

• \( \sum_i^{-1} \) describes the shape of the color categorical distribution
• \( \mu_i \) corresponds to the center of gravity of this color categorical distribution

• Categorical basic color names
  – Nine color names
  – Red, Brown, Pink, Orange, Yellow, Green, Blue, Purple and Achromatic (white, black and gray)
To realize Step 2

- Categorical color matching operator $V_i$
  
  $$D_{b,i} = V_i D_{s,i}$$
  
  $$= \left[ \sum_{j=1}^{n} W_{v,j} v_{ij} \right] D_{s,i}$$

  where $D_{s,i}$: Mahalanobis distance of a test vector

- Middle point mapping scaling factor
  
  $$v_{i,j} = \begin{cases} 
  \frac{N_{d,ij}}{N_{s,ij}} & (i \neq j) \\
  0 & (i = j)
  \end{cases}$$

  where $N_{s,ij}$: Mahalanobis distance in the source space from $i$ to $j$
  
  $N_{d,ij}$: Mahalanobis distance in the destination space from $i$ to $j$
• Middle point mapping weighting factor

\[
\begin{align*}
  w_{v,j} &= \frac{1}{D_{s,j}} \\
  &= \frac{\sum_{p=1}^{n} \frac{1}{D_{s,p}}}{\sum_{p=1}^{n}} \\
  \text{if } D_{s,i} &= 0 \quad \text{then } w_{v,i} = 1, w_{v,k \neq i} = 0 \\
  \text{if } D_{s,k \neq i} &= 0 \quad \text{then } w_{v,i} = 0, w_{v,k \neq i} = 1, w_{v,l \neq i \neq k} = 0
\end{align*}
\]
Mapping using color categorcial normalized distance transformation

- Considering device gamut information
  - Dynamics range mapping operator

\[
D_{t,i} = R_i V_i D_{s,i} \\
= [F + (1 - F)U_i]V_i D_{s,j} \\
= FV_i D_{s,i} + (1 - F)U_i V_i D_{s,i} \quad (0 \leq F \leq 1)
\]

where \( F \) : the categorical color matching weighting factor

\( U_i \) : the gamut surface constraint mapping operator
Fig. 1. Function of Gamut-surface constraint mapping operator $U_i$
Gamut surface constraint mapping operator $U_i$

- Eight constraint point
  1. White (1, 1, 1)  
  2. Black (0, 0, 0)  
  3. Red (1, 0, 0)  
  4. Green (0, 1, 0)  
  5. Blue (0, 0, 1)  
  6. Cyan (0, 1, 1)  
  7. Magenta (1, 0, 1)  
  8. Yellow (1, 1, 0)

- Equation

$$U_i = \sum_{h=1}^{m} w_{r,h} u_{i,h}$$  \hspace{1cm} (6)$$

where $u_{i,h}$ : the gamut surface constraint mapping scaling factor  
$w_{r,h}$ : the gamut surface mapping weighting factor
• Gamut surface constraint mapping scaling factor

\[ u_{ih} = \begin{cases} 
\frac{D_{d,c,ih}}{D_{d,b,ig}} & (i \neq h) \\
0 & (i = h) 
\end{cases} \]

(7)

where \( D_{d,c,ih} \) : the Mahalanobis distance of \( \alpha_{d,h} \) from \( \mu_{d,i} \)

\( D_{d,b,ig} \) : the Mahalanobis distance of \( \alpha'_{d,h} \) from \( \mu_{d,i} \)

• Gamut surface mapping weighting factor

\[ w_{r,h} = \frac{1}{\sum_{q=1}^{n} \frac{1}{E_{s,a,q}}} \]

if \( E_{s,a,q} = 0 \) then \( w_{r,h} = 1, w_{r,k \neq h} = 0 \)

if \( E_{s,a,k \neq h} = 0 \) then \( w_{r,h} = 0, w_{r,k \neq h} = 1, w_{r,l \neq h \neq k} = 0 \)

where \( E_{s,a,h} \) : the Euclidian distance between \( \mathbf{X} \) and \( \alpha_{s,h} \)
Fig. 2. Mapping in Mahalanobis’ distance space using Gamut-surface constraint mapping operator $U_i$; three categories are applied in order to simplify the graphical explanation.
**Categorical color matching weighting factor** $F$

- Categorical color matching weighting factor

$$F = \sum_{j=1}^{n} w_{f,j} f_j$$  \(9\)

where $f_j$ : a degree of contribution of categorical color matching operator

$w_{f,j}$ : the weighting factor for $f_j$
• Degree of contribution $f_j$

$$f_j = \frac{1}{\sum_{h=1}^{m} \frac{1}{E_{s,a,h}} + \frac{1}{E_{s,f,j}}}
$$

if $E_{s,f,j} = 0$ then $f_j = 1$

if $E_{s,a,h} = 0$ then $f_j = 0$

(10)

• Weighting factor

$$w_{f,j} = \frac{1}{\sum_{p=1}^{n} \frac{1}{D_{s,f,j}}}
$$

if $D_{s,f,j} = 0$ then $w_{f,j} = 1$, $w_{f,k\neq j} = 0$

if $D_{s,f,k\neq j} = 0$ then $w_{f,j} = 0$, $w_{f,k\neq j} = 1$, $w_{f,l\neq j\neq k} = 0$

(11)
Converting $D_i$ to CIELAB

- Simplex iteration using the following estimation function

$$f(P) = \sqrt{\left(\frac{D_{t,1} - D_{p,1}}{D_{t,1}}\right)^2 + \left(\frac{D_{t,2} - D_{p,2}}{D_{t,2}}\right)^2 + \cdots + \left(\frac{D_{t,9} - D_{p,9}}{D_{t,9}}\right)^2}$$  \hspace{1cm} (11)

where $D_{p,i}$: Mahalanobis distance of candidate vector $P$ as a mapping point from average vector $\mu_{d,i}$

$D_{t,i}$: Mahalanobis distance of the most optimal point
Fig. 3. Flowchart of categorical color mapping
Using color-categorical normalized distance transformation
Experimental

Design of viewing conditions

- Two CRT monitors
  - Nanao FX-C6 : 17-inch
  - 9300K of the white point of the source CRT
  - 5000K of the white point of the destination CRT
- The ambient light environment
  - Dark room
  - 3750K fluorescent light
- Contrast effect
  - Lower degree of adaptation to a CRT
  - Focusing on contrast effect
– Color appearance matching

**Fig. 4.** Design of stimulus patterns on CRT monitors for color appearance matching

<table>
<thead>
<tr>
<th></th>
<th>Source CRT (9300K-whitepoint)</th>
<th>Destination CRT (5000K-whitepoint)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>in dark room</td>
<td>under ambient light</td>
</tr>
<tr>
<td><strong>X</strong></td>
<td>138.9</td>
<td>121.9</td>
</tr>
<tr>
<td><strong>Y (cd/m²)</strong></td>
<td>152.0</td>
<td>131.3</td>
</tr>
<tr>
<td><strong>Z</strong></td>
<td>180.4</td>
<td>177.7</td>
</tr>
</tbody>
</table>

**Table 1.** Whitepoint of two CRT monitors
- Result of color appearance matching

**Fig. 5.** Luminance of the test color when the test color matches to the reference color: (a) luminance (b) luminance contrast to background
Color naming experiment

- Determining average vector and covariance matrix
  - 11 color names
  - 9 color cluster
- Required 2,400 samples

Fig. 6. The center of gravity of category defined as the average vector for the source CRT and the destination CRT

(a) In dark room  (b) Under ambient light

*Fig. 6. The center of gravity of category defined as the average vector for the source CRT and the destination CRT*
Color appearance matching experiment
  - Different appearance between average vectors
    - Doing 17 color appearance matching experiment
    - 9 average
    - 8 gamut surface constraints

Fig. 7. Corresponding matched colors in the destination CRT which the observer selected as same color appearance to the source vector
Paired comparison experiment 1: in a dark room

- 3 categorical color mapping
  - CCM#1
    - Maximizing color reproducibility
  - CCM#2
    - Minimizing the operational cost
  - CCM#3
    - Intermediate specification
    - Color appearance matching experiment to achromatic component

- Comparison with CIECAM97s, RLAB and CIELAB
  - Specification for maximize the similarity of a reproduction to an original
### TABLE II. Specifications of Categorical Color Mapping Using Color-Categorical Normalized Distance Transformation Applied to the Paired Comparison Method in Dark Room

<table>
<thead>
<tr>
<th>Type</th>
<th>Average vectors</th>
<th>Gamut-surface constraint vectors</th>
</tr>
</thead>
<tbody>
<tr>
<td>CCM#1</td>
<td>Perceptual matching</td>
<td>Minimizing perceptual difference</td>
</tr>
<tr>
<td>CCM#2</td>
<td>Arithmetic averages on 5000K</td>
<td>Minimizing perceptual difference</td>
</tr>
<tr>
<td>CCM#3</td>
<td>Arithmetic average on 5000K except L* of Achromatic, which is given as perceptual matching.</td>
<td>Minimizing perceptual difference</td>
</tr>
</tbody>
</table>

### TABLE III. Specifications of RLAB

<table>
<thead>
<tr>
<th>Source 9300K-CRT</th>
<th>Destination 5000K-CRT</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Dark room</td>
</tr>
<tr>
<td>$Y_s$</td>
<td>152 (cd/m²)</td>
</tr>
<tr>
<td>$(X_w, Y_w, Z_w)$</td>
<td>(91.4 100 118.7)</td>
</tr>
<tr>
<td>$\sigma$</td>
<td>1 / 2.9</td>
</tr>
<tr>
<td>$D$</td>
<td>0</td>
</tr>
</tbody>
</table>

### TABLE IV. Specifications of CIECAM97s

<table>
<thead>
<tr>
<th>Source 9300K-CRT</th>
<th>Destination 5000K-CRT</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Dark room</td>
</tr>
<tr>
<td>$L_a$</td>
<td>30.4 (cd/m²)</td>
</tr>
<tr>
<td>$(X_w, Y_w, Z_w)$</td>
<td>(91.4 100 118.7)</td>
</tr>
<tr>
<td>c</td>
<td>0.525</td>
</tr>
<tr>
<td>$N_c$</td>
<td>0.8</td>
</tr>
<tr>
<td>$F_{\text{uk}}$</td>
<td>1</td>
</tr>
<tr>
<td>F</td>
<td>0.9</td>
</tr>
</tbody>
</table>
Fig. 8. Comparison between corresponding matched colors in the destination CRT

(a) In dark room

(b) Under ambient light

Fig. 8. Comparison between corresponding matched colors in the destination CRT
Fig. 9. Interval scale values derived from the paired comparison in a dark room
1) CCM#1, 2) CCM#2, 3) CCM#3, 4) CIELAB, 5) RLAB, 6) CIECAM97s
◆ Paired comparison experiment 2: under ambient light
  – CCM#4
    • Same as CCM#1 except the lightness of destination average
    • To test the reduction of operational costs

<table>
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<th>Type</th>
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<th>Gamut-surface constraint vectors</th>
</tr>
</thead>
<tbody>
<tr>
<td>CCM#2</td>
<td>Arithmetic averages on 5000K</td>
<td>Minimizing perceptual difference</td>
</tr>
<tr>
<td>CCM#3</td>
<td>Arithmetic average on 5000K; except L* of Achromatic, which is given as perceptual matching.</td>
<td>Minimizing perceptual difference</td>
</tr>
<tr>
<td>CCM#4</td>
<td>L*: linear scaling a*, b*: Perceptual matching</td>
<td>Minimizing perceptual difference</td>
</tr>
</tbody>
</table>
Fig. 10. Interval scale values derived from the paired comparison under ambient lighting: 1) CCM#1, 2) CCM#2, 3) CCM#3, 4) CIELAB, 5) RLAB, 6) CIECAM97s
(1) Portrait  (2) Mountain view  (3) Musicians

(4) Fruit basket  (5) Macaws

Color Plate 1. Reproductions using CCM#1 in a dark room
Color Plate 2. Reproductions using CCM#4 under ambient lighting.
Conclusion

◆ CCM
  – Higher performance than conventional CAM
  – Operation reduction by CCM#4
  – Absence of trial and error procedure for defining parameter
    • By color appearance matching experiments
  – Time cost for color naming
  – Image dependency
    • RLAB performing well for gray balance and memory color
    • CIECAM97s is good at predicting colorfulness