Colorimetric and spectral characterization of a color scanner using local statistics

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Journal of Imaging Science and Technology, vol. 48, no. 4, July/August 2004

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Abstract

- Accuracy of scanner characterization
  - Statistics
    - Varying for individual color samples
  - Behavior of the scanner
    - Depart from the linear reflectance model

- Proposed method of colorimetric and spectral characterization
  - Using local statistics to deal with these problems
  - Significantly outperforming one using global statistics
  - Slightly better accuracy, but cross-media metamerism exists
1. Introduction

◆ Colorimetric characterization
  – Least squares based polynomial regression
    • Most frequently adopted
    • Simplicity and good performance
  – Look up table with interpolation and extrapolation
  – Artificial neural networks

◆ Spectral characterization
  – Recovering from samples responses produced by imaging devices
  – For real scanner, depart from the liner reflectance model
  – Mathematically recovering is not accurate enough
Proposed method

- Estimating method of Colorimetric and spectral reflectance values from device response
  - Using the local statistics of the training samples
2. Colorimetric and spectral characterization

- CIE XYZ tristimulus values

\[
X = K \int_{\Lambda} L_e(\lambda) \bar{x}(\lambda) r(\lambda) d\lambda = \int_{\Lambda} h_1(\lambda) r(\lambda) d\lambda \tag{1}
\]

\[
Y = K \int_{\Lambda} L_e(\lambda) \bar{y}(\lambda) r(\lambda) d\lambda = \int_{\Lambda} h_2(\lambda) r(\lambda) d\lambda \tag{2}
\]

\[
Z = K \int_{\Lambda} L_e(\lambda) \bar{z}(\lambda) r(\lambda) d\lambda = \int_{\Lambda} h_3(\lambda) r(\lambda) d\lambda \tag{3}
\]

where \( K = \frac{100}{\int_{\Lambda} L_e(\lambda) \bar{y}(\lambda) d\lambda} \tag{4} \)

- Denoting integration as summation with \( N \) uniformly spaced samples in visible spectrum range

\[
X = hr \tag{5}
\]
- Response of the kth (k=1,2,3) sensor

\[ v_k = \int_{\Lambda} L_s(\lambda) f_k(\lambda) d(\lambda) r(\lambda) d\lambda + b_k + n_k \]

\[ = \int_{\Lambda} m_k(\lambda) r(\lambda) d\lambda + b_k + n_k \]  

- Constant bias response, \( b_k \), and signal independent noise, \( n_k \)
- Transmittance of the kth color filter, \( f_k(\lambda) \), and spectral sensitivity of the detector in the measurement, \( d(\lambda) \)
- Matrix vector notation

\[ V = Mr + b + n \]  

\[ U = Mr + n \]
- Actual response of a scanner $\rho_k$ of the kth sensor
  - Nonlinear input-output function known as optoelectronic conversion function (OECF)

$$\rho_k = F_k(v_k)$$  \hspace{1cm} (9)

- Colorimetric characterization
  - Technical reasons such as signal-to-noise ratio and filter design
  - $X$ is not a linear transformation of $V$ or $U$
  - High order and cross-term in polynomial regression
– Using second-order polynomial term
\[ x = Qg \]  
(10)
where  
\[ g = [v_1, v_2, v_3, v_1^2, v_2^2, v_3^2, v_1v_2, v_1v_3, v_2v_3, 1]^T \]  
(11)
– Moore-Penrose pseudoinverse
\[ Q = (XG^T)(GG^T)^{-1} \]  
(12)
where  
\[ X = [x_1, x_2, x_3, ...], \text{ and } G = [g_1, g_2, g_3, ...] \]

◆ Spectral characterization
– Reflectance vector
\[ \hat{r} = WU \]  
(13)

• Estimation from linear response as determining the linear transform matrix
- Minimum mean square error sense

\[ J = E \{ \| \hat{\mathbf{r}} - \mathbf{r} \|^2 \} \]  
(14)

- Determine \( \mathbf{W} \) that minimizes \( J \)

- Using Wiener-Hopf equation

\[ \mathbf{W} = \mathbf{R}_{ru} \mathbf{R}_r^{-1} \]  
(15)

where \( \mathbf{R}_{ru} = E(\mathbf{rU}^T) \), \( \mathbf{R}_r = E(\mathbf{rr}^T) \)  
(16,17)

- Transform matrix \( \mathbf{W} \) by introducing the orthogonality principle

\[ \mathbf{W} = \mathbf{K}_r \mathbf{M}^T (\mathbf{MK}_r \mathbf{M}^T + \mathbf{K}_n)^{-1} \]  
(18)

where \( \mathbf{K}_r = \langle \mathbf{rr}^T \rangle \), \( \mathbf{K}_n = \langle \mathbf{nn}^T \rangle \)  
(19,20)

\( \langle \mathbf{\cdot} \rangle \) is ensemble average
3. Characterization using local statistics

◆ Calculation of matrix $Q$
  - Highly relevant to the correlation between $V$ and $X$ of the training samples
  - Global correlation matrix might be insufficient to describe the transform relationship

◆ Local statistics
  - Using neighboring training samples instead of the global one
  - How many training samples should be involved, $N_c, N_s$
  - Linear response of the candidate sample, $V_t$, and the $i$th training sample in database, $V_i$

$$d_i = \|V_t - V_i\|$$ (21)
4. Experiments and discussion

◆ Experiments conditions
  – Flatbed color scanner, Epson GT-10000+
  – Color target
    • GretagMacbeth ColorChecker Chart (MCC)
    • GretagMacbeth ColorChecker DC (CDC)
    • Kodak Gray Scale Q-14 (Q14)
  – Measured reflectance by GretagMacbeth spectrophotometer CE-7000A
  – Calculated CIEXYZ under D65 and CIE1931 observer function

◆ Inverse OECF
  – built using the gray color patches
Several constraints

- Smoothness, positivity, and reproduction accuracy
  \[ |2M_k(i) - M_k(i - 1) - M_k(i + 1)| \leq \varepsilon \]  
  \[ M_k \geq 0 \]  
  \[ |v_k - M_k r| \leq \delta \]

- Solving the constrained linear least squares with Matlab

Spectral responsivity using 24 patches on MCC

Fig. 1. Recovered spectral responsivity of the scanner using color patches on MCC.
Linear response of MCC and CDC

- Using the measured reflectance data and the recovered M
- Assumed the noise vector \( n=[0,0,0] \)
- The errors
  - Between actual and simulated linear responses

| TABLE I. Comparison of the actual linear responses \( V_k \) and predicted ones \( \hat{V}_k \) using mathematically recovered spectral responsivity. The error of a color is calculated using \( \left| \frac{V_k - \hat{V}_k}{V_{k,max}} \right| \times 100\% \), where \( V_{k,max} \) is the maximum linear response of the \( k \)th channel of the white patch of MCC. |
|-----------------|---|---|---|---|---|---|
|                | MCC |          |    | CDC |          |    |
|                | Red | Green | Blue| Red | Green | Blue|
| Mean error (%) | 0.80| 0.75  | 1.41| 1.88| 1.66  | 2.78|
| Maximum error (%) | 1.90| 1.56  | 4.65| 4.70| 5.05  | 9.69|
◆ Using local statistics with CDC
  – Mean CIE1994 color difference under standard illuminant D65 for different values of \( N_c \) and \( N_s \)

Fig. 2. Relationship between the mean color difference under D65 and the number of training samples in colorimetric (left) and spectral characterization (right) for target CDC.
– Spectral root mean square error in spectral characterization

\[ SRMS\ error = \left[ \frac{(r - \hat{r})^T (r - \hat{r})}{N} \right]^{1/2} \]  

(25)

– Alternative metric under various illuminants such as CIE D65, CIE A and CIE F2

Table 2. Color difference and SRMS error when using local and global statistics.

<table>
<thead>
<tr>
<th>Method</th>
<th>Metrics</th>
<th>Mean</th>
<th>Std</th>
<th>Max.</th>
<th>Same targets</th>
<th>Mean</th>
<th>Std</th>
<th>Max.</th>
<th>Different targets</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CIE D65 ( \Delta E^*_{10} )</td>
<td>3.14</td>
<td>2.41</td>
<td>14.76</td>
<td>4.18</td>
<td>3.14</td>
<td>4.18</td>
<td>3.14</td>
<td>14.67</td>
<td></td>
</tr>
<tr>
<td>Spectral (Global)</td>
<td>CIE A ( \Delta E^*_{10} )</td>
<td>2.44</td>
<td>2.30</td>
<td>9.65</td>
<td>3.86</td>
<td>4.31</td>
<td>15.97</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CIE F2 ( \Delta E^*_{10} )</td>
<td>3.27</td>
<td>2.89</td>
<td>14.18</td>
<td>4.48</td>
<td>3.62</td>
<td>15.63</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SRMS error</td>
<td></td>
<td>0.022</td>
<td>0.149</td>
<td></td>
<td>0.041</td>
<td>0.021</td>
<td>0.099</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CIE D65 ( \Delta E^*_{10} )</td>
<td>1.76</td>
<td>1.34</td>
<td>6.54</td>
<td>3.45</td>
<td>2.22</td>
<td>9.30</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Spectral (Local)</td>
<td>CIE A ( \Delta E^*_{10} )</td>
<td>1.19</td>
<td>0.96</td>
<td>4.78</td>
<td>3.17</td>
<td>3.03</td>
<td>13.81</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CIE F2 ( \Delta E^*_{10} )</td>
<td>1.63</td>
<td>1.32</td>
<td>7.66</td>
<td>3.19</td>
<td>2.15</td>
<td>9.03</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SRMS error</td>
<td></td>
<td>0.018</td>
<td>0.093</td>
<td></td>
<td>0.029</td>
<td>0.012</td>
<td>0.058</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
– Colorimetric characterization

**Table 3.** color difference when using local and global statistics.

<table>
<thead>
<tr>
<th>Method</th>
<th>Same targets</th>
<th></th>
<th>Different targets</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Std.</td>
<td>Max.</td>
<td>Mean</td>
</tr>
<tr>
<td>Colorimetric (Global)</td>
<td>2.69</td>
<td>2.48</td>
<td>10.48</td>
<td>4.07</td>
</tr>
<tr>
<td>Colorimetric (Local)</td>
<td>1.37</td>
<td>1.24</td>
<td>9.45</td>
<td>3.26</td>
</tr>
</tbody>
</table>

◆ Cross-media metamerism

– Color difference using different color targets are considerably larger than those using the same targets

– Transform form spectral reflectance to device response is a many-to-one problem
5. Conclusion

◆ Colorimetric and spectral characterization
  – Using local statistics of training samples
  – Colorimetric characterization
    • Based on polynomial regression
  – Spectral characterization
    • Based on minimum mean square error criterion
  – Significantly outperforms the traditional ones using global statistical information