Practical Spectral Characterization of Trichromatic Cameras

ACM Transaction on Graphics
vol. 30, No. 6, 2011
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Abstract

- Problem of radiometric calibration on camera device
  - Requiring costly hardware
  - Limitation of Controlled acquisition conditions
  - Rarely consideration with spectral response of camera

- Proposed method
  - Approach for Multi spectral characterization of trichromatic camera
    - Estimating wide range of environment
      - Taking color chart and Measuring average light
      - Using spectrophotometer effective spectral response of camera
    - Generating ICC profile
      - Compared with state-of-the-art ICC profile
        » Higher accuracy
        » Less constrained capturing condition
Introduction

Calibration process
- Geometric calibration
  - Estimating parameters determining image projection
- Radiometric calibration
  - Compensation for nonlinearities in energy response
- Spectral calibration
  - Determining spectral response of red, green, blue color channels
Practical method for estimating spectral response of camera

- Application of spectral response
  - Highly desirable for color correction and color processing
  - Designing image based measurement or photographic setup
- Problem of existing approaches for measuring spectral response
  - Requiring costly hardware
  - Limitation of Controlled acquisition conditions
  - Rarely consideration with spectral response of camera
Main contribution

- Practical method for measuring spectral response of camera
  - Devising method for estimating spectral response of trichromatic camera
  - Considering spatial non-uniformity of illumination
    - Shadowing and specularity effect
    - Robust reconstruction of spectral camera response
  - Showing ICC color profile benefit from acquired spectral response
  - Comprehensive evaluation including reference measurement
    - Proving proposed method result better than state-of-the-art techniques
Previous Work

- Measuring effective spectral response of camera
  - Capturing response of camera under monochromatic illumination
    - Suggesting EMVA standard
    - Requiring high limiting applicability of technique
  - Recovering effective spectral response from color chart
    - Reducing effort of monochromator-based approaches
    - Taking photography of Macbeth color chart
      - Using 16 narrowband and 8 broadband filter
      - Recovering coarse shape of spectral response by narrowband illumination
      - Recovering finer detail of spectral response by broadband illumination
- Using image color chart or different color field under broadband illumination
  - Employing spectral reflectance estimation
  - Rely on linear method
    - Least-squares pseudo-inverse matrix
- Spectral characterization of scanner by acquiring color chart
- Camera calibration
  - Solving energy minimization problem
Problem of previous method
- Needing controlled lighting condition
- Needing specialized hardware
Overview

- Influencing factor for digital camera imaging processing
  - Idealization system response
    - Not considering non-linearity
      - Between incoming radiance and pixel value

\[
P(x) \propto \int_{N_x} C(x, x') \int_{\Lambda} E(\lambda) T_c(\lambda) T_o(\lambda) L_{\text{scene}}(\lambda, x') d\lambda dx'
\]  

(1)

where \( \lambda \) denote wavelength, \( \Lambda \) respective range of integration, \( L_{\text{scene}} \) is the scene radiance imaged in pixel \( x' \). \( T_o \) Transmission of optical system \( T_c \) transmission of color filter array, \( E \) quantum efficiency of sensor and \( C \) crosstalk between pixels \( x \) and \( x' \) in neighborhood \( N_x \) of \( x \)
Effective spectral response by summarizing equation 1

\[ P(x) \propto \int_{\lambda} R_{\text{eff}}(\lambda)L_{\text{scene}}(\lambda, x) d\lambda \]  

- Effective spectral response \( R_{\text{eff}} \)
  - Relating scene radiance between pixel value
  - Assuming \( R_{\text{eff}} \) independent of \( x \) pixel
  - \( R_{\text{eff}} \) depend on brightness differences between nearby pixel
Proposed method

- Reconstructing effective spectral response of trichromatic camera
  - Determining effective spectral response $R_{\text{eff}}$ of trichromatic camera
    - Taking photograph of color chart
      » Using Gretag Macbeth ColorChecker
  - Assumption of proposed method
    - Knowing spectral power distribution of dominant illumination
    - Knowing color temperature of illumination
  - Proposed novel imaging model
    - Accounting for specularity and spatially varying illumination
- Workflow of proposed method

**Fig. 1.** Illustrating the workflow of our approach. By introducing a novel imaging model accounting for specularity and spatially varying illumination.
Data Acquisition

- Estimating effective spectral response of camera
  - Requiring radiometrically calibrated photographs of color chart
  - Requiring relative spectral power distribution of respective illumination
- Measuring illumination
  - Uncontrolled light condition
    - Standard spectrophotometer hardware
      » EyeOne from X-rite or similar cost devices
  - Certain light condition
    - Measuring color temperature to illumination spectrum
Estimating Effective Spectral Response

- Basic idea of estimation process
  - Optimization of effective spectral response curve
    - Minimizing using $R^{\text{eff}}$
      - Trichromatic colors of color filed captured by camera
      - Reflected spectral radiance projected to trichromatic color space
Basic approach
- Estimating spectral response from color chart image
  - Requiring model color of color filed
    - Assuming light spectrum and measured spectral reflectance
  - Minimizing object function

\[
E^{\text{basic}} \left( R^{\text{eff}} \right) = \sum_{c=1}^{3} \left( E^{\text{basic}} \left( R_{c}^{\text{eff}} \right) + \alpha E_{\text{sm}}^{\text{basic}} \left( R_{c}^{\text{eff}} \right) \right)
\]  

(3)

\[
E_{d}^{\text{basic}} \left( R^{\text{eff}} \right) = \sum_{j} \left\| \sum_{i=1}^{k} \left[ S_{i,j} L_{i} R_{i,c}^{\text{eff}} \right] \right\|^2
\]  

(4)

\[
E_{\text{sm}}^{\text{basic}} \left( R^{\text{eff}} \right) = \sum_{i=1}^{k-1} \left\| R_{i,c}^{\text{eff}} - R_{i+1,c}^{\text{eff}} \right\|^2
\]  

(5)

where \( R^{\text{eff}} \) are unknown effective spectral response for color channel \( c \) and discrete wavelength \( \lambda_{i} \). \( k \) is number of spectral bands. \( j \) field on color checker, \( J \) total number of color fields, \( L \) spectral power distribution of illuminant, \( S \) the known reflectance spectra of color field and \( D \) average camera response to respective color field in photograph.
• Data term $E_d^{basic}$
  – Minimizing color difference between observed and reconstructed data
• Data term $E_{sm}$
  – Enforcing smoothness on spectral response curve
  – Using factor alpha
• Global optimization
  – Standard linear least squares optimization
Using $E^{basic}$ with synthetic data work

- 33 spectral band and measured day light illumination

Fig. 2. Synthetic example: Exemplary reconstruction of effective spectral response $R^{eff}$ minimizing $E^{basic}$ for a synthetic dataset. In this example, the camera response was generated assuming perfectly Lambertian color fields and isotropic daylight illumination.
Using real data

- Applying real data for basic algorithm
  - Do not hold in practice
    - Considering only light spectrum and spectral reflectance

![Graph showing wavelength response](image)

**Fig. 3.** Using real data: the reconstruction suffers from serious artifacts if $E^{basic}$ is used as objective function, neglecting spatial non-uniformity of illumination and specularity of color fields. The image in the upper right shows the illumination conditions under which the image was captured.
- Mainly two source of bias
  - Color filed of Macbeth color chart contain specularity
  - Out-of-lab conditions illumination
    - Color chart to non-homogeneous due to occluding object

*Fig. 4.* Top row: The fields in (a) are considerably brighter and less saturated than the ones in (b), revealing the amount of specularity of the color fields.
– Problem of specularity
  • Controlling condition in laboratory
    – Continues to pose serious problem in out-of lab condition
    – Considering spatial inhomogeneity in previous work
      » Correcting illumination by hand
– Proposed method
  • Integrating spatial homogeneity
    – Correcting specularity directly into estimation process
  • Eliminating manual work
  • Account for both specularity and shadowing effect
    – Using extended basic image model
    – Assumption of basic image model
      » Including BRDFs of color filed in diffuse and white specular component
      » Assumption of incident illumination
        » Independent of viewing angle
    – Shadowing
      » Single scaling factor per color field
    – Specularity
      » Adding individual wavelength independent constant to diffuse reflectance spectrum of each color field
• Proposed imaging model

**Fig. 5.** Illustrating the proposed imaging model considering specularity and spatially varying illumination. Assuming a dominant illuminant, specularity is approximated by adding an individual wavelength-independent constant to each color field. Spatial non-uniformity is modeled by a scaling factor per field.
– New image model
  - Implementing specularity and shadowing in object function

\[
E(R^\text{eff}, F, \sigma) = \sum_{c=1}^{3} \left( E_d(R_c^\text{eff}, F, \sigma) + \alpha E_{sm}(R_c^\text{eff}) \right) + \sum_{c=1}^{3} \left( \gamma E_{damp}(R_c^\text{eff}) + \delta E_{border}(R_c^\text{eff}) \right) + \beta E_{sm}^\text{illu}(F)
\]  

(6)

– Data term

\[
E_d(R_c^\text{eff}, F, \sigma) = \sum_{j} \omega_{j,c} \left\| \sum_{i=1}^{k} \left[ (S_{i,j} + \sigma_j) L_i R_c^\text{eff} \right] - F_j D_{j,c} \right\|^2
\]

(7)

where scaling factor \( F_j \) determine shadowing of each of color fields of color chart. Parameter \( \sigma_j \) is unknown specularity per color field \( j \) and is controlling amount of white added to spectral reflectance \( S \) of color field. weight \( \omega_{j,c} \) reflecting importance of different color filed.
• Regularization
  - Extending basic regularization term $E_{sm}^{basic}$ from equation (5)

  \[
  E_{sm} \left( R_c^{eff} \right) = \sum_{i=1}^{k-1} \left( \frac{\left\| R_{i,c}^{eff} - R_{i+1,c}^{eff} \right\|}{R_{i,c}^{preveff} + R_{i+1,c}^{preveff}} \right)^2
  \]  
  \( (8) \)

  \[
  E_{sm}^{illu} \left( F \right) = \sum_{j} \sum_{n \in N_j} \left\| F_j - F_n \right\|^2
  \]  
  \( (9) \)

  \[
  E_{damp} \left( R_c^{eff} \right) = \sum_{i=1}^{k} \left\| R_{i,c}^{eff} \left( \lambda_i \right) - R_{i,c}^{preveff} \left( \lambda_i \right) \right\|^2
  \]  
  \( (10) \)

  \[
  E_{border} \left( R_c^{eff} \right) = \left( R_c^{eff} + R_{k,c}^{eff} \right)
  \]  
  \( (11) \)
Choosing field weights

- Reason of choosing weight
  - Not evenly distribution in spectral domain
  - Obtaining reliable result

- Choice of weight on three ideas
  - Optimization with respect to equal spectral distribution all spectral bands
    » Particularly important for shorter wavelength
  - Selecting field with spectral reflectance of effective response curve
    » Steep slopes and good support in spectrum reflectance
  - High weight of certain filed and Avoiding good noise to signal ratio
    » Minimizing reconstruction bias
• Sum of weighting terms
  - Term $\omega_j^{\text{distrib}}$
    » Use to enforce spectral equalization
  - Term $\omega_{j,c}^{\text{slopes}}$
    » Attempt to model slope constraints

\[
\omega_{j,c} = \omega_j^{\text{distrib}} + \omega_{j,c}^{\text{slopes}} 
\]

(12)

\[
\omega_{1,\ldots,J}^{\text{distrib}} = \arg\min_{\{\omega_1,\ldots,\omega_J\}} \text{var}_i \left( \sum_{j=1}^J \omega_j S_i L_i \right) 
\]

(13)

- Finite differencing characterizing slope
  » $\partial SL_{i,j} = \frac{\partial (S_{i,j} L_i)}{\partial i}$ and $\partial R_{i,c}^{\text{eff}} = \frac{\partial R_{i,c}^{\text{eff}}}{\partial i}$

\[
\omega_{j,c}^{\text{slopes}} = \sum_{i=1}^k \left( \left( \partial SL_{i,j} \right) \left( R_{i,c}^{\text{eff}} \right) + \left( \partial SL_{i,j} \right) \left( \partial R_{i,c}^{\text{eff}} \right) + \left( S_{j,i} L_i \right) R_{i,c}^{\text{eff}} \right) 
\]

(14)
– Weight map for halogen lighting

Fig. 6. (a) Reflectancespectra of all 240 color fields of ColorChecker DC together with the mean spectrum (bold red). (b) The result when illuminated with halogen light. In this case short wavelengths are clearly underrepresented. (c) The corresponding weight map according to equation (12). (d) Weights applied to the spectra.
– Parameter settings
  • Controlling proposed objective function $E(R^{\text{eff}})$
    – Using four different weights $\alpha, \beta, \gamma, \delta$
  • Parameter value for good reconstruction result
    – $\alpha = 3, \beta = 500, \gamma = 1, \delta = 10$
Results

Acquire datasets

- Using five different camera models
  - Kodak DCS 760 SLR (kodak 760)
  - Kodak DCS Pro 14n SLR (kodak 14n)
  - SVS Vistek svs4022COGE industry video camera (vistek 4022)
  - Canon PowerShot G9 (consumer level DSC)
  - CCam Bci-6600-USB CMOS industry video camera

- Using raw image data
  - Taking images of Macbeth Color Checker DC
  - Acquisition of images in wide range different lighting conditions
    - Outdoor and indoor illumination
Reference data

- Measuring spectral response of camera model
  - Using monochromatic illumination
- Measurement setup
  - Consist of calibrated lamp illuminating white Lambertian surface
  - Liquid crystal tunable filter in front of camera
    - Producing nearly monochromatic light
    - Tuning wavelengths between 400 and 720 nm

Fig. 7. Sketch of our measurement setup for measuring the reference spectral responses.
• Measuring data
  - Acquiring image by Varying exposure time tuning filter
    » Operating range in 10nm steps
  - Extracting average pixel value \( \Delta_{i,c} \)

\[
\Delta_{i,c} = \int_{\lambda} \tilde{R}_{c}^{\text{eff}}(\lambda) \rho(\lambda) T_{b,i}(\lambda) d\lambda
\]  
(15)

\[
\Delta_{i,c} = \sum_{j=1}^{k} \tilde{R}_{c}^{\text{eff}}(j) \rho(j) T_{b,i}(j) L(j)
\]  
(16)

where \( T_{b,i} \) is transmittance of bandpass filter tune to a peak wavelength \( \lambda_i \), \( \rho \) is BRDF of white Lambertian reflector and \( R_{c}^{\text{eff}} \) is effective spectral response for color channel \( c \). Using matrix notation gives \( \Delta_{c} = T_{b} \left( \tilde{R}_{c}^{\text{eff}} \rho L \right) \) with transmission matrix
Fig. 8. Comparing spectral responses estimated by our method to reference measurements acquired using the monochromator setup depicted in Figure 7. For halogen lighting our methods is less accurate in the blue part of the spectrum due to the low support of the illuminant.
Cross validation

- Using cross validation for compare spectral response curve
  - Testing consistency and accuracy of fitting result
    - Acquiring data
      » Using camera response curve under different illumination condition
  - Using illuminant for test
    - Neon lamp, HMI lamp, and halogen lamp
- Estimating effective response of camera
  - Using proposed method under sunlight and monochromatic lighting
- Calculating difference $d_j$ for color field $j$

$$d_j = |S_jLR^{eff} - D_j|$$ (17)
Fig. 9. Cross validation: Average errors for predicting camera responses across different lighting conditions using the spectral response curves estimated by our method (blue bars) from the sunlight datasets as well as the measured references (red bars). The error was computed using $L^1$ distance in device RGB space (see equation (17)) as well as perceptual $\Delta E^*_{94}$. Per camera, three photographs of the color chart lit by neon, HMI and halogen lamps have been used. Even though our method is much simpler, the accuracy is comparable to the technically much more involved monochromator approach.
Fig. 10. Cross validation example for predicting camera response with different illumination for Kodak DCS Pro14n and a neon lamp.
- Validation of imaging model
  - Testing of secpularity and shadowing condition
    - Using halogen illuminant
      - Causing strong specularity
    - Placing occluders near color chart
Fig. 11. Validating shadow compensation: comparing photographs (“Window” dataset, see supplemental material) to estimated scale factors $F$. As can be seen the scale factors are consistent with the shadowed regions in the original images indicating that our algorithm can deal with environments strongly deviating from ideal conditions.
Fig. 12. Color temperature vs measured spectral power distribution of illumination: comparing spectral responses reconstructed using cloudy sky as well as sunlight. Dashed lines indicate results based on color temperature only. For typical daylight conditions the simplified light model works extremely well.
- Resolving small difference in effective response
  - Using different UV cut filter with Kodak DCS Pro 14n camera

Fig. 13. Resolving small differences in effective response: Our technique is able to recover even subtle differences of the effective response caused for example by different optical filters.
ICC Profiling

- ICC profiling
  - Transformation of color space for connecting independent device
  - Applying ICC profiling for color space transformation
    - Using shaper curves characterizing energy response curve
  - Computing profile M incorporating new illuminant

\[
M = \left( \begin{array}{c} R^{\text{eff}} \\ L \end{array} \right)^+ M_{XYZ}
\]

(18)

where \( A^+ \) denotes pseudo-inverse of A and \( M_{XYZ} \) is matrix containing XYZ primaries spectra
Resulting average $\Delta E_{94}$ error per camera for different illumination conditions.

**Fig. 14.** Using our method for ICC profiling. The quality of the generated ICC profiles was evaluated by measuring perceptual distances between true XYZ values of the color chart and XYZ values inferred from device RGB values using whitebalancing and device-RGB-to-XYZ transformation. The E94 error (red bars) has been computed for each of the camera models and for three different lighting conditions: neon, HMI and halogen. For comparison purposes, a state-of-the-art ICC profiling software (Argyll) was evaluated as well (blue bars).
Limitation

- Limitation in assumption
  - Causing camera response curve by light of visible spectrum
    - Decay for wavelengths in near UV range
      - Acquiring reflectance data in visible range
  - Limitation of spectrum range by infrared filter
  - Avoiding certain lighting condition
    - little support in spectral bands like halogen bulb
Conclusion

- Proposed method
  - Practical method for spectral characterization of trichromatic camera
    - Estimating spectral response
      - Taking images of color chart
      - Measuring illumination using spectrometer
  - Advantage of proposed method
    - Unlike previous method
      - Not rely on specialized and costly hardware
      - Not rely on laboratory environment
        » Completely measuring spectral under daylight conditions
    - Using ICC profiling
      - Superior in terms of accuracy and flexibility