**Laboration 1**

Bildreproduktion och Bildkvalitet

(TNM097)

Device characterization and modeling

Part 1 – Input devices

**Preparations**

As preparation for this lab, focusing on modeling and characterization for input devices**, it is**

**necessary and very important that you read the theory part of this document (written in**

**black)** prior to the scheduled time for the lab. It will also be very useful to repeat Lab 4 from

TNM059 (*Grafisk teknik*). You will partly work with the same data, and you will have good use of

the functions and assignments. This lab from TNM059 and the functions are all in the folder

***Course\_documents/Labs/preparation\_TNM059*** in Lisam. Besides that, it is very useful to read

Chapter 6 in Digital Halftoning and Color Reproduction, which is put in the folder

***Course\_documents/Literature/0\_preparation***. For a deeper understanding of Device

Characterization, read Chapter 5 in Digital Color Imaging Handbook under

***Course\_documents/Literature/2\_Lecture2\_Daniel***. Colorimetric computations, spectral

computations with surfaces and illuminants, conversions between CIEXYZ and CIELAB, as well

as the correct use of normalization factors and white point conversions, are all necessary

prerequisites for this lab.

**Introduction:**

The joint Labs 1 & 2 will focus on modeling and characterization of a complete color reproduction

workflow, including both input and output devices. You will investigate both model-based and

empirical characterization approaches. The workflow you will work with includes typical input

devices with 3 channels (RGB-cameras), and output devices, using additive color mixing (RGB)

for reproducing colors. The input data are spectral signals from different light sources and a set of

color samples (which you have previously used in TNM059 – Lab 4). Much of the data you

acquire in Lab 1, focusing on input devices, will be further used in Lab 2, as input to the output

devices. Figure 1 shows an overview of the complete color reproduction in these two labs, where

the upper part to (XYZ) is done in Lab 1 and the lower part after XYZ is done in Lab 2.

*Figure 1. Overview of the complete color reproduction workflow used in Lab 1 & 2, including input- and*

*output- RGB devices.*

Input

Output

XYZ

*Dc*

*R*

*G*

*B*

!

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&&&

*Dc*'

*R*'

*G*'

*B*'

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*D*'*R*

*D*'*G*

*D*'*B*

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*DR*

*DG*

*DB*

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*SRGB* (λ )

calibration

calibration

Input device (Camera)

Inverse charactarization

Output device

Inverse charactarization

3

All spectral data used in these two labs are given at the visible wavelength interval [400 nm, 700

nm], with a step of 5 nm. Therefore, all spectral data includes 61 elements.

The data you need is available in the file Lab1.zip, including:

- The file *chips20.mat* contains spectral reflectance data for 20 different surfaces, representing

**object** in Fig. 1 and 2. *chips20* is a *20 x 61* matrix, in which, each row contains the spectral

reflectance data for each object. The data are given at wavelengths 400:5:700 nm, giving 61

elements for each row.

- The file *illum.mat* contains spectral data for eight different light sources, i.e. CIEA, CIEB,

CIED65, Halogen 75W, Tungsten60W, plank50k, plank65k and plank90k. Each light source is

defined by a *1 x 61* matrix, representing the light intensity value at wavelengths 400:5:700. In this

file, there is also a vector *1 x 61* called *waverange*, representing the wavelengths 400:5:700.

- The file *xyz.mat* contains the color matching functions (CMFs), used for computing tristimulus

values (XYZ) from spectral data. *xyz* is a *61 x 3* matrix, in which column 1, 2 and 3 represent the

x, y and z color matching functions, respectively.

- The files *Ad.mat* and *Ad2.mat* contain spectral sensitivity functions for two input devices (RGBcameras),

mapping input spectral radiance to RGB. *Ad* and *Ad2* are both *61 x 3* matrices, in

which column 1, 2 and 3 represent the R, G and B sensitivity functions of the camera.

**Input device calibration and characterization**

***1. Spectral model of color image acquisition***

Let’s start by looking at the forward spectral model for color image acquisition, expressing the

relationship between the spectral input and the resulting camera response. Remember that the

general model that describes the response for each channel, *i*, of an image capture device with *M*

color channels is given by:

*Di* = *E*(λ )*Si* (λ )*d*λ + *ni*

λ∈*V*

∫ (1)

where *i* = 1,…,*M* (*M* = 3 for RGB devices), *Di* is the output sensor response, *E(λ)* is the input

spectral radiance, *Si(λ)* is the spectral sensitivity of the *i*:th sensor, *ni* is the measurement noise

and *V* is the spectral sensitivity region of the device. For more detail, please see **Section 6.4.1** in

Digital Halftoning and Color Reproduction (in the folder Course\_documents/Labs/preparation\_TNM059

in Lisam).

Figure 2 illustrates the spectral image acquisition model for an RGB-camera. The input to the

camera, *E(λ)* is spectral radiance, given by the product of the light source *I(λ)* and the reflectance

of the surface*, R(λ). S(λ)* shows the cameras spectral sensitivity functions for the channels R, G

and B. The resulting camera output is 3 signals R, G and B, corresponding to *Di* in Eq. 1.

Based on the data you have in this lab, *R(λ)* is represented by the rows in *chips20* (representing

20 different objects in 20 rows), *I(λ)* is represented by the variables in *illum.mat* (eight different

variables or light sources), and *S(λ)*, i.e. camera characteristic, is represented by *Ad* and *Ad2* for

two different cameras, respectively.

*Figure 2. Color image acquisition for an input device (RGB camera).*

Assume that, we want to find the camera response for the Red-sensor when capturing surface 1

(𝑅"(𝜆)) under illuminant 1 (𝐼"(𝜆)). Using Eq. 1, we will have:

𝑅'()\*+( = 𝑅"

-..

/.. 𝜆 𝐼" 𝜆 𝑆1 𝜆 𝑑𝜆, (2)

where, 𝑆1 𝜆 represents the camera characteristic for the Red-sensor of the camera. The G and

B responses of the camera can be calculated by replacing 𝑆1 𝜆 by 𝑆4 𝜆 and 𝑆5 𝜆 , respectively.

As discussed before, the spectral signals are sampled, being represented by vectors, and

therefore Eq. 2 can be rewritten as,

𝑅'()\*+( = 𝑅"

6"

78" 𝑖 𝐼" 𝑖 𝑆1 𝑖 , (3)

where, R1, I1 and SR are vectors representing object 1, illuminant 1 and the characteristic of the

Red-sensor of the camera. The G and B responses can be calculated accordingly. Using Matlab

notions, Eq. 3 can be rewritten as,

𝑅'()\*+( = 𝑠𝑢𝑚(𝑅".∗ 𝐼".∗ 𝑆1), (4)

where, *sum* returns the sum of the elements in a vector and *.\** represents element-wise

multiplication between vectors. The G and B camera responses are found by:

𝐺'()\*+( = 𝑠𝑢𝑚(𝑅".∗ 𝐼".∗ 𝑆4), (5)

𝐵'()\*+( = 𝑠𝑢𝑚(𝑅".∗ 𝐼".∗ 𝑆5), (6)

Notice now that, in the data you have, the reflectance spectrum of the first object (R1) is found in

row 1 in chips20. The illuminant (I1) is one of the eight available light sources in *illum.mat* and the

R, G and B sensor characteristic of a camera is found in column 1, 2 and 3 in *Ad* (or *Ad2*),

respectively.

R" G" B"

**Camera&output&**

*S(λ)*

If we now assume 𝑒 = 𝑅".∗ 𝐼", which is a *1 x 61* matrix, and the characteristic of the RGB-sensors

of the camera to be represented by Ad, which is a *61 x 3* matrix, then Equations 4, 5 and 6 can be

calculated at the same time by,

𝑑 = 𝐴D

E 𝑒E, (7)

where 𝐴D

E and 𝑒E are the transpose of *Ad* and *e* being *3 x 61* and *61 x 1* matrices, respectively.

The vector **d** is now a *3 x 1* matrix (vector), containing the R, G and B response of the camera. To

simplify, the measurement noise term in Eq. 1 is ignored.

For example, if you want to calculate the camera response for object number 10, under illuminant

CIEA, for the camera represented by Ad, in Matlab you simply write:

𝑑 = 𝐴𝑑F ∗ 𝑐ℎ𝑖𝑝𝑠20 10, : .∗ 𝐶𝐼𝐸𝐴 F. (8)

**1.1**

In the files provided, you will find the matrices **A***d* and **A***d2* containing spectral sensitivity functions

for two RGB-cameras. As discussed, the sensitivity functions, as well as the spectral data for

illuminants and surfaces, are all in the interval 400:5:700 nm (giving L=61).

Start by comparing the spectral sensitivity functions for the two cameras by plotting **A***d* and **A***d2*

against the wavelengths 400:5:700 nm. Based on the sensitivity functions, do you predict that the

output from the two cameras will be the same for the same input? Note that these curves actually

correspond to two real RGB-cameras.

Answer: With respect to the figure below I would assume that the output would be different, where data (1-3) and (4-6) are the output of Ad and Ad2 respectively. Not very different, but at least slightly.

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Automatiskt genererad beskrivning

**1.2**

Compute the resulting RGB-output for the first camera, for the 20 different color samples in the

file chips20. Use the illuminant CIED65 (which corresponds to the standard illuminant D65,

representing daylight) for the computations. Corresponding to Eq. 7, **d** is the output RGB-values,

**Ad** is the 61x3 matrix representing the camera sensitivity functions for the channels R, G and B,

and **e** is the input spectral radiance, given by the product of the illuminant and the surface

reflectance in chips20. The resulting 20 RGB-triplets represent the raw (i.e. un-calibrated) camera

output for the 20 surfaces, captured under the illuminant D65. Save your data as RGB\_raw\_D65

(or similar) for later use. Note that the RGB data is in double format (16 bits), in the range [0,1],

while for 8-bit devices it would be converted to integers in the interval [0,255]. You can use the

provided file showRGB to display the RGB-values for the 20 color samples.

Now compute the corresponding RGB-output for the second camera (represented by **A***d2*) using

the same 20 color samples and D65 illuminant. What you have now is device dependent RGBoutput

for two different RGB-cameras, representing the same 20 color samples under the same

illuminant. Compare the resulting RGB-values for the two cameras (you can also use showRGB).

Considering identical input, what is your comment to the output RGB-values for the two (real)

RGB-cameras? Can you relate the difference in the device-dependent RGB values to the spectral

sensitivity curves for the two cameras?

Answer: With respect to the spectral sensitivity curves, the results are indeed very similar. The green channel of Ad had overall lower values, which also resulted in the middle square becoming much darker.

A close-up of a color palette

Description automatically generated

So far, you have calculated the un-calibrated (raw) camera response, denoted by Dc in Fig. 1.

The next step in the workflow is to calibrate the camera response.

***2. Calibration of input devices***

The spectral model you used for the input device defines the forward function, determining the

device response, RGB, for a spectral input signal, *E(λ)* (product of illuminant and the surface

reflectance). The results have (hopefully) illustrated the need to further process the raw RGBsignals

using device calibration and characterization, to achieve a consistent color reproduction

workflow. Input device calibration is performed prior to the characterization, to compensate for the

device characteristics, and keeping it in a fixed, known state. Device characterization then derives

the relationship between device-dependent, **d’**, and device-independent data, **c**, for the calibrated

device (Fig. 3).

*Figure 3. Calibration and characterization for an input device (e.g. an RGB-camera).*

Calibration of input devices, such as RGB-cameras, generally involves determining the

relationship between scene radiance and camera response, in order to linearize and graybalance

the camera. For this camera, it has previously been established that the response is

linear to scene radiance, and it is not necessary to compute linearization curves. The calibration

thus reduces to computing normalization factors to scale the response for the R, G and B

channels, compensating for the filter characteristics. In Fig. 3, this corresponds to converting the

raw RGB-signals **d** (calculated in assignment 1.2) to calibrated RGB-signals **d’**.

**2.1**

Start by computing normalization factors for the two cameras, to compensate for the sensor

characteristics. For each of the R, G and B channels, find the factor that can be used for scaling

the channel so that R’=G’=B’=1 for an ideal “white” input spectrum (i.e. *e*=ones(1,61)). This

means that the normalization factors can be found by replacing *e* in Eq. 7 by a vector of ones.

Can you relate the normalization factors to the spectral sensitivity curves for the two cameras?

Answer: Seemingly it boosts the highest values and mutes the lowest values.  
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Automatiskt genererad beskrivningEn bild som visar text, diagram, linje, Graf

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**2.2**

Now use your normalization factors found in assignment 2.1 to compute calibrated R’G’B’-data for

the 20 color samples, by scaling your RGB\_raw data. The result is calibrated device-dependent

data, corresponding to **d’** in Fig. 3. For Camera 1, make sure to save the data as RGB\_cal\_D65

(or similar), for later use. Now compare the resulting RGB-signals after calibration, for the two

cameras, in the same way as in 1.2. Comments?

Answer: The two results are now almost or atleast seemingly identical.  
A close up of a color

Description automatically generated

**2.3**

So far, all experiments have been made using the same light source, standard illuminant D65

(representing daylight). In practice, image acquisition is not always made under a controlled and

constant light source. In the file *illum.mat*, you will also find data for CIEA, which is a standard

illuminant representing indoor light (tungsten filament light). Compare the illuminants D65 and A

by plotting their spectral power distributions against the wavelengths 400:5:700 nm. What can

you say about the difference between typical outdoor and indoor light?

Answer: CIEA has a lot more red while D65 is far more balanced over the spectrum.  
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**2.4**

Now compute the resulting RGB-output for Camera 1 under Illuminant A (the same way as you

did in 1.2 for D65). Then use your normalization factors to compute the calibrated camera

response. Compare the calibrated RGB-signals for Illuminant A to the corresponding ones for

D65 (RGB\_cal\_D65). This corresponds to images of the same 20 surfaces, captured by the same

calibrated camera, using two different light sources. Comments?

Answer: CIEA gives very red colors overall while D65 is far more balanced.  
A screenshot of a color palette

Description automatically generated

The reason for the results is that the camera calibration is based on the camera characteristics

alone. The normalization factors are computed to generate a neutral RGB response for a neutral

input spectrum, E(λ). Since E(λ) is the product of the illuminant I(λ) and the object R(λ) (see Fig.

2), the characteristics of the illuminant will inherently affect the resulting color balance in the

resulting RGB-image. This is suitable for absolute camera calibration, compensating for device

characteristics and keeping it in a fixed state, independent of the light source. However, in many

practical applications, we actually do want to compensate for the illumination, using white point

normalization. The aim is then to mimic human color vision, which automatically compensates for

the scene illumination. If you instead would compute the normalization factors based on a specific

illumination and a reference white (i.e. using R=ones(1,61) in Eq. 8 instead of *chips20(10,:)*), the

system would be calibrated for that specific light source, which would be a type of white point

normalization.

**2.5**

Now compute new normalization factors based on the specific light sources D65 and A for

Camera 1 (in the same way as in 2.1, but instead using R=ones(1,61)). Use the new factors to

scale the RGB\_raw data, for D65 and A, respectively, and compare the results. This corresponds

to the same set-up as in 2.4 (same 20 surfaces under 2 light sources), but including the light

source in the calibration. Comments?

Answer:The calculated for illuminant A is now very blue, while the cal for D65 looks like previously.  
A screenshot of a color palette

Description automatically generated

***3 Characterization of input devices***

Now you have used the forward spectral model to simulate the camera sensor, generating RGBsignals

from a spectral input, and applied calibration routines to modify the RGB-signals.

However, the calibrated RGB-signals are still device-dependent. The next step in a color

management workflow is device characterization, deriving the relationship between camera RGB

and the device-independent color space CIEXYZ. For an input device, this refers to the inverse

function, which compensates for the device characteristics and determines colorimetric data

(XYZ) from the recorded device signals (RGB). In Fig. 3, this corresponds to deriving the

relationship between the calibrated RGB-values, **d’**, and colorimetric values, **c**.

Figure 4 shows the workflow for evaluating the accuracy of device characterization. The input is

the spectral signals *E*(*λ*), which after image acquisition generate the device response, **d**, modified

by camera calibration to **d’** (lower row in Fig. 4). The characterization function then estimates

XYZ-values, from the calibrated RGB-values **d’**. To evaluate the result, we need to compare the

estimated XYZ-values to reference values. The reference values are simply computed by

applying the color matching functions (CMFs) to the spectral input *E*(*λ*), which gives us XYZvalues,

representing the color appearance for a “standard observer” (upper row in Fig. 4).

However, since XYZ is not a perceptually uniform color space, it is not optimal for describing color

differences. Instead, the XYZ-values are converted into CIELAB color space, using standard

transformations. In CIELAB, the perceptually relevant ΔEab color difference can be computed, as

the Euclidian distance between the CIELAB values for the references and the estimations (Fig.

4).

*Figure 4. Evaluation of input device characterization.*

Spectral

measurement

Spectral

Input

CIE

XYZ

(ref)

CIE

L\*a\*b\*

(ref)

CIE

XYZ

(est)

CIE

L\*a\*b\*

(est)

CMFs Transform

Transform

Color difference

ΔEab

*E*(λ)

Image

acquisition

Calibrated

response

**d’**

Device

response

**d**

Calibration

Characterization

**3.1**

Start by computing XYZ-values for the 20 surfaces in *chips20*, under the illuminant D65, which

you will use as references (Fig. 4). Save it as XYZ\_D65\_ref (or similar). When you compute XYZ

from spectra, always make sure that you use the correct normalization factor, so that Y=100 for a

reference white (i.e. R=ones(1,61)). You can simply use Eq. 7, replacing the camera sensitivity

functions with the CMFs (available in the file *xyz.mat*) and then multiplied by the normalization

factor.

**3.2**

In the previous labs in TNM059, you were given a 3x3 matrix that you used for conversions

between RGB and XYZ. This is a general conversion, based on sRGB, and not always optimal for

all devices. In the data, you have the matrix MXYZ2RGB. Let’s start to evaluate the performance

of this general matrix conversion, for this specific camera. Use your calibrated R’G’B’ values

(RGB\_cal\_D65) to compute the corresponding XYZ values for the 20 objects, using the **inverse**

of the matrix MXYZ2RGB. To evaluate the result, you need to first convert the XYZ-values to

CIELAB and then compute the ΔEab color difference between the references and the estimations.

For the CIELAB conversion you can use the function *xyz2lab.* What is the mean and maximum

ΔEab color difference for the 20 colors/objects? Are the results acceptable?

(Hint: you will perform the operation of converting XYZ-values to CIELAB and computing mean

and maximum ΔEab several times (in this lab and the next), so writing a function for this could

prove useful.)

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To have an exact characterization using a simple 3x3 matrix is only possible if there exists a

unique non-singular transform between the sensor sensitivities and the color matching functions

(this is called the *Luther Ives condition*). In such cases the device is called a *colorimetric device*,

and the characterization is simple and exact. However, in practice, it is difficult to construct color

filters and sensors that fulfill this condition.

**3.3**

Compare the spectral sensitivity functions for the camera (**A***d*) to the CMFs of the standard

observer (**xyz**) by plotting them against the wavelengths 400:5:700 nm. Comments?

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Since the camera is not a colorimetric device, it is difficult to derive the inverse function, based on

the camera characteristics. Instead, we will use empirical techniques for the inverse

characterization. Least-squares regression techniques are widely used in color imaging, device

characterization and modeling. The simplest form is Linear least squares regression, where the

characterization function is approximated by a linear relationship **c** = **d** ∙ **A**, where **d** is a 1 x *m*

input color vector and **c** is a *1 x n* output color vector. The *m x n* matrix **A** is derived by minimizing

the mean squared error of the linear fit to a set of training samples ({di},{ci}), as:

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- = å=

2

1

argmin 1

*T*

*i*

*i i*

*A*

*opt T*

**A c d A** (9)

For a conversion from RGB (*m*=3) to XYZ (*n*=3), **A** is 3x3. If the XYZ-values for *T* samples are

collected into a *T* x *3* matrix **C** = [**c**1; …;**c**T] and the corresponding RGB-values into a *T* x *3* matrix

**D** = [**d**1; …;**d**T], the linear relationship is given by **C** = **D** ∙ **A**. The optimal **A** is then given by **A** = **D**†

**C,** where **D**† is the Moore-Penrose pseudo-inverse of **D** (in Matlab: *pinv*). This requires for *T* ≥ *m*,

i.e. we need at least as many sample points as the dimensionality of the input data. For the

preferred case, *T* > *m*, we have an overdetermined system of equations for which we derive the

least-squares solution.

To summarize, the conversion matrix **A** is calculated by **A**=pinv(**D**)\*C. The matrix **D** is a *20 x 3*

matrix containing the RGB values (the matrix you found in assignment 2.2, notice that you might

need to transpose that matrix to make it *20 x 3*). The matrix **C** is a *20 x 3* matrix containing the

corresponding XYZ-values (the matrix you found in assignment 3.1, notice that you might need to

transpose that matrix to make it *20 x 3*). When **A** is found, the conversion from RGB to XYZ could

be found by **D**\***A**, where **D** and **A** are the matrices specified before.

**3.4**

Use your calibrated R’G’B’ values (RGB\_cal\_D65) to compute the optimal matrix **A**, using linear

regression. This 3x3 matrix defines the conversion between device RGB and XYZ, based on the

relation between measured XYZ-vales and recorded RGB-signals, for the specific 20 color

samples. Now use your 3x3 matrix **A** to estimate XYZ-values for the 20 color samples. As earlier,

compute the ΔEab color difference between the references and the estimations and report the

mean and maximum ΔEab for the 20 objects. Comments?

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Polynomial regression is a special case of least squares fitting, where the characterization

function is approximated by a polynomial. The inverse characterization function of a 3-channel

system, mapping RGB values to XYZ tristimulus values, is obtained by expressing XYZ as a

polynomial function of R, G and B. As an example, a second order polynomial approximation is

given by:

*X Y Z* !"

#$

= 1,*R*,*G*,*B*,*R*2 ,*RG*,*RB*,*G*2 ,*GB*,*B*2 ,*RGB* !"

#$

*wX* ,1 *wY* ,1 *wZ* ,1

*wX* ,2 *wY* ,2 *wZ* ,2

...

*wX* ,11 *wY* ,11 *wZ* ,11

!

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#

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(10)

By rearranging the data into a polynomial vector, the polynomial regression is reduced into a

linear least squares regression, to determine the optimal weights, *w*.

**3.5**

You are provided with the function *Optimize\_poly.m* that can be used to compute the optimal

11x3-matrix **A**, containing weights for polynomial regression, according to Eq. 10. The function

*Polynomial\_regression.m* then uses the matrix **A** to compute XYZ-values from RGB. Make use of

these functions to compute XYZ-values for the 20 samples, using polynomial regression.

Compare the results (i.e. the mean and max ΔEab color difference) to your previous results.

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Note that in a “real” camera characterization set-up, the training set used for deriving the inverse

characterization by regression, should optimally be larger than 20 samples. The result should

also be evaluated using a different set of color samples, for verification. Since the parameters

have been optimized for these specific color samples, the estimation errors will always be smaller

for the training set.

**Summary**

In this lab, you have used a model-based approach for the forward image acquisition model, i.e.

you have simulated the camera response based on the interaction between light-sources, object

reflectance and the characteristics of two real RGB-camera sensors. The resulting RGB-signals

have then been calibrated, to compensate for the characteristics of the camera sensors, and also

to compensate for the illumination, using white point normalization.

For the inverse device characterization function, describing the transformation from the devicedependent

RGB to the device-independent CIEXYZ color space, you used empirical

characterization. This is a kind of “black-box”-approach, where the characterization functions are

based only on the input and output for a training set of color samples, thus ignoring the

characteristics of the device. The drawback of least-squared regression optimization is that the

characterization will be accurate only for these specific conditions, and e.g. changing the

illuminant would require a new characterization process.

Much of the data that you have required in this lab, such as the camera RGB-response (both uncalibrated

and calibrated), the reference XYZ-values and the different XYZ-estimations from

device characterization, will be further used in the next lab, focusing on characterization and

modeling of output devices.