Computational color

ITÄ-SUOMEN YLIOPISTO

Two main topics in this course

- How to represent color as device independent
  - how to produce device independent color representation from device dependent color representation
- How to represent accurate color spectrum information
  - how to compress the high dimensional spectral information into a low dimensional approximation
  - how to reconstruct accurate spectral information from a low dimensional color representation

Study forms in the course

- lectures: Wednesday 10 - 12 and Friday 10 - 12
- home exercises, "theoretical problems"
- practical exercises, testing the studied methods by using real spectral sets and spectral images

- Final exam

- lectures Professor Jussi Parkkinen
- exercises researcher Ville Heikkinen
  researcher Alexey Andriyashin

Form and color are important in object recognition

How do you separate the peppers from each other?

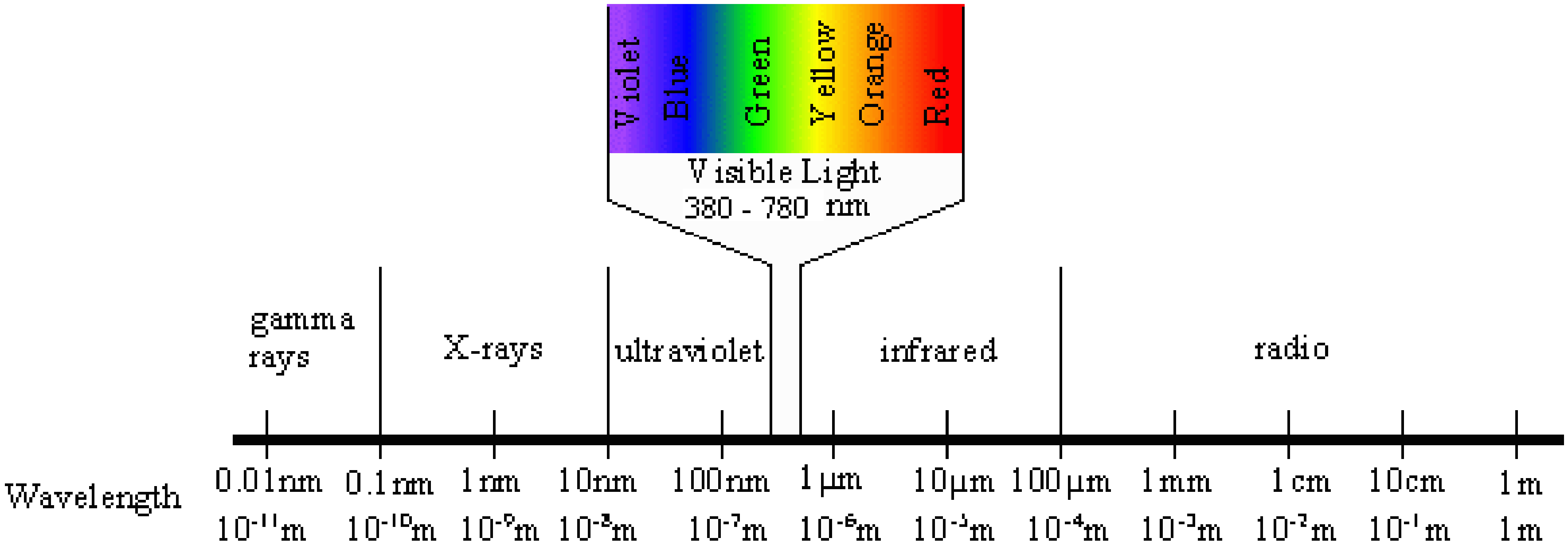
What is Color?
i.e. what are the goals in previous slide?

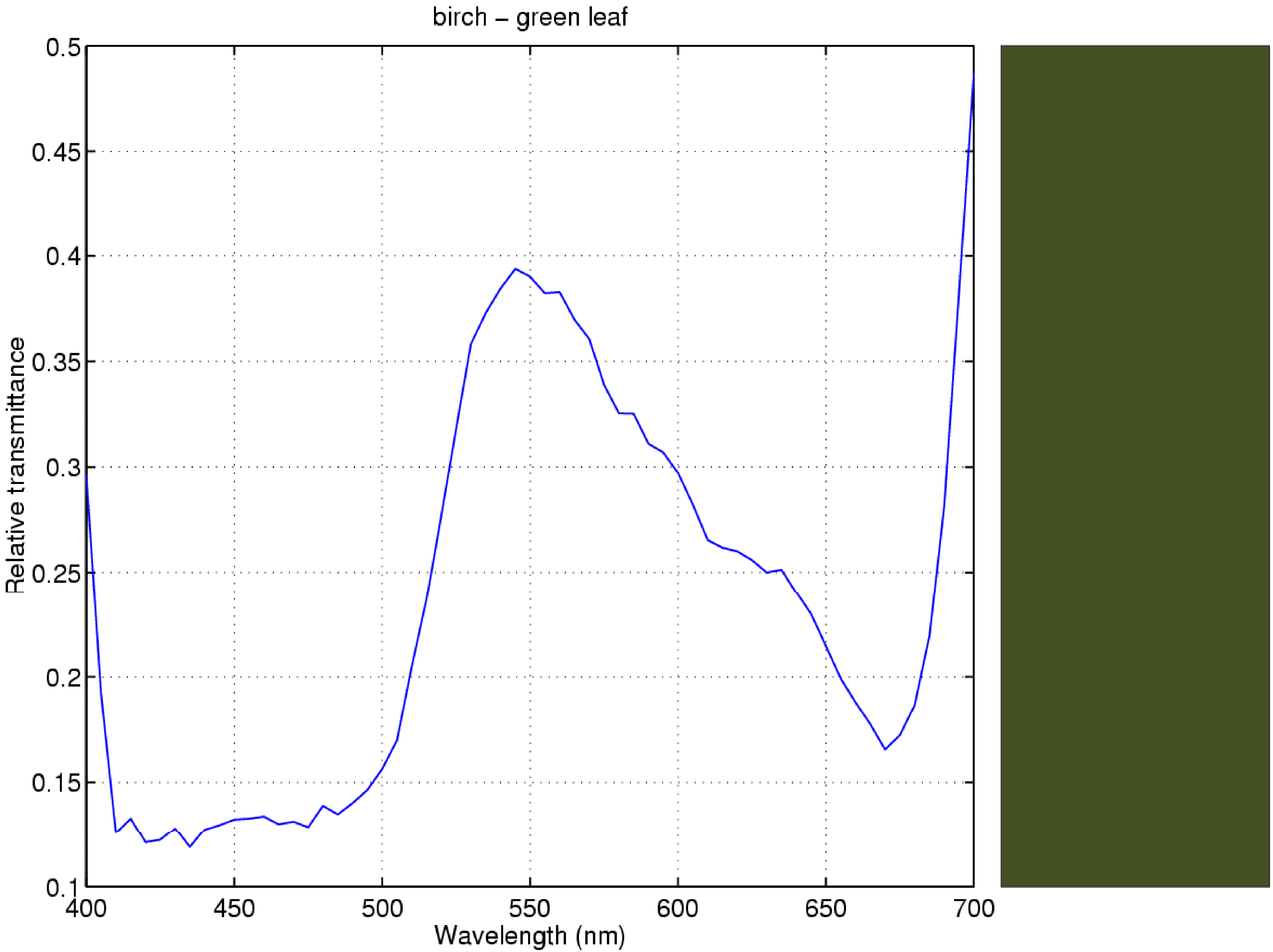
- "Color is what human see" - colorimetric approach
  - color is represented by RGB, L*a*b*, etc.
  - wavelength range limited by human visual system

- "Color is a property of an object and color information is carried in the color signal, electromagnetic radiation from object to detector" - photometric or physical approach
  - color is represented by color spectrum
  - not limited wavelength range

Approach in this course

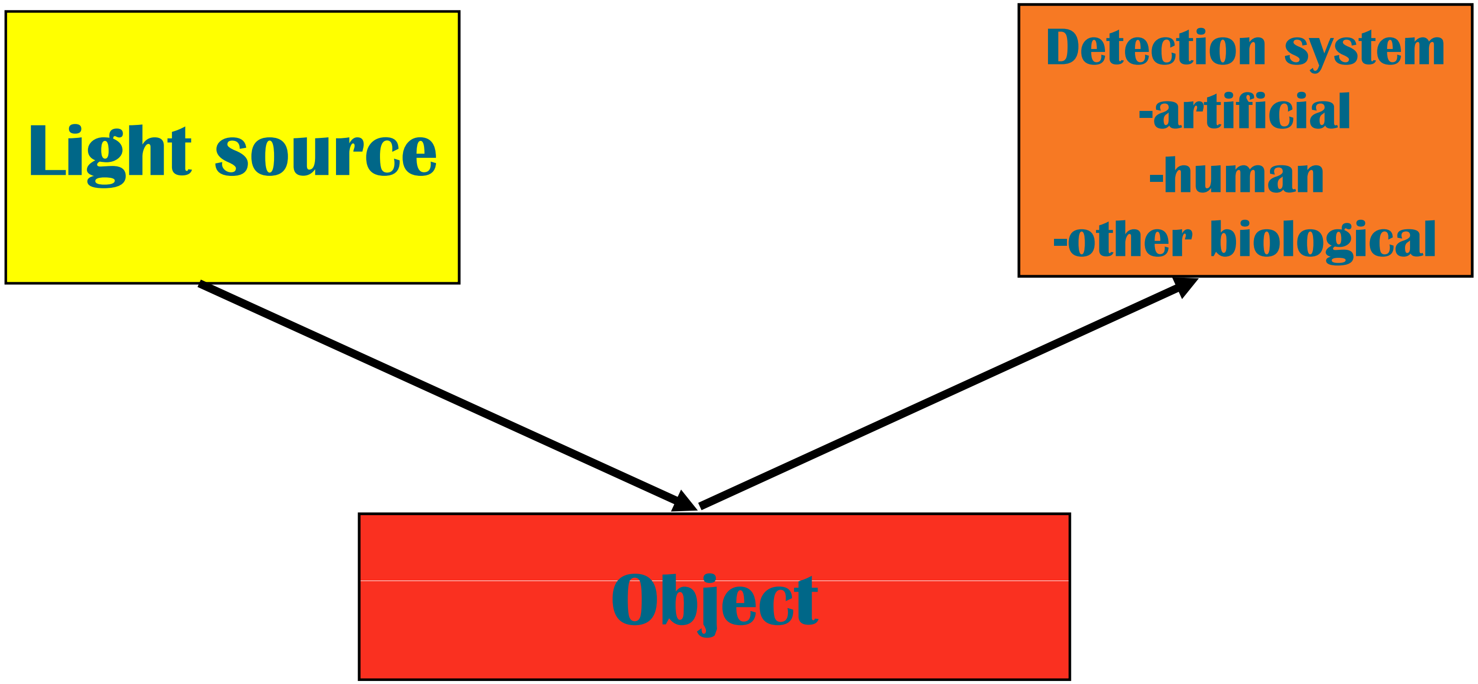
The visible spectrum



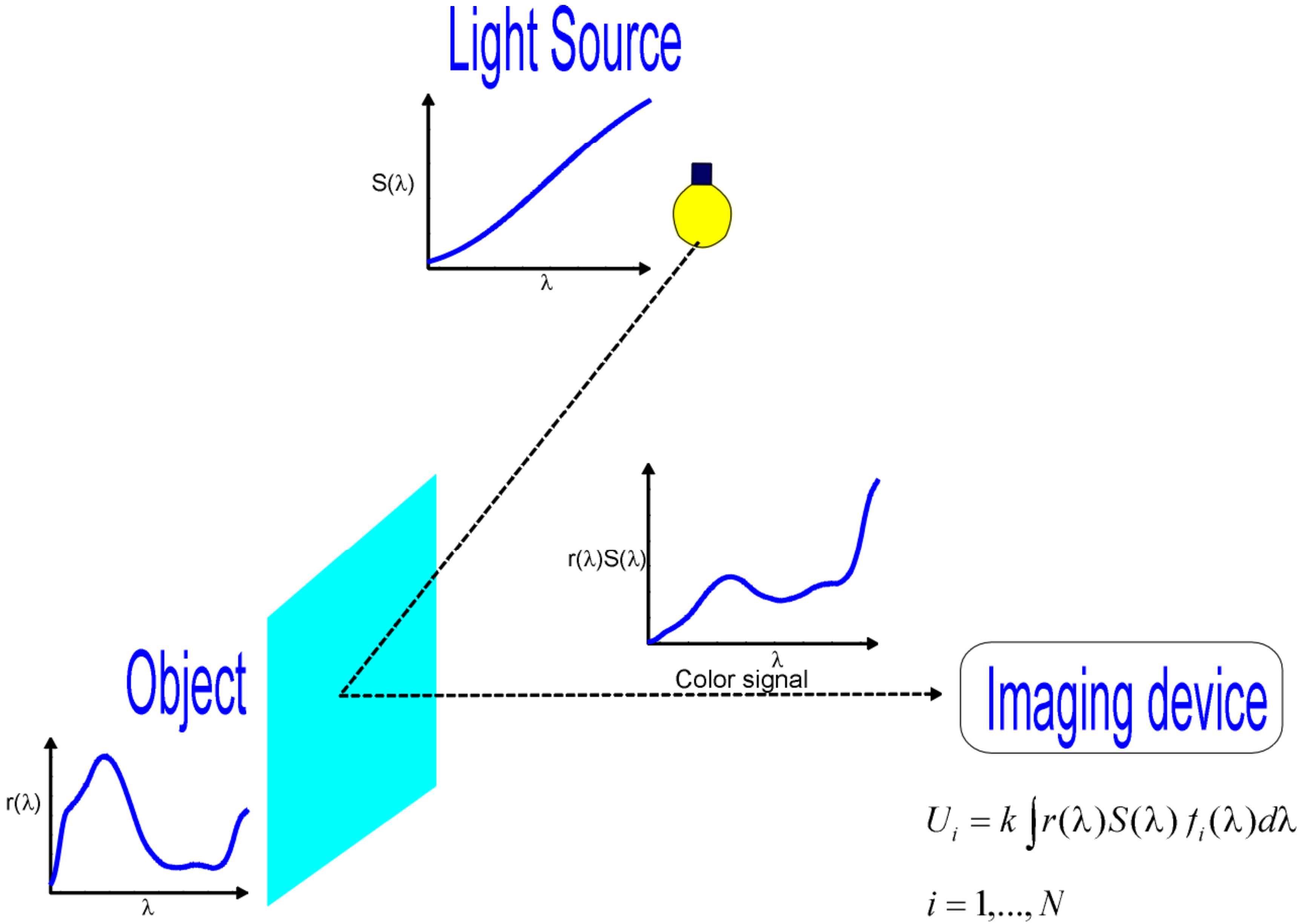

birch – green leaf
Relative transmittance
0.5
0.45
0.4
0.35
0.3
0.25
0.2
0.15
0.1
400
450
500
550
600
650
700
Wavelength (nm)

Our approach to color

- Color information is carried by the light signal originated from the colored object
- This signal is measurable and unique

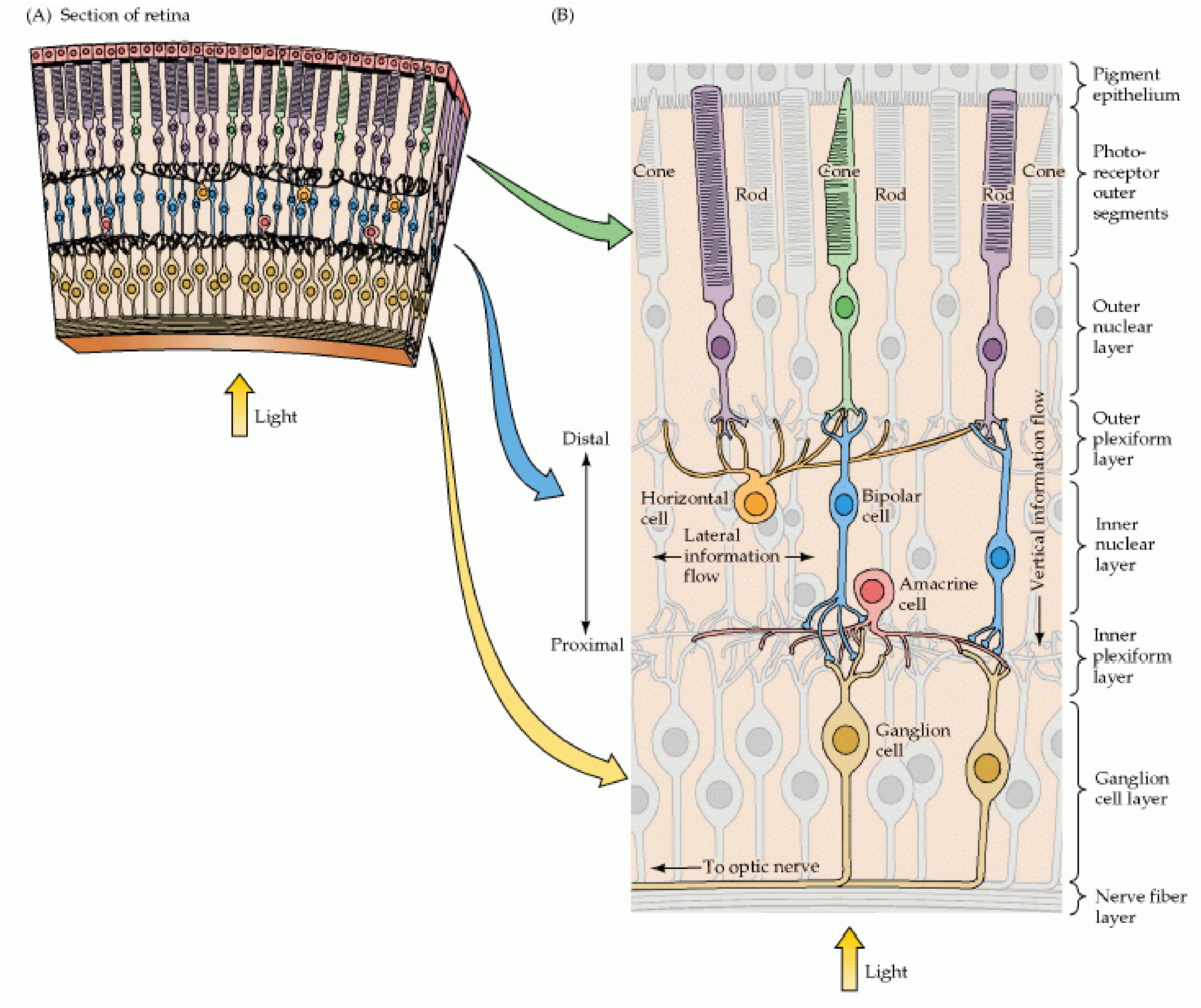


Formation of the Color Signal

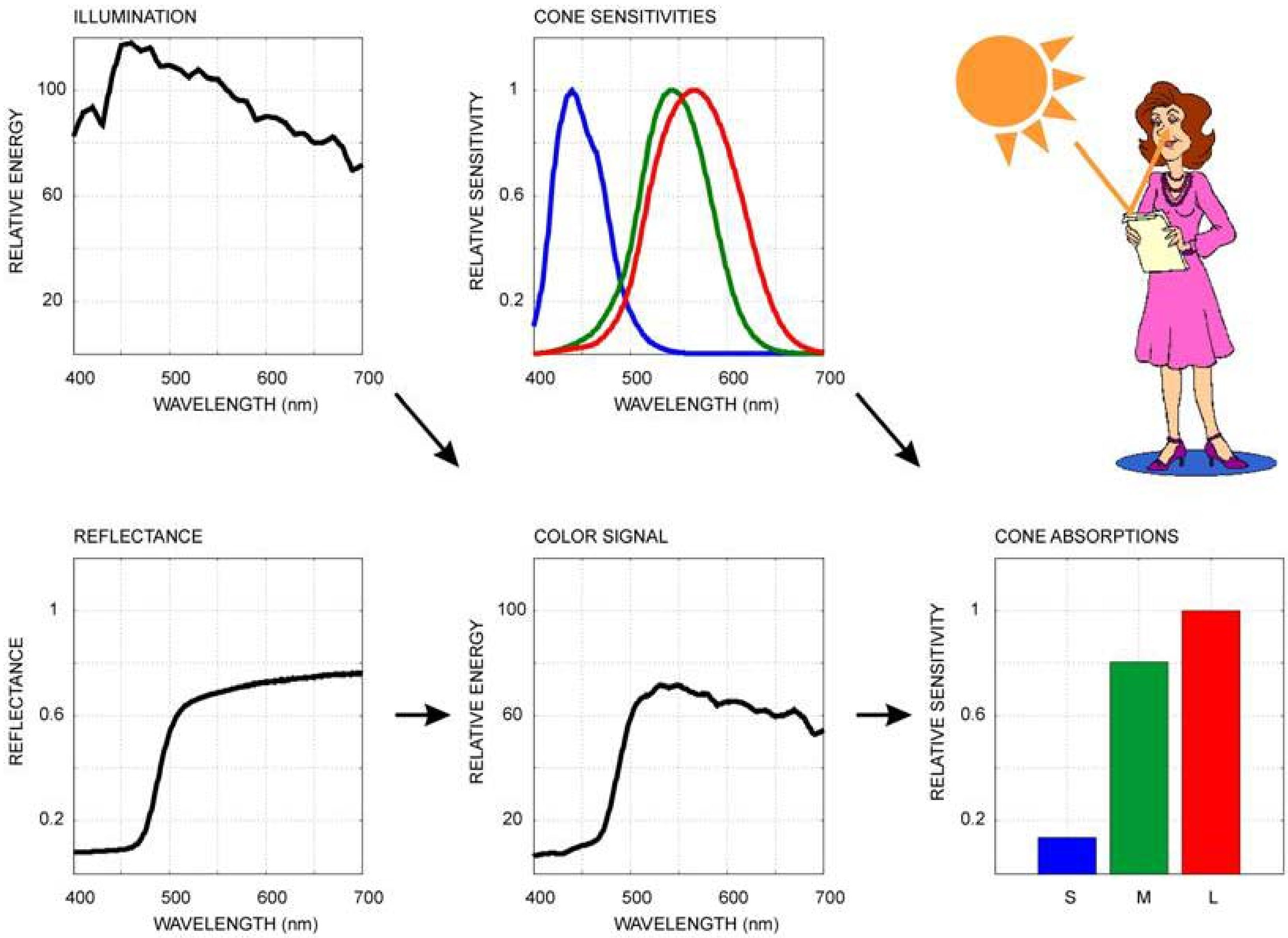


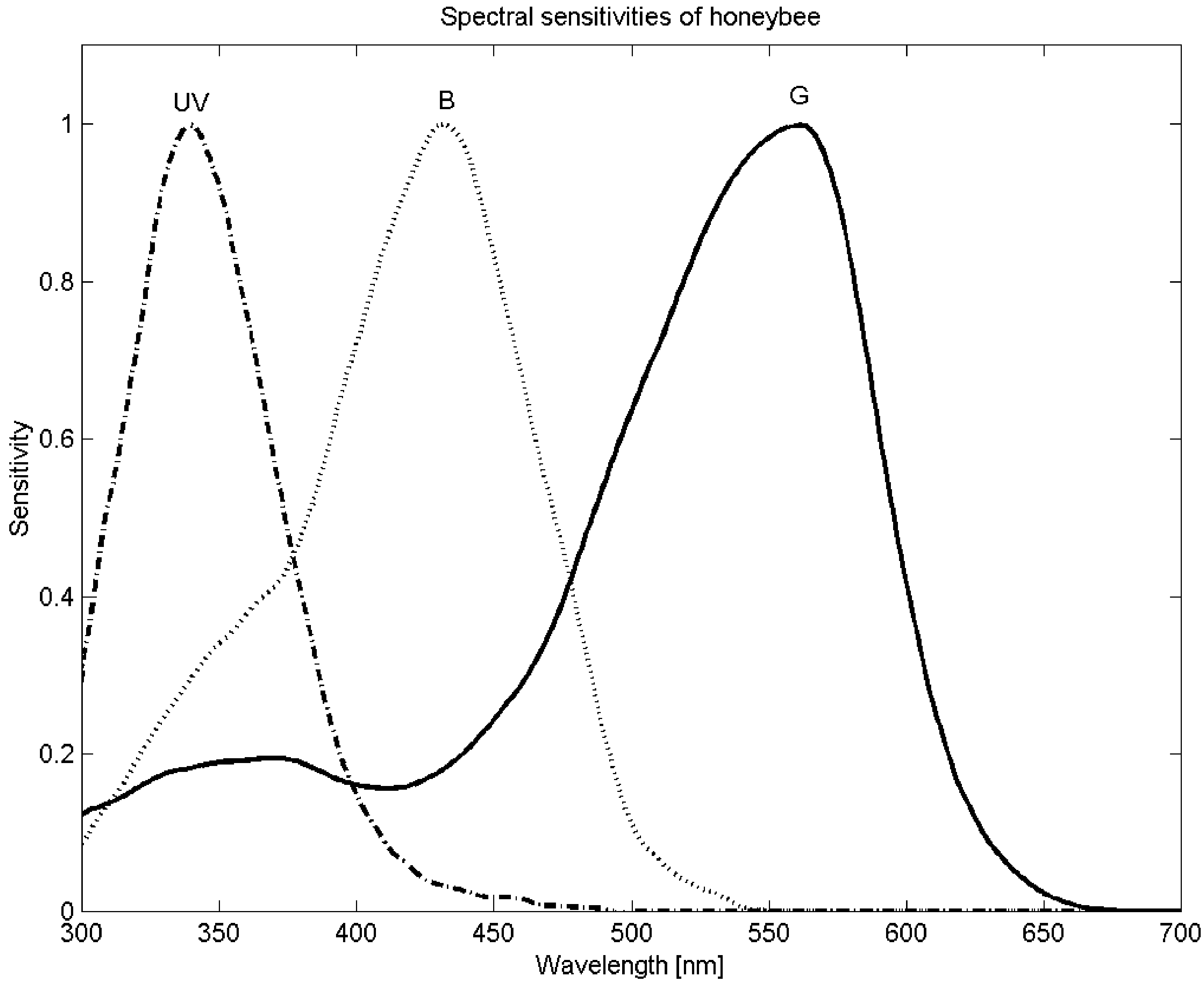
$$U_i = k \int r(\lambda) S(\lambda) f_i(\lambda) d\lambda$$

$$i = 1, \ldots, N$$

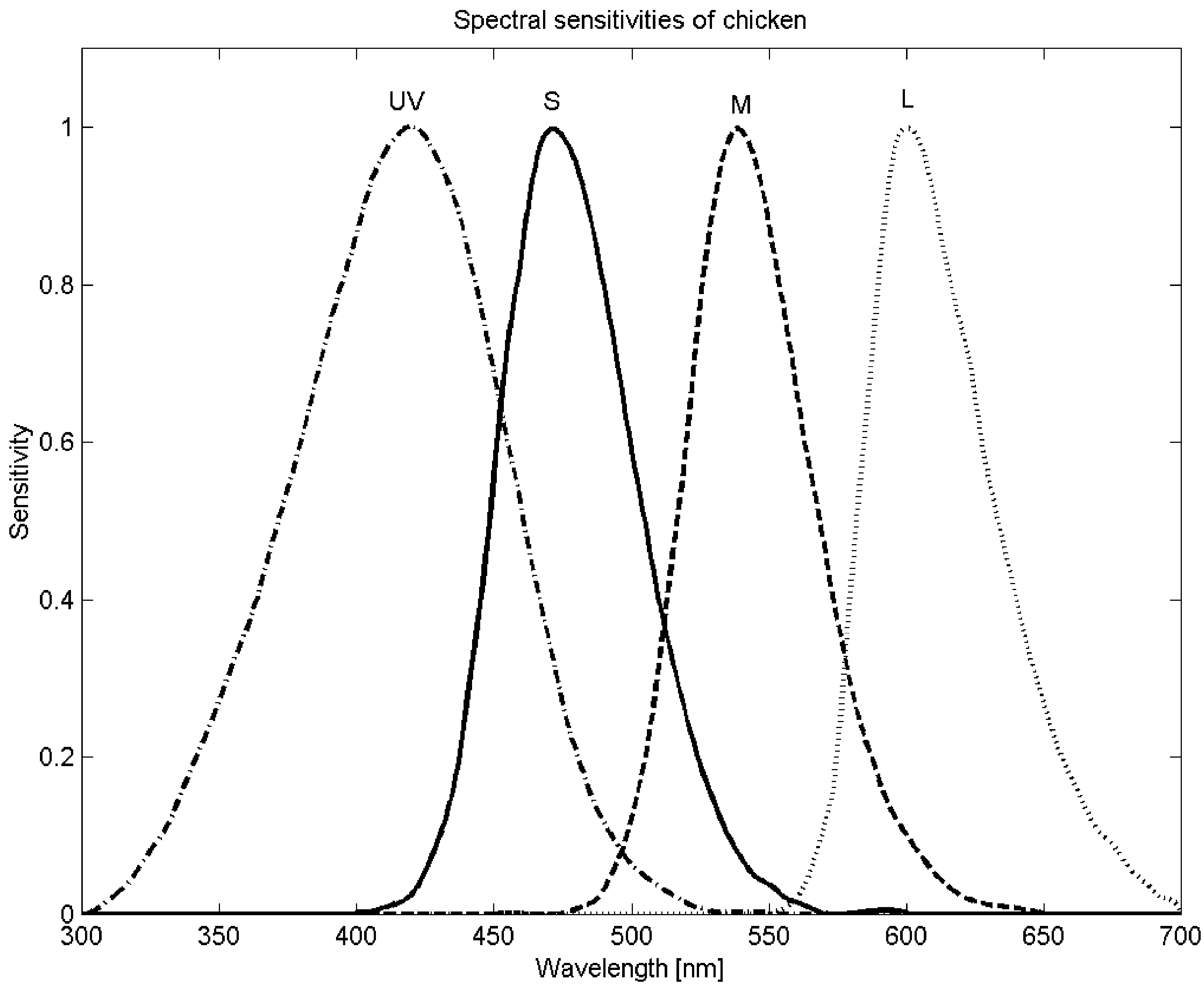


Purves et al., Neuroscience, 2nd ed., Sinauer Associates (web-pages, 23.1.2007)

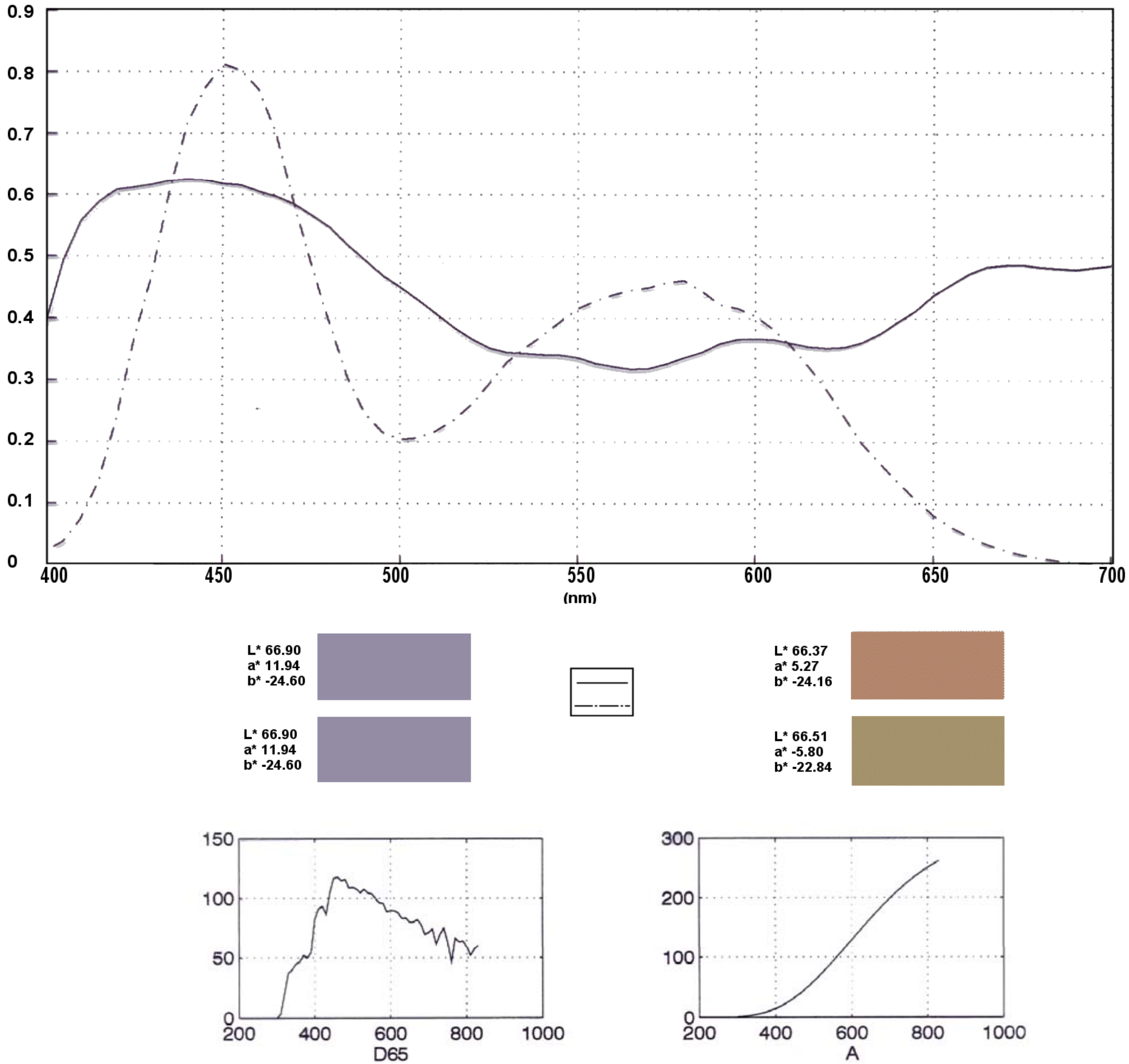

ILLUMINATION
RELATIVE ENERGY
100
60
20
400
500
600
700
WAVELENGTH (nm)
CONE SENSITIVITIES
RELATIVE SENSITIVITY
1
0.6
0.2
400
500
600
700
WAVELENGTH (nm)
REFLECTANCE
REFLECTANCE
1
0.6
0.2
400
500
600
700
WAVELENGTH (nm)
COLOR SIGNAL
RELATIVE ENERGY
100
60
20
400
500
600
700
WAVELENGTH (nm)
CONE ABSORPTIONS
RELATIVE SENSITIVITY
1
0.6
0.2
S
M
L



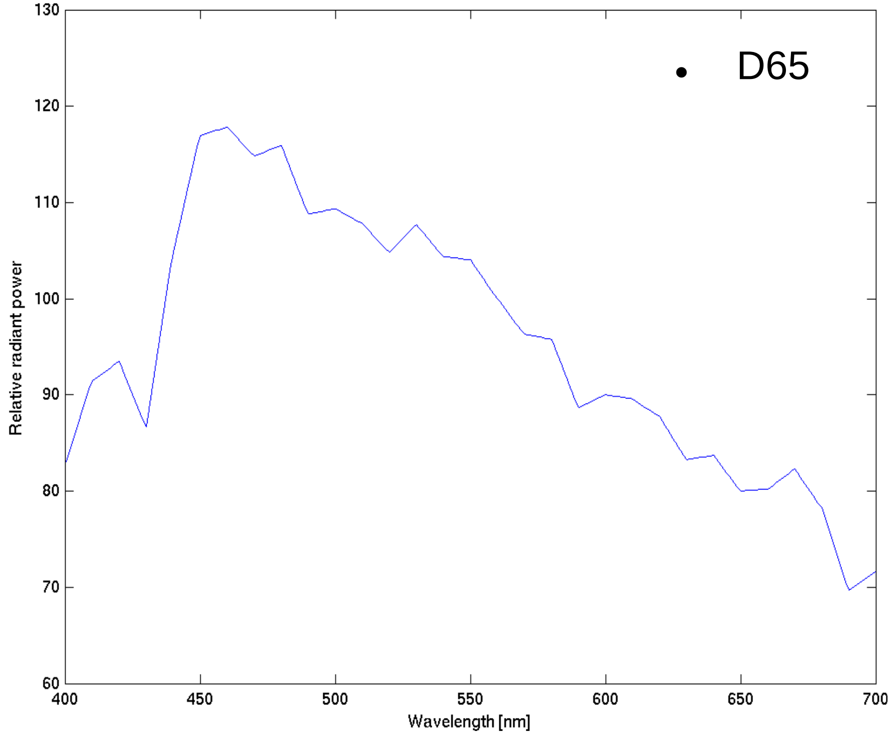
Spectral sensitivities of honeybee
UV
B
G
Sensitivity
0
0.2
0.4
0.6
0.8
1
300
350
400
450
500
550
600
650
700
Wavelength [nm]

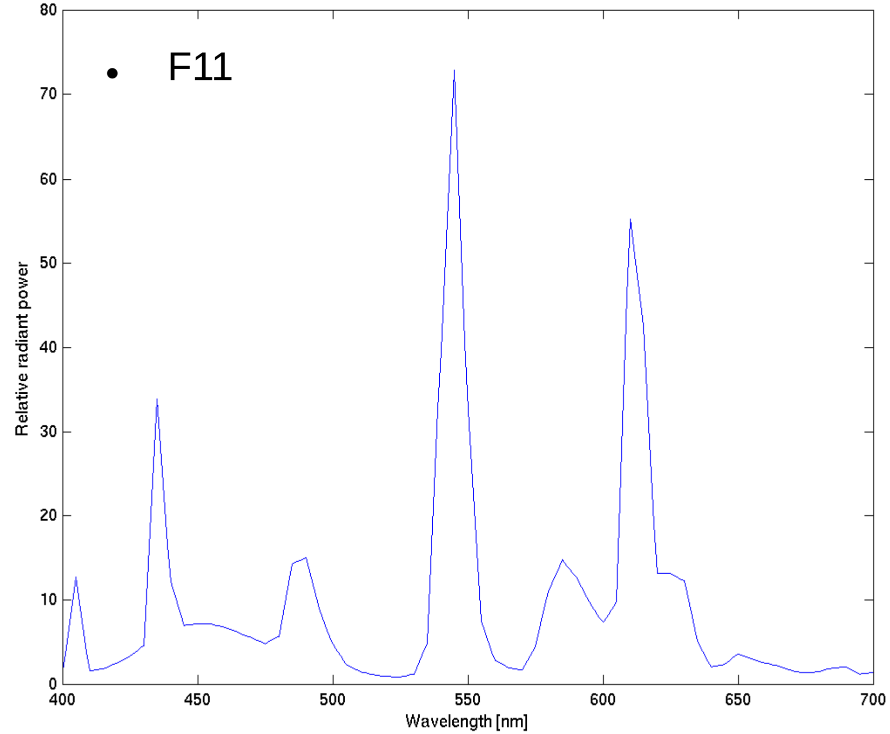

Spectral sensitivities of chicken
UV
S
M
L
Sensitivity
0
0.2
0.4
0.6
0.8
1
300
350
400
450
500
550
600
650
700
Wavelength [nm]

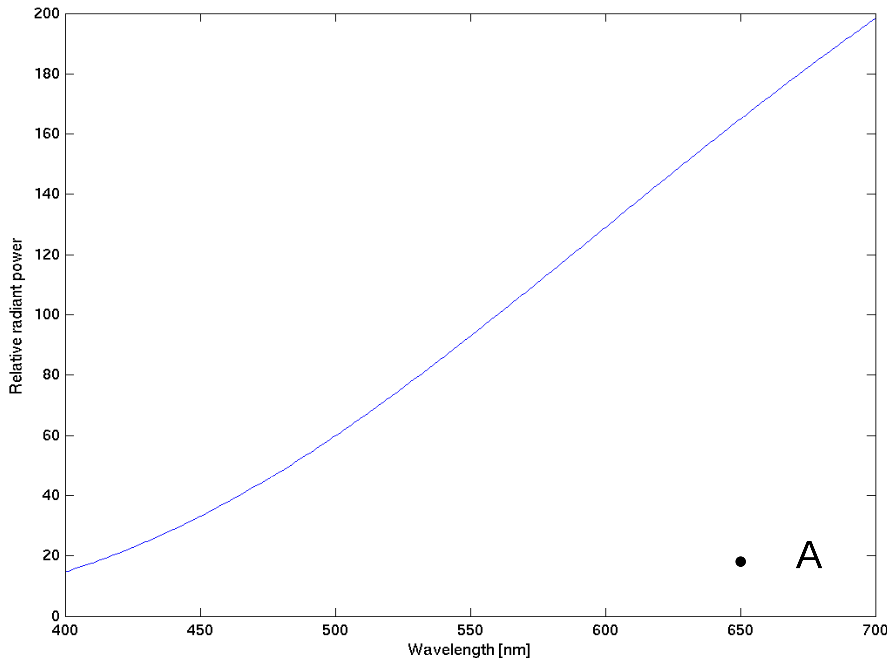
Metamerism

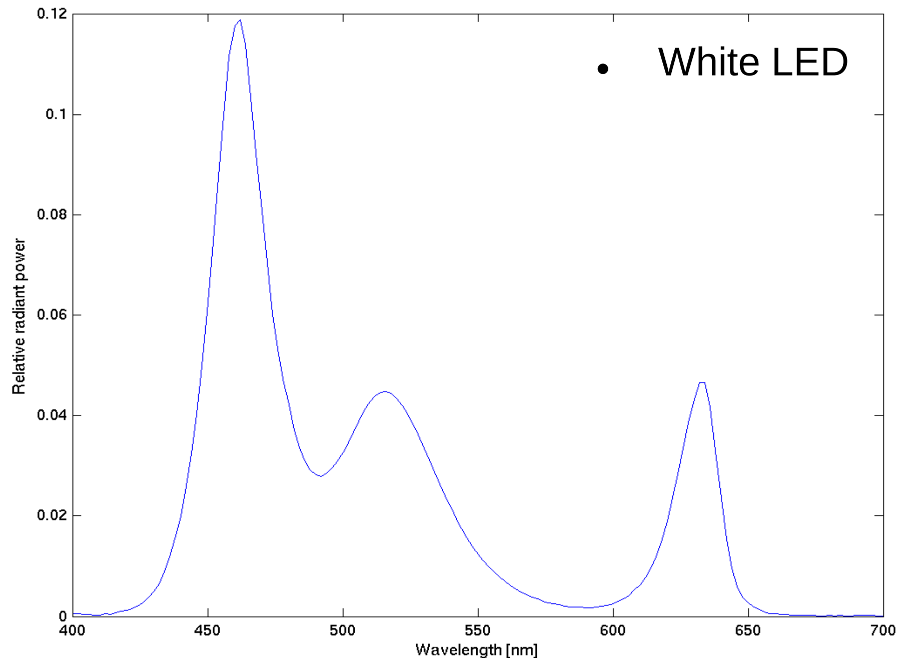


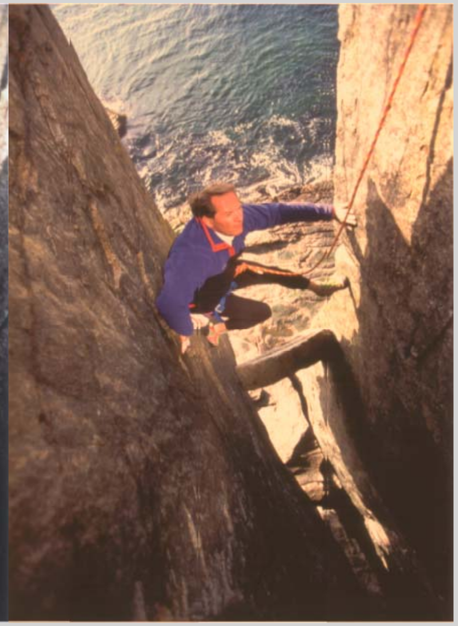
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
400
450
500
550
600
650
700
(nm)
L* 66.90
a* 11.94
b* -24.60
L* 66.90
a* 11.94
b* -24.60
L* 66.37
a* 5.27
b* -24.16
L* 66.51
a* -5.80
b* -22.84
150
100
50
0
200
400
600
800
1000
D65
300
200
100
0
200
400
600
800
1000
A


D65
Relative radiant power
Wavelength [nm]
130
120
110
100
90
80
70
60
400
450
500
550
600
650
700

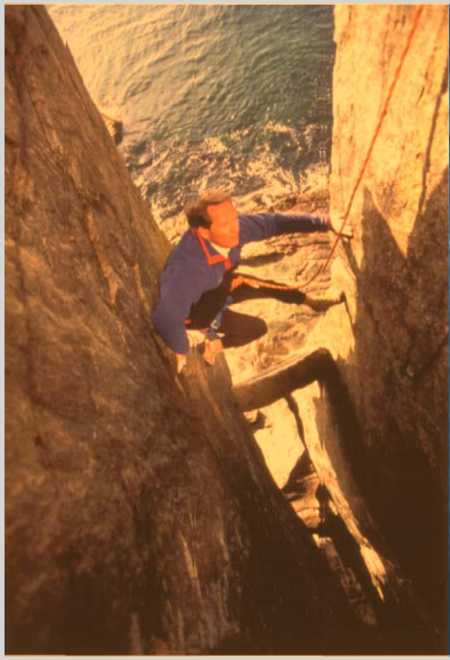

F11
Relative radiant power
Wavelength [nm]
80
70
60
50
40
30
20
10
0
400
450
500
550
600
650
700

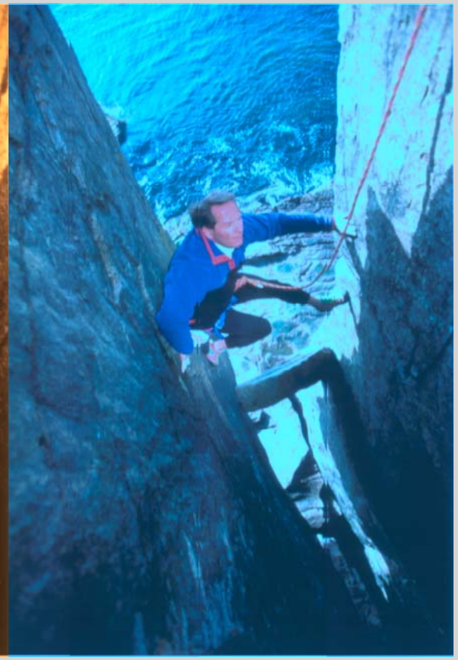

A
Relative radiant power
Wavelength [nm]
200
180
160
140
120
100
80
60
40
20
0
400
450
500
550
600
650
700


White LED
Relative radiant power
Wavelength [nm]
0.12
0.1
0.08
0.06
0.04
0.02
0
400
450
500
550
600
650
700

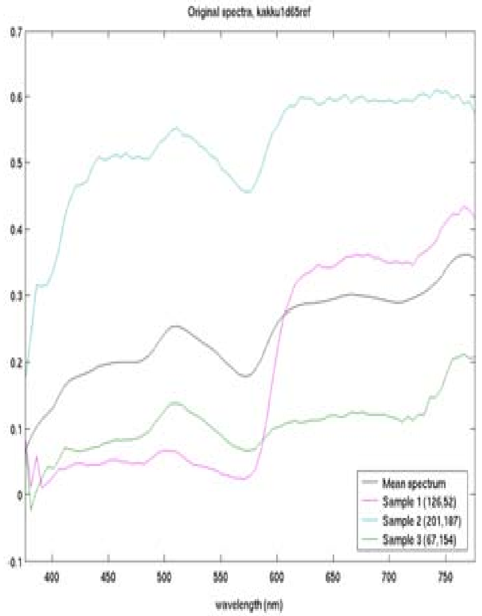


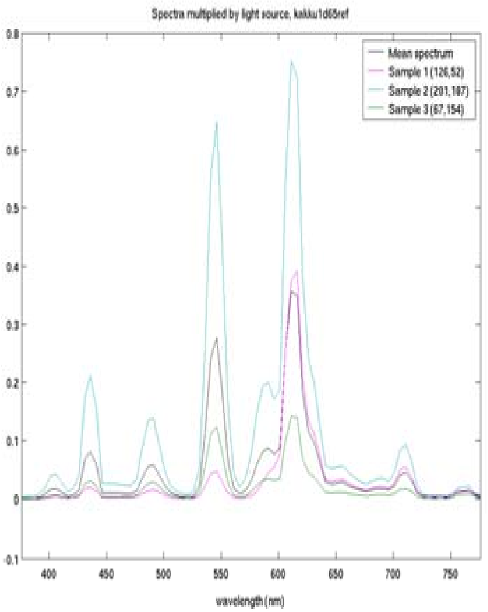
- D65
- F11

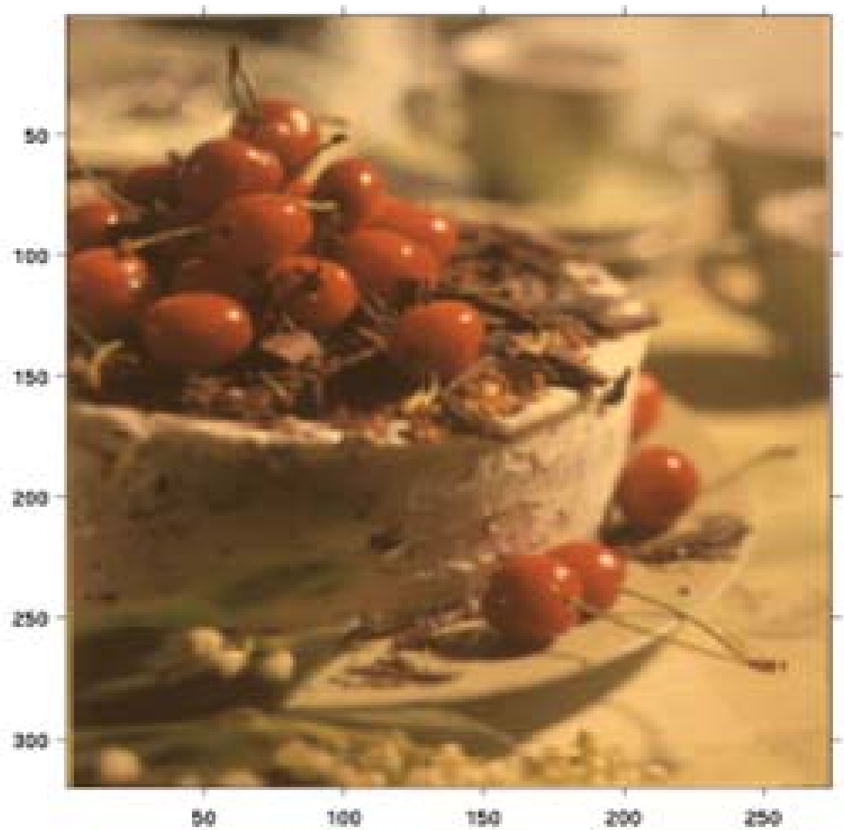




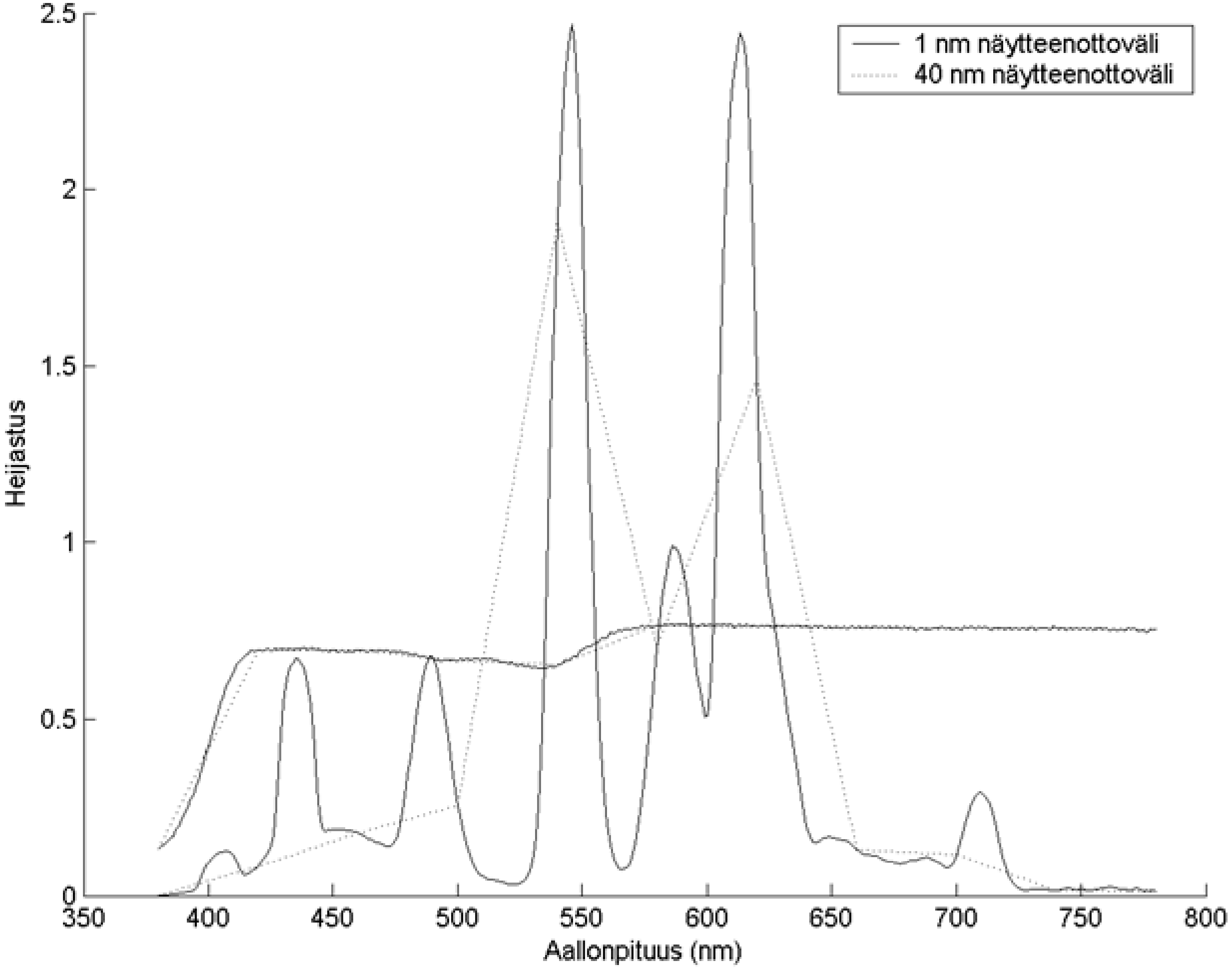
- A
- White LED

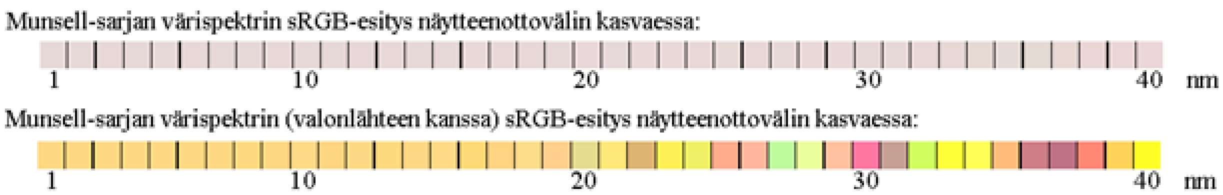

Original spectra, kakku1d65ref
Mean spectrum
Sample 1 (126,52)
Sample 2 (201,187)
Sample 3 (67,154)
wavelength (nm)


Spectra multiplied by light source, kakku1d65ref
Mean spectrum
Sample 1 (126,52)
Sample 2 (201,187)
Sample 3 (67,154)
wavelength (nm)

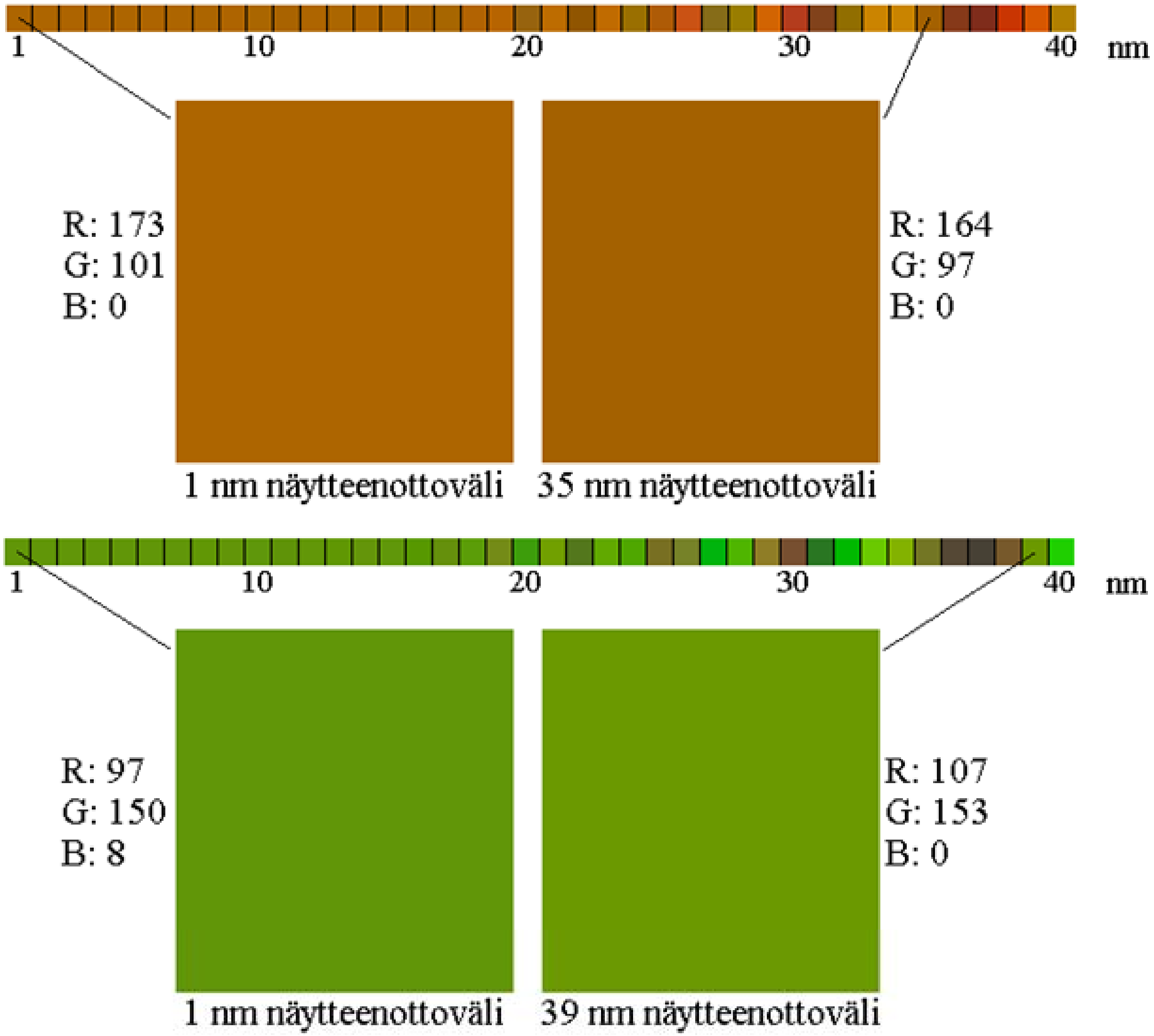


Spectral dependence on sampling

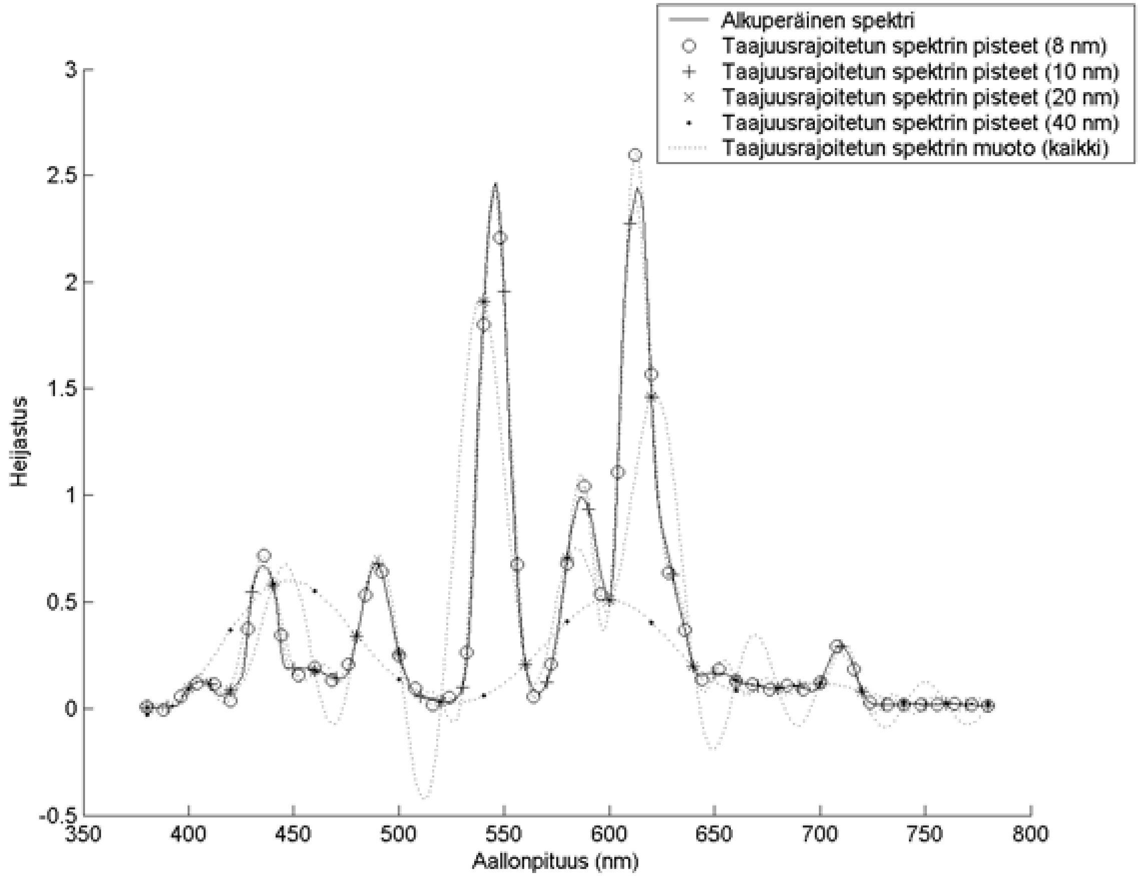




Color dependence on sampling



Change of RGB-values due to sampling



Alkuperäinen: RGB = (146, 75, 56)

	Suoraan harvennettu:	Taajuusrajoitettu:
8 nm:	RGB = (145, 75, 55)	RGB = (146, 74, 57)
10 nm:	RGB = (143, 75, 59)	RGB = (143, 75, 59)
20 nm:	RGB = (126, 75, 63)	RGB = (126, 75, 63)
40 nm:	RGB = (148, 101, 24)	RGB = (96, 29, 82)

Device independent color representation

- polynomial approximation of spectrum from RGB
- kernel estimation of spectrum from RGB

- learning phase in the process
- training set is needed for parameter selection

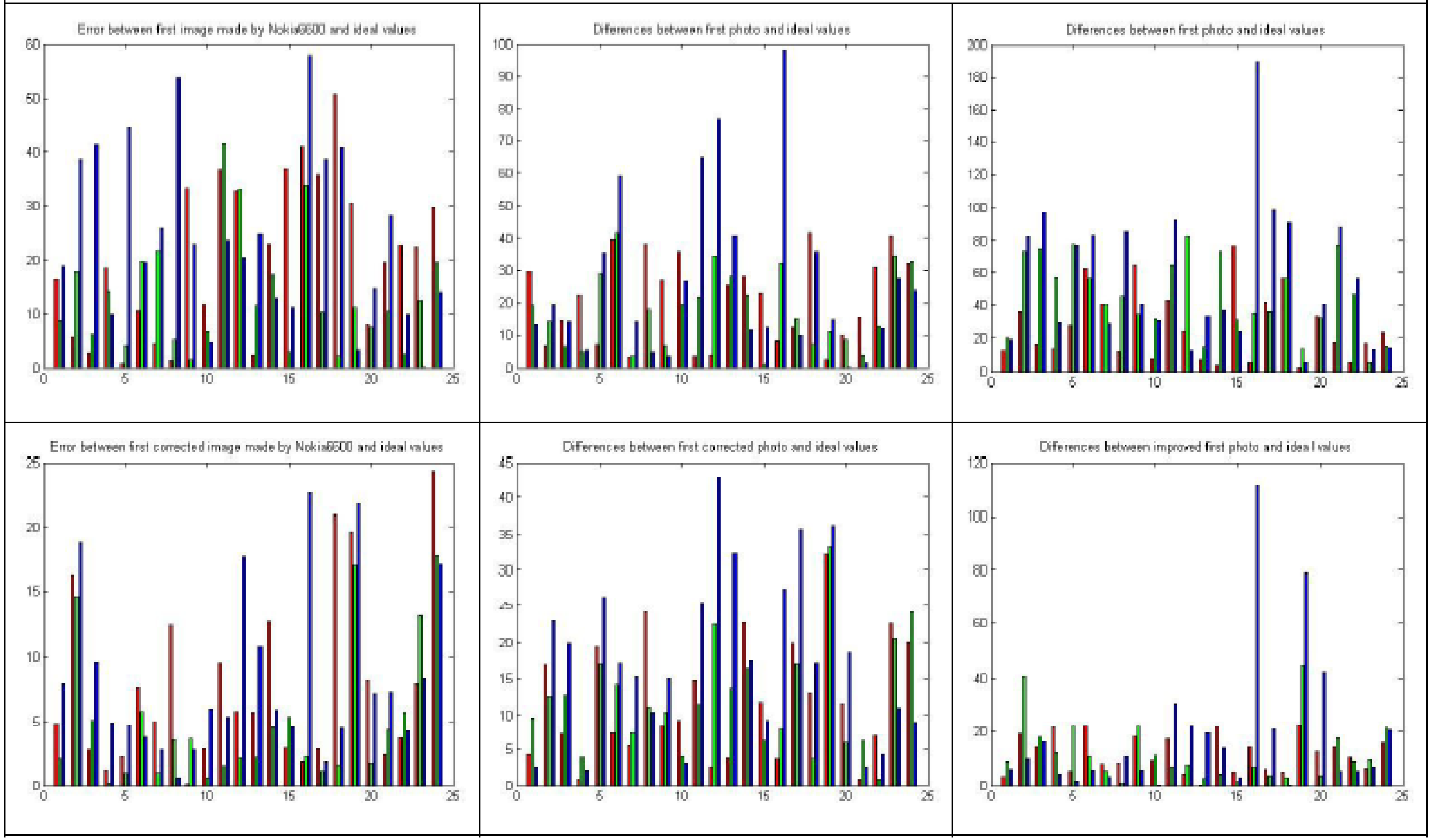
Some tests with mobile phones cameras

Nokia 6600	*Siemens S65*	*Samsung SGH-D500*
Original mobile phone images		
		
Images improved using 2nd order polynomial model		
		

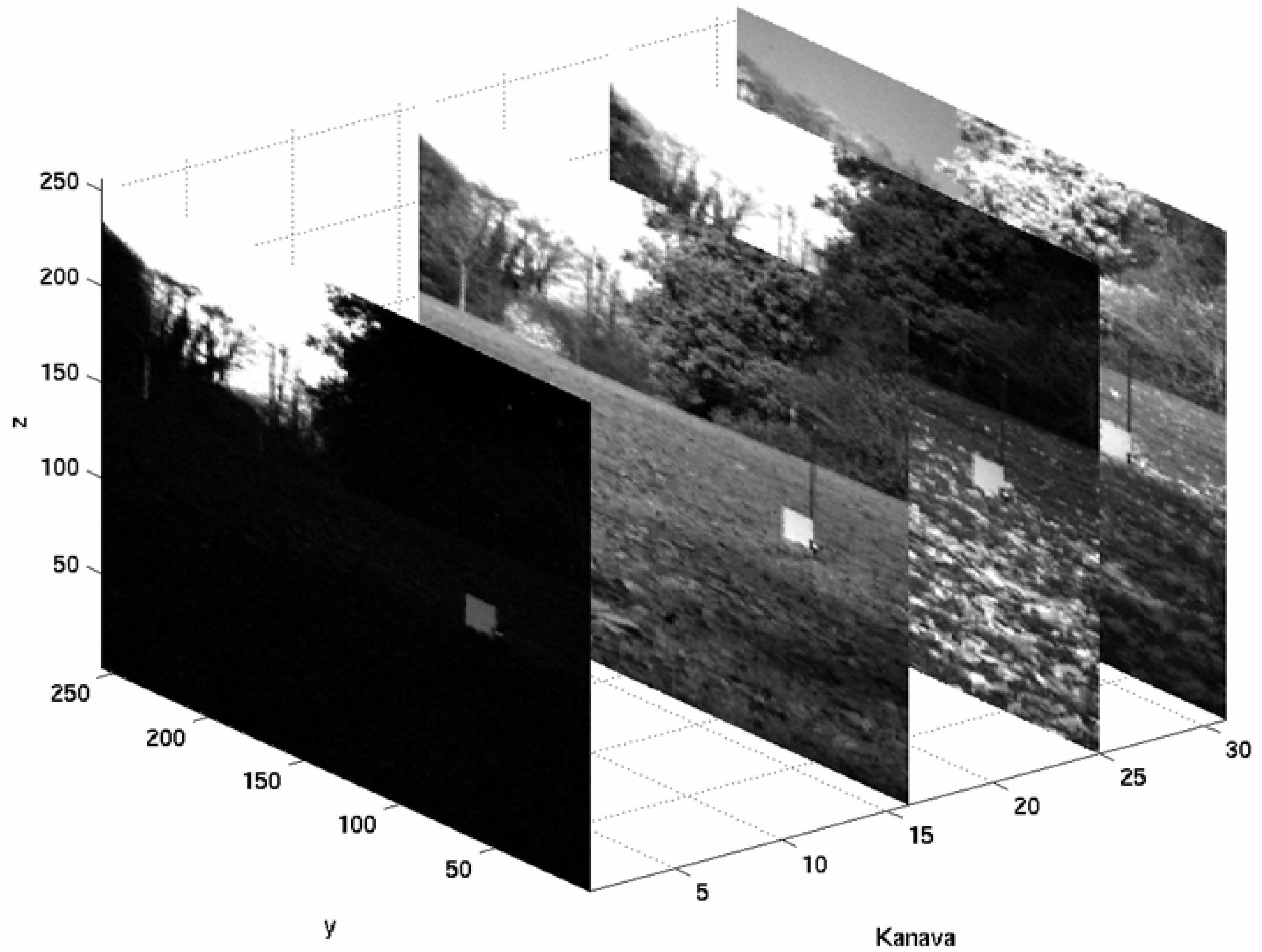
Some tests with mobile phones cameras

Error between RGB values of camera image and ideal sRGB values calculated from spectra.

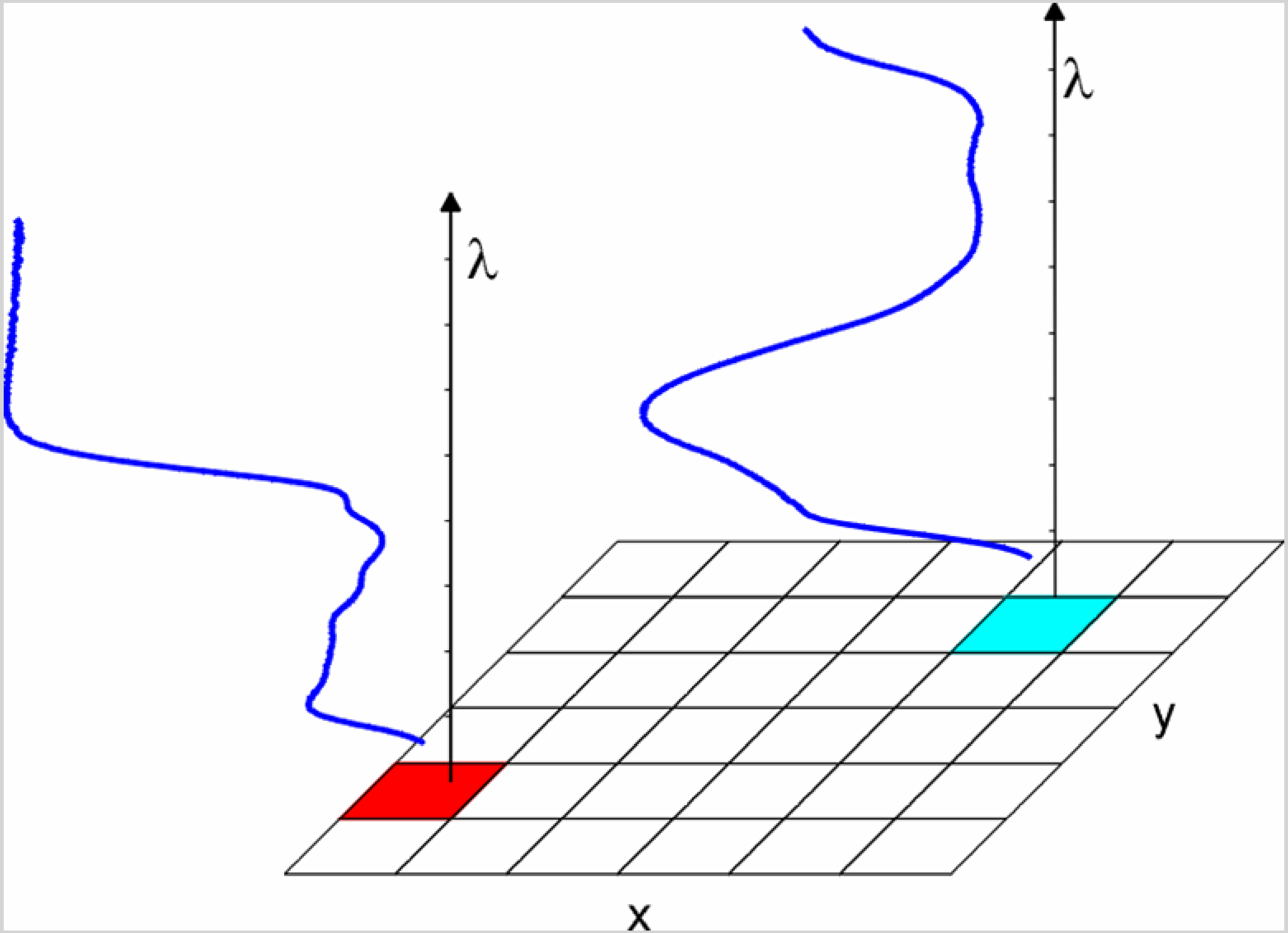
First row: error between the original image and ideal values.
Second row: error between the corrected image and ideal values.
Note that the scale of y-axis of diagrams varies between images.



Spectral component images



Spectral Image



Definitions

- Spectral image

  An image, where each pixel is represented by a spectrum

- Hyperspectral

  A term used for spectral images with large number of spectral components

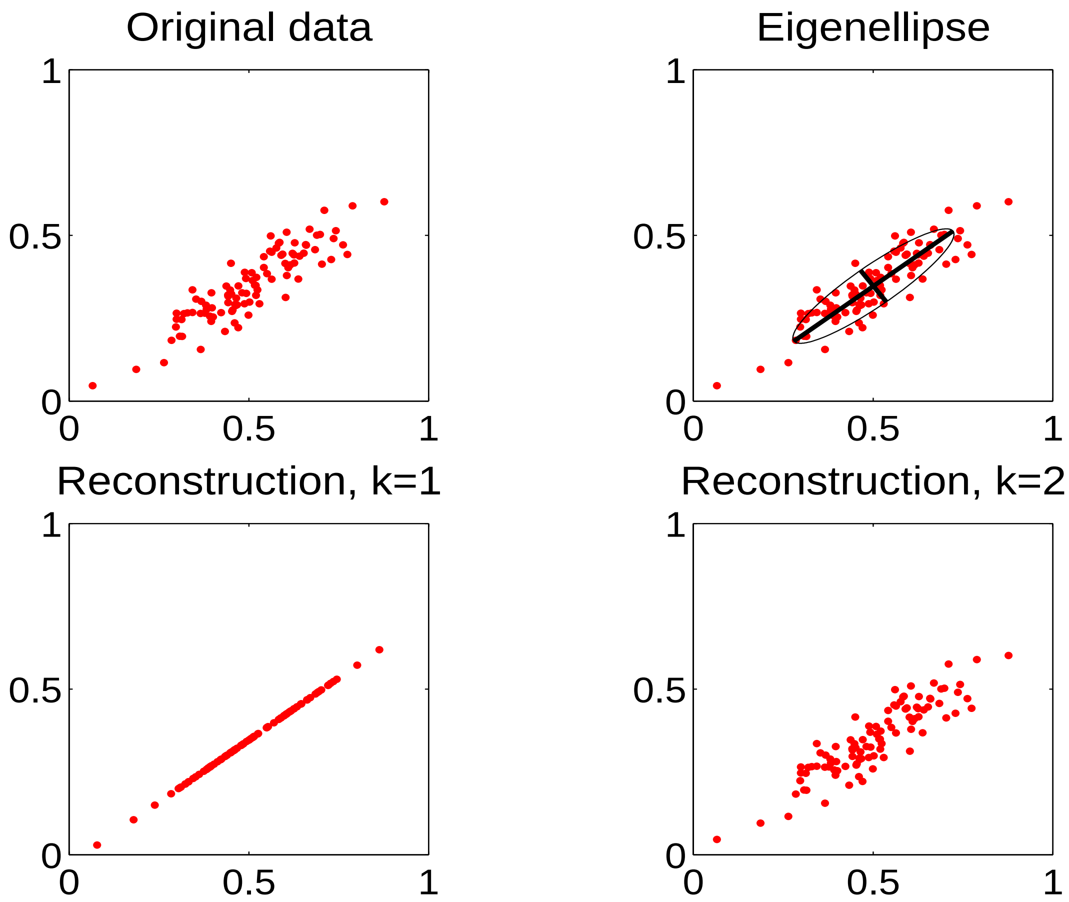
- Multispectral
- RGB-image

  spectrum in visible region,

  three components

Standard PCA. Example

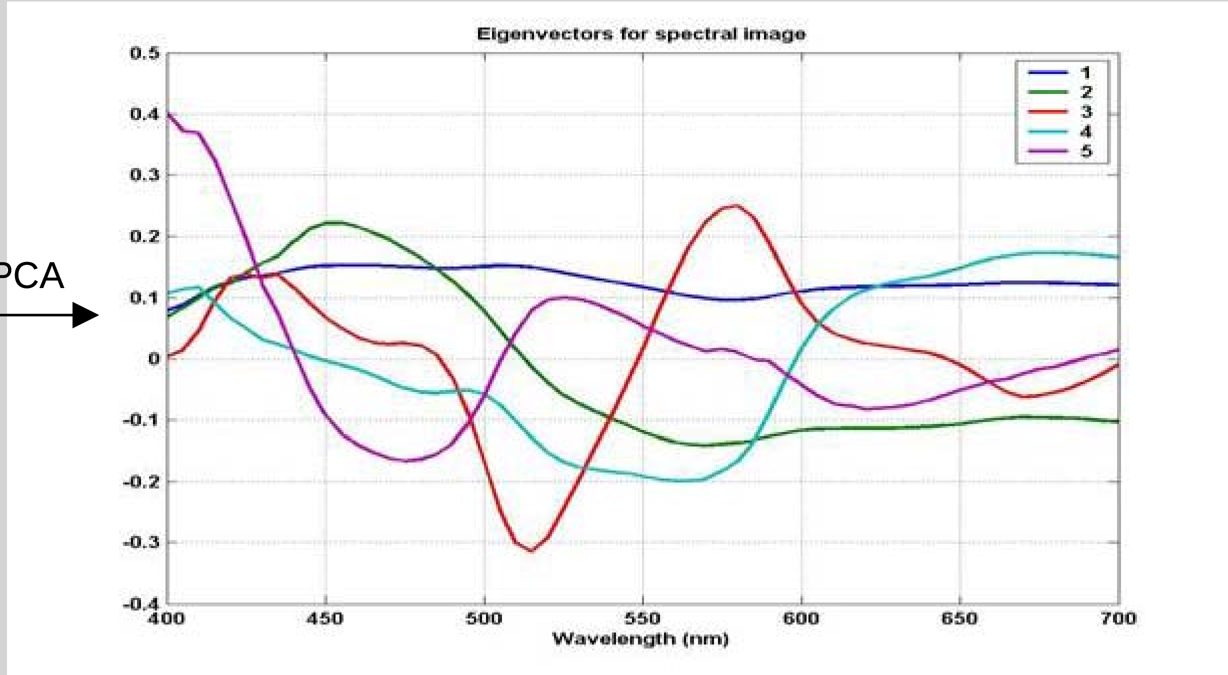
- The first principal component is used when *k=1*
- The first and second principal components are used when *k=2*. Reconstruction is perfect



Component images of a spectral image

Spectral image as RGB-image

PCA →



Inner-product images between the spectral image and eigenvectors:

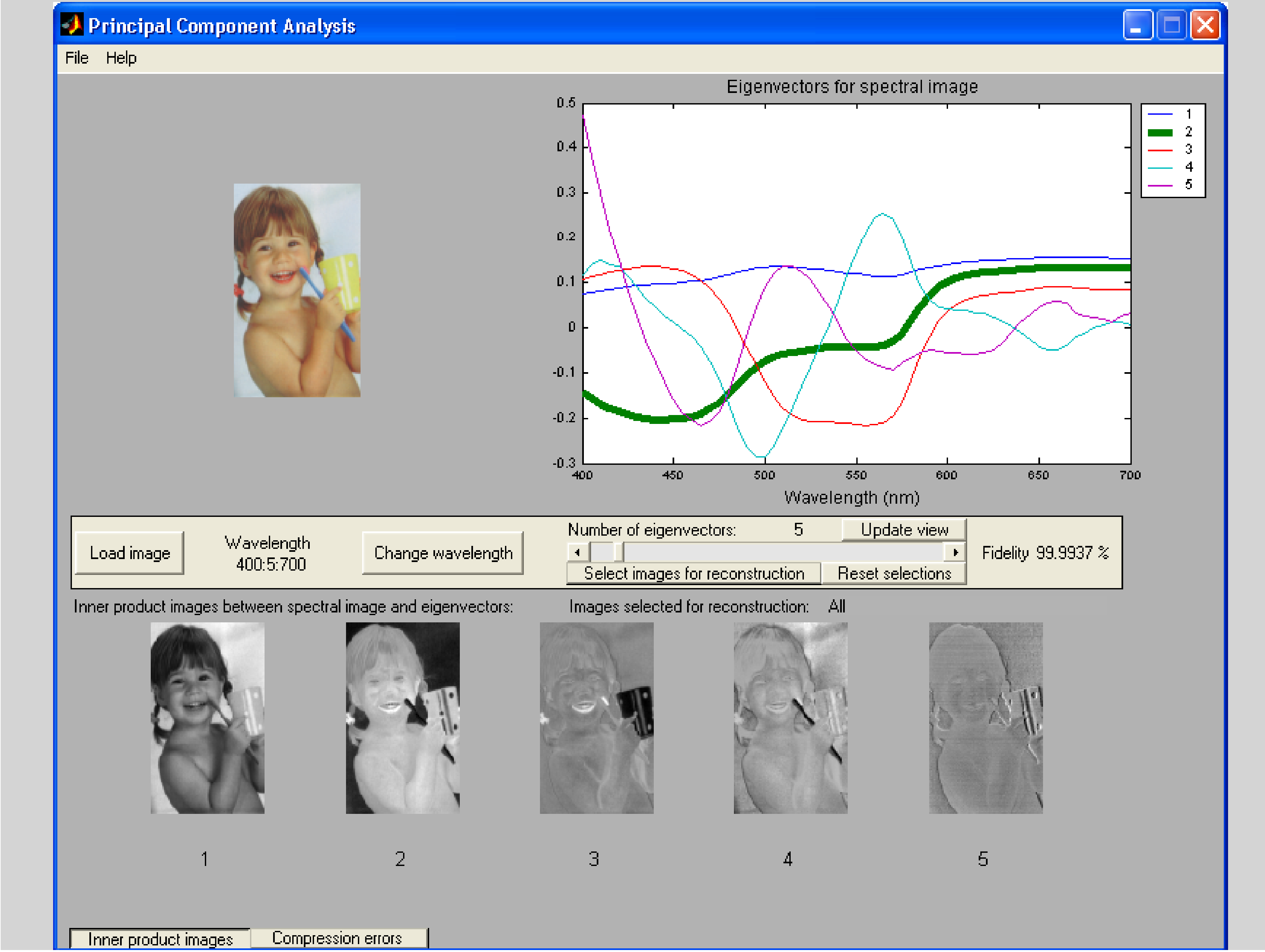
1

2

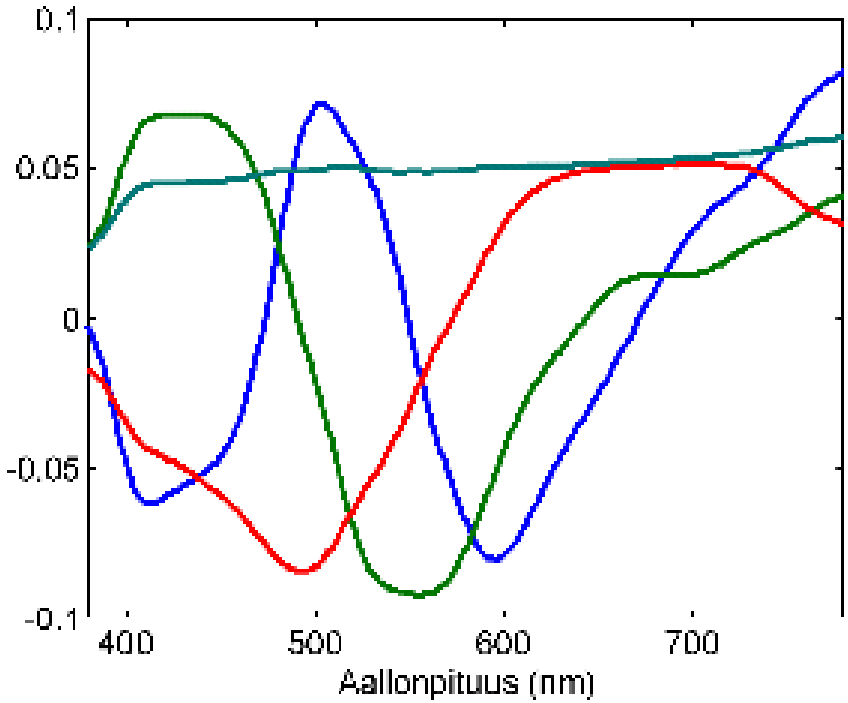
3

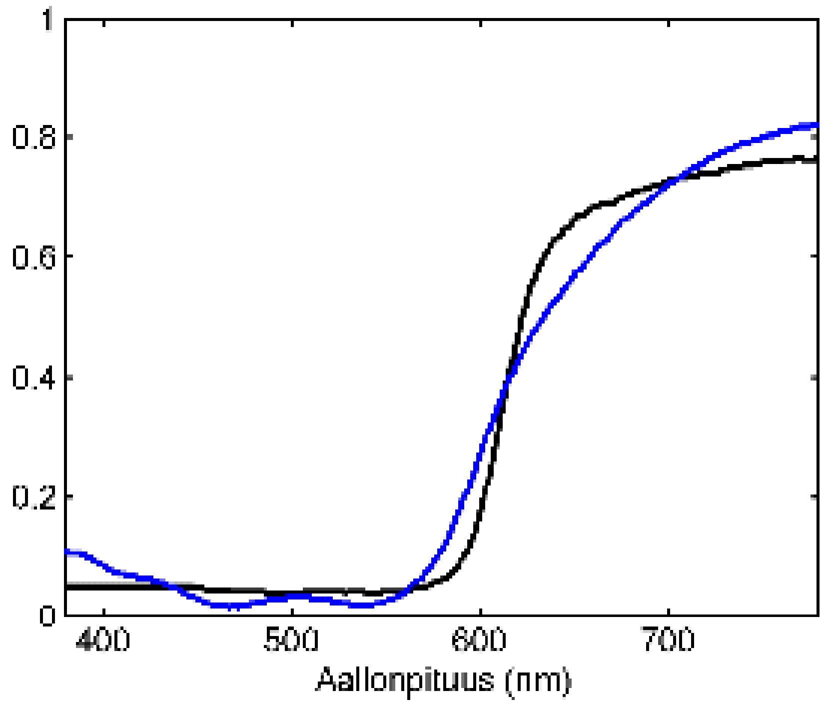
4

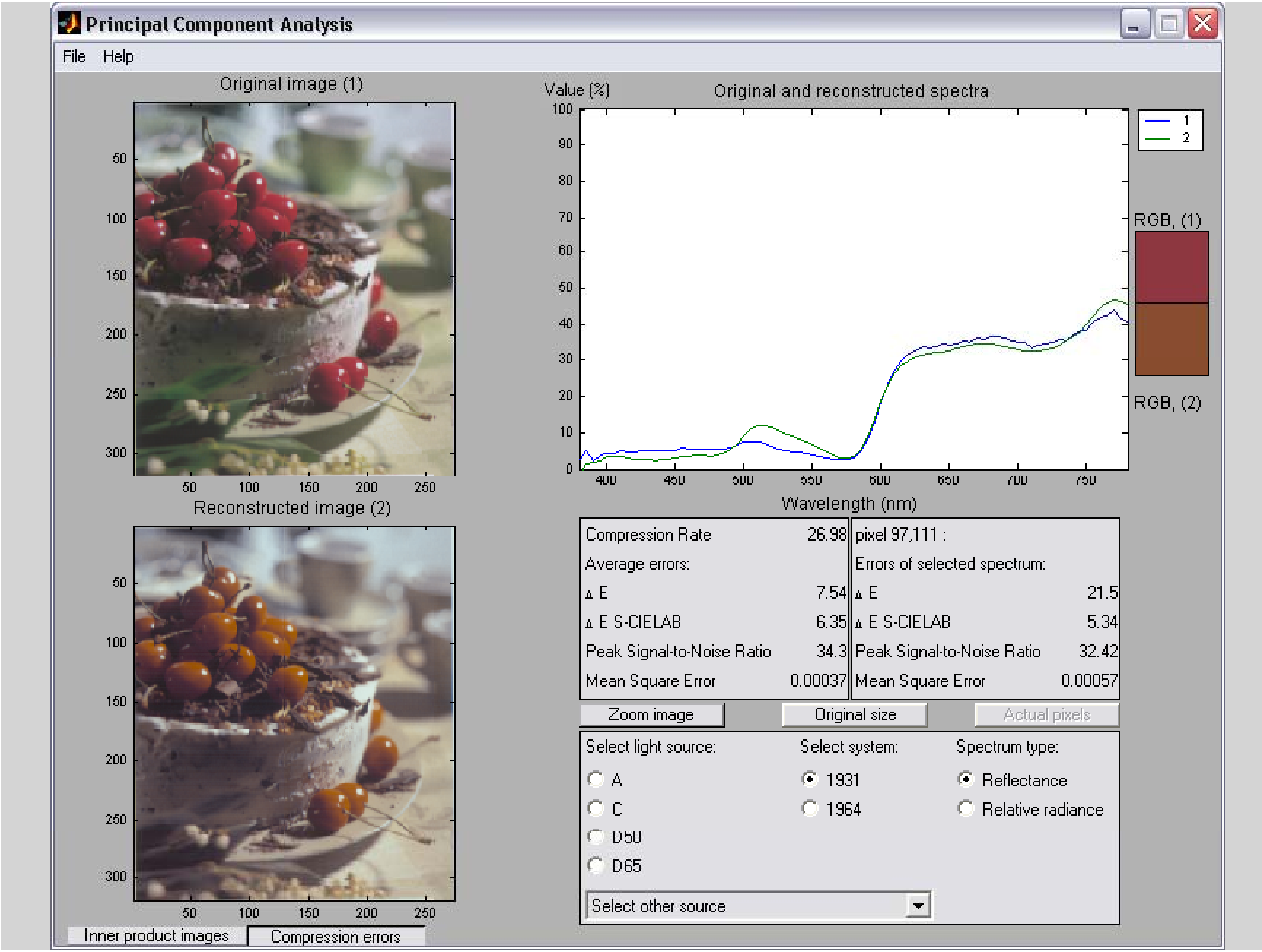
5


Principal Component Analysis
File
Help
Eigenvectors for spectral image
0.5
0.4
0.3
0.2
0.1
0
-0.1
-0.2
-0.3
400
450
500
550
600
650
700
Wavelength (nm)
1
2
3
4
5
Load image
Wavelength
400:5:700
Change wavelength
Number of eigenvectors:
5
Update view
Select images for reconstruction
Reset selections
Fidelity 99.9937 %
Inner product images between spectral image and eigenvectors:
Images selected for reconstruction: All
1
2
3
4
5
Inner product images
Compression errors

Reconstruction of the spectrum

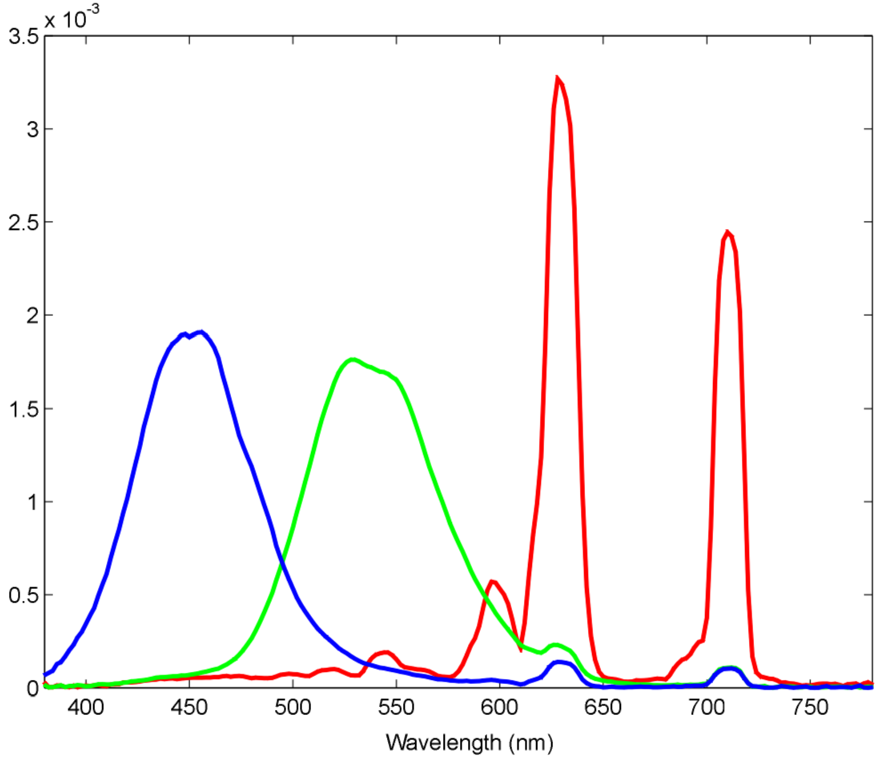




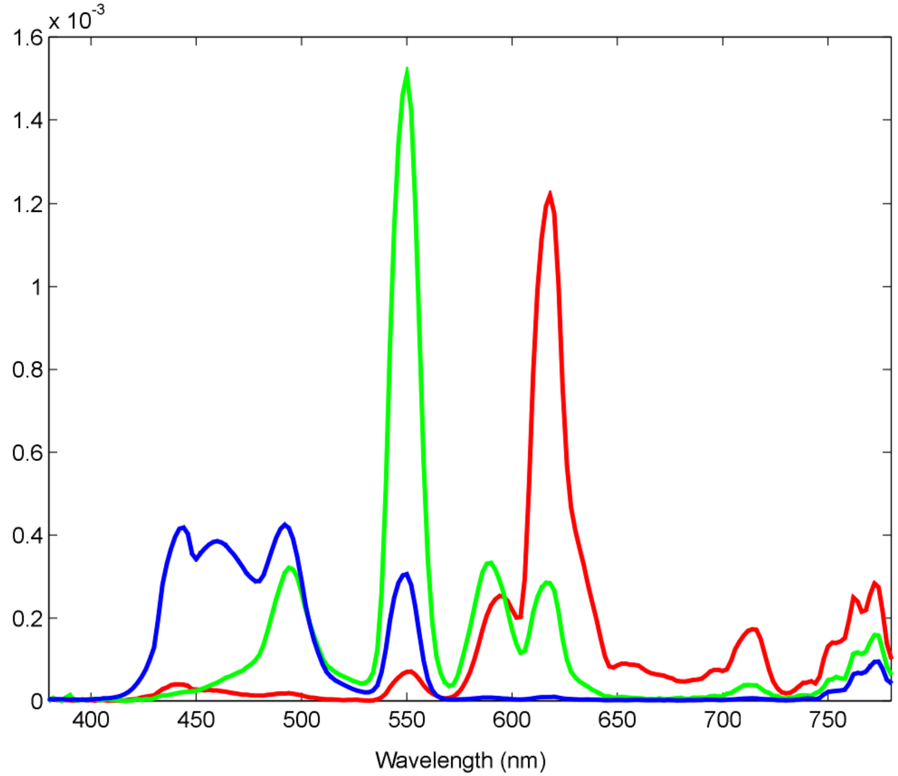

Principal Component Analysis
File
Help
Original image (1)
Reconstructed image (2)
Value (%)
Original and reconstructed spectra
Wavelength (nm)
RGB, (1)
RGB, (2)
Compression Rate 26.98
Average errors:
Δ E 7.54
Δ E S-CIELAB 6.35
Peak Signal-to-Noise Ratio 34.3
Mean Square Error 0.00037
pixel 97,111 :
Errors of selected spectrum:
Δ E 21.5
Δ E S-CIELAB 5.34
Peak Signal-to-Noise Ratio 32.42
Mean Square Error 0.00057
Zoom image
Original size
Actual pixels
Select light source:
A
C
D50
D65
Select other source
Select system:
1931
1964
Spectrum type:
Reflectance
Relative radiance
Inner product images
Compression errors

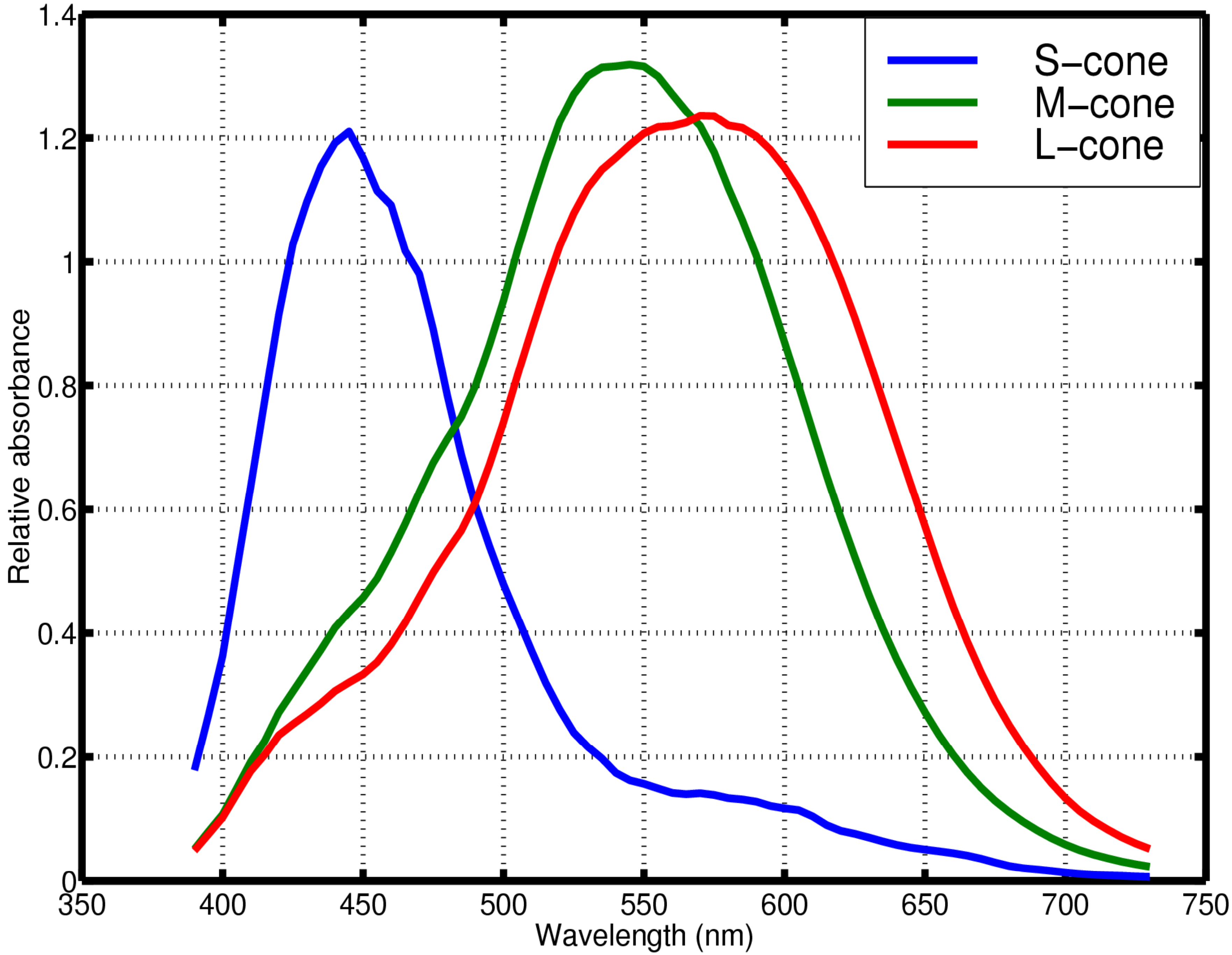
Display characterictics

CRT primaries



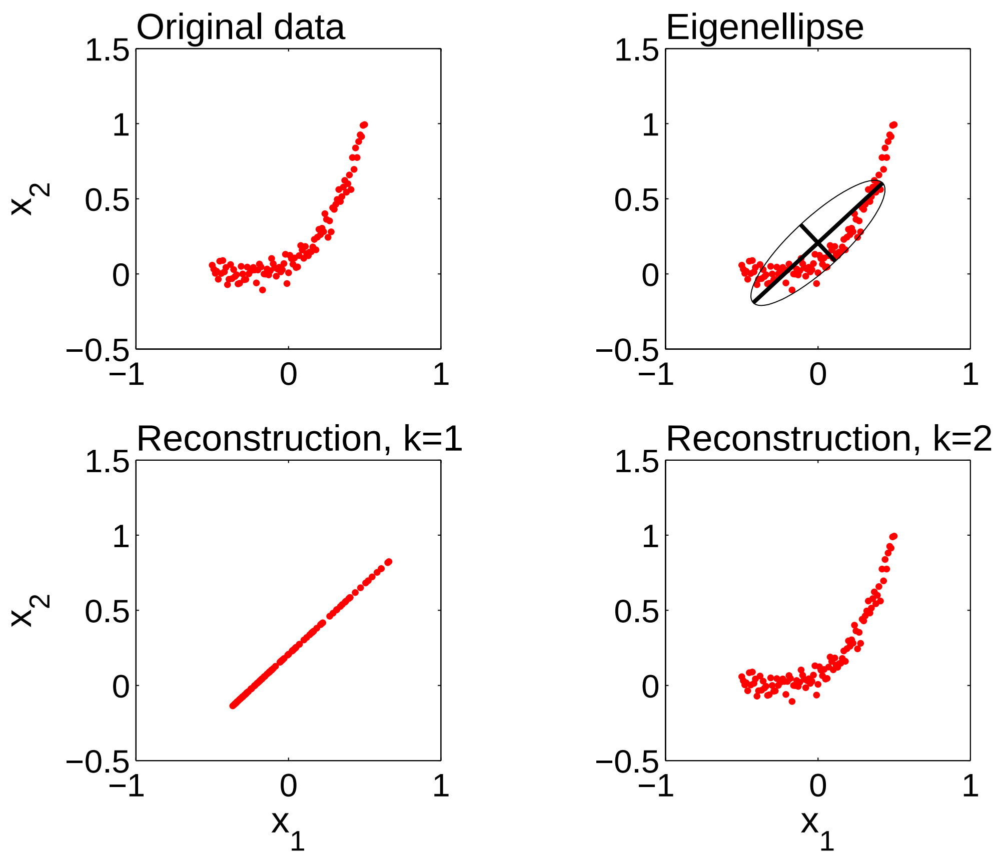
LCD primaries



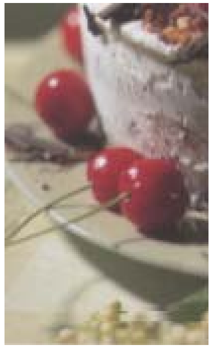


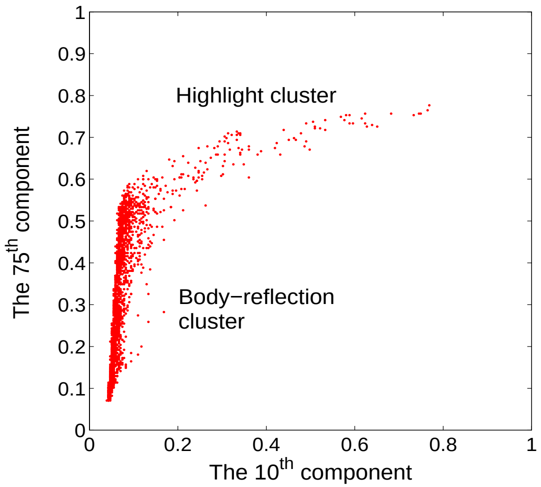
S–cone
M–cone
L–cone
Relative absorbance
Wavelength (nm)
0
0.2
0.4
0.6
0.8
1
1.2
1.4
350
400
450
500
550
600
650
700
750

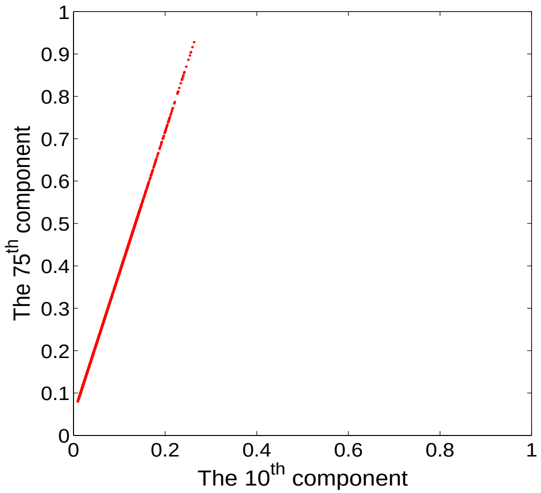
Nonlinear data

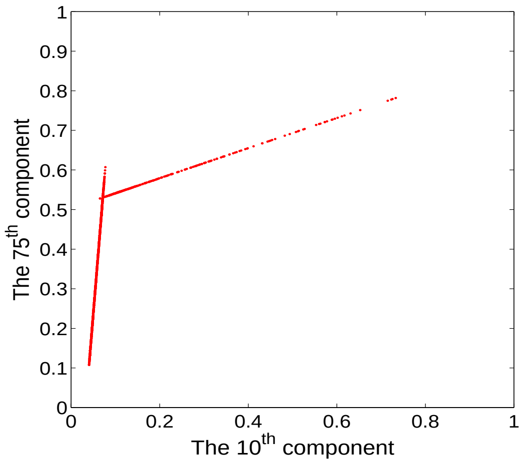


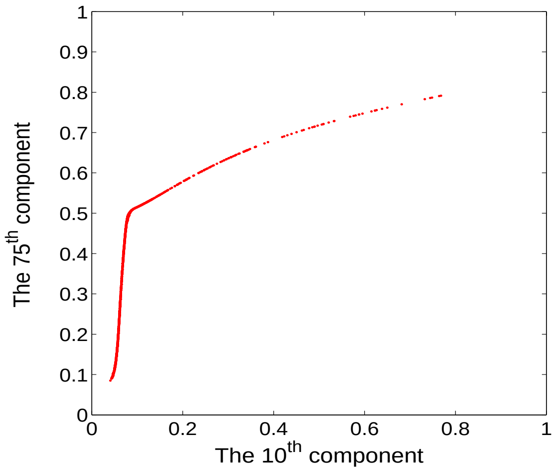
Spectral color analysis









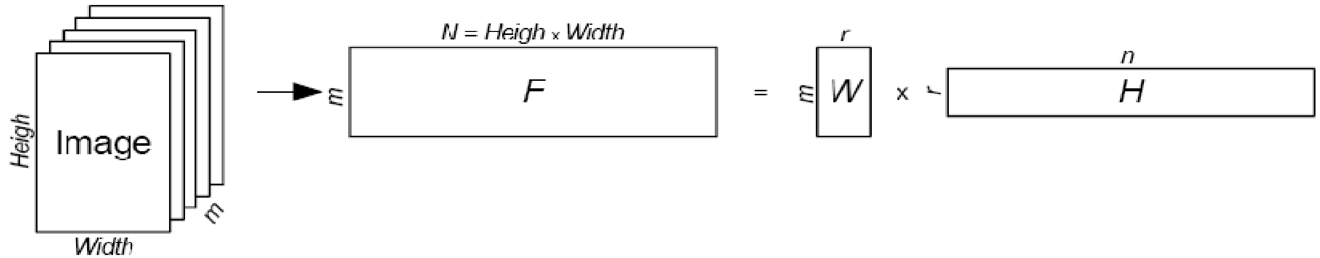


Non-negative Matrix Factorization

Given a data matrix $F = \{Fij\}mxn$, non-negative matrix factorization refers to the decomposition of the matrix F into matrices W and H of size $n \times r$ and $r \times m$, respectively, such that:

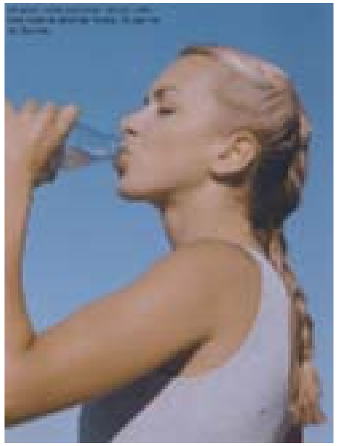
$$F = WH$$

Where the elements in W and H are all positive values. From this decomposition, a reduced representation is achieved by choosing r such that $r < n$ and $r < m$.

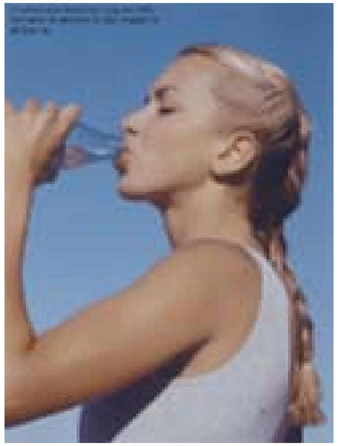


Results

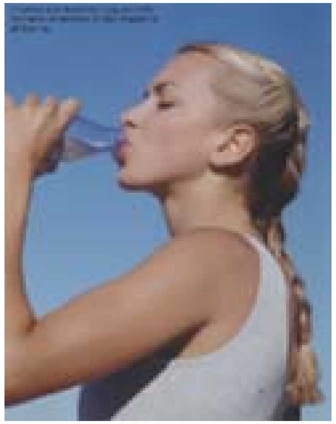
r = 1;



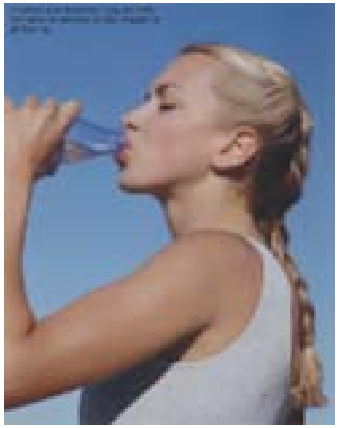
r = 2;



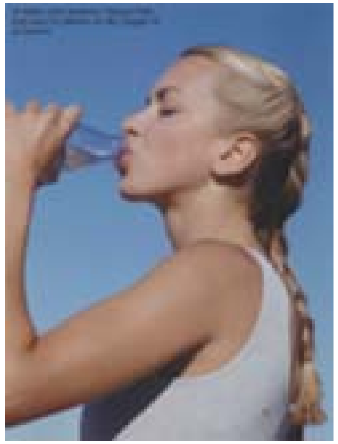
r = 3;



r = 5;



r = 81;

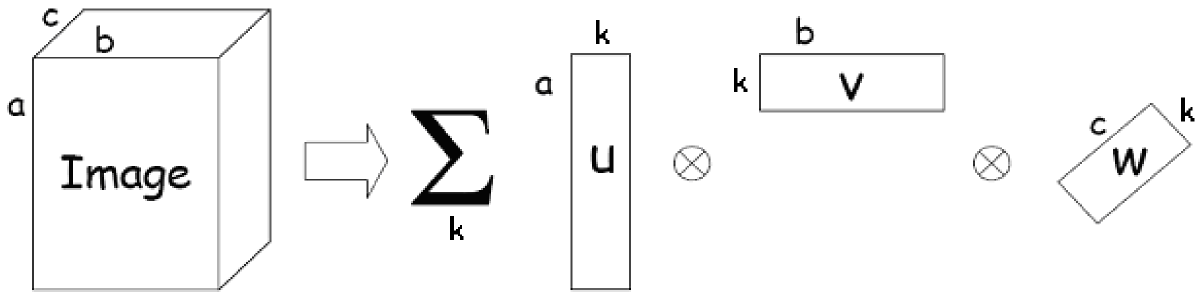


original

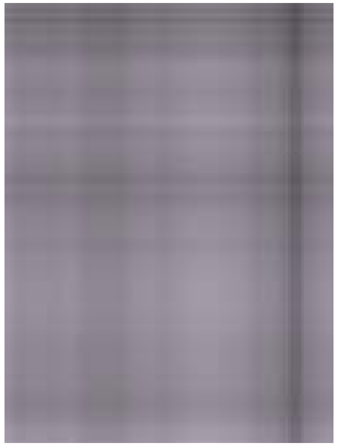
Non-negative Tensor Factorization

- The basic approach of NTF is to find a solution for the problem:

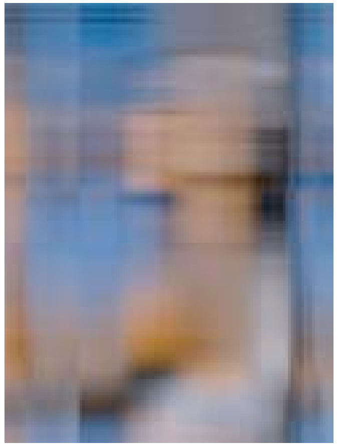
$$\min_{u^m, v^m, w^m \geq 0} \left\| G - \sum_{m=1}^{k} u^m \otimes v^m \otimes w^m \right\|$$



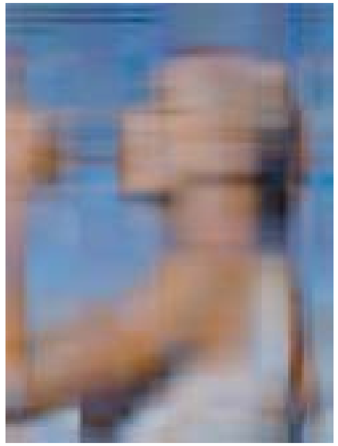
Results



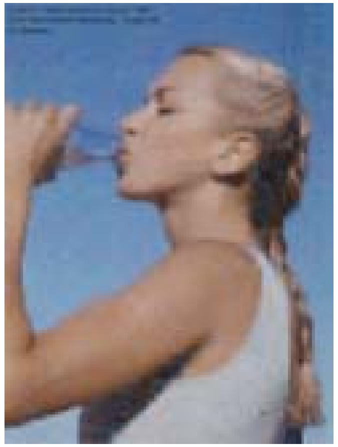
m = 1;



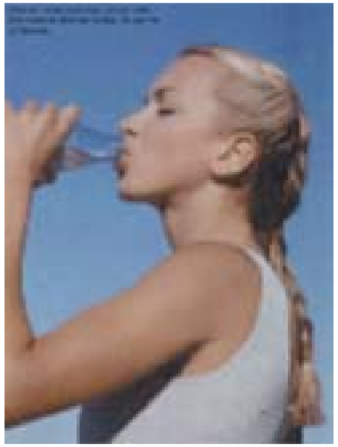
m = 5;



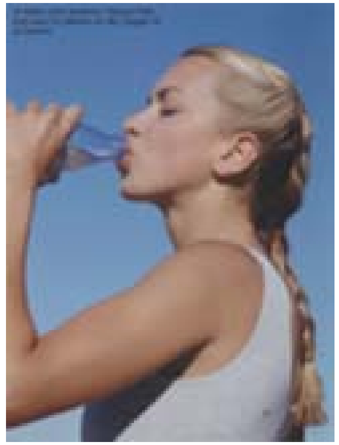
m = 10;



m = 50;



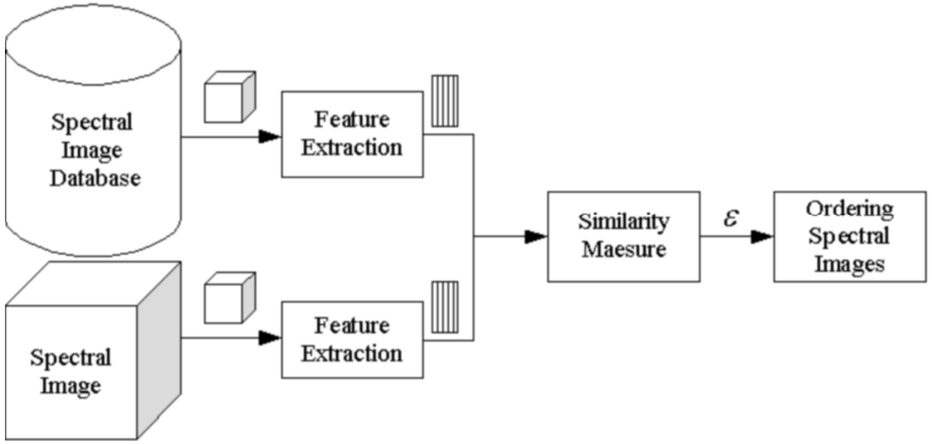
m = 100;



original

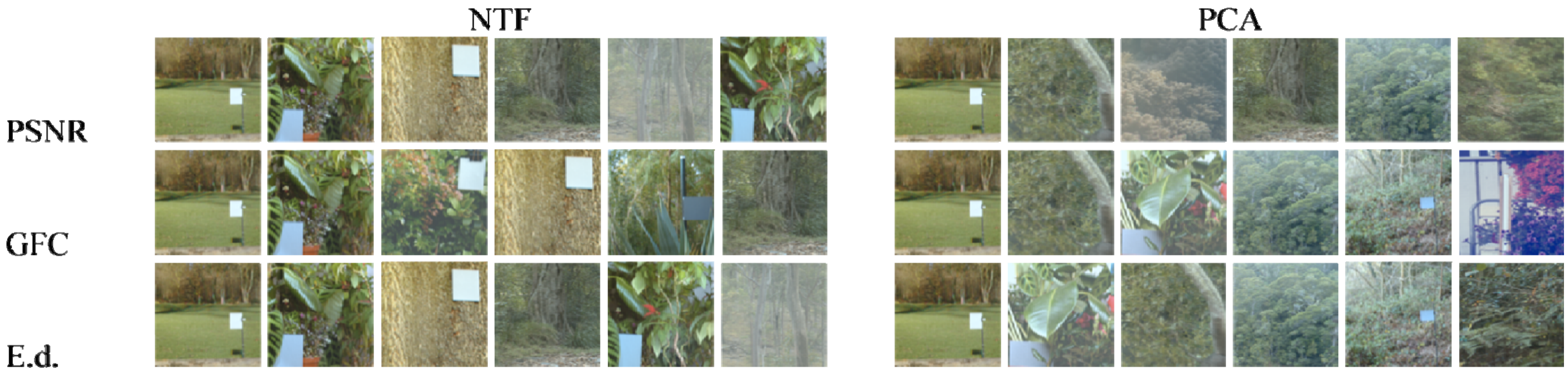
Searching Method

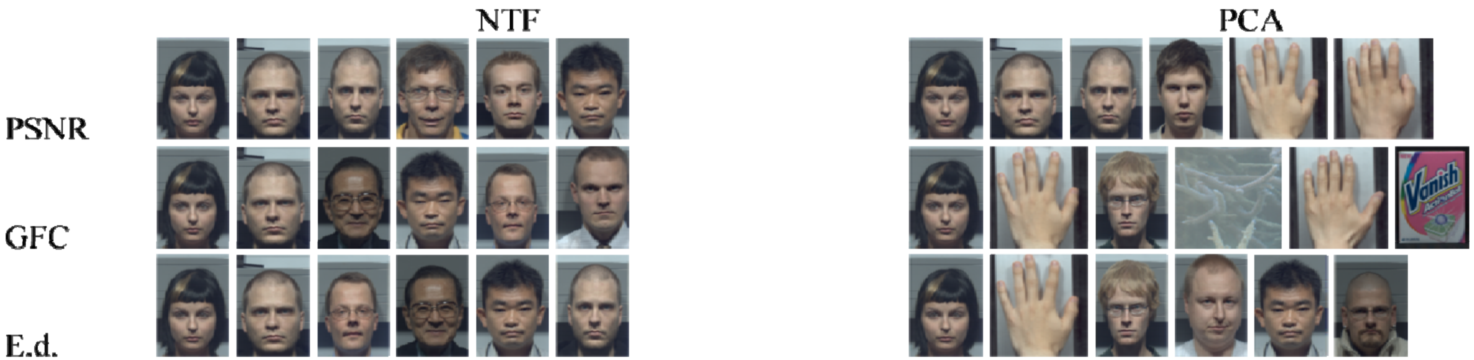
- NTF and PCA take spectra domain basis from each spectral image. Those basis defines as spectral color features.
- Similarity measures (Euclidian distance, goodness of fit coefficient (GFC) and peak signal-to-noise ratio (PSNR)) are calculated between spectra color features.



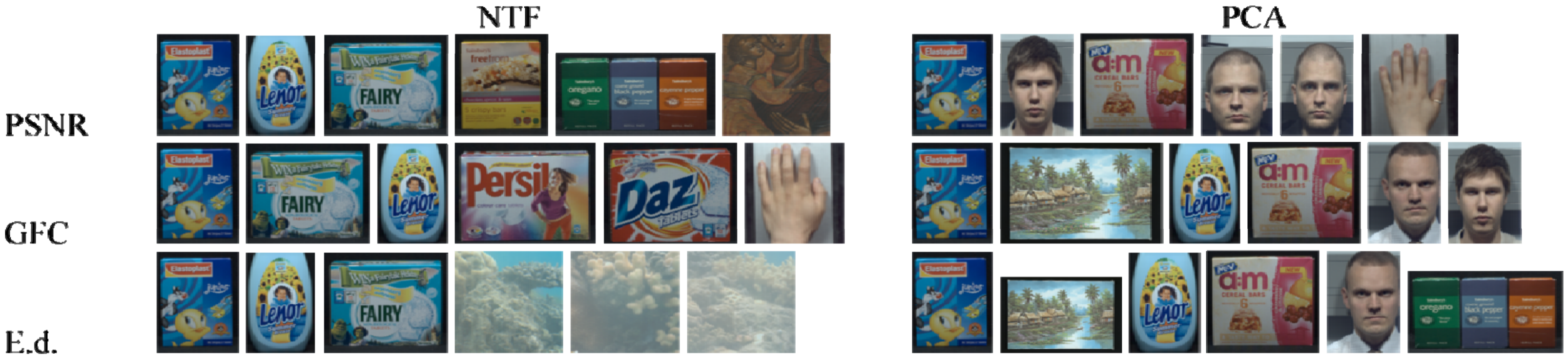
Experiments

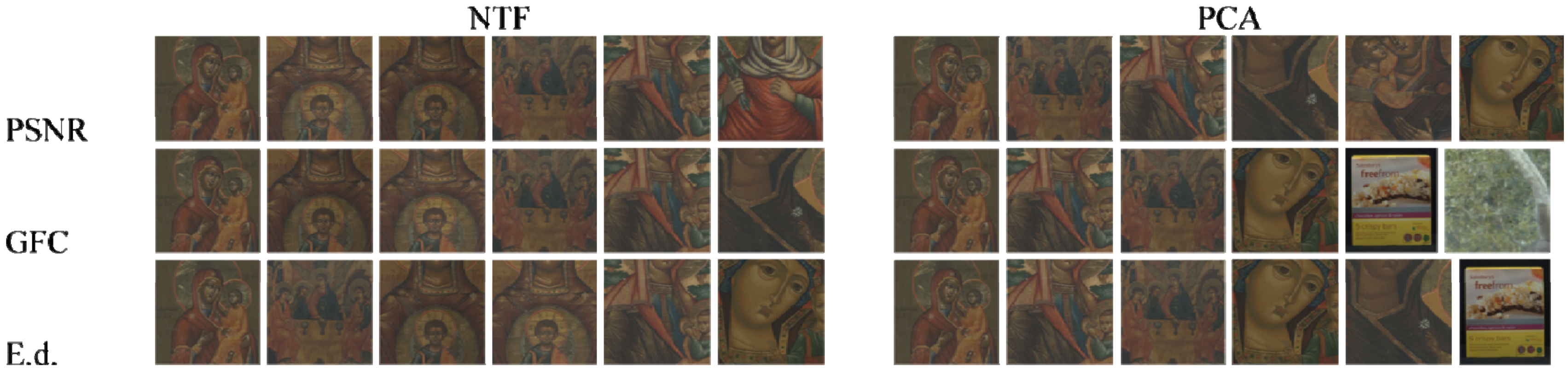
Results



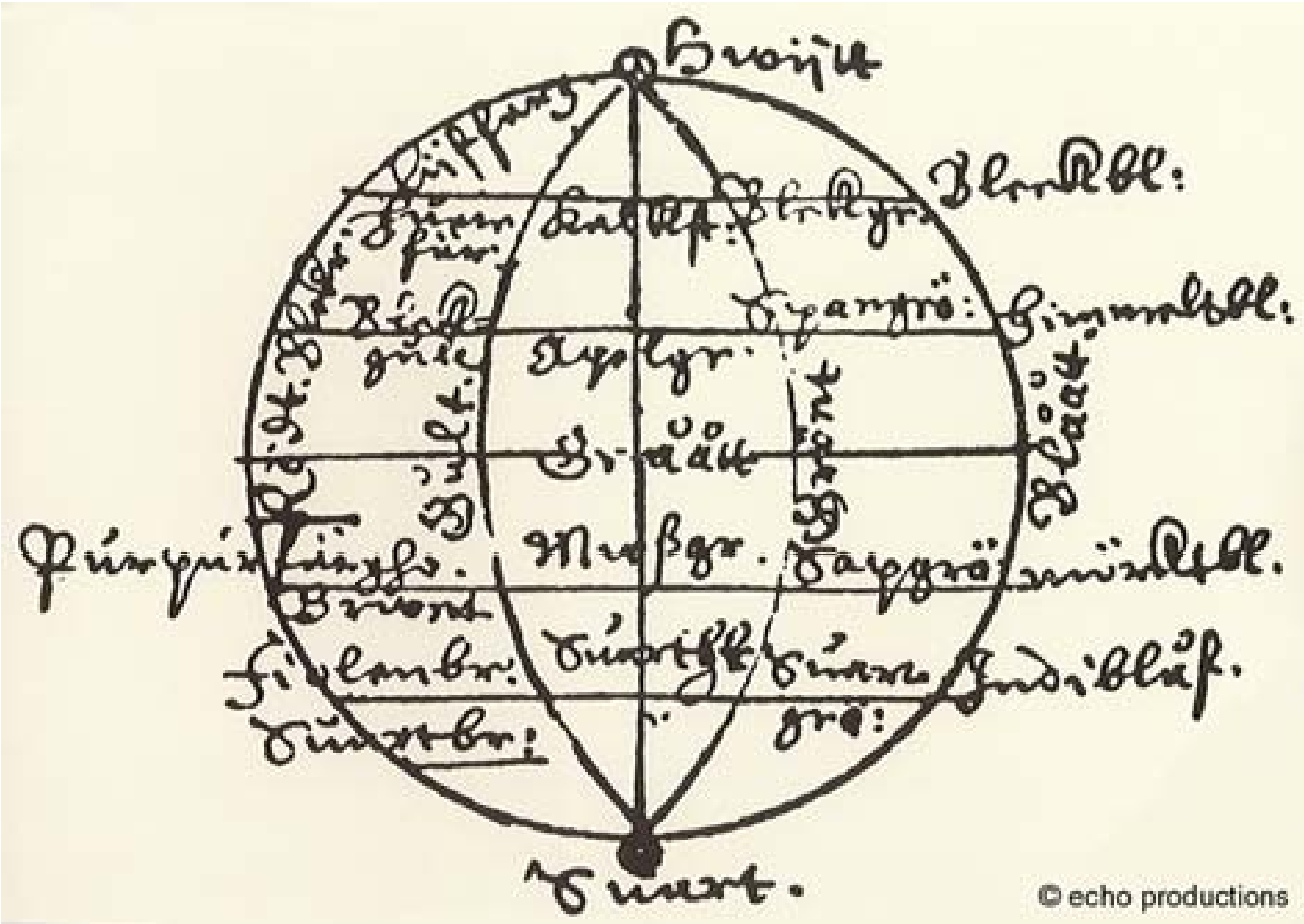


Results

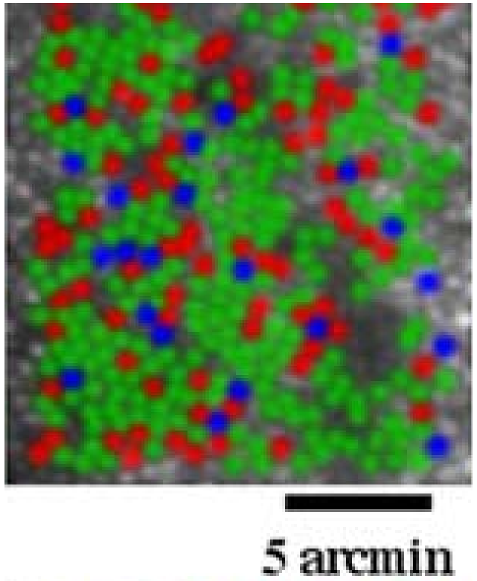


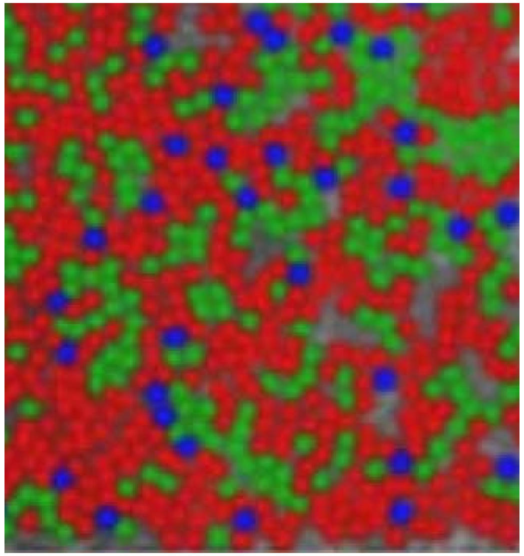


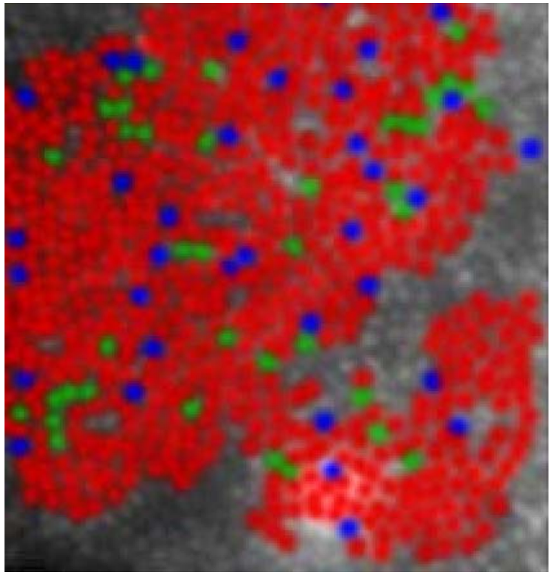
Color ordering and coordinates



Distribution of Cone Cells in Human Eye







Reference: Hofer *et al*., Organization of the Human Trichromatic Cone Mosaic. J. Neurosci. (2005)