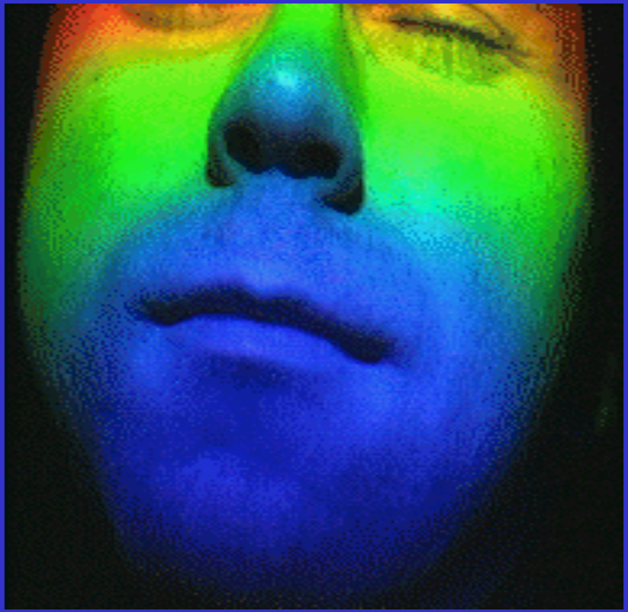
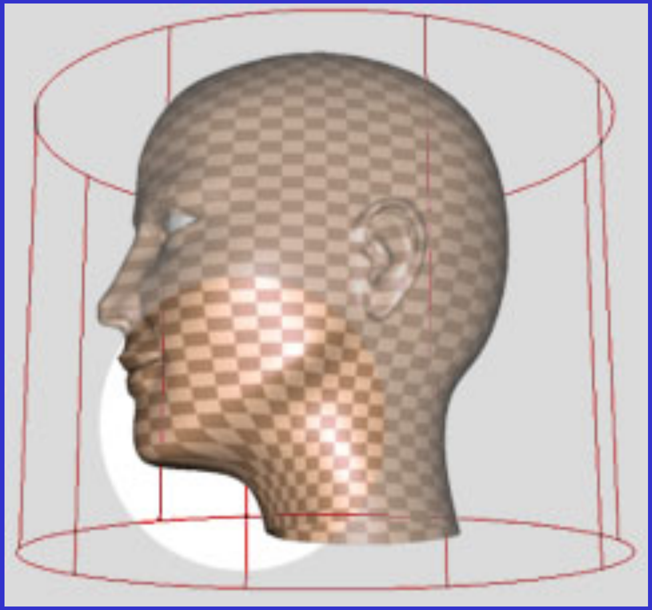
Surface Features: colour and texture





Introduction

colour

- color spaces
- colour constancy
- surface reflectance revisited
- illumination invariant colour features
- the holy grail: BRDFs

texture

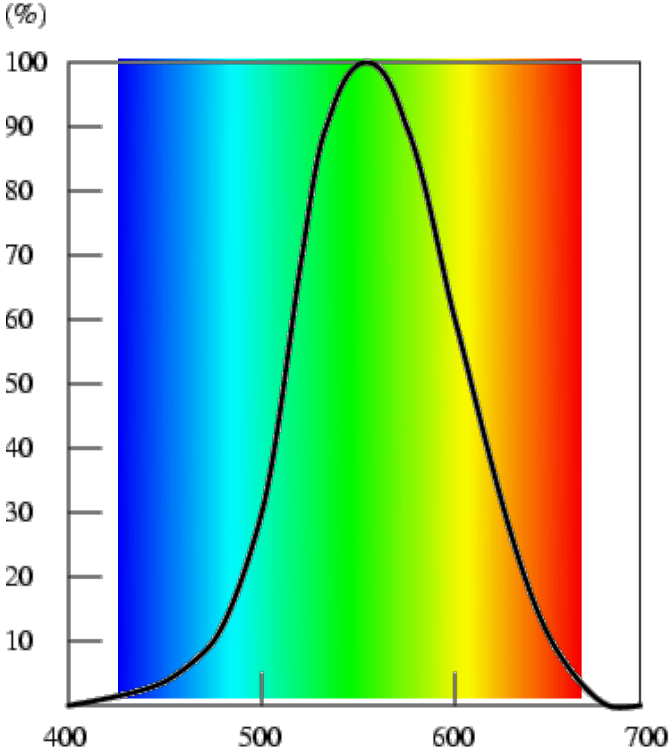
- Fourier features
- cooccurrence matrices
- filter banks (Laws, Gabor, eigenfilters)
- stochastic model

Computer Vision

COLOUR

The perception of brightness

- Luminous efficiency function : relates radiometry & photometry



- C.I.E.(Commission Internationale de l’Eclairage) → standards

The study of colour…

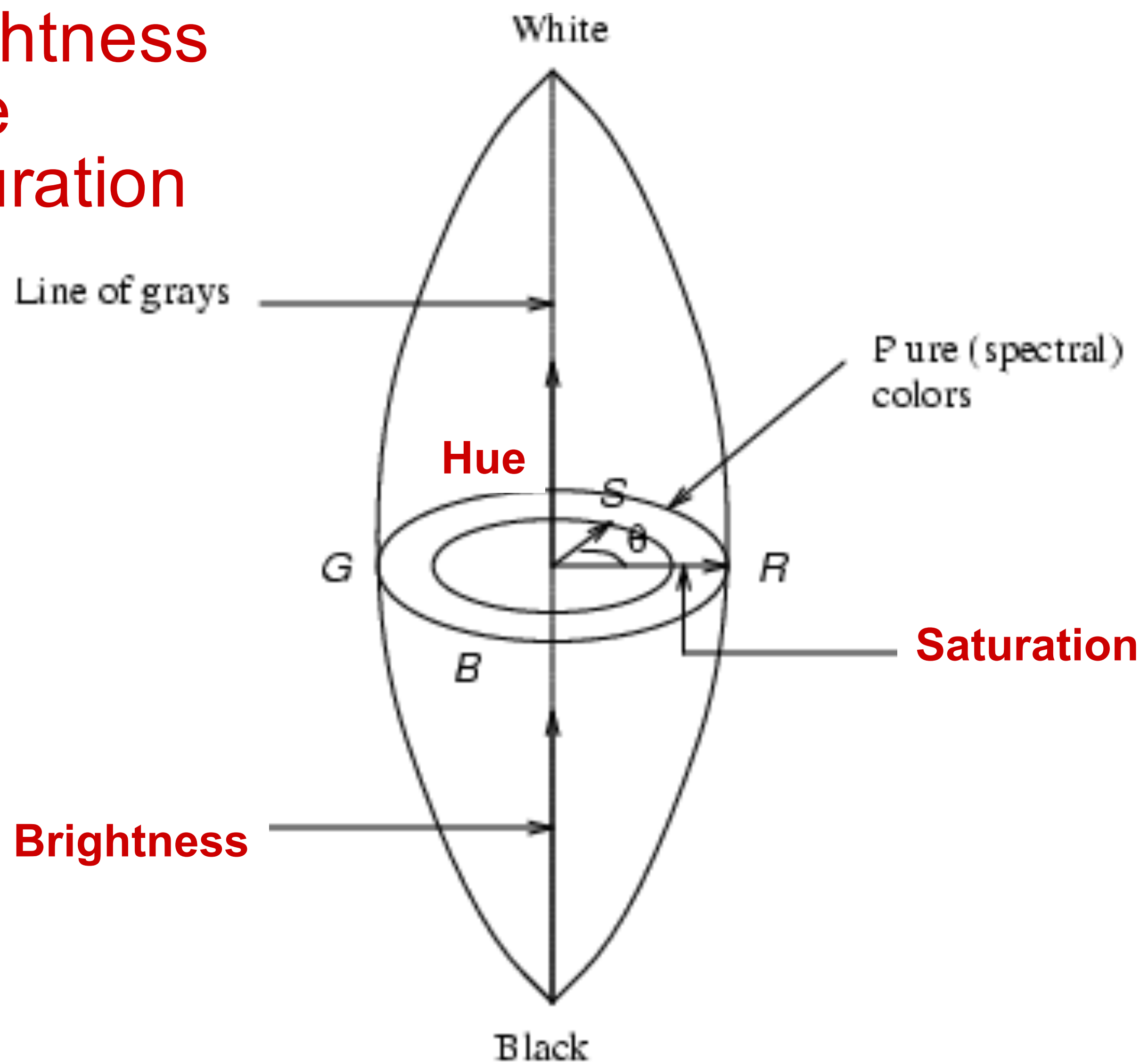
Use :

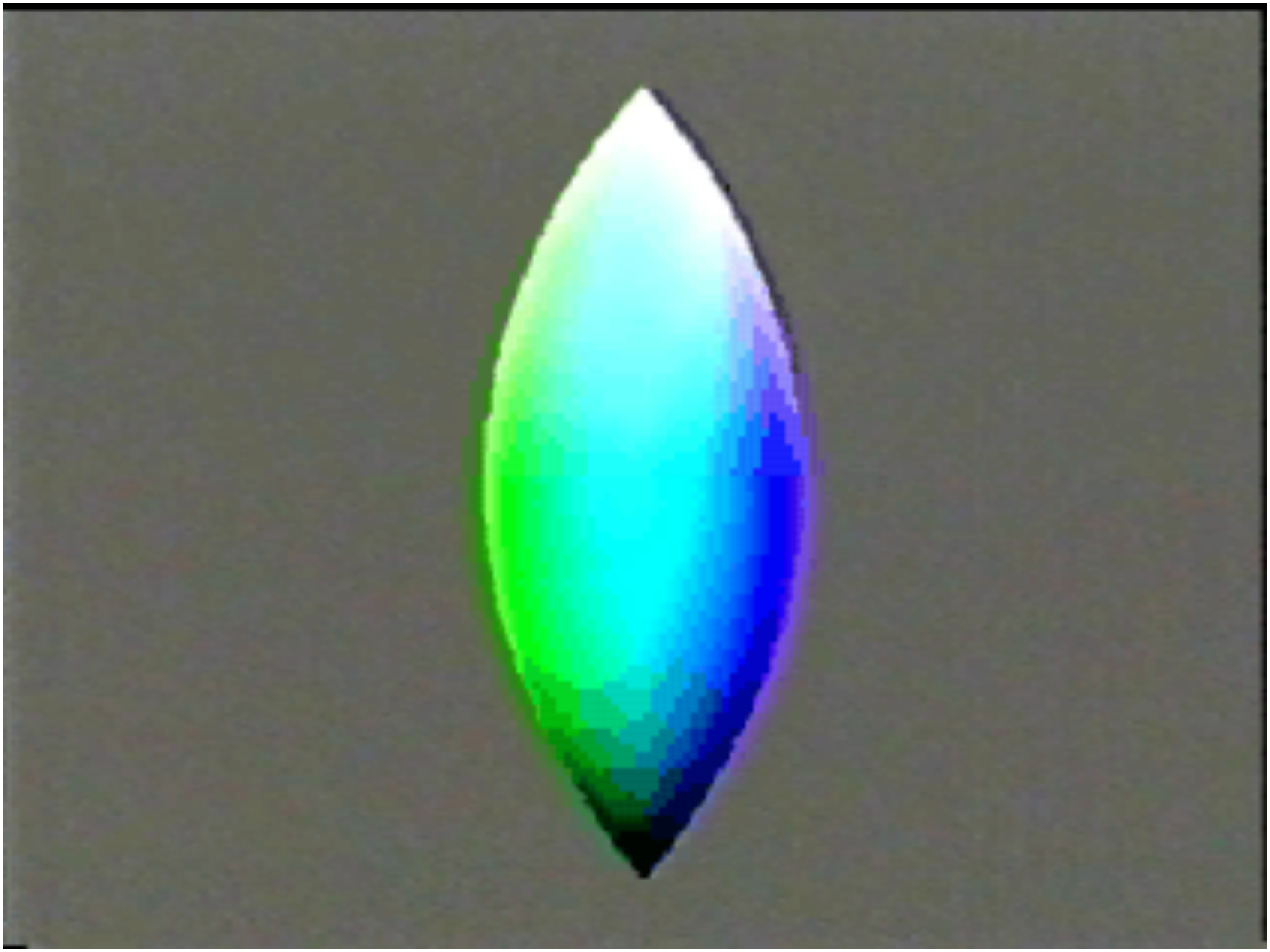
- pleasing to the eye (visualisation of results)
- characterising colours (features e.g. for recognition)
- generating colours (displays, light for inspection)
- understanding human vision

Computer Vision

The perceptual attributes of colour

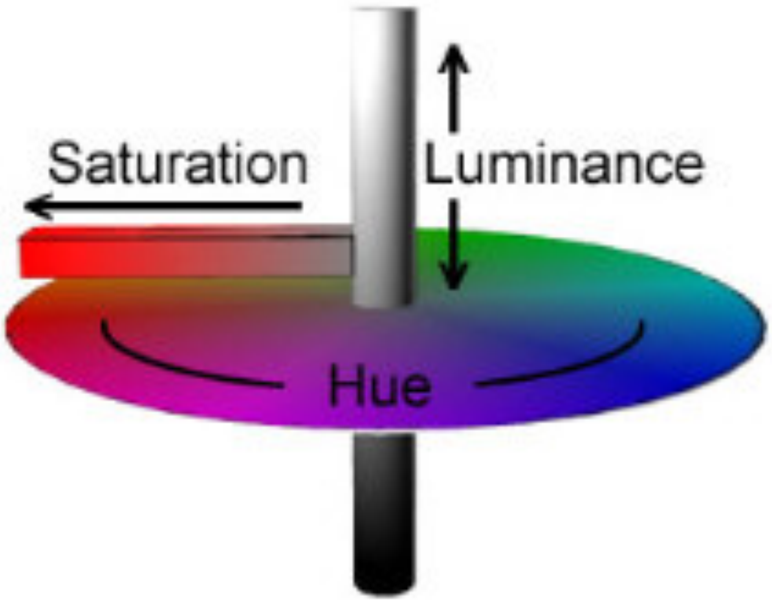
1. brightness
2. hue
3. saturation





Computer Vision

Reminder: perception of color = 3 dim.



The history of colour

Newton → spectrum

Young → tristimulus mod

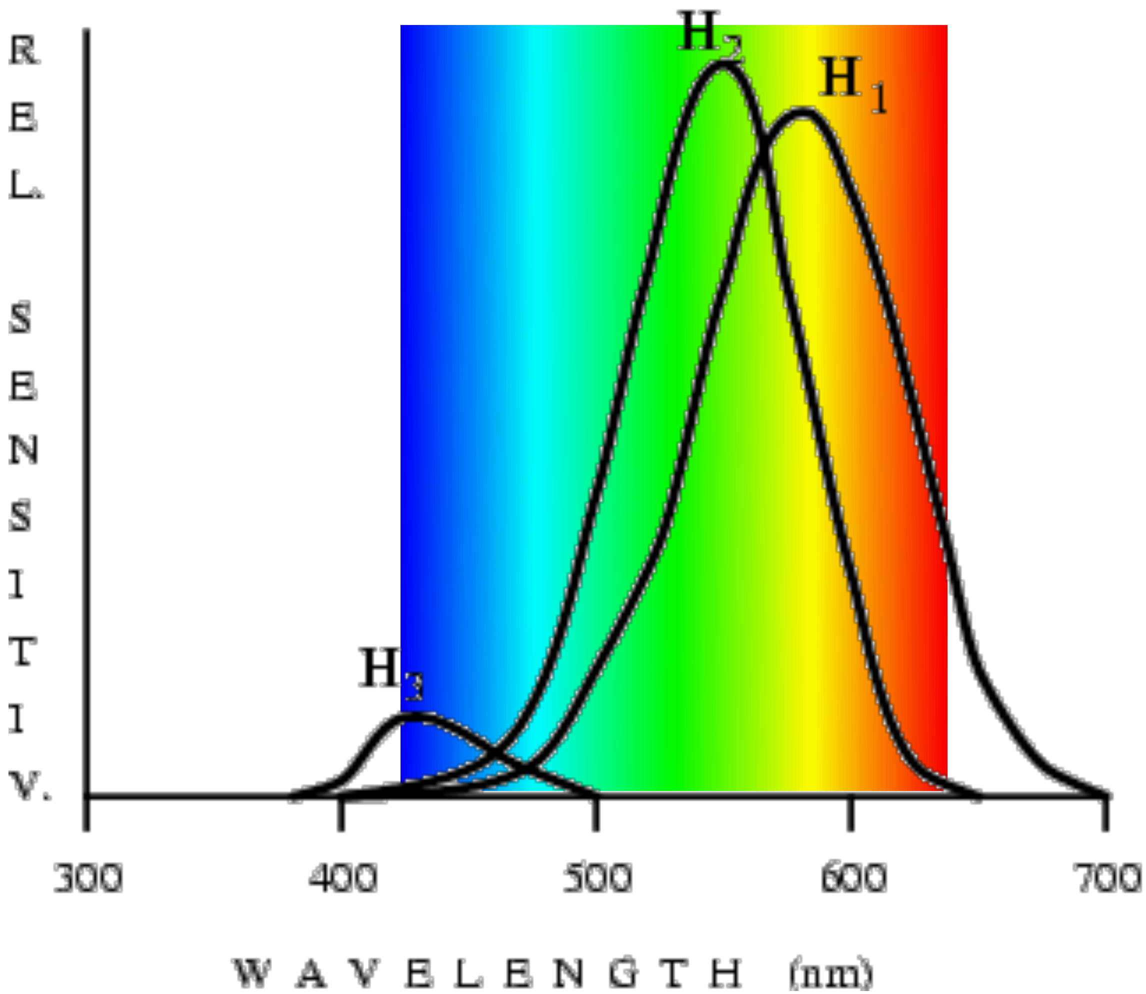
later : physiological underpinning :

3 cone types

Computer Vision

The retinal cones

3 types : blue, green, yellow-green

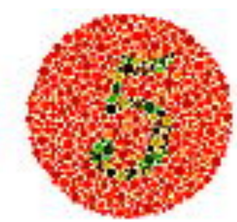


Prediction of colour sensation

source with spectral radiant flux $C(\lambda)$ produces responses R_i, with i = 1,2,3

$$R_i(c) = \int H_i(\lambda) C(\lambda) d\lambda, \; i = 1,2,3$$

- 2 sources with equal R_i' s ⇒ observed as same colour!
- luminance ⊥ chrominance
- 10% of population have abnormal colour vision



- several birds have 4 cone types (incl. UV)
- colour constancy

Tristimulus representation of colour

Camera $\Longrightarrow$ tristimulus values $\Longrightarrow$ display

3 primaries $P_j(\lambda)$, j = 1,2,3

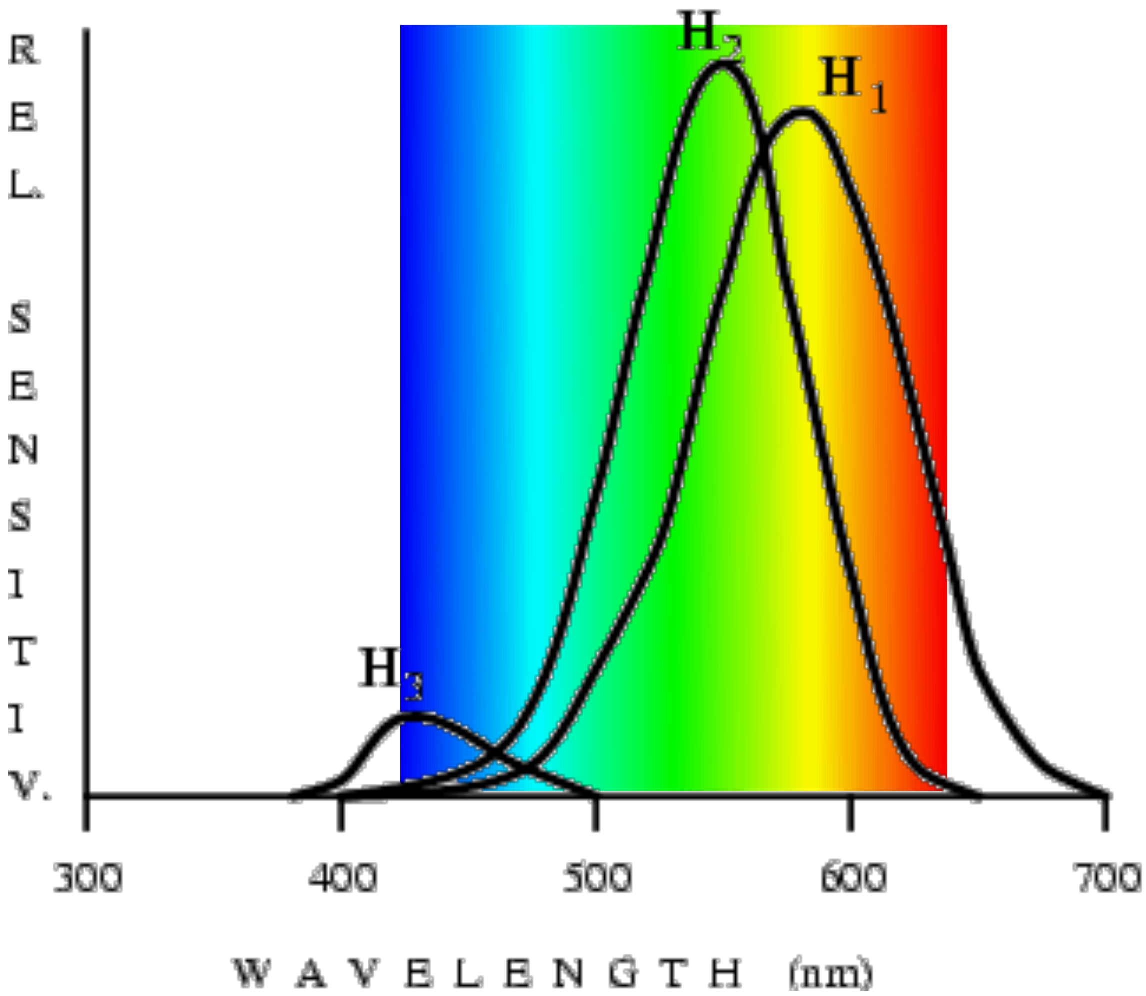
CIE primaries : λ_1 = 700
λ_2 = 546.1
λ_3 = 435.8

applications : practical primaries
e.g. TV : EBU and NTSC

Computer Vision

The retinal cones

3 types : blue, green, yellow-green



The matching of colour

source $C(\lambda)$ matched by primaries

$$\sum_{j=1}^{3} m_j P_j(\lambda)$$

$$R_i(C) = \int C(\lambda) \quad H_i(\lambda) d\lambda$$

The matching of colour

source $C(\lambda)$ matched by primaries

$$\sum_{j=1}^{3} m_j P_j(\lambda)$$

$$R_i(C) = \int \sum_{j=1}^{3} m_j P_j(\lambda) \ H_i(\lambda) d\lambda$$

The matching of colour

source $C(\lambda)$ matched by primaries

$$\sum_{j=1}^{3} m_j P_j(\lambda)$$

$$R_i(C) = \int \sum_{j=1}^{3} m_j P_j(\lambda)\ H_i(\lambda) d\lambda$$

$$= \sum_{j=1}^{3} m_j \int H_i(\lambda) P_j(\lambda) d\lambda$$

The matching of colour

source $C(\lambda)$ matched by primaries

$$\sum_{j=1}^{3} m_j P_j(\lambda)$$

$$R_i(C) = \int \sum_{j=1}^{3} m_j P_j(\lambda) H_i(\lambda) d\lambda$$

$$= \sum_{j=1}^{3} m_j \underbrace{\int H_i(\lambda) P_j(\lambda) d\lambda}_{l_{i,j}}$$

can be determined "off-line"

The math

extremely simple : linear equations

$$\sum_{j=1}^{3} m_j \, l_{i,j} = R_i$$

implies inverting the matrix :
independent primaries!

also linear transform between the m_j' s
for different choices of primaries:

$$L\,m = R$$
$$L'\,m' = R$$

gives

$$m' = L'^{(-1)}\,L\,m$$

Tristimulus values

"white" considered a reference :
specify relative values w.r.t. m_js for white : w_j

Tristimulus values : $$T_j = \frac{m_j}{w_j}$$

The scaling preserves the linearity

CIE tristimulus values : **R**, **G**, **B**
(for CIE white = flat spectrum & $w_1 = w_2 = w_3$)

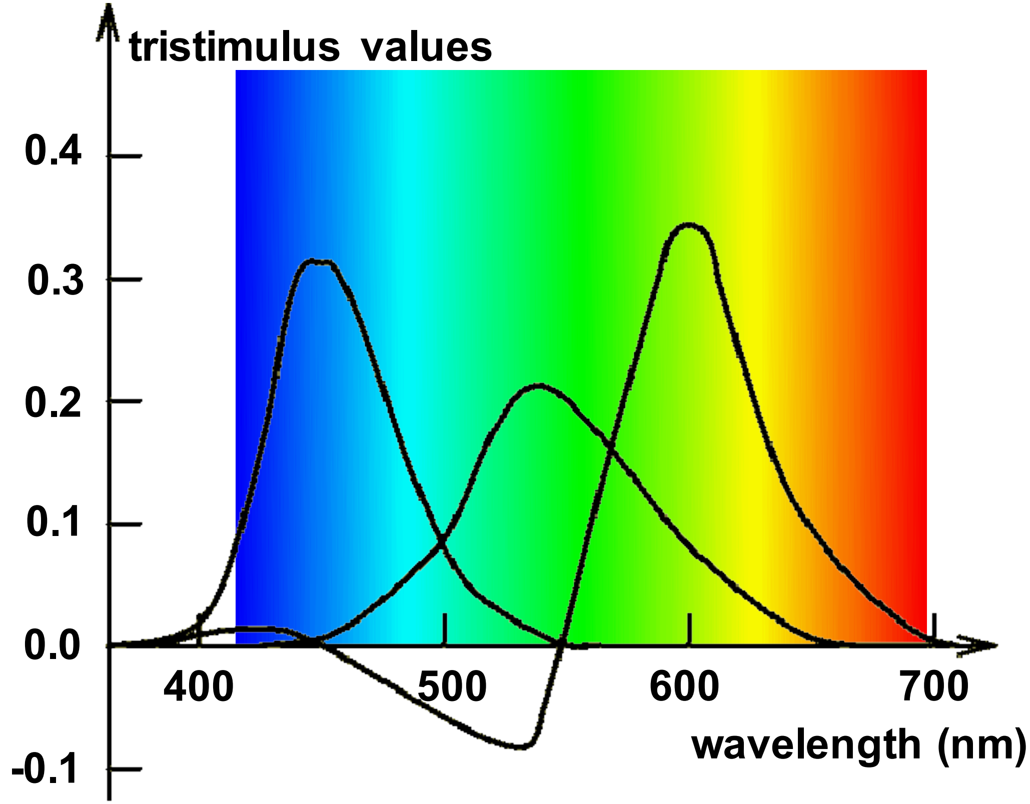
Note that for white $T_1 = T_2 = T_3 = 1$

Spectral matching curves

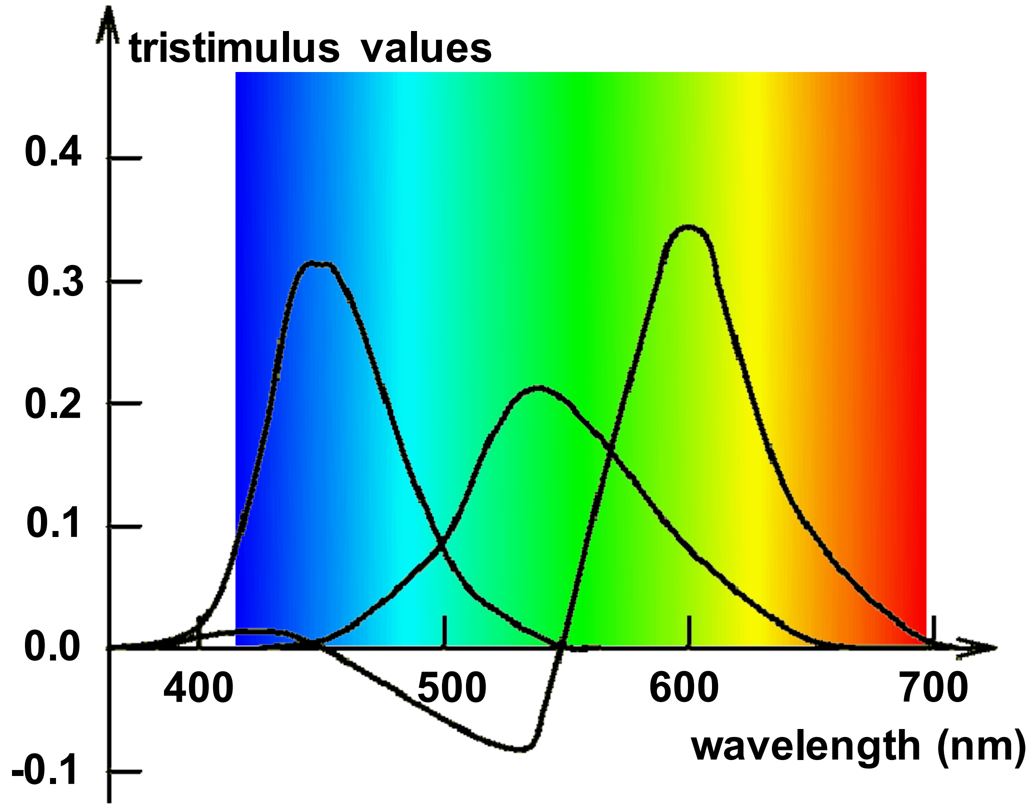
Spectral matching curves $T_j(\lambda)$:
values for monochromatic sources

$$R_i(C_\lambda) = H_i(\lambda) = \sum_{j=1}^{3} m_j \, l_{i,j} = \sum_{j=1}^{3} w_j \, l_{i,j} \, T_j(\lambda)$$

for the CIE primaries:



Interpretation of these curves



negative values : colours that cannot be produced

In such case:
mix(target , neg. primary) = mix(pos. primaries)

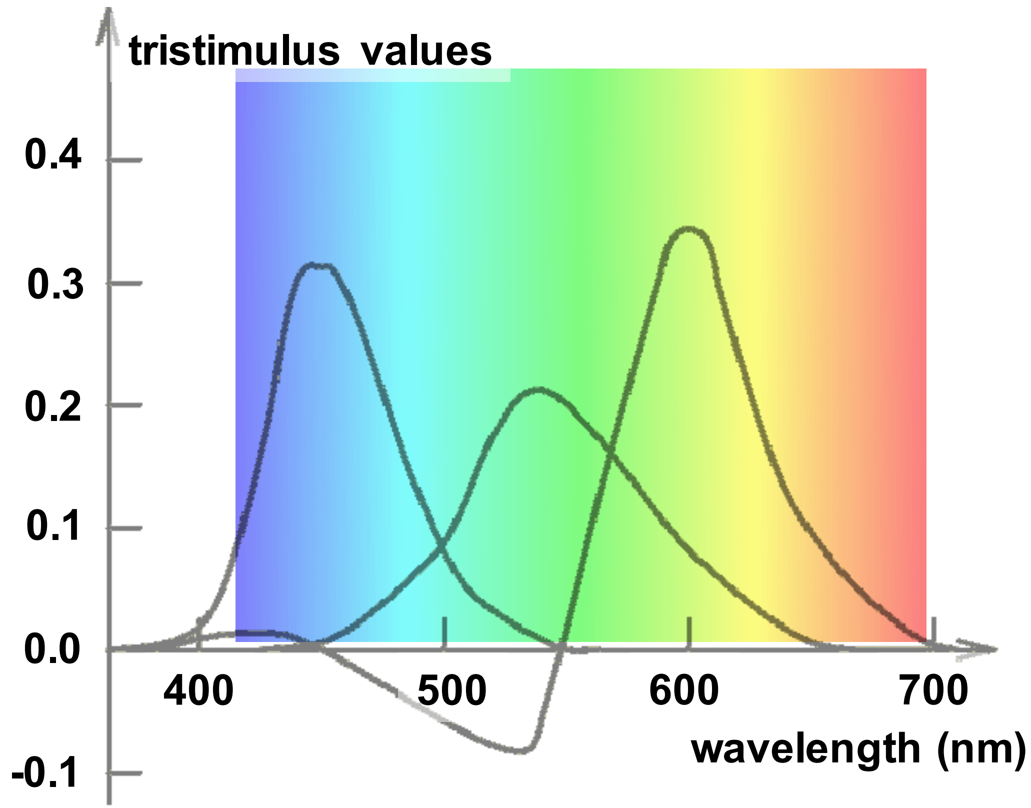
for any primary triple some colours cannot be produced

Computer Vision

Interpretation of these curves

for arbitrary source $C(\lambda)$:

$$T_j(C) = \int C(\lambda) T_j(\lambda) d\lambda$$



Chromaticity coordinates

tristimulus values still contain brightness info

chrominance info pure : normalising the tristimulus values

↓

chromaticity coordinates :

$$t_j = \frac{T_j}{T_1 + T_2 + T_3}$$

$t_1 + t_2 + t_3 = 1$ allows to eliminate one

2 chromaticity coordinates specify saturation and hue

Chromaticity coordinates

tristimulus values still contain brightness info

chrominance info pure : normalising the tristimulus values

↓

chromaticity coordinates :

$$t_j = \frac{T_j}{T_1 + T_2 + T_3}$$

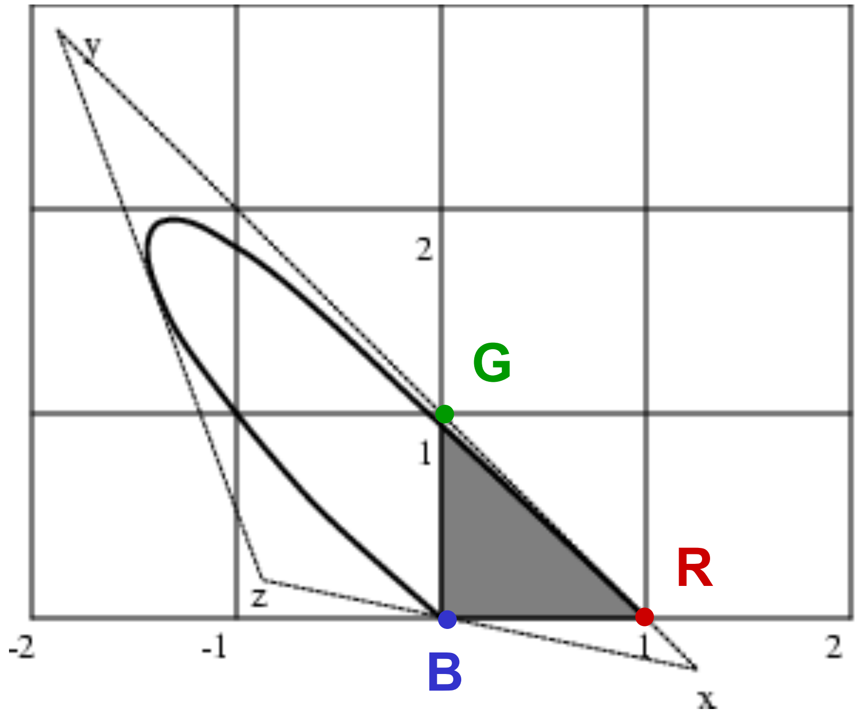
Note that for white $t_1 = t_2 = t_3 = 1/3$

CIE chromaticity diagram

chromaticity coordinates (r, g) for CIE primaries :

$$r = \frac{R}{R+G+B} \qquad g = \frac{G}{R+G+B}$$

The corresponding colour space :



CIE x-y coordinates

In order to get rid of the negative values :
virtual tristimulus colour system X,Y,Z

linear transf. from R,G,B to X,Y,Z coordinates :

$$\begin{pmatrix} X \\ Y \\ Z \end{pmatrix} = \begin{pmatrix} 0.490 & 0.310 & 0.200 \\ 0.177 & 0.813 & 0.011 \\ 0.000 & 0.010 & 0.990 \end{pmatrix} \begin{pmatrix} R \\ G \\ B \end{pmatrix}$$

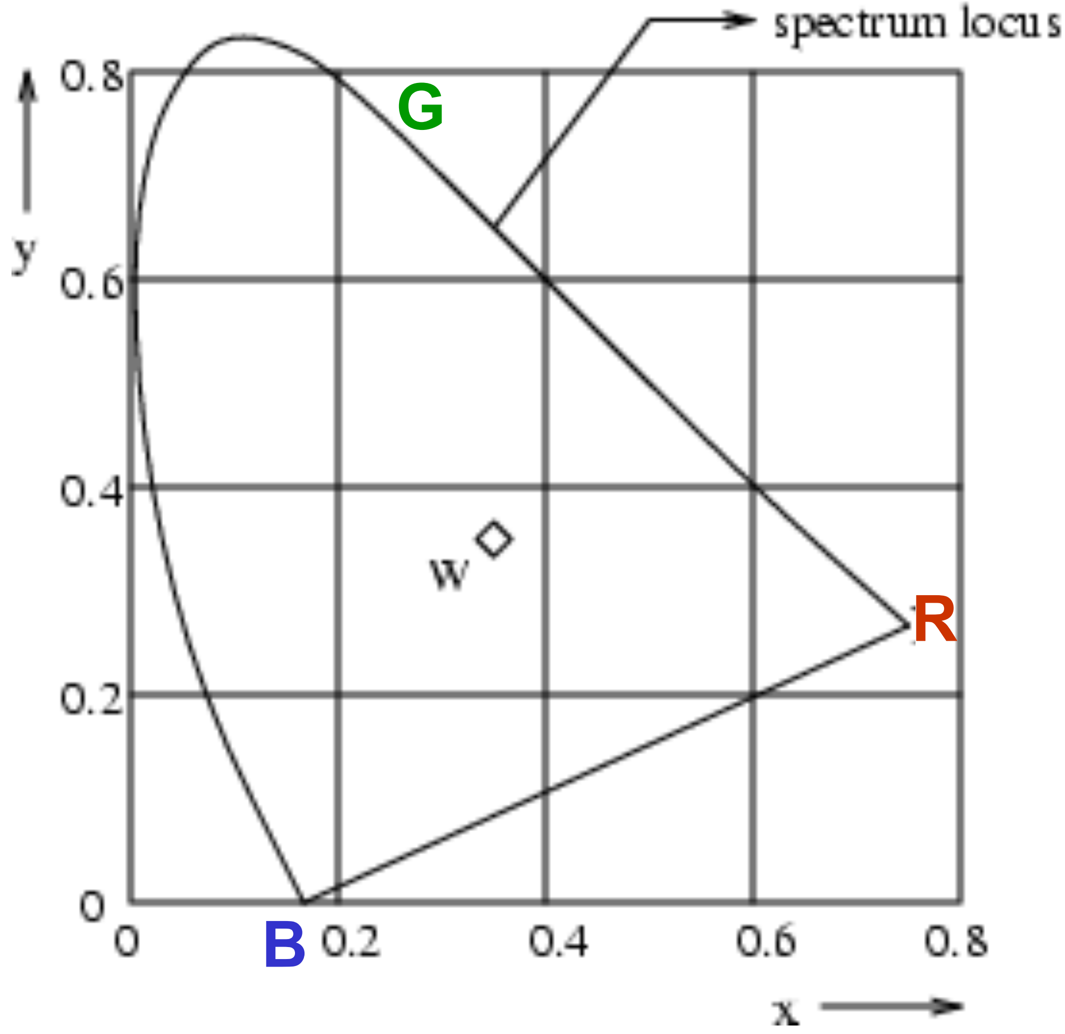
chosen as to make Y represent luminance :
its matrix coefficients obtained as

white (R=G=B=1) mapped to X=Y=Z=1

$$x = \frac{X}{X+Y+Z} \qquad y = \frac{Y}{X+Y+Z}$$

Computer Vision

CIE x,y colour triangle



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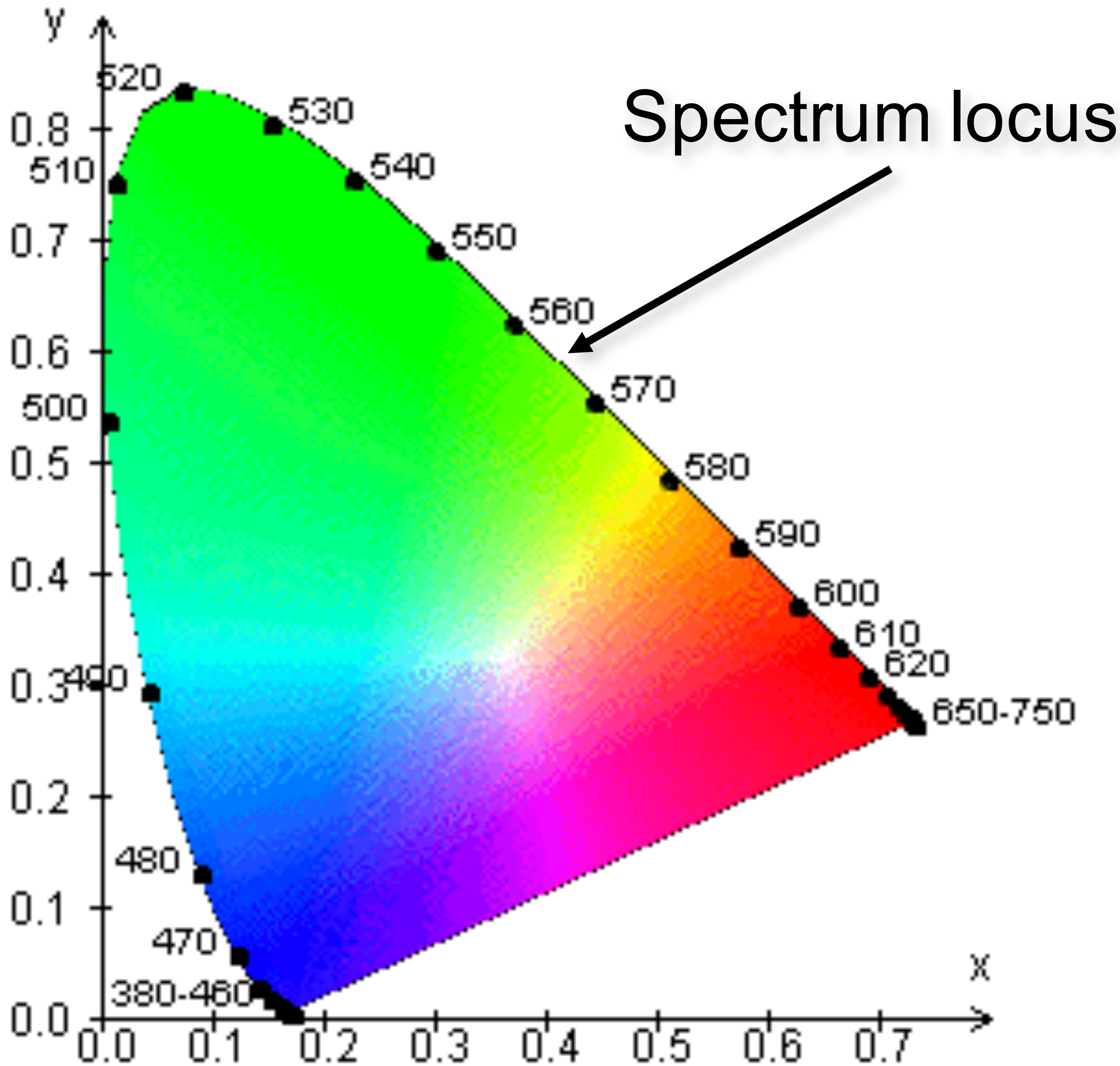
CIE x,y colour triangle



TV primaries

the EBU primaries have coordinates

$$R_r: \quad x = 0.64 \quad y = 0.33$$

$$G_r: \quad x = 0.29 \quad y = 0.60$$

$$B_r: \quad x = 0.15 \quad y = 0.06$$

the NTSC primaries have coordinates

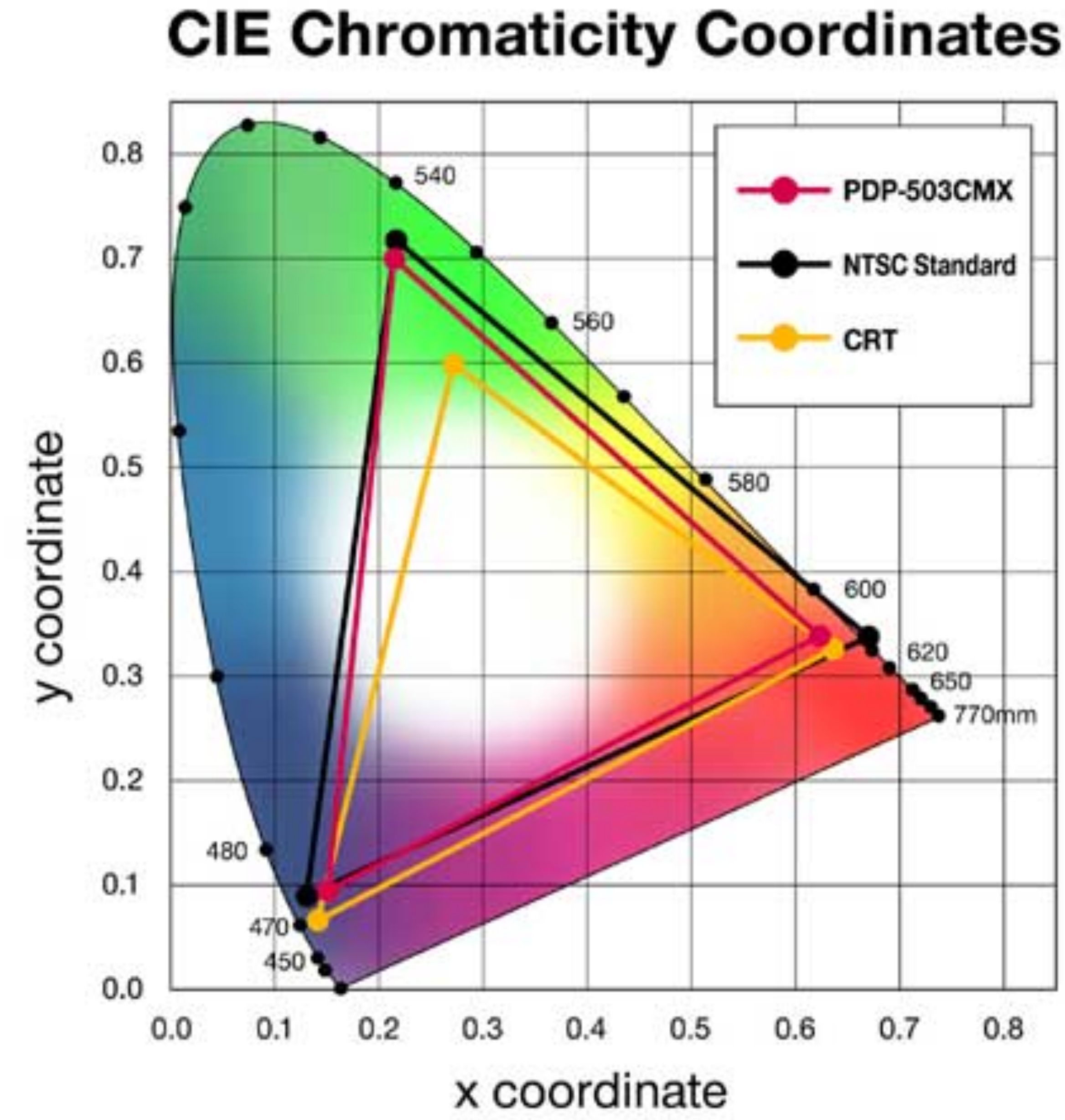
$$R_N: \quad x = 0.67 \quad y = 0.33$$

$$G_N: \quad x = 0.21 \quad y = 0.71$$

$$B_N: \quad x = 0.14 \quad y = 0.08$$

Computer Vision

primaries



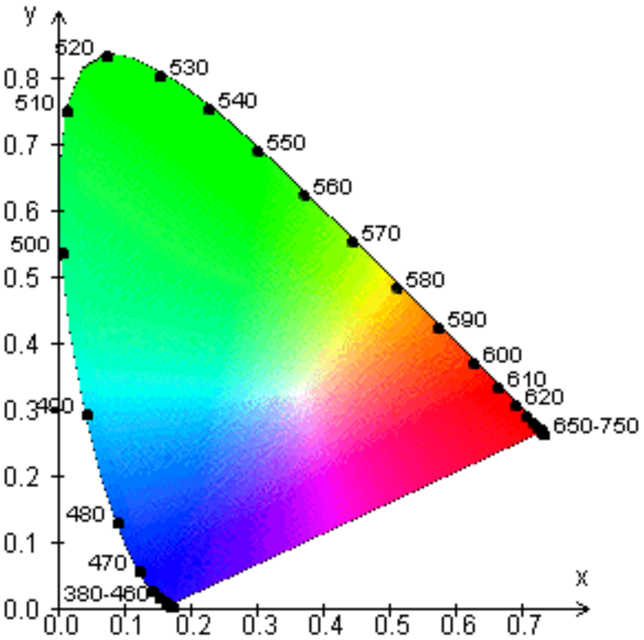
Computer Vision

Notes

Minimize colours outside the triangle!

Area dubious criterion :
projective transf. between chromaticity coordinates

distance in triangle no faithful indication of perceptual difference



pure spectrum colours are rare in nature

Chromaticity coordinate transitions

So, colour coordinates need for their definition 3 primaries + white : 4 points

4 points define a projective frame :

primaries $\Longrightarrow$ (0,0), (1,0), (0,1)
white $\Longrightarrow$ (0.33, 0.33)

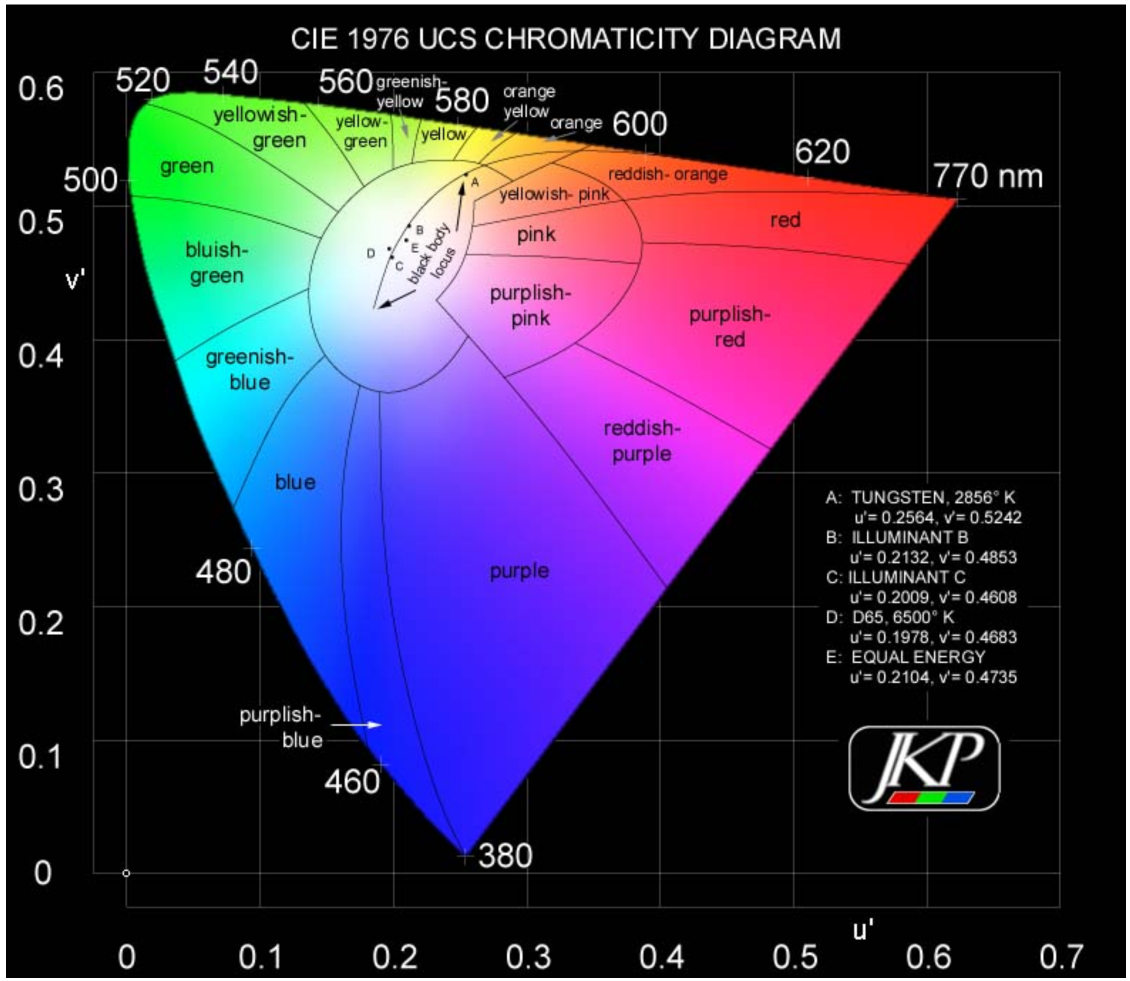
a chromaticity coordinate transformation can be shown to be projective, i.e. non-linear

We discuss 2D projective transformations in a coming lecture about invariant features

CIE u-v color coordinates

$u - v$ diagram +/- faithfully represents perceptual distance :

$$u = \frac{4x}{-2x + 12y + 3} \qquad v = \frac{6y}{-2x + 12y + 3}$$



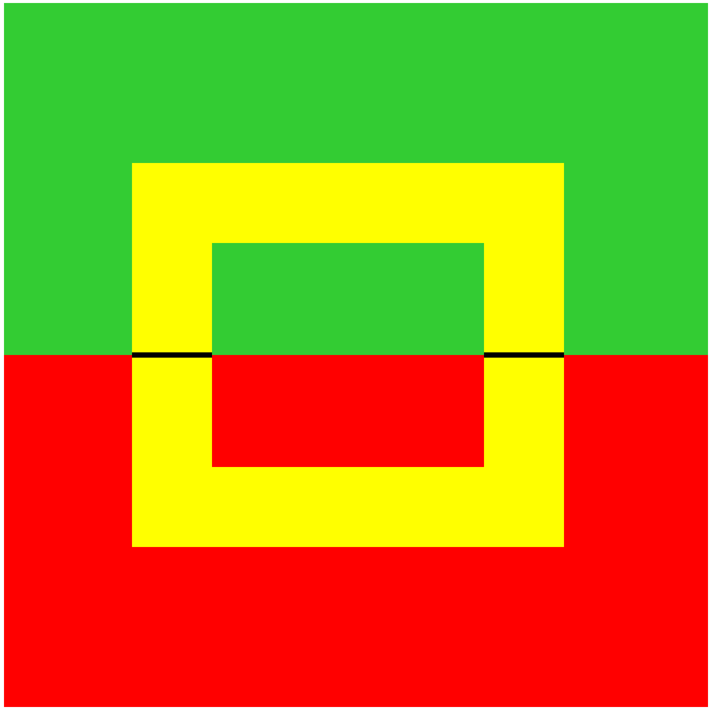
Using colour as a feature:

- colour constancy

- illumination invariant colour features

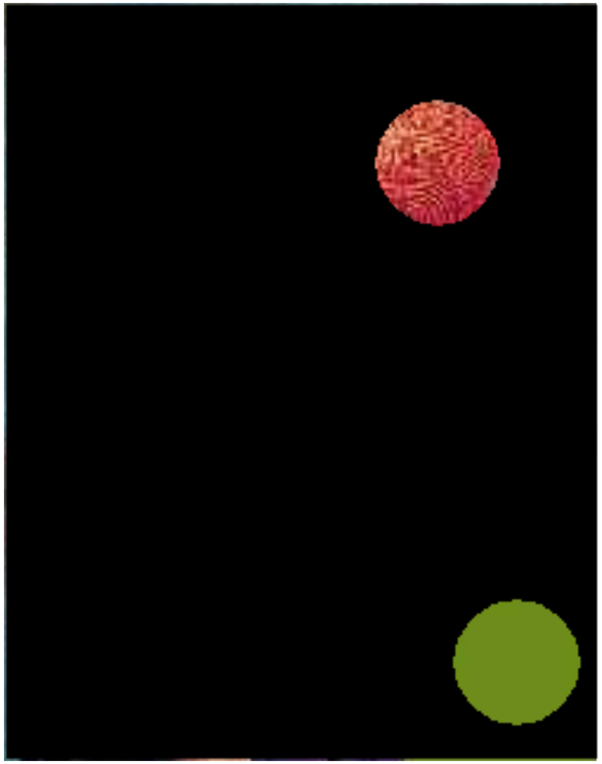
Computer Vision

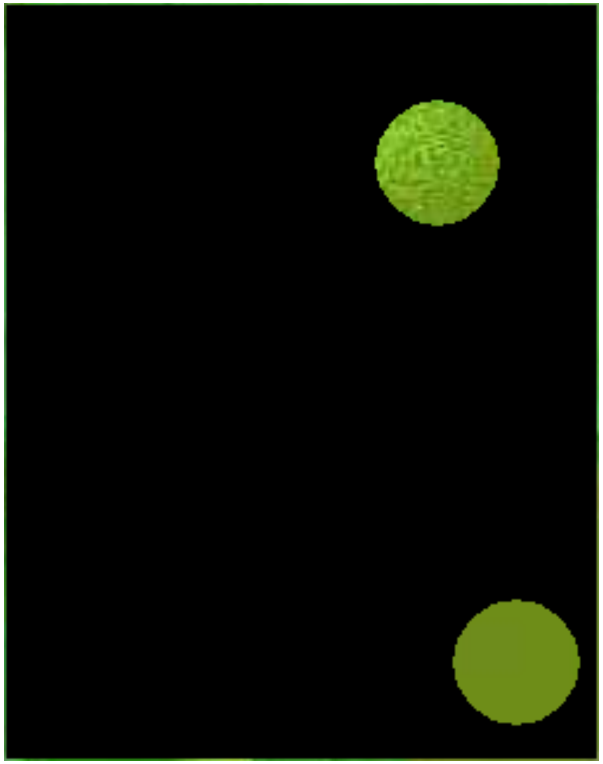
Koffka ring with colours



Computer Vision

Colour constancy





Colour constancy

Patches keep their colour appearance even if they reflect differently (e.g. the hat)

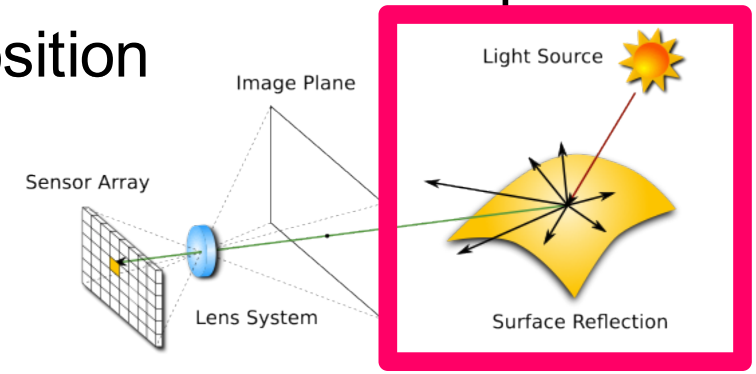
Patches change their colour appearance if they reflect identically but surrounding patches reflect differently (e.g. the background)

There is more to colour perception than 3 cone responses

Edwin Land performed in-depth experiments (psychophysics)

Colour constancy - notes

The colour of a surface is the result of the product of spectral reflectance and spectral light source composition



Our visual system can from a single product determine the two factors, it seems

The colour of the light source can be guessed via that of specular reflections, but the visual system does not critically depend on this trick

On the menu:

- colour constancy
- illumination invariant colour features

Illumination invariant colour features

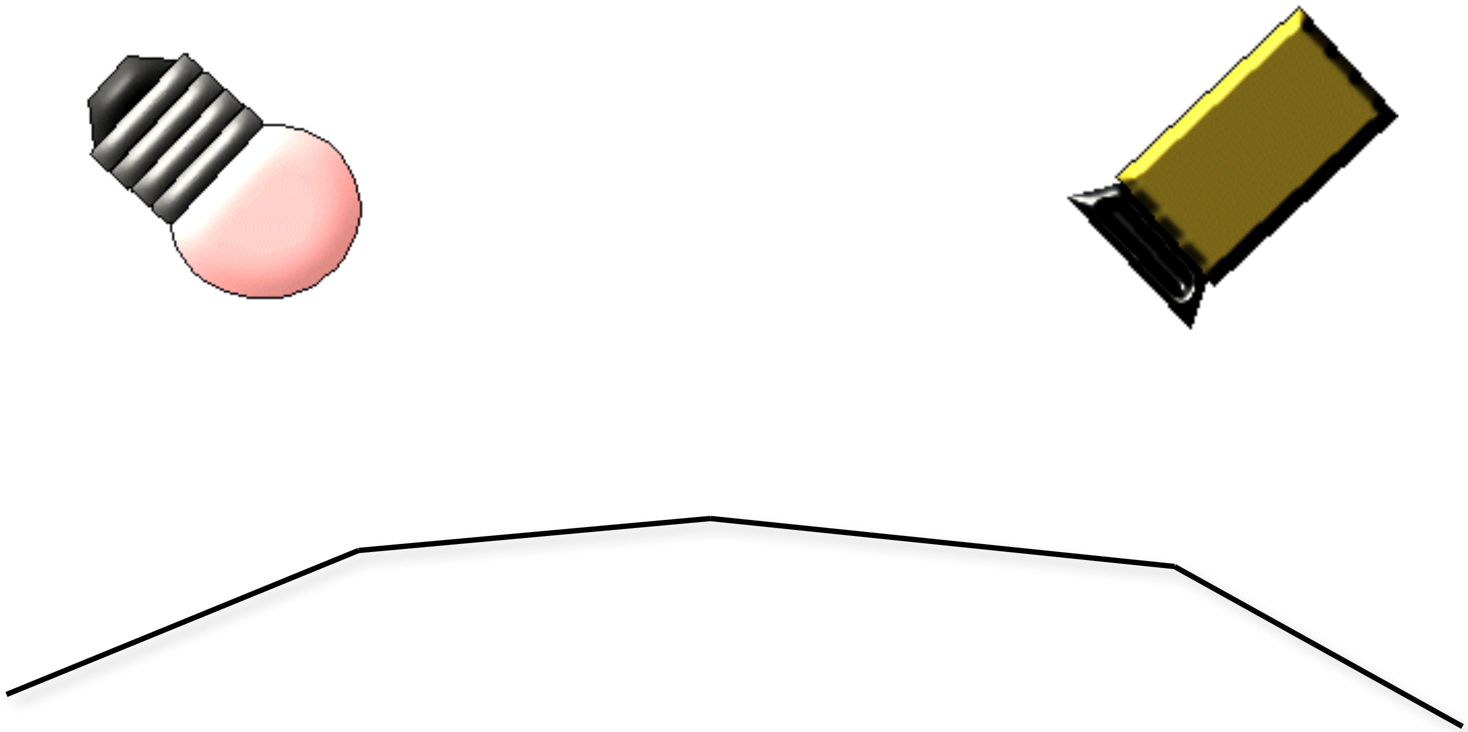
Extracting the true surface colour under varying illumination - as the HVS can - is very difficult

A less ambitious goal is to extract colour features that do not change with illumination

1) Spectral or `internal' changes
2) Geometric or `external' changes
3) Spectral + geometric changes

Illumination invariant colour features

1) Spectral changes



Illumination invariant colour features

1) Spectral changes

Let $I_{R,} I_{G,} I_{B}$ represent the irradiances at the camera for red, green, blue

A simple model: the irradiances change by

$$\alpha, \beta, \gamma : \left(I'_{R}, I'_{G}, I'_{B} \right) = \left(\alpha\, I_{R}, \beta\, I_{G}, \gamma\, I_{B} \right)$$

Consider irradiances at 2 points:

I_{R1}, I_{G1}, I_{B1} and I_{R2}, I_{G2}, I_{B2}

$$I'_{R1} / I'_{R2} = \left(\alpha I_{R1} \right) / \left(\alpha I_{R2} \right) = I_{R1} / I_{R2}$$

Illumination invariant colour features

For a camera with a non-linear response:

$$(\alpha I_{R1})^{\gamma} / (\alpha I_{R2})^{\gamma} = (I_{R1})^{\gamma} / (I_{R2})^{\gamma}$$

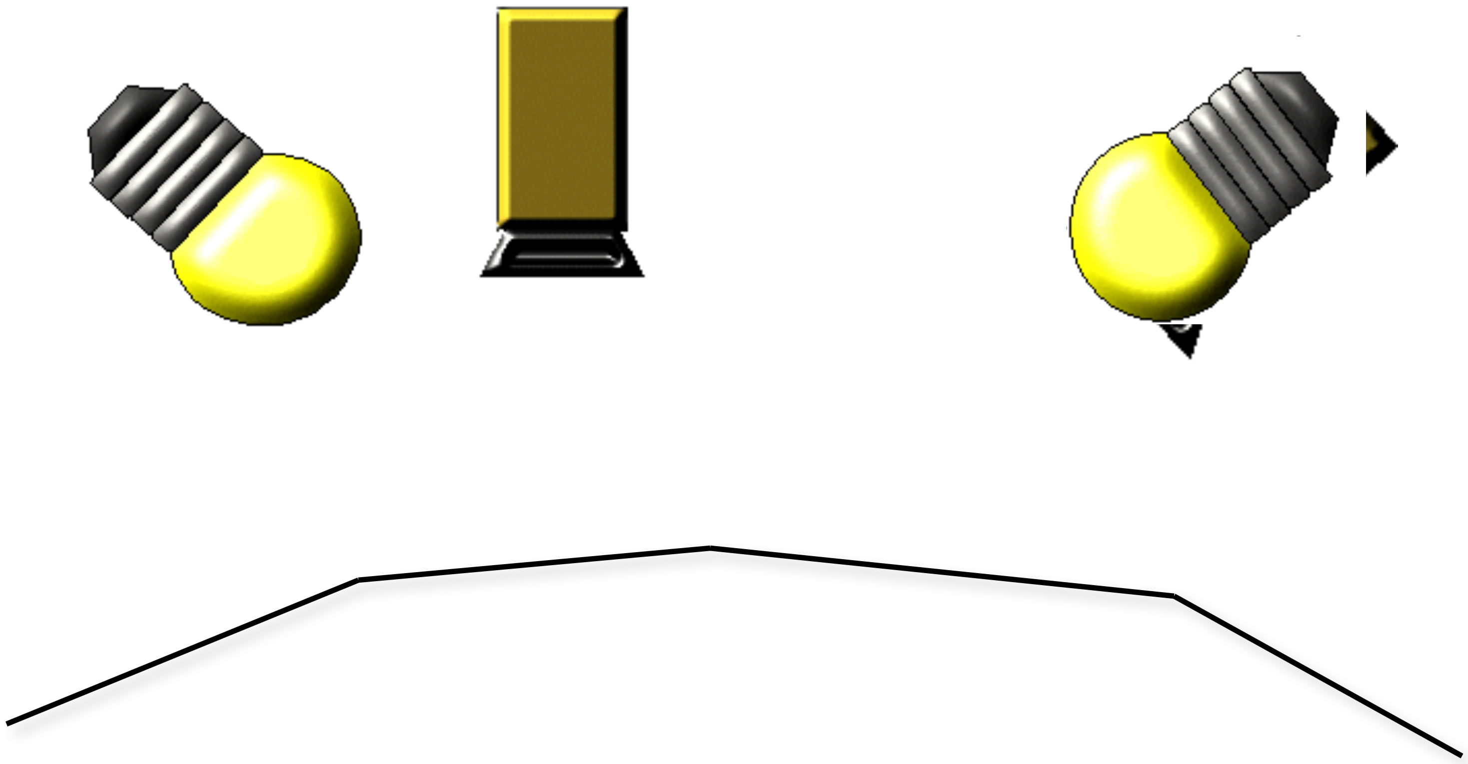
And in the case of a log-response:

$$\log I'_{R1} - \log I'_{R2} = \log\left(I'_{R1} / I'_{R2}\right) =$$
$$\log\left(I_{R1} / I_{R2}\right) = \log I_{R1} - \log I_{R2}$$

Computer Vision

Illumination invariant colour features

2) Geometric changes



Illumination invariant colour features

1) Geometric changes

$$\left(I'_R, I'_G, I'_B\right) = \left(s(x,y)I_R,\ s(x,y)I_G,\ s(x,y)I_B\right)$$

$$I'_R / I'_G = I_R / I_G$$

and

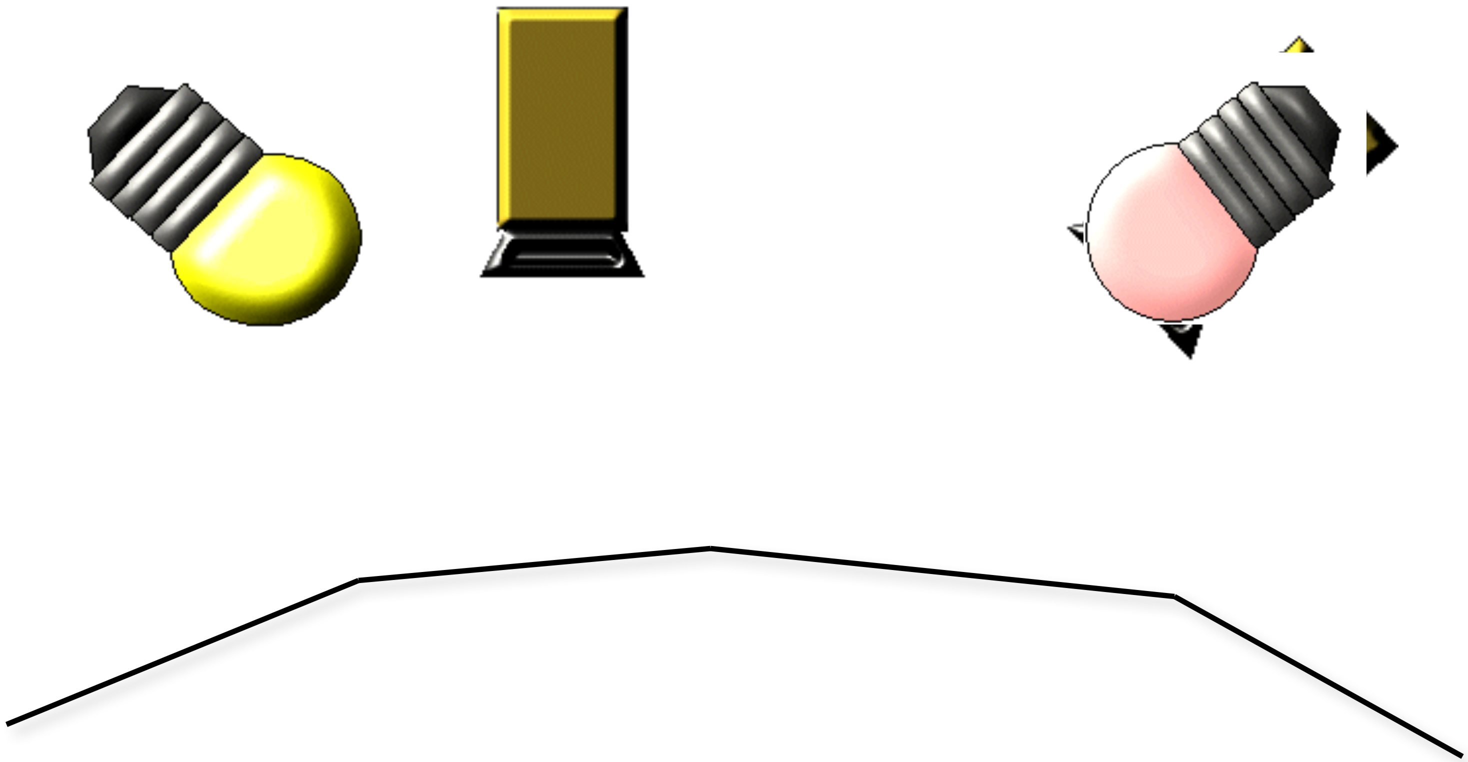
$$I'_R / I'_B = I_R / I_B$$

are invariant

Computer Vision

Illumination invariant colour features

3) Spectral + geometric changes



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Illumination invariant colour features

3) Geometric + spectral changes

$$\frac{I'_{R1} I'_{G2}}{I'_{R2} I'_{G1}} = \frac{\alpha\, s(x_1, y_1) I_{R1}\ \beta\, s(x_2, y_2) I_{G2}}{\alpha\, s(x_2, y_2) I_{R2}\ \beta\, s(x_1, y_1) I_{G1}} = \frac{I_{R1} I_{G2}}{I_{R2} I_{G1}}$$

(for log response

$$\log I_{R1} + \log I_{G2} - \log I_{R2} - \log I_{G1} \;)$$

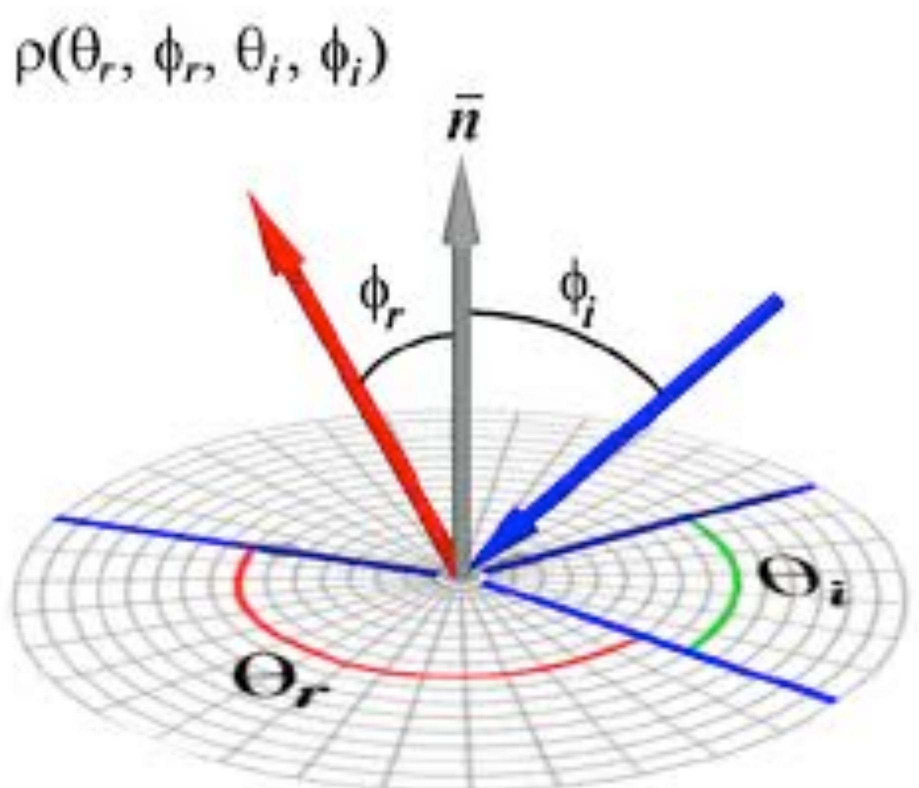
for points on both sides of a colour edge $s(x_1, y_2) \cong s(x_2, y_2)$ and hence I_{R1} / I_{R2} is invariant

Computer Vision

The elusive BRDF

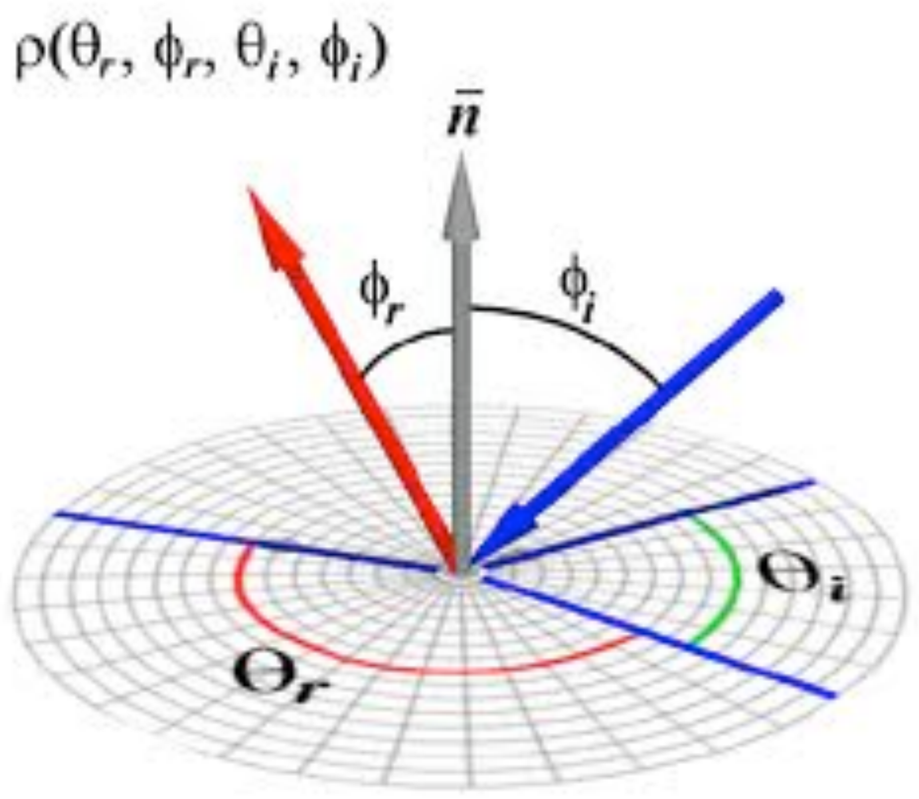
Bidirectional Reflection Distribution Function

…. for different wavelengths



The elusive BRDF

A 4D function, specifying the radiance for an outgoing direction given an irradiance for an incoming direction, relative to the normal and ideally for 1 wavelength at a time



Mini-dome to study reflectance

KATHOLIEKE UNIVERSITEIT
LEUVEN

Mini-dome to study reflectance

Mini-dome to study reflectance

The system automatically segments the scene into `materials' (incl. determining their nmb)

\+

Assumes some isotropy and symmetry to reduce the BRDF to 2D

\+

Extracts a BRDF model for each material

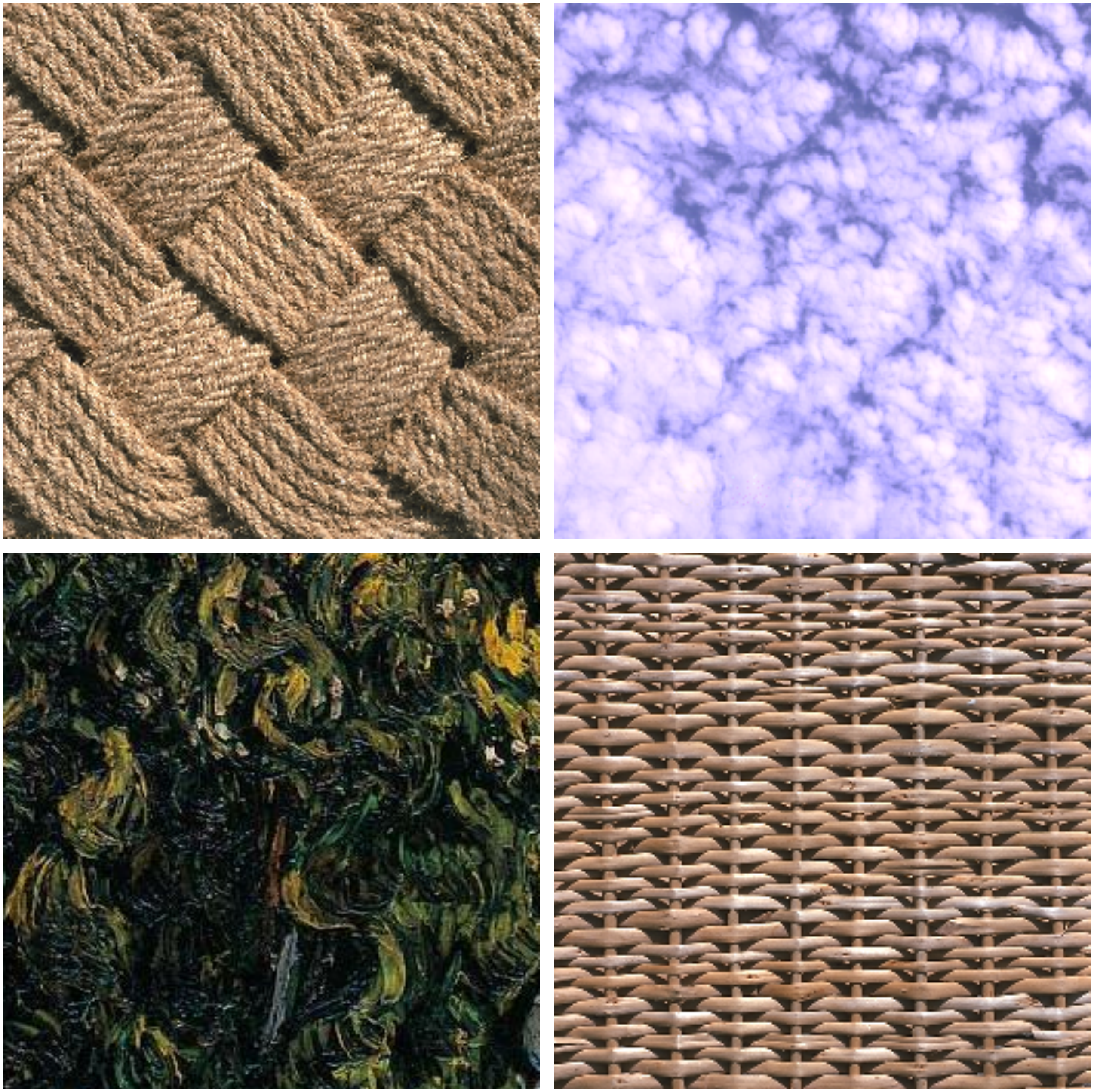
Computer Vision

Mini-dome to study reflectance

REAL SIMULATED

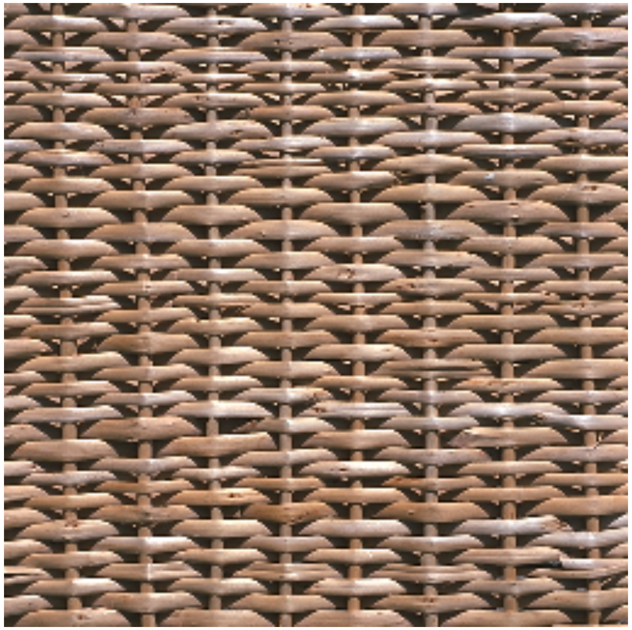
TEXTURE

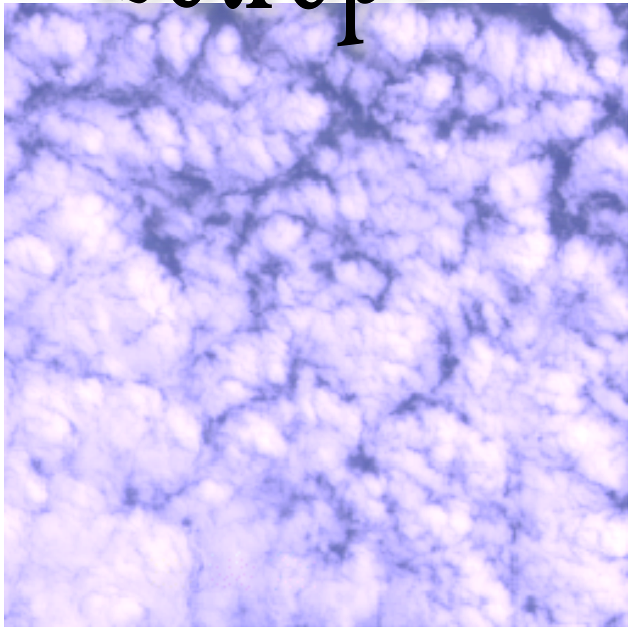
Example textures



Texture characteristics

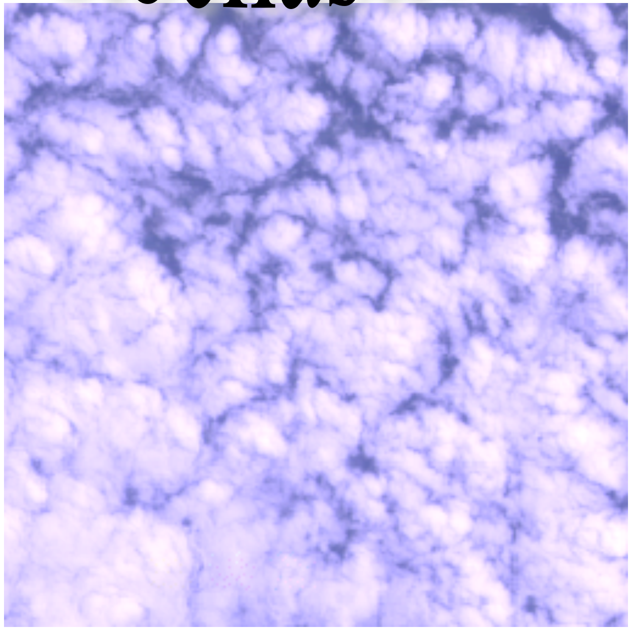
oriented vs. isotropic





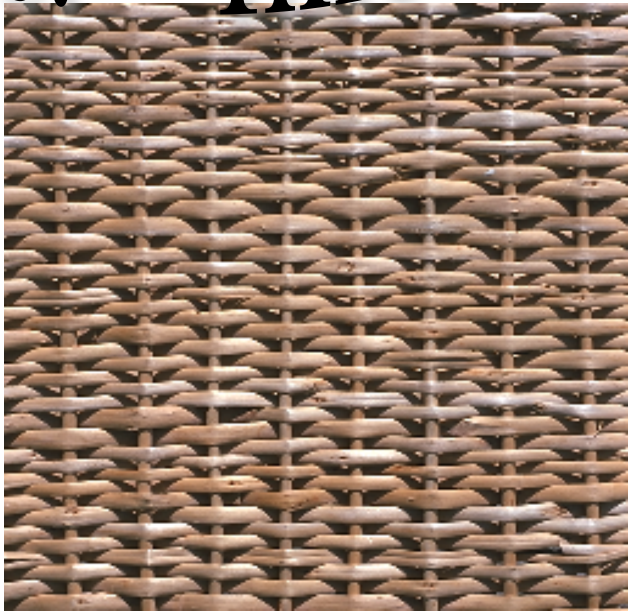
Texture characteristics

regular vs. stochastic



Texture characteristics

coarse vs. fine



On the menu:

- Fourier features
- cooccurrence matrices
- filter banks (Laws, Gabor, eigenfilters)
- stochastic models)

Fourier features

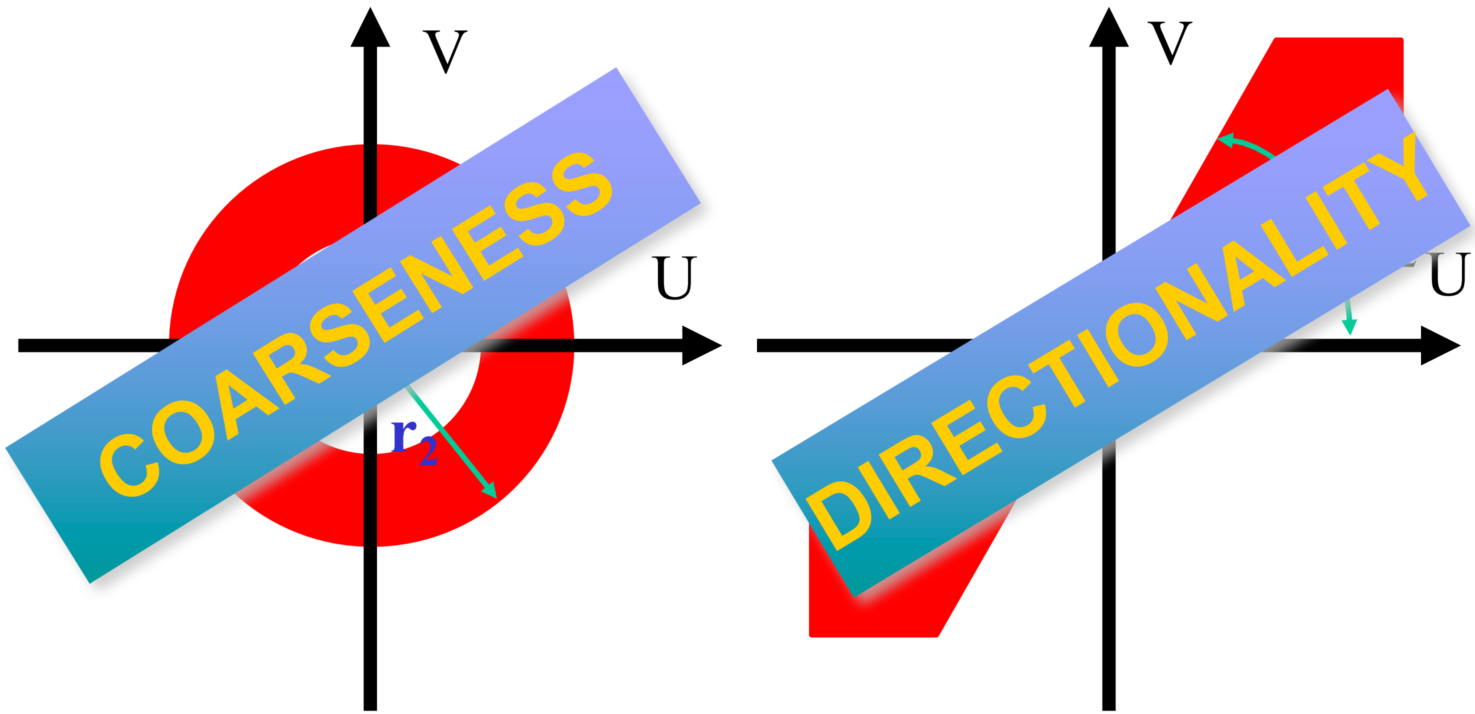
Based on the integration of regions of the Fourier power spectrum $\int_A \int \left| F(u,v) \right|^2 du dv$

Intuitively appealing

- peaks if periodic
- mostly low/high freq. if coarse resp. fine
- the sine patterns each have an orientation

Computer Vision

Fourier features



$$r_1^2 \le u^2 + v^2 < r_2^2$$

$$\theta_1 \le \arctan\left(\frac{u}{v}\right) < \theta_2$$

Fourier features

THE FOURIER TRANSFORM COLLECTS INFORMATION GLOBALLY OVER THE ENTIRE IMAGE

NOT GOOD FOR SEGMENTATION OR INSPECTION

On the menu:

- Fourier features
- cooccurrence matrices
- filter banks (Laws, Gabor, eigenfilters)
- stochastic models

Histograms: principle

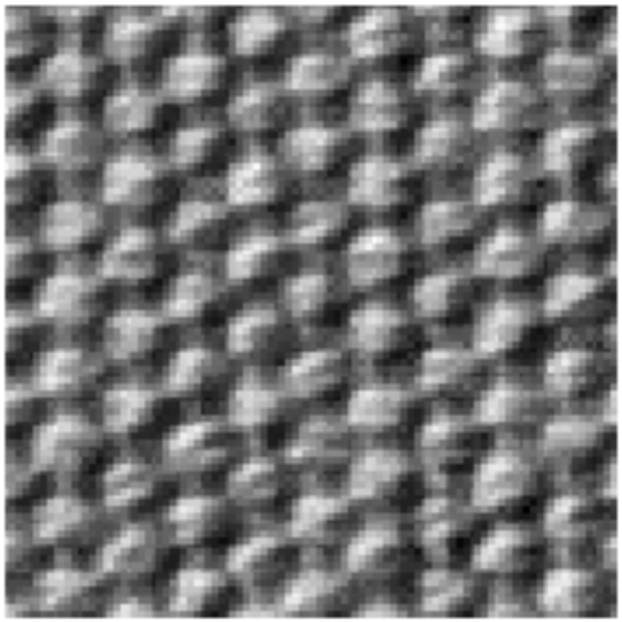
Intensity probability distribution

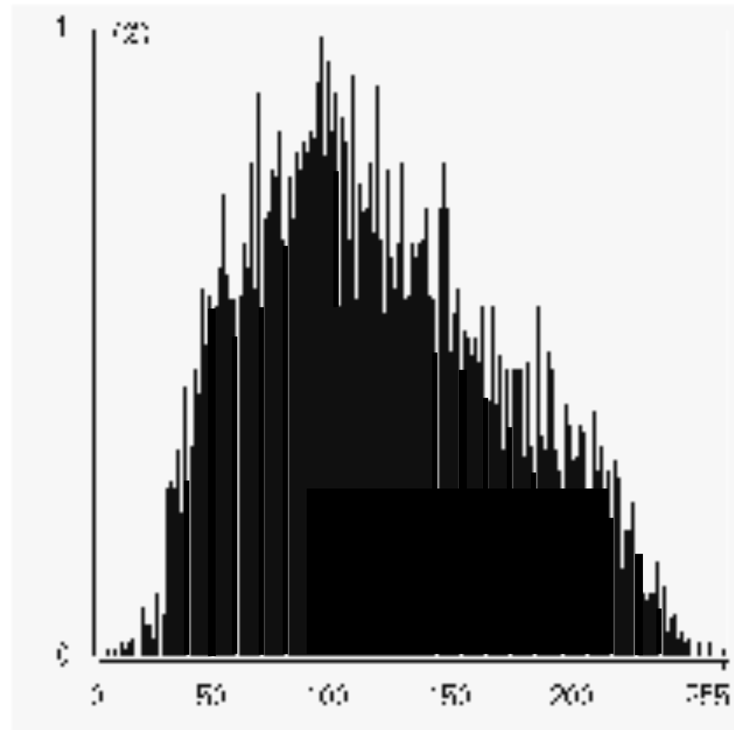
Captures global brightness information in a compact, but incomplete way

Doesn't capture spatial relationships

Computer Vision

Histograms : example

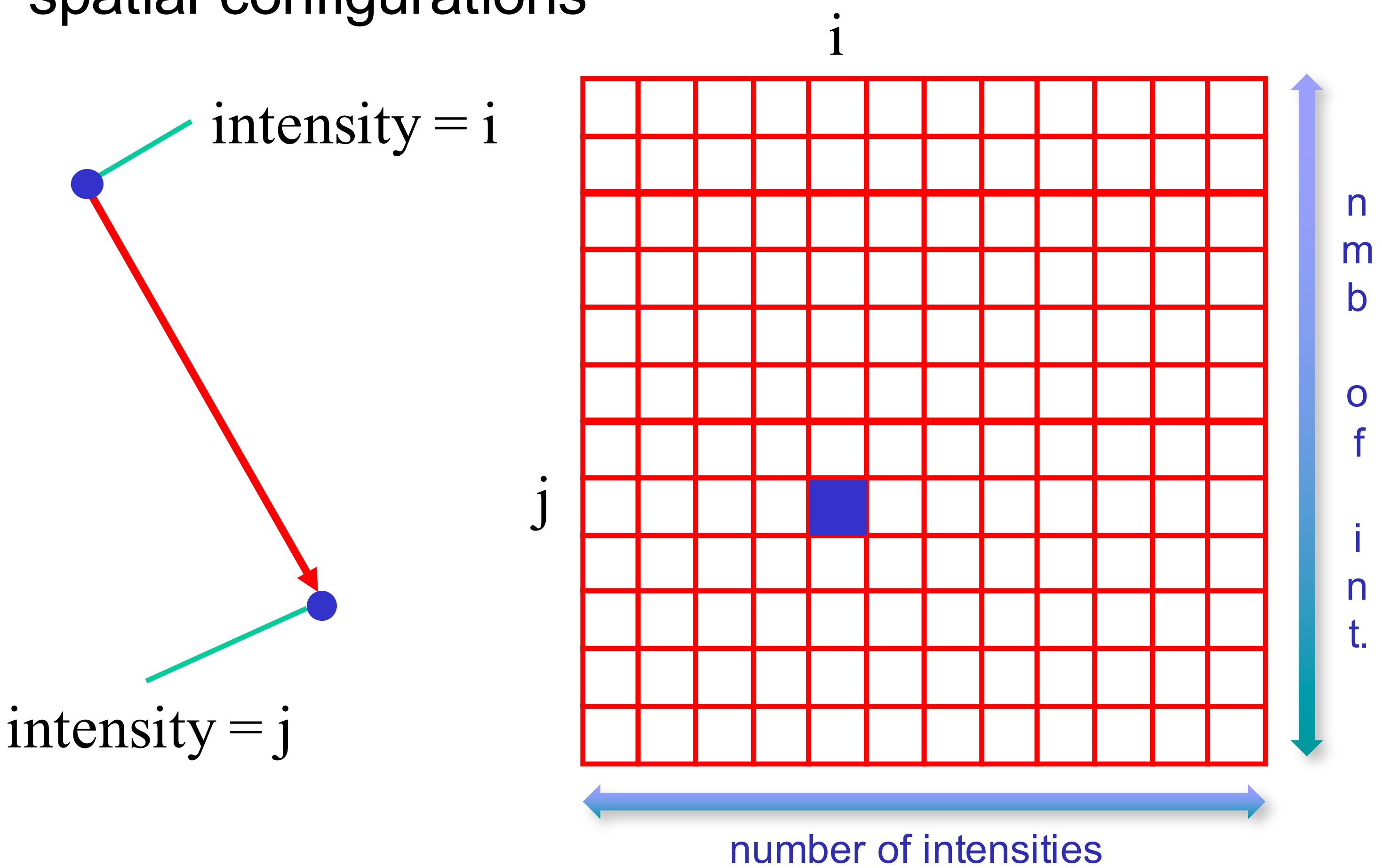




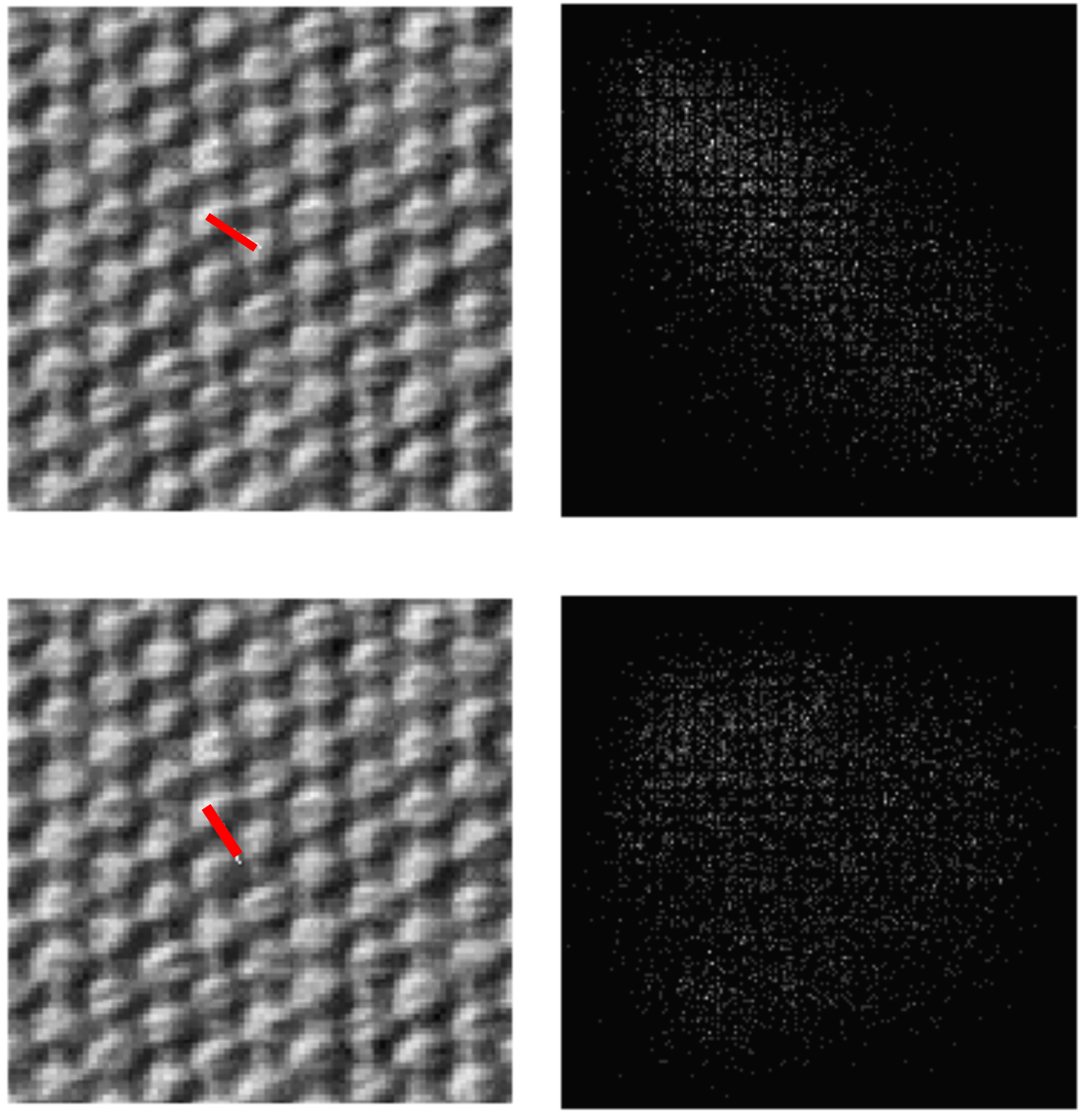
Cooccurrence matrix

probability distributions for intensity pairs

Contains information on some aspects of the spatial configurations



Cooccurrence matrix



Computer Vision

Cooccurrence matrix

Features calculated from the matrix:

feature	expression
energy	$\sum_i \sum_j C^2(i,j)$
entropy	$-\sum_i \sum_j C(i,j) \log C(i,j)$
contrast	$\sum_i \sum_j (i-j)^2 C(i,j)$
homogeneity	$\sum_i \sum_j \mathrm{C}(\mathrm{i},\mathrm{j}) / (1+\lvert \mathrm{i}-\mathrm{j} \rvert)$
max. probability	$\max_{i,j} C(i,j)$

On the menu:

- Fourier features
- cooccurrence matrices
- filter banks (Laws, Gabor, eigenfilters)
- stochastic models)

Computer Vision

Laws filters

Feature	1D filter
L3	[1 2 1]
E3	[-1 0 1]
S3	[-1 2 -1]
L5	[1 4 6 4 1]
E5	[-1 -2 0 2 1]
S5	[-1 0 2 0 -1]
W5	[-1 2 0 -2 1]
R5	[1 -4 6 -4 1]
L7	[1 6 15 20 15 6 1]
E7	[-1 -4 -5 0 5 4 1]
S7	[-1 -2 1 4 1 -2 -1]
W7	[-1 0 3 0 -3 0 1]
R7	[1 -2 -1 4 -1 -2 1]
O7	[-1 6 -15 20 -15 6 -1]

Laws filters

This fixed filter set yields simple convolutions but has proven very effective in some cases

Gabor filters

Gaussian envelope multiplied by cosine

$$g(x,y) = e^{-\frac{x^2+y^2}{4\Delta_{x,y}^2}} \cos\left(2\pi u^* x + \varphi\right)$$

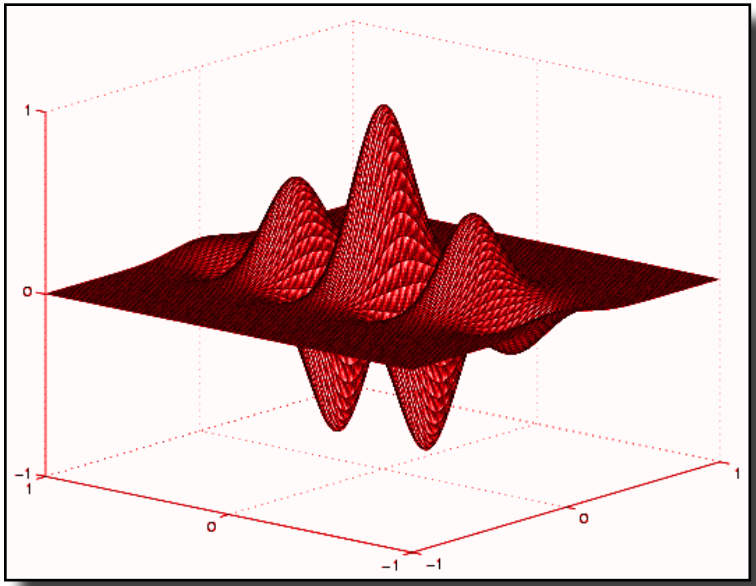
The filter's Fourier power spectrum

$$G(u,v) = \frac{1}{4\pi\Delta_{u,v}^2}\left(e^{-\left(\left(u-u^*\right)^2+v^2\right)/\left(4\Delta_{u,v}^2\right)} + e^{-\left(\left(u+u^*\right)^2+v^2\right)/\left(4\Delta_{u,v}^2\right)}\right)$$

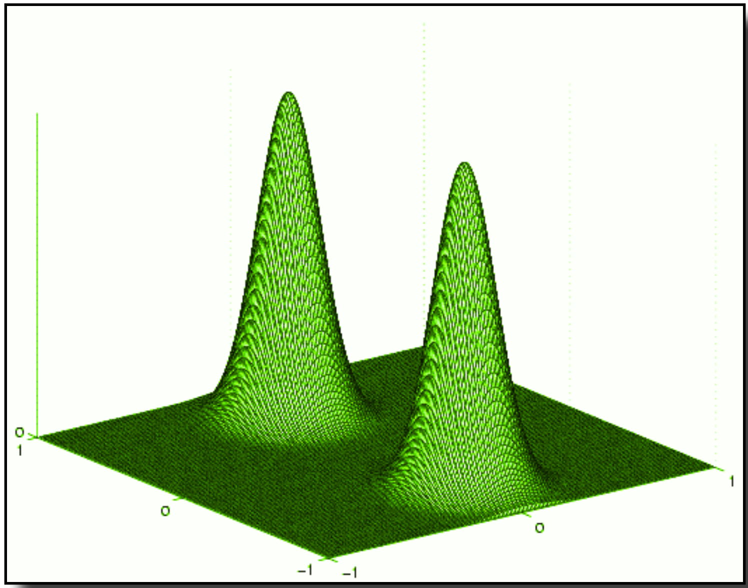
Computer Vision

Gabor filters

Spatial domain



Frequency domain



Good localisation in both domains

Gabor filters

$$f = f(x, y) \qquad F = F(u, v)$$

$$x_{av} = \frac{\int_{-\infty}^{\infty} x\, f\, \bar{f}\, dx}{\int_{-\infty}^{\infty} f\, \bar{f}\, dx} \qquad u_{av} = \frac{\int_{-\infty}^{\infty} u F \bar{F}\, du}{\int_{-\infty}^{\infty} F \bar{F}\, du}$$

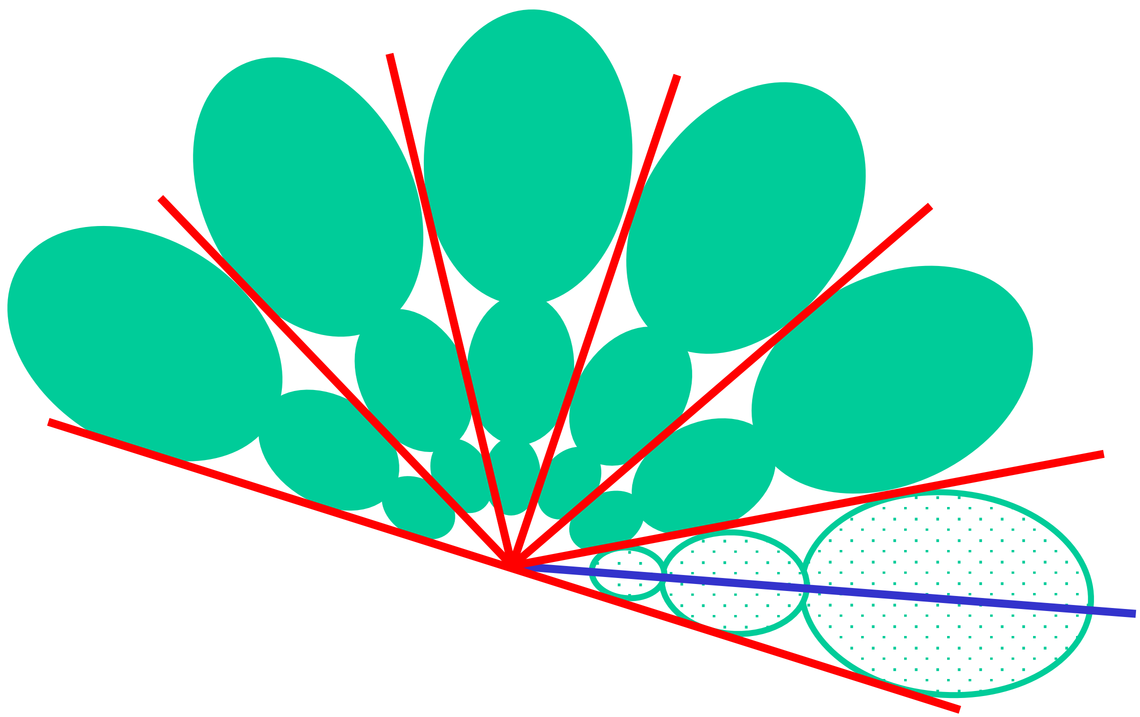
$$(\Delta x)^2 = \frac{\int_{-\infty}^{\infty} (x - x_{av})^2 f\, \bar{f} dx}{\int_{-\infty}^{\infty} f\, \bar{f} dx} \qquad (\Delta u)^2 = \frac{\int_{-\infty}^{\infty} (u - u_{av})^2 F\, \bar{F} du}{\int_{-\infty}^{\infty} F\, \bar{F} du}$$

the Heisenberg uncertainty principle

$$\Delta x\, \Delta u \geq 1/4\pi$$

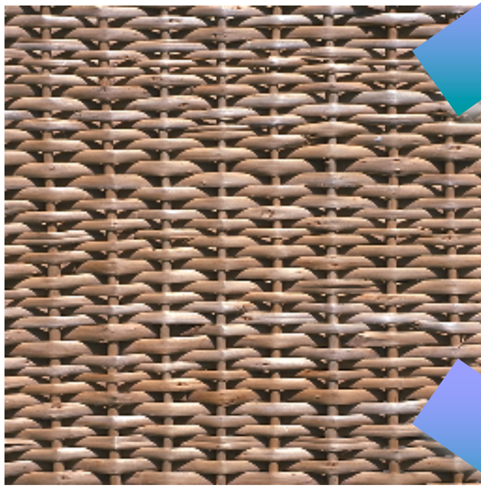
Gabor filters

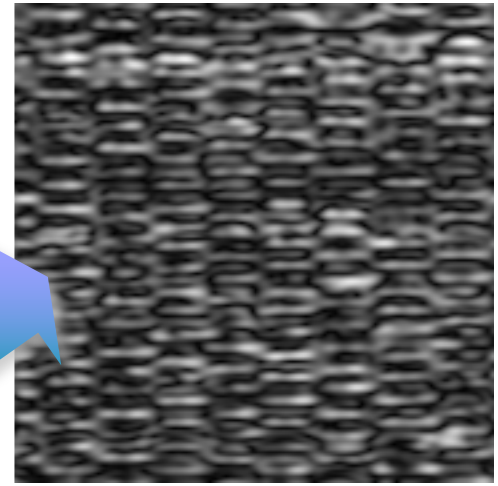
Covering the Fourier domain with responses
- to probe for directionality
- to look at different scales



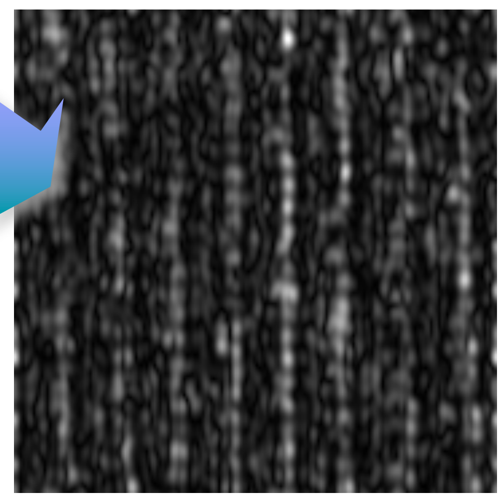
Gabor filters

Input texture





Output for filter responsive to horizontal structures



Output for filter responsive to vertical structures

Eigenfilters (Ade, ETH)

Filters adapted to the texture

1) shift mask over training image

2) collect intensity statistics

3) PCA -> eigenvectors -> `eigenfilters'

4) energies of eigenfilter outputs

Eigenfilters

Filters adapted to the texture

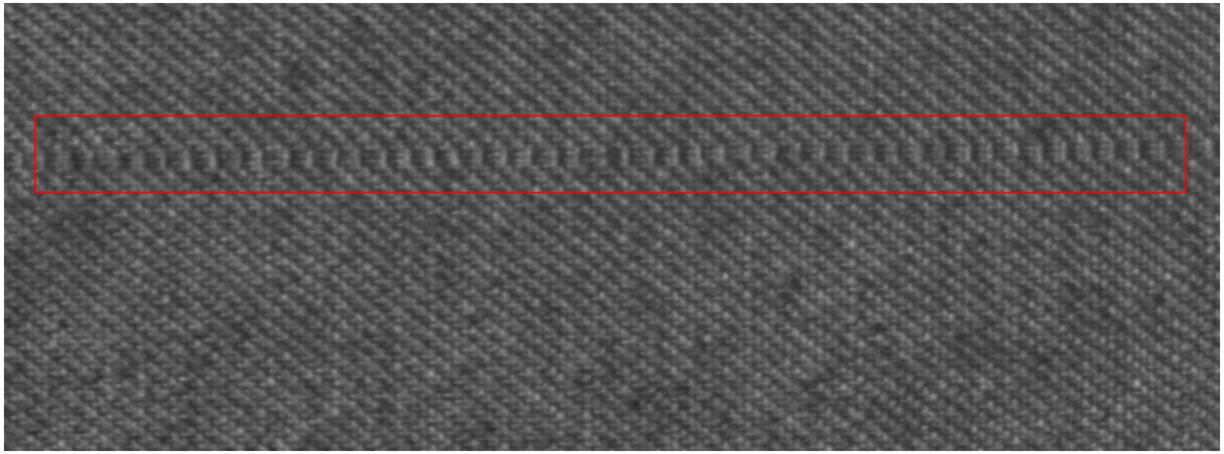
but small filters may reduce efficacy

hence large, but sparse filters

Computer Vision

Eigenfilters

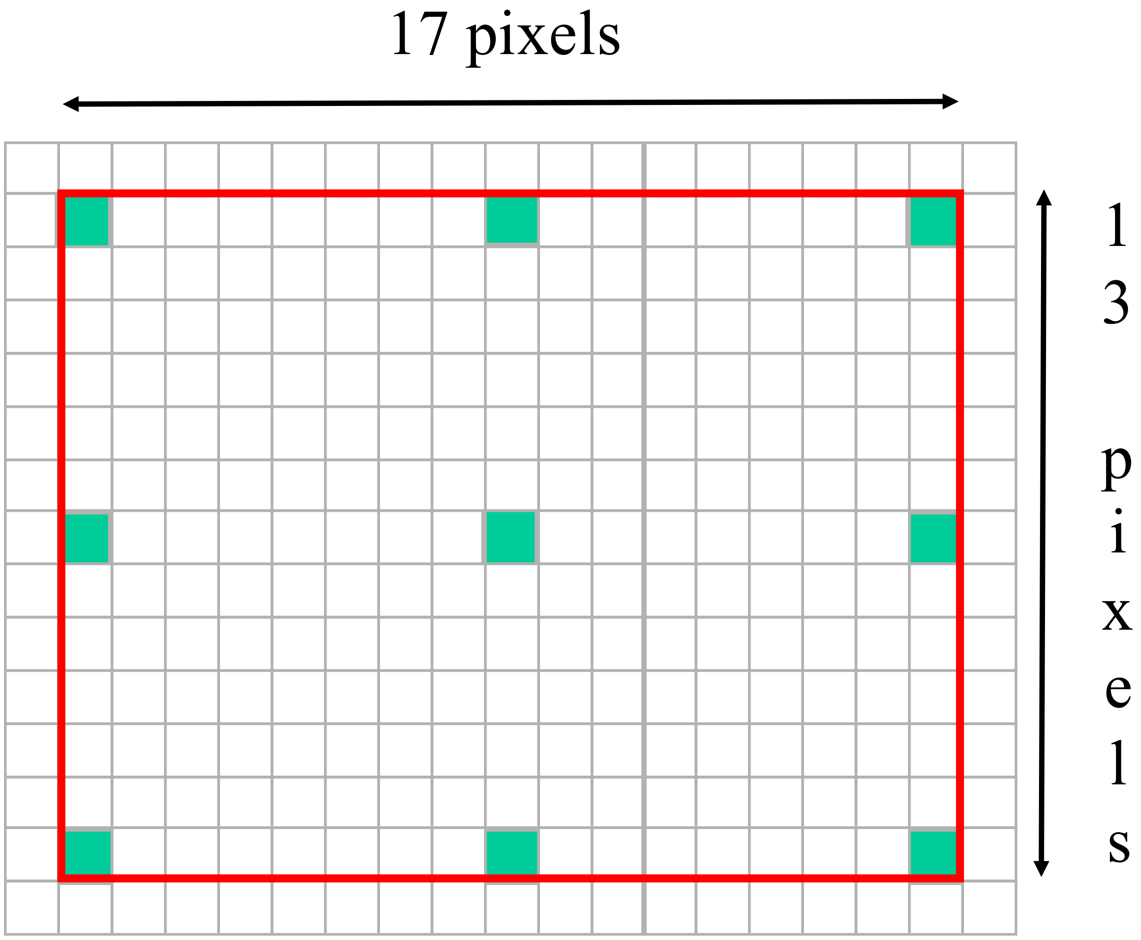
Example applications: textile inspection



Filters with size of one period

(period found as peak in autocorrelation)

Eigenfilters



Eigenfilters

Covariance matrix needed for PCA

$$\begin{pmatrix}
174.1 & -77.6 & 101.6 & -60.8 & 72.7 & -71.5 & 116.5 & -77.9 & 91.4 \\
-77.6 & 173.9 & -78.2 & 71.5 & -61.7 & 73.1 & -76.4 & 116.4 & -78.4 \\
101.6 & -78.2 & 173.5 & -70.4 & 71.7 & -62.1 & 95.3 & -77.0 & 116.3 \\
-60.8 & 71.5 & -70.4 & 173.9 & -76.5 & 101.0 & -59.4 & 71.8 & -70.1 \\
72.7 & -61.7 & 71.7 & -76.5 & 173.7 & -77.1 & 70.6 & -60.3 & 72.1 \\
-71.5 & 73.1 & -62.1 & 101.0 & -77.1 & 173.4 & -69.3 & 70.9 & -60.7 \\
116.5 & -76.4 & 95.3 & -59.4 & 70.6 & -69.3 & 173.4 & -75.3 & 99.8 \\
-77.9 & 116.4 & -77.0 & 71.8 & -60.3 & 70.9 & -75.3 & 173.2 & -75.9 \\
91.4 & -78.4 & 116.3 & -70.1 & 72.1 & -60.7 & 99.8 & -75.9 & 172.8
\end{pmatrix}$$

Computer Vision

Eigenfilters

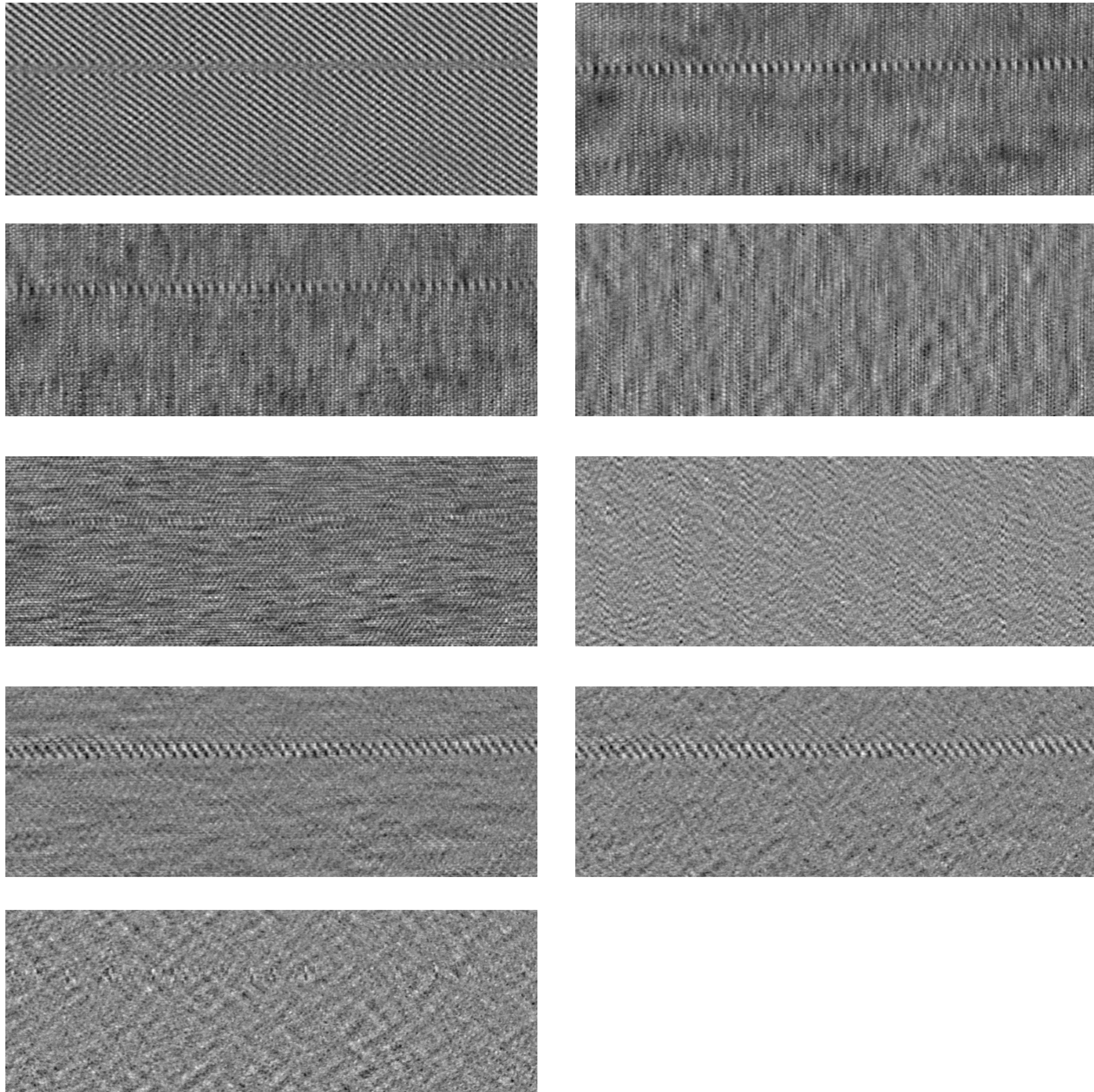
$$\begin{pmatrix} 0.35 \\ -0.33 \\ 0.35 \\ -0.30 \\ 0.30 \\ -0.30 \\ 0.35 \\ -0.33 \\ 0.35 \end{pmatrix} \quad \begin{pmatrix} 0.31 \\ 0.12 \\ 0.31 \\ 0.51 \\ -0.20 \\ 0.49 \\ 0.34 \\ 0.12 \\ 0.31 \end{pmatrix} \quad \begin{pmatrix} 0.10 \\ 0.58 \\ 0.10 \\ -0.19 \\ 0.41 \\ -0.19 \\ 0.11 \\ 0.59 \\ 0.09 \end{pmatrix} \quad \begin{pmatrix} 0.46 \\ -0.00 \\ -0.43 \\ 0.30 \\ 0.03 \\ -0.28 \\ 0.41 \\ -0.02 \\ -0.49 \end{pmatrix} \quad \begin{pmatrix} -0.10 \\ -0.15 \\ -0.09 \\ 0.33 \\ 0.83 \\ 0.33 \\ -0.13 \\ -0.14 \\ -0.06 \end{pmatrix}$$

$$\begin{pmatrix} 0.27 \\ 0.11 \\ -0.11 \\ -0.62 \\ 0.00 \\ 0.63 \\ 0.11 \\ -0.12 \\ -0.27 \end{pmatrix} \quad \begin{pmatrix} -0.43 \\ -0.06 \\ -0.54 \\ -0.10 \\ 0.00 \\ 0.09 \\ 0.55 \\ 0.05 \\ 0.40 \end{pmatrix} \quad \begin{pmatrix} 0.08 \\ -0.69 \\ 0.02 \\ -0.09 \\ -0.00 \\ 0.10 \\ -0.02 \\ 0.69 \\ -0.09 \end{pmatrix} \quad \begin{pmatrix} -0.50 \\ -0.00 \\ 0.50 \\ 0.00 \\ 0.02 \\ 0.00 \\ 0.47 \\ -0.01 \\ -0.50 \end{pmatrix}$$

Computer
Vision

Eigenfilters

eigenfilter outputs

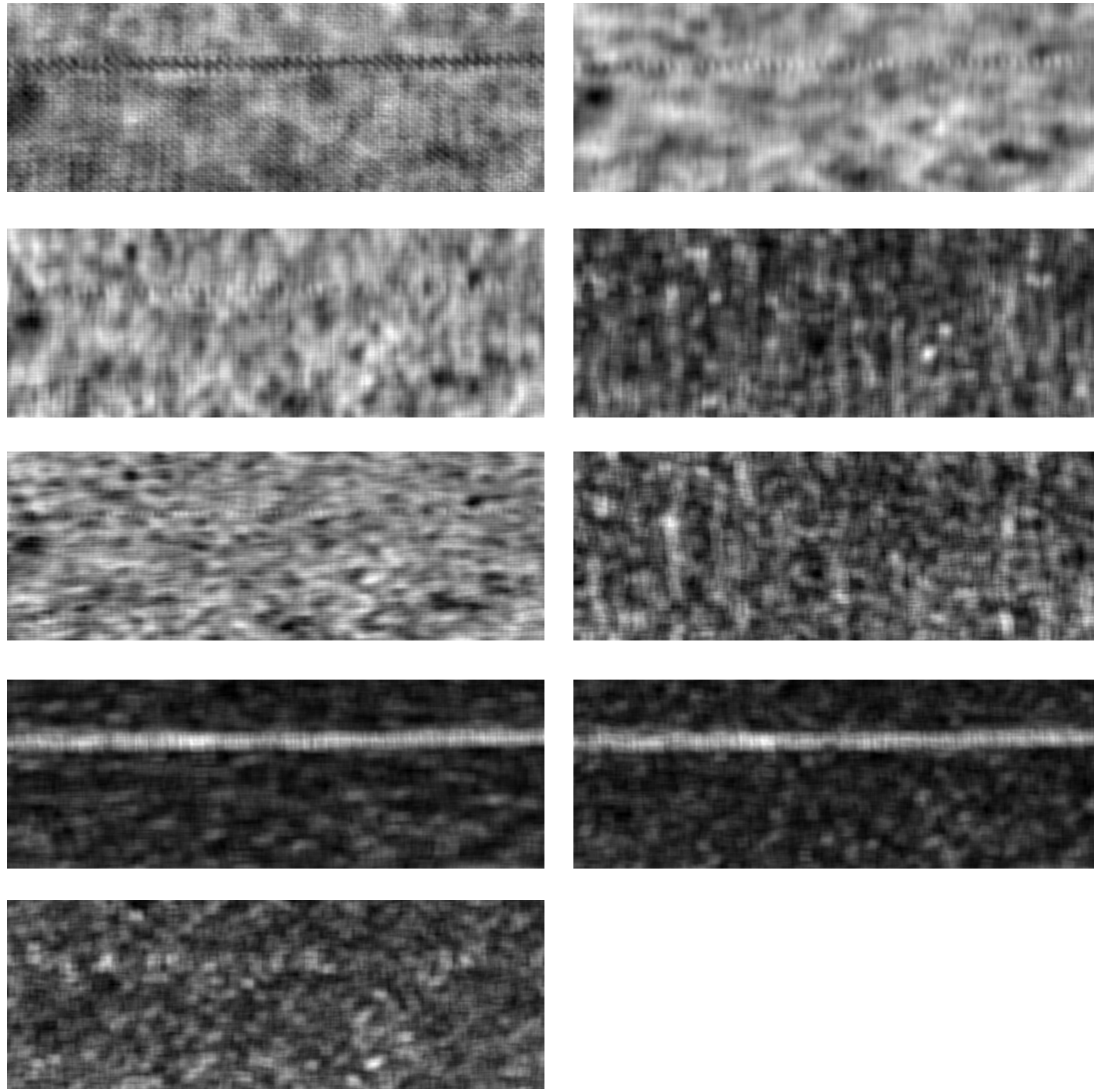


Computer Vision

Eigenfilters

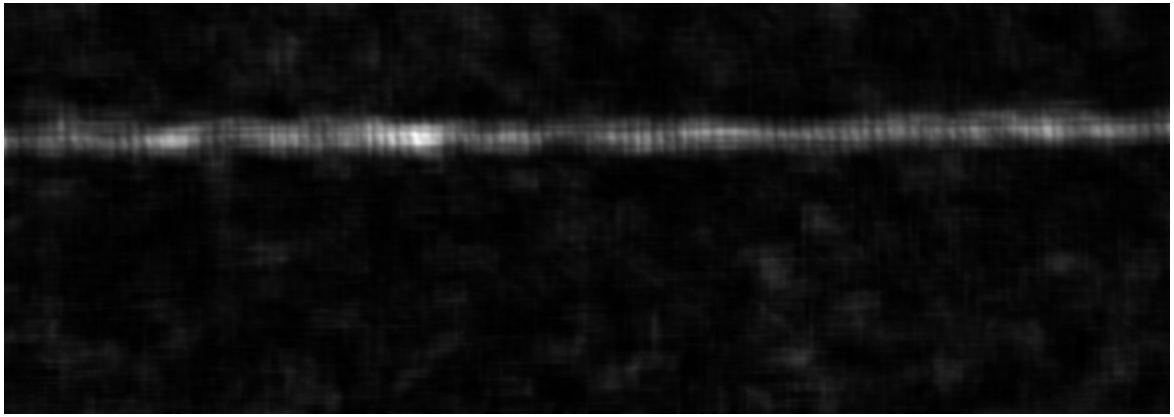
eigenfilter

energies

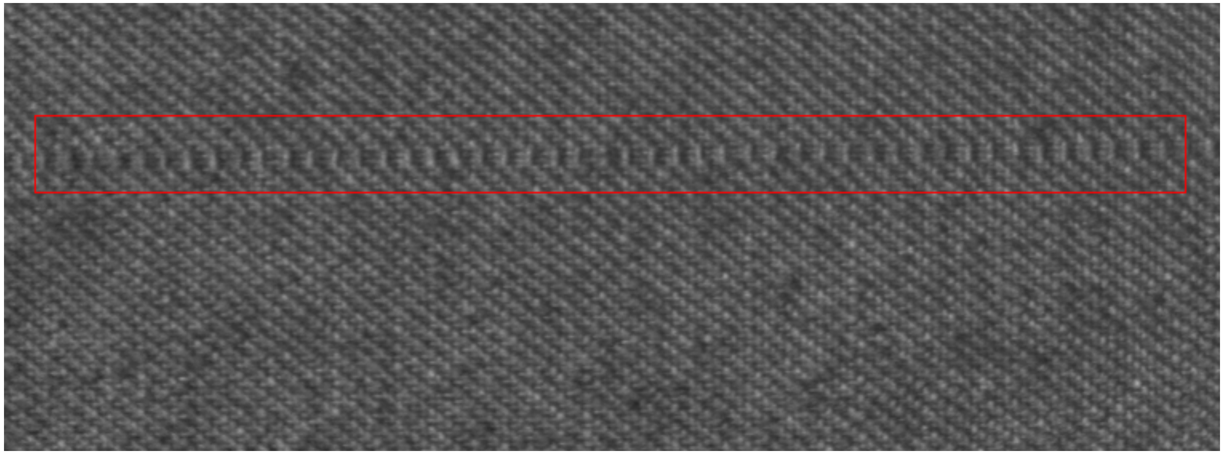


Eigenfilters

Mahalanobis distance of the energies:

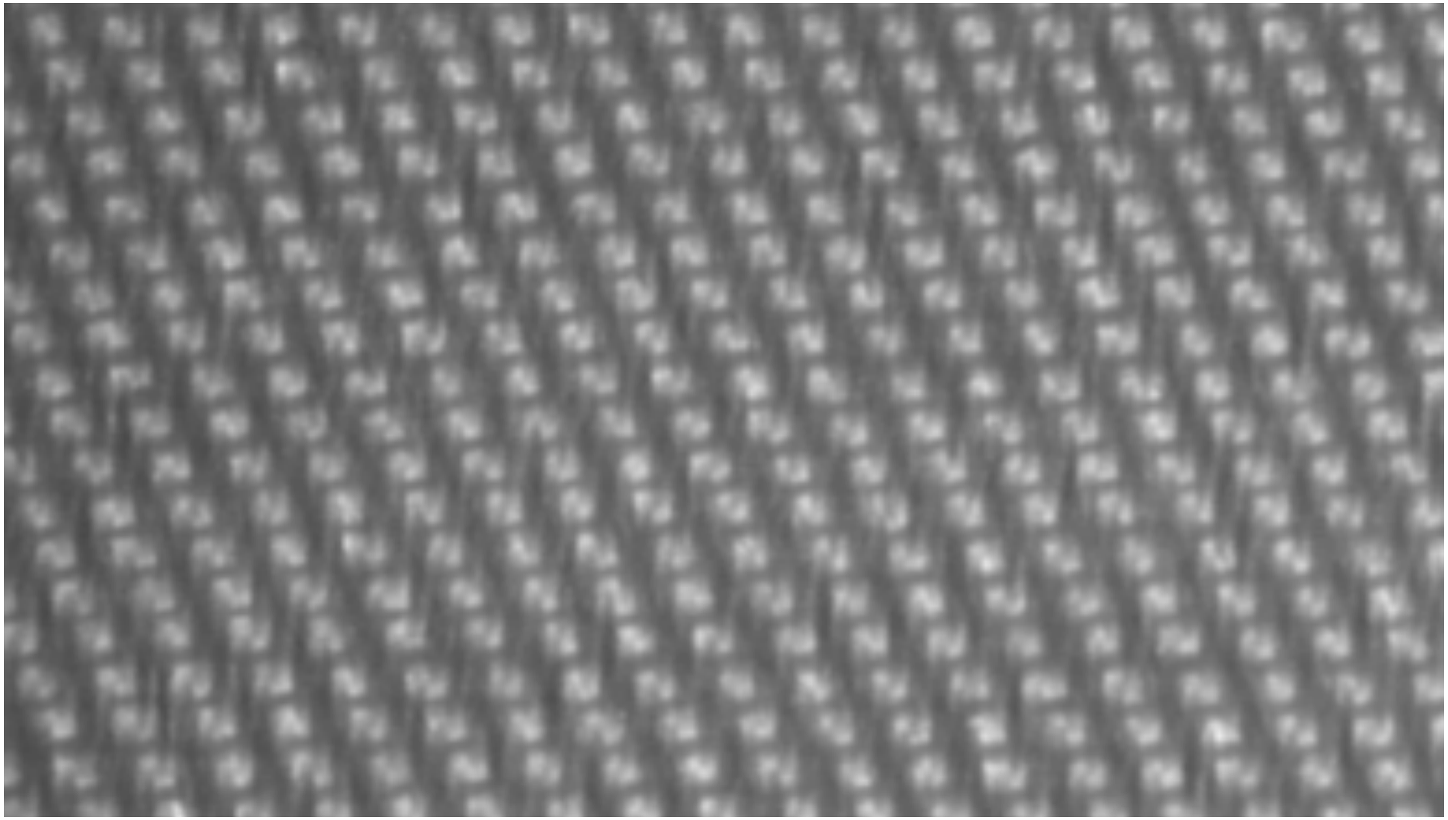


Flaw region found by thresholding:



Eigenfilters

Textile inspection: a second example



The texture is coarser, the filters are larger…

Eigenfilters

Textile inspection: eigenfilter blueprint

1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1

47 rows

21 columns

Computer Vision

Eigenfilters

The covariance matrix

Covariance Matrix :

743,89	-331,82	632,59	-316,03	618,47	-298,31	632,41	-302,50	548,84
-331,82	741,71	-345,42	641,76	-330,40	614,36	-334,25	629,22	-316,68
632,59	-345,42	738,28	-338,50	638,50	-343,03	618,37	-347,55	624,75
-316,03	641,76	-338,50	746,54	-328,93	634,29	-314,59	619,83	-297,11
618,47	-330,40	638,50	-328,93	743,82	-343,16	643,10	-329,00	615,32
-298,31	614,36	-343,03	634,29	-343,16	739,56	-337,44	639,40	-342,03
632,41	-334,25	618,37	-314,59	643,10	-337,44	748,53	-328,18	636,26
-302,50	629,22	-347,55	619,83	-329,00	639,40	-328,18	745,57	-342,19
548,84	-316,68	624,75	-297,11	615,32	-342,03	636,26	-342,19	741,04

Eigenfilters

Eigenvectors / eigenvalues

Eigenvalues :

4428,70	1432,36	215,64	126,57	126,19	113,86	98,41	85,21	62,01

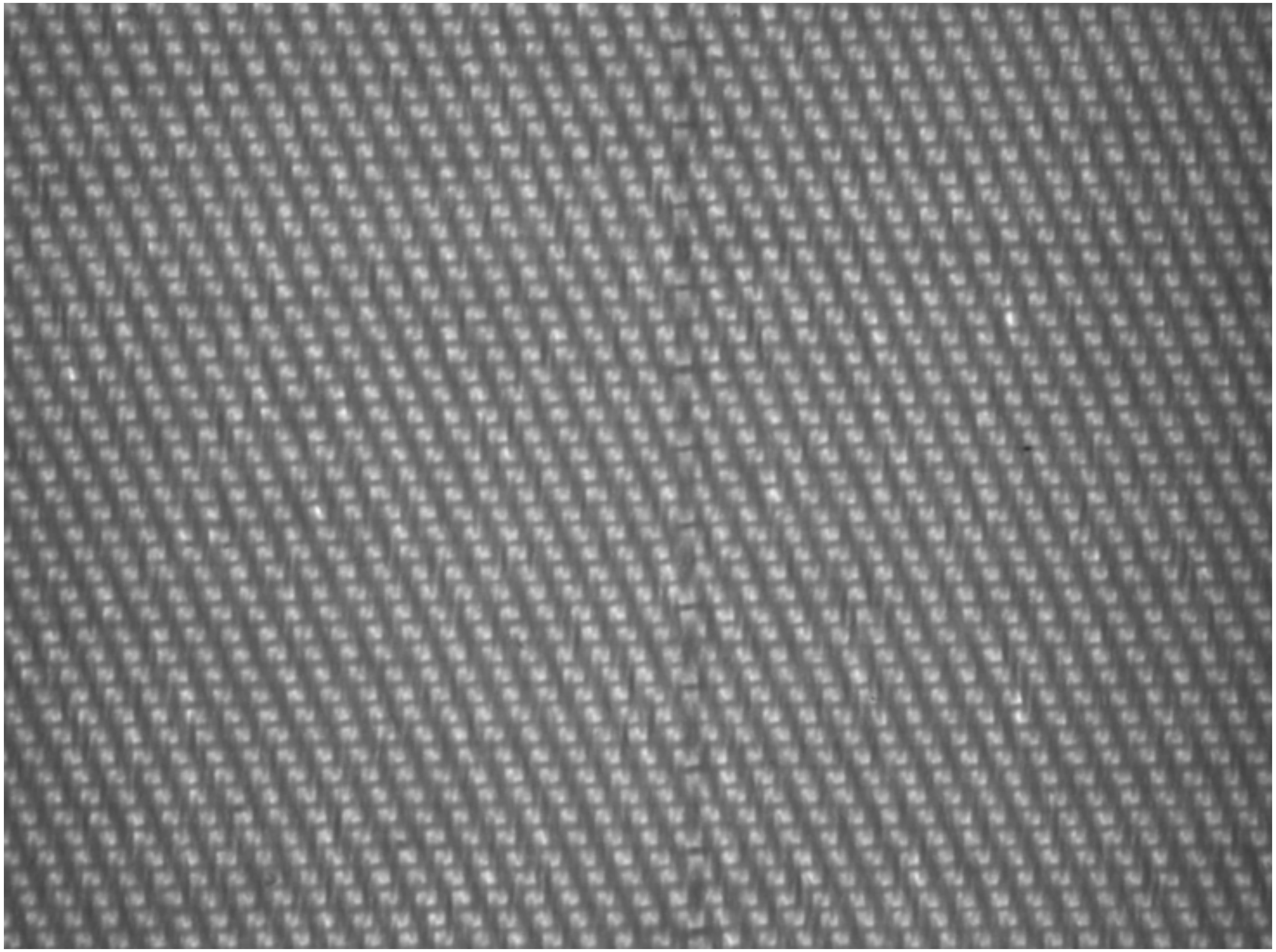
Eigenvectors :

0,337	0,292	-0,621	-0,121	0,119	-0,319	-0,229	0,040	-0,480
-0,317	0,382	0,225	0,273	-0,369	-0,465	-0,302	-0,429	-0,025
0,353	0,271	-0,055	-0,434	-0,536	0,069	-0,179	0,155	0,513
-0,314	0,400	0,240	-0,294	0,259	-0,399	0,266	0,548	0,034
0,350	0,285	-0,005	0,404	-0,292	-0,005	0,734	-0,004	-0,096
-0,318	0,381	-0,234	-0,410	0,161	0,353	0,295	-0,541	0,033
0,350	0,294	0,056	0,312	0,610	-0,056	-0,144	-0,163	0,518
-0,317	0,386	-0,219	0,421	-0,081	0,530	-0,261	0,412	-0,025
0,340	0,274	0,630	-0,173	0,079	0,330	-0,198	-0,046	-0,475

Computer Vision

Eigenfilters

example of defect

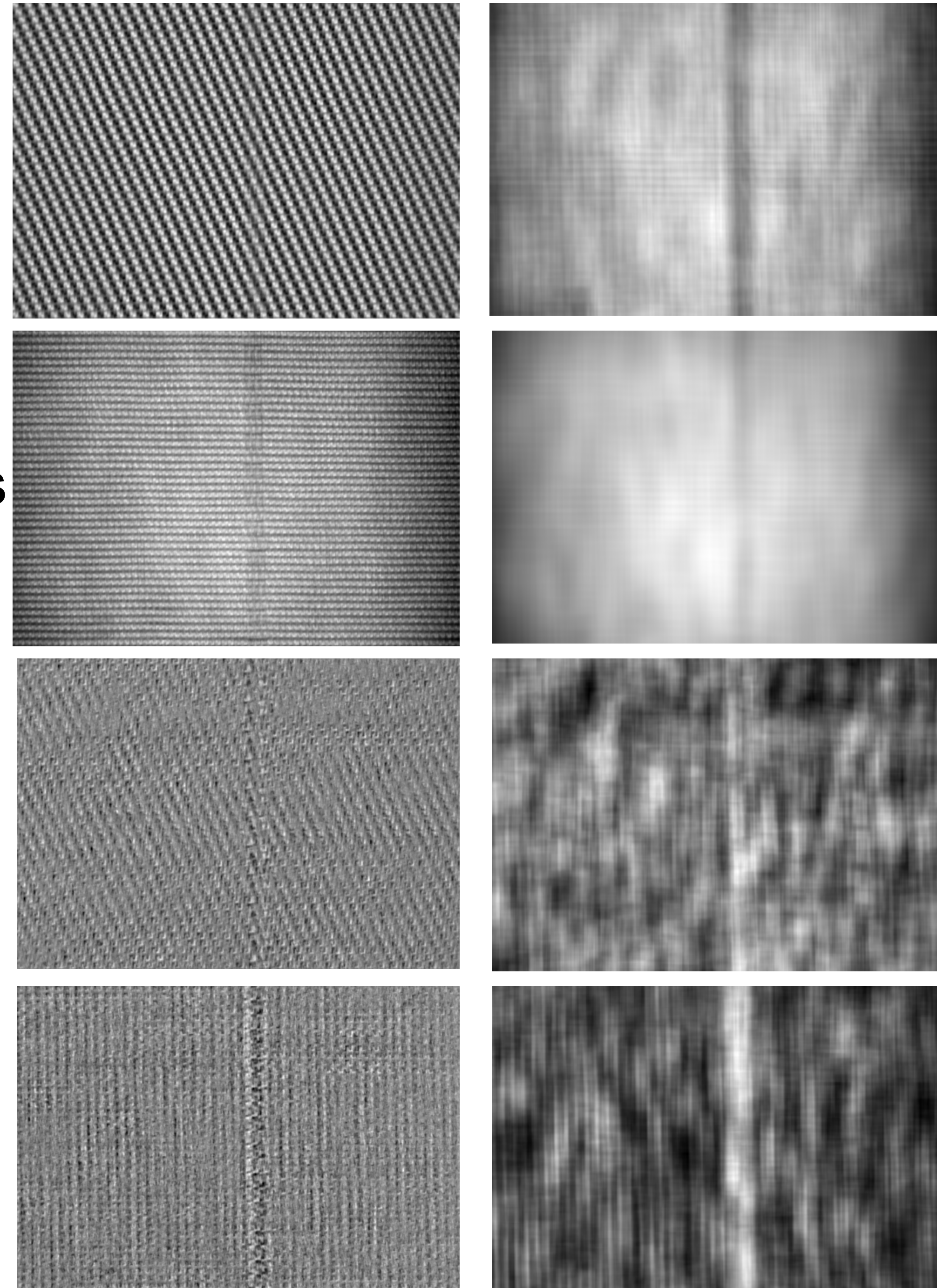


Computer Vision

Eigenfilters

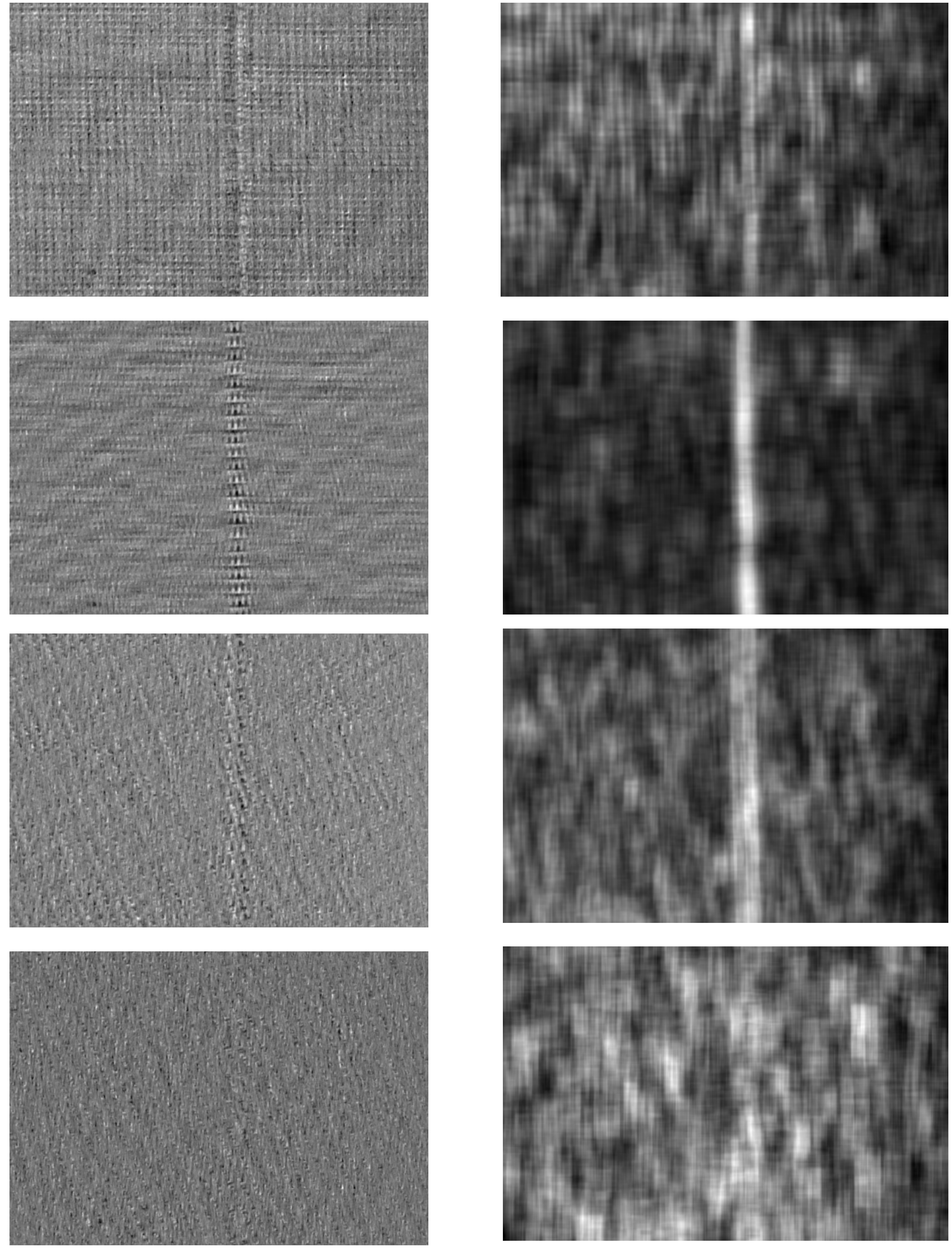
Outputs/energies for the

4 largest eigenvalues



Eigenfilters

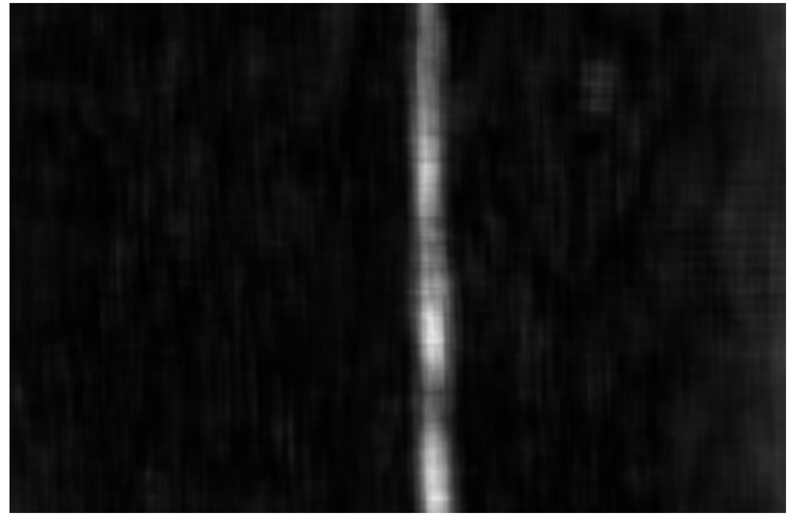
4 smallest eigenvalues



Computer Vision

Eigenfilters

Mahalanobis distance



Threshold

On the menu:

- Fourier features
- cooccurrence matrices
- filter banks (Laws, Gabor, eigenfilters)
- stochastic models

On the menu:

- Fourier features
- cooccurrence matrices
- filter banks (Laws, Gabor, eigenfilters)
- stochastic models   not to be studied