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
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
The perceptual attributes of colour

1. brightness
2. hue
3. saturation
Reminder: perception of color = 3 dim.
The history of colour

Newton → spectrum

Young → tristimulus model

later : physiological underpinning :

3 cone types
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 $\Rightarrow$ observed as same colour!
- luminance $\perp$ chrominance
- 10% of population have abnormal colour vision

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

Camera $\Rightarrow$ tristimulus values $\Rightarrow$ display

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

CIE primaries: $\lambda_1 = 700$
$\lambda_2 = 546.1$
$\lambda_3 = 435.8$

applications: practical primaries
e.g. TV: EBU and NTSC
The retinal cones

3 types: blue, green, yellow-green
The matching of colour

source \( C(\lambda) \) matched by primaries

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

\[
R_i(C) = \int \sum_{j=1}^{3} G_{i, j}(\lambda) H_i(\lambda) d\lambda
\]

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

\( l_{i,j} \)

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. $m_j$'s for white: $w_j$

$$T_j = \frac{m_j}{w_j}$$

The scaling preserves the linearity

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

\[ t_j = \frac{T_j}{T_1 + T_2 + T_3} \]

\[ t_1 + t_2 + t_3 = 1 \] allows to eliminate one

2 chromaticity coordinates specify saturation and hue
CIE chromaticity diagram

chromaticity coordinates \((r, g)\) for CIE primaries:

\[
r = \frac{R}{R + G + B} \quad g = \frac{G}{R + G + B}
\]

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

\[
x = \frac{X}{X + Y + Z} \quad y = \frac{Y}{X + Y + Z}
\]
CIE x,y colour triangle
CIE x,y colour triangle

Spectrum locus
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

\[ R_N : \quad x = 0.67 \quad y = 0.33 \]
\[ G_N : \quad x = 0.21 \quad y = 0.71 \]
\[ B_N : \quad x = 0.14 \quad y = 0.08 \]
primaries
Notes

Minimize number of 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

3 primaries + white : 4 points

4 points define a projective frame:

primaries $\Rightarrow$ (0,0), (1,0), (0,1)
white $\Rightarrow$ (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:

\[
\begin{align*}
    u &= \frac{4x}{-2x + 12y + 3} \\
    v &= \frac{6y}{-2x + 12y + 3}
\end{align*}
\]
Using colour as a feature:

- colour constancy

- illumination invariant colour features
Koffka ring with colours
Colour constancy
Colour constancy

Patches keep their colour appearance even if they reflect differently.

Patches change their colour appearance if they reflect identically but surrounding patches reflect differently.

There is more to colour perception than 3 cone responses

Edwin Land performed in-depth experiments.
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

$$\alpha, \beta, \gamma : (I'_R, I'_G, I'_B) = (\alpha I_R, \beta I_G, \gamma I_B)$$

Consider irradiances at 2 points:

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

$$\frac{I'_R}{I'_R} = \frac{(\alpha I_{R1})}{(\alpha I_{R2})} = I_{R1} / I_{R2}$$
Illumination invariant colour features

For a camera with a non-linear response:

\[ \left( \alpha d I_{R1} \right)^{\gamma} \left/ \left( \alpha d I_{R2} \right) \right)^{\gamma} = \left( I_{R1} \right)^{\gamma} \left/ \left( I_{R2} \right) \right)^{\gamma} \]

And in the case of a log-response:

\[ \log I'_{R1} - \log I'_{R2} = \log \left( I'_{R1} / I'_{R2} \right) = \log \left( I_{R1} / I_{R2} \right) = \log I_{R1} - \log I_{R2} \]
Illumination invariant colour features

2) Geometric changes
Illumination invariant colour features

1) Geometric changes

\[(I'_R, I'_G, I'_B) = (s(x, y)I_R, s(x, y)I_G, s(x, y)I_B)\]

\[I'_R / I'_G = I_R / I_G\]

and

\[I'_R / I'_B = I_R / I_B\]

are invariant
Illumination invariant colour features

3) Spectral + geometric changes
Illumination invariant colour features

3) Geometric + spectral changes

\[
\frac{I'_R I'_G}{I'_R I'_G} = \frac{\alpha s(x_1, y_1) I_R}{\alpha s(x_2, y_2) I_R} \frac{\beta s(x_2, y_2) I_G}{\beta s(x_1, y_1) I_G} = \frac{I_R I_G}{I_R I_G}
\]

(for log response

\[
\log I_R + \log I_G - \log I_R - \log I_G
\]

for points on both sides of a colour edge

\[
s(x_1, y_2) \equiv s(x_2, y_2)
\]

and hence \( \frac{I_R}{I_G} \) is invariant
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
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
Mini-dome to study reflectance
Computer Vision

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

\[ \int_A \int \left| F(u,v) \right|^2 dudv \]

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

\[ r_1^2 \leq u^2 + v^2 < r_2^2 \]

\[ \theta_1 \leq \arctan \left( \frac{u}{v} \right) < \theta_2 \]
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
Histograms : example
Cooccurrence matrix

probability distributions for intensity pairs

Contains information on some aspects of the spatial configurations
Cooccurrence matrix
Cooccurrence matrix

Features calculated from the matrix:

<table>
<thead>
<tr>
<th>feature</th>
<th>expression</th>
</tr>
</thead>
<tbody>
<tr>
<td>energy</td>
<td>$\sum_i\sum_j C^2(i,j)$</td>
</tr>
<tr>
<td>entropy</td>
<td>$-\sum_i\sum_j C(i,j) \log C(i,j)$</td>
</tr>
<tr>
<td>contrast</td>
<td>$\sum_i\sum_j (i-j)^2 C(i,j)$</td>
</tr>
<tr>
<td>homogeneity</td>
<td>$\sum_i\sum_j C(i,j) / (1 +</td>
</tr>
<tr>
<td>max. probability</td>
<td>$\max_{i,j} C(i,j)$</td>
</tr>
</tbody>
</table>
On the menu:

- Fourier features
- cooccurrence matrices
- filter banks (Laws, Gabor, eigenfilters)
- stochastic models
<table>
<thead>
<tr>
<th>Feature</th>
<th>1D filter</th>
</tr>
</thead>
<tbody>
<tr>
<td>L3</td>
<td>[ 1 2 1 ]</td>
</tr>
<tr>
<td>E3</td>
<td>[ -1 0 1 ]</td>
</tr>
<tr>
<td>S3</td>
<td>[ -1 2 -1 ]</td>
</tr>
<tr>
<td>L5</td>
<td>[ 1 4 6 4 1 ]</td>
</tr>
<tr>
<td>E5</td>
<td>[ -1 -2 0 2 1 ]</td>
</tr>
<tr>
<td>S5</td>
<td>[ -1 0 2 0 -1 ]</td>
</tr>
<tr>
<td>W5</td>
<td>[ -1 2 0 -2 1 ]</td>
</tr>
<tr>
<td>R5</td>
<td>[ 1 -4 6 -4 1 ]</td>
</tr>
<tr>
<td>L7</td>
<td>[ 1 6 15 20 15 6 1 ]</td>
</tr>
<tr>
<td>E7</td>
<td>[ -1 -4 -5 0 5 4 1 ]</td>
</tr>
<tr>
<td>S7</td>
<td>[ -1 -2 1 4 1 -2 -1 ]</td>
</tr>
<tr>
<td>W7</td>
<td>[ -1 0 3 0 -3 0 1 ]</td>
</tr>
<tr>
<td>R7</td>
<td>[ 1 -2 -1 4 -1 -2 1 ]</td>
</tr>
<tr>
<td>O7</td>
<td>[ -1 6 -15 20 -15 6 -1 ]</td>
</tr>
</tbody>
</table>
This fixed filter set yields simple convolutions but has proven very effective in some cases.
Gabor filters

Gaussian envelope multiplied by cosine

\[ g(x, y) = e^{-\frac{x^2 + y^2}{4\Delta_{x,y}^2}} \cos(2\pi u^* x + \phi) \]

The filter’s Fourier power spectrum

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

Spatial domain

Frequency domain

Good localisation in both domains
Gabor filters

\[ f = f(x, y) \quad F = F(u, v) \]

\[ x_{av} = \frac{\int_{-\infty}^{\infty} x f \tilde{f} \, dx}{\int_{-\infty}^{\infty} f \tilde{f} \, dx} \quad u_{av} = \frac{\int_{-\infty}^{\infty} u F \tilde{F} \, du}{\int_{-\infty}^{\infty} F \tilde{F} \, du} \]

\[ (\Delta x)^2 = \frac{\int_{-\infty}^{\infty} (x - x_{av})^2 f \tilde{f} \, dx}{\int_{-\infty}^{\infty} f \tilde{f} \, dx} \quad (\Delta u)^2 = \frac{\int_{-\infty}^{\infty} (u - u_{av})^2 F \tilde{F} \, du}{\int_{-\infty}^{\infty} F \tilde{F} \, du} \]

the Heisenberg uncertainty principle

\[ \Delta x \Delta u = 1 / 4\pi \]
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
Eigenfilters

Example applications: textile inspection

Filters with size of one period (period found as peak in autocorrelation)
Eigenfilters

17 pixels
Eigenfilters

Covariance matrix needed for PCA

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

\[
\begin{pmatrix}
0.35 \\
-0.33 \\
0.35 \\
-0.30 \\
0.30 \\
-0.30 \\
0.35 \\
-0.33 \\
0.35
\end{pmatrix}
\begin{pmatrix}
0.31 \\
0.12 \\
0.31 \\
0.51 \\
-0.20 \\
0.49 \\
0.34 \\
0.12 \\
0.31
\end{pmatrix}
\begin{pmatrix}
0.10 \\
0.58 \\
0.10 \\
-0.19 \\
0.41 \\
-0.19 \\
0.11 \\
0.59 \\
0.09
\end{pmatrix}
\begin{pmatrix}
0.46 \\
-0.00 \\
-0.43 \\
-0.30 \\
-0.43 \\
-0.28 \\
0.41 \\
-0.02 \\
-0.49
\end{pmatrix}
\begin{pmatrix}
-0.10 \\
-0.15 \\
-0.09 \\
0.33 \\
0.83 \\
0.33 \\
-0.13 \\
-0.14 \\
-0.06
\end{pmatrix}
\begin{pmatrix}
0.27 \\
0.11 \\
-0.11 \\
-0.62 \\
0.00 \\
0.63 \\
0.11 \\
-0.12 \\
-0.27
\end{pmatrix}
\begin{pmatrix}
-0.43 \\
-0.06 \\
-0.54 \\
-0.10 \\
0.00 \\
0.09 \\
0.55 \\
0.05 \\
0.40
\end{pmatrix}
\begin{pmatrix}
0.08 \\
-0.69 \\
0.02 \\
-0.09 \\
-0.00 \\
0.10 \\
-0.02 \\
0.69 \\
-0.09
\end{pmatrix}
\begin{pmatrix}
-0.50 \\
-0.00 \\
0.50 \\
0.00 \\
0.02 \\
0.00 \\
0.47 \\
-0.01 \\
-0.50
\end{pmatrix}
\]
Eigenfilters
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 | 0 | 0 | 0 | 0 | 0 | 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 | 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 | 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 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 |

21 columns

47 rows
### Eigenfilters

#### The covariance matrix

Covariance Matrix:

<p>| | | | | | | | |</p>
<table>
<thead>
<tr>
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</thead>
<tbody>
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<td>743.89</td>
<td>-331.82</td>
<td>632.59</td>
<td>-316.03</td>
<td>618.47</td>
<td>-298.31</td>
<td>632.41</td>
<td>-302.50</td>
</tr>
<tr>
<td>-331.82</td>
<td>741.71</td>
<td>-345.24</td>
<td>641.76</td>
<td>-330.40</td>
<td>614.36</td>
<td>-334.25</td>
<td>629.22</td>
</tr>
<tr>
<td>632.59</td>
<td>-345.24</td>
<td>738.28</td>
<td>-338.50</td>
<td>638.50</td>
<td>-343.03</td>
<td>618.37</td>
<td>-347.55</td>
</tr>
<tr>
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<td>641.76</td>
<td>-338.50</td>
<td>746.54</td>
<td>-328.93</td>
<td>634.29</td>
<td>-314.59</td>
<td>619.83</td>
</tr>
<tr>
<td>618.47</td>
<td>-330.40</td>
<td>638.50</td>
<td>-328.93</td>
<td>743.82</td>
<td>-343.16</td>
<td>643.10</td>
<td>-329.00</td>
</tr>
<tr>
<td>-298.31</td>
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<td>634.29</td>
<td>-343.16</td>
<td>739.56</td>
<td>-337.44</td>
<td>639.40</td>
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<tr>
<td>632.41</td>
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<td>618.37</td>
<td>-314.59</td>
<td>643.10</td>
<td>-337.44</td>
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<td>-328.18</td>
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<td>-302.50</td>
<td>629.22</td>
<td>-347.55</td>
<td>619.83</td>
<td>-329.00</td>
<td>639.40</td>
<td>-328.18</td>
<td>745.57</td>
</tr>
<tr>
<td>548.84</td>
<td>-316.68</td>
<td>624.75</td>
<td>-297.11</td>
<td>615.32</td>
<td>-342.03</td>
<td>636.26</td>
<td>-342.19</td>
</tr>
</tbody>
</table>
# Eigenfilters

## Eigenvectors / eigenvalues

### Eigenvalues:

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<table>
<thead>
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</tr>
</thead>
<tbody>
<tr>
<td>4428.70</td>
<td>1432.36</td>
<td>215.64</td>
<td>126.57</td>
<td>126.19</td>
<td>113.86</td>
<td>98.41</td>
<td>85.21</td>
<td>62.01</td>
</tr>
</tbody>
</table>

### Eigenvectors:

<p>| | | | | | | | | |</p>
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<thead>
<tr>
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Eigenfilters

example of defect
Eigenfilters

Outputs/energies for the 4 largest eigenvalues
Eigenfilters

4 smallest eigenvalues
Eigenfilters

Mahalanobis distance

Threshold
On the menu:

- Fourier features
- cooccurrence matrices
- filter banks (Laws, Gabor, eigenfilters)
- stochastic models
A 2-component texture model

1. Neighbourhood system

Pairs of pixels (Cliques)

Clique types:

- Same type
- Different types

2. Statistical parameter set

Intensity difference histograms:

- Appearance frequency

(additionally histogram of singletons is used)
Histogram distance:

\[ \Delta - \text{signal difference} \]

\[ f(\Delta) - \text{appearance frequency} \]

\[ \forall \text{type } t: \quad d_t = \sqrt{\sum_{\Delta} (f_t(\Delta) - f_t^{0}(\Delta))^2} \]

reference texture
Analysis (clique type selection algorithm)

0. Collect reference histograms for all clique types (restriction on maximal clique length)

1. Collect histograms for the current synthesized texture (initially random noise)

2. Select the clique type with a maximal distance

3. If maximal distance < threshold => STOP

4. Add clique type to the texture model

5. Synthesize texture based on new model

6. Go to 1
Clique type selection

reference texture

analysis steps

final synthesis

Successive neighborhood system update

9 clique types
Interaction structure for color textures
Synthesized textures

Original

Synthesis
Ex2: cedars on Sagalassos’ mountain
Ex.: cedars on Sagalassos’ mountain
Ex.: cedars on Sagalassos’ mountain

Note that texture synthesis was also used to remove the crane and van
Filling in of vegetation maps
Sagalassos landscape, synthetic
Sagalassos landscape, with interactions

AUTOMATIC
Sagalassos landscape with interactions

Example image

Synthetic image

AUTOMATIC
Viewpoint / lighting dependent textures

Real orange

Synthetic orange
Computer Vision

Real tangerine

"Banarine"

Synthetic tangerine

Banarine
Example of `smart copying`

Modified Bush 2004 election campaign ad

Bush campaign digitally altered TV ad
President Bush’s campaign acknowledged Thursday that it had digitally altered a photo that appeared in a national cable television commercial. In the photo, a handful of soldiers were multiplied many times.