Computergrafik 2: Übung 8

Corner-Detektoren, Bildsegmentierung

Organisation

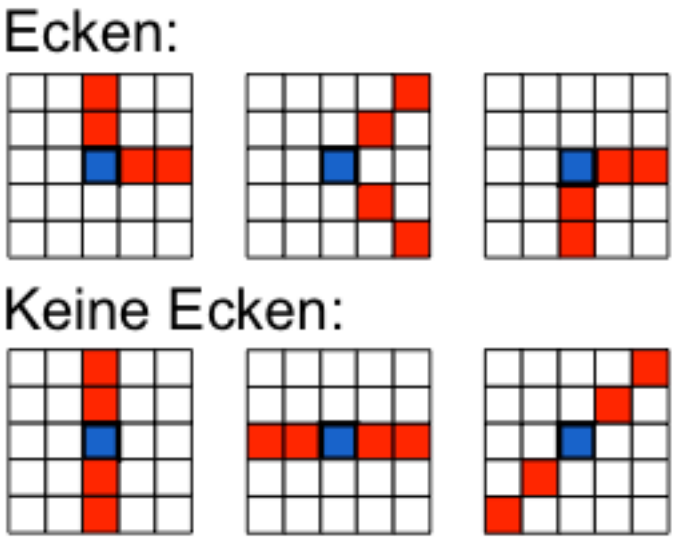
KLAUSURANMELDUNG (UNIWORX) NICHT VERGESSEN!

Besprechung Übung 7

- Anmerkungen?

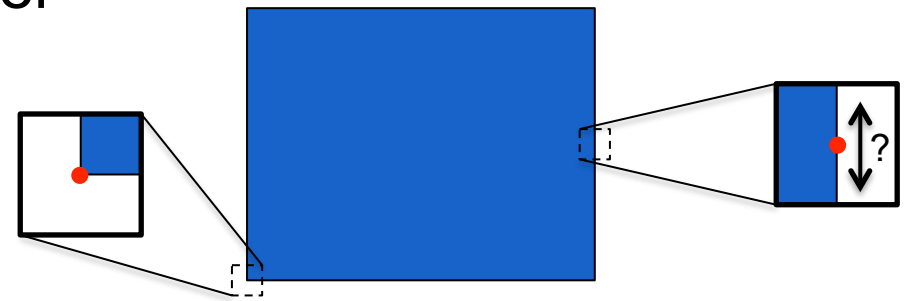
Quiz

- Was ist Non-Maximum Suppression und wofür braucht man das?
- Simple Corner Detektor: auf welchem Prinzip beruht er?
- Shading?
  - Wie kann man Shading-Probleme beheben?
- Was macht der Algorithmus von Otsu?
- Segmentierung?
  - Eigenschaften?
  - Arten?



Erkennung von Ecken

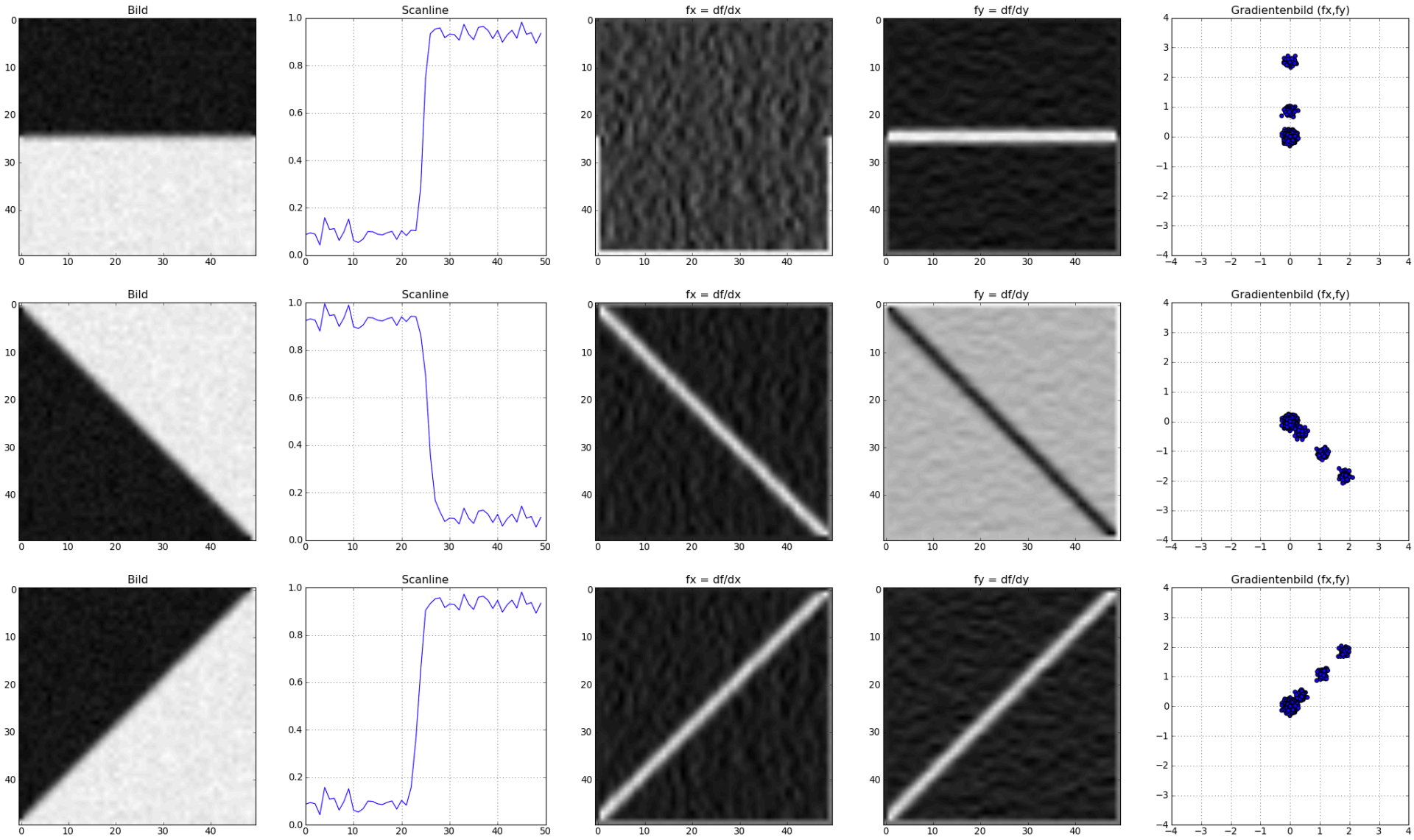
- Viele Bilderkennungsalgorithmen benötigen Merkmale, die eine stabile Position in (x,y) haben
- Kanten sind nur in einer Richtung lokalisiert
  → Ecken in zwei



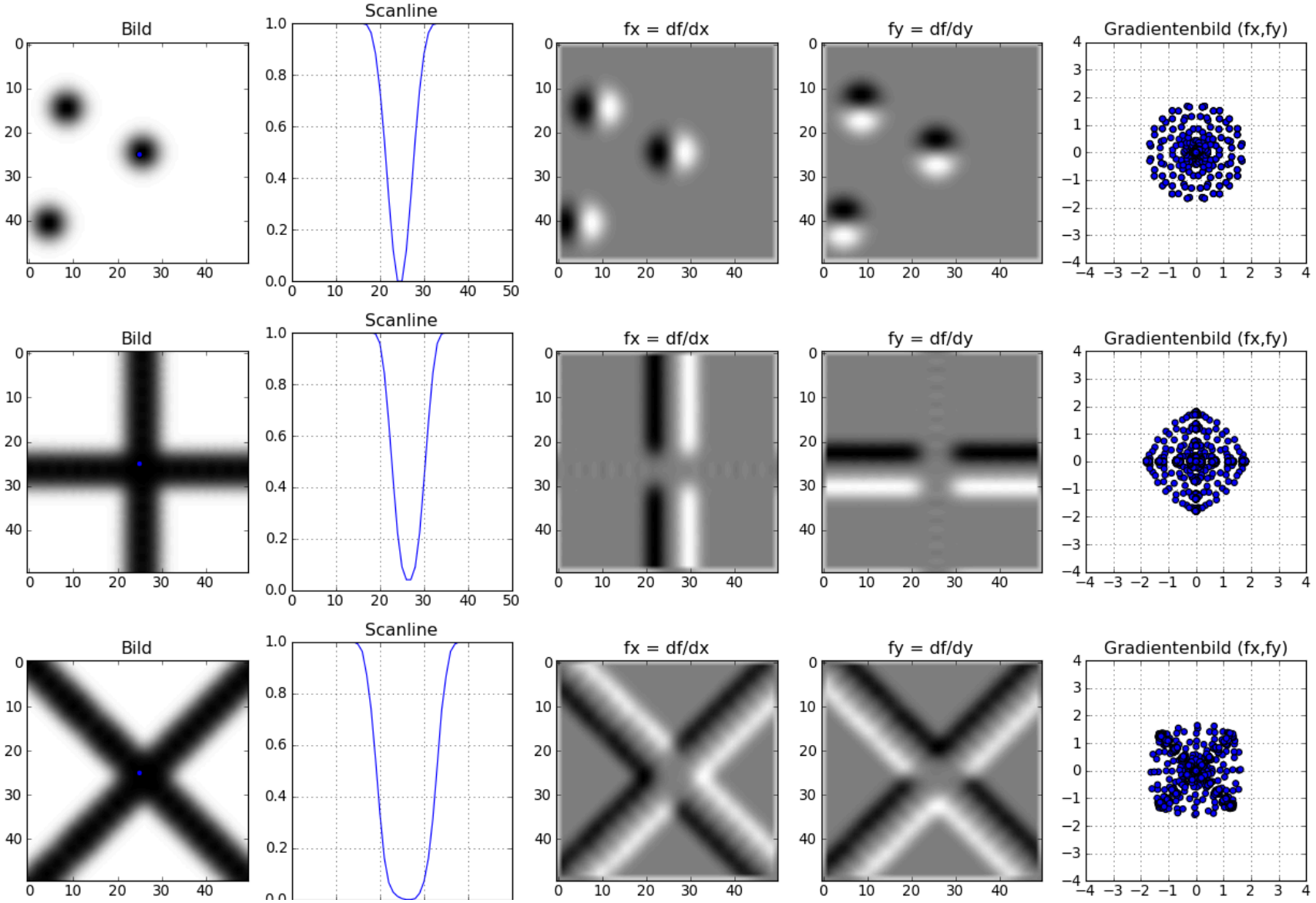
- Gewünschte Eigenschaften von Merkmalen (in verschiedenen Bildern vom gleichem Objekt / der gleichen Szene)
  - Genaue Lokalisierbarkeit
  - Invarianz gegenüber Rotation, Skalierung, Helligkeitsänderung
  - Robust gegenüber Rauschen

Slide and illustration adapted from Bernd Girod, Digital Image Processing

Verteilung der Gradienten

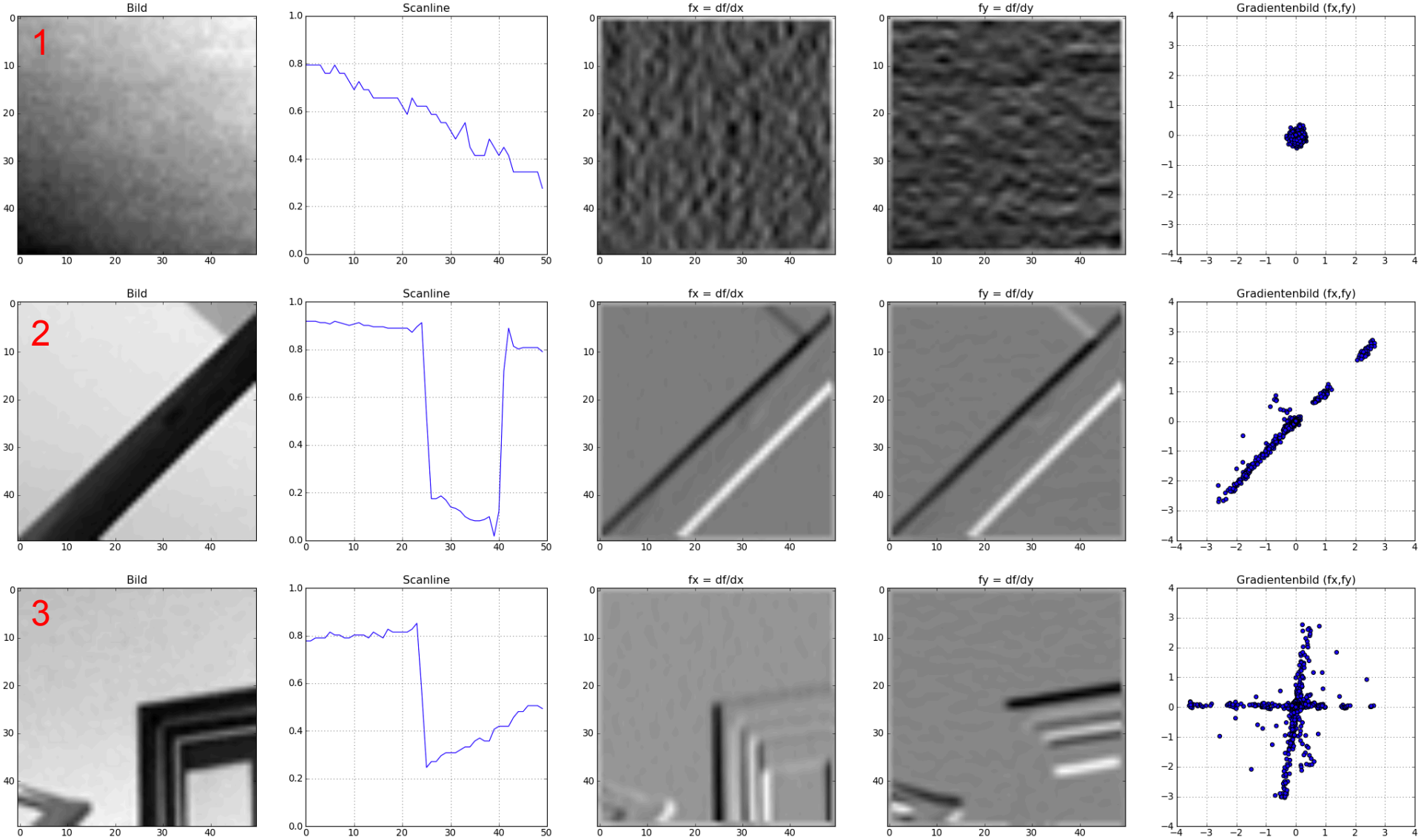


Verteilung der Gradienten



Verteilung der Gradienten in realem Bild

Verteilung der Gradienten in Bild



Gewichtete Kovarianzmatrix

$$M = \sum_{(x,y)\in window} w(x,y) * \begin{pmatrix} f_x^2(x,y) & f_x(x,y)f_y(x,y) \\ f_x(x,y)f_y(x,y) & f_y^2(x,y) \end{pmatrix}$$

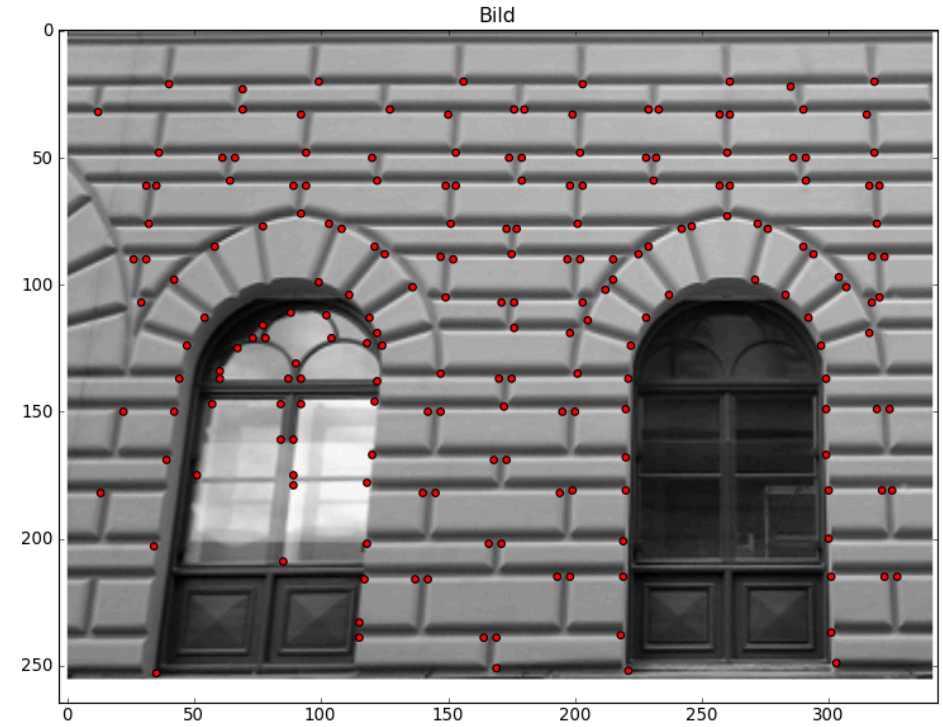
w(x,y): Gewichtungsfunktion, z.B. Gauß-Funktion

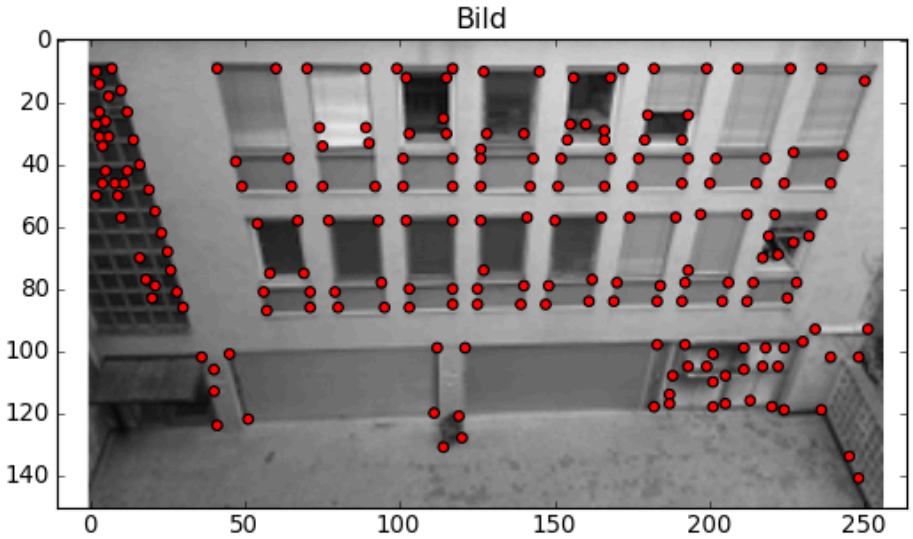
- Maß für die Stärke der Ecken

$$C(x,y) = \det(M) - k(trace(M))^2 = \lambda_1\lambda_2 - k(\lambda_1 + \lambda_2)^2$$

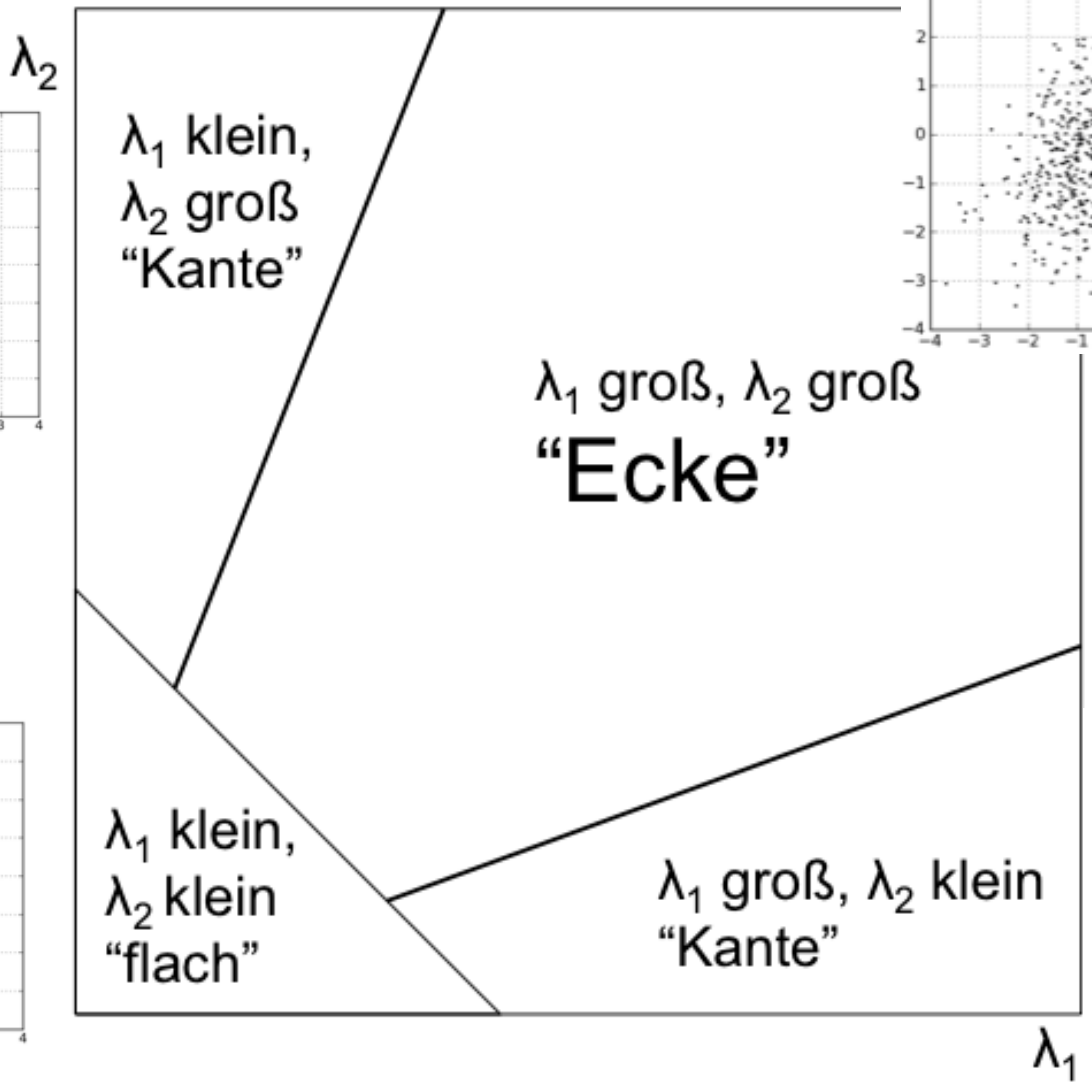
k = 0.04..0.06

Harris Corner-Detektor: Ergebnis

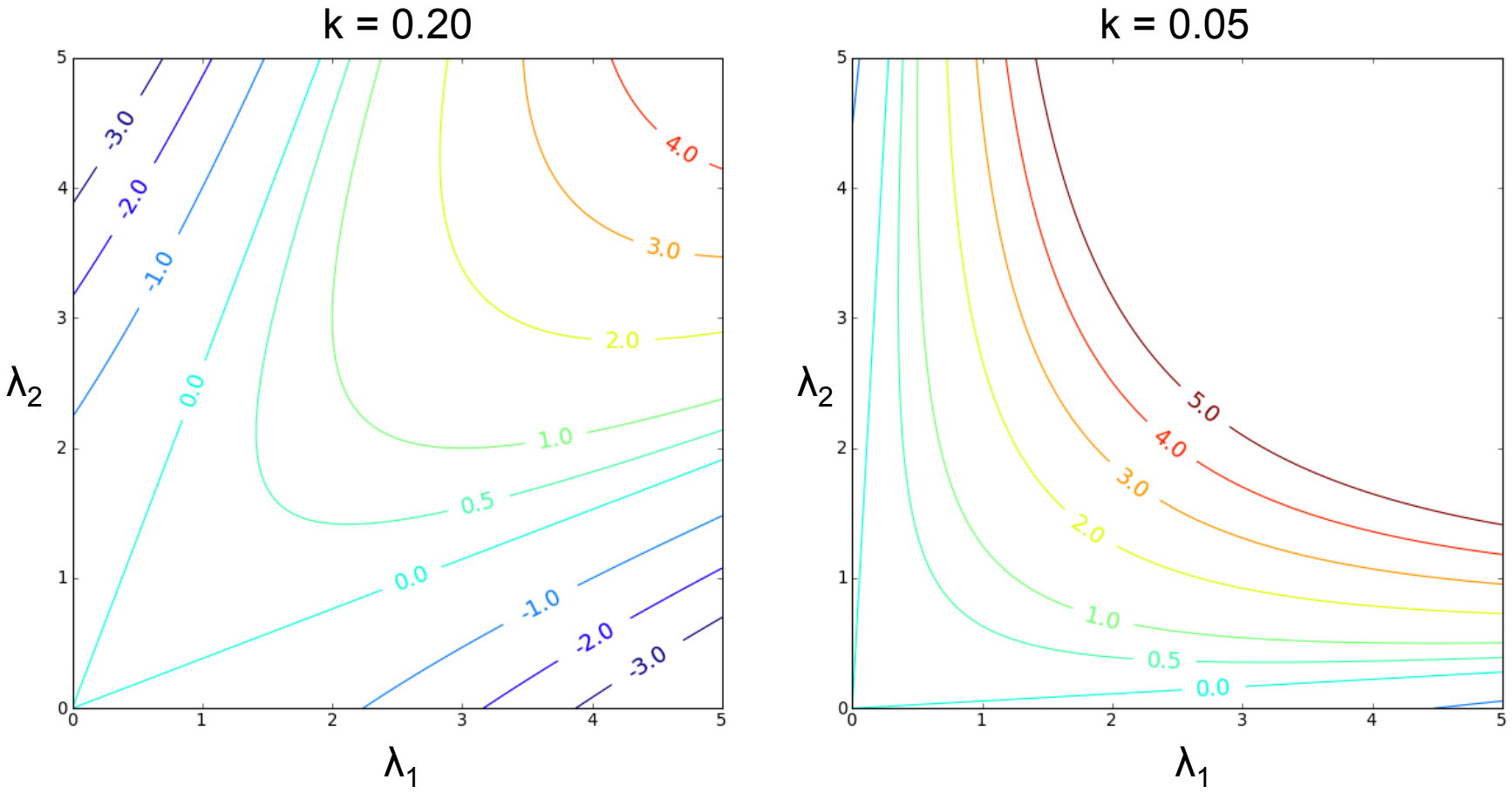




Klassifikation mittels Eigenvektoren

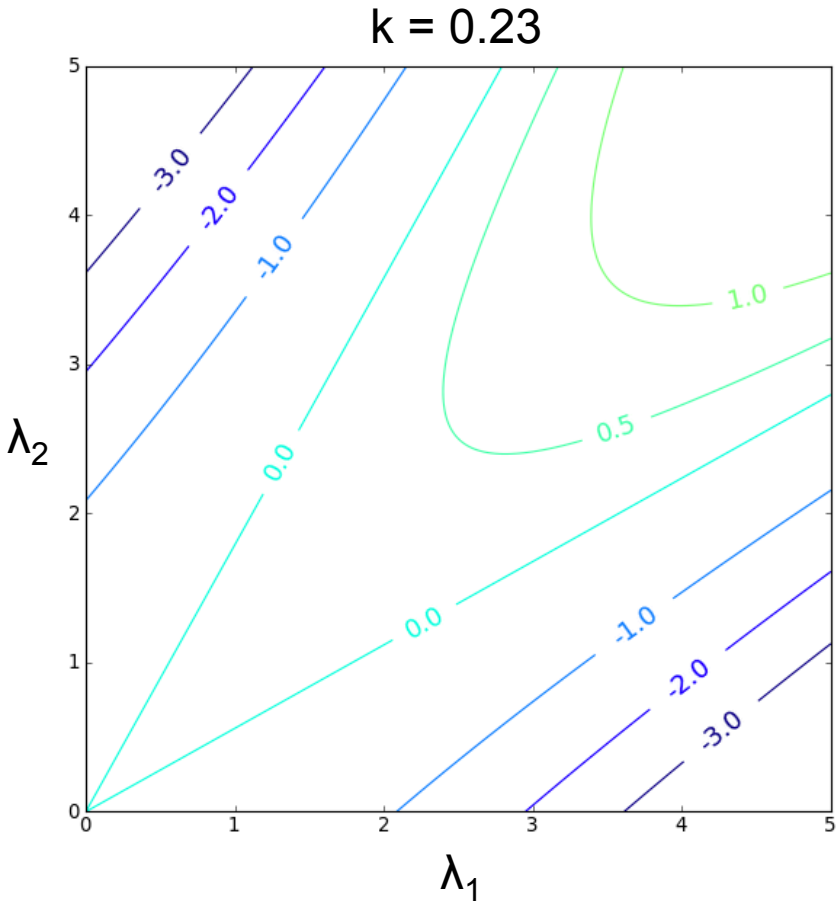


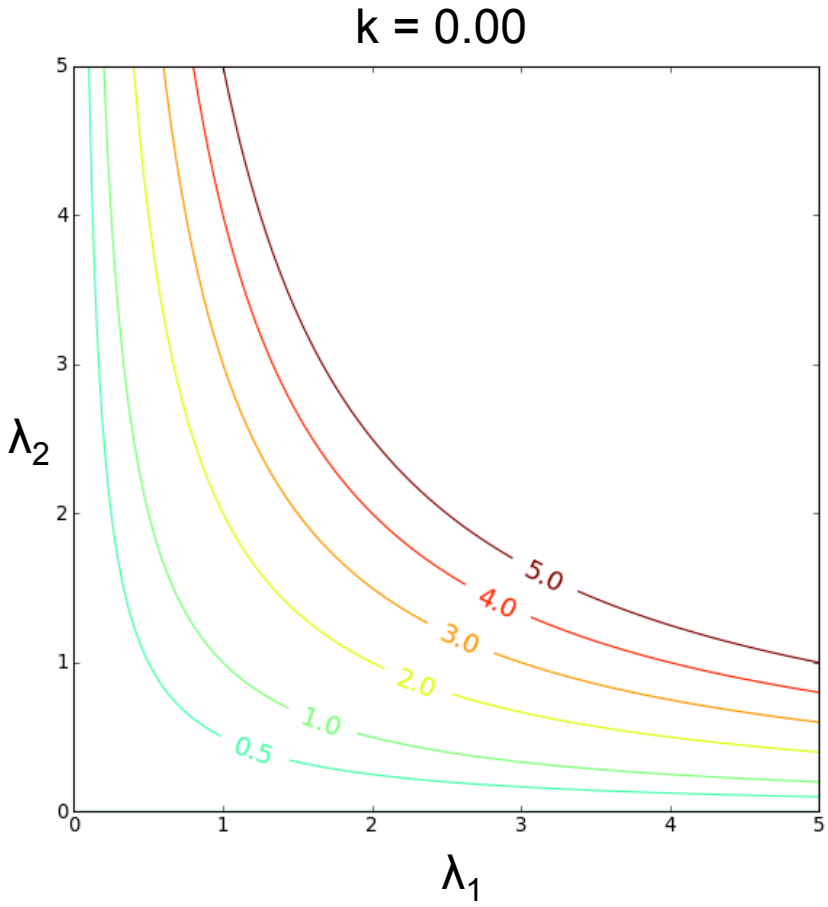
Harris Corner Detektor: Parameter “k”



- $C = \det(M) - k\ \mathrm{trace}(M)^2 = \lambda_1 \lambda_2 - k\ (\lambda_1 + \lambda_2)$

Harris Corner Detektor: Parameter “k”





- $C = \det(M) - k\ \mathrm{trace}(M)^2 = \lambda_1 \lambda_2 - k\ (\lambda_1 + \lambda_2)$

→ “Sensitivity Parameter”

Harris Corner-Detektor: Algorithmus

1. Ableitungen f_x und f_y berechnen
2. Elementweise Produkte der Ableitungen berechnen:
   $f_x^2 = f_x f_x, \quad f_y^2 = f_y f_y, \quad f_{xy} = f_x f_y$
3. Konvolution von f_x^2, f_y^2, f_{xy} mit
$$w = \begin{pmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{pmatrix}$$
4. Für jedes Pixel (x,y) definiere:
$$M(x,y) = \begin{pmatrix} f_{xxSum}(x,y) & f_{xySum}(x,y) \\ f_{xySum}(x,y) & f_{yySum}(x,y) \end{pmatrix}$$

Harris Corner-Detektor: Algorithmus

5. Maß der Eckenstärke berechnen

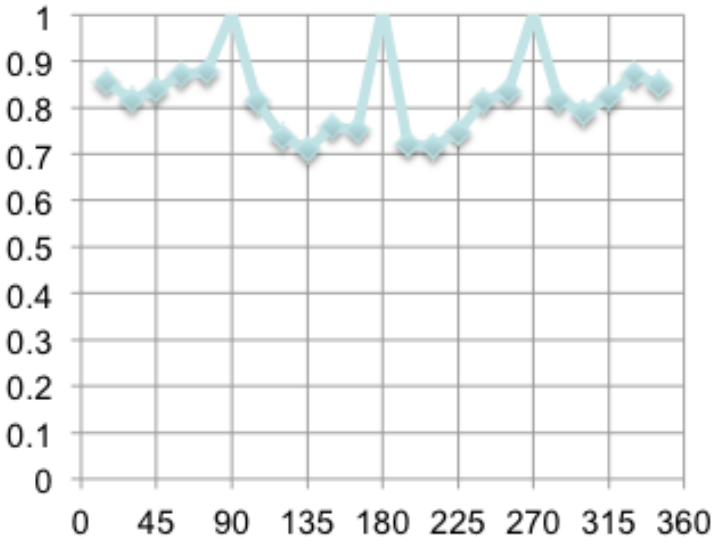
$$C(x,y) = \det(M) - k(trace(M))^2 = \lambda_1\lambda_2 - k(\lambda_1 + \lambda_2)^2$$

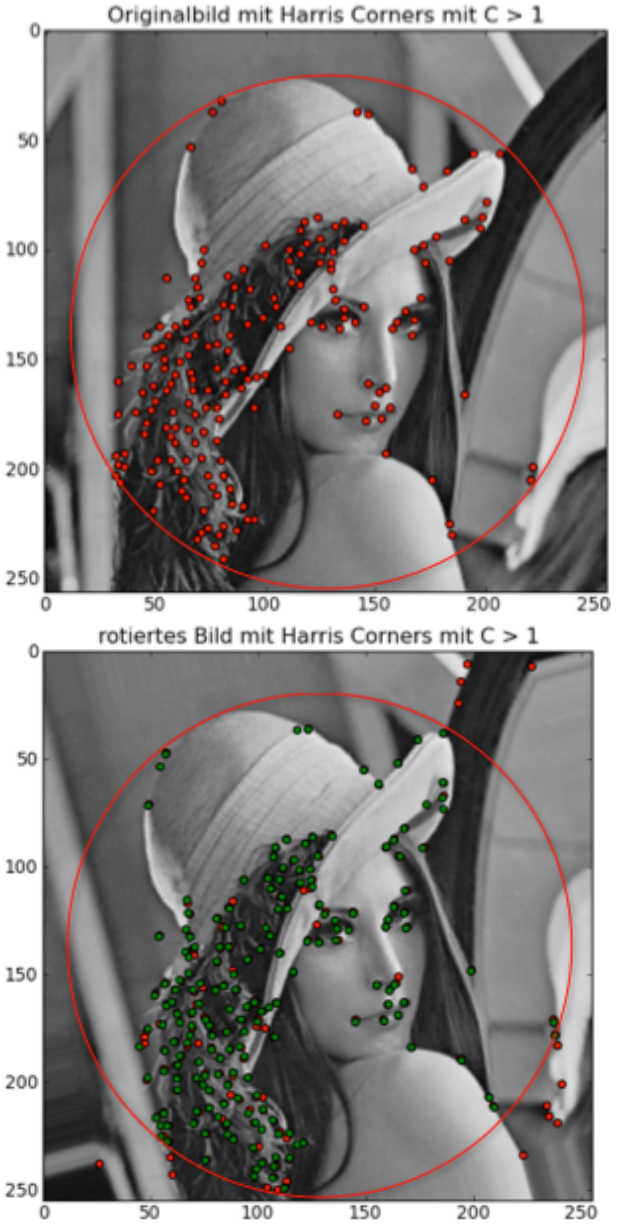
   - k = 0.04..0.06

6. Non-Maximum Suppression (R=2) anwenden

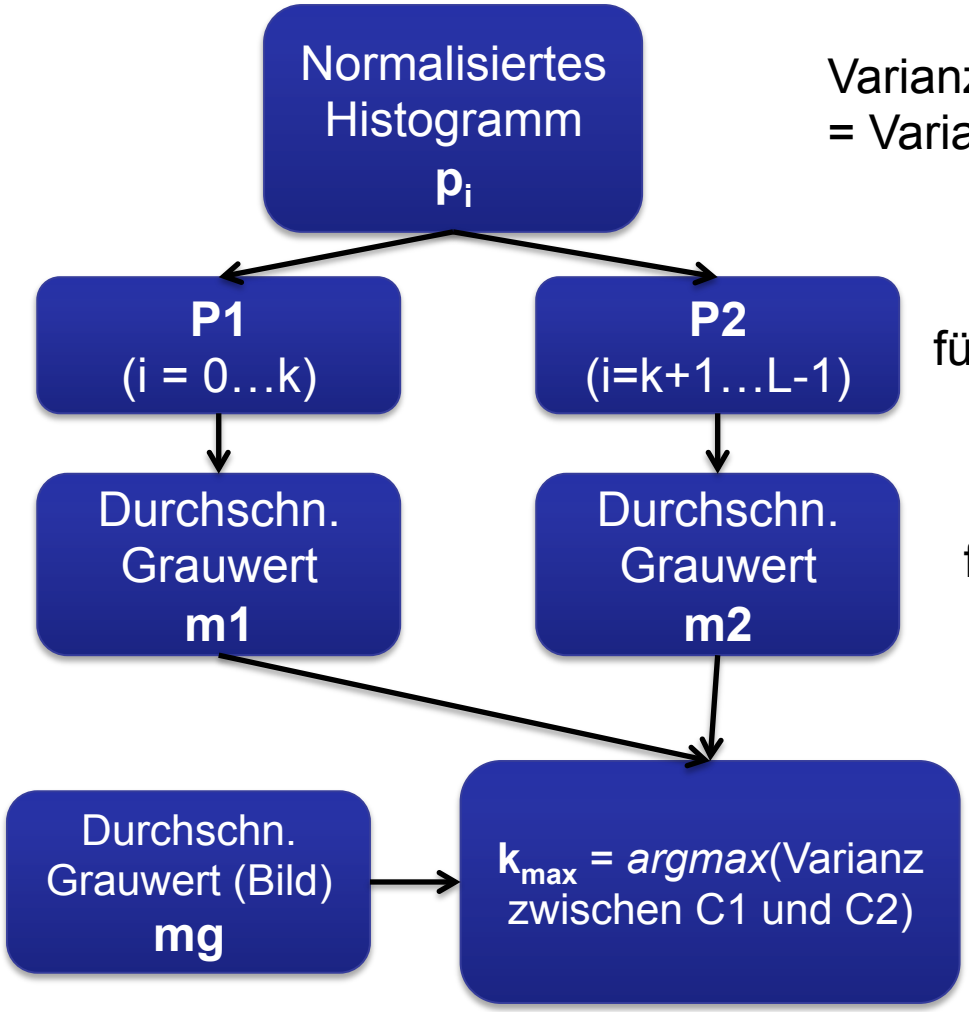
Repeatability

- Invarianz gegenüber
  - Rotation
  - Translation
  - Skalierung
  - [Perspektive]
  - [Beleuchtingsverhältnisse]





Algorithmus von Otsu



Varianz innerhalb der Klasse **minimieren**
= Varianz zwischen den Klassen **maximieren**

für alle k = 1..len(p_i) - 1

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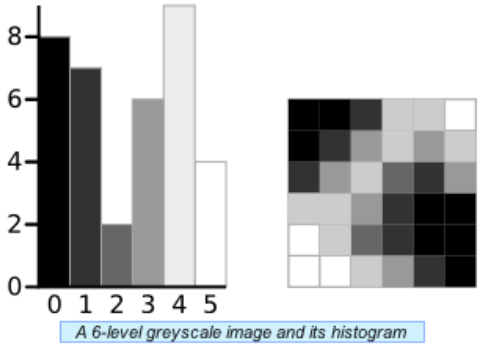
für alle k = 1..len(p_i) - 1

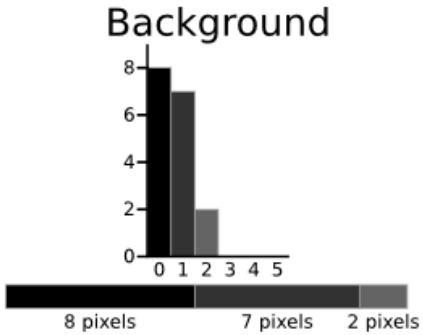
$$\sigma_B^2(k) = P_1(k) \cdot (m_1(k) - m_G)^2 + P_2(k) \cdot (m_2(k) - m_G)^2$$

Algorithmus von Otsu



A 6-level greyscale image and its histogram

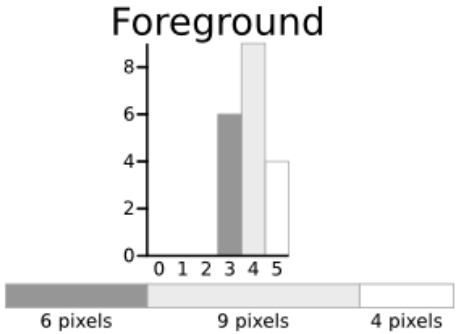
$$\text{Within Class Variance} \quad \sigma_W^2 = W_b\,\sigma_b^2 + W_f\,\sigma_f^2 = 0.4722 * 0.4637 + 0.5278 * 0.5152 = 0.4909$$



$$\text{Weight} \quad W_b = \frac{8+7+2}{36} = 0.4722$$

$$\text{Mean} \quad \mu_b = \frac{(0\times 8)+(1\times 7)+(2\times 2)}{17} = 0.6471$$

$$\text{Variance} \quad \sigma_b^2 = \frac{((0-0.6471)^2\times 8)+((1-0.6471)^2\times 7)+((2-0.6471)^2\times 2)}{17} = \frac{(0.4187\times 8)+(0.1246\times 7)+(1.8304\times 2)}{17} = 0.4637$$



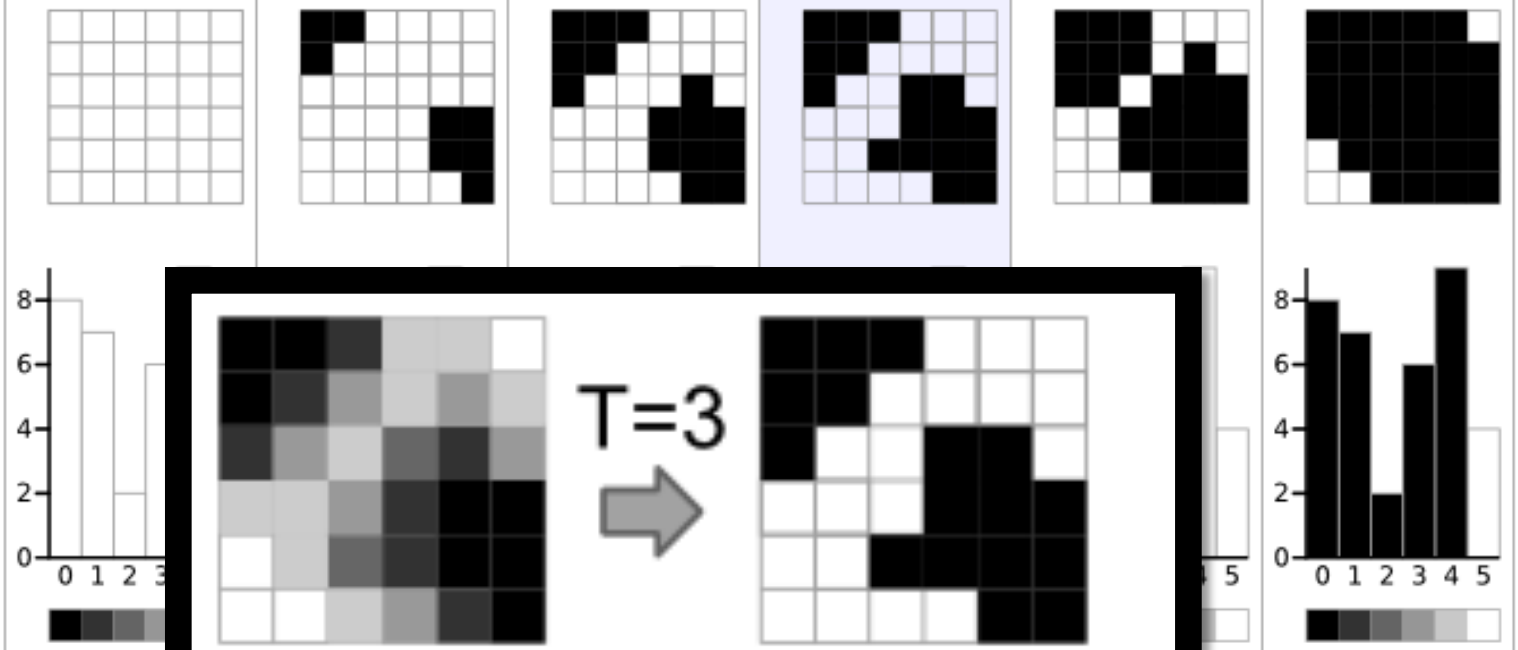
$$\text{Weight} \quad W_f = \frac{6+9+4}{36} = 0.5278$$

$$\text{Mean} \quad \mu_f = \frac{(3\times 6)+(4\times 9)+(5\times 4)}{19} = 3.8947$$

$$\text{Variance} \quad \sigma_f^2 = \frac{((3-3.8947)^2\times 6)+((4-3.8947)^2\times 9)+((5-3.8947)^2\times 4)}{19} = \frac{(4.8033\times 6)+(0.0997\times 9)+(4.8864\times 4)}{19} = 0.5152$$

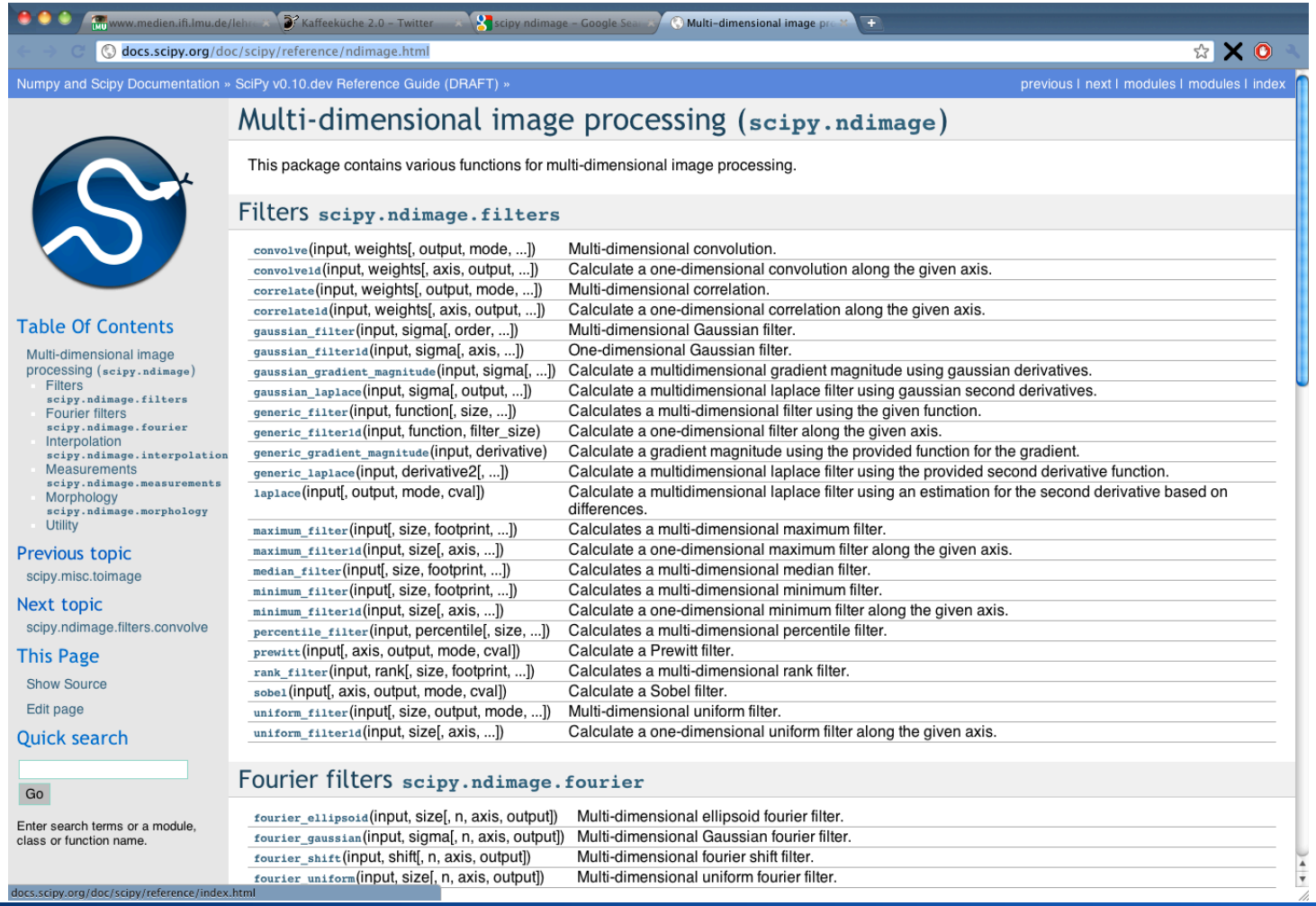
[http://www.labbookpages.co.uk/software/imgProc/otsuThreshold.html]

Algorithmus von Otsu

Threshold	T=0	T=1	T=2	T=3	T=4	T=5
						
Weight, Background	W_b =				89	W_b = 0.8889
Mean, Background	M_b =				09	M_b = 2.0313
Variance, Background	σ^2_b = 0	σ^2_b = 0	σ^2_b = 0.2489	σ^2_b = 0.4637	σ^2_b = 1.4102	σ^2_b = 2.5303
Weight, Foreground	W_f = 1	W_f = 0.7778	W_f = 0.5833	W_f = 0.5278	W_f = 0.3611	W_f = 0.1111
Mean, Foreground	M_f = 2.3611	M_f = 3.0357	M_f = 3.7143	M_f = 3.8947	M_f = 4.3077	M_f = 5.000
Variance, Foreground	σ^2_f = 3.1196	σ^2_f = 1.9639	σ^2_f = 0.7755	σ^2_f = 0.5152	σ^2_f = 0.2130	σ^2_f = 0
Within Class Variance	σ^2_W = 3.1196	σ^2_W = 1.5268	σ^2_W = 0.5561	**σ^2_W = 0.4909**	σ^2_W = 0.9779	σ^2_W = 2.2491

Numpy: ndImage Library

- http://docs.scipy.org/doc/scipy/reference/ndimage.html



Numpy: Array-Sortierung

- Mit index-Arrays lässt sich der Sortierschlüssel bestimmen

```
A.shape = (<n>,3)
A[A[:,2].argsort(),:]
```

→Sortiert alle Einträge aus a nach dem 3. Eintrag

- Alternativ: Python `itemgetter` und `sorted()` verwenden

```
from operator import itemgetter
sorted_items = sorted(A, key=itemgetter(2), reverse =
True)
```

Numpy: Nützliche Funktionen

- Rotation

```
f = scipy.ndimage.rotate(img, alpha, reshape=False,
mode='nearest')
```

`mode` : Beschreibt, wie Randpunkte "aufgefüllt" werden

- Skalierung

```
f = scipy.ndimage.zoom(img, scale, mode='nearest')
```

- Text

```
plt.text(x,y, str(label), color='red')
```