Image Preprocessing 1

KKY/USVP Lecture 2

Ing. Petr Neduchal

Department of Cybernetics
Faculty of Applied Sciences
University of West Bohemia

ESF projekt Západočeské univerzity v Plzni
reg. č. CZ.02.2.69/0.0/0.0/16_015/0002287

EVROPSKÁ UNIE
Evropské strukturální a investiční fondy
Operační program Výzkum, vývoj a vzdělávání

MINISTERSTVO ŠKOLSTVÍ, MLÁDEŽE A TĚLOVÝCHOVY

DEPARTMENT OF CYBERNETICS

Digital image processing

- **input:** image $f(i,j)$
- **output:** usually processed image $g(i,j)$
- Preprocessing method are in general los-making w.r.t. information contained in the input image. $\Rightarrow$ The best preprocessing is **NO** preprocessing.
- **GOAL:** suppress distortion, highlight parts of the image
- types of preprocessing methods based on the neighborhood:
  - brightness transformations
  - local operations
  - geometrix transformations
  - frequency analysis

EVROPSKÁ UNIE
Evropské strukturální a investiční fondy
Operační program Výzkum, vývoj a vzdělávání
MINISTERSTVO ŠKOLSTVÍ, MLÁDEŽE A TĚLOVÝCHOVY
DEPARTMENT OF CYBERNETICS

Image Brightness Characteristics

Histograms

Basic statistic description of the image brightness.

- Histogram:

$$H(p) = \sum_{i,j} h(i,j,p) = \begin{cases} 1 & for\ I(i,j) = p \\ 0 & otherwise \end{cases} \tag{1}$$

  where I is an input image, i and j are spatial coordination of pixel and p is a pixel value.

- Relative histogram:

$$H_R(p) = \frac{H(p)}{\sum_p H(p)} = \frac{H(p)}{i \cdot j}, \quad \sum_p H_R(p) = 1 \tag{2}$$

Image Brightness Characteristics

Histograms

Basic statistic description of the image brightness.

- Cumulative Histogram:

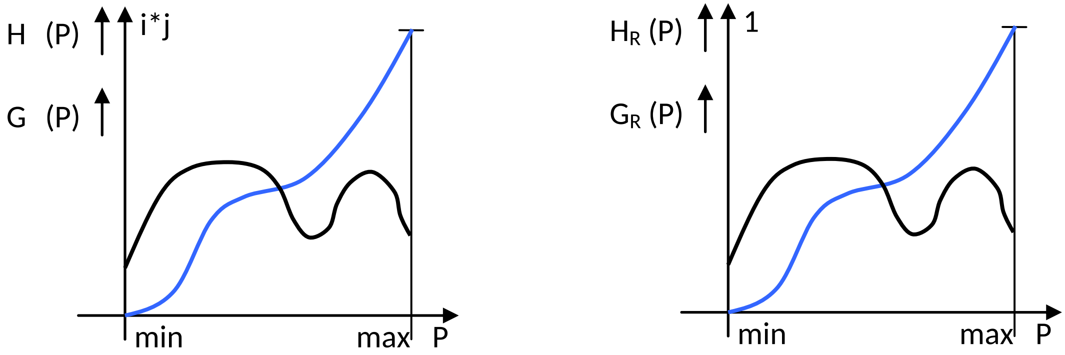
$$G(p) = \sum_{q=min}^{p} H(q) \tag{3}$$

$$G(max) = \sum_{p} H(p) = i \cdot j \tag{4}$$

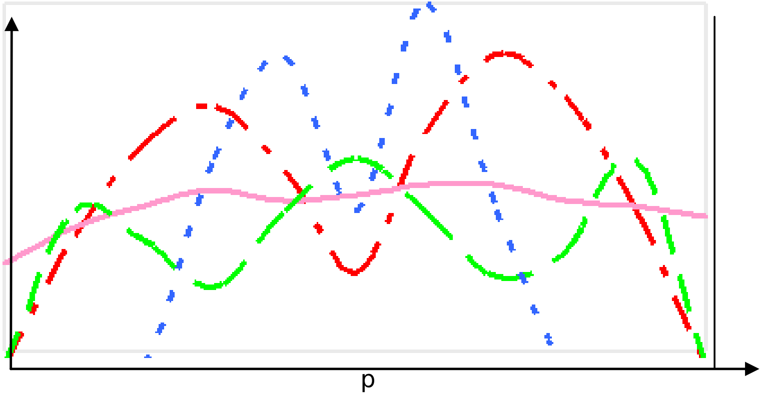
- Relative cumulative histogram:

$$G_R(p) = \frac{G(p)}{\sum_p G(p)} = \frac{G(p)}{i \cdot j}, \quad \sum_p G_R(p) = 1 \tag{5}$$

Histograms



Histogram examples



Coocurence matrix

Definition

$$S = [s_{pq}] \qquad s_{pq} = \sum_{i,j} g(i,j,p,q) \tag{6}$$

$$g(i,j,p,q) = \begin{cases} l0 & f(i,j) \neq p \\ 0 & f(i,j) = p \wedge \nexists [k,l] \in O_8 \ where \ f(k,l) = q \\ num \ of \ points & f(i,j) = p \wedge \forall [k,l] \in O_8 \ where \ f(k,l) = q \end{cases} \tag{7}$$

where $O_8(i,j)$ is 8-neighborhood of pixel i,j

EVROPSKÁ UNIE
Evropské strukturální a investiční fondy
Operační program Výzkum, vývoj a vzdělávání
MINISTERSTVO ŠKOLSTVÍ, MLÁDEŽE A TĚLOVÝCHOVY
DEPARTMENT OF CYBERNETICS

Coocurence matrix

Properties

- matrix element - expresses how many times the brightness p is neighbor to the brightness q
- is symetric
- elements on the diagonal - the brightness is neighbor to itself - a measure of the size of continuous areas
- the sum of the elements in a given row outside the diagonal - the measurement of angularity

Brightness transformations

Brightness corrections

- the new point brightness is a function of position and brightness

$$g(i,j) = FUNC(i,j,f(i,j)) \tag{8}$$

- most often: $g(i,j) = FUNC(i,j) \cdot corr(i,j)$ where corr is a matrix of correction coefficients.
- use: correction of systematic errors of the digitization process
- approach:
  - Calibration - we scan an image with known values on a scanning device. From these known correct values and from the measured values, we calculate a matrix of correction coefficients. Multiply each image by this matrix

$$corr(i,j) = \frac{correct(i,j)}{measured(i,j)} \tag{9}$$

Brightness transformations

Brightness transformations

- function the same for all pixels

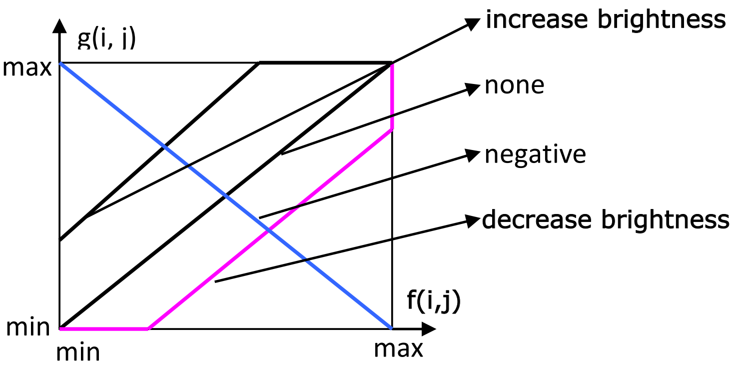
$$g(i,j) = FUNC(f(i,j)) \tag{10}$$

- FUNC does not depend on i, j
- LookUp Table

EVROPSKÁ UNIE
Evropské strukturální a investiční fondy
Operační program Výzkum, vývoj a vzdělávání
MINISTERSTVO ŠKOLSTVÍ, MLÁDEŽE A TĚLOVÝCHOVY

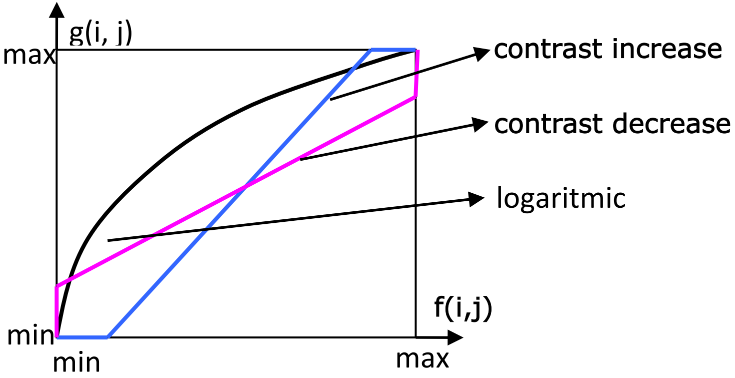
Brightness transformations

Brightness transformations - Brightness



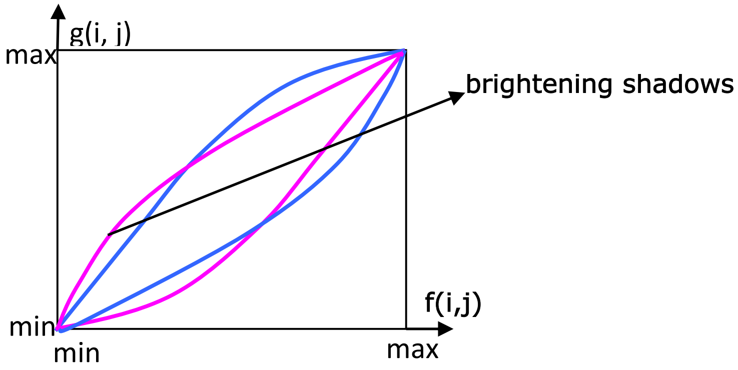
Brightness transformations

Brightness transformations - Contrast



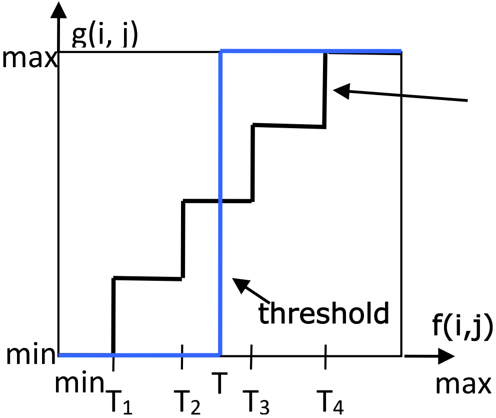
Brightness transformations

Brightness transformations - Shadows



Brightness transformations

Brightness transformations - Thresholding



More information will be provided in the next lecture.

Brightness transformations

Brightness transformations - Histogram equalization

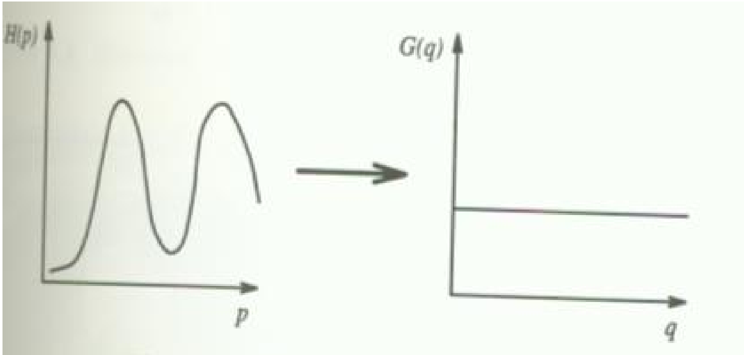


Figure 4.2 *Histogram equalization.*

Brightness transformations

Brightness transformations – Histogram equalization – Example

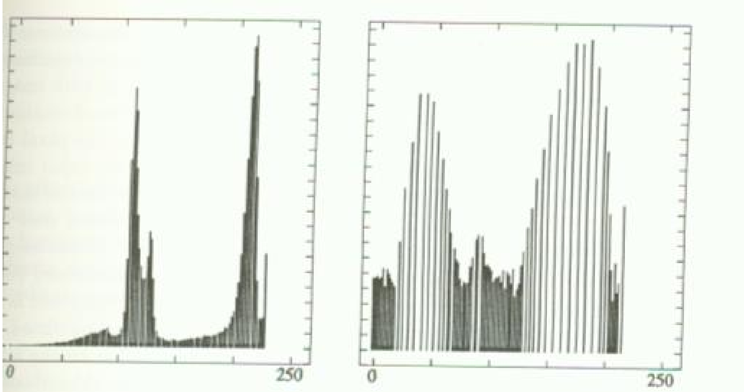


Figure 4.4 *Histogram equalization: Original and equalized histograms.*

EVROPSKÁ UNIE
Evropské strukturální a investiční fondy
Operační program Výzkum, vývoj a vzdělávání
MINISTERSTVO ŠKOLSTVÍ, MLÁDEŽE A TĚLOVÝCHOVY

Geometric Transformations

- Transformation T_G

$$i' = u(i,j) \quad j' = v(i,j) \Rightarrow g(i',j') = f(i,j) \tag{11}$$

- transformation relationship is known - e.g. rotation, translation, resize,...
- the relationship can be found based on the original and transformed image
- e.g. correspondence of coordinates on a satellite image and on a map (so-called fitting points are used)

EVROPSKÁ UNIE
Evropské strukturální a investiční fondy
Operační program Výzkum, vývoj a vzdělávání
MINISTERSTVO ŠKOLSTVÍ, MLÁDEŽE A TĚLOVÝCHOVY

Geometric Transformations

Spatial transformation

$$x' = \sum_{r=0}^{m} \sum_{k=0}^{m-r} a_{rk} x^r y^k \qquad y' = \sum_{r=0}^{m} \sum_{k=0}^{m-r} b_{rk} x^r y^k \tag{12}$$

polynomial of the mth degree

billinear

$$x^i = a_0 + a_1 x + a_2 y + a_3 xy \tag{13}$$

$$y^i = b_0 + b_1 x + b_2 y + b_3 xy \tag{14}$$

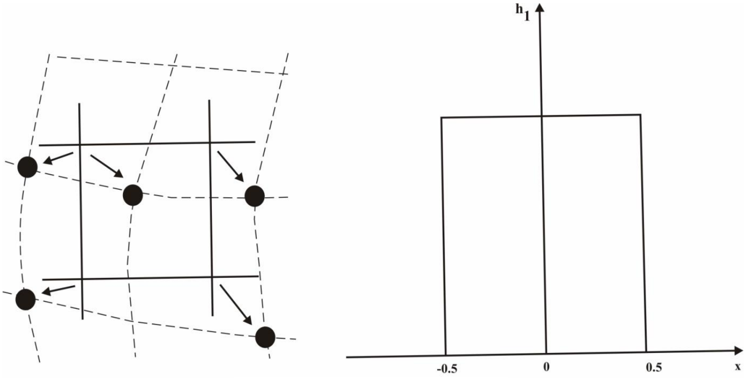
affine – rotation, translation, resize, ...

$$x^i = a_0 + a_1 x + a_2 y \tag{15}$$

$$y^i = b_0 + b_1 x + b_2 y \tag{16}$$

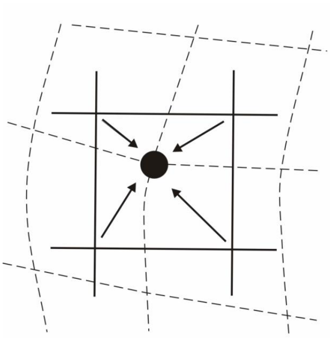
Geometric Transformations

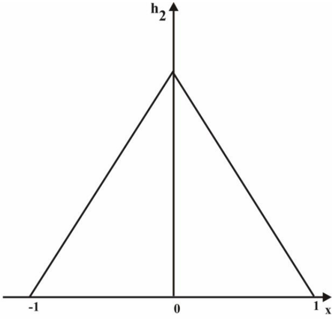
Brightness interpolation – Nearest Neighbor usually the inverse transformation is performed and the nearest value is subtracted in the original image.



Geometric Transformations

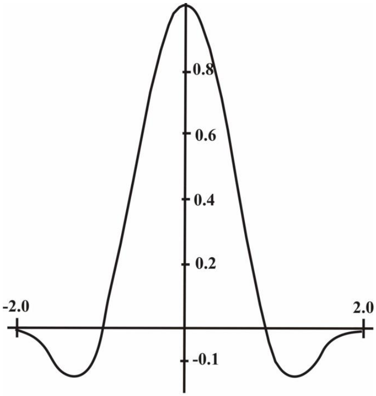
Brightness interpolation – Billinear





Geometric Transformations

Brightness interpolation – Bicubic

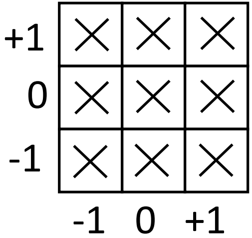


Local preprocessing

Discrete convolution

$$g(i,j) = \sum_{(m,n)\in o} \sum f(j-m, j-n) \cdot h(m,n) \tag{17}$$

where h is a mask



Local preprocessing

Smoothing

- **Goal:** noise reduction
- global smoothing trough more images ⇒ averaging over more images

$$g(i,j) = \frac{1}{n} \sum_{k=1}^{n} f_k(j,j) \tag{18}$$

  where f_k is the image function of k-th image. Image number n is usually 30-50.
- local smoothing – edges are blurred, details are lost.
  - The size of the mask should be smaller than the smallest detail in the image we want to keep.

Local preprocessing

Local smoothing masks

even mask

$$h = \frac{1}{9}\begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$$

center point advantage

$$h = \frac{1}{10}\begin{bmatrix} 1 & 1 & 1 \\ 1 & 2 & 1 \\ 1 & 1 & 1 \end{bmatrix}$$

advantage of the center point and the main axes

$$h = \frac{1}{16}\begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix}$$

disadvantage of the center point

$$h = \frac{1}{8}\begin{bmatrix} 1 & 1 & 1 \\ 1 & 0 & 1 \\ 1 & 1 & 1 \end{bmatrix}$$

EVROPSKÁ UNIE
Evropské strukturální a investiční fondy
Operační program Výzkum, vývoj a vzdělávání
MINISTERSTVO ŠKOLSTVÍ, MLÁDEŽE A TĚLOVÝCHOVY
DEPARTMENT OF CYBERNETICS

Local preprocessing

Maximum incidence smoothing - example

$$f(i,j) = \begin{bmatrix} 22 & 31 & 31 \\ 22 & 25 & 31 \\ 27 & 30 & 36 \end{bmatrix}, \qquad g(i,j) = 31 \tag{19}$$

Problems:

$$f(i,j) = \begin{bmatrix} 21 & 22 & 23 \\ 24 & 25 & 26 \\ 27 & 28 & 29 \end{bmatrix} \qquad f(i,j) = \begin{bmatrix} 8 & 19 & 26 \\ 8 & 18 & 26 \\ 8 & 19 & 26 \end{bmatrix} \tag{20}$$

EVROPSKÁ UNIE
Evropské strukturální a investiční fondy
Operační program Výzkum, vývoj a vzdělávání
MINISTERSTVO ŠKOLSTVÍ, MLÁDEŽE A TĚLOVÝCHOVY
DEPARTMENT OF CYBERNETICS

Local preprocessing

Quantile sellection - median smoothing - example

$$f(i,j) = \begin{bmatrix} 100 & 90 & 85 \\ 93 & 99 & 110 \\ 154 & 86 & 79 \end{bmatrix}, \qquad g(i,j) = 31 \tag{21}$$

Sorted:

$$79 \;\; 85 \;\; 86 \;\; 90 \;\; [93] \;\; 99 \;\; 100 \;\; 110 \;\; 154 \Rightarrow g(i,j) = 93 \tag{22}$$

- solves the problem of outlier/s – i.e., biased values
- is nonlinear
- breaks thin lines and corners

Local preprocessing

Gradient operators

- gray level discontinuity detection in the image
- can be used for segmentation
- requirements: size and orientation of the gradient
- Gradient (continuous)

$$| grad(g) | = \sqrt{\left(\frac{\partial g}{\partial x}\right)^2 + \left(\frac{\partial g}{\partial y}\right)^2} \tag{23}$$

$$\varphi = arctg\left(\frac{\partial g}{\partial y} / \frac{\partial g}{\partial x}\right) \tag{24}$$

EVROPSKÁ UNIE
Evropské strukturální a investiční fondy
Operační program Výzkum, vývoj a vzdělávání
MINISTERSTVO ŠKOLSTVÍ, MLÁDEŽE A TĚLOVÝCHOVY

DEPARTMENT OF CYBERNETICS

Local preprocessing

Gradient operators

- Gradient (discrete)

$$\Delta_x g(i,j) = g(i,j) - g(i,j-1) \qquad \Delta_y g(i,j) = g(i,j) - g(i-1,j) \tag{25}$$

$$\mid grad(g) \mid = \sqrt{(\Delta_x g)^2 + (\Delta_y g)^2} \tag{26}$$

$$\varphi = arctg\left(\Delta_y g / \Delta_x g\right) \tag{27}$$

- three types of gradient operators
  - approximation of derivatives by differences (1st and 2nd order)
  - comparison with parametric edge model
  - zero crossings of 2. derivation of image function (Marr's theory of edge detection)

Local preprocessing

Gradient operators – approximation of derivatives by differences

- Roberts

$$\begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix}, \qquad \begin{bmatrix} 0 & 1 \\ -1 & 0 \end{bmatrix} \tag{28}$$

$$g(i,j) = \mid f(i,j) - f(i+1,j+1) \mid + \mid f(i,j+1) - f(i+1,j) \mid \tag{29}$$

- Laplace

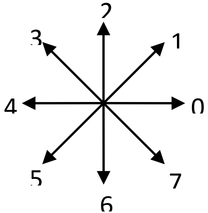
$$\begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix} \tag{30}$$

- It only specifies the size of the edge, not its direction. If we also want to know the direction of the edge, we use directionally dependent gradient operator.

Local preprocessing

Gradient operators – comparison with parametric edge model

- orientations:



$$| \, grad(g) \, | \widehat{=} max_{k=0...7}(g * h_k) \tag{31}$$

$$\varphi \widehat{=} k^* = argmax_{k=0...7}(g * h_k) \tag{32}$$

EVROPSKÁ UNIE
Evropské strukturální a investiční fondy
Operační program Výzkum, vývoj a vzdělávání
MINISTERSTVO ŠKOLSTVÍ, MLÁDEŽE A TĚLOVÝCHOVY
DEPARTMENT OF CYBERNETICS

Local preprocessing

Gradient operators – comparison with parametric edge model

- Prewitt

$$h_0 = \begin{bmatrix} 1 & 1 & 1 \\ 0 & 0 & 0 \\ -1 & -1 & -1 \end{bmatrix} \quad h_1 = \begin{bmatrix} 1 & 1 & 0 \\ 1 & 0 & -1 \\ 0 & -1 & -1 \end{bmatrix} \quad h_2 = \begin{bmatrix} 1 & 0 & -1 \\ 1 & 0 & -1 \\ 1 & 0 & -1 \end{bmatrix} \quad h_3 = \begin{bmatrix} 0 & -1 & -1 \\ 1 & 0 & -1 \\ 1 & 1 & 0 \end{bmatrix}$$

$$h_4 = \begin{bmatrix} -1 & -1 & -1 \\ 0 & 0 & 0 \\ 1 & 1 & 1 \end{bmatrix} \quad h_5 = \begin{bmatrix} -1 & -1 & 0 \\ -1 & 0 & 1 \\ 0 & 1 & 1 \end{bmatrix} \quad h_6 = \begin{bmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{bmatrix} \quad h_7 = \begin{bmatrix} 0 & 1 & 1 \\ -1 & 0 & 1 \\ -1 & -1 & 0 \end{bmatrix}$$

EVROPSKÁ UNIE
Evropské strukturální a investiční fondy
Operační program Výzkum, vývoj a vzdělávání
MINISTERSTVO ŠKOLSTVÍ, MLÁDEŽE A TĚLOVÝCHOVY
DEPARTMENT OF CYBERNETICS

Local preprocessing

Gradient operators – comparison with parametric edge model

- Sobel

$$h_0 = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix} \quad h_1 = \begin{bmatrix} 2 & 1 & 0 \\ 1 & 0 & -1 \\ 0 & -1 & -2 \end{bmatrix} \quad h_2 = \begin{bmatrix} 1 & 0 & -1 \\ 2 & 0 & -2 \\ 1 & 0 & -1 \end{bmatrix} \quad h_3 = \begin{bmatrix} 0 & -1 & -2 \\ 1 & 0 & -1 \\ 2 & 1 & 0 \end{bmatrix}$$

$$h_4 = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix} \quad h_5 = \begin{bmatrix} -2 & -1 & 0 \\ -1 & 0 & 1 \\ 0 & 1 & 2 \end{bmatrix} \quad h_6 = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} \quad h_7 = \begin{bmatrix} 0 & 1 & 2 \\ -1 & 0 & 1 \\ -2 & -1 & 0 \end{bmatrix}$$

EVROPSKÁ UNIE
Evropské strukturální a investiční fondy
Operační program Výzkum, vývoj a vzdělávání
MINISTERSTVO ŠKOLSTVÍ, MLÁDEŽE A TĚLOVÝCHOVY
DEPARTMENT OF CYBERNETICS

Local preprocessing

Gradient operators – comparison with parametric edge model

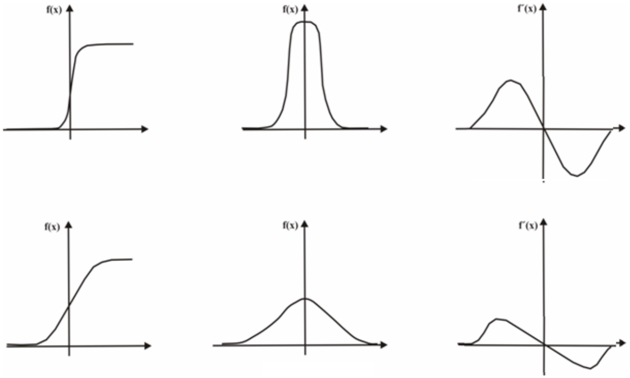
- Kirsch

$$h_0 = \begin{bmatrix} 3 & 3 & 3 \\ 3 & 0 & 3 \\ -5 & -5 & -5 \end{bmatrix} \quad h_1 = \begin{bmatrix} 3 & 3 & 3 \\ 3 & 0 & -5 \\ 3 & -5 & -5 \end{bmatrix} \quad h_2 = \begin{bmatrix} 3 & 3 & -5 \\ 3 & 0 & -5 \\ 3 & 3 & -5 \end{bmatrix} \quad h_3 = \begin{bmatrix} 3 & -5 & -5 \\ 3 & 0 & -5 \\ 3 & 3 & 3 \end{bmatrix}$$

$$h_4 = \begin{bmatrix} -5 & -5 & -5 \\ 3 & 0 & 3 \\ 3 & 3 & 3 \end{bmatrix} \quad h_5 = \begin{bmatrix} -5 & -5 & 3 \\ -5 & 0 & 3 \\ 3 & 3 & 3 \end{bmatrix} \quad h_6 = \begin{bmatrix} -5 & 3 & 3 \\ -5 & 0 & 3 \\ -5 & 3 & 3 \end{bmatrix} \quad h_7 = \begin{bmatrix} 3 & 3 & 3 \\ -5 & 0 & 3 \\ -5 & -5 & 3 \end{bmatrix}$$

EVROPSKÁ UNIE
Evropské strukturální a investiční fondy
Operační program Výzkum, vývoj a vzdělávání
MINISTERSTVO ŠKOLSTVÍ, MLÁDEŽE A TĚLOVÝCHOVY
DEPARTMENT OF CYBERNETICS

Gradient operators – Marr's theory of edge detection



zero crossings of 2. derivation of image function (1D case)

Gradient operators – Marr's theory of edge detection

- edge detection mask

$$h_0 = \begin{bmatrix} -1 & -1 & -1 \\ 2 & 2 & 2 \\ -1 & -1 & -1 \end{bmatrix} \quad h_7 = \begin{bmatrix} -1 & -1 & 2 \\ -1 & 2 & -1 \\ 2 & -1 & -1 \end{bmatrix} \quad h_2 = \begin{bmatrix} -1 & 2 & -1 \\ -1 & 2 & -1 \\ -1 & 2 & -1 \end{bmatrix} \quad h_3 = \begin{bmatrix} 2 & -1 & -1 \\ -1 & 2 & -1 \\ -1 & -1 & 2 \end{bmatrix}$$

- point detection mask

$$h = \begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix}$$

EVROPSKÁ UNIE
Evropské strukturální a investiční fondy
Operační program Výzkum, vývoj a vzdělávání
MINISTERSTVO ŠKOLSTVÍ, MLÁDEŽE A TĚLOVÝCHOVY
DEPARTMENT OF CYBERNETICS

Thank you for your attention!

Questions?