

# Computer Vision (ZDO) - Segmentation

## Introduction, Image thresholding

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# Content:

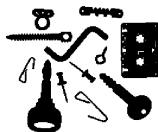
- ▶ Introduction to image segmentation
- ▶ Basic segmentation techniques
- ▶ Image thresholding
- ▶ Searching a threshold value



# Image Segmentation

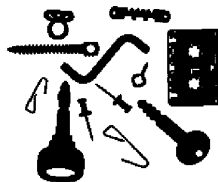
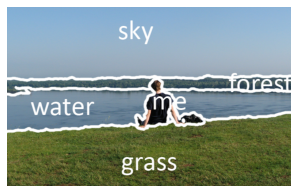
**INPUT:** INTENSITY IMAGE

**OUTPUT:** IMAGE DIVIDED INTO THE WORLD-RELATED PARTS



- ▶ The next level of image processing (does the following levels processing easier);
- ▶ Reduces the complexity by assigning a label to each pixel.

# Complete segmentation:



- ▶ The segmented areas correspond to the objects in the input image;
- ▶ For contrasting backgrounds and objects with constant brightness - we achieve good results at this level of image processing.;
- ▶ In general, however, collaboration with a higher level of processing is required, i.e. using knowledge about the problem.

## Partial segmentation:

- ▶ Segmented areas do not correspond to objects on the input image
- ▶ We get only the parts with semantic meaning;
- ▶ Segmented areas are homogeneous with respect to certain properties (brightness, color, texture, set of edges, etc.)
- ▶ Segmented areas may generally overlap;
- ▶ Additional processing needs to be applied - object description and detection.

*Examples: text segmentation, blood cells, back-light illuminated details inspected in industry - screw counting*

# Image segmentation - what method to use?

The more knowledge we have, the better. The options are:

- ▶ Required shape and appearance;
- ▶ Given pose (translation, scale, orientation)
- ▶ The start and end points of the boundary;
- ▶ The relationship of the area to other areas with the given properties.

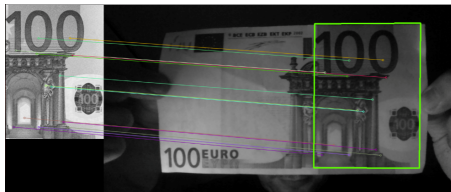
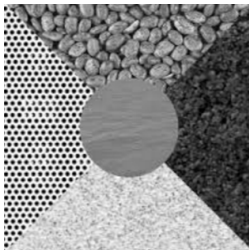
*Examples:*

- ▶ *search for ships at sea*
- ▶ *geometric properties of railways, motorways (eg maximum curvature, etc.)*
- ▶ *the rivers do not intersect*



# Main methods of segmentation:

- ▶ brightness analysis - image thresholding
- ▶ creating areas by boundaries (Active contours, ...)
- ▶ creating areas by processing regions (Split and merge; MRF; Graph-cut)
- ▶ template matching (keypoint matching)
- ▶ texture segmentation (Gabor filters, ...)
- ▶ segmentation with the model of shape and appearance (ASM, AAM, ...)
- ▶ various combinations







Variant 2: image thresholding by a set of known image brightnesses

$$g(i, j) = \begin{cases} 0 & \text{for } f(i, j) \in D \\ 1 & \text{otherwise} \end{cases} \quad (2)$$

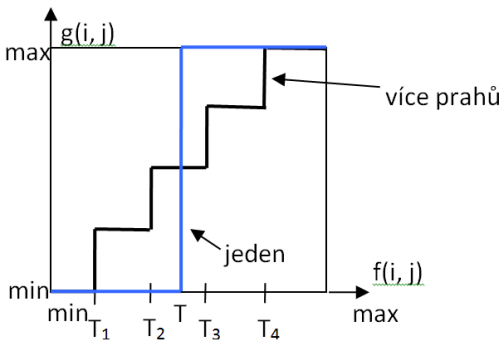
where  $D$  is the set of image pixel values corresponding to the background

*E.g. human face (skin color) or blood cell images - the cytoplasm appears in a certain range of brightness, the background is lighter, the nucleus is darker*

### Variant 3: image thresholding with multiple thresholds

$$g(i,j) = \begin{cases} 1 & \text{for } f(i,j) \in D_1 \\ 2 & \text{for } f(i,j) \in D_2 \\ \vdots & \\ n & \text{for } f(i,j) \in D_n \\ 0 & \text{other} \end{cases} \quad (3)$$

where  $D_i \cap D_j = \emptyset \quad i \neq j$



#### variant 4: partial image thresholding

$$g(i, j) = \begin{cases} f(i, j) & \text{pro } f(i, j) \in D \\ 0 & \text{otherwise} \end{cases} \quad (4)$$

where  $D$  is a set of brightnesses corresponding to multiple regions, for example, several objects

- ▶ We remove the background but keep the brightness in the areas. For example, it is used in human visual assessment of results.
- ▶  $f(i, j)$  **doesn't have to be** just a brightness function (e.g. gradient value, local texture properties, depth map, color - RGB, hue, saturation, etc.).

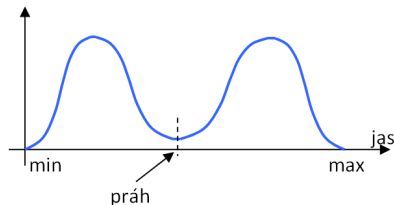
# Adaptive thresholding

- ▶ One global threshold value for the image may product segmentation errors;
- ▶ **Problem:** the image has different lighting conditions in different places;
- ▶ In this case, adaptive thresholding calculates the threshold for small regions of the image (sliding window)



# Searching for a threshold value

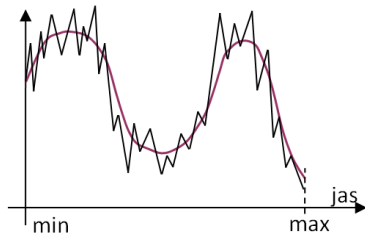
- ▶ Usually thresholding uses a threshold value as an input parameter (is known);
- ▶ How to determine this threshold **automatically**?; we can use the "trial and error" technique;
- ▶ We can use the histogram:



- ▶ a bimodal histogram (2 maxima far enough apart) is a good case;
- ▶ in this case the threshold can be identified as the value between the two hills;

## Histogram smoothing:

- ▶ We are looking for a local minimum between the two largest and sufficiently distant local maxima
- ▶ but often the decision **is not robust**



- ▶ Histogram smoothing suppresses local extremes and ideally provides a bimodal histogram (local averaging - e.g. Gaussian window or median filtering etc.).

- ▶ **automatic** threshold search method (Nobuyuki Otsu)
- ▶ Principle:
  - ▶ discrimination of two classes (histogram hills)
  - ▶ provides the optimal threshold value  $T$
- ▶ Algorithm **minimizes** the weighted variance  $\sigma_W^2$  of two brightness classes - ie background class  $b$  and foreground class  $f$
- ▶ 
$$\sigma_W^2(t) = W_b(t)\sigma_b^2(t) + W_f(t)\sigma_f^2(t)$$

# Otsu's Binarization - Algorithm

- ▶  $\sigma_W^2(t) = W_b(t)\sigma_b^2(t) + W_f(t)\sigma_f^2(t)$
- ▶ where:
  - $W_b(t) = \sum_{i=1}^t P(i)$
  - $W_f(t) = \sum_{i=t+1}^I P(i)$
- ▶  $M_b(t) = \sum_{i=1}^t \frac{iP(i)}{W_b(t)}$     $M_f(t) = \sum_{i=t+1}^I \frac{iP(i)}{W_f(t)}$
- ▶  $\sigma_b^2(t) = \sum_{i=1}^t [i - M_b(t)]^2 \frac{P(i)}{W_b(t)}$   
 $\sigma_f^2(t) = \sum_{i=t+1}^I [i - M_f(t)]^2 \frac{P(i)}{W_f(t)}$
- ▶ optimal threshold value  $T = \underset{t}{\operatorname{argmin}} \sigma_W^2(t)$  so the overall variance of both hills is minimal



Threshold	T=0	T=1	T=2	T=3	T=4	T=5
<b>Weight, Background</b>	$W_b = 0$	$W_b = 0.222$	$W_b = 0.4167$	$W_b = 0.4722$	$W_b = 0.6389$	$W_b = 0.8889$
<b>Mean, Background</b>	$M_b = 0$	$M_b = 0$	$M_b = 0.4667$	$M_b = 0.6471$	$M_b = 1.2609$	$M_b = 2.0313$
<b>Variance, Background</b>	$\sigma_b^2 = 0$	$\sigma_b^2 = 0$	$\sigma_b^2 = 0.2489$	$\sigma_b^2 = 0.4637$	$\sigma_b^2 = 1.4102$	$\sigma_b^2 = 2.5303$
<b>Weight, Foreground</b>	$W_f = 1$	$W_f = 0.7778$	$W_f = 0.5833$	$W_f = 0.5278$	$W_f = 0.3611$	$W_f = 0.1111$
<b>Mean, Foreground</b>	$M_f = 2.3611$	$M_f = 3.0357$	$M_f = 3.7143$	$M_f = 3.8947$	$M_f = 4.3077$	$M_f = 5.000$
<b>Variance, Foreground</b>	$\sigma_f^2 = 3.1196$	$\sigma_f^2 = 1.9639$	$\sigma_f^2 = 0.7755$	$\sigma_f^2 = 0.5152$	$\sigma_f^2 = 0.2130$	$\sigma_f^2 = 0$
<b>Within Class Variance</b>	$\sigma_w^2 = 3.1196$	$\sigma_w^2 = 1.5268$	$\sigma_w^2 = 0.5561$	$\sigma_w^2 = 0.4909$	$\sigma_w^2 = 0.9779$	$\sigma_w^2 = 2.2491$

Obrázek: source: <http://computervisionwithvaibhav.blogspot.cz>

# Percentage thresholding

WE have a priori knowledge of what **percent** of the image area is covered by objects; For example, the text in a printed page is around 5 % We set the threshold value so that just as many percent of the pixels have the color of the objects, the rest the background color; See fig. **cumulative histogram** for 2x different lighted scenes 70 %

