University of Ljubljana, Faculty of Electrical Engineering
Robot Vision (RV)

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Exercise 11: Visual quality control

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Instructions

Visual quality control is a process of pattern recognition based on visual or image information, the aim of which is to determined whether the object of interest of good or bad quality. Interpretation of raw image data is often very time consuming, tedious and demanding, therefore, t facilitate this task computer aided systems and methods were developed based on imaging the objects of interest and their automated extraction, analysis and classification. A general scheme of pattern recognition consists of six basic functional subsystems: **data acquisition, data preprocessing, segmentation, feature extraction, classification and evaluation of the classification performance**. During this exercise you will perform basic image segmentation, feature extraction and classification for the purpose of visual quality control of pharmaceutical tablets.

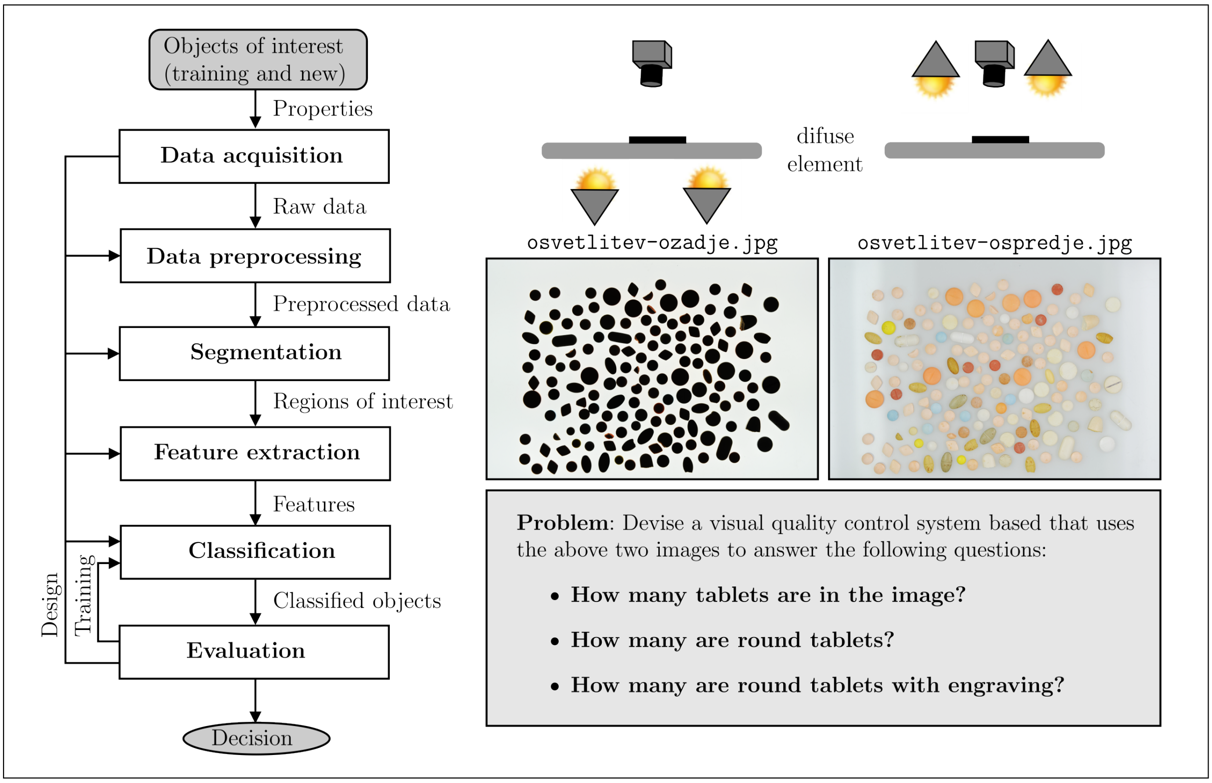


Image segmentation is a class of methods, which decompose an image into two or more regions of the objects of interest. Herein segmentation will be performed using grayscale thresholding of back-illuminated image and object labeling. The goal of object labeling is to assign a unique number or code to each of the objects in the image.

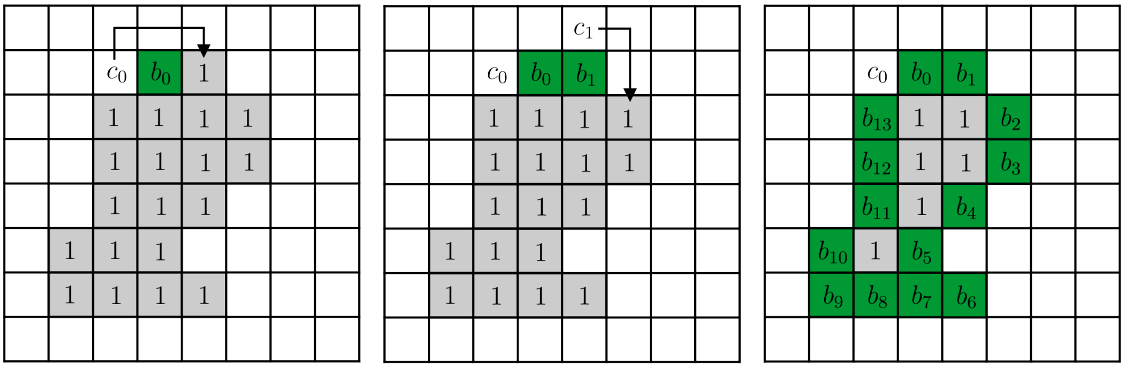
Object analysis in the segmented image can be performed based on extracting features or quantitative descriptions of the properties in each of the segmented regions. For each region we can obtain descriptions of **external properties** (e.g. region contours) and **internal properties** (e.g. regional intensity values). External properties are used to describe region shape features like circumference, orientation, largest diameter, contour smoothness, etc. Internal properties are used to describe region appearance features like intensity homogeneity, color, texture, etc.

Most basic feature of **external region properties** is its area A, which is computed as the number of pixels belonging to the region. Region contour in the binary image (0 – background, 1 - object) can be extracted using Moor's contour tracking method. Circumference P of a region is computed as the length of its contour. A feature describing the shape of an object regardless of its size and orientation is a roundness ratio:

$$K = \frac{4\pi A}{P^2}$$

which has a value of 1 for circular region, while it is less than 1 for non-circular shapes.

Moor's contour tracking method



Contour is represented as a sequence of point coordinates at the object border, ordered in the clock-wise direction:

1. Determine the initial point b_0 as the upper leftmost point of the region with value 1 and mark as c_0 the neighboring point on the left, which has value 0. Search through 8 neighboring points around b_0 by starting in point c_0 and continuing in clock-wise direction. Mark as b_1 the first neighboring point with value 1 and as c_1 the point with value 0 just before b_1 in the sequence of visited points. Remember points b_0 and b_1.
2. Let $b = b_1$ and $c = c_1$.
3. Mark 8 neighboring points $n_1, n_2, \dots, n_8$ of point b, which start in point c and continue in clock-wise direction, then search for the first point n_k with value 1.
4. Let $b = n_k$ and $c = n_{k-1}$.
5. Repeat steps 3 and 4 until you reach the initial point $b = b_0$, which is followed by the same previously determined point b_1.

After termination the list of points b_i represents the points on the object contour ordered in clock-wise direction.

Internal region properties can be simply described by computing statistical moments of the intensity values in pixels within the region. Let $p(z)$ represent a probability distribution of grayscale intensity values within each region, which can be approximated by normalizing the histogram of the intensity values of pixels within region. Central moment of n-th order can be computed as:

$$\mu_n = \sum_{i=0}^{L-1} (z_i - m)^n \, p(z_i), \text{ kjer povprečje } m \text{ izračunamo kot } m = \sum_{i=0}^{L-1} z_i \, p(z_i)$$

Zeroth moment μ_0 is always 1, while the first moment is always 0. Second moment represents variance σ^2, which indicates the amount of intensity dispersion or intensity contrast and can be used to describe the homogeneity of the region:

$$G = \frac{1}{1 + \sigma^2}$$

This feature has value 1 on regions with perfectly homogeneous intensity and approaches value 0 on regions of high intensity variance.

Texture of an object can be described using principal components, for instance, by computing image gradient $\nabla I = [g_x \; g_y]^{\mathrm{T}}$ and then, for pixels within the region, compose a $N \times 2$ array of gradients $\boldsymbol{\nabla I}$ and compute a gradient covariance matrix $\boldsymbol{C} = (\boldsymbol{\nabla I})^{\mathrm{T}} \boldsymbol{\nabla I}$ with dimensions 2×2.

Finally, we can determine the eigenvalues of the matrix $\boldsymbol{C} \rightarrow \lambda_1, \lambda_2$, which encode the properties of the object texture. To indicate objects with textures dominantly oriented in one direction we can derive the following feature:

$$R = 1 - \frac{\min\{\lambda_1,\, \lambda_2\}}{\max\{\lambda_1,\, \lambda_2\}}\,.$$

Feature R will take on value 0, if object texture has no dominant direction, or value 1 if it has a single dominant direction.

Materials for this exercise are two color images `osvetlitev-ozadje.jpg` and `osvetlitev-ospredje.jpg`, which were acquired by illuminating the objects of interest (pharmaceutical tablets) from back and front, respectively. The images depict pharmaceutical tablets of different shape, colors and textures, while some of the tablets also have an engraving.

1. Load image `osvetlitev-ozadje.jpg` and convert to grayscale, then apply thresholding t that results in a binary image that separate the tables from the background. The optimal threshold t can be determined based on grayscale image histogram.

2. Verify the influence of functions for morphologic binary image filtering, such as `erosion()`, `dilation()`, `opening()` and `closing()` that can be found in Python library package `skimage.morphology`. Filter kernel can be obtained using function `disk()`. Use the thresholded binary image to test the impact of these functions.

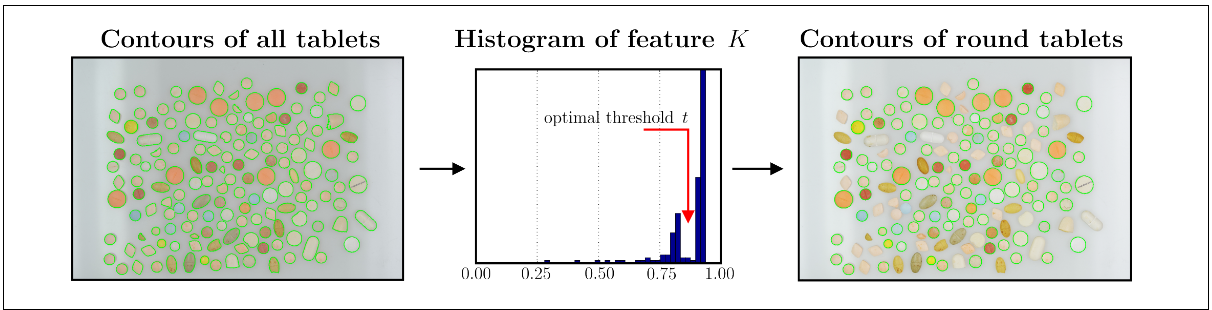
   After filtering the binary image, each object can be assigned a unique number or code using function `label()` in Python library package `skimage.measure`. Use these functions to determine how many tablets are depicted on the image. Verify the influence of morphologic filtering and its parameters on the number of detected tablets in the image.

3. Write a function that determines the coordinates of the contour of each object on the 2D image:

   ```
   def trackContour( iLabel, iObject ):
       return oContour
   ```

   where `iLabel` is the thresholded and labeled image, `iObject` the object label, for which we want to determine the contour. Function should return a variable `oContour` in the form of $2 \times M$ array with contour coordinates $[x_i y_i]^{\mathrm{T}}$, $i = 1, \ldots, M$.

   Determine the contours of all labeled objects obtained in Assignment 1. Display image `osvetlitev-ospredje.jpg` and superimpose the found contours of labeled objects as shown on the *left* in figure below.



4. Write a function that extracts features of labeled object on the 2D image:

   ```
   def extractFeatures( iImage, iLabel ):
       return oFeatures
   ```

   where `iImage` is grayscale image with front illumination, `iLabel` an image of labeled objects, for which we want to extract the features. Function should return a variable `oFeatures` in the form of feature vector $[A, P, K, \mu_2, G, R]^{\mathrm{T}}$ with dimensions $6 \times N_{obj}$. Features describing the inner properties of the objects should be computed on an eroded object mask, which can be obtained using `iMask = erosion(iLabel, disk(3))`.

   Draw 1D histograms of each of the features across all object in the image. Consider which feature or which combination of features are most suitable to detect round tablets and tablets with engraving?

5. Devise binary classifiers based on the images of labeled objects `iLabel` and their features $[A, P, K, \mu_2, G, R]^{\mathrm{T}}$ so as to answer the following questions:

   - How many tablets are in the image?
   - How many are round tablets?
   - How many are round tablets with engraving?

   Consider how the performance in terms of accuracy and reliability of this classification process could be evaluated.