



Image Analysis and Object Recognition

Exercise 5

Summer Semester 2024

(Course materials for internal use only!)

Computer Vision in Engineering – Prof. Dr. Rodehorst

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Agenda

Topics:

- Assignment 1.** Image enhancement, Binarization, Morphological operators
- Assignment 2.** Gradient of Gaussian filtering, Förstner interest operator
- Assignment 3.** Shape detection based on Hough-voting
- Assignment 4.** Frequency domain filtering, Shape recognition via Fourier descriptors
- Assignment 5.** **Clustering and Region Growing for Image Segmentation**
- Assignment 6.** Convolutional neural networks for image classification
- Final Project.** - *Will be announced during the last exercise class* -

Agenda

Start date and submission deadlines:

Assignment 1.	18.04.24 – 01.05.24
Assignment 2.	02.05.24 – 15.05.24
Assignment 3.	16.05.24 – 29.05.24
Assignment 4.	30.05.24 – 12.06.24
Assignment 5.	20.06.24 – 26.06.24
Assignment 6.	27.06.24 – 10.07.24
Final Project.	11.07.24 – 22.09.24

Wednesday by 23:00
(Central European Time)

Online Course Evaluation

Teaching Evaluation:

URL: <https://evasys.uni-weimar.de/evasys/online/>

Code: GYA9W



TAN /
Lösung:

Formularformat:

OK



Assignment 4: **Sample Solution**

Assignment 4: Overview

Topics:

- Filtering in frequency domain
- Shape recognition using Fourier descriptors

Goal:

- Practice noise removal in the frequency domain (Task A)
- Practice automatic shape detection using Fourier descriptors (Task B)

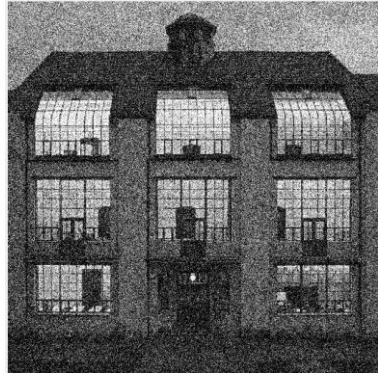
Input:

- All images provided for this assignment can be found on Moodle course page

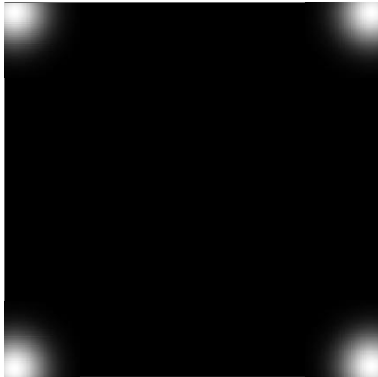
Task A

Note:
All Fourier spectra are on this slide have been logarithmically **scaled** and **shifted** for better **visualization only**.

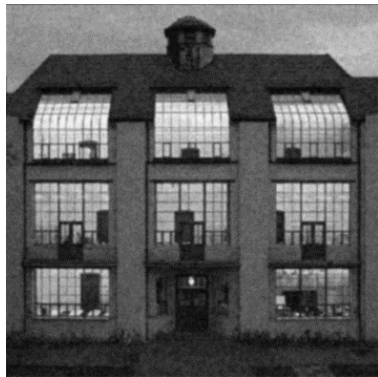
$$f(x, y)$$



$$h(x, y)$$



$$g(x, y)$$



FFT



1

FFT

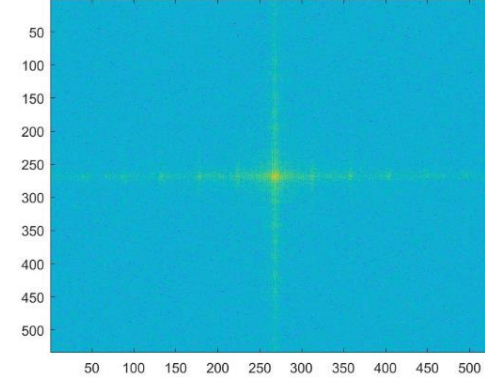


FFT⁻¹



3

Spectrum of noisy image



$$F(u, v)$$

*

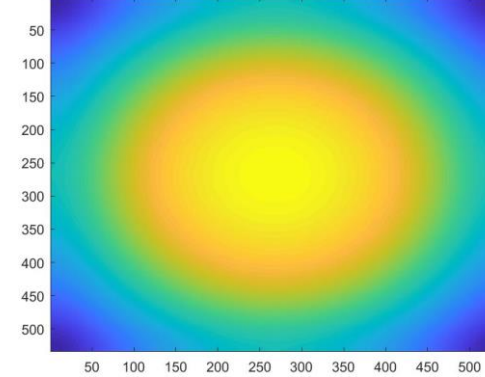
2

$$H(u, v)$$

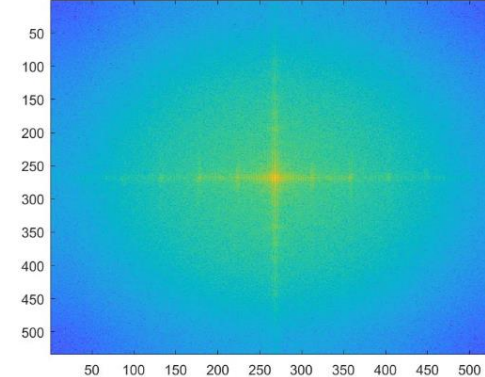


$$G(u, v)$$

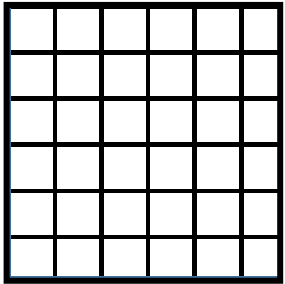
Spectrum of Gaussian filter



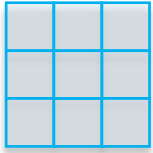
Spectrum of filtered image



Task A

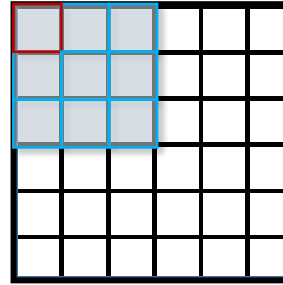


image

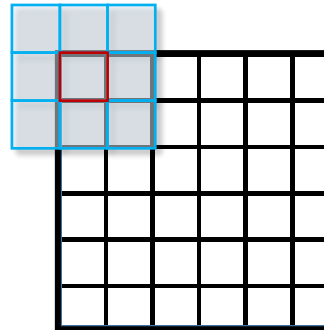


filter mask

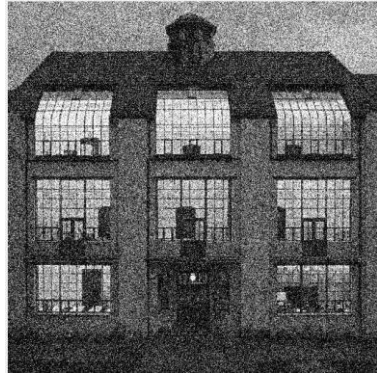
No Filter Centering



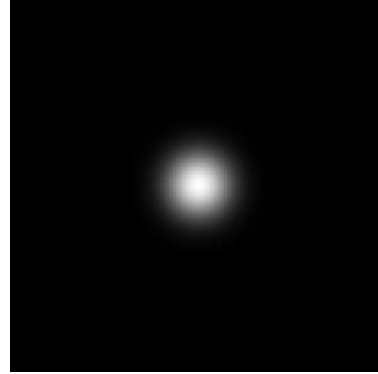
With Filter Centering



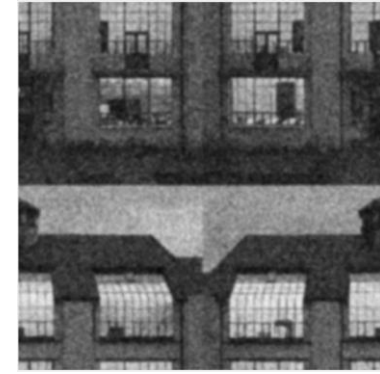
Task A



$f(x, y)$

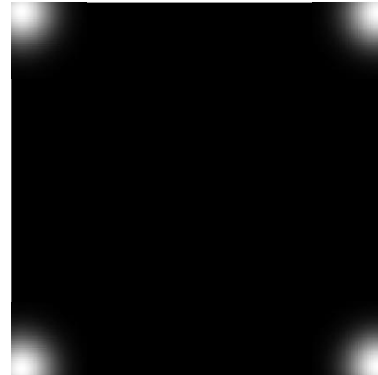
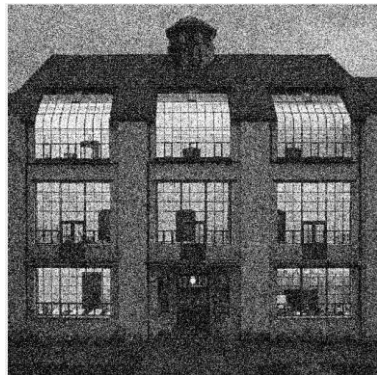


$h(x, y)$



$g(x, y)$

No Filter Centering in spatial domain



With Filter Centering in spatial domain

★ - filtering in the frequency domain
without any spectrum shifting

Task A

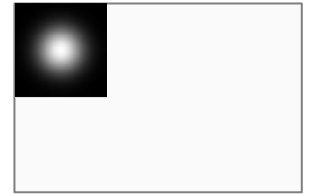
```
function A_fft_filtering
% =====
sigma = 1.4; % standard deviation
Img = double(mean(imread('taskA.png'), 3)) / 255; % read input image
Nsy = imnoise(Img, 'gaussian', 0, 0.01); % add noise
NsyFFT = fft2(Nsy); % Fourier transform

kernel = Gauss1d(sigma)' * Gauss1d(sigma); % 2D Gaussian kernel
filter = zeros(size(Nsy));
filter(1:size(kernel, 1), 1:size(kernel, 2)) = kernel; % Filter padding
filter = circshift(filter, -floor(size(kernel)/2)); % Center filter
FilFFT = fft2(filter); % Fourier transform

MulFFT = NsyFFT .* FilFFT; % Multiply image with filter
Res = ifft2(MulFFT); % Inverse Fourier transform

figure, imshow(Img), title('Original image');
figure, imshow(Nsy), title('Noisy image');
figure, imagesc(log(abs(fftshift(NsyFFT)))), title('Spectrum of noisy image');
figure, imagesc(log(abs(fftshift(FilFFT)))), title('Spectrum of Gaussian filter');
figure, imagesc(log(abs(fftshift(MulFFT)))), title('Spectrum of filtered image');
figure, imshow(Res), title('Filtered image');

function g = Gauss1d(sigma)
% =====
r = round(3*sigma); i = -r:r;
g = exp(-i.^2 / (2*sigma^2)) / (sigma*sqrt(2*pi));
```



Task A

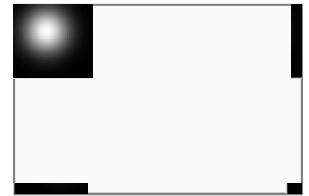
```
function A_fft_filtering
% =====
sigma = 1.4; % standard deviation
Img = double(mean(imread('taskA.png'), 3)) / 255; % read input image
Nsy = imnoise(Img, 'gaussian', 0, 0.01); % add noise
NsyFFT = fft2(Nsy); % Fourier transform

kernel = Gauss1d(sigma)' * Gauss1d(sigma); % 2D Gaussian kernel
filter = zeros(size(Nsy));
filter(1:size(kernel, 1), 1:size(kernel, 2)) = kernel; % Filter padding
filter = circshift(filter, -floor(size(kernel)/2)); % Center filter
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figure, imshow(Img), title('Original image');
figure, imshow(Nsy), title('Noisy image');
figure, imagesc(log(abs(fftshift(NsyFFT)))), title('Spectrum of noisy image');
figure, imagesc(log(abs(fftshift(FilFFT)))), title('Spectrum of Gaussian filter');
figure, imagesc(log(abs(fftshift(MulFFT)))), title('Spectrum of filtered image');
figure, imshow(Res), title('Filtered image');

function g = Gauss1d(sigma)
% =====
r = round(3*sigma); i = -r:r;
g = exp(-i.^2 / (2*sigma^2)) / (sigma*sqrt(2*pi));
```



`circshift(Filter, [-1 -1]);`

Task A

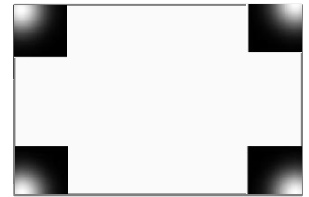
```
function A_fft_filtering
% =====
sigma = 1.4; % standard deviation
Img = double(mean(imread('taskA.png'), 3)) / 255; % read input image
Nsy = imnoise(Img, 'gaussian', 0, 0.01); % add noise
NsyFFT = fft2(Nsy); % Fourier transform

kernel = Gauss1d(sigma)' * Gauss1d(sigma); % 2D Gaussian kernel
filter = zeros(size(Nsy));
filter(1:size(kernel, 1), 1:size(kernel, 2)) = kernel; % Filter padding
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figure, imshow(Img), title('Original image');
figure, imshow(Nsy), title('Noisy image');
figure, imagesc(log(abs(fftshift(NsyFFT)))), title('Spectrum of noisy image');
figure, imagesc(log(abs(fftshift(FilFFT)))), title('Spectrum of Gaussian filter');
figure, imagesc(log(abs(fftshift(MulFFT)))), title('Spectrum of filtered image');
figure, imshow(Res), title('Filtered image');

function g = Gauss1d(sigma)
% =====
r = round(3*sigma); i = -r:r;
g = exp(-i.^2 / (2*sigma^2)) / (sigma*sqrt(2*pi));
```



`circshift(Filter, [-r -r]);`

Task B

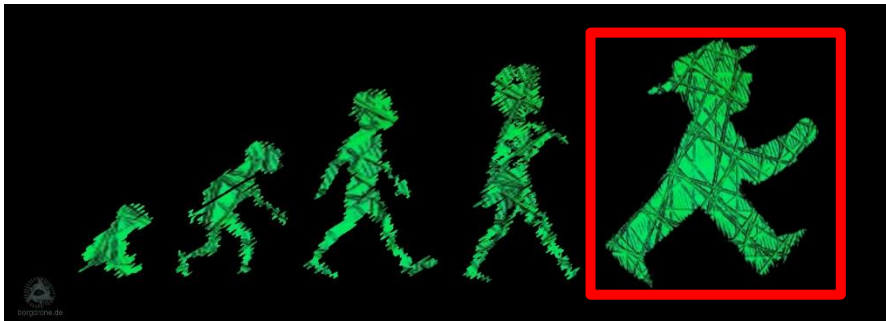
Input data



training image



test image 1



test image 2



test image 3

Task B

```
function B_fourier_descr
%
% =====
train_image = double(mean(imread('trainB.png'), 3)) / 255; % read train image
[D_t, ~] = fourier_descr(Thresholding(train_image)); % build model descriptor

for k = 1:3
    name = strcat('test', num2str(k), 'B.jpg'); % name of current test image
    image = double(mean(imread(name), 3)) / 255; % read test image
    mask = Thresholding(image); % binary mask
    [D, B] = fourier_descr(mask); % build all descriptors
    figure, imshow(mask), hold on;
    for i = 1 : size(D, 1) % for each descriptor
        dist = norm(D_t - D(i, :)); % if descriptor is similar to model
        if dist < 0.07
            plot(B{i}(:, 2), B{i}(:, 1), 'r', 'LineWidth', 1); % plot boundary
        end
    end
end

function [fd, B] = fourier_descr(Img)
%
% =====
n = 25; % number of descriptor elements
B = bwboundaries(Img); % extract all boundaries
fd = zeros(length(B), n-1);
for i = 1 : length(B) % for each boundary
    if length(B{i}) > n
        desc = fft(B{i}(:,2) + j*B{i}(:,1)); % points as imaginary numbers
        fd(i, :) = abs(desc(2:n) / desc(2)); % normalize descriptor
    end
end

function mask = Thresholding(Image) % image thresholding
%
% =====
mask = im2bw(Image, graythresh(Image));
```

Output of bwboundaries:
($k \times 1$) cell,

where k is the number of
identified closed boundaries

```
My_Cell =
    [682x2 double]
    [686x2 double]
    [654x2 double]
    [685x2 double]
    [154x2 double]
    [168x2 double]
    [328x2 double]
    [335x2 double]
    [377x2 double]
    [332x2 double]
    [ 52x2 double]
```



Task B

```
function B_fourier_descr
% =====
train_image = double(mean(imread('trainB.png'), 3)) / 255; % read train image
[D_t, ~] = fourier_descr(Thresholding(train_image)); % build model descriptor

for k = 1:3
    name = strcat('test', num2str(k), 'B.jpg'); % name of current test image
    image = double(mean(imread(name), 3)) / 255; % read test image
    mask = Thresholding(image); % binary mask
    [D, B] = fourier_descr(mask); % build all descriptors
    figure, imshow(mask), hold on;
    for i = 1 : size(D, 1) % for each descriptor
        dist = norm(D_t - D(i, :)); % if descriptor is similar to model
        if dist < 0.07
            plot(B{i}(:, 2), B{i}(:, 1), 'r', 'LineWidth', 1); % plot boundary
        end
    end
end

function [fd, B] = fourier_descr(Img)
% =====
n = 25; % number of descriptor elements
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fd = zeros(length(B), n-1);
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    if length(B{i}) > n
        desc = fft(B{i}(:,2) + j*B{i}(:,1)); % points as imaginary numbers
        fd(i, :) = abs(desc(2:n) / desc(2)); % normalize descriptor
    end
end

function mask = Thresholding(Image) % image thresholding
% =====
mask = im2bw(Image, graythresh(Image));
```

Translation

$$D_f(1) := 0$$

Scale

$$D_f := \frac{D_f}{|D_f(2)|}$$

Orientation

$$D_f := |D_f|$$

Output of bwboundaries:
($k \times 1$) cell,

where k is the number of
identified closed boundaries

```
My_Cell =

    [682x2 double]
    [686x2 double]
    [654x2 double]
    [685x2 double]
    [154x2 double]
    [168x2 double]
    [328x2 double]
    [335x2 double]
    [377x2 double]
    [332x2 double]
    [ 52x2 double]
```

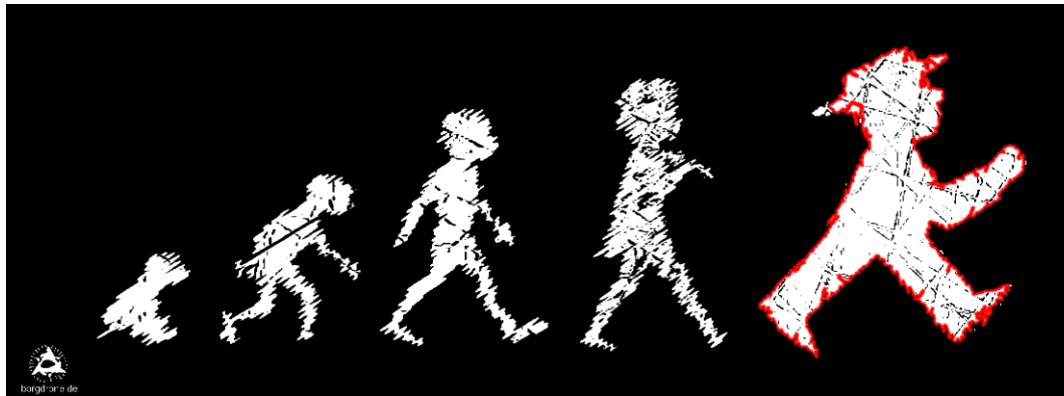


Expected results

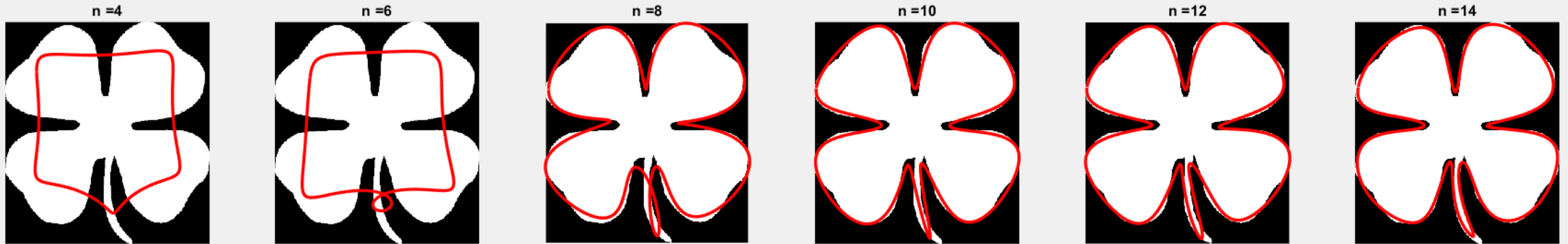
Task B



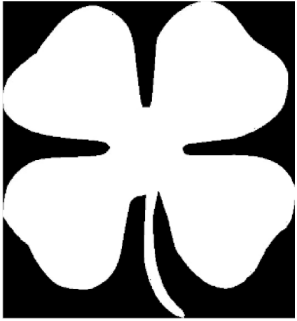
training image



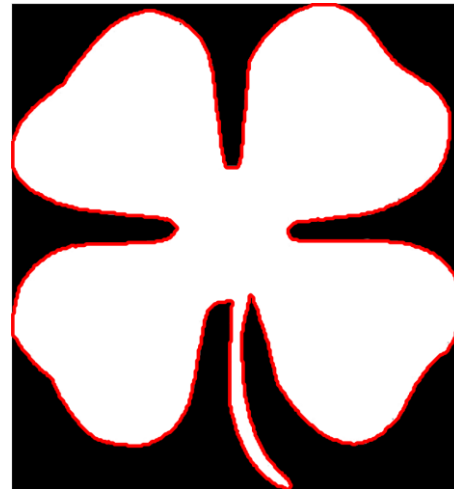
Discussion: Visualization of the simplified shape boundary



Discussion: Visualization of the simplified shape boundary



Binary Input Image

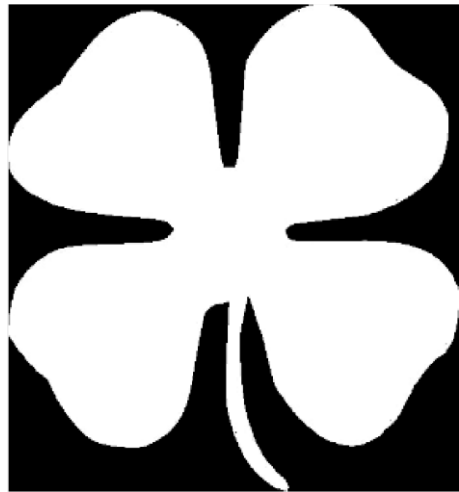


Binary Input Image
+
Complete Boundary Overlay



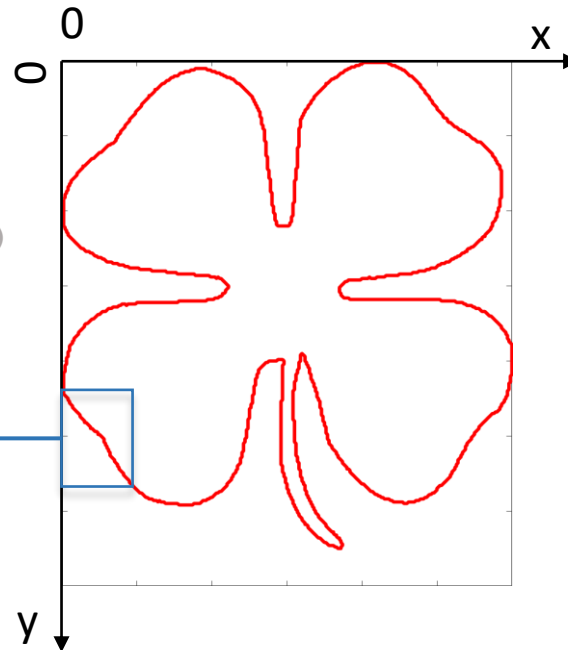
Binary Input Image
+
Simplified Boundary Overlay

Discussion: Visualization of the simplified shape boundary

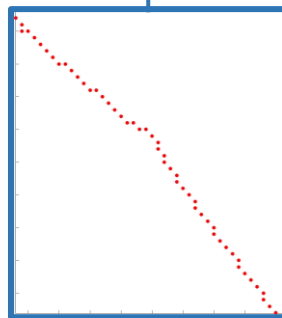


Binary Input Image

Plot the
output of
`bwboundaries()`



Boundary Points



Close-Up of a
Boundary Segment



$$D = x + j * y$$

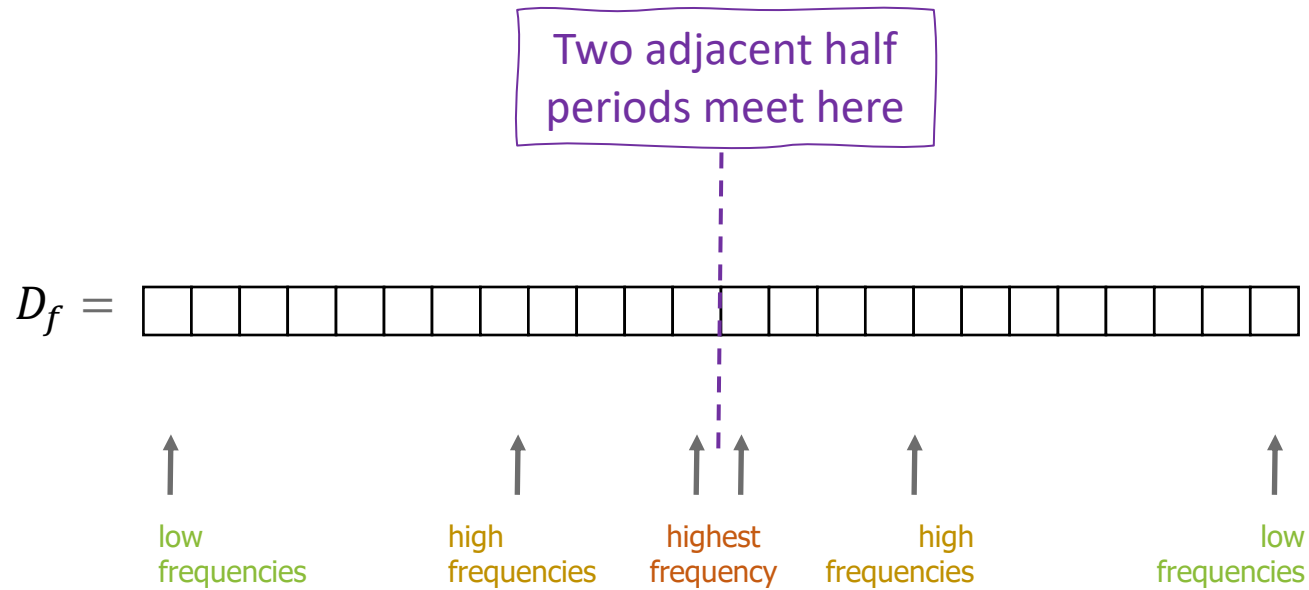
Complex-valued
vector D



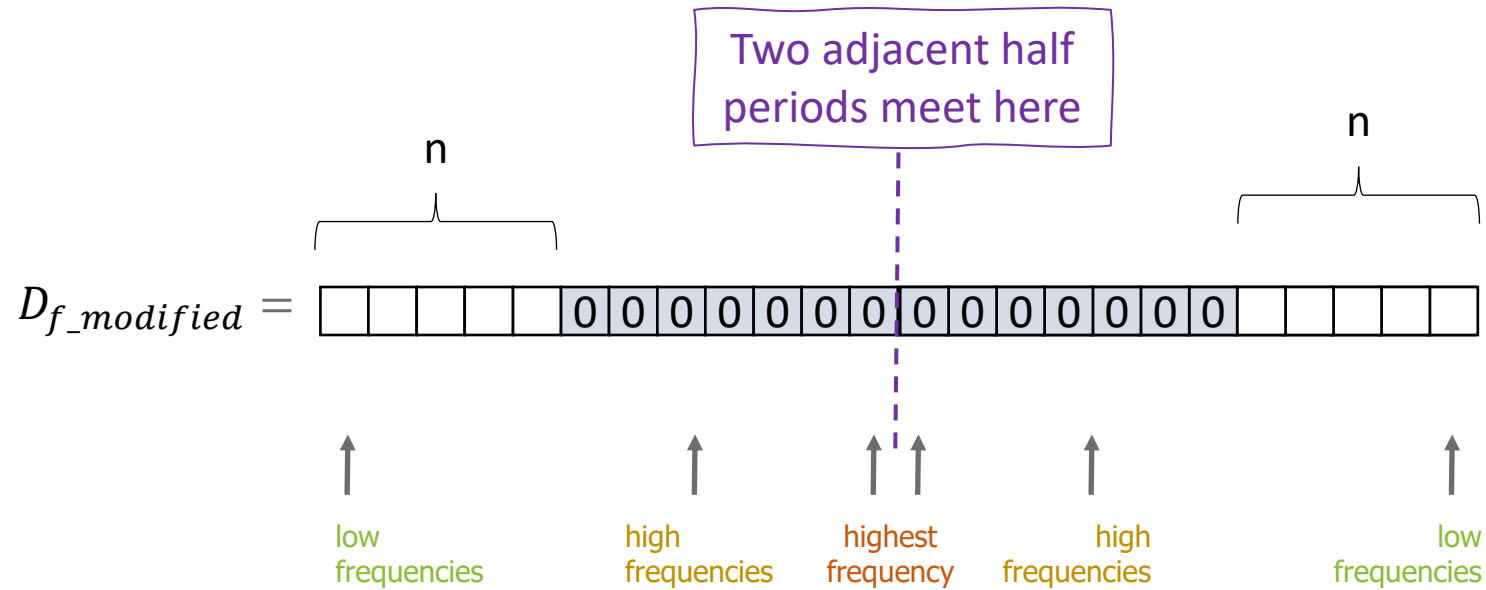
$$D_f = FFT(D)$$

Fourier Descriptor
 D_f

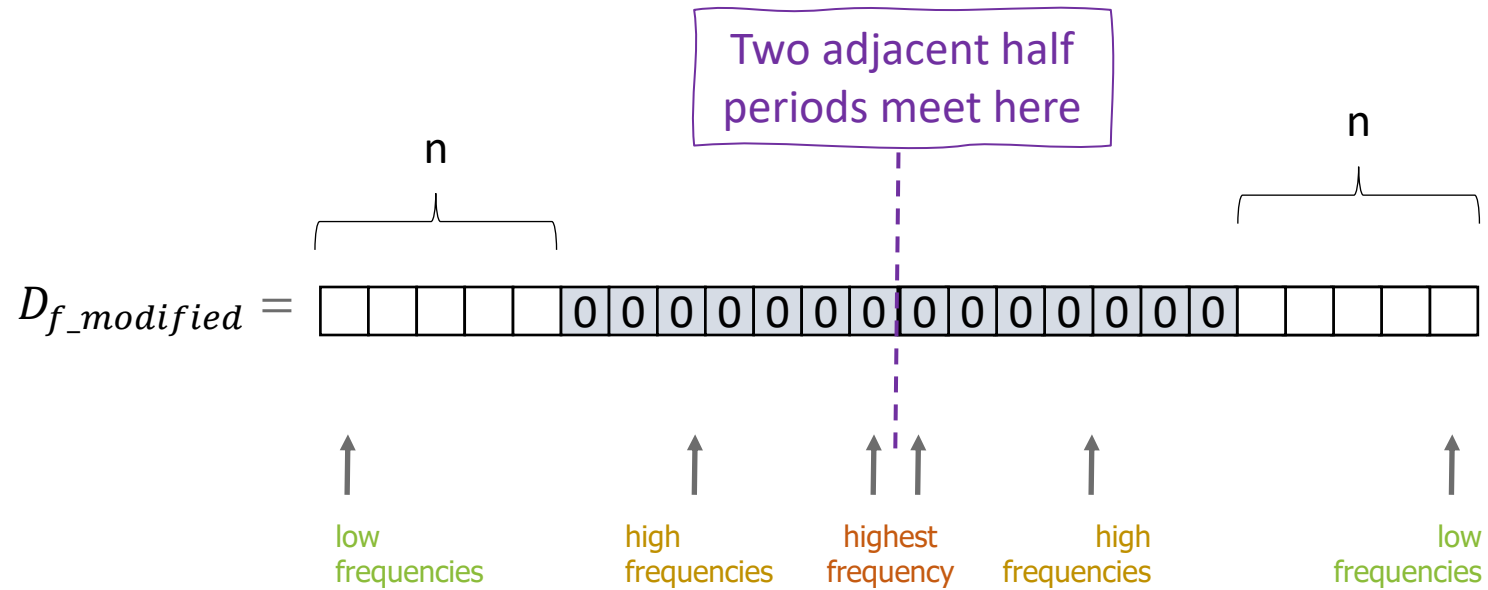
Discussion: Visualization of the simplified shape boundary



Discussion: Visualization of the simplified shape boundary



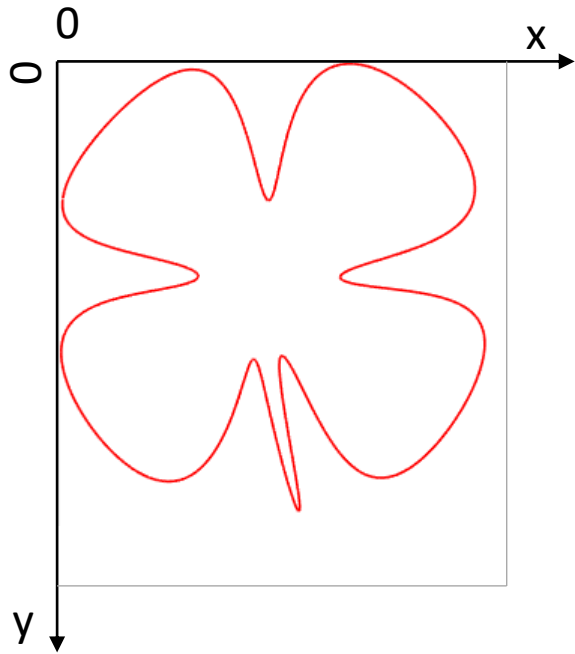
Discussion: Visualization of the simplified shape boundary



Implementation Tip:

- 1) Modify only the values in the first half period
- 2) Mirror the modified segment to complete the descriptor

Discussion: Visualization of the simplified shape boundary



Boundary Points

$$x = \text{real}(D_{\text{simplified}})$$
$$y = \text{imag}(D_{\text{simplified}})$$





Assignment 5

Assignment 5: Overview

Topics:

- *k-means* clustering
- Watershed segmentation

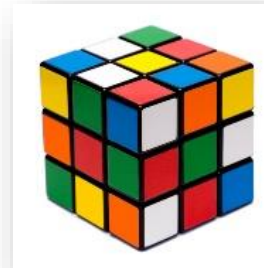
Goal:

- Practice unsupervised image segmentation

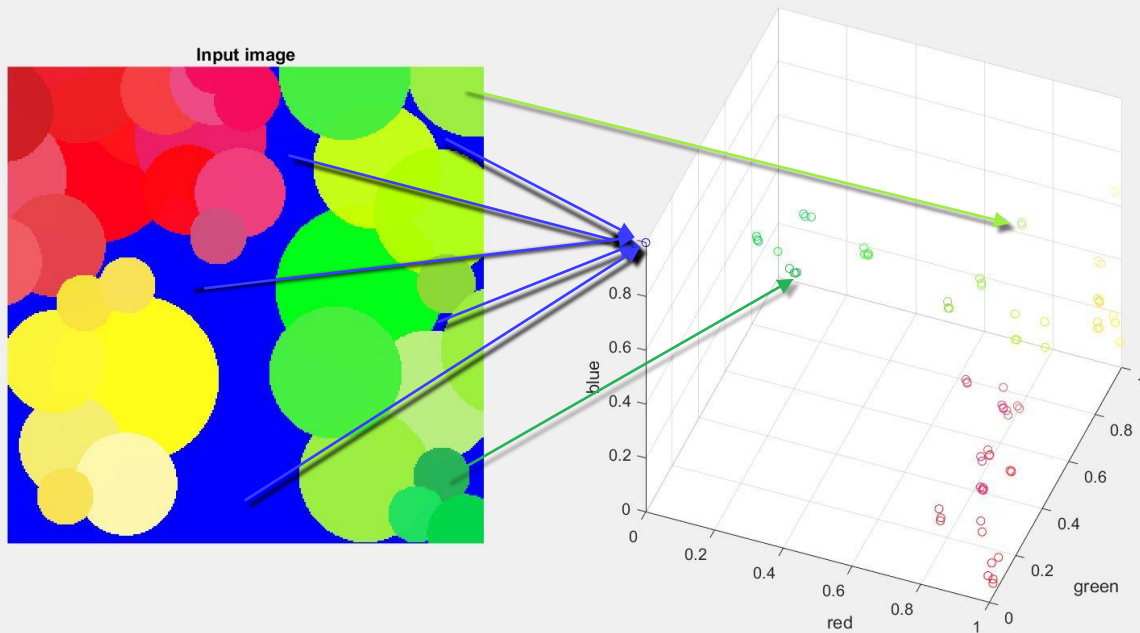
Input:

- The required input images can be found on the Moodle course page

Due to the time schedule changes, **only one** of the two subtasks is compulsory.



Assignment 5: Feature Space



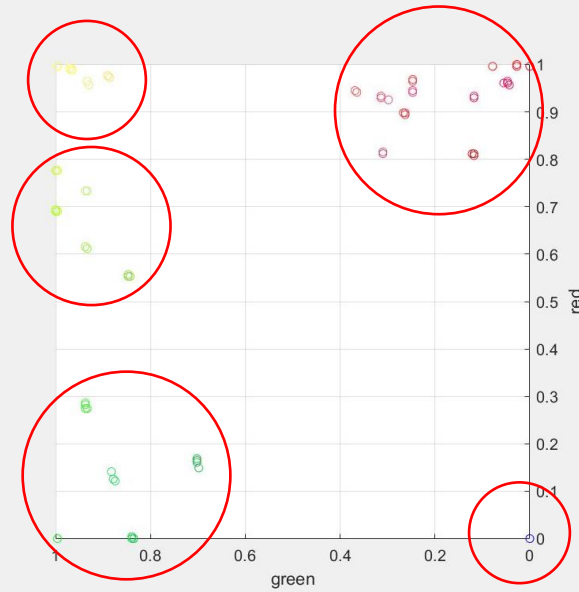
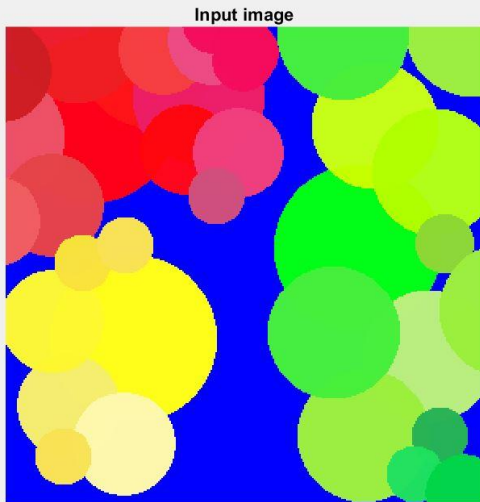
Artificially
generated
image

Given: 3-channel color image

- Each channel (r, g, b) represents one dimension of a feature space
- Each pixel of the image maps to a point in that space
- Additional spatial support is given by the position (x, y) in the image

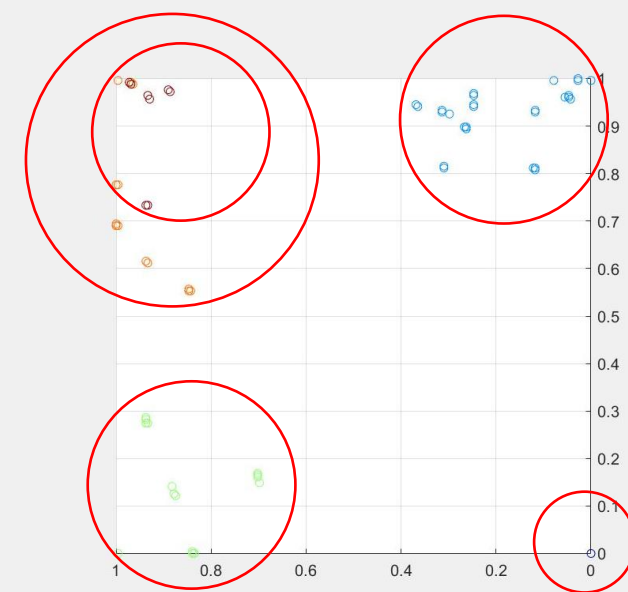
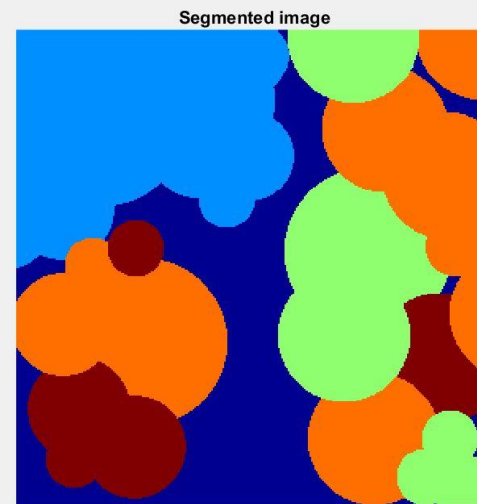
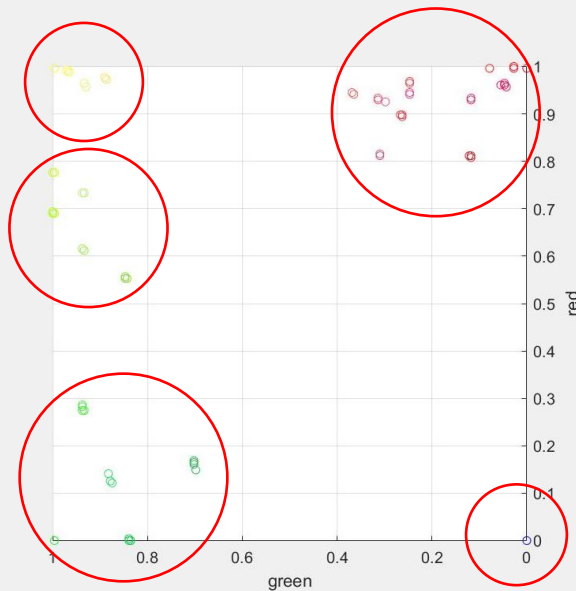
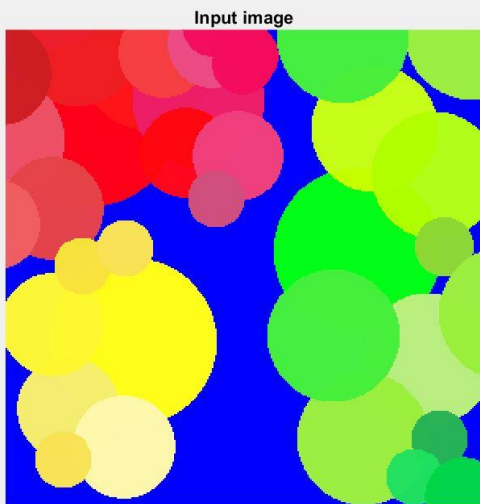
=> **5D feature space**

Assignment 5: Clustering



Artificially
generated
image

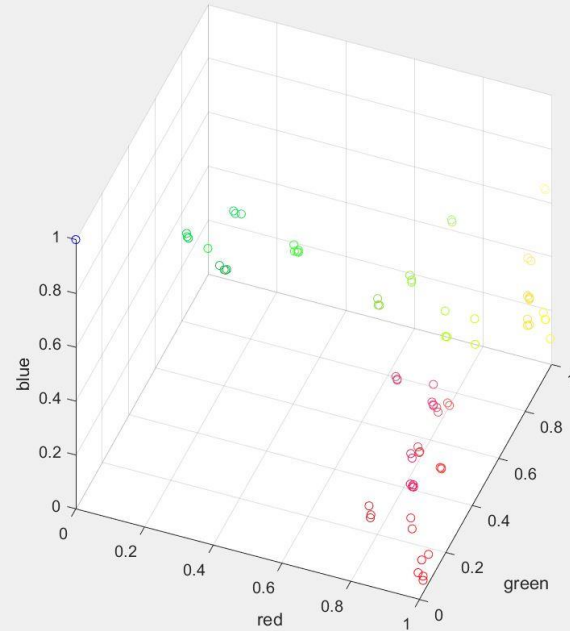
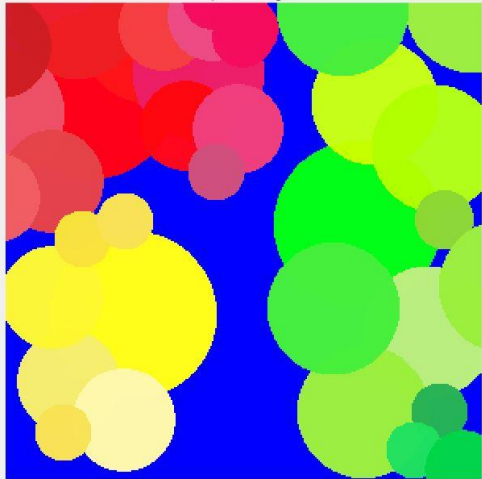
Assignment 5: Clustering Results



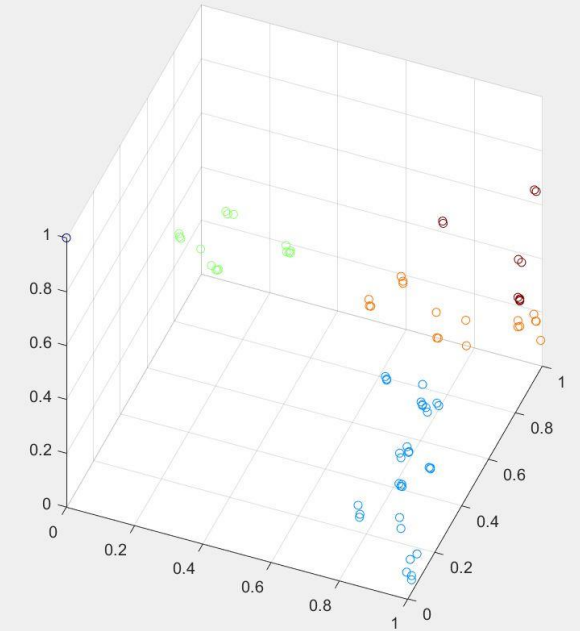
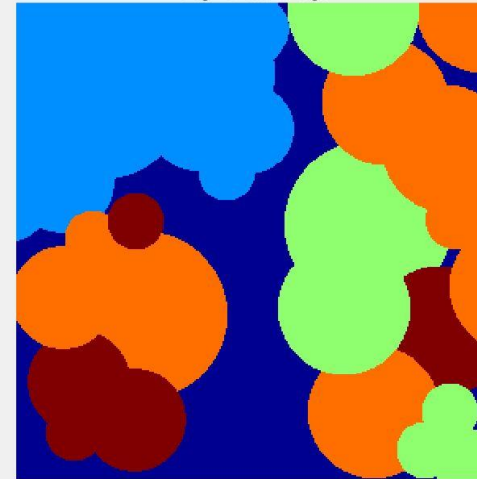
Artificially
generated
image

Assignment 5: Clustering Results

Input image

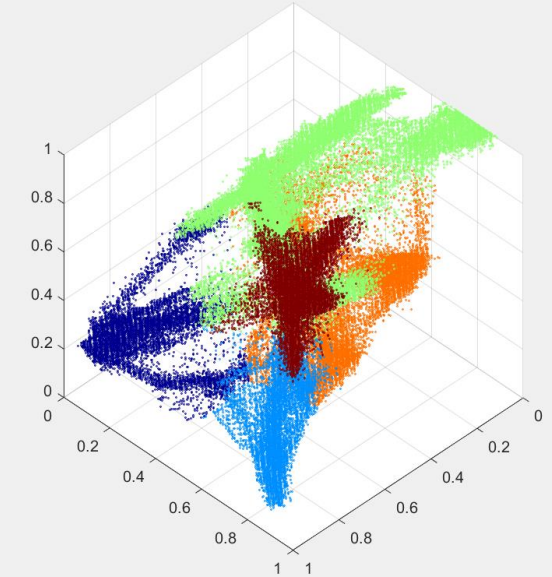
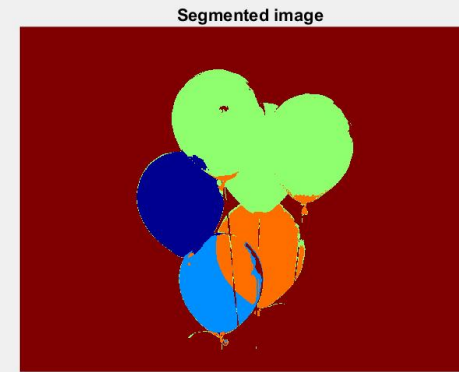
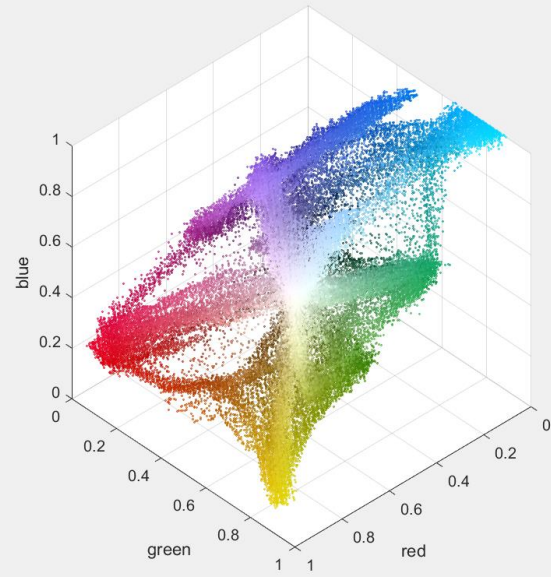
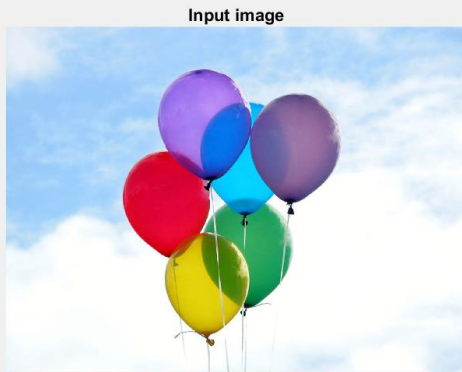


Segmented image



Artificially
generated
image

Assignment 5: Clustering Results



Real photo
example

Assignment 5: Task A

Task A: *k-means* clustering

- Read the exemplary color input image `inputEx5_1.jpg` and set up a **three-dimensional RGB feature space** (`reshape`).
- Implement your **own** *k-means* clustering approach with random initialization (see lecture notes) to group the color features.
- Select an appropriate number of clusters k , apply the algorithm and visualize the detected groups in feature and image space (e.g. with color coding: `colormap`).
- Extend the three-dimensional feature space with **additional spatial support** using the pixel positions (x, y) and test your algorithm on the five-dimensional feature space. Are the results different or significantly better?

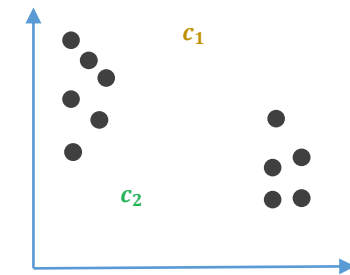
k-means: Overview

Algorithm description:

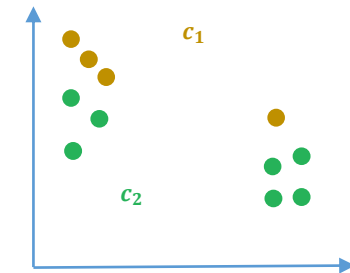
1. Randomly initialize k cluster centers
2. Assign each point to the closest center
3. Update cluster centers as the mean of the points
4. Repeat steps 2 and 3 until no data points are re-assigned

Free parameters:

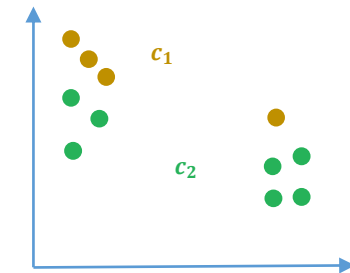
k – the number of clusters



1



2

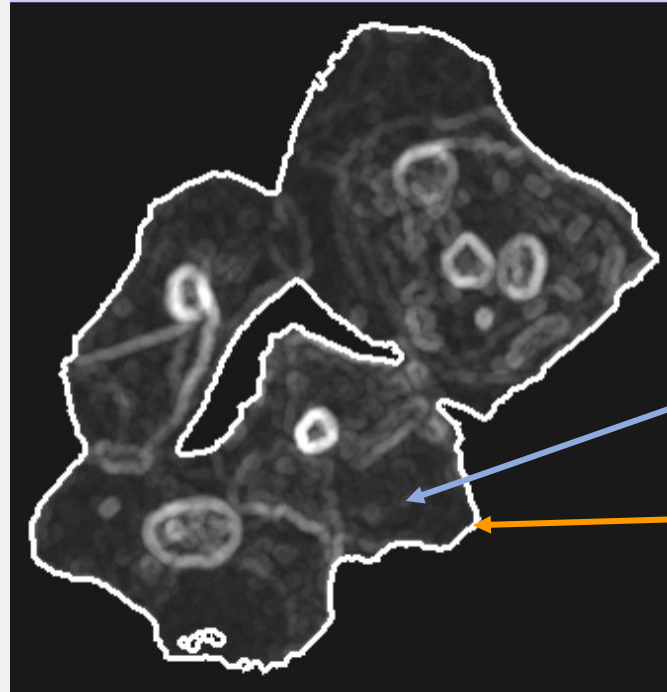


3

Assignment 5: Watershed Segmentation



Input image



Gradient magnitude image

The **gradient magnitude image** can be interpreted as a **topographic surface** (3D relief), with valleys and mountains.

As **valley** we interpret larger regions with **homogeneous intensity**, whereas **strong intensity changes** can be seen as **mountains**.

Assignment 5: Task B

Task B: *Watershed Segmentation*

- a. Load the provided image `inputEx4_2.jpg`, convert it to grayscale image and compute its **gradient magnitude**.
- b. The starting flooding points, also known as *seeds* or *markers*, can be determined automatically or manually. To avoid oversegmentation, you should either implement an interactive user selection for the **marker points** (`ginput`) or use the provided pre-selected points.
- c. Implement the *watershed segmentation* method **by yourself**. Use the seeds selected in step **b**. as the starting points for region growing. It is recommended to apply a *4-neighbor topology* (introduced in lecture number 3).
- d. Visualize the final segmentation result, as well as at least **two intermediate steps** during the region growing procedure. Apply an appropriate colormap to the segmented regions (`colormap`).
- e. Shortly describe the benefits and drawbacks of the watershed segmentation method.



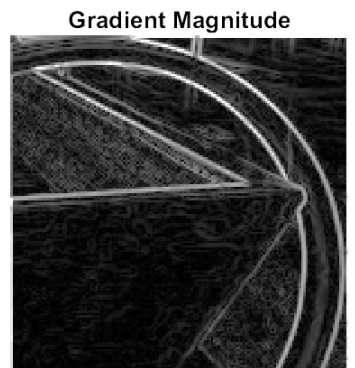
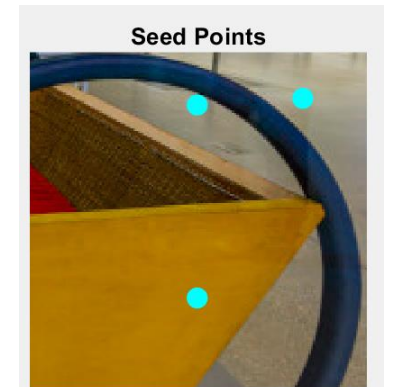
Watershed: Overview

Algorithm description:

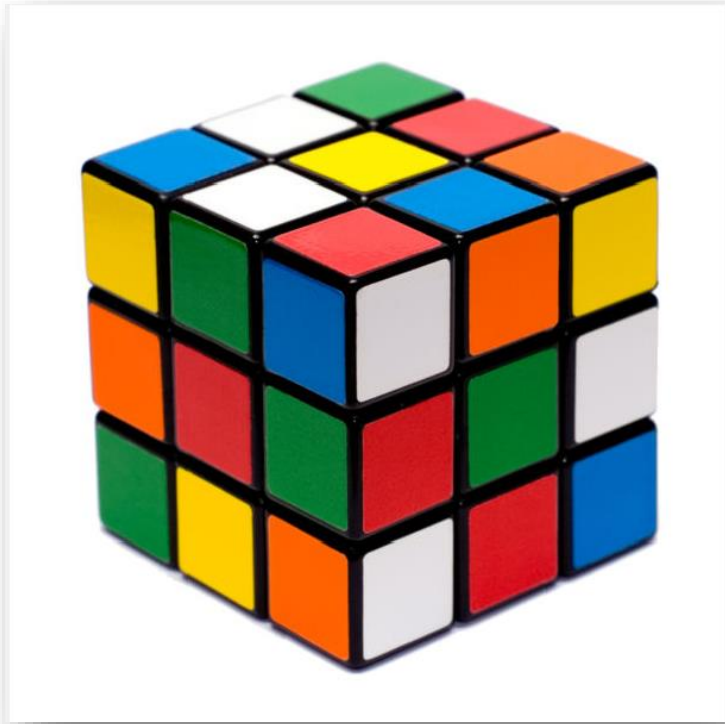
1. Select n seed points (each seed belongs to a different catchment basin)
2. Compute the gradient magnitude image G
3. Flood (grow) regions starting from every seed point
until a valley ridge (mountain) is reached according to the
gradient magnitude intensities of the neighboring pixels

Free parameters:

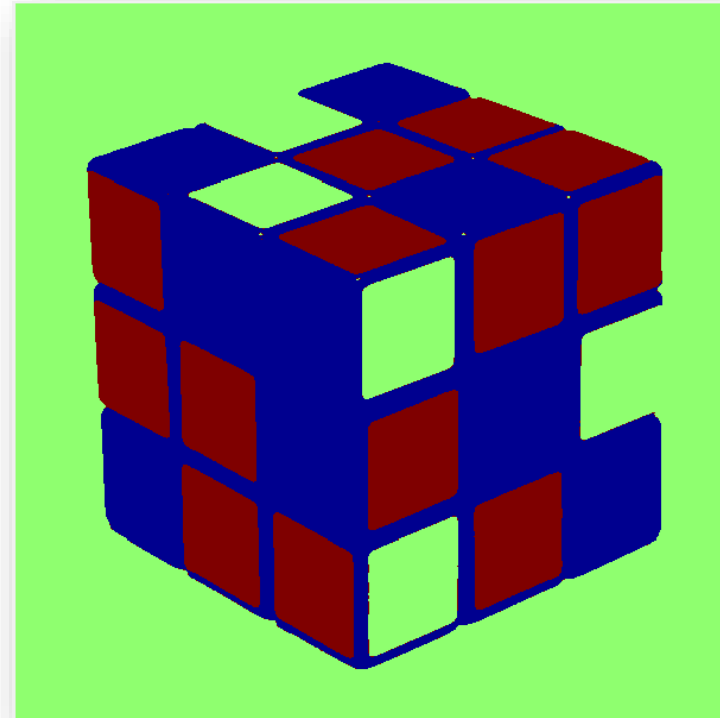
seed (marker) points – number and location



Assignment 5: Sample results - Task A



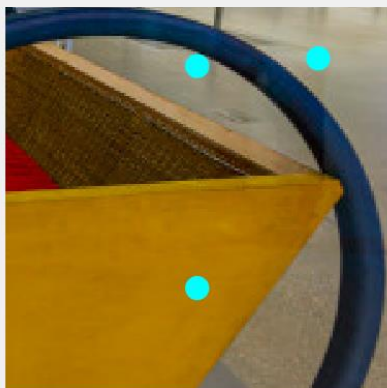
Input image



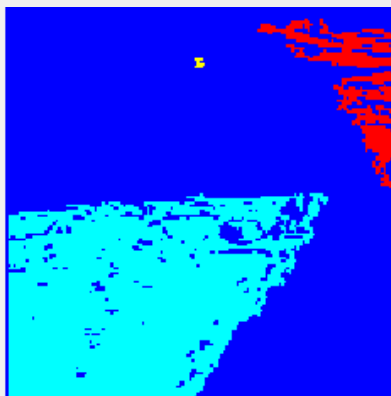
Segmented image:
3 clusters using k-means

Assignment 5: Sample results - Task B

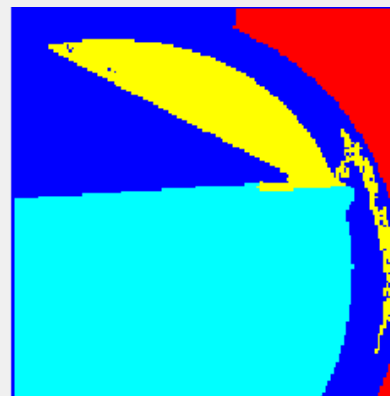
Input image
with 3 markers



segmentation
results at 33%



segmentation
results at 67%



final
segmentation



Input image
with 6 markers

