IMA204_TP_DEFMODEL_LS_IMA201_2024-25_STUDENTS_shared

January 19, 2025

[ ]:
```
import numpy as np
import matplotlib
import skimage
import IPython
import imagecodecs #(New 2025)


import matplotlib.pyplot as plt
from IPython.display import HTML
from matplotlib import animation, rc

from skimage.color import rgb2gray
from skimage import data
from skimage.filters import gaussian
from skimage.segmentation import active_contour # For active_contour function
from skimage.util import random_noise

# For active_contour function
from skimage.segmentation import chan_vese, morphological_chan_vese,␣
 ↪checkerboard_level_set,morphological_geodesic_active_contour

# For some image filtering
from skimage.morphology import white_tophat, black_tophat, disk

import skimage.io

from IPython.core.interactiveshell import InteractiveShell
InteractiveShell.ast_node_interactivity = "all"

# PRINT VERSIONS
print("np.__version__",np.__version__)
print("matplotlib.__version__",matplotlib.__version__)
print("skimage.__version__",skimage.__version__)
print("IPython.__version__",IPython.__version__)
print("imagecodecs.__version__",imagecodecs.__version__)
```

[1]:
```python
def edge_map(img,sigma):
    blur = skimage.filters.gaussian(img,sigma)
    return skimage.filters.sobel(blur)

def edge_map2(img,sigma):
    blur = skimage.filters.gaussian(img,sigma)
    return skimage.filters.scharr(blur)

def subtract_background(image, radius=5, light_bg=False):
        str_el = disk(radius)
        if light_bg:
            return black_tophat(image, str_el)
        else:
            return white_tophat(image, str_el)


def define_initial_circle(R0,r0,c0,Nber_pts=400):
    # Define initial contour shape
    s      = np.linspace(0, 2*np.pi, Nber_pts)
    Radius = R0
    r      = r0 + Radius*np.sin(s)
    c      = c0 + Radius*np.cos(s) #col
    init   = np.array([r, c]).T
    return init


## Create slides for animation
def animate_cv(image, segs, interval=1000):
    fig, ax = plt.subplots(figsize=(8, 8))
    ax.imshow(image, cmap='gray');
    im = ax.imshow(segs[0], alpha=0.5, cmap='inferno');
    ax.axis('off')

    def init():
        im.set_data(segs[0])
        return [im]

    def animate(i):
        im.set_array(segs[i])
        return [im]

    anim = animation.FuncAnimation(fig, animate, init_func=init,
                                   frames=len(segs), interval=1000, blit=True);
    return anim


def animate_snake(image, segs, interval=500):
```

```
    fig, ax = plt.subplots(figsize=(6, 6))
    ax.imshow(image, cmap='gray');
    #    im = ax.imshow(segs[0], alpha=0.5, cmap='inferno');
    #ax.plot(segs[0][:, 1], segs[0][:, 0], '--r', lw=3)
    ax.axis('off')
    line, = ax.plot([], [], '-r', lw=2)

    def init():
        line.set_data(segs[0,:,1],segs[0,:,0])
        return [line,]

    def animate(i):
        line.set_data(segs[i,:,1],segs[i,:,0])
        return [line,]

    anim = animation.FuncAnimation(fig, animate, init_func=init,
                                   frames=len(segs), interval=1000, blit=True);
    return anim



###########################
def store_evolution_in(lst):
    """Returns a callback function to store the evolution of the level sets in
    the given list.
    """

    def _store(x):
        lst.append(np.copy(x))

    return _store
```

1 Read images

This part reads a series of images that you can then use in various tests. Note that some images are provided with ground-truth masks of structures of interest: 1. OCT_tissue 2. CTabd (CT of the abdomen) 3. US nodule (Ultrasound image with a nodule) 4. images_blood_cells/000016.png [several images available]

[ ]:
```
# import warnings
# warnings.filterwarnings( "ignore", module = "matplotlib\..*" )
# skimage.io.imshow(img_mask)

# Binary images  - w/o ground truth
```

```python
img_star          = skimage.io.imread('./images_misc/smooth_star.png', as_gray = True)
edge_star         = edge_map(img_star, sigma=0)
img_star_noisy    = skimage.io.imread('./images_misc/smooth_star_noisy.png', as_gray = True)
edge_star_noisy   = edge_map(img_star_noisy, sigma=0)
img_binshape      = skimage.io.imread('./images_misc/binary_shape_2024.png', as_gray = True)
edge_binshape     = edge_map(img_binshape, sigma=0)
img_cardiacshape  = skimage.io.imread('./images_misc/cardiac_mri_mask.png', as_gray = True)
edge_cardiacshape = edge_map(img_cardiacshape, sigma=0)

# Microscopy images - w/o ground truth # line changed 2025
img_hela          = skimage.io.imread('./images_misc/hela_big.png')


# OCT eye images  - w/o ground truth
img_oct_eye  = skimage.io.imread('./images_misc/OCT_normal.jpeg', as_gray = True)
img_oct_eye  = np.squeeze(img_oct_eye)
img_oct_eye  = img_oct_eye.astype('float64')
img_oct_eye  = img_oct_eye/np.max(img_oct_eye)

edge_oct_eye = edge_map(img_oct_eye, sigma=2)

# CT abdo images  - with ground truth
img_CTabd     = skimage.io.imread('./images_misc/CT_kidney_im.png', as_gray = True)
edge_CTabd    = edge_map(img_CTabd, sigma=2)
gt_CTabd      = skimage.io.imread('./images_misc/CT_kidney_mask.png', as_gray = True)
edge_gt_CTabd = edge_map(gt_CTabd, sigma=2)


# Cell images  - with ground truth
img_cell  = skimage.io.imread('./images_blood_cells/0000152.png', as_gray = True)
edge_cell = edge_map(img_cell, sigma=2)
#skimage.io.imshow(img_cell)
gt_cell = skimage.io.imread('./masks_blood_cells/0000152.png', as_gray = True)
edge_gt_cell = edge_map(gt_cell, sigma=2)

# Cell image - challenge multi
img_cell2     = skimage.io.imread('./images_misc/cell_00236.tif', as_gray = True)
```

```
edge_cell2    = edge_map(img_cell2, sigma=2)
gt_cell2      = skimage.io.imread('./images_misc/cell_00236_label.tiff',␣
 ↪as_gray = True)
edge_gt_cell2 = edge_map(gt_cell2, sigma=2)

# Hela Cell image - Cell tracking challenge
img_helat1     = skimage.io.imread('./images_misc/hela_t001.tif', as_gray =␣
 ↪True)
edge_helat1    = edge_map(img_helat1, sigma=2)
gt_helat1      = skimage.io.imread('./images_misc/hela_mask001.tif', as_gray =␣
 ↪True)
edge_gt_helat1 = edge_map(gt_helat1, sigma=2)

# Fluo Cell image - Cell tracking challenge
img_fluo     = skimage.io.imread('./images_misc/fluo000.tif', as_gray = True)
edge_fluo    = edge_map(img_fluo, sigma=2)
gt_fluo      = skimage.io.imread('./images_misc/fluo000_seg.tif', as_gray =␣
 ↪True)
edge_gt_fluo = edge_map(gt_fluo, sigma=2)


# OCT image of tissue  - with ground truth
img_oct_tissue  = skimage.io.imread('./OCT_myocardium/case272.tif', as_gray =␣
 ↪True)
edge_oct_tissue = edge_map(img_oct_tissue, sigma=2)
gt_oct_tissue  = skimage.io.imread('./OCT_myocardium/case272_label.tiff',␣
 ↪as_gray = True)
edge_gt_oct_tissue = edge_map(gt_oct_tissue, sigma=2)

# US image of a nodule  - with ground truth
img_USnodule  = skimage.io.imread('./thyroid_nodule/1074.png', as_gray = True)
edge_USnodule = edge_map(img_USnodule, sigma=2)
gt_USnodule   = skimage.io.imread('./thyroid_nodule/1074_mask.png', as_gray =␣
 ↪True)
edge_gt_USnodule = edge_map(gt_USnodule, sigma=2)

# PLOTS

fig, axes = plt.subplots(6,4, figsize=(8, 8))
ax = axes.ravel()

ax[0].imshow(img_cell, cmap=plt.cm.gray);
ax[1].imshow(edge_cell, cmap=plt.cm.gray);
ax[2].imshow(gt_cell, cmap=plt.cm.gray);
ax[3].imshow(edge_gt_cell, cmap=plt.cm.gray);
```

```
ax[4].imshow(img_CTabd, cmap=plt.cm.gray);
ax[5].imshow(edge_CTabd, cmap=plt.cm.gray);
ax[6].imshow(gt_CTabd, cmap=plt.cm.gray);
ax[7].imshow(edge_gt_CTabd, cmap=plt.cm.gray);

ax[8].imshow(img_fluo, cmap=plt.cm.gray);
ax[9].imshow(edge_fluo, cmap=plt.cm.gray);
ax[10].imshow(gt_fluo, cmap=plt.cm.gray);
ax[11].imshow(edge_gt_fluo, cmap=plt.cm.gray);

ax[12].imshow(img_oct_tissue, cmap=plt.cm.gray);
ax[13].imshow(edge_oct_tissue, cmap=plt.cm.gray);
ax[14].imshow(gt_oct_tissue, cmap=plt.cm.gray);
ax[15].imshow(edge_gt_oct_tissue, cmap=plt.cm.gray);

ax[16].imshow(img_cardiacshape, cmap=plt.cm.gray);
ax[17].imshow(edge_cardiacshape, cmap=plt.cm.gray);

ax[18].imshow(img_oct_eye, cmap=plt.cm.gray);
ax[19].imshow(edge_oct_eye, cmap=plt.cm.gray);

ax[20].imshow(img_star, cmap=plt.cm.gray);
ax[21].imshow(edge_star, cmap=plt.cm.gray);
ax[22].imshow(img_star_noisy, cmap=plt.cm.gray);
ax[23].imshow(edge_star_noisy, cmap=plt.cm.gray);

for i in range(0,24):
    ax[i].set_xticks([]), ax[i].set_yticks([]);
fig.tight_layout()
plt.show();
```

2 Image properties:

2.1 Range of values and data type matter …

Some routines won't work if your image type is int8 or uint8… Here is how to check your image data type

And regularly check your image content in terms of: * intensities range of values * distributions of intensities via its histogram

[ ]:
```
img_test  = img_cell #img_star_noisy#img_oct_eye #img_CTabd #img_cell
Sigma_val = 2
edge_test = edge_map(img_test, sigma=Sigma_val)
```

```
## Print some basic image properties
print("Image size of img_test is: ", img_test.shape)
print("Data type of img_test is: ", img_test.dtype)
print("min - max value in image:" , np.min(img_test), np.max(img_test))


## Hot to plot a Histogram
hist_test, bins_test             = np.histogram(img_test.flatten(), bins=256)
hist_edge_test, bins_edges_test  = np.histogram(edge_test.flatten(), bins=256)

fig, axes = plt.subplots(2,2, figsize=(4, 4))
ax        = axes.ravel()
ax[0].imshow(img_test, cmap=plt.cm.gray);
ax[0].set_title("Original Im", fontsize=6);
ax[1].plot(bins_test[0:-1],hist_test);
ax[1].set_title("Hist Im", fontsize=6);
ax[2].imshow(edge_test, cmap=plt.cm.gray);
ax[2].set_title("Edge Map Im", fontsize=6);
ax[3].plot(bins_edges_test[0:-1],hist_edge_test);
ax[3].set_title("Hist Edge map", fontsize=6);
fig.tight_layout()
plt.show();
```

3 Edge maps

Deformable models rely on edge maps. Most routines have their own strategy coded to compute the edge map.

- Edge maps usually involve smoothing of the image, to be robust to noise. Make sure you understand how this is controlled in the routine you use.
- Edge maps usually show pixels with high gradient magnitudes in white (high values)
- Most deformable model routines can be fed directly with an Edge Map rather than the original image as its input
- Some routine expect to be fed with an inverse edge map where high gradient locations have small values, to stop the contour via a velocity set to ~zero.

[ ]:
```
img_to_test = img_oct_eye
print("Data type of img_test is: ", img_test.dtype)
print("min - max value in image:" , np.min(img_test), np.max(img_test))

Font_size  = 9

# Classic Edge map with Gaussian smoothing controled by sigma
edge_test1         = edge_map(img_to_test, sigma=1)
edge_test2         = edge_map(img_to_test, sigma=2)
edge_test2_l       = np.log2((edge_test2*100)+1)
```

```
edge_testl_2       = edge_map(np.log2((img_to_test+1)*100), sigma=2)

# Inversed Edge map
# Returns Edge map = 1.0 / np.sqrt(1.0 + alpha * gradnorm)
edge_inv_test  = skimage.segmentation.inverse_gaussian_gradient(img_to_test,␣
↪alpha=1.0, sigma=2.0)


fig, axes = plt.subplots(2,3, figsize=(6, 6))
ax = axes.ravel()

ax[0].imshow(img_to_test, cmap=plt.cm.gray);
ax[0].set_title("Original image", fontsize=Font_size);
ax[1].imshow(edge_test1, cmap=plt.cm.gray);
ax[1].set_title("Edge map sigma = 1", fontsize=Font_size);
ax[2].imshow(edge_test2, cmap=plt.cm.gray);
ax[2].set_title("Edge map sigma = 2", fontsize=Font_size);
ax[3].imshow(edge_inv_test, cmap=plt.cm.gray);
ax[3].set_title("Edge map inversed + sigma = 2", fontsize=Font_size);
ax[4].imshow(edge_test2_l, cmap=plt.cm.gray);
ax[4].set_title("Log(Edge map) + sigma = 2", fontsize=Font_size);
ax[5].imshow(edge_testl_2, cmap=plt.cm.gray);
ax[5].set_title("Edge map on Log+ sigma = 2", fontsize=Font_size);

for i in range(0,6):
    ax[i].set_xticks([]), ax[i].set_yticks([]);

fig.tight_layout()
plt.show();
```

4 Image transforms

Let you test some image transformations based on morphological operators and histogram manipulation. When transforming image contrast, it is always interesting to look at the differences between the original image and the transformed version.

[ ]:
```
img_ori_to_test = img_fluo #img_CTabd #img_oct_eye #img_CTabd
img_to_test     = img_ori_to_test
epsilon         = 0.000001 #to prevent log on 0
img_eps         = np.full_like(img_to_test, epsilon)
PRE_ENHANCE     = 1
OPTION_ENHANCE  = 4 # can be 0 (nothing) OR 1,2,3,4 for different enchancement␣
↪options
Font_size  = 9
```

```
# Run all  OPTION_ENHANCE for display here
gamma_corrected       = skimage.exposure.adjust_gamma(img_to_test, 0.8)
logarithmic_corrected = skimage.exposure.adjust_log(img_to_test, gain=␣
 ↪1,inv=True)
img_open              = skimage.morphology.diameter_opening(img_to_test, 40,␣
 ↪connectivity=2)
img_adapteq           = skimage.exposure.equalize_adapthist(img_to_test,␣
 ↪clip_limit=0.03)

# PRE ENHANCEMENT OPTIONS:
if PRE_ENHANCE==1:
    if OPTION_ENHANCE==1:
        # Gamma
        img_to_test     = gamma_corrected
    elif OPTION_ENHANCE==2:
        # Logarithmic (O = gain*log(1 + I)) or if Inv (O = gain*(2**I - 1))
        img_to_test           = logarithmic_corrected
    elif OPTION_ENHANCE==3:
        # Morpho Opening
        img_to_test           = img_open
    elif OPTION_ENHANCE==4:
        # Contrast Limited Adaptive Histogram Equalization (CLAHE).
        img_to_test           = img_adapteq

# Enhance details either dark around light background of vice versa with the␣
 ↪Top-Hat transform
Radius_val = 15
img_test1  = subtract_background(img_to_test, radius=Radius_val, light_bg=False)
img_test2  = subtract_background(img_to_test, radius=Radius_val, light_bg=True)

# SHOW OUTPUTS
fig, axes = plt.subplots(2,5, figsize=(10, 4),constrained_layout=True)
ax        = axes.ravel()
Shrink_factor_colormap = 0.5
ax[0].imshow(img_ori_to_test, cmap=plt.cm.gray);
ax[0].set_title("Ori", fontsize=6);

ax[1].imshow(img_open, cmap=plt.cm.gray);
ax[1].set_title("Opening", fontsize=Font_size);
ax[2].imshow(gamma_corrected, cmap=plt.cm.gray);
ax[2].set_title("Gamma correction", fontsize=Font_size);
ax[3].imshow(logarithmic_corrected, cmap=plt.cm.gray);
ax[3].set_title("Log correction", fontsize=Font_size);
ax[4].imshow(img_adapteq, cmap=plt.cm.gray);
ax[4].set_title("Adapt Hist Eq", fontsize=Font_size);

ax[5].imshow(img_test1, cmap=plt.cm.gray);
```

```
ax[5].set_title("Tophat Dark bkg", fontsize=Font_size);
ax[6].imshow(img_test2, cmap=plt.cm.gray);
ax[6].set_title("Tophat Light bkg", fontsize=Font_size);

tmp_show = ax[7].imshow(img_to_test-img_test2, cmap=plt.cm.gray);
ax[7].set_title("Diff: (Ori-Light bkg)", fontsize=Font_size);
plt.colorbar(tmp_show,ax=ax[7], shrink=Shrink_factor_colormap, location='right')

tmp_show = ax[8].imshow(abs(img_to_test-img_test2), cmap=plt.cm.gray);
ax[8].set_title("Diff: abs(Ori-Light bkg)", fontsize=Font_size);
plt.colorbar(tmp_show,ax=ax[8], shrink=Shrink_factor_colormap, location='right')

tmp_show = ax[9].imshow(np.log2(abs(img_to_test-img_test2+img_eps)), cmap=plt.
 ↪cm.gray);
ax[9].set_title("Diff: log(abs(Ori-Light bkg))", fontsize=Font_size);
plt.colorbar(tmp_show,ax=ax[9], shrink=Shrink_factor_colormap, location='right')

for i in range(0,10):
    ax[i].set_xticks([]), ax[i].set_yticks([]);

#fig.tight_layout() # not compatible with option constrained_layout=True in plt.
 ↪subplots needed to display the colorbar
plt.show();
```

5 Seg #1:

5.0.1 Snake on a binary shape + noise effects

This part of the practical work uses the routine **active_contour** from skimage. Default **parameter values** are: * alpha=0.01 (Snake length shape parameter. Higher values makes snake contract faster.) * beta=0.1 (Snake smoothness shape parameter. Higher values makes snake smoother.) * gamma=0.01 (Explicit time stepping parameter - Equivalent to the viscosity of the environment) * max_px_move=1.0

There are two **other parameters** that define the final image information used to define external forces used to define regions.img = w_line x img + w_edge x edge: * w_line_val= 0 (default) | =1 if want to input_edge map directly. Use negative values to attract toward dark * w_edge_val= 1 (default) | = 0 if do not want to use internal edge map. Use negative values to repel snake from edges

5.1 TODO:

Provide answers in text boxes ***Q1.1. Run the code for*** *img_to_seg=img_cardiacshape* ***using*** *img_ori* ***and all parameter values as provided, except for changing the R0 value. Comment on behavior for: - R0=10: - R0=20:***

- R0=30:
- R0=50:
Q1.2. For R0=30 test the segmentation without smoothing and then with Niter_smooth = 1 and 2. Comment on the segmentation quality for: - no smoothing:
- Niter_smooth = 1:
- Niter_smooth = 2:
Q1.3. Now run the segmentation on the** noisy version **or the image. 2 types of noise are simulated: (1) Additive Gaussian noise, (2) Speckle (multiplicative) noise. Q1.3.1 Check** appearance **of the 2 noisy images. Why is there no noise in the background in the speckle case? Answer: Q1.3.2 Using** R0=50**, run the segmentation on the noisy images** without **and with** smoothing **(Niter_smooth= 1). Comment on segmentation quality or issues for the 4 observations:
- Speckle noise + no smoothing: - Speckle noise + smoothing: - Gaussian noise + no smoothing: - Gaussian noise + smoothing:

[ ]:
```
# 1ST image
img_ori           = img_cardiacshape; r0 = 175; c0=175; R0 = 10
img_noisy         = random_noise(img_ori, mode='gaussian', mean = 0.1,clip =␣
 ↪True)
img_noisy         = random_noise(img_ori, mode='speckle', mean = 0.1,clip = True)

# Choose image to segment
img_to_seg     = img_ori
img_to_seg_raw = img_to_seg # to plot later on

alpha_val  = 0.01 ; beta_val = 0.1 ;gamma_val = 0.01;
convergence_val = 1e-4;Niter_snake = 1800;


# Initialise contour
init = define_initial_circle(R0,r0,c0)

# Pre-smooth the image
Niter_smooth    = 1 # set to 0 for no smoothing
img_to_seg      = gaussian(img_to_seg, Niter_smooth, preserve_range=False)

# Run active contour
snake1  = active_contour(img_to_seg,
                       init, max_num_iter=1, convergence=convergence_val,
                         alpha=alpha_val, beta=beta_val, gamma=gamma_val)
snake10 = active_contour(img_to_seg,
                       init, max_num_iter=10, convergence=convergence_val,
                         alpha=alpha_val, beta=beta_val, gamma=gamma_val)
snake_max = active_contour(img_to_seg,
                       init, max_num_iter=Niter_snake,␣
 ↪convergence=convergence_val,
                           alpha=alpha_val, beta=beta_val, gamma=gamma_val)
```

```
# Display results
fig, axes = plt.subplots(1,2, figsize=(8, 4),constrained_layout=True)
ax        = axes.ravel()
Font_size = 9
ax[0].imshow(img_to_seg_raw, cmap=plt.cm.gray);
ax[0].set_xticks([]), ax[0].set_yticks([]);
ax[0].set_title("Image to segment", fontsize=Font_size);

ax[1].imshow(img_to_seg, cmap=plt.cm.gray);
ax[1].plot(init[:, 1], init[:, 0], '--y', lw=1);
ax[1].plot(snake10[:, 1], snake1[:, 0], '-b', lw=1);
ax[1].plot(snake10[:, 1], snake10[:, 0], '-g', lw=1);
ax[1].plot(snake_max[:, 1], snake_max[:, 0], '-r', lw=2);
ax[1].set_xticks([]), ax[1].set_yticks([]);
ax[1].axis([0, img_to_seg.shape[1], img_to_seg.shape[0], 0]);
ax[1].set_title("Smoothed image + Seg", fontsize=Font_size);

plt.show();
```

6 Seg #2:

6.0.1 Snake on Cell image

We are using here **img_to_seg = img_cell** for which you have a ground truth mask **gt_cell** of the target segmentation for the bright right cell.

6.1 TODO

Q2.1 Segment large right cell: Run with code as provided and check quality of the segmentation versus the ground-truth. Did it work? **Answer**: ***

Q2.2 Now aiming to segment the internal dark part of the cell: change only values for Niter_smooth and R0 and propose a solution that works. **Answer**: managed to obtain a correct segmentation with Niter_smooth = XX and R0 = XX ***

Q2.3 Segment small left cell: Run with the proposed initialisation and check correct segmentation of the whole left cell. Now change ONLY some initial contour parameter(s) [**r0 = 153; c0=66; R0 = 25**] to obtain a perfect segmentation of the internal bright center of the cell. **Answer**: managed to obtain a correct segmentation with [r0 = XX; c0=XX; R0 = XX] ***

[ ]:

```
# Input image and parameter values
img_to_seg   = img_cell;
img_gt       = gt_cell;

# Large rigt cell - ground truth provided
r0 = 128; c0=128; R0 = 53
# Small left cell - no ground truth
#r0 = 153; c0=66; R0 = 25


alpha_val = 0.01 ; beta_val = 0.1 ;gamma_val = 0.01;
convergence_val = 1e-4; Niter_snake = 1200;


# Pre smooth the image
Niter_smooth = 1
img_to_seg   = gaussian(img_to_seg, Niter_smooth, preserve_range=False)


# Initialise contour
init = define_initial_circle(R0,r0,c0)

# Run active contour
snake30 = active_contour(img_to_seg,
                       init, max_num_iter=30, convergence=convergence_val,
                        alpha=alpha_val, beta=beta_val, gamma=gamma_val)
snake = active_contour(img_to_seg,
                       init, max_num_iter=Niter_snake,␣
 ↪convergence=convergence_val,
                       alpha=alpha_val, beta=beta_val, gamma=gamma_val)

# Display results
fig, axes = plt.subplots(1,2, figsize=(8, 4),constrained_layout=True)
ax        = axes.ravel()
Font_size = 9

ax[0].imshow(img_to_seg, cmap=plt.cm.gray)
ax[0].plot(init[:, 1], init[:, 0], '--y', lw=1)
ax[0].plot(snake30[:, 1], snake30[:, 0], '-b', lw=1.5)
ax[0].plot(snake[:, 1], snake[:, 0], '-r', lw=2)
ax[0].set_xticks([]), ax[0].set_yticks([])
ax[0].axis([0, img_to_seg.shape[1], img_to_seg.shape[0], 0])

ax[1].imshow(img_gt, cmap=plt.cm.gray)
ax[1].plot(init[:, 1], init[:, 0], '--y', lw=1)
ax[1].plot(snake30[:, 1], snake30[:, 0], '-b', lw=1.5)
ax[1].plot(snake[:, 1], snake[:, 0], '-r', lw=2)
```

```
ax[1].set_xticks([]), ax[1].set_yticks([])
ax[1].axis([0, img_to_seg.shape[1], img_to_seg.shape[0], 0])

plt.show();
```

7 Seg # 3

7.0.1 A tool to visualise the deformations of the snake over iterations

7.1 TO DO:

Run the code with provided parameter values. * **Q3.1 Checking the video, would you confirm that the snake has converged and is stable?** Answer**:

Q3.2 Change R0 to R0 = 52. Has convergence time been shorter or longer? Did you expect such observation (yes/no)? **Answer**: convergence time shorter/longer. It was (not?) expected since XX…

[ ]:
```
img_to_seg        = img_cell
img_to_seg_ori    = img_to_seg

# Init to segment cell
r0 = 128; c0=128; R0 = 53
alpha_val = 0.01 ; beta_val = 0.1 ;gamma_val = 0.01;
convergence_val = 1e-4; Niter_snake = 800;




# Pre filter the image
img_adapteq = skimage.exposure.equalize_adapthist(img_to_seg, clip_limit=0.03)
#img_to_seg = img_adapteq

# Pre smooth the image
Niter_smooth = 1
img_to_seg   = gaussian(img_to_seg, Niter_smooth, preserve_range=False)

# Initialise contour
init = define_initial_circle(R0,r0,c0)


# Run active contour while saving intermediate contours to see deformations
segs = []
print('start')
for i in range(1,Niter_snake,20):
    print(i, " ", end='')
```

```
    segs.append(active_contour(img_to_seg, init, max_num_iter=i,␣
↪convergence=convergence_val,
                 alpha=alpha_val, beta=beta_val, gamma=gamma_val))

print('stop')
np.save('ANIM_contours.npy', np.array(segs))

# display animation
segs = np.load('ANIM_contours.npy')
anim = animate_snake(img_to_seg, segs);
HTML(anim.to_html5_video())
```

8 Seg # 4

8.0.1 Snake with Gradient Vector Flow (GVF)

This implementation of the GVF is performed by computing the edge map, diffusing the gradient over the whole image and directly input the GVF_edge_map to be used as external forces by setting w_line=1 and w_edge=0 in the active_contour function.

8.1 TODO:

Q4.1.1 Report the visual differences in the GVF_map between mu=5 and mu=15. **Answer**:

Q4.1.2 What is the mu parameter controling? **Answer**: The mu parameter controls for XX. **Q4.2** Why does mu=15 enable to obtain a correct segmentation? **Answer**: **Q4.3** Report what happens when segmenting with the classic Edge_map rather than the GVF_map. **Answer**: ***

[ ]:
```
import gvf_elsa2
from gvf_elsa2 import  gradient_field, gradient_vector_flow



# Image to seg
img_to_seg = img_star
r0 = 64; c0=64; R0 = 50

alpha_val  = 0.01 ; beta_val = 0.1; gamma_val = 0.01;
convergence_val = 1e-4; Niter_snake = 200;



# Initialise contour
init        = define_initial_circle(R0,r0,c0,Nber_pts=400)

# Compute edge map and gvf
```

```
img_to_seg = img_to_seg.astype(np.float32) / np.max(img_to_seg)
Edge_map   = edge_map(img_to_seg,sigma=1)

fx, fy = gradient_field(img_to_seg)
gx, gy = gradient_vector_flow(fx, fy, mu=5)
GVF_map = np.sqrt(gx**2 + gy**2)

# Run active contour while saving intermediate contours to see deformations
Map_to_seg = Edge_map

# Run active contour while saving intermediate contours to see deformations
segs = []
print('start')
for i in range(1,Niter_snake,10):
    print(i, " ", end='')
    segs.append(active_contour(Map_to_seg, init, max_num_iter=i,␣
 ↪convergence=convergence_val,
                alpha=alpha_val, beta=beta_val, gamma=gamma_val,
                    w_line=1,w_edge=0))

print('stop')
np.save('ANIM_contours.npy', np.array(segs))

# display animation
segs = np.load('ANIM_contours.npy')
anim = animate_snake(Map_to_seg, segs);
HTML(anim.to_html5_video())
```

9 Seg # 5:

9.0.1 The active contour with fixed end points

You will now run the active_contour with the option to maintain some points from the inital contour fixed. You are working with the **img_oct_eye** which shows different layers of the retina. The **active_contour** routine is called to used directly the **Edge_map** as input.

9.1 TO DO:

Q5.1 Rank the 4 options for the Edge_map options from top to worst to segment the two layers wrt to segmentation quality and robustness to leyer selection. **Answer**: Ranked Edge_map options from best to worst: 1. edge_test1 2. edge_test2 3. edge_test2_l 4. edge_testl_2 ***

[ ]:
```
img_to_seg = img_oct_eye

# init for 1st layer
r_left = 103; r_right=138; c_left=0; c_right = 510
# init for 2nd layer
#r_left = 158; r_right=204; c_left=0; c_right = 510


alpha_val  = 0.01 ; beta_val = 0.1; gamma_val = 0.01;
convergence_val = 1e-4; Niter_snake = 500;
w_line_val=1; w_edge_val=0;

# Computation of edge maps
edge_test1         = edge_map(img_to_seg, sigma=1)
edge_test2         = edge_map(img_to_seg, sigma=2)
edge_test2_l       = np.log2((edge_test2*100)+1)
edge_testl_2       = edge_map(np.log2((img_to_seg+1)*100), sigma=2)

# Selection of edge_map to use
Edge_map           = edge_test1

# Initialise contour
Nber_pts_contour = 200
r          = np.linspace(r_left, r_right, Nber_pts_contour)
c          = np.linspace(c_left, c_right, Nber_pts_contour)
init       = np.array([r, c]).T


snake = active_contour(Edge_map,
                       init,
 ↪boundary_condition='fixed-fixed',max_num_iter=Niter_snake,
                       alpha=alpha_val, beta=beta_val, gamma=gamma_val,
                       w_line=w_line_val, w_edge=w_edge_val)



# FIGURE

fig, ax = plt.subplots(figsize=(9, 5));
ax.imshow(Edge_map[0:300,:], cmap=plt.cm.gray);
ax.plot(init[:, 1], init[:, 0], '--y', lw=2);
ax.plot(snake[:, 1], snake[:, 0], '-r', lw=3);
ax.set_xticks([]), ax.set_yticks([]);
ax.set(xlim=(0, 500));
plt.show();
```

10 Seg # 6

BONUS - Optional ### Your turn on proposing a motivated pipeline using the snake capabilities from the active_contour function

10.1 TODO:

Choose a new image in the pool provided and propose a segmentation pipeline using the active_contour approach. Options on points to work on include: * Pre-filter the image as you wish * Manually or automatically position the initial contour * Provide one segmentation result or merge several solutions in a probability map * Detect issues in contour shape during deformations and propose an early stop criteria.

Q6 Provide code + visual illustrations of results **Answer** ***

11 Seg #7

11.0.1 Test on the Geometric Level-Set formulation using the Chan-Vese model.

Skimage provides two implementations of the Chan-Vese approach: **[1]** **chan_vese**: implementation or original paper and **[2]** **morphological_chan_vese**: faster implementation but less precise. "Active contours without edges implemented with morphological operators. It is required that the inside of the object looks different on average than the outside (i.e., the inner area of the object should be darker or lighter than the outer area on average)."

The contours of objects are now encoded in a level set function **Phi**.

The **initialisation** tested here is with a "checkerboard" pattern for 2 classes (object and background).

For the **chan_vese** original implementation, the **hyper-parameters** include: * mu = 0.25 (default) | edge regularisation terms. Similar to 'edge length' weight parameter. Higher mu values will produce 'smoother' contours. * dt = 0.5 (default) | delta time step for each optimisation step.
* lambda1=1, lambda2=1 (default) | weights in the cost metric to balance inside and outside homogeneity terms. * tol=1e-3 (default) | Tolerance to test if the contours are "stable" and stop early.

The output contains: cv[0]=Seg and cv[1]=Phi

For the **morphological_chan_vese** implementation, the only **hyper-parameter** is the number of smoothing iterations (1 to 4 recommended).

11.1 TO DO:

Using **Chan-Vese** original implementation: *** **Q7.1** Run the code on **img_hela** with 200 iterations using **raw image** and the same image after **histogram equalisation**. What are differences observed in the Segmentation results and in the numerical values of the Phi level set function? **Answer**: Differences in the segmentation results: Differences in the Phi values:

Q7.2 Run the code on img_hela with **2** iterations using raw image. Why does the Segmentation image show the structures to segment but with "gray" values while this is a binary image? **Answer**: ***

Q7.3 Run the code on img_hela with 200 iterations using raw image but changing the tol_val = 10-5. Comment on major differences observed compared to tol_val = 10-3 and propose an explanation: **Answer**: ***

Q7.4 Run the code on **img_cell** with 200 iterations using raw image. Comment on the issue observed with this method if you compare to the segmentation targeted given in **gt_cell**: **Answer**: ***

Using **morphological_chan_vese** implementation: *** **Q7.5** Run the code on **img_cell** with 100 iterations using raw image. Compare using Init_method_cv_morpho= "checkerboard" or "disk". : **Answer**: General benefits from this implementation of Chan-Vese: Common issue seen on both segmentation results: Issue seen when using Morpho CV + disk:

Using one of the **chan_vese** implementation: *** **Q7.6** Segment the image: **img_fluo** and report the setup that lead to the best result. Include a display of the prefiltered-image and the segmentation results in the notebook. You can use any filtering you want : **Answer**: Parameters used: Initialisation used: Pre-processing used:

11.2 Bonus points

Q7.7 Evaluate the quality of the segmentation of **img_fluo** Display together your segmentation results and the ground-truth provided. Propose a measure to compare these segmentations. Provide code and display results in a new cell below : **Answer**: Add here any comment you would like to add ***

[ ]:
```
img_raw    = img_hela  # img_hela[0] changed 2025 for some environments -
 ↪img_cell, img_fluo
img_to_seg = img_raw


# PARAMETERS
mu_val=0.5 ; lambda1_val=1; lambda2_val=1;
tol_val=1e-3; dt_val=0.5
```

```
smoothing_val = 1
PRE_FILTER    = 0

Num_iter_cv_ori      = 200
Num_iter_cv_morpho   = 200

CHAN_VESE_ORI  = 1
Init_method_cv_ori       = "checkerboard" # "checkerboard" or "disk" or "small␣
↪disk" (alternative to use to set init_level_set)
Init_method_cv_morpho    = "checkerboard" # "disk" #  or "disk" or "small disk"␣
↪(alternative to use to set init_level_set)


# Pre-filter (TO TURN ON IF ASKED)
if PRE_FILTER:
    img_adapteq = skimage.exposure.equalize_adapthist(img_raw, clip_limit=0.03)
    img_to_seg = img_adapteq

# Select image to segment and print information
print("min - max value in image:" , np.min(img_to_seg), np.max(img_to_seg))
print("size of image:" , img_to_seg.shape)


# run segmentation
if CHAN_VESE_ORI == 1:
    # STANDARD implementation from original paper
    init_ls = checkerboard_level_set(img_to_seg.shape, 45)

    cv = chan_vese(img_to_seg, mu=mu_val, lambda1=lambda1_val,␣
↪lambda2=lambda2_val,
                   tol=tol_val, dt=dt_val,
                   max_num_iter=Num_iter_cv_ori,␣
↪init_level_set=Init_method_cv_ori,
                   extended_output=True)

    # Show results
    Nber_plots = 4
    fig, axes = plt.subplots(2,2,figsize=(7, 7))
    ax        = axes.ravel()
    ax[0].imshow(img_to_seg, cmap=plt.cm.gray)
    ax[0].set_title("Image to segment", fontsize=12);
    ax[1].imshow(1-cv[0], cmap=plt.cm.gray)
    title = f'C-V with - {len(cv[2])} iterations'
    ax[1].set_title(title, fontsize=12)
    ax[2].imshow(1-cv[0][0:64,0:64], cmap=plt.cm.gray)
    ax[2].set_title("Zoom on segmentation result", fontsize=12);
```

```
    tmp_show =ax[3].imshow(cv[1][0:64,0:64], cmap=plt.cm.jet)
    ax[3].set_title("Zoom on final Phi", fontsize=12);
    plt.colorbar(tmp_show,ax=ax[3], shrink=0.75, location='right')


    print("min - max value in Seg (cv[0]):" , np.min(cv[0]), np.max(cv[0]))

else:
    # FASTER implementation implemented with morphological operators BUT LESS␣
 ↪PRECISE
    cv      = morphological_chan_vese(img_to_seg, num_iter=Num_iter_cv_morpho,
                                      smoothing=smoothing_val,␣
 ↪init_level_set=Init_method_cv_morpho)
    # Show results
    Nber_plots = 2
    fig, ax = plt.subplots(1,2,figsize=(7, 7))
    ax[0].imshow(img_to_seg, cmap=plt.cm.gray)
    ax[1].imshow(1-cv, cmap=plt.cm.gray)
    title = f'C-V_morph with - {Num_iter_cv_morpho} iterations'
    ax[1].set_title(title, fontsize=12)

for i in range(0,Nber_plots):
    ax[i].set_xticks([]), ax[i].set_yticks([]);

plt.show();
```

12 Seg # 8

12.1 Geometric active contours with balloon force

Controling level-set deformable model with speed values acting on the contour. You are provided with a tool to track the deformation patterns of the active contour over iterations.

The geometric active contour routine is **morphological_geodesic_active_contour** which deforms a level set function with local speed values. It has the following **hyper-parameters** : * **Thresh_cont_val** = ‘auto’=> np.percentile(image, 40) (default if ‘auto’) | pixels < Thresh_cont_val are considered borders. The evolution of the contour will stop on these pixels. (It is used in the code to cancel the balloon speed using: Threshold_mask_balloon = image > threshold / np.abs(Balloon_weight)) * **Balloon_weight** = 1 (default) | weight of the balloon force. Can be negative to inflate/deflate * **Smooth_cont_iter** = 1 (default) | Number of times a smoothing operator is applied per iteration

13 TO DO:

Q8.1: Segment the **img__cell** with the provided configuration to **inflate** the initial contour using Conf #1. What is the issue when compared to the targeted ground-truth (GT) segmentation ? **Answer**: ***

Q8.2: Segment the **img__cell** with the provided configuration to **inflate** the initial contour using Conf #2. - What is the issue when compared to the targeted ground-truth (GT) segmentation ? **Answer**: - What benefit(s) do you observe when using this "implicit" formulation of a deformable model versus a snake-like "explicit" model using the same initialisation set-up and a balloon force: ? **Answer**: ***

Q8.3: Now Segment the **img__CTabd** with the provided configuration Conf #3 to **deflate** the initial contour (Adjust balloon parameter accordingly). Comment with your own words the quality and properties of the obtained segmentation: **Answer**: ***

13.1 Bonus points

Q8.4a: Check by yourself and explain why you think pre-processing using skimage.morphology.diameter__closing help the segmentation on **img__CTabd** ? **Answer**:

Q8.4b: Provide a different set up (with printed code and results) with different initialisation and/or pre-processing set-up that leads to a correct segmentation of the 2 kidneys (as in the ground truth). **Answer**: ***

[ ]:
```
# img_cell:
img_raw    = img_cell ;
gt_seg     = gt_cell

# img_CTabd:
# img_raw    = img_CTabd ;
# gt_seg     = gt_CTabd


# Select img to segment
img_to_seg = img_raw;

# Conf #1: Disk parameters to initialise shape for INFLATION on img_cell
r0 = 130;  c0 = 125 ; R0 = 30  # inflate
# Conf #2: Disk parameters to initialise shape for INFLATION on img on img_cell
#r0 = 130;  c0 = 125 ; R0 = 45  # inflate
# Conf #3: Disk parameters to initialise shape for DEFLATION on img
#r0 = 130;  c0 = 145 ; R0 = 85  # deflate TO KEEP ON CTabd

# Hyper-parameter for Balloon velocity:
Balloon_weight   = 1 ; # +1 or -1 to Inflate or deflate
```

```
# Additional Hyper-parameters for geodesic deformable model:
Threshold_contour_level = 20;
Smooth_cont_iter        = 1 ; # Number of times a smoothing operator is applied␣
 ↪per iteration
Niter_snake             = 600

# Hyper-parameter for preparing the input data:
INV_EDGE_MAP = 1; # needed when using the Balloon force

# Pre-processing the image with closing
img_to_seg = skimage.morphology.diameter_closing(img_to_seg, 40, connectivity=2)

# Inverse edge image: Compute the magnitude of the gradients in the image and
# then inverts the result in the range [0, 1]
if INV_EDGE_MAP:
     img_to_seg = skimage.segmentation.inverse_gaussian_gradient(
                                 img_to_seg,alpha=50,sigma=2)

# Print information
print("min - max value in image to seg:" , np.min(img_to_seg), np.
 ↪max(img_to_seg))
print("size of image to seg:" , img_to_seg.shape)

# Set and print threshold used in morphological_geodesic_active_contour
# Areas of the inverse edge map with value < Threshold will be considered␣
 ↪borders
Threshold_contour = np.percentile(img_to_seg, Threshold_contour_level);
Thresh_cont_val   = Threshold_contour ; # 'auto' ; # pixels < Thresh_cont_val␣
 ↪are considered borders. The evolution of the contour will stop on these␣
 ↪pixels.
print("threshold used in morphological_geodesic", Thresh_cont_val)


# initialise call back
evolution = []
callback = store_evolution_in(evolution)

# Initialise contour as a disk
init_ls  = skimage.segmentation.disk_level_set(img_to_seg.shape,␣
 ↪center=[r0,c0], radius=R0)

# Run geodesic active contour
ls       = morphological_geodesic_active_contour(
            img_to_seg, Niter_snake, init_ls,
            smoothing=Smooth_cont_iter, balloon=Balloon_weight,
            threshold=Thresh_cont_val,
```

```
        iter_callback=callback);

# Figure with plots of level-set evolution
fig, axes = plt.subplots(2, 2, figsize=(8, 8));
ax = axes.flatten();

ax[0].imshow(img_raw, cmap="gray");
ax[0].set_axis_off();
contour = ax[0].contour(evolution[0], [0.5], colors='y');
#contour.collections[0].set_label("Contours"); #removed 2025
ax[0].contour(ls, [0.5], colors='r');
ax[0].set_title("Img ori + contours", fontsize=12);

ax[1].imshow(img_to_seg, cmap="gray");
ax[1].set_axis_off();
contour = ax[1].contour(evolution[0], [0.5], colors='y');
#contour.collections[0].set_label("Contours"); #removed 2025
#contour.set_label("Contours"); # option to update 2025
#ax[0].contour(ls, [0.5], colors='r');#removed 2025
ax[1].contour(ls, [0.5], colors='r');
ax[1].set_title("Img to seg + contours", fontsize=12);
#ax[1].contour(ls, [0.5], colors='r');#removed 2025

ax[2].imshow(img_to_seg, cmap="gray");
ax[2].set_axis_off();
contour = ax[2].contour(evolution[0], [0.5], colors='y');
#contour.collections[0].set_label("Contours"); # removed 2025
title = f'Morphological GAC Curve evolution';
ax[2].set_title(title, fontsize=12);
for i in range(1, Niter_snake-1, 5):
    contour = ax[2].contour(evolution[i], [0.5], linewidths=0.5, colors='r'); #␣
 ↪changed 2025 0.01 to 0.5

ax[3].imshow(gt_seg, cmap="gray");
ax[3].set_axis_off();
ax[3].contour(ls, [0.5], colors='r');
ax[3].set_title("GT segmentation mask", fontsize=12);

plt.show();
```

[ ]: