Done in pair:

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In [1]:
```python
import numpy as np
import matplotlib
import skimage
import IPython

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 functio
from skimage.util import random_noise

# For active_contour function
from skimage.segmentation import chan_vese, morphological_chan_vese, checker

# 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__)
```

```
np.__version__ 2.2.1
matplotlib.__version__ 3.10.0
skimage.__version__ 0.25.0
IPython.__version__ 8.31.0
```

In [2]:
```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=Tru
    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=Tru
    return anim
```

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

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

    return _store
```

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]

In [3]:
```
# import warnings
# warnings.filterwarnings( "ignore", module = "matplotlib\..*" )
# skimage.io.imshow(img_mask)

# Binary images  - w/o ground truth
img_star          = skimage.io.imread('./images_misc/smooth_star.png', as_gr
edge_star         = edge_map(img_star, sigma=0)
img_star_noisy    = skimage.io.imread('./images_misc/smooth_star_noisy.png',
edge_star_noisy   = edge_map(img_star_noisy, sigma=0)
img_binshape      = skimage.io.imread('./images_misc/binary_shape_2024.png',
edge_binshape     = edge_map(img_binshape, sigma=0)
img_cardiacshape  = skimage.io.imread('./images_misc/cardiac_mri_mask.png',
edge_cardiacshape = edge_map(img_cardiacshape, sigma=0)


# OCT eye images  - w/o ground truth
img_oct_eye  = skimage.io.imread('./images_misc/OCT_normal.jpeg', as_gray =
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
edge_CTabd    = edge_map(img_CTabd, sigma=2)
gt_CTabd      = skimage.io.imread('./images_misc/CT_kidney_mask.png', as_gra
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 =
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 = Tru
edge_gt_cell = edge_map(gt_cell, sigma=2)


# OCT image of tissue  - with ground truth
img_oct_tissue  = skimage.io.imread('./OCT_myocardium/case272.tif', as_gray
edge_oct_tissue = edge_map(img_oct_tissue, sigma=2)
gt_oct_tissue  = skimage.io.imread('./OCT_myocardium/case272_label.tiff', as
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 = Tru
edge_USnodule = edge_map(img_USnodule, sigma=2)
gt_USnodule   = skimage.io.imread('./thyroid_nodule/1074_mask.png', as_gray
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_USnodule, cmap=plt.cm.gray);
ax[9].imshow(edge_USnodule, cmap=plt.cm.gray);
ax[10].imshow(gt_USnodule, cmap=plt.cm.gray);
ax[11].imshow(edge_gt_USnodule, 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();
```

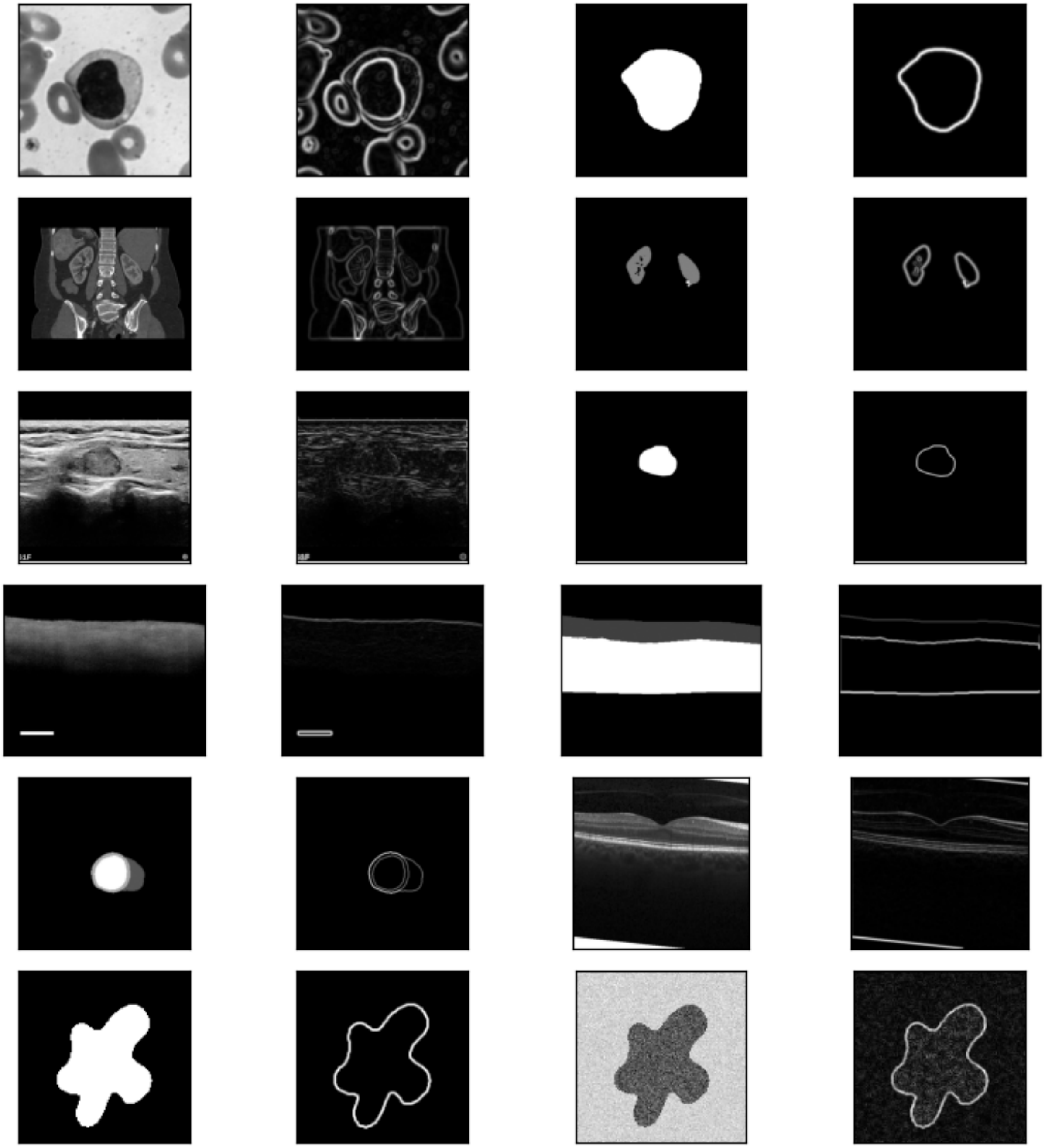


Image properties:

Range of values and data type matter ...

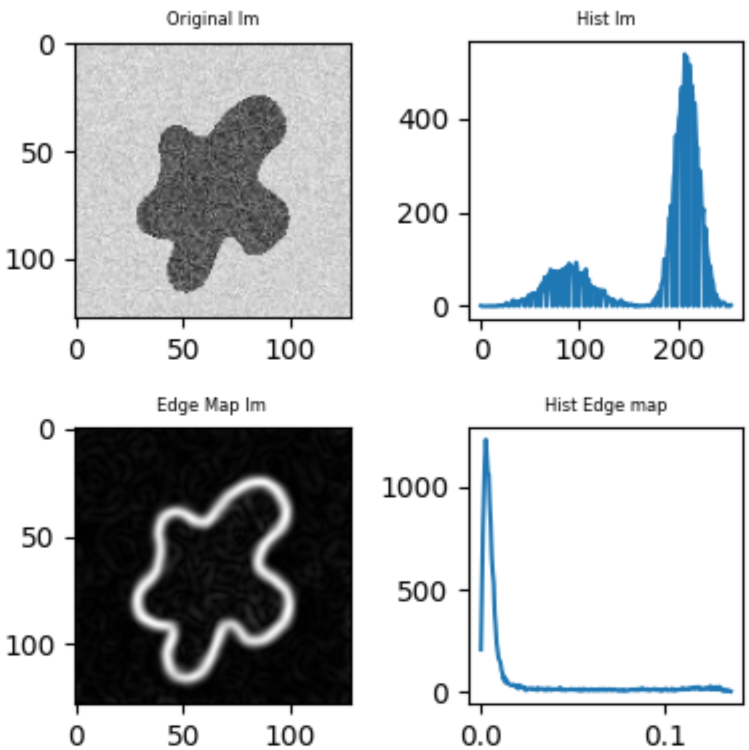
Some routines won't work if your image type is int8 or uint8... Here is how to check your image data type

And regularly check your image content in terms of:

- intensities range of values
- distributions of intensities via its histogram

In [4]:
```
img_test  = 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("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=25

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();
```

```
Data type of img_test is:  uint8
min - max value in image: 0 255
```



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.

In [5]:

```
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,


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();
```

```
Data type of img_test is:  uint8
min - max value in image: 0 255
```

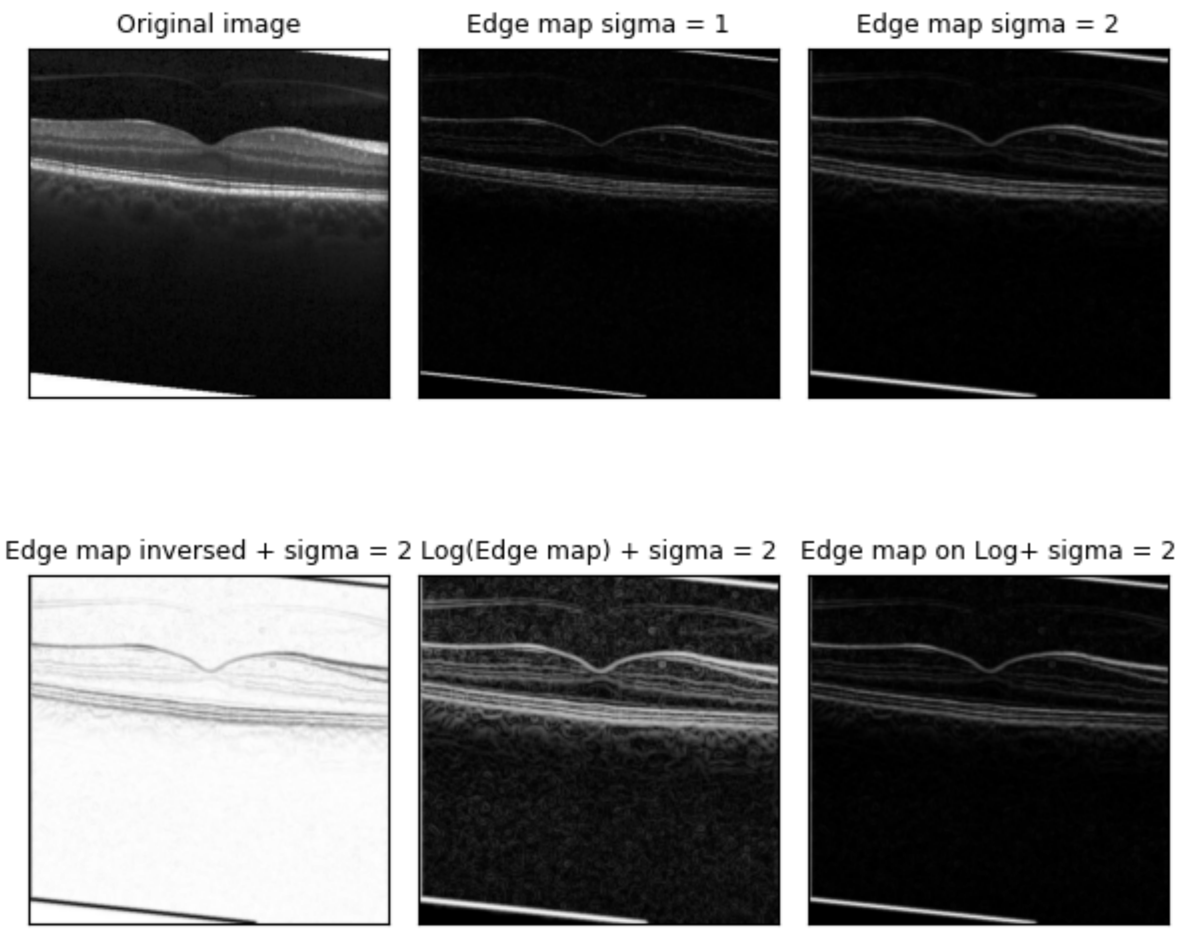
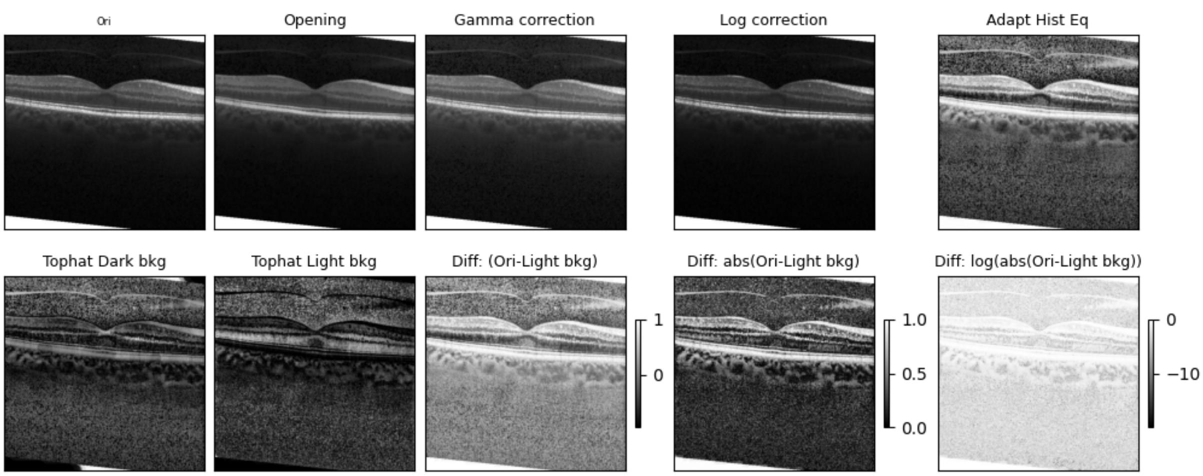


Image transforms

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.

In [6]:
```
img_ori_to_test = 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 enchanceme
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
img_open              = skimage.morphology.diameter_opening(img_to_test, 40,
img_adapteq           = skimage.exposure.equalize_adapthist(img_to_test, cli

# 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
Radius_val = 15
img_test1  = subtract_background(img_to_test, radius=Radius_val, light_bg=Fa
img_test2  = subtract_background(img_to_test, radius=Radius_val, light_bg=Tr

# 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='rig

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='rig

tmp_show = ax[9].imshow(np.log2(abs(img_to_test-img_test2+img_eps)), cmap=pl
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='rig

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.show();
```



Seg #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

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: Segmentation looks like a circle, but nothing meaningful is segmented.
- R0=20: Segmentation is no longer a circle. It expands to all the white area.
- R0=30: Expansion to gray area as well, but still confined to circular glob.
- R0=50: Segmentation now involves even the "tail" of the glob, making every non-black region selected

---

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: The segmentation is more curvy, with many contours. In a way, it is less rigid.
- Niter_smooth = 1: The segmented area is more circular, more rigid.
- Niter_smooth = 2: The image is now blurrier. The segmented region is very rigid and looks almost like a circle.

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: Speckle noise is multiplicative. Since the background is already 0, it stays 0 after multiplication.

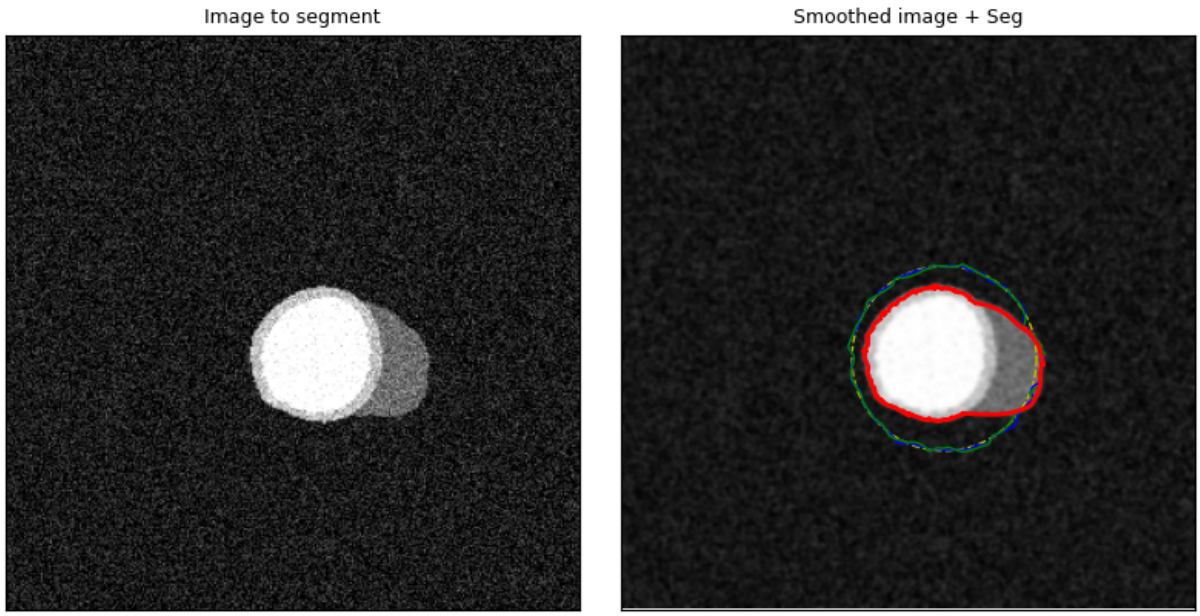
Q1.3.2 Using **R0=50**, run the segmentation on the noisy images **without** and with **smoothing** (Niter_smooth= 1). Comment on segmentation quality or issues for the 4 observations:

- Speckle noise + no smoothing: The segmentation correctly separeted the region from the background. It is very non-rigid since it has a lot of curves.
- Speckle noise + smoothing: The segmentations appears correct again, but the line is smoother, with less curvature
- Gaussian noise + no smoothing: The segmentation includes regions of the background too. It is not a very good segmentation.
- Gaussian noise + smoothing: With smoothing, the segmentations seems to fix the issues and it correctly separates the background from the object.

In [23]:

```
# 1ST image
img_ori          = img_cardiacshape; r0 = 175; c0=175; R0 = 50
img_noisy        = random_noise(img_ori, mode='gaussian', mean = 0.1,clip =
# img_noisy        = random_noise(img_ori, mode='speckle', mean = 0.1,clip =

# Choose image to segment
img_to_seg     = img_noisy
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=convergen
                           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();
```



Seg #2:

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.

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:
The segmentation worked as expected.

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 = 1 and R0 = 40

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 = 153; c0=66; R0 = 9] Naturally, as both the whole cell and the bright area share a simmilar center, changing the radious of the initial circle is enough to change the segmentation.

In [ ]:

```
# 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=convergen
                       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();
```

Seg # 3

A tool to visualise the deformations of the snake over iterations

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: Yes, the snake seems to have converged and to be stable. It completely envolves the gray area around the black cell and does not move further.

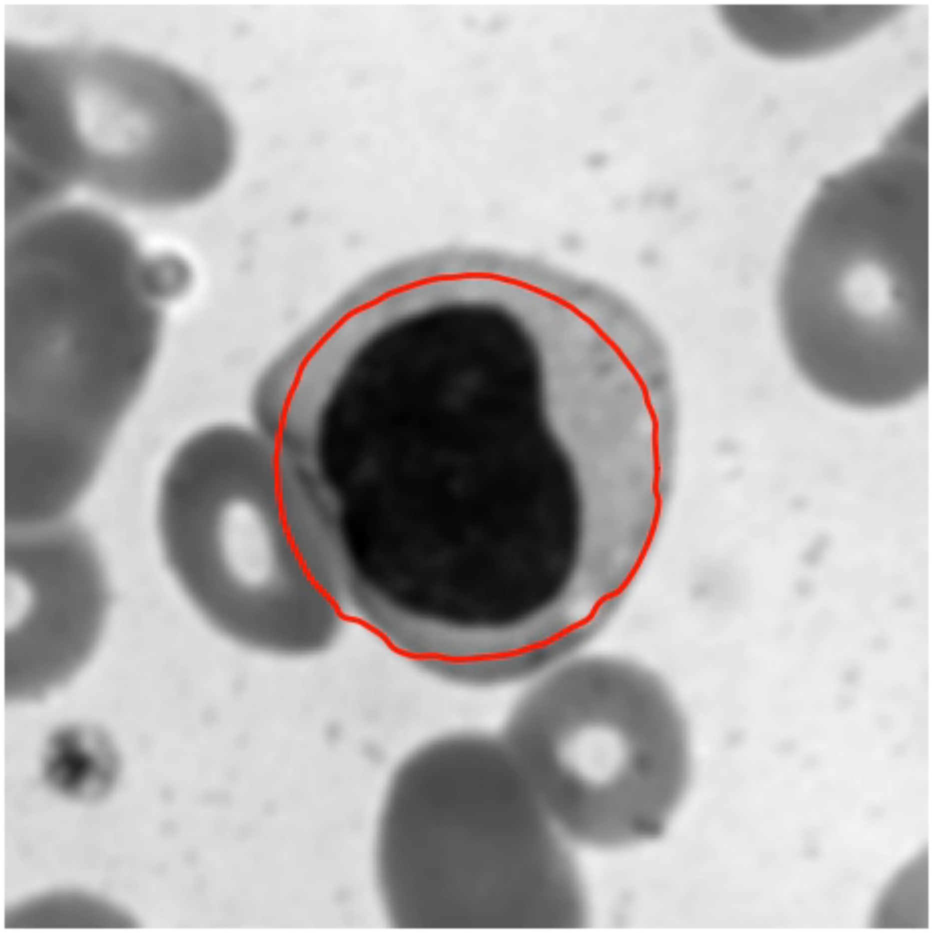
Q3.2 Change R0 to R0 = 52. Has convergence time been shorter or longer? Did you expect such observation (yes/no)?
Answer: Convergence time was longer. It was expected since the initial radius is smaller, so it takes longer to segment the gray area (which is larger than the original circle).

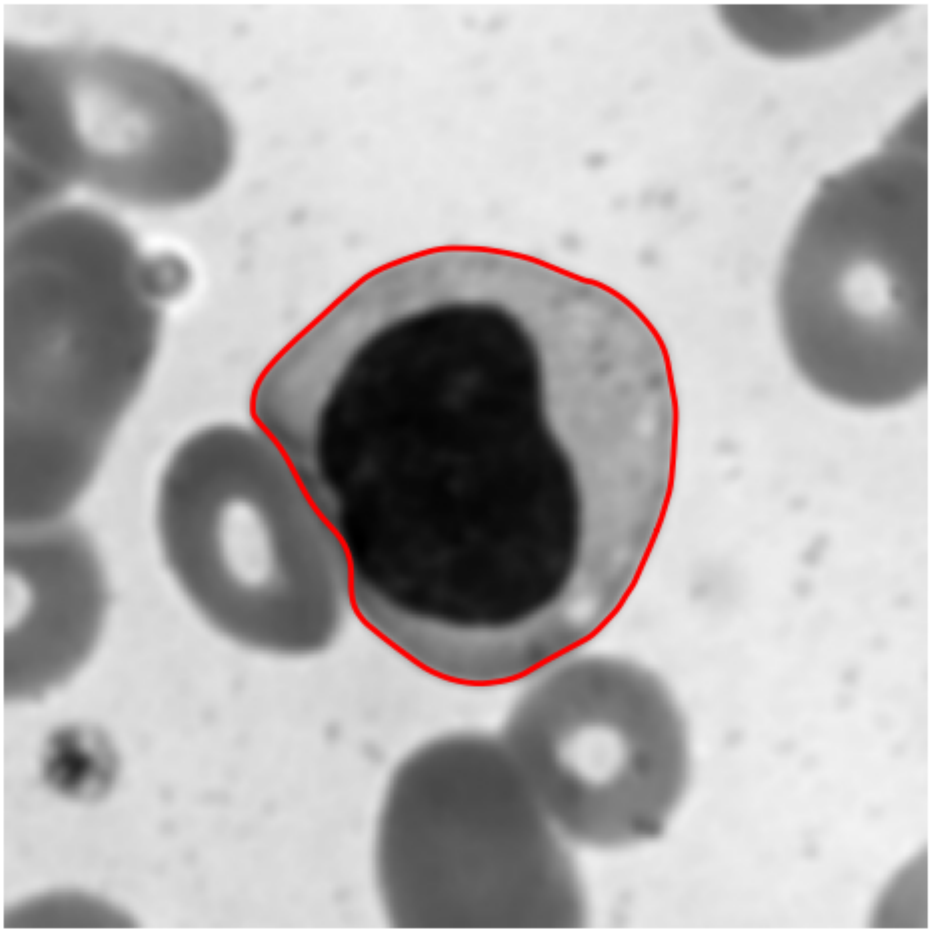
In [27]:
```
img_to_seg        = img_cell
img_to_seg_ori    = img_to_seg

# 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=0.0
#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
                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())
```

```
start
141  161  181  201  221  241  261  281  301  321  341  361  381  401  421  4
41  461  481  501  521  541  561  581  601  621  641  661  681  701  721  74
1  761  781  stop
```

Out[27]:





Seg # 4

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.

TODO:

Q4.1.1 Report the visual differences in the GVF_map between mu=5 and mu=15.
Answer: $\mu = 5$ makes the result not converge at all. The segmentation area is strange and does not represent anything. With $\mu = 15$, the segmentation converges correctly, highlighting the blob in the middle of the image.

Q4.1.2 What is the mu parameter controling?
Answer: The μ parameter controls the weight of the gradient for the energy calculation.

Q4.2 Why does mu=15 enable to obtain a correct segmentation?
Answer: With a higher weight on the gradient, the gradient has a greater influence on the energy calculation, making the curve smoother and enabling the algorithm to converge.

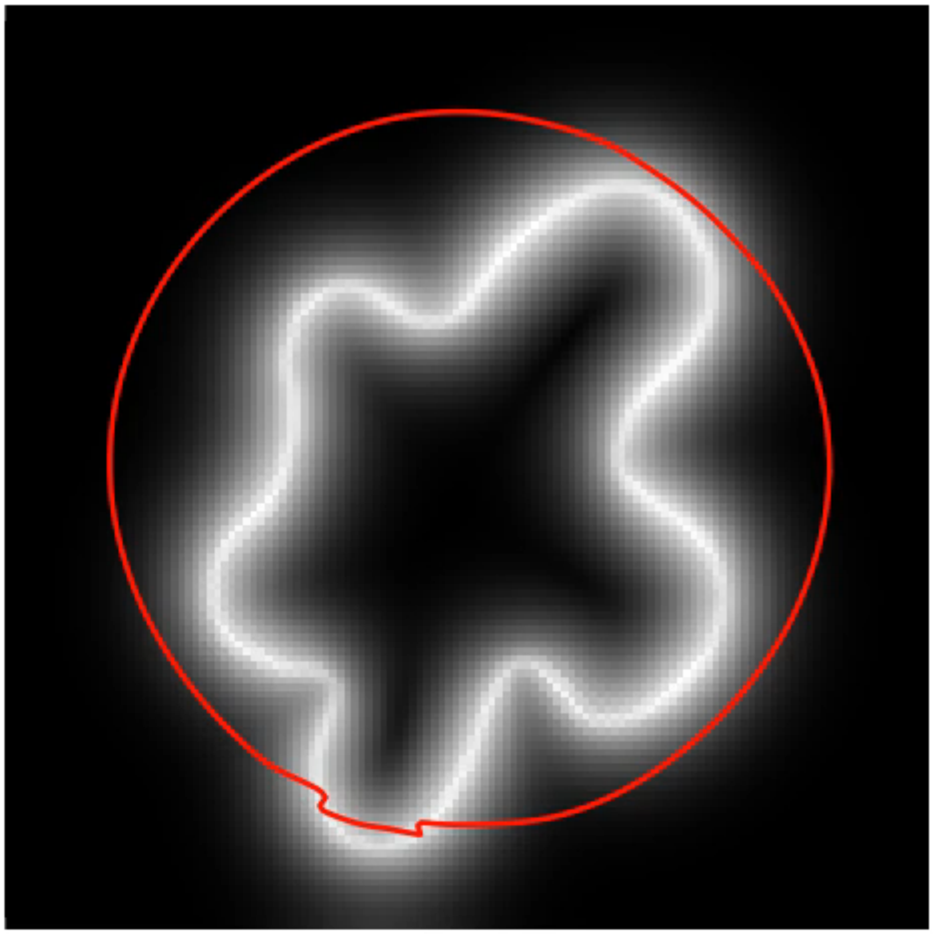
Q4.3 Report what happens when segmenting with the classic Edge_map rather than the GVF_map.
Answer: The object being segmented is way sharper now. The snake is highly non-smooth, containing various corners throughout the curve being highlighted.

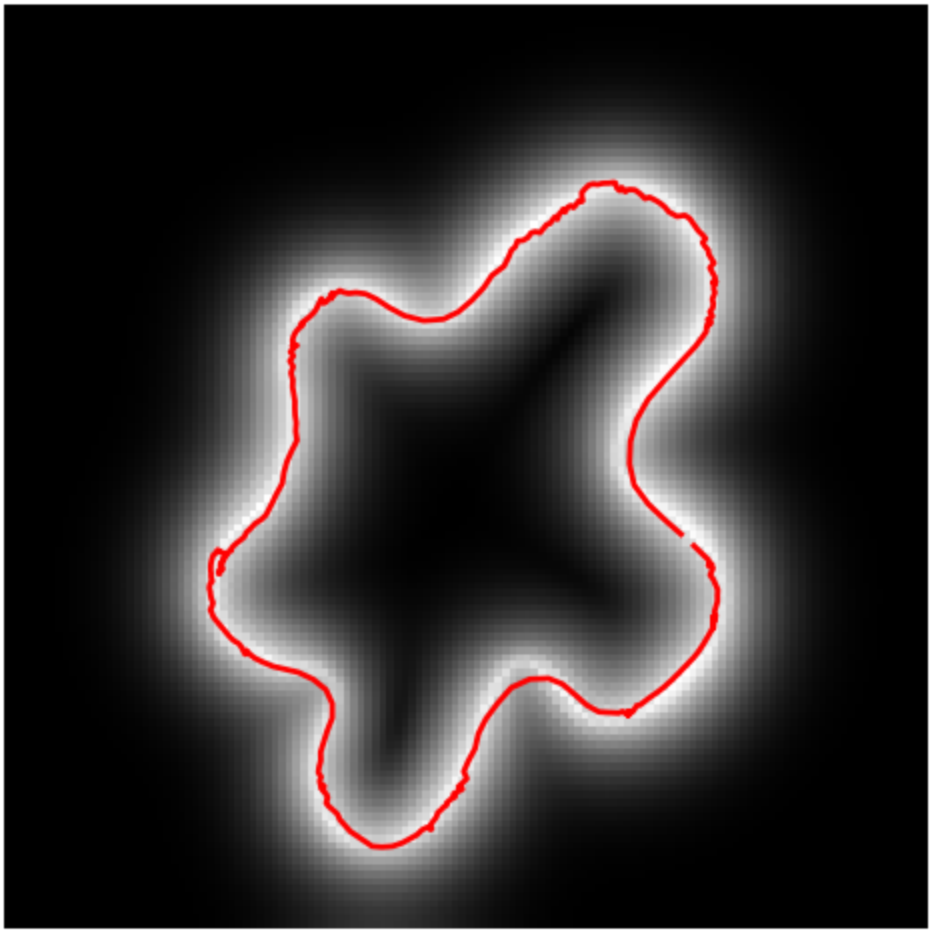
In [40]:
```
import gvf_elsa2
from gvf_elsa2 import  gradient_field, gradient_vector_flow


# 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=15)
GVF_map = np.sqrt(gx**2 + gy**2)

# Run active contour while saving intermediate contours to see deformations
Map_to_seg = GVF_map
# 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
                   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())
```

```
.............................................................................
....................................................
start
141  151  161  171  181  191  stop 91  101  111  121  131
```

Out[40]:





Seg # 5:

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.

TO DO:

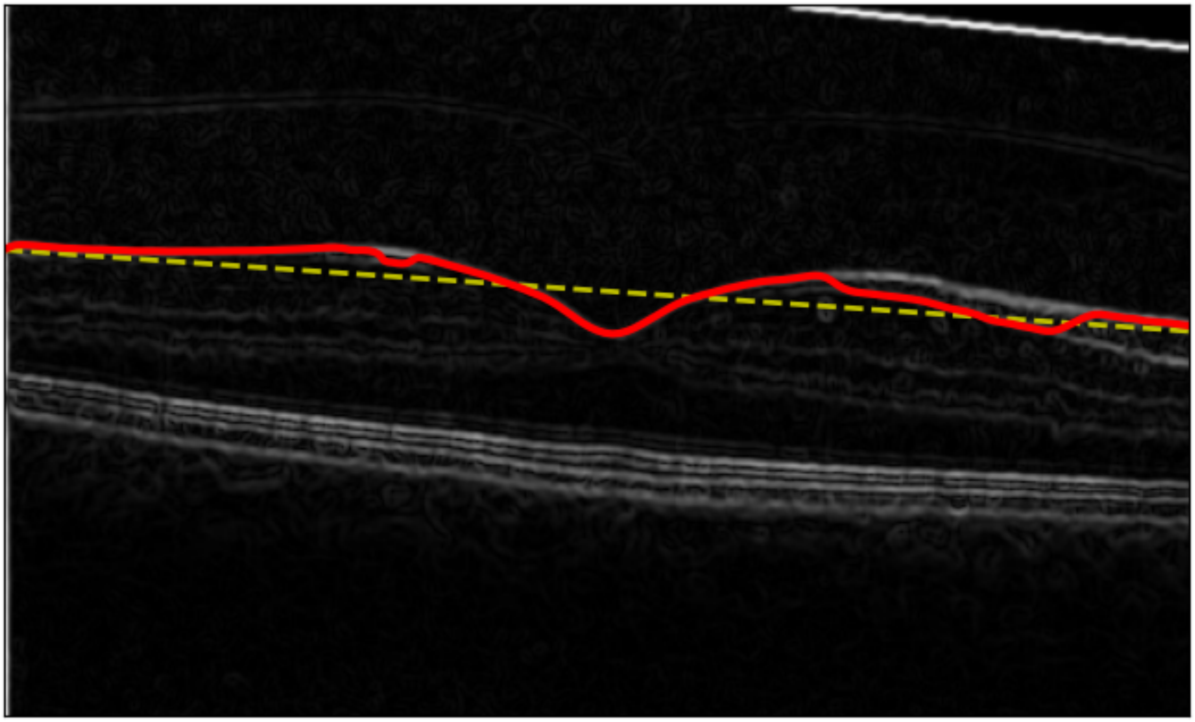
Q5.1 Rank the 4 options for the Edge_map options from top to worst to segment the two layers wrt to segmentation quality and robustness to leyer selection.
Answer: Ranked Edge_map options from best to worst:

1. edge_test2
2. edge_testl_2
3. edge_test1
4. edge_test2_l

Edge_test1 and edge_test2_l yield bad results, as they do not filter efficiently the noise in the gradient filter. On the other hand, both edge_test2 and edge_testl_2 give good results, as the regularization works better.

In [41]:

```
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=N
                       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();
```



Seg # 6

BONUS - Optional

Your turn on proposing a motivated pipeline using the snake capabilities from the active_contour function

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

Seg #7

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

Skimage provides two implementations of the Chan-Vese approach: **morphological_chan_vese** and **chan_vese**.

The contours of ojects 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).

TO DO:

1. C-V ori: Run the code on img_hela. Visualise and explain evolution of Phi over first iterations. Figure out how to see the initial Phi configuration.
2. Run now on img_cell without and with pre-processing with histogram equalisation and explain difference in results.
3. Propose and implement method(s) and metrics to compare two segmentation results when handling segmentation masks. Use the one(s) implemented to quantify the differences obtained on one test case of your choice with the two implementations of chan-vese provided here.
4. Make the level set work when initialising with "disk" on img_MRIf

In [ ]:
```
img_to_seg= img_hela

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

Num_iter_cv_ori    = 100
Num_iter_cv_fast   = 1
```

```
CHAN_VESE_ORI  = 1
Init_method    = "checkerboard" # "checkerboard" or "disk" or "small disk" (


# 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=lambd
                   tol=tol_val, dt=dt_val,
                   max_num_iter=Num_iter_cv_ori, init_level_set=Init_method,
                   extended_output=True)
    fig, ax = plt.subplots(1,2,figsize=(7, 7))
    ax[0].imshow(img_to_seg, cmap=plt.cm.gray)
    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)

else:
    # FASTER implementation implemented with morphological operators BUT LES
    cv      = morphological_chan_vese(img_to_seg, num_iter=Num_iter_cv_fast,
                                      smoothing=smoothing_val, init_level_se
    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_fast} iterations'
    ax[1].set_title(title, fontsize=12)


plt.show();
```

Seg # 8

Geometric active contours with balloon force

You are now also 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. Threshold_mask_balloon = image > threshold / np.abs(Balloon_weight)
- Balloon_weight = 1 (default) | weight of the balloon force. Can be negative to inflate/ deflat
- Smooth_cont_iter = 1 (default) | Number of times a smoothing operator is applied per iteration

TO DO:

- Segment the img_cell with the provided configuration in line 1 to inflate the initial contour. What is the issue?
- Now Segment the img_cell with the provided configuration in line 2 to deflate the initial contour. Adjust balloon parameter accordingly. Fix the issues observed to get a perfect segmentation in 30 iterations.
- Segment the img_MRIb image with the configuration in line 3 set to inflate an initial contour. Comment issues seen with high and low smoothness regularisation over 300 iterations.
- Now propose and run a setup to attempt to segment the gray matter contours in img_MRIb or some structure in another image. Comment on your choice of parameters, number of iterations and observed quality of contours.

In [ ]:

```
img_to_seg = img_cell ; r0 = 130;  c0 = 125 ; R0 = 30  # inflate
#img_to_seg = img_cell ; r0 = 130;  c0 = 125 ; R0 = 70  # deflate
#img_to_seg = img_MRIb ; r0 = 500 ; c0 = 530 ; R0 = 30  # for spine and infl



SMOOTHING    = 0; Niter_smooth = 3
INV_EDGE_MAP = 1; # needed when using the Balloon force

img_ori    = img_to_seg

# Hyper parameters for snake and balloon
Thresh_cont_val  = 'auto' ; Balloon_weight   = 1 ; Smooth_cont_iter = 1 ;
Niter_snake      = 100

# smoothing
if SMOOTHING:
    img_to_seg = gaussian(img_to_seg, Niter_smooth, preserve_range=False)

# Test segment directly on edge image [QUESTION: WHY IS THE RESULT DIFFERENT
if INV_EDGE_MAP:
    img_to_seg = skimage.segmentation.inverse_gaussian_gradient(img_to_seg)

#Print threshold used by "auto"
print(np.percentile(img_to_seg, 40))


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

# Initialise contour
init_ls  = skimage.segmentation.disk_level_set(img_to_seg.shape, center=[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);


fig, axes = plt.subplots(2, 2, figsize=(8, 8));
ax = axes.flatten();

ax[0].imshow(img_ori, cmap="gray");
ax[0].set_axis_off();
ax[0].contour(ls, [0.5], colors='r');
ax[0].set_title("Morphological GAC segmentation", fontsize=12);

ax[1].imshow(img_to_seg, cmap="gray");
ax[1].set_axis_off();
ax[1].contour(ls, [0.5], colors='r');
ax[1].set_title("Morphological GAC segmentation", fontsize=12);

ax[2].imshow(ls, cmap="gray");
ax[2].set_axis_off();
contour = ax[2].contour(evolution[0], [0.5], colors='r');
contour.collections[0].set_label("Contours");
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], [0.01], linewidths=0.5, colors='y'

plt.show();
```

In [ ]: