ImSegm Documentation

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CHAPTER

ONE

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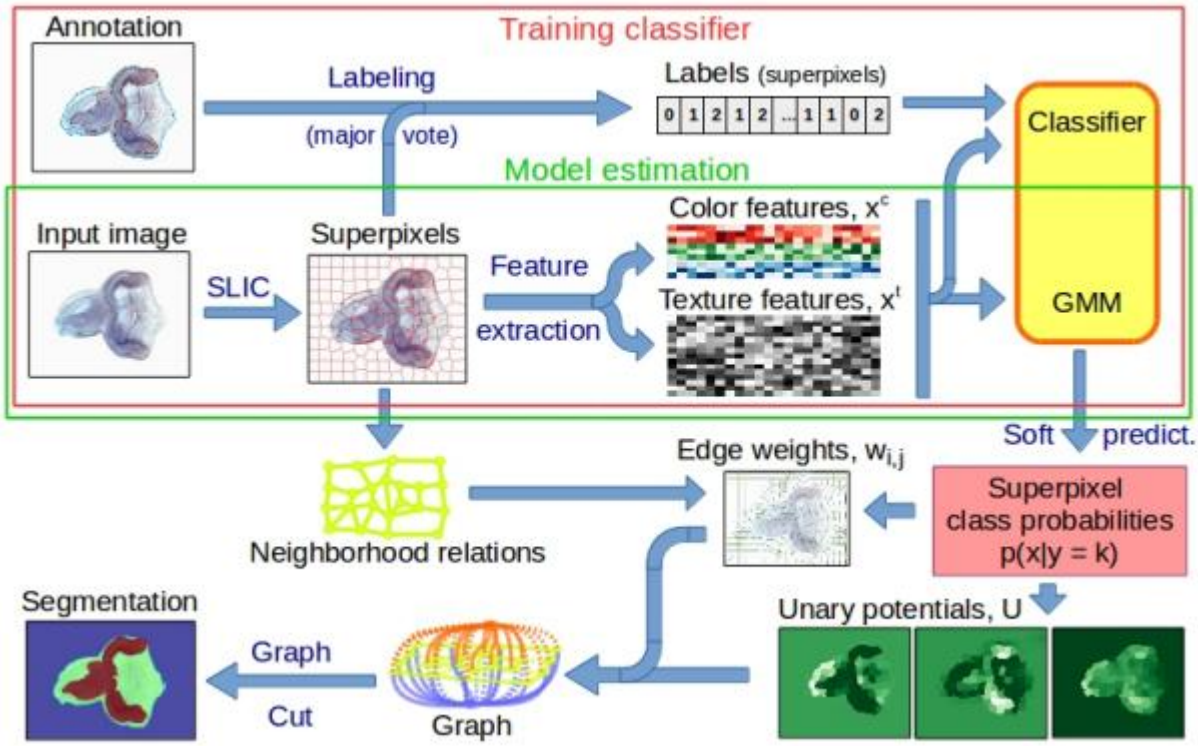
1.1 Image segmentation toolbox

1.1.1 Superpixel segmentation with GraphCut regularisation

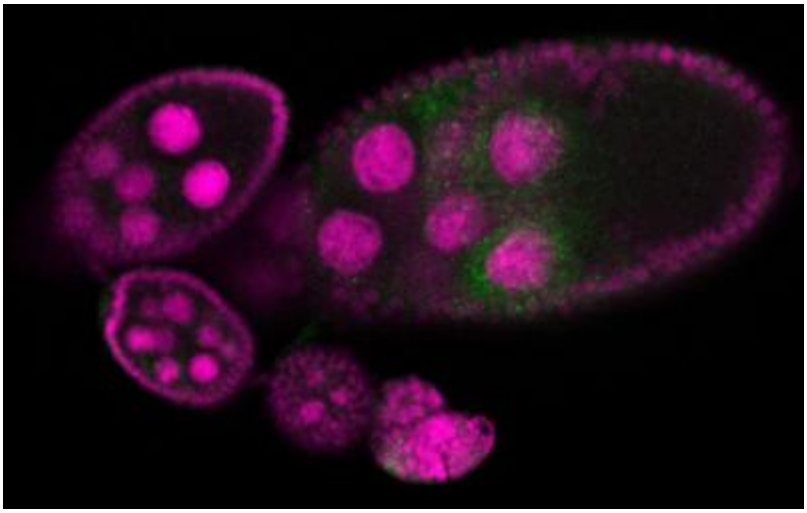
Image segmentation is widely used as an initial phase of many image processing tasks in computer vision and image analysis. Many recent segmentation methods use superpixels because they reduce the size of the segmentation problem by order of magnitude. Also, features on superpixels are much more robust than features on pixels only. We use spatial regularisation on superpixels to make segmented regions more compact. The segmentation pipeline comprises (i) computation of superpixels; (ii) extraction of descriptors such as colour and texture; (iii) soft classification, using a standard classifier for supervised learning, or the Gaussian Mixture Model for unsupervised learning; (iv) final segmentation using Graph Cut. We use this segmentation pipeline on real-world applications in medical imaging (see sample images. We also show that unsupervised segmentation is sufficient for some situations, and provides similar results to those obtained using trained segmentation.



Sample ipython notebooks:

- Supervised segmentation requires training annotation
- Unsupervised segmentation just asks for expected number of classes
- **partially annotated images** with missing annotation is marked by a negative number

Illustration



Reference: *Borovec J., Svihlik J., Kybic J., Habart D. (2017).* ***Supervised and unsupervised segmentation using superpixels, model estimation, and Graph Cut.*** *In: Journal of Electronic Imaging.*

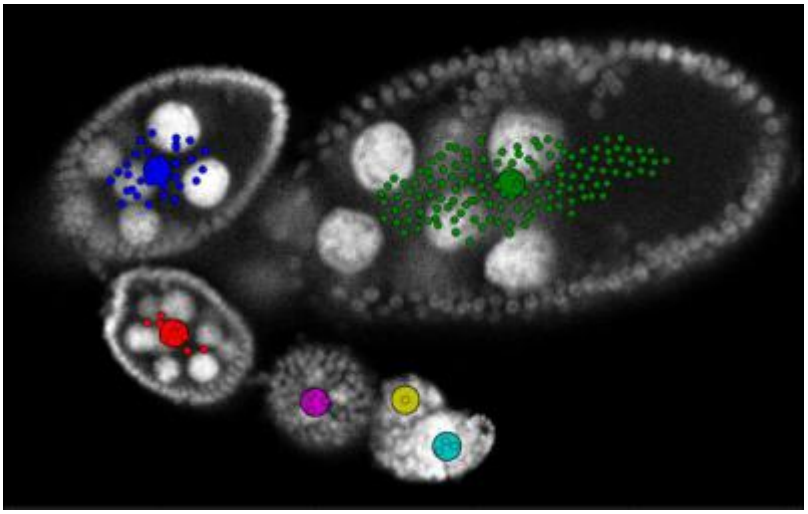
1.1.2 Object centre detection and Ellipse approximation

An image processing pipeline to detect and localize Drosophila egg chambers that consists of the following steps: (i) superpixel-based image segmentation into relevant tissue classes (see above); (ii) detection of egg center candidates using label histograms and ray features; (iii) clustering of center candidates and; (iv) area-based maximum likelihood ellipse model fitting. See our Poster related to this work.

Sample ipython notebooks:

- Center detection consists of center candidate training and prediction, and candidate clustering.
- Ellipse fitting with given estimated center structure segmentation.

Illustration



Reference: *Borovec J., Kybic J., Nava R. (2017)* ***Detection and Localization of Drosophila Egg Chambers in Microscopy Images.*** *In: Machine Learning in Medical Imaging.*

1.1.3 Superpixel Region Growing with Shape prior

Region growing is a classical image segmentation method based on hierarchical region aggregation using local similarity rules. Our proposed approach differs from standard region growing in three essential aspects. First, it works on the level of superpixels instead of pixels, which leads to a substantial speedup. Second, our method uses learned statistical shape properties which encourage growing leading to plausible shapes. In particular, we use ray features to describe the object boundary. Third, our method can segment multiple objects and ensure that the segmentations do not overlap. The problem is represented as energy minimisation and is solved either greedily, or iteratively using GraphCuts.

Sample ipython notebooks:

- General GraphCut from given centers and initial structure segmentation.
- Shape modeling estimation from training examples.
- Region growing from given centers and initial structure segmentation with shape models.

Illustration

Reference: *Borovec J., Kybic J., Sugimoto, A. (2017).* ***Region growing using superpixels with learned shape prior.*** *In: Journal of Electronic Imaging.*

1.1.4 Installation and configuration

Configure local environment

Create your own local environment, for more see the User Guide, and install dependencies requirements.txt contains list of packages and can be installed as

```
@duda:~$ cd pyImSegm
@duda:~/pyImSegm$ virtualenv env
@duda:~/pyImSegm$ source env/bin/activate
(env)@duda:~/pyImSegm$ pip install -r requirements.txt
(env)@duda:~/pyImSegm$ python ...
```

and in the end terminating...

```
(env)@duda:~/pyImSegm$ deactivate
```

Compilation

We have implemented `cython` version of some functions, especially computing descriptors, which require to compile them before using them

```
python setup.py build_ext --inplace
```

If loading of compiled descriptors in `cython` fails, it is automatically swapped to use `numpy` which gives the same results, but it is significantly slower.

Installation

The package can be installed via pip

```
pip install git+https://github.com/Borda/pyImSegm.git
```

or using `setuptools` from a local folder

```
python setup.py install
```

1.1.5 Experiments

Short description of our three sets of experiments that together compose single image processing pipeline in this order:

1. **Semantic (un/semi)supervised segmentation**
2. **Center detection and ellipse fitting**
3. **Region growing with the learned shape prior**

Annotation tools

We introduce some useful tools for work with image annotation and segmentation.

- **Quantization:** in case you have some smooth colour labelling in your images you can remove them with following quantisation script.

```
python handling_annotations/run_image_color_quantization.py \
    -imgs "./data-images/drosophila_ovary_slice/segm_rgb/*.png" \
    -m position -thr 0.01 --nb_workers 2
```

- **Paint labels:** concerting image labels into colour space and other way around.

```
python handling_annotations/run_image_convert_label_color.py \
    -imgs "./data-images/drosophila_ovary_slice/segm/*.png" \
    -out ./data-images/drosophila_ovary_slice/segm_rgb
```

- **Visualisation:** having input image and its segmentation we can use simple visualisation which overlap the segmentation over input image.

```
python handling_annotations/run_overlap_images_segms.py \
    -imgs "./data-images/drosophila_ovary_slice/image/*.jpg" \
    -segs ./data-images/drosophila_ovary_slice/segm \
    -out ./results/overlap_ovary_segment
```

- **In-painting** selected labels in segmentation.

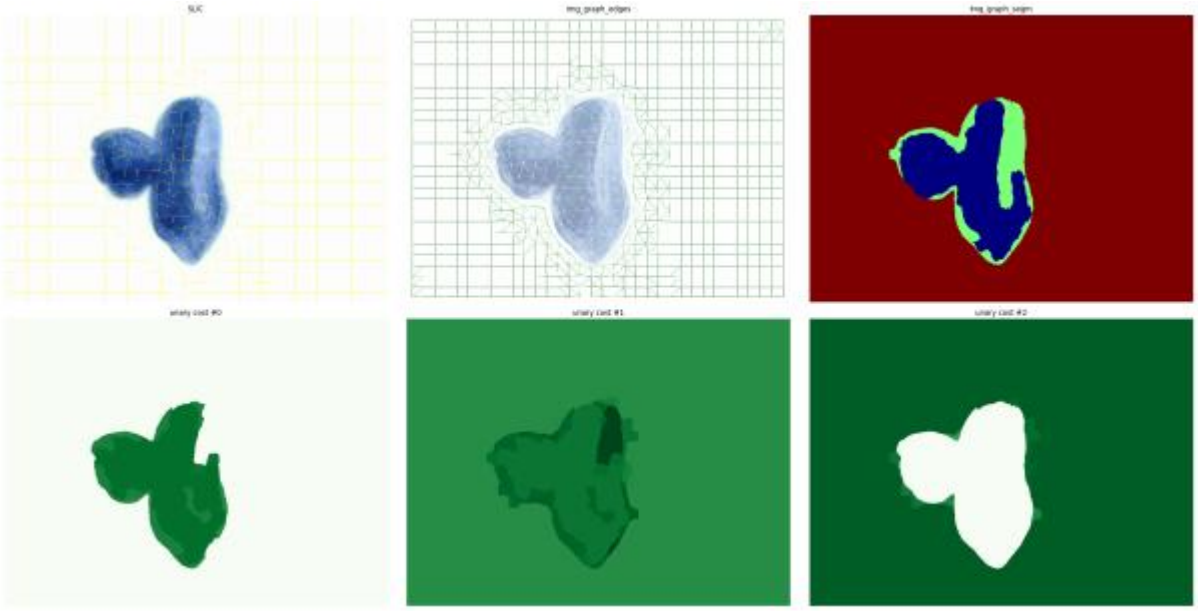
```
python handling_annotations/run_segm_annot_inpaint.py \
    -imgs "./data-images/drosophila_ovary_slice/segm/*.png" \
    --label 4
```

- **Replace labels:** change labels in input segmentation into another set of labels in 1:1 schema.

```
python handling_annotations/run_segm_annot_relabel.py \
    -out ./results/relabel_center_levels \
    --label_old 2 3 --label_new 1 1
```

Semantic (un/semi)supervised segmentation

We utilise (un)supervised segmentation according to given training examples or some expectations.



- Evaluate superpixels (with given SLIC parameters) quality against given segmentation. It helps to find out the best SLIC configuration.

```
python experiments_segmentation/run_eval_superpixels.py \
    -imgs "./data-images/drosophila_ovary_slice/image/*.jpg" \
    -segm "./data-images/drosophila_ovary_slice/annot_eggs/*.png" \
    --img_type 2d_split \
    --slic_size 20 --slic_regul 0.25 --slico
```

- Perform **Un-Supervised** segmentation in images given in CSV

```
python experiments_segmentation/run_segm_slic_model_graphcut.py \
   -l ./data-images/langerhans_islets/list_lang-isl_imgs-annot.csv -i "" \
```

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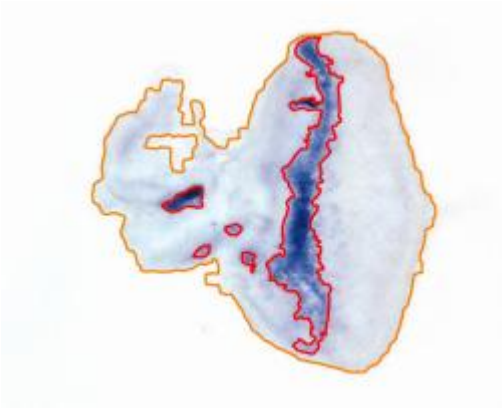
```
    -cfg experiments_segmentation/sample_config.yml \
    -o ./results -n langIsl --nb_classes 3 --visual --nb_workers 2
```

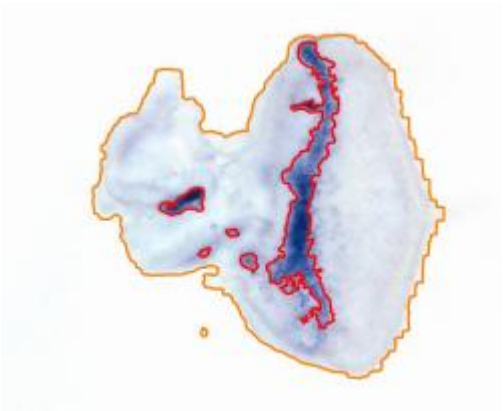
OR specified on particular path:

```
python experiments_segmentation/run_segm_slic_model_graphcut.py \
    -l "" -i "./data-images/langerhans_islets/image/*.jpg" \
    -cfg ./experiments_segmentation/sample_config.yml \
    -o ./results -n langIsl --nb_classes 3 --visual --nb_workers 2
```



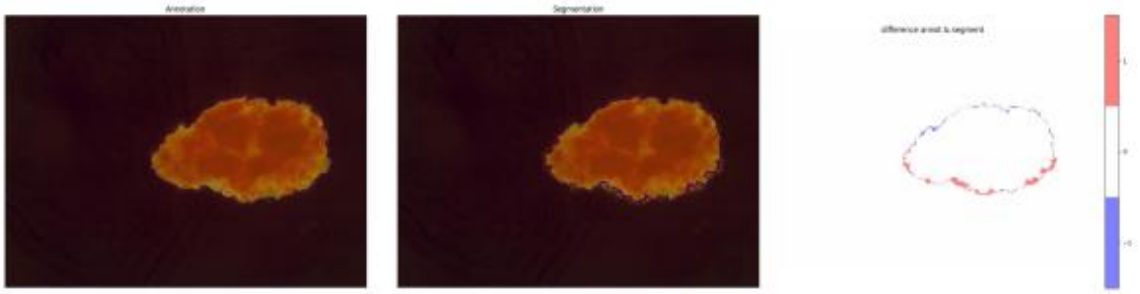
- Perform **Supervised** segmentation with afterwards evaluation.

```
python experiments_segmentation/run_segm_slic_classif_graphcut.py \
    -l ./data-images/drosophila_ovary_slice/list_imgs-annot-struct.csv \
    -i "./data-images/drosophila_ovary_slice/image/*.jpg" \
    --path_config ./experiments_segmentation/sample_config.yml \
    -o ./results -n Ovary --img_type 2d_split --visual --nb_workers 2
```



- Perform **Semi-Supervised** is using the the supervised pipeline with not fully annotated images.
- For both experiment you can evaluate segmentation results.

```
python experiments_segmentation/run_compute-stat_annot-segm.py \
    -a "./data-images/drosophila_ovary_slice/annot_struct/*.png" \
    -s "./results/experiment_segm-supervise_ovary/*.png" \
    -i "./data-images/drosophila_ovary_slice/image/*.jpg" \
    -o ./results/evaluation --visual
```



The previous two (un)segmentation accept configuration file (YAML) by parameter `-cfg` with some extra parameters which was not passed in arguments, for instance:

```
slic_size: 35
slic_regul: 0.2
features:
  color_hsv: ['mean', 'std', 'eng']
classif: 'SVM'
nb_classif_search: 150
gc_edge_type: 'model'
gc_regul: 3.0
run_LOO: false
run_LPO: true
cross_val: 0.1
```

Center detection and ellipse fitting

In general, the input is a formatted list (CSV file) of input images and annotations. Another option is set by `-list none` and then the list is paired with given paths to images and annotations.

Experiment sequence is the following:

1. We can create the annotation completely manually or use the following script which uses annotation of individual objects and create the zones automatically.

```
python experiments_ovary_centres/run_create_annotation.py
```

2. With zone annotation, we train a classifier for centre candidate prediction. The annotation can be a CSV file with annotated centres as points, and the zone of positive examples is set uniformly as the circular neighbourhood around these points. Another way (preferable) is to use an annotated image with marked zones for positive, negative and neutral examples.

```
python experiments_ovary_centres/run_center_candidate_training.py -list none \
    -segs "./data-images/drosophila_ovary_slice/segm/*.png" \
    -imgs "./data-images/drosophila_ovary_slice/image/*.jpg" \
    -centers "./data-images/drosophila_ovary_slice/center_levels/*.png" \
    -out ./results -n ovary
```

3. Having trained classifier we perform center prediction composed from two steps: i) center candidate clustering and ii) candidate clustering.

```
python experiments_ovary_centres/run_center_prediction.py -list none \
    -segs "./data-images/drosophila_ovary_slice/segm/*.png" \
    -imgs "./data-images/drosophila_ovary_slice/image/*.jpg" \
    -centers ./results/detect-centers-train_ovary/classifier_RandForest.pkl \
    -out ./results -n ovary
```

4. Assuming you have an expert annotation you can compute static such as missed eggs.

```
python experiments_ovary_centres/run_center_evaluation.py
```

5. This is just cut out clustering in case you want to use different parameters.

```
python experiments_ovary_centres/run_center_clustering.py \
    -segs "./data-images/drosophila_ovary_slice/segm/*.png" \
    -imgs "./data-images/drosophila_ovary_slice/image/*.jpg" \
    -centers "./results/detect-centers-train_ovary/candidates/*.csv" \
    -out ./results
```

6. Matching the ellipses to the user annotation.

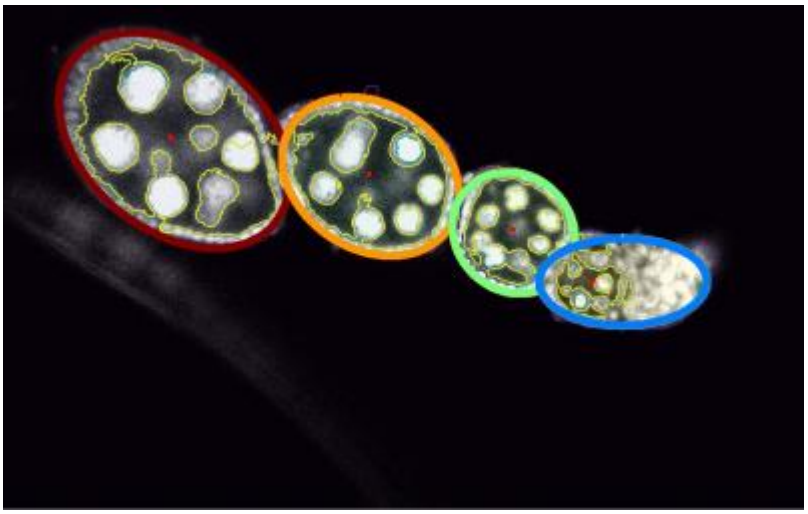
```
python experiments_ovary_detect/run_ellipse_annot_match.py \
    -info "~/Medical-drosophila/all_ovary_image_info_for_prague.txt" \
    -ells "~/Medical-drosophila/RESULTS/3_ellipse_ransac_crit_params/*.csv" \
    -out ~/Medical-drosophila/RESULTS
```

7. Cut eggs by stages and norm to mean size.

```
python experiments_ovary_detect/run_ellipse_cut_scale.py \
    -info ~/Medical-drosophila/RESULTS/info_ovary_images_ellipses.csv \
    -imgs "~/Medical-drosophila/RESULTS/0_input_images_png/*.png" \
    -out ~/Medical-drosophila/RESULTS/images_cut_ellipse_stages
```

8. Rotate (swap) extracted eggs according the larger mount of mass.

```
python experiments_ovary_detect/run_egg_swap_orientation.py \
    -imgs "~/Medical-drosophila/RESULTS/atlas_datasets/ovary_images/stage_3/*.png
↪" \
    -out ~/Medical-drosophila/RESULTS/atlas_datasets/ovary_images/stage_3
```



Region growing with a shape prior

In case you do not have estimated object centres, you can use plugins for landmarks import/export for Fiji.

Note: install the multi-snake package which is used in multi-method segmentation experiment.

```
pip install --user git+https://github.com/Borda/morph-snakes.git
```

Experiment sequence is the following:

1. Estimating the shape model from set training images containing a single egg annotation.

```
python experiments_ovary_detect/run_RG2Sp_estim_shape-models.py  \
    -annot "~/Medical-drosophila/egg_segmentation/mask_2d_slice_complete_ind_egg/
↪*.png" \
    -out ./data-images -nb 15
```

2. Run several segmentation techniques on each image.

```
python experiments_ovary_detect/run_ovary_egg-segmentation.py  \
    -list ./data-images/drosophila_ovary_slice/list_imgs-segm-center-points.csv \
    -out ./results -n ovary_image --nb_workers 1 \
    -m ellipse_moments \
       ellipse_ransac_mmt \
       ellipse_ransac_crit \
       GC_pixels-large \
       GC_pixels-shape \
       GC_slic-large \
       GC_slic-shape \
       rg2sp_greedy-mixture \
       rg2sp_GC-mixture \
       watershed_morph
```

3. Evaluate your segmentation ./results to expert annotation.

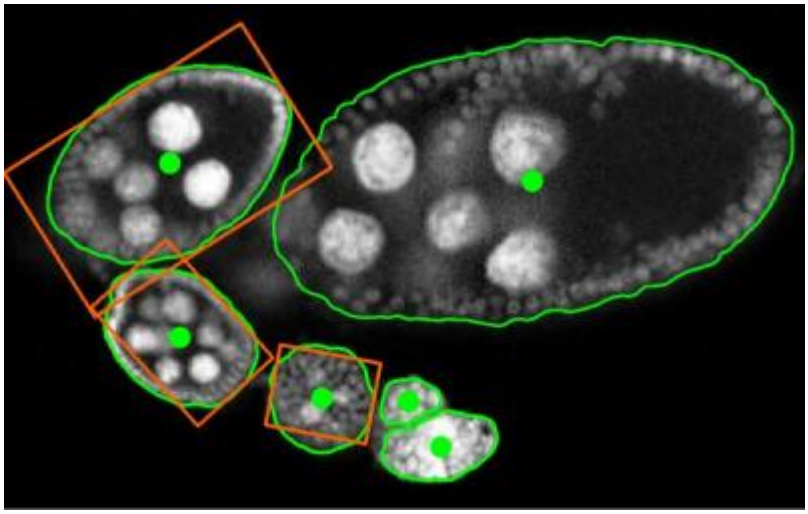
```
python experiments_ovary_detect/run_ovary_segm_evaluation.py --visual
```

4. In the end, cut individual segmented objects comes as minimal bounding box.

```
python experiments_ovary_detect/run_cut_segmented_objects.py \
    -annot "./data-images/drosophila_ovary_slice/annot_eggs/*.png" \
    -img "./data-images/drosophila_ovary_slice/segm/*.png" \
    -out ./results/cut_images --padding 50
```

5. Finally, performing visualisation of segmentation results together with expert annotation.

```
python experiments_ovary_detect/run_export_user-annot-segm.py
```



1.1.6 References

For complete references see BibTex.

1. Borovec J., Svihlik J., Kybic J., Habart D. (2017). **Supervised and unsupervised segmentation using superpixels, model estimation, and Graph Cut.** SPIE Journal of Electronic Imaging 26(6), 061610. DOI: 10.1117/1.JEI.26.6.061610.
2. Borovec J., Kybic J., Nava R. (2017) **Detection and Localization of Drosophila Egg Chambers in Microscopy Images.** In: Wang Q., Shi Y., Suk HI., Suzuki K. (eds) Machine Learning in Medical Imaging. MLMI 2017. LNCS, vol 10541. Springer, Cham. DOI: 10.1007/978-3-319-67389-9_3.
3. Borovec J., Kybic J., Sugimoto, A. (2017). **Region growing using superpixels with learned shape prior.** SPIE Journal of Electronic Imaging 26(6), 061611. DOI: 10.1117/1.JEI.26.6.061611.

1.2 imsegm package

1.2.1 Subpackages

imsegm.utilities package

Submodules

imsegm.utilities.data_io module

Framework for handling input/output

Copyright (C) 2015-2018 Jiri Borovec <jiri.borovec@fel.cvut.cz>

`imsegm.utilities.data_io.`**`add_padding`**(*img_size*, *padding*, *min_row*, *min_col*, *max_row*, *max_col*)

add some padding but still be inside image

Parameters

- **`img_size`** (*tuple(int,int)*) –

- **padding** (*int*) – set padding around segmented object
- **min_row** (*int*) – setting top left corner of bounding box
- **min_col** (*int*) – setting top left corner of bounding box
- **max_row** (*int*) – setting bottom right corner of bounding box
- **max_col** (*int*) – setting bottom right corner of bounding box

Return tuple(int,int,int,int)

```
>>> add_padding((50, 50), 5, 15, 25, 35, 55)
(10, 20, 40, 50)
```

imsegm.utilities.data_io.**convert_img_2_nifti_gray**(*path_img*, *path_out*)
converting standard image to Nifti format

Parameters

- **path_img** (*str*) – path to input image
- **path_out** (*str*) – path to output directory

Return str path to output image

```
>>> np.random.seed(0)
>>> img = np.random.random((150, 125))
>>> p_in = './temp_sample-image.png'
>>> io.imsave(p_in, img)
>>> p_out = convert_img_2_nifti_gray(p_in, '.')
>>> p_out
'temp_sample-image.nii'
>>> os.remove(p_out)
>>> os.remove(p_in)
```

imsegm.utilities.data_io.**convert_img_2_nifti_rgb**(*path_img*, *path_out*)
converting standard image to Nifti format

Parameters

- **path_img** (*str*) – path to input image
- **path_out** (*str*) – path to output directory

Return str path to output image

```
>>> np.random.seed(0)
>>> p_in = './temp_sample-image.png'
>>> io.imsave(p_in, np.random.random((150, 125, 3)))
>>> p_nifty = convert_img_2_nifti_rgb(p_in, '.')
>>> p_nifty
'temp_sample-image.nii'
>>> os.remove(p_nifty)
>>> os.remove(p_in)
```

imsegm.utilities.data_io.**convert_img_color_from_rgb**(*image*, *color_space*)
convert image colour space from RGB to xxx

Parameters

- **image** (*ndarray*) – rgb image
- **color_space** (*str*) –

Return ndarray image

```
>>> convert_img_color_from_rgb(np.ones((50, 75, 3)), 'hsv').shape
(50, 75, 3)
```

imsegm.utilities.data_io.**convert_img_color_to_rgb**(*image*, *color_space*)
convert image colour space to RGB to xxx

Parameters

- **image** (*ndarray*) – rgb image
- **color_space** (*str*) –

Return ndarray image

```
>>> convert_img_color_to_rgb(np.ones((50, 75, 3)), 'hsv').shape
(50, 75, 3)
```

imsegm.utilities.data_io.**convert_nifti_2_img**(*path_img_in*, *path_img_out*)
given input and output path convert from nifti to image

Parameters

- **path_img_in** (*str*) – path to input image
- **path_img_out** (*str*) – path to output image

Return str path to output image

```
>>> np.random.seed(0)
>>> p_in = './temp_sample-image.png'
>>> io.imsave(p_in, np.random.random((150, 125, 3)))
>>> p_nifty = convert_img_2_nifti_rgb(p_in, '.')
>>> p_nifty
'temp_sample-image.nii'
>>> p_img = convert_nifti_2_img(p_nifty, './temp_sample-image.jpg')
>>> p_img
'./temp_sample-image.jpg'
>>> os.remove(p_nifty)
>>> os.remove(p_img)
>>> os.remove(p_in)
```

imsegm.utilities.data_io.**cut_object**(*img*, *mask*, *padding*, *use_mask=False*, *bg_color=None*, *allow_rotate=True*)
cut an object from image according binary object segmentation

Parameters

- **img** (*ndarray*) – inout image
- **mask** (*ndarray*) – segmentation
- **padding** (*int*) – set padding around segmented object
- **use_mask** (*bool*) – fill BG values also outside the mask
- **bg_color** – set as default values outside bounding box
- **allow_rotate** (*bool*) – allowing rotate object to get minimal bbox

Returns

```
>>> img = np.ones((10, 20), dtype=int)
>>> img[3:7, 4:16] = 2
>>> mask = np.zeros((10, 20), dtype=int)
>>> mask[4:6, 5:15] = 1
>>> cut_object(img, mask, 2)
array([[1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1],
       [1, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 1],
       [1, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 1],
       [1, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 1],
       [1, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 1],
       [1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1]])
>>> cut_object(img, mask, 2, use_mask=True, allow_rotate=False)
array([[1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1],
       [1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1],
       [1, 1, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 1, 1],
       [1, 1, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 1, 1],
       [1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1],
       [1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1]])
```

imsegm.utilities.data_io.**export_image**(*path_img*, *img*, *stretch_range=True*)

export an image with given path and optional pattern for image name

Parameters

- **path_img** (*str*) – path to the output image
- **img** (*ndarray*) – image np.array<height, width>
- **stretch_range** (*bool*) –

Return str path to the image

```
>>> # PNG image
>>> np.random.seed(0)
>>> img = np.random.random([5, 10])
>>> path_img = export_image(os.path.join('.', 'testing-image'), img)
>>> os.path.basename(path_img)
'testing-image.png'
>>> os.path.exists(path_img)
True
>>> im, name = load_image_2d(path_img)
>>> im.shape
(5, 10)
>>> im
array([[143, 186, 157, 141, 110, 168, 114, 232, 251,  99],
       [206, 137, 148, 241,  18,  22,   5, 216, 202, 226],
       [255, 208, 120, 203,  30, 166,  37, 246, 135, 108],
       [ 68, 201, 118, 148,   4, 160, 159, 160, 245, 177],
       [ 93, 113, 181,  15, 173, 174,  54,  33,  82,  94]], dtype=uint8)
>>> os.remove(path_img)
```

```
>>> # TIFF image
>>> img = np.random.random([5, 20, 25])
>>> path_img = export_image(os.path.join('.', 'testing-image'), img)
>>> os.path.basename(path_img)
'testing-image.tiff'
>>> os.path.exists(path_img)
True
>>> im, name = load_image_2d(path_img)
```

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```
>>> im.shape
(5, 20, 25)
>>> os.remove(path_img)
```

imsegm.utilities.data_io.**find_files_match_names_across_dirs**(*list_path_pattern*, *drop_none=True*)

walk over dir with images and segmentation and pair those with the same name and if the folder with centers exists also add to each par a center

Note: returns just paths

Parameters

- **list_path_pattern** (*list(str)*) – list of paths with image name patterns
- **drop_none** (*bool*) – drop if there are some none - missing values in rows

Returns DF<path_1, path_2, ...>

```
>>> def _mp(d, n):
...     return os.path.join(update_path('data-images'), 'drosophila_ovary_slice',␣
↪d, n)
>>> df = find_files_match_names_across_dirs([
...     _mp('image', '*.jpg'),
...     _mp('segm', '*.png'),
...     _mp('center_levels', '*.csv')])
>>> len(df) > 0
True
>>> df.columns.tolist()
['path_1', 'path_2', 'path_3']
>>> df = find_files_match_names_across_dirs([
...     _mp('image', '*.png'),
...     _mp('segm', '*.jpg'),
...     _mp('center_levels', '*.csv')])
>>> len(df)
0
```

imsegm.utilities.data_io.**get_image2d_boundary_color**(*image*, *size=1*)

extract background color as median along image boundaries

Parameters

- **image** (*ndarray*) –
- **size** (*float*) –

Returns

```
>>> img = np.zeros((5, 15), dtype=int)
>>> img[:4, 3:9] = 1
>>> img
array([[0, 0, 0, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0]])
```

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```
>>> get_image2d_boundary_color(img)
0
>>> get_image2d_boundary_color(np.ones((5, 15, 3), dtype=int), size=2)
array([1, 1, 1])
>>> get_image2d_boundary_color(np.ones((5, 15, 3, 1), dtype=int))
array(0)
```

imsegm.utilities.data_io.**image_open**(*path_img*)
just a wrapper to suppers debug messages from the PIL function

Parameters **path_img** (*str*) –

Return Image

imsegm.utilities.data_io.**io_image_decorate**(*func*)
costume decorator to suppers debug messages from the PIL function to suppress PIl debug logging - DEBUG:PIL.PngImagePlugin:STREAM b'IHDR' 16 13

Parameters **func** –

Returns

imsegm.utilities.data_io.**io_imread**(*path_img*)
just a wrapper to suppers debug messages from the PIL function

Parameters **path_img** (*str*) –

Return ndarray

imsegm.utilities.data_io.**io_imsave**(*path_img*, *img*)
just a wrapper to suppers debug messages from the PIL function

Parameters

- **path_img** (*str*) –
- **img** (*ndarray*) – image

imsegm.utilities.data_io.**load_complete_image_folder**(*path_dir*, *img_name_pattern='*.png'*, *nb_sample=None*, *im_range=255*, *skip=None*)
load complete image folder with specific name pattern

Parameters

- **path_dir** (*str*) – loading dictionary
- **img_name_pattern** (*str*) – image name pattern
- **nb_sample** (*int*) – load just some subset of images
- **im_range** – range to scale image values (1. or 255)
- **skip** (*list(str)|None*) – skip some prticular images by name

Returns

```
>>> p_imgs = os.path.join(update_path('data-images'), 'drosophila_ovary_slice',
↪'image')
>>> l_imgs, l_names = load_complete_image_folder(p_imgs, '*.jpg')
>>> len(l_imgs)
5
```

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```
>>> l_names
['insitu4174', 'insitu4358', 'insitu7331', 'insitu7544', 'insitu7545']
```

imsegm.utilities.data_io.**load_image**(*path_im*, *im_range=255*)

imsegm.utilities.data_io.**load_image_2d**(*path_img*)

loading any supported image type

Parameters **path_img** (*str*) – path to the input image

Return str, ndarray image name, image as matrix

```
>>> # PNG image
>>> img_name = 'testing-image'
>>> img = np.random.randint(0, 255, size=(20, 20, 3))
>>> path_img = export_image(os.path.join('.', img_name), img, stretch_range=False)
>>> os.path.basename(path_img)
'testing-image.png'
>>> os.path.exists(path_img)
True
>>> img_new, _ = load_image_2d(path_img)
>>> np.array_equal(img, img_new)
True
>>> io.imsave(path_img, np.random.random((50, 65, 4)))
>>> img_new, _ = load_image_2d(path_img)
>>> img_new.shape
(50, 65, 3)
>>> Image.fromarray(np.random.randint(0, 2, (65, 50)), mode='1').save(path_img)
>>> img_new, _ = load_image_2d(path_img)
>>> img_new.shape
(65, 50)
>>> os.remove(path_img)
```

```
>>> # TIFF image
>>> img_name = 'testing-image'
>>> img = np.random.randint(0, 255, size=(5, 20, 20))
>>> path_img = export_image(os.path.join('.', img_name), img, stretch_range=False)
>>> os.path.basename(path_img)
'testing-image.tiff'
>>> os.path.exists(path_img)
True
>>> img_new, _ = load_image_2d(path_img)
>>> img_new.shape
(5, 20, 20)
>>> np.array_equal(img, img_new)
True
>>> os.remove(path_img)
```

imsegm.utilities.data_io.**load_image_tiff_volume**(*path_img*, *im_range=None*)

loading TIFF image

Parameters

- **path_img** (*str*) – path to the input image
- **im_range** (*float*) – range to scale image values (1. or 255)

Return ndarray

```
>>> p_img = os.path.join(update_path('data-images'), 'drosophila_ovary_3D', 'AU10-
↪13_f0011.tif')
>>> img = load_image_tiff_volume(p_img)
>>> img.shape
(30, 323, 512)
>>> p_img = os.path.join(update_path('data-images'), 'drosophila_ovary_slice',
↪'image', 'insitu7545.tif')
>>> img = load_image_tiff_volume(p_img)
>>> img.shape
(647, 1024, 3)
```

imsegm.utilities.data_io.**load_images_list**(*path_imgs*, *im_range=255*)

load list of images together with image names

Parameters

- **path_imgs** (*list(str)*) – paths to input images
- **im_range** – range to scale image values (1. or 255)

Return [ndarray], list(str)

```
>>> np.random.seed(0)
>>> path_in = './temp_sample-image.png'
>>> io.imsave(path_in, np.random.random((150, 125, 3)))
>>> l_imgs, l_names = load_images_list([path_in, './temp_sample.img'])
>>> l_names
['temp_sample-image']
>>> [img.shape for img in l_imgs]
[(150, 125, 3)]
>>> [img.dtype for img in l_imgs]
[dtype('uint8')]
>>> os.remove(path_in)
>>> path_in = './temp_sample-image.tif'
>>> io.imsave(path_in, np.random.random((150, 125, 3)))
>>> l_imgs, l_names = load_images_list([path_in, './temp_sample.img'])
>>> l_names
['temp_sample-image']
>>> os.remove(path_in)
```

imsegm.utilities.data_io.**load_img_double_band_split**(*path_img*, *im_range=1.0*, *quantiles=(2, 98)*)

load image and split channels

Parameters

- **path_img** (*str*) – path to the image
- **im_range** (*float|None*) – range to scale image values (1. or 255)
- **quantiles** (*tuple(int,int)*) – scale image values in certain percentile range

Returns

```
>>> p_imgs = os.path.join(update_path('data-images'), 'drosophila_ovary_slice',
↪'image')
>>> p_img = os.path.join(p_imgs, 'insitu7545.jpg')
>>> img_b1, img_b2 = load_img_double_band_split(p_img)
>>> img_b1.shape
(647, 1024)
```

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```
>>> p_img = os.path.join(p_imgs, 'insitu7545.tif')
>>> img_b1, img_b2 = load_img_double_band_split(p_img)
>>> img_b1.shape
(647, 1024)
>>> p_img = os.path.join(update_path('data-images'), 'drosophila_ovary_3D', 'AU10-
↪13_f0011.tif')
>>> img_b1, img_b2 = load_img_double_band_split(p_img)
>>> img_b1.shape
(15, 323, 512)
```

imsegm.utilities.data_io.**load_landmarks_csv**(*path_file*)

load the landmarks from a given file of TXT type and return array

Parameters **path_file** (*str*) – name of the input file(whole path)

Return ndarray array of landmarks of size <nbLandmarks> x 2

```
>>> lnds = np.array([[1, 2], [2, 4], [5, 6]])
>>> fp = save_landmarks_csv('./sample_landmarks.test', lnds)
>>> fp
'./sample_landmarks.csv'
>>> lnds_new = load_landmarks_csv(fp)
>>> np.array_equal(lnds, lnds_new)
True
>>> os.remove(fp)
```

imsegm.utilities.data_io.**load_landmarks_txt**(*path_file*)

load the landmarks from a given file of TXT type and return array

Parameters **path_file** (*str*) – name of the input file(whole path)

Return ndarray array of landmarks of size <nbLandmarks> x 2

```
>>> lnds = np.array([[1, 2], [2, 4], [5, 6]])
>>> fp = save_landmarks_txt('./sample_landmarks.test', lnds)
>>> fp
'./sample_landmarks.txt'
>>> lnds_new = load_landmarks_txt(fp)
>>> np.array_equal(lnds, lnds_new)
True
>>> os.remove(fp)
```

imsegm.utilities.data_io.**load_params_from_txt**(*path_file*)

parse the parameter file which was coded by repr function

Parameters **path_file** (*str*) – path to file with parameters

Return dict

```
>>> p = {'abc': 123}
>>> path_file = './sample_config.txt'
>>> with open(path_file, 'w') as fp:
...     lines = ['"{}" : {},'.format(k, p[k]) for k in p]
...     _ = fp.write(os.linesep.join(lines))  # it may return nb characters
>>> p2 = load_params_from_txt(path_file)
>>> p2
{'abc': '123'}
>>> os.remove(path_file)
```

imsegm.utilities.data_io.**load_tiff_volume_split_double_band**(*path_img*, *im_range=None*)

load TIFF volume assuming that there are two bands in zip style: c1, c2, c1, c2, c1, ... and split each odd index belong to one of two bands

Parameters

- **path_img** (*str*) – path to the input image
- **im_range** (*float*) – range to scale image values (1. or 255)

Return ndarray, ndarray

```
>>> p_img = os.path.join(update_path('data-images'), 'drosophila_ovary_3D', 'AU10-
↪13_f0011.tif')
>>> img_b1, img_b2 = load_tiff_volume_split_double_band(p_img)
>>> img_b1.shape, img_b2.shape
((15, 323, 512), (15, 323, 512))
>>> p_img = os.path.join(update_path('data-images'), 'drosophila_ovary_slice',
↪'image', 'insitu7545.tif')
>>> img_b1, img_b2 = load_tiff_volume_split_double_band(p_img)
>>> img_b1.shape, img_b2.shape
((1, 647, 1024), (1, 647, 1024))
>>> img = np.random.randint(0, 255, (1, 3, 250, 200))
>>> p_img = './sample-multistack.tif'
>>> io.imsave(p_img, img)
>>> img_b1, img_b2 = load_tiff_volume_split_double_band(p_img)
>>> img_b1.shape, img_b2.shape
((1, 250, 200), (1, 250, 200))
>>> os.remove(p_img)
```

imsegm.utilities.data_io.**load_zvi_volume_double_band_split**(*path_img*)

loading zvi image and split by bands

Parameters **path_img** (*str*) – path to the image

Return ndarray, ndarray

```
>>> p_img = os.path.join(update_path('data-images'), 'others', 'sample.zvi')
>>> img_b1, img_b2 = load_zvi_volume_double_band_split(p_img)
>>> img_b1.shape
(2, 488, 648)
```

imsegm.utilities.data_io.**merge_image_channels**(*img_ch1*, *img_ch2*, *img_ch3=None*)

merge 2 or 3 image channels into single image

Parameters

- **img_ch1** (*ndarray*) – image channel
- **img_ch2** (*ndarray*) – image channel
- **img_ch3** (*ndarray*) – image channel

Return ndarray

```
>>> np.random.seed(0)
>>> merge_image_channels(np.random.random((150, 125)),
...                      np.random.random((150, 125))).shape
(150, 125, 3)
>>> merge_image_channels(np.random.random((150, 125)),
...                      np.random.random((150, 125)),
```

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```
...                         np.random.random((150, 125))).shape
(150, 125, 3)
```

imsegm.utilities.data_io.**save_landmarks_csv**(*path_file*, *landmarks*, *dtype=<class 'float'>*)
save the landmarks into a given file of CSV type

Parameters

- **path_file** (*str*) – fName is name of the input file(whole path)
- **int]] landmarks** (*[[int,]*) – array of landmarks of size nb_landmarks x 2
- **dtype** (*type*) – data type

Return str path to output file

imsegm.utilities.data_io.**save_landmarks_txt**(*path_file*, *landmarks*)
save the landmarks into a given file of TXT type

Parameters

- **path_file** (*str*) – name of the input file(whole path)
- **landmarks** – array of landmarks of size nb_landmarks x 2

Return str path to output file

imsegm.utilities.data_io.**scale_image_intensity**(*img*, *im_range=1.0*, *quantiles=(2, 98)*)
scale image values with in give quntile range to filter some outlaiers

Parameters

- **img** (*ndarray*) – input image
- **im_range** – range to scale image values (1. or 255)
- **quantiles** (*tuple(int,int)*) – scale image values in certain quantile range

Return ndarray

```
>>> np.random.seed(0)
>>> img = np.random.randint(10, 255, (25, 30))
>>> im = scale_image_intensity(img)
>>> im.min()
0.0
>>> im.max()
1.0
```

imsegm.utilities.data_io.**scale_image_size**(*path_img*, *size*, *path_out=None*)
load image - scale image - export image on the same path

Parameters

- **path_img** (*str*) – path to the image
- **int] size** (*[int,]*) – new image size
- **path_out** (*str*) – path to output image, if none overwrite the input

Return str path to output image

```
>>> np.random.seed(0)
>>> path_in = './test_sample_image.png'
>>> io.imsave(path_in, np.random.random((150, 125, 3)))
>>> path_out = scale_image_size(path_in, [75, 50])
>>> Image.open(path_out).size
(75, 50)
>>> os.remove(path_out)
```

imsegm.utilities.data_io.**scale_image_vals_in_range**(*img*, *im_range=1.0*)
scale image values in given range

Parameters

- **img** (*ndarray*) – input image
- **im_range** – range to scale image values (1. or 255)

Return ndarray

```
>>> np.random.seed(0)
>>> img = np.random.randint(10, 255, (25, 30))
>>> im = scale_image_vals_in_range(img)
>>> im.min()
0.0
>>> im.max()
1.0
```

imsegm.utilities.data_io.**swap_coord_x_y**(*points*)
swap X and Y coordinates in vector of possitions

Parameters **int]] points** (*[[int,*) –

Return [[int, int]]

```
>>> swap_coord_x_y(np.array([[1, 2], [2, 4], [5, 6]]))
[[2, 1], [4, 2], [6, 5]]
```

imsegm.utilities.data_io.**update_path**(*path_file*, *lim_depth=5*, *absolute=True*)
bubble in the folder tree up until it found desired file otherwise return original one

Parameters

- **path_file** (*str*) – path to the input file / folder
- **lim_depth** (*int*) – maximal depth for going up
- **absolute** (*bool*) – format absolute path

Return str path to output file / folder

```
>>> path = 'sample_file.test'
>>> f = open(path, 'w')
>>> update_path(path, absolute=False)
'sample_file.test'
```

imsegm.utilities.data_io.**COLUMNS_COORDS = ['X', 'Y']**
position columns

imsegm.utilities.data_io.**DICT_CONVERT_COLOR_FROM_RGB = {'hed': skimage.color.rgb2hed, 'hsv**
conversion function from RGB color space

imsegm.utilities.data_io.**DICT_CONVERT_COLOR_TO_RGB = {'hed': skimage.color.hed2rgb, 'hsv':**
conversion function to RGB color space

imsegm.utilities.data_samples module

Sandbox with some sample images

Some images are taken from following sources:

- [ANHIR challenge](https://anhir.grand-challenge.org)
- [PhD Thesis](https://www.researchgate.net/publication/323120618)

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imsegm.utilities.data_samples.**get_image_path**(*name_img*, *path_base='/home/docs/checkouts/readthedocs.org/user_images'*)
merge default image path and sample image

Parameters

- **name_img** (*str*) –
- **path_base** (*str*) –

Return str

```
>>> p = get_image_path(IMAGE_LENNA)
>>> os.path.isfile(p)
True
>>> os.path.basename(p)
'lena.png'
```

imsegm.utilities.data_samples.**load_sample_image**(*name_img='others/lena.png'*)
load sample image

Parameters **name_img** (*str*) –

Return ndarray

```
>>> img = load_sample_image(IMAGE_LENNA)
>>> img.shape
(512, 512, 3)
```

imsegm.utilities.data_samples.**sample_color_image_rand_segment**(*im_size=(150, 100)*, *nb_classes=3*, *rand_seed=None*)
create samoe image and segmentation

Parameters

- **im_size** (*tuple(int, int)*) –
- **nb_classes** (*int*) –
- **rand_seed** –

Returns

```
>>> im, seg = sample_color_image_rand_segment((5, 6), 2, rand_seed=0)
>>> im.shape
(5, 6, 3)
>>> seg
array([[1, 1, 0, 0, 1, 0],
       [0, 1, 1, 0, 1, 0],
       [0, 1, 0, 0, 0, 1],
       [1, 0, 1, 0, 0, 0],
       [0, 0, 1, 0, 1, 0]])
```

imsegm.utilities.data_samples.**sample_segment_vertical_2d**(*seg_size=(20, 10), nb_labels=3*)

create sample segmentation with vertical stripes

Parameters

- **seg_size** (*tuple(int,int)*) –
- **nb_labels** (*int*) –

Return ndarray

```
>>> sample_segment_vertical_2d((7, 5), 2)
array([[0, 0, 0, 1, 1, 1],
       [0, 0, 0, 1, 1, 1],
       [0, 0, 0, 1, 1, 1],
       [0, 0, 0, 1, 1, 1],
       [0, 0, 0, 1, 1, 1]])
```

imsegm.utilities.data_samples.**sample_segment_vertical_3d**(*seg_size=(10, 5, 6), nb_labels=3, levels=2*)

create sample regular 3D segmentation

Parameters

- **int, int) seg_size** (*tuple(int,int)|(int,)*) –
- **nb_labels** (*int*) –
- **levels** (*int*) –

Return ndarray

```
>>> im =  sample_segment_vertical_3d((10, 5, 6), 3)
>>> im[:, :, 3]
array([[1, 1, 1, 1, 1],
       [1, 1, 1, 1, 1],
       [1, 1, 1, 1, 1],
       [4, 4, 4, 4, 4],
       [4, 4, 4, 4, 4],
       [4, 4, 4, 4, 4]])
```

imsegm.utilities.data_samples.**ANNOT_DROSOPHILA_DISC = 'drosophila_disc/annot/img_6.png'**

three class tissue annotation of microscopy image of Drosophila imaginal disc

imsegm.utilities.data_samples.**ANNOT_DROSOPHILA_OVARY_2D = 'drosophila_ovary_slice/annot_st**

four class tissue annotation of microscopy image of Drosophila ovary

imsegm.utilities.data_samples.**IMAGE_3CLS = 'synthetic/texture_rgb_3cls.jpg'**

sample image with three different textures

imsegm.utilities.data_samples.**IMAGE_DROSOPHILA_DISC = 'drosophila_disc/image/img_6.jpg'**
sample microscopy image of Drosophila imaginal disc

imsegm.utilities.data_samples.**IMAGE_DROSOPHILA_OVARY_2D = 'drosophila_ovary_slice/image/ins**
sample microscopy image of Drosophila ovary

imsegm.utilities.data_samples.**IMAGE_DROSOPHILA_OVARY_3D = 'drosophila_ovary_3D/AU10-13_f00**
sample 3D microscopy image of Drosophila ovary

imsegm.utilities.data_samples.**IMAGE_HISTOL_CIMA = 'histology_CIMA/29-041-Izd2-w35-CD31-3-le**
sample image of histology tissue from CIMA dataset - ANHIR challenge

imsegm.utilities.data_samples.**IMAGE_HISTOL_FLAGSHIP = 'histology_Flagship/Case001_Cytokerat**
sample image of histology tissue

imsegm.utilities.data_samples.**IMAGE_LANGER_ISLET = 'langerhans_islets/image/gtExoIsl_21.jpg**
sample microscopy image of Langernat islets

imsegm.utilities.data_samples.**IMAGE_LENNA = 'others/lena.png'**
sample Lenna image

imsegm.utilities.data_samples.**IMAGE_OBJECTS = 'synthetic/reference.jpg'**
sample image with three color objects of different shape

imsegm.utilities.data_samples.**IMAGE_STAR = 'others/sea_starfish-2.jpg'**
sample image of sea starfish

imsegm.utilities.data_samples.**LIST_ALL_IMAGES = ['others/lena.png', 'synthetic/texture_rgb_**
list of all default images

imsegm.utilities.data_samples.**PATH_IMAGES = '/home/docs/checkouts/readthedocs.org/user_buil**
path to the folder with all sample image/data

imsegm.utilities.data_samples.**SAMPLE_SEG_NB_CLASSES = 3**
number of classes for segmentation

imsegm.utilities.data_samples.**SAMPLE_SEG_SIZE_2D_NORM = (150, 100)**
image size for normal 2D sample image

imsegm.utilities.data_samples.**SAMPLE_SEG_SIZE_2D_SMALL = (20, 10)**
image size for small 2D sample image

imsegm.utilities.data_samples.**SAMPLE_SEG_SIZE_3D_SMALL = (10, 5, 6)**
image size for small 3D sample image

imsegm.utilities.drawing module

Framework for visualisations

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imsegm.utilities.drawing.**_ellipse**(*r*, *c*, *r_radius*, *c_radius*, *orientation=0.0*, *shape=None*)
temporary wrapper until release New version scikit-image v0.13

Parameters

- **r** (*int*) – center position in rows
- **c** (*int*) – center position in columns
- **r_radius** (*int*) – ellipse diam in rows
- **c_radius** (*int*) – ellipse diam in columns

- **orientation** (*float*) – ellipse orientation
- **shape** (*tuple(int,int)*) – size of output mask

Return tuple(list(int),list(int)) indexes of filled positions

```
>>> img = np.zeros((10, 12), dtype=int)
>>> rr, cc = _ellipse(5, 6, 3, 5, orientation=np.deg2rad(30))
>>> img[rr, cc] = 1
>>> img
array([[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 0, 0],
       [0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 0],
       [0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 0],
       [0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0],
       [0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0],
       [0, 0, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0],
       [0, 0, 0, 1, 1, 1, 1, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0]])
```

imsegm.utilities.drawing.**closest_point_on_line**(*start*, *end*, *point*)
projection of the point to the line

Parameters

- **start** (*list(int)*) – line starting point
- **end** (*list(int)*) – line ending point
- **point** (*list(int)*) – point for extimation

Return list(int) point on the line

```
>>> closest_point_on_line([0, 0], [1, 2], [0, 2])
array([ 0.8,  1.6])
```

imsegm.utilities.drawing.**create_figure_by_image**(*img_size*, *subfig_size*, *nb_subfigs=1*, *extend=0.0*)
crearting image according backround_image

Parameters

- **img_size** (*tuple(int,int)*) – image size
- **subfig_size** (*float*) – maximal sub-figure size
- **nb_subfigs** (*int*) – number of sub-figure
- **extend** (*float*) – extension

Return tuple(Figure,list)

imsegm.utilities.drawing.**draw_color_labeling**(*segments*, *lut_labels*)
visualise the graph cut results

Parameters

- **segments** (*ndarray*) – np.array<height, width>
- **lut_labels** (*list(int)*) – look-up-table

Return ndarray np.array<height, width, 3>

imsegm.utilities.drawing.**draw_eggs_ellipse**(*mask_shape*, *pos_ant*, *pos_lat*, *pos_post*, *threshold_overlap=0.6*)

from given 3 point estimate the ellipse

Parameters

- **mask_shape** (*tuple(int,int)*) –
- **pos_ant** (*[tuple(int,int)]*) – anterior
- **pos_lat** (*[tuple(int,int)]*) – latitude
- **pos_post** (*[tuple(int,int)]*) – postlude
- **threshold_overlap** (*float*) –

Return ndarray

```
>>> pos_ant, pos_lat, pos_post = [10, 10], [20, 20], [35, 20]
>>> points = np.array([pos_ant, pos_lat, pos_post])
>>> _= plt.plot(points[:, 0], points[:, 1], 'og')
>>> mask = draw_eggs_ellipse([30, 50], [pos_ant], [pos_lat], [pos_post])
>>> mask.shape
(30, 50)
>>> _= plt.imshow(mask, alpha=0.5, interpolation='nearest')
>>> _= plt.xlim([0, mask.shape[1]]), plt.ylim([0, mask.shape[0]]), plt.grid()
>>> # plt.show()
```

imsegm.utilities.drawing.**draw_eggs_rectangle**(*mask_shape*, *pos_ant*, *pos_lat*, *pos_post*)

from given 3 point estimate the ellipse

Parameters

- **mask_shape** (*tuple(int,int)*) – segmentation size
- **pos_ant** (*[tuple(int,int)]*) – points
- **pos_lat** (*[tuple(int,int)]*) – points
- **pos_post** (*[tuple(int,int)]*) – points

Return [ndarray]

```
>>> pos_ant, pos_lat, pos_post = [10, 10], [20, 20], [35, 20]
>>> points = np.array([pos_ant, pos_lat, pos_post])
>>> _= plt.plot(points[:, 0], points[:, 1], 'og')
>>> masks = draw_eggs_rectangle([30, 50], [pos_ant], [pos_lat], [pos_post])
>>> [m.shape for m in masks]
[(30, 50)]
>>> for mask in masks:
...     _= plt.imshow(mask, alpha=0.5, interpolation='nearest')
>>> _= plt.xlim([0, mask.shape[1]]), plt.ylim([0, mask.shape[0]]), plt.grid()
>>> # plt.show()
```

imsegm.utilities.drawing.**draw_graphcut_unary_cost_segments**(*segments*, *unary_cost*)

visualise the unary cost for each class

Parameters

- **segments** (*ndarray*) – np.array<height, width>
- **unary_cost** (*ndarray*) – np.array<nb_spx, nb_classes>

Return [] [np.array<height, width, 3>] * nb_cls

```
>>> seg = np.random.randint(0, 100, (100, 150))
>>> u_cost = np.random.random((100, 3))
>>> imgs = draw_graphcut_unary_cost_segments(seg, u_cost)
>>> len(imgs)
3
>>> [img.shape for img in imgs]
[(100, 150, 3), (100, 150, 3), (100, 150, 3)]
```

imsegm.utilities.drawing.**draw_graphcut_weighted_edges**(*segments*, *centers*, *edges*, *edge_weights*, *img_bg=None*, *img_alpha=0.5*)

visualise the edges on the overlapping a background image

Parameters

- **centers** (*[tuple(int,int)]*) – list of centers
- **segments** (*ndarray*) – np.array<height, width>
- **edges** (*ndarray*) – list of edges of shape <nb_edges, 2>
- **edge_weights** (*ndarray*) – weight per edge <nb_edges, 1>
- **img_bg** (*ndarray*) – image background
- **img_alpha** (*float*) – transparency

Return ndarray np.array<height, width, 3>

```
>>> slic = np.array([[0] * 3 + [1] * 3 + [2] * 3+ [3] * 3] * 4 +
...                 [[4] * 3 + [5] * 3 + [6] * 3 + [7] * 3] * 4)
>>> centres = [[1, 1], [1, 4], [1, 7], [1, 10],
...            [5, 1], [5, 4], [5, 7], [5, 10]]
>>> edges = [[0, 1], [1, 2], [2, 3], [0, 4], [1, 5],
...          [4, 5], [2, 6], [5, 6], [3, 7], [6, 7]]
>>> img = np.random.randint(0, 256, slic.shape + (3,))
>>> edge_weights = np.ones(len(edges))
>>> edge_weights[0] = 0
>>> img = draw_graphcut_weighted_edges(slic, centres, edges, edge_weights, img_
↪bg=img)
>>> img.shape
(8, 12, 3)
```

imsegm.utilities.drawing.**draw_image_clusters_centers**(*ax*, *img*, *centres*, *points=None*, *labels_centre=None*, *segm=None*)

draw imageas bacround and clusters centers

Parameters

- **ax** – figure axis
- **img** (*ndarray*) – image
- **centres** (*ndarray*) – points
- **points** (*ndarray*) – optional list of all points
- **labels_centre** (*list(int)*) – optional list of labels for points
- **segm** (*ndarray*) – optional segmentation

```
>>> img = np.random.randint(0, 256, (100, 100, 3))
>>> seg = np.random.randint(0, 3, (100, 100))
>>> centres = np.random.randint(0, 100, (3, 2))
>>> points = np.random.randint(0, 100, (25, 2))
>>> labels = np.random.randint(0, 4, 25)
>>> draw_image_clusters_centers(plt.Figure().gca(), img[:, :, 0], centres, points,
↪ labels, seg)
```

imsegm.utilities.drawing.**draw_image_segm_points**(*ax*, *img*, *points*, *labels=None*, *slic=None*, *color_slic='w'*, *lut_label_marker={-1: ('.', '#7E7E7E'), 0: ('x', '#7E7E7E'), 1: ('.', '#FFFB00')}*, *seg_contour=None*)

on plane draw background image or segmentation, overlap with SLIC contours, add contour of adative segmentation like annot. for centers plot point with specific property (shape and colour) according label

Parameters

- **ax** – figure axis
- **img** (*ndarray*) – image
- **points** (*list(tuple(int,int))*) – collection of points
- **labels** (*list(int)*) – LUT labels for superpixels
- **slic** (*ndarray*) – superpixel segmentation
- **color_slic** (*str*) – color dor superpixels
- **lut_label_marker** (*dict*) – dictionary {int: (str, str)} of label and markers
- **seg_contour** (*ndarray*) – segmentation contour

```
>>> img = np.random.randint(0, 256, (100, 100))
>>> points = np.random.randint(0, 100, (25, 2))
>>> labels = np.random.randint(0, 5, len(points))
>>> slic = np.random.randint(0, 256, (100, 100))
>>> draw_image_segm_points(plt.Figure().gca(), img, points, labels, slic)
```

imsegm.utilities.drawing.**draw_rg2sp_results**(*ax*, *seg*, *slic*, *debug_rg2sp*, *iter_index=-1*)

drawing Region Growing with shape prior

Parameters

- **ax** – figure axis
- **seg** (*ndarray*) – segmentation
- **slic** (*ndarray*) – superpixels
- **debug_rg2sp** (*dict*) – dictionary with debug results
- **iter_index** (*int*) – iteration index

Returns ax

imsegm.utilities.drawing.**ellipse**(*r*, *c*, *r_radius*, *c_radius*, *orientation=0.0*, *shape=None*)

temporary wrapper until release New version scikit-image v0.13

Note: Should be solved in skimage v0.13

Parameters

- **r** (*int*) – center position in rows
- **c** (*int*) – center position in columns
- **r_radius** (*int*) – ellipse diam in rows
- **c_radius** (*int*) – ellipse diam in columns
- **orientation** (*float*) – ellipse orientation
- **shape** (*tuple(int,int)*) – size of output mask

Return tuple(list(int),list(int)) indexes of filled positions

```
>>> img = np.zeros((14, 20), dtype=int)
>>> rr, cc = ellipse(7, 10, 3, 9, np.deg2rad(30), img.shape)
>>> img[rr, cc] = 1
>>> img
array([[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0],
       [0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0],
       [0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0]])
```

imsegm.utilities.drawing.**ellipse_perimeter**(*r*, *c*, *r_radius*, *c_radius*, *orientation=0.0*, *shape=None*)

see New version scikit-image v0.14

Note: Should be solved in skimage v0.14

Parameters

- **r** (*int*) – center position in rows
- **c** (*int*) – center position in columns
- **r_radius** (*int*) – ellipse diam in rows
- **c_radius** (*int*) – ellipse diam in columns
- **orientation** (*float*) – ellipse orientation
- **shape** (*tuple(int,int)*) – size of output mask

Return tuple(list(int),list(int)) indexes of filled positions

```
>>> img = np.zeros((14, 20), dtype=int)
>>> rr, cc = ellipse_perimeter(7, 10, 3, 9, np.deg2rad(30), img.shape)
>>> img[rr, cc] = 1
>>> img
array([[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 0, 0, 0, 0, 1, 0],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0],
       [0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0],
       [0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0],
       [0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0],
       [0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0],
       [0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0],
       [0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 1, 0, 0, 0, 0, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0]])
```

imsegm.utilities.drawing.**figure_annot_slic_histogram_labels**(*dict_label_hist*, *slic_size=-1*, *slic_regul=-1*)

plot ration of labels assigned to each superpixel

Parameters

- **dict_label_hist** – dictionary of label name and histogram
- **slic_size** (*int*) – used for figure title
- **slic_regul** (*float*) – used for figure title

Return Figure

```
>>> np.random.seed(0)
>>> dict_label_hist = {'a': np.tile([1, 0, 0, 0, 1], (25, 1)),
...                    'b': np.tile([0, 1, 0, 0, 1], (30, 1))}
>>> fig = figure_annot_slic_histogram_labels(dict_label_hist)
>>> isinstance(fig, matplotlib.figure.Figure)
True
```

imsegm.utilities.drawing.**figure_ellipse_fitting**(*img*, *seg*, *ellipses*, *centers*, *crits*, *fig_size=9*)

show figure with result of the ellipse fitting

Parameters

- **img** (*ndarray*) – image
- **seg** (*ndarray*) – segmentation
- **ellipses** (*list(tuple(int,int,int,int,float))*) – collection of ellipse parameters ell. parameters: (x, y, height, width, orientation)
- **centers** (*list(tuple(int,int))*) – points
- **crits** (*list(float)*) –
- **fig_size** (*float*) – maximal figure size

Return Figure

```
>>> img = np.random.random((100, 150, 3))
>>> seg = np.random.randint(0, 2, (100, 150))
>>> ells = np.random.random((3, 5)) * 25
>>> centers = np.random.random((3, 2)) * 25
>>> crits = np.random.random(3)
>>> fig = figure_ellipse_fitting(img[:, :, 0], seg, ells, centers, crits)
>>> isinstance(fig, matplotlib.figure.Figure)
True
```

imsegm.utilities.drawing.**figure_image_adjustment**(*fig*, *img_size*)

adjust figure as nice image without axis

Parameters

- **fig** – Figure
- **img_size** (*tuple(int, int)*) – image size

Return Figure

```
>>> fig = figure_image_adjustment(plt.figure(), (150, 200))
>>> isinstance(fig, matplotlib.figure.Figure)
True
```

imsegm.utilities.drawing.**figure_image_segm_centres**(*img*, *segm*, *centers=None*, *cmap_contour=<matplotlib.colors.LinearSegmentedColor object>*)

visualise the input image and segmentation in common frame

Parameters

- **img** (*ndarray*) – image
- **segm** (*ndarray*) – segmentation
- **centers** (*[tuple(int, int)] | ndarray*) – or np.array
- **cmap_contour** (*obj*) –

Return Figure

```
>>> img = np.random.random((100, 150, 3))
>>> seg = np.random.randint(0, 2, (100, 150))
>>> centre = [[55, 60]]
>>> fig = figure_image_segm_centres(img, seg, centre)
>>> isinstance(fig, matplotlib.figure.Figure)
True
```

imsegm.utilities.drawing.**figure_image_segm_results**(*img*, *seg*, *subfig_size=9*, *mid_labels_alpha=0.2*, *mid_image_gray=True*)

creating subfigure with original image, overlapped segmentation contours and clean result segmentation... it turns the sequence in vertical / horizontal according major image dim

Parameters

- **img** (*ndarray*) – image as background
- **seg** (*ndarray*) – segmentation
- **subfig_size** (*int*) – max image size
- **mid_image_gray** (*fool*) – used color image as bacround in middele

- **mid_labels_alpha** (*float*) – alpha for middle segmentation overlap

Return Figure

```
>>> img = np.random.random((100, 150, 3))
>>> seg = np.random.randint(0, 2, (100, 150))
>>> fig = figure_image_segm_results(img, seg)
>>> isinstance(fig, matplotlib.figure.Figure)
True
```

imsegm.utilities.drawing.**figure_overlap_annot_segm_image**(*annot*, *segm*, *img=None*, *subfig_size=9*, *drop_labels=None*, *segm_alpha=0.2*)

figure showing overlap annotation - segmentation - image

Parameters

- **annot** (*ndarray*) – user annotation
- **segm** (*ndarray*) – segmentation
- **img** (*ndarray*) – original image
- **subfig_size** (*int*) – maximal sub-figure size
- **segm_alpha** (*float*) – use transparency
- **drop_labels** (*list(int)*) – labels to be ignored

Return Figure

```
>>> img = np.random.random((100, 150, 3))
>>> seg = np.random.randint(0, 2, (100, 150))
>>> fig = figure_overlap_annot_segm_image(seg, seg, img, drop_labels=[5])
>>> isinstance(fig, matplotlib.figure.Figure)
True
```

imsegm.utilities.drawing.**figure_ray_feature**(*segm*, *points*, *ray_dist_raw=None*, *ray_dist=None*, *points_reconst=None*, *title=''*)

visualise the segmentation with specific point and estimated ray dist.

Parameters

- **segm** (*ndarray*) – segmentation
- **float)] points** (*[(float,)* – collection of points
- **ray_dist_raw** (*list(float)*) –
- **ray_dist** (*list(float)*) – Ray feature distances
- **points_reconst** (*ndarray*) – collection of reconstructed points
- **title** (*str*) – figure title

Return Figure

Note: for more examples, see unittests

---

imsegm.utilities.drawing.**figure_rg2sp_debug_complete**(*seg*, *slic*, *debug_rg2sp*, *iter_index=-1*, *max_size=5*)

draw figure with all debug (intermediate) segmentation steps

Parameters

- **seg** (*ndarray*) – segmentation
- **slic** (*ndarray*) – superpixels
- **debug_rg2sp** – dictionary with some debug parameters
- **iter_index** (*int*) – iteration index
- **max_size** (*int*) – max figure size

Return Figure

```
>>> seg = np.random.randint(0, 4, (100, 150))
>>> slic = np.random.randint(0, 80, (100, 150))
>>> dict_debug = {
...     'lut_data_cost': np.random.random((80, 3)),
...     'lut_shape_cost': np.random.random((15, 80, 3)),
...     'labels': np.random.randint(0, 4, (15, 80)),
...     'centres': [np.array([np.random.randint(0, 100, 80),
...                           np.random.randint(0, 150, 80)]).T] * 15,
...     'shifts': np.random.random((15, 3)),
...     'criteria': np.random.random(15),
... }
>>> fig = figure_rg2sp_debug_complete(seg, slic, dict_debug)
>>> isinstance(fig, matplotlib.figure.Figure)
True
```

imsegm.utilities.drawing.**figure_segm_boundary_dist**(*segm_ref*, *segm*, *subfig_size=9*)

visualise the boundary distances between two segmentation

Parameters

- **segm_ref** (*ndarray*) – reference segmentation
- **segm** (*ndarray*) – estimated segmentation
- **subfig_size** (*int*) – maximal sub-figure size

Return Figure

```
>>> seg = np.zeros((100, 100))
>>> seg[35:80, 10:65] = 1
>>> fig = figure_segm_boundary_dist(seg, seg.T)
>>> isinstance(fig, matplotlib.figure.Figure)
True
```

imsegm.utilities.drawing.**figure_segm_graphcut_debug**(*images*, *subfig_size=9*)

creating subfigure with slic, graph edges and results in the first row and individual class unary terms in the second row

Parameters

- **images** (*dict*) – dictionary composed from name and image array
- **subfig_size** (*int*) – maximal sub-figure size

Return Figure

```
>>> images = {
...     'image': np.random.random((100, 150, 3)),
...     'slic': np.random.randint(0, 2, (100, 150)),
...     'slic_mean': np.random.random((100, 150, 3)),
...     'img_graph_edges': np.random.random((100, 150, 3)),
...     'img_graph_segm': np.random.random((100, 150, 3)),
...     'imgs_unary_cost': [np.random.random((100, 150, 3))],
... }
>>> fig = figure_segm_graphcut_debug(images)
>>> isinstance(fig, matplotlib.figure.Figure)
True
```

imsegm.utilities.drawing.**figure_used_samples**(*img*, *labels*, *slic*, *used_samples*, *fig_size=12*)

draw used examples (superpixels)

Parameters

- **img** (*ndarray*) – input image for background
- **labels** (*list(int)*) – labels associated for superpixels
- **slic** (*ndarray*) – superpixel segmentation
- **used_samples** (*list(bool)*) – used samples for training
- **fig_size** (*int*) – figure size

Return Figure

```
>>> img = np.random.random((50, 75, 3))
>>> labels = [-1, 0, 2]
>>> used = [1, 0, 0]
>>> seg = np.random.randint(0, 3, img.shape[:2])
>>> fig = figure_used_samples(img, labels, seg, used)
>>> isinstance(fig, matplotlib.figure.Figure)
True
```

imsegm.utilities.drawing.**make_overlap_images_chess**(*images*, *chess_field=50*)

overlap images and show them

Parameters

- **images** (*[ndarray]*) – collection of images
- **chess_field** (*int*) – size of chess field size

Return ndarray combined image

```
>>> im1 = np.zeros((5, 10), dtype=int)
>>> im2 = np.ones((5, 10), dtype=int)
>>> make_overlap_images_chess([im1, im2], chess_field=2)
array([[0, 0, 1, 1, 0, 0, 1, 1, 0, 0],
       [0, 0, 1, 1, 0, 0, 1, 1, 0, 0],
       [1, 1, 0, 0, 1, 1, 0, 0, 1, 1],
       [1, 1, 0, 0, 1, 1, 0, 0, 1, 1],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0]])
```

imsegm.utilities.drawing.**make_overlap_images_optical**(*images*)

overlap images and show them

Parameters **images** (*[ndarray]*) – collection of images

Return ndarray combined image

```
>>> im1 = np.zeros((5, 8), dtype=float)
>>> im2 = np.ones((5, 8), dtype=float)
>>> make_overlap_images_optical([im1, im2])
array([[ 0.5,  0.5,  0.5,  0.5,  0.5,  0.5,  0.5,  0.5],
       [ 0.5,  0.5,  0.5,  0.5,  0.5,  0.5,  0.5,  0.5],
       [ 0.5,  0.5,  0.5,  0.5,  0.5,  0.5,  0.5,  0.5],
       [ 0.5,  0.5,  0.5,  0.5,  0.5,  0.5,  0.5,  0.5],
       [ 0.5,  0.5,  0.5,  0.5,  0.5,  0.5,  0.5,  0.5]])
```

imsegm.utilities.drawing.**merge_object_masks**(*masks*, *overlap_thr=0.7*)

merge several mask into one multi-class segmentation

Parameters

- **masks** (*[ndarray]*) – collection of masks
- **overlap_thr** (*float*) – threshold for overlap

Return ndarray

```
>>> m1 = np.zeros((5, 6), dtype=int)
>>> m1[:4, :4] = 1
>>> m2 = np.zeros((5, 6), dtype=int)
>>> m2[2:, 2:] = 1
>>> merge_object_masks([m1, m1])
array([[1, 1, 1, 1, 0, 0],
       [1, 1, 1, 1, 0, 0],
       [1, 1, 1, 1, 0, 0],
       [1, 1, 1, 1, 0, 0],
       [0, 0, 0, 0, 0, 0]])
>>> merge_object_masks([m1, m2])
array([[1, 1, 1, 1, 0, 0],
       [1, 1, 1, 1, 0, 0],
       [1, 1, 2, 2, 2, 2],
       [1, 1, 2, 2, 2, 2],
       [0, 0, 2, 2, 2, 2]])
```

imsegm.utilities.drawing.**norm_aplha**(*alpha*)

normalise alpha in range (0, 1)

Parameters **alpha** (*float*) –

Return float

```
>>> norm_aplha(0.5)
0.5
>>> norm_aplha(255)
1.0
>>> norm_aplha(-1)
0
```

imsegm.utilities.drawing.**parse_annot_rectangles**(*rows_slice*)

parse annotation fromDF to lists

Parameters **rows_slice** – a row from a table

Return tuple the three points

```
>>> import pandas as pd
>>> dict_row = dict(ant_x=1, ant_y=2, lat_x=3, lat_y=4, post_x=5, post_y=6)
>>> row = pd.DataFrame([dict_row])
>>> parse_annot_rectangles(row)
([(1, 2)], [(3, 4)], [(5, 6)])
>>> rows = pd.DataFrame([dict_row, {n: dict_row[n] + 10 for n in dict_row}])
>>> rows
   ant_x  ant_y  lat_x  lat_y  post_x  post_y
0      1      2      3      4       5       6
1     11     12     13     14      15      16
>>> parse_annot_rectangles(rows)
([(1, 2), (11, 12)], [(3, 4), (13, 14)], [(5, 6), (15, 16)])
```

imsegm.utilities.drawing.**COLUMNS_POSITION_EGG_ANNOT = ('ant_x', 'ant_y', 'post_x', 'post_y**
columns from description files which marks the egg annotation by expert

imsegm.utilities.drawing.**DICT_LABEL_MARKER = {-1: ('.', '#7E7E7E'), 0: ('x', '#7E7E7E'), 1**
define markers for labels of positive (+1) neutral (0) and negative (-1) class

imsegm.utilities.drawing.**SIZE_CHESS_FIELD = 50**
for blending two images define chess field size in pixels

imsegm.utilities.experiments module

Framework for general experiments

Copyright (C) 2014-2018 Jiri Borovec <jiri.borovec@fel.cvut.cz>

class imsegm.utilities.experiments.**Experiment**(*params*, *time_stamp=True*)
Bases: object

Basic experiment class

Example

```
>>> import shutil
>>> params = {'path_out': './my_experiments', 'name': 'My-Sample'}
>>> expt = Experiment(params)
Traceback (most recent call last):
...
Exception: given folder "./my_experiments" does not exist!
>>> os.mkdir(params['path_out'])
>>> expt = Experiment(params, time_stamp=False)
>>> expt.run()
>>> params = expt.params.copy()
>>> del expt
>>> shutil.rmtree(params['path_out'], ignore_errors=True)
```

constructor

Parameters

- **params** (*dict*) – define experimenatl parameters
- **time_stamp** (*bool*) – add to experiment unique time stamp

_check_exist_paths()
Check all required paths in parameters whether they exist

_create_folder(*time_stamp=True*)
Create the experiment folder and iterate while there is no available

Parameters **time_stamp** (*bool*) – mark if you want an unique folder per experiment

_evaluate()

_load_data(*gt=True*)
loading the experiment data

Parameters **gt** (*bool*) – try to load ground truth

_perform()

_summarise()

run(*gt=True*)
run the main Experimental body

Parameters **gt** (*bool*) – try to load Ground Truth

class imsegm.utilities.experiments.**WrapExecuteSequence**(*wrap_func*, *iterate_vals*, *nb_workers=2*, *desc=''*, *ordered=False*)

Bases: object

wrapper for execution paralle of single thread as for ...

Example

```
>>> it = WrapExecuteSequence(lambda x: (x, x ** 2), range(5), nb_workers=1,␣
↪ordered=True)
>>> list(it)
[(0, 0), (1, 1), (2, 4), (3, 9), (4, 16)]
>>> it = WrapExecuteSequence(sum, [[0, 1]] * 5, nb_workers=2, desc=None)
>>> [o for o in it]
[1, 1, 1, 1, 1]
>>> it = WrapExecuteSequence(min, ([0, 1] for i in range(5)))
>>> [o for o in it]
[0, 0, 0, 0, 0]
```

the init of this wrapper fro parallelism

Parameters

- **wrap_func** – function which will be excited in the iterations
- **iterate_vals** (*[]*) – list or iterator which will ide in iterations
- **nb_workers** (*int*) – number og jobs running in parallel
- **desc** (*str*) – deception for the bar, if it is set None, bar is suppressed
- **ordered** (*bool*) – whether enforce ordering in the parallelism

imsegm.utilities.experiments.**append_final_stat**(*out_dir*, *y_true*, *y_pred*, *time_sec*, *file_name='resultStat.txt'*)

append (export) statistic to existing default file

Parameters

- **out_dir** (*str*) –
- **y_true** (*[int]*) – annotation

- **y_pred** (*[int]*) – predictions
- **time_sec** (*int*) –
- **file_name** (*str*) –

Return str

```
>>> import numpy as np
>>> np.random.seed(0)
>>> y_true = np.random.randint(0, 2, 25)
>>> y_pred = np.random.randint(0, 2, 25)
>>> f_path = append_final_stat('.', y_true, y_pred, 256)
>>> os.path.exists(f_path)
True
>>> os.remove(f_path)
```

imsegm.utilities.experiments.**create_experiment_folder**(*params*, *dir_name*, *stamp_unique=True*, *skip_load=True*)

create the experiment folder and iterate while there is no available

Parameters

- **params** (*dict*) – configuration
- **dir_name** (*str*) – folder name
- **stamp_unique** (*bool*) – use unique timestamp
- **skip_load** (*bool*) – skip loading folder params

Return dict

```
>>> import shutil
>>> import pandas as pd
>>> p = {'path_out': '.'}
>>> p = create_experiment_folder(p, 'my_test', False, skip_load=True)
>>> pd.Series(p).sort_index()
computer                    [...
path_exp     ...my_test_EXAMPLE
path_out                      .
dtype: object
>>> p = create_experiment_folder(p, 'my_test', False, skip_load=False)
>>> shutil.rmtree(p['path_exp'], ignore_errors=True)
>>> p = create_experiment_folder(p, 'my_test', stamp_unique=True)
>>> pd.Series(p).sort_index()
computer                           [...
path_exp   ...my_test_EXAMPLE_...-...
path_out                             .
dtype: object
>>> shutil.rmtree(p['path_exp'], ignore_errors=True)
```

imsegm.utilities.experiments.**create_subfolders**(*path_out*, *folders*)

create subfolders in rood directory

Parameters

- **path_out** (*str*) – root dictionary
- **folders** (*list (str)*) – list of subfolders

Return int

```
>>> import shutil
>>> dir_name = 'sample_dir'
>>> create_subfolders('.', [dir_name])
1
>>> os.path.exists(dir_name)
True
>>> shutil.rmtree(dir_name, ignore_errors=True)
```

imsegm.utilities.experiments.**extend_list_params**(*params*, *name_param*, *options*)
extend the parameter list by all sub-datasets

Parameters

- **params** (*list(dict)*) – list of parameters
- **name_param** (*str*) – parameter name
- **options** (*[]*) – lost of options

Return list(dict)

```
>>> import pandas as pd
>>> params = extend_list_params([{'a': 1}], 'a', [3, 4])
>>> pd.DataFrame(params)[sorted(pd.DataFrame(params))]
   a param_idx
0  3     a-2#1
1  4     a-2#2
>>> params = extend_list_params([{'a': 1}], 'b', 5)
>>> pd.DataFrame(params)[sorted(pd.DataFrame(params))]
   a  b param_idx
0  1  5     b-1#1
```

imsegm.utilities.experiments.**is_iterable**(*var*)
check if the variable is iterable

Parameters **var** –

Return bool

```
>>> is_iterable('abc')
False
>>> is_iterable([0])
True
>>> is_iterable((1, ))
True
```

imsegm.utilities.experiments.**load_config_yaml**(*path_config*)
loading the

Parameters **path_config** (*str*) –

Return dict

```
>>> p_conf = './testing-congif.yaml'
>>> save_config_yaml(p_conf, {'a': 2})
>>> load_config_yaml(p_conf)
{'a': 2}
>>> os.remove(p_conf)
```

imsegm.utilities.experiments.**nb_workers**(*ratio*)
get fraction of of available CPUs

Parameters **ratio** (*float*) – range (0, 1)

Return int number of workers with lower bound 1

```
>>> nb_workers(0)
1
```

imsegm.utilities.experiments.**save_config_yaml**(*path_config*, *config*)
exporting configuration as YAML file

Parameters

- **path_config** (*str*) –
- **config** (*dict*) –

imsegm.utilities.experiments.**set_experiment_logger**(*path_out*, *file_name='logging.txt'*, *reset=True*)
set the logger to file

imsegm.utilities.experiments.**string_dict**(*d*, *offset=30*, *desc='DICTIONARY'*)
transform dictionary to a formatted string

Parameters

- **d** (*dict*) –
- **offset** (*int*) – length between name and value
- **desc** (*str*) – dictionary title

Return str

```
>>> string_dict({'abc': 123})
'DICTIONARY: \n"abc": 123'
```

imsegm.utilities.experiments.**try_decorator**(*func*)
costume decorator to wrap function in try/except

Parameters **func** –

Returns

imsegm.utilities.experiments.**CONFIG_YAML = 'config.yml'**
default file for loading/exporting experiment configuration

imsegm.utilities.experiments.**CPU_COUNT = 2**
total number of avalaible CPUs/treads

imsegm.utilities.experiments.**FILE_LOGS = 'logging.txt'**
default file for streaming experimeny messages

imsegm.utilities.experiments.**FORMAT_DT = '%Y%m%d-%H%M%S'**
default date-time format

imsegm.utilities.experiments.**RESULTS_TXT = 'resultStat.txt'**
default name of file for exporting statistics

imsegm.utilities.read_zvi module

https://searchcode.com/codesearch/view/40141634/

read ZVI (Zeiss) image file

- incomplete support
- open uncompressed image from multi item image (Count>0)
- require OleFileIO_PL - a Python module to read MS OLE2 files http://www.decalage.info/en/python/olefileio#attachments

```
>>> import os, sys
>>> sys.path += [os.path.abspath(os.path.join('..', '..'))]
>>> import imsegm.utilities.data_io as tl_io
>>> path_file = os.path.join('data-images', 'others', 'sample.zvi')
>>> path_file = tl_io.update_path(path_file)
>>> n = get_layer_count(path_file)
>>> get_dir(path_file)
[...]
>>> for p in range(n):
...     zvi = zvi_read(path_file, p)
...     arr = zvi.Image.Array
...     arr.shape
(488, 648)
(488, 648)
(488, 648)
(488, 648)
>>> img = load_image(path_file)
>>> img.shape
(4, 488, 648)
```

class imsegm.utilities.read_zvi.**ImageTuple**(*Version*, *Width*, *Height*, *Depth*, *PixelWidth*, *PIXEL_FORMAT*, *ValidBitsPerPixel*, *Array*)

Bases: tuple

Create new instance of ImageTuple(Version, Width, Height, Depth, PixelWidth, PIXEL_FORMAT, ValidBitsPerPixel, Array)

_asdict()
Return a new OrderedDict which maps field names to their values.

classmethod _make(*iterable*, *new=<built-in method __new__ of type object>*, *len=<built-in function len>*)
Make a new ImageTuple object from a sequence or iterable

_replace(***kwds*)
Return a new ImageTuple object replacing specified fields with new values

property Array
Alias for field number 7

property Depth
Alias for field number 3

property Height
Alias for field number 2

property PIXEL_FORMAT
Alias for field number 5

property PixelWidth
Alias for field number 4

property ValidBitsPerPixel
Alias for field number 6

property Version
Alias for field number 0

property Width
Alias for field number 1

_fields = ('Version', 'Width', 'Height', 'Depth', 'PixelWidth', 'PIXEL_FORMAT', 'Valid

_source = "from builtins import property as _property, tuple as _tuple\nfrom operator

class imsegm.utilities.read_zvi.**ZviImageTuple**(*Version*, *FileName*, *Width*, *Height*, *Depth*, *PIXEL_FORMAT*, *Count*, *ValidBitsPerPixel*, *m_PluginCLSID*, *Others*, *Layers*, *Scaling*)

Bases: tuple

Create new instance of ZviImageTuple(Version, FileName, Width, Height, Depth, PIXEL_FORMAT, Count, ValidBitsPerPixel, m_PluginCLSID, Others, Layers, Scaling)

_asdict()
Return a new OrderedDict which maps field names to their values.

classmethod _make(*iterable*, *new=<built-in method __new__ of type object>*, *len=<built-in function len>*)
Make a new ZviImageTuple object from a sequence or iterable

_replace(***kwds*)
Return a new ZviImageTuple object replacing specified fields with new values

property Count
Alias for field number 6

property Depth
Alias for field number 4

property FileName
Alias for field number 1

property Height
Alias for field number 3

property Layers
Alias for field number 10

property Others
Alias for field number 9

property PIXEL_FORMAT
Alias for field number 5

property Scaling
Alias for field number 11

property ValidBitsPerPixel
Alias for field number 7

property Version
Alias for field number 0

property Width
Alias for field number 2

_fields = ('Version', 'FileName', 'Width', 'Height', 'Depth', 'PIXEL_FORMAT', 'Count',

_source = "from builtins import property as _property, tuple as _tuple\nfrom operator

property m_PluginCLSID
Alias for field number 8

class imsegm.utilities.read_zvi.**ZviItemTuple**(*Version*, *FileName*, *Width*, *Height*, *Depth*, *PIXEL_FORMAT*, *Count*, *ValidBitsPerPixel*, *Others*, *Layers*, *Scaling*, *Image*)

Bases: tuple

Create new instance of ZviItemTuple(Version, FileName, Width, Height, Depth, PIXEL_FORMAT, Count, ValidBitsPerPixel, Others, Layers, Scaling, Image)

_asdict()
Return a new OrderedDict which maps field names to their values.

classmethod _make(*iterable*, *new=<built-in method __new__ of type object>*, *len=<built-in function len>*)
Make a new ZviItemTuple object from a sequence or iterable

_replace(***kwds*)
Return a new ZviItemTuple object replacing specified fields with new values

property Count
Alias for field number 6

property Depth
Alias for field number 4

property FileName
Alias for field number 1

property Height
Alias for field number 3

property Image
Alias for field number 11

property Layers
Alias for field number 9

property Others
Alias for field number 8

property PIXEL_FORMAT
Alias for field number 5

property Scaling
Alias for field number 10

property ValidBitsPerPixel
Alias for field number 7

property Version
Alias for field number 0

property Width
Alias for field number 2

_fields = ('Version', 'FileName', 'Width', 'Height', 'Depth', 'PIXEL_FORMAT', 'Count',

_source = "from builtins import property as _property, tuple as _tuple\nfrom operator

imsegm.utilities.read_zvi.**get_dir**(*file_name*, *ole=None*)
returns the content structure(streams) of the zvi file + length of each streams

imsegm.utilities.read_zvi.**get_hex**(*data*, *n=16*)

imsegm.utilities.read_zvi.**get_layer_count**(*file_name*, *ole=None*)
returns the number of image planes

imsegm.utilities.read_zvi.**i32**(*data*)
return int32 from len4 string

imsegm.utilities.read_zvi.**load_image**(*path_img*)

imsegm.utilities.read_zvi.**parse_image**(*data*)
returns ImageTuple from raw image data(header+image)

imsegm.utilities.read_zvi.**read_image_container_content**(*stream*)
returns a ZviImageTuple from a stream

imsegm.utilities.read_zvi.**read_item_storage_content**(*stream*)
returns ZviItemTuple from the stream

imsegm.utilities.read_zvi.**read_struct**(*data*, *t*)
read a t type from data(str)

imsegm.utilities.read_zvi.**zvi_read**(*fname*, *plane*, *ole=None*)
returns ZviItemTuple of the plane from zvi file fname

Module contents

1.2.2 Submodules

imsegm.annotation module

Framework for handling annotations

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imsegm.annotation.**convert_img_colors_to_labels**(*img_rgb*, *lut_label_color*)
take a RGB image and dictionary of labels and apply this dictionary it returns relabels image according given dictionary

Parameters

- **img_rgb** (*ndarray*) – np.array<height, width, 3> input RGB image
- **{int** – (int, int, int)} lut_label_color:

Return ndarray np.array<height, width> labeling

```
>>> np.random.seed(0)
>>> seg = np.random.randint(0, 2, (5, 7))
>>> img = np.array([(0.2, 0.2, 0.2), (0.9, 0.9, 0.9)])[seg]
>>> d_lb_clr = {0: (0.2, 0.2, 0.2), 1: (0.9, 0.9, 0.9)}
```

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```
>>> convert_img_colors_to_labels(img, d_lb_clr)
array([[0, 1, 1, 0, 1, 1, 1],
       [1, 1, 1, 1, 0, 0, 1],
       [0, 0, 0, 0, 0, 1, 0],
       [1, 1, 0, 0, 1, 1, 1],
       [1, 0, 1, 0, 1, 0, 1]])
```

imsegm.annotation.**convert_img_colors_to_labels_reverted**(*img_rgb*, *dict_color_label*)

take a RGB image and dictionary of labels and apply this dictionary it returns relabels image according given dictionary

Parameters

- **img_rgb** (*ndarray*) – np.array<height, width, 3> input RGB image
- **int, int)** (*{(int,*) – int} dict_color_label:

Return ndarray np.array<height, width> labeling

```
>>> np.random.seed(0)
>>> seg = np.random.randint(0, 2, (5, 7))
>>> img = np.array([(0.2, 0.2, 0.2), (0.9, 0.9, 0.9)])[seg]
>>> d_clr_lb = {(0.2, 0.2, 0.2): 0, (0.9, 0.9, 0.9): 1}
>>> convert_img_colors_to_labels_reverted(img, d_clr_lb)
array([[0, 1, 1, 0, 1, 1, 1],
       [1, 1, 1, 1, 0, 0, 1],
       [0, 0, 0, 0, 0, 1, 0],
       [1, 1, 0, 0, 1, 1, 1],
       [1, 0, 1, 0, 1, 0, 1]])
```

imsegm.annotation.**convert_img_labels_to_colors**(*segm*, *lut_label_colors*)

convert labeling according given dictionary of colors

Parameters

- **segm** (*ndarray*) – np.array<height, width>
- **{int** – (int, int, int)} lut_label_colors:

Return ndarray np.array<height, width, 3>

```
>>> np.random.seed(0)
>>> seg = np.random.randint(0, 2, (5, 7))
>>> d_lb_clr = {0: (0.2, 0.2, 0.2), 1: (0.9, 0.9, 0.9)}
>>> img = convert_img_labels_to_colors(seg, d_lb_clr)
>>> img[:, :, 0]
array([[ 0.2,  0.9,  0.9,  0.2,  0.9,  0.9,  0.9],
       [ 0.9,  0.9,  0.9,  0.9,  0.2,  0.2,  0.9],
       [ 0.2,  0.2,  0.2,  0.2,  0.2,  0.9,  0.2],
       [ 0.9,  0.9,  0.2,  0.2,  0.9,  0.9,  0.9],
       [ 0.9,  0.2,  0.9,  0.2,  0.9,  0.2,  0.9]])
```

imsegm.annotation.**group_images_frequent_colors**(*paths_img*, *ratio_threshold=0.001*)

look all images and estimate most frequent colours

Parameters

- **paths_img** (*list (str)*) – path to images
- **ratio_threshold** (*float*) – percentage of nb, clr pixels to be assumed as important

Return list(int)

```
>>> from skimage import data
>>> from imsegm.utilities.data_io import io_imsave
>>> path_img = './sample-image.png'
>>> io_imsave(path_img, data.astronaut())
>>> d_clrs = group_images_frequent_colors([path_img], ratio_threshold=3e-4)
>>> sorted([d_clrs[c] for c in d_clrs], reverse=True)
[27969, 1345, 1237, 822, 450, 324, 313, 244, 229, 213, 163, 160, 158, 157,
 150, 137, 120, 119, 117, 114, 98, 92, 92, 91, 81]
>>> os.remove(path_img)
```

imsegm.annotation.**image_color_2_labels**(*img*, *colors=None*)

quantize input image according given list of possible colours

Parameters

- **img** (*ndarray*) – np.array<height, width, 3>, input image
- **int, int)] colors** (*[(int,*) – list of possible colours

Return ndarray np.array<height, width>

```
>>> np.random.seed(0)
>>> rand = np.random.randint(0, 2, (5, 7)).astype(np.uint8)
>>> img = np.rollaxis(np.array([rand] * 3), 0, 3)
>>> image_color_2_labels(img)
array([[1, 0, 0, 1, 0, 0, 0],
       [0, 0, 0, 0, 1, 1, 0],
       [1, 1, 1, 1, 1, 0, 1],
       [0, 0, 1, 1, 0, 0, 0],
       [0, 1, 0, 1, 0, 1, 0]]...)
```

imsegm.annotation.**image_frequent_colors**(*img*, *ratio_threshold=0.001*)

look all images and estimate most frequent colours

Parameters

- **img** (*ndarray*) – np.array<height, width, 3>
- **ratio_threshold** (*float*) – percentage of nb color pixels to be assumed as important

Return {(int, int, int) int}

```
>>> np.random.seed(0)
>>> img = np.random.randint(0, 2, (50, 50, 3)).astype(np.uint8)
>>> d = image_frequent_colors(img)
>>> sorted(d.keys())
[(0, 0, 0), (0, 0, 1), (0, 1, 0), (0, 1, 1), (1, 0, 0), (1, 0, 1),
 (1, 1, 0), (1, 1, 1)]
>>> sorted(d.values())
[271, 289, 295, 317, 318, 330, 335, 345]
```

imsegm.annotation.**image_inpaint_pixels**(*img*, *valid_mask*)

imsegm.annotation.**load_info_group_by_slices**(*path_txt*, *stages*, *pos_columns=('ant_x', 'ant_y', 'post_x', 'post_y', 'lat_x', 'lat_y')*, *dict_slice_tol={1: 1, 2: 2, 3: 2, 4: 3, 5: 3, 6: 0}*)

load all info and group position info according name if stack

Parameters

- **path_txt** (*str*) –
- **stages** (*list (int)*) – stages
- **pos_columns** (*list (str)*) –
- **dict_slice_tol** (*dict (list (int))*) – mapping of int to list

Returns DF

```
>>> from imsegm.utilities.data_io import update_path
>>> path_txt = os.path.join(update_path('data-images'), 'drosophila_ovary_slice',
↪'info_ovary_images.txt')
>>> df = load_info_group_by_slices(path_txt, [4])
>>> df.sort_index(axis=1)
            ant_x  ant_y  lat_x  lat_y post_x post_y
image
insitu7569  [298]  [327]  [673]  [411]  [986]  [155]
```

imsegm.annotation.**quantize_image_nearest_color**(*img*, *colors*)

quantize input image according given list of possible colours

Parameters

- **img** (*ndarray*) – np.array<height, width, 3>, input image
- **int, int)] colors** ([*(int,*) – list of possible colours

Return ndarray np.array<height, width, 3>

```
>>> np.random.seed(0)
>>> img = np.random.randint(0, 2, (5, 7, 3)).astype(np.uint8)
>>> im = quantize_image_nearest_color(img, [(0, 0, 0), (1, 1, 1)])
>>> im[:, :, 0]
array([[1, 1, 1, 1, 0, 0, 0],
       [1, 1, 1, 1, 1, 1, 0],
       [1, 1, 0, 1, 1, 0, 1],
       [0, 0, 1, 0, 1, 0, 1],
       [1, 1, 1, 0, 1, 0, 0]], dtype=uint8)
>>> [np.array_equal(im[:, :, 0], im[:, :, i]) for i in [1, 2]]
[True, True]
```

imsegm.annotation.**quantize_image_nearest_pixel**(*img*, *colors*)

quantize input image according given list of possible colours

Parameters

- **img** (*ndarray*) – np.array<height, width, 3>, input image
- **int, int)] colors** ([*(int,*) – list of possible colours

Return ndarray np.array<height, width, 3>

```
>>> np.random.seed(0)
>>> img = np.random.randint(0, 2, (5, 7, 3)).astype(np.uint8)
>>> im = quantize_image_nearest_pixel(img, [(0, 0, 0), (1, 1, 1)])
>>> im[:, :, 0]
array([[1, 1, 1, 1, 0, 0, 0],
       [1, 1, 1, 1, 0, 0, 0],
       [1, 1, 1, 1, 1, 0, 0],
       [0, 0, 0, 0, 0, 0, 0],
       [1, 0, 0, 0, 0, 0, 0]])
```

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```
>>> [np.array_equal(im[:, :, 0], im[:, :, i]) for i in [1, 2]]
[True, True]
```

imsegm.annotation.**unique_image_colors**(*img*)
find all unique color in image and return its list

Parameters **img** (*ndarray*) – np.array<height, width, 3>

Returns [(int, int, int)]

```
>>> np.random.seed(0)
>>> img = np.random.randint(0, 2, (50, 50, 3))
>>> unique_image_colors(img)
[(1, 0, 0), (1, 1, 0), (0, 1, 0), (1, 1, 1),
 (0, 1, 1), (0, 0, 1), (1, 0, 1), (0, 0, 0)]
>>> img = np.random.randint(0, 256, (150, 150, 3))
>>> unique_image_colors(img)
[...]
```

imsegm.annotation.**ANNOT_SLICE_DIST_TOL = {1: 1, 2: 2, 3: 2, 4: 3, 5: 3, 6: 0}**
set distance in Z axis whether near slice may still belong to the same egg

imsegm.annotation.**COLUMNS_POSITION = ('ant_x', 'ant_y', 'post_x', 'post_y', 'lat_x', 'lat_y**
names of annotated columns

imsegm.annotation.**DICT_COLOURS = {0: (0, 0, 255), 1: (255, 0, 0), 2: (0, 255, 0), 3: (255,**
default colors for particular label

imsegm.classification module

Supporting file to create and set parameters for scikit-learn classifiers and some prepossessing functions that support classification

Copyright (C) 2014-2018 Jiri Borovec <jiri.borovec@fel.cvut.cz>

class imsegm.classification.**CrossValidate**(*nb_samples*, *nb_hold_out*, *rand_seed=None*, *ignore_overflow=0.01*)

Bases: object

Cross-validator generator. In the hold-out, the data is split only once into a train set and a test set.

Parameters

- **nb_samples** (*integer, total number of samples*) –
- **nb_hold_out** (*integer, number of samples hold out*) –
- **rand_seed** (*seed for the random number generator*) –
- **ignore_overflow** (*float, tolerance while dividing dataset to folds*) –

Examples

```
>>> # balanced split
>>> cv = CrossValidate(6, 3, rand_seed=False)
>>> cv.indexes
[0, 1, 2, 3, 4, 5]
>>> len(cv)
2
>>> list(cv)
[([3, 4, 5], [0, 1, 2]),
 ([0, 1, 2], [3, 4, 5])]
>>> [(len(tr), len(ts)) for tr, ts in CrossValidate(340, 0.41)]
[(201, 139), (201, 139), (201, 139)]
```

```
>>> # not rounded split
>>> cv = CrossValidate(7, 3, rand_seed=0)
>>> list(cv)
[([3, 0, 5, 4], [6, 2, 1]),
 ([6, 2, 1, 4], [3, 0, 5]),
 ([1, 3, 0, 5], [4, 6, 2])]
>>> len(cv)
3
>>> cv.indexes
[6, 2, 1, 3, 0, 5, 4]
```

```
>>> # larger test then train
>>> cv = CrossValidate(7, 5, rand_seed=0)
>>> list(cv)
[([6, 2], [1, 3, 0, 5, 4]),
 ([1, 3], [6, 2, 0, 5, 4]),
 ([0, 5], [6, 2, 1, 3, 4]),
 ([4, 6], [2, 1, 3, 0, 5])]
>>> [(len(tr), len(ts)) for tr, ts in CrossValidate(340, 0.55)]
[(153, 187), (153, 187), (153, 187)]
```

```
>>> # impact of tolerance
>>> len(CrossValidate(340, 0.33, ignore_overflow=0.0))
4
>>> len(CrossValidate(340, 0.33, ignore_overflow=0.05))
3
```

```
>>> [(len(tr), len(ts)) for tr, ts in CrossValidate(4651, 0.25, ignore_overflow=0.
↪)]
[(3488, 1163), (3488, 1163), (3488, 1163), (3488, 1163)]
>>> [(len(tr), len(ts)) for tr, ts in CrossValidate(4651, 0.25, ignore_
↪overflow=1e-2)]
[(3488, 1163), (3488, 1163), (3488, 1163), (3489, 1162)]
```

constructor

Parameters

- **nb_samples** (*int*) – list of sizes
- **nb_hold_out** (*int | float*) – how much hold out
- **rand_seed** (*int | None*) – random seed for shuffling
- **ignore_overflow** (*float*) – tolerance while dividing dataset to folds

_CrossValidate__steps()
adjust this iterator, tol_balance

Return list(int) indexes of steps

class imsegm.classification.**CrossValidateGroups**(*set_sizes*, *nb_hold_out*, *rand_seed=None*, *ignore_overflow=0.01*)

Bases: *imsegm.classification.CrossValidate*

Cross-validator generator. In the hold-out, the data is split only once into a train set and a test set.

Parameters

- **set_sizes** (*list of integers, number of samples in each set*) –
- **nb_hold_out** (*integer, number of sets hold out*) –
- **rand_seed** (*seed for the random number generator*) –
- **ignore_overflow** (*float, tolerance while dividing dataset to folds*) –

Examples

```
>>> # balance split
>>> cv = CrossValidateGroups([2, 3, 2, 3], 2, rand_seed=False)
>>> cv.set_indexes
[[0, 1], [2, 3, 4], [5, 6], [7, 8, 9]]
>>> len(cv)
2
>>> list(cv)
[([5, 6, 7, 8, 9], [0, 1, 2, 3, 4]),
 ([0, 1, 2, 3, 4], [5, 6, 7, 8, 9])]
>>> [(len(tr), len(ts)) for tr, ts in CrossValidateGroups([7] * 340, 0.41)]
[(1407, 973), (1407, 973), (1407, 973)]
```

```
>>> # unbalanced split
>>> cv = CrossValidateGroups([2, 2, 1, 2, 1], 2, rand_seed=0)
>>> cv.set_indexes
[[0, 1], [2, 3], [4], [5, 6], [7]]
>>> list(cv)
[([2, 3, 5, 6, 7], [4, 0, 1]),
 ([4, 0, 1, 7], [2, 3, 5, 6]),
 ([0, 1, 2, 3, 5, 6], [7, 4])]
>>> len(cv)
3
>>> cv.indexes
[2, 0, 1, 3, 4]
```

```
>>> # larger test then train
>>> cv = CrossValidateGroups([2, 2, 1, 2, 1, 1], 4, rand_seed=0)
>>> list(cv)
[([8, 4], [2, 3, 5, 6, 0, 1, 7]),
 ([2, 3, 5, 6], [8, 4, 0, 1, 7]),
 ([0, 1, 7], [8, 4, 2, 3, 5, 6])]
>>> [(len(tr), len(ts)) for tr, ts in CrossValidateGroups([7] * 340, 0.55)]
[(1071, 1309), (1071, 1309), (1071, 1309)]
```

construct

Parameters

- **set_sizes** (*list (int)*) – list of sizes
- **nb_hold_out** (*int | float*) – how much hold out
- **rand_seed** (*int | None*) – random seed for shuffling
- **ignore_overflow** (*float*) – tolerance while dividing dataset to folds

_CrossValidateGroups__iter_indexes(*sets*)
return enrol indexes from sets

Parameters **sets** (*list (int)*) – selection of indexes

Return list(int)

class imsegm.classification.**HoldOut**(*nb_samples*, *hold_out*, *rand_seed=0*)
Bases: object

Hold-out cross-validator generator. In the hold-out, the data is split only once into a train set and a test set. Unlike in other cross-validation schemes, the hold-out consists of only one iteration.

Parameters

- **nb_samples** (*int, total number of samples*) –
- **hold_out** (*int, number where the test starts*) –
- **rand_seed** (*seed for the random number generator*) –

Example

```
>>> ho = HoldOut(10, 7, rand_seed=None)
>>> len(ho)
1
>>> list(ho)
[([0, 1, 2, 3, 4, 5, 6], [7, 8, 9])]
>>> ho = HoldOut(10, 7, rand_seed=0)
>>> list(ho)
[([2, 8, 4, 9, 1, 6, 7], [3, 0, 5])]
```

constructor

Parameters

- **nb_samples** (*int*) – total number of samples
- **hold_out** (*int*) – index where the test starts
- **rand_seed** (*obj*) – Seed for the random number generator.

imsegm.classification.**balance_dataset_by_**(*features*, *labels*, *balance_type='random'*, *min_samples=None*)
balance number of training examples per class by several method

Parameters

- **features** (*ndarray*) – features in dimension nb_samples x nb_features
- **labels** (*list (int)*) – annotation for samples
- **balance_type** (*str*) – type of balancing dataset

- **min_samples** (*int | None*) – if None take the smallest class

Return tuple(ndarray,ndarray)

```
>>> np.random.seed(0)
>>> fts, lbs = balance_dataset_by_(np.random.random((25, 3)), np.random.randint(0,
↪ 2, 25))
>>> fts.shape
(24, 3)
>>> lbs
[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1]
```

imsegm.classification.**compose_dict_label_features**(*features*, *labels*)

convert vector of features and related labels to a dictionary of features where key is the lables

Parameters

- **features** (*ndarray*) – features in dimension nb_samples x nb_features
- **labels** (*list(int)*) – annotation for samples

Return {int ndarray}: {int: np.array<nb, nb_features>}

imsegm.classification.**compute_classif_metrics**(*y_true*, *y_pred*, *metric_averages=('macro', 'weighted')*)

compute standard metrics for multi-class classification

Parameters

- **y_true** (*list(int)*) –
- **y_pred** (*list(int)*) –
- **metric_averages** (*str|list(str)*) –

Return dict(float)

```
>>> np.random.seed(0)
>>> y_true = np.random.randint(0, 3, 25) * 2
>>> y_pred = np.random.randint(0, 2, 25) * 2
>>> d = compute_classif_metrics(y_true, y_true)
>>> d['accuracy']
1.0
>>> d['confusion']
[[10, 0, 0], [0, 10, 0], [0, 0, 5]]
>>> d = compute_classif_metrics(y_true, y_pred)
>>> d['accuracy']
0.32...
>>> d['confusion']
[[3, 7, 0], [5, 5, 0], [1, 4, 0]]
>>> d = compute_classif_metrics(y_pred, y_pred)
>>> d['accuracy']
1.0
```

imsegm.classification.**compute_classif_stat_segm_annot**(*annot_segm_name*, *drop_labels=None*, *relabel=False*)

compute classification statistic between annotation and segmentation

Parameters

- **annot_segm_name** (*tuple(ndarray,ndarray,str)*) –
- **drop_labels** (*list(int)*) – labels to be ignored

- **relabel** (*bool*) – whether relabel

Returns

```
>>> np.random.seed(0)
>>> annot = np.random.randint(0, 2, (5, 10))
>>> segm = np.random.randint(0, 2, (5, 10))
>>> d = compute_classif_stat_segm_annot((annot, annot, 'ttt'), relabel=True, drop_
↪labels=[5])
>>> d['(FP+FN)/(TP+FN)']
0.0
>>> d['(TP+FP)/(TP+FN)']
1.0
>>> d = compute_classif_stat_segm_annot((annot, segm, 'ttt'), relabel=True, drop_
↪labels=[5])
>>> d['(FP+FN)/(TP+FN)']
0.846...
>>> d['(TP+FP)/(TP+FN)']
1.153...
>>> d = compute_classif_stat_segm_annot((annot, segm + 1, 'ttt'), relabel=False,␣
↪drop_labels=[0])
>>> d['confusion']
[[13, 17], [0, 0]]
```

imsegm.classification.**compute_metric_fpfn_tpfn**(*annot*, *segm*, *label_positive=None*)

compute measure (FP + FN) / (TP + FN)

Parameters

- **annot** (*ndarray*) – annotation
- **segm** (*ndarray*) – segmentation
- **label_positive** (*int*) – indexes of positive labels

Return float

```
>>> np.random.seed(0)
>>> annot = np.random.randint(0, 2, (50, 75)) * 3
>>> segm = np.random.randint(0, 2, (50, 75)) * 3
>>> compute_metric_fpfn_tpfn(annot, segm)
1.02...
>>> compute_metric_fpfn_tpfn(annot, annot)
0.0
>>> compute_metric_fpfn_tpfn(annot, np.ones((50, 75)))
nan
```

imsegm.classification.**compute_metric_tpfp_tpfn**(*annot*, *segm*, *label_positive=None*)

compute measure (TP + FP) / (TP + FN)

Parameters

- **annot** (*ndarray*) –
- **segm** (*ndarray*) –
- **label_positive** (*int*) –

Return float

```
>>> np.random.seed(0)
>>> annot = np.random.randint(0, 2, (50, 75)) * 3
```

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```
>>> segm = np.random.randint(0, 2, (50, 75)) * 3
>>> compute_metric_tpfp_tpfn(annot, segm)
1.03...
>>> compute_metric_tpfp_tpfn(annot, annot)
1.0
>>> compute_metric_tpfp_tpfn(annot, np.ones((50, 75)))
nan
>>> compute_metric_tpfp_tpfn(annot, np.zeros((50, 75)))
0.0
```

imsegm.classification.**compute_stat_per_image**(*segms*, *annots*, *names=None*, *nb_workers=2*, *drop_labels=None*, *relabel=False*)

compute statistic over multiple segmentations with annotation

Parameters

- **segms** (*[ndarray]*) – segmntations
- **annots** (*[ndarray]*) – annotations
- **names** (*list(str)*) – list of names
- **drop_labels** (*list(int)*) – labels to be ignored
- **relabel** (*bool*) – whether relabel
- **nb_workers** (*int*) – running jobs in parallel

Return DF

```
>>> np.random.seed(0)
>>> img_true = np.random.randint(0, 3, (50, 100))
>>> img_pred = np.random.randint(0, 2, (50, 100))
>>> df = compute_stat_per_image([img_true], [img_true], nb_workers=2,␣
↪relabel=True)
>>> from pprint import pprint
>>> pprint(pd.Series(df.iloc[0]).sort_index().to_dict())
{'ARS': 1.0,
 'accuracy': 1.0,
 'confusion': [[1672, 0, 0], [0, 1682, 0], [0, 0, 1646]],
 'f1_macro': 1.0,
 'precision_macro': 1.0,
 'recall_macro': 1.0,
 'support_macro': None}
>>> df = compute_stat_per_image([img_true], [img_pred], drop_labels=[-1])
>>> pd.Series(df.round(4).iloc[0]).sort_index()
ARS                                                    0.0002
accuracy                                               0.3384
confusion          [[836, 826, 770], [836, 856, 876], [0, 0, 0]]
f1_macro                                               0.2701
precision_macro                                        0.3363
recall_macro                                           0.2257
support_macro                                            None
Name: 0, dtype: object
```

imsegm.classification.**compute_tp_tn_fp_fn**(*annot*, *segm*, *label_positive=None*)

compute measure TruePositive, TrueNegative, FalsePositive, FalseNegative

Parameters

- **annot** (*ndarray*) – annotation
- **segm** (*ndarray*) – segmentation
- **label_positive** (*int*) – indexes of positive labels

Return tuple(float,float,float,float)

```
>>> np.random.seed(0)
>>> annot = np.random.randint(0, 2, (5, 7)) * 9
>>> segm = np.random.randint(0, 2, (5, 7)) * 9
>>> annot - segm
array([[-9,  9,  0, -9,  9,  9,  0],
       [ 9,  0,  0,  0, -9, -9,  9],
       [-9,  0, -9, -9, -9,  0,  0],
       [ 0,  9,  0, -9,  0,  9,  0],
       [ 9, -9,  9,  0,  9,  0,  9]])
>>> compute_tp_tn_fp_fn(annot, annot)
(20, 15, 0, 0)
>>> compute_tp_tn_fp_fn(annot, segm)
(9, 5, 11, 10)
>>> compute_tp_tn_fp_fn(annot, np.ones((5, 7)))
(nan, nan, nan, nan)
>>> compute_tp_tn_fp_fn(np.zeros((5, 7)), np.zeros((5, 7)))
(35, 0, 0, 0)
```

imsegm.classification.**convert_dict_label_features_2_vectors**(*dict_features*)

convert dictionary of features where key is the labels to vector of all features and related labels

Parameters **{int** – [list(float)]} dict_features: {int: [list(float) * nb_features] * nb_samples}

Return tuple(ndarray,list(int)) np.array<nb_samples, nb_features>, list(int)

imsegm.classification.**convert_set_features_labels_2_dataset**(*imgs_features*, *imgs_labels*, *drop_labels=None*, *balance_type=None*)

with dictionary for each image we concentrate all features over images and labels into simple form

Parameters

- **{str** – ndarray} imgs_features: dictionary of name and features
- **{str** – ndarray} imgs_labels: dictionary of name and labels
- **drop_labels** (*list(int)*) – labels to be ignored
- **balance_type** (*bool*) – whether balance_type number of sampler per class

Return tuple(ndarray,ndarray,ndarray)

```
>>> np.random.seed(0)
>>> d_fts = {'a': np.random.random((25, 3)),
...          'b': np.random.random((30, 3)), }
>>> d_lbs = {'a': np.random.randint(0, 2, 25),
...          'b': np.random.randint(0, 2, 30)}
>>> fts, lbs, sizes = convert_set_features_labels_2_dataset(d_fts, d_lbs)
>>> fts.shape
(55, 3)
>>> lbs.shape
(55,)
```

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```
>>> sizes
[25, 30]
```

imsegm.classification.**create_classif_search**(*name_clf*, *clf_pipeline*, *nb_labels*, *search_type='random'*, *cross_val=10*, *eval_metric='f1'*, *nb_iter=250*, *nb_workers=5*)

create sklearn search depending on spec. random or grid

Parameters

- **nb_labels** (*int*) – number of labels
- **search_type** (*str*) – hyper-params search type
- **eval_metric** (*str*) – evaluation metric
- **nb_iter** (*int*) – for random number of tries
- **name_clf** (*str*) – name of classif.
- **clf_pipeline** (*obj*) – object
- **cross_val** (*obj*) – obj specific CV for fix train-test
- **nb_workers** (*int*) – number jobs running in parallel

Returns

imsegm.classification.**create_classif_search_train_export**(*clf_name*, *features*, *labels*, *cross_val=10*, *nb_search_iter=100*, *search_type='random'*, *eval_metric='f1'*, *nb_workers=1*, *path_out=None*, *params=None*, *pca_coef=0.98*, *feature_names=None*, *label_names=None*)

create classifier and train it once or find best parameters. whether tha path out is given export it for later use

Parameters

- **clf_name** (*str*) – name of selected classifier
- **features** (*ndarray*) – features in dimension nb_samples x nb_features
- **labels** (*list(int)*) – annotation for samples
- **cross_val** (*int|obj*) – Cross validation
- **search_type** (*str*) – search type
- **eval_metric** (*str*) – evaluation metric
- **params** (*dict*) – extra parameters
- **pca_coef** (*float*) – sklearn PCA - int/float/None
- **nb_search_iter** (*int*) – number of searcher for hyper-parameters
- **path_out** (*str*) – path to directory for exporting classifier
- **nb_workers** (*int*) – parallel processes

- **feature_names** (*list (str)*) – list of extracted features - names
- **label_names** (*list (str)*) – list of label names

Returns (obj, str): classifier, path to the exported classifier

```
>>> np.random.seed(0)
>>> lbs = np.random.randint(0, 3, 150)
>>> fts = np.random.random((150, 5)) + np.tile(lbs, (5, 1)).T
>>> _, _ = create_classif_search_train_export('LogistRegr', fts, lbs, nb_search_
↪iter=0)
>>> clf, p_clf = create_classif_search_train_export('AdaBoost', fts, lbs,
...     nb_search_iter=2, path_out='', search_type='grid')
Fitting ...
>>> clf
Pipeline(...)
>>> clf, p_clf = create_classif_search_train_export('RandForest', fts, lbs,
...     nb_search_iter=2, path_out='.', search_type='random')
Fitting ...
>>> clf
Pipeline(...)
>>> os.path.basename(p_clf)
'classifier_RandForest.pkl'
>>> os.remove(p_clf)
>>> import glob
>>> files = glob.glob(os.path.join('.', 'classif_*.txt'))
>>> sorted([os.path.basename(fp) for fp in files])
['classif_RandForest_search_params_best.txt',
 'classif_RandForest_search_params_scores.txt']
>>> for p in files: os.remove(p)
```

imsegm.classification.**create_classifiers**(*nb_workers=-1*)

create all classifiers with default parameters

Parameters **nb_workers** (*int*) – number of parallel if possible

Return dict {str: clf}

```
>>> classifs = create_classifiers()
>>> classifs
{...}
>>> sum([isinstance(create_clf_param_search_grid(k), dict) for k in classifs.
↪keys()])
7
>>> sum([isinstance(create_clf_param_search_distrib(k), dict) for k in classifs.
↪keys()])
7
```

imsegm.classification.**create_clf_param_search_distrib**(*name_classif='RandForest'*)

create parameter distribution for random search

Parameters **name_classif** (*str*) – key name of classifier

Returns dict

```
>>> create_clf_param_search_distrib()
{...}
>>> dict_classif = create_classifiers()
>>> all(len(create_clf_param_search_distrib(k)) > 0 for k in dict_classif)
True
```

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```
>>> create_clf_param_search_distrib('none')
{}
```

imsegm.classification.**create_clf_param_search_grid**(*name_classif='RandForest'*)
create parameter grid for search

Parameters **name_classif** (*str*) – key name of selected classifier

Returns dict

```
>>> create_clf_param_search_grid('RandForest')
{'classif__...': ...}
>>> dict_classif = create_classifiers()
>>> all(len(create_clf_param_search_grid(k)) > 0 for k in dict_classif)
True
>>> create_clf_param_search_grid('none')
{}
```

imsegm.classification.**create_clf_pipeline**(*name_classif='RandForest'*, *pca_coef=0.95*)
create complete pipeline with all required steps

Parameters

- **pca_coef** (*int* | *float* | *None*) – sklearn PCA
- **name_classif** (*str*) – key name of classif.

Returns object

```
>>> create_clf_pipeline()
Pipeline(...)
```

imsegm.classification.**create_pipeline_neuron_net**()
create classifier for simple neuronal network

Returns clf

```
>>> create_pipeline_neuron_net()
Pipeline(...)
```

imsegm.classification.**down_sample_dict_features_kmean**(*dict_features*, *nb_samples*)
cluser with kmeans the features with nb cluster == given nb_samples and the retirn features which are closer to each cluster center

Parameters

- **dict_features** (*dict*) – {int: [list(float) * nb_features] * nb}
- **nb_samples** (*int*) –

Return dict {int: [list(float) * nb_features] * nb_samples}

```
>>> np.random.seed(0)
>>> d_fts = {'a': np.random.random((100, 3))}
>>> d_fts = down_sample_dict_features_kmean(d_fts, 5)
>>> d_fts['a'].shape
(5, 3)
```

imsegm.classification.**down_sample_dict_features_random**(*dict_features*, *nb_samples*)
browse all label features and take random subset of features to have given nb_samples per class

Parameters

- **dict_features** (*dict*) – {int: [list(float) * nb_features] * nb}
- **nb_samples** (*int*) –

Return dict {int: [list(float) * nb_features] * nb_samples}

```
>>> np.random.seed(0)
>>> d_fts = {'a': np.random.random((100, 3))}
>>> d_fts = down_sample_dict_features_random(d_fts, 5)
>>> d_fts['a'].shape
(5, 3)
```

imsegm.classification.**down_sample_dict_features_unique**(*dict_features*)

browse all label features and take unique features

Parameters **dict_features** (*dict*) – {int: [list(float) * nb_features] * nb_samples}

Return dict {int: [list(float) * nb_features] * nb}

```
>>> np.random.seed(0)
>>> d_fts = {'a': np.random.random((100, 3))}
>>> d_fts = down_sample_dict_features_unique(d_fts)
>>> d_fts['a'].shape
(100, 3)
```

imsegm.classification.**eval_classif_cross_val_roc**(*clf_name*, *classif*, *features*, *labels*, *cross_val*, *path_out=None*, *nb_steps=100*)

compute mean ROC curve on cross-validation schema

http://scikit-learn.org/0.15/auto_examples/plot_roc_crossval.html

Parameters

- **clf_name** (*str*) – name of selected classifier
- **classif** (*obj*) – sklearn classifier
- **features** (*ndarray*) – features in dimension nb_samples x nb_features
- **labels** (*list(int)*) – annotation for samples
- **cross_val** (*object*) –
- **path_out** (*str*) – path for exporting statistic
- **nb_steps** (*int*) – number of thresholds

Returns

```
>>> np.random.seed(0)
>>> labels = np.array([0] * 150 + [1] * 100 + [3] * 50)
>>> data = np.tile(labels, (6, 1)).T.astype(float)
>>> data += np.random.random(data.shape)
>>> data.shape
(300, 6)
>>> from sklearn.model_selection import StratifiedKFold
>>> cv = StratifiedKFold(n_splits=5, random_state=0, shuffle=True)
>>> classif = create_classifiers()[DEFAULT_CLASSIF_NAME]
>>> fp_tp, auc = eval_classif_cross_val_roc(DEFAULT_CLASSIF_NAME, classif, data,␣
↪labels, cv, nb_steps=11)
```

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```
>>> fp_tp
     FP   TP
0   0.0  0.0
1   0.1  1.0
2   0.2  1.0
3   0.3  1.0
4   0.4  1.0
5   0.5  1.0
6   0.6  1.0
7   0.7  1.0
8   0.8  1.0
9   0.9  1.0
10  1.0  1.0
>>> auc
0.94...
>>> labels[-50:] -= 1
>>> data[-50:, :] -= 1
>>> path_out = 'temp_eval-cv-roc'
>>> os.mkdir(path_out)
>>> fp_tp, auc = eval_classif_cross_val_roc(
...     DEFAULT_CLASSIF_NAME, classif, data, labels, cv, nb_steps=5, path_
↪out=path_out)
>>> fp_tp
     FP   TP
0  0.00  0.0
1  0.25  1.0
2  0.50  1.0
3  0.75  1.0
4  1.00  1.0
>>> auc
0.875
>>> import shutil
>>> shutil.rmtree(path_out, ignore_errors=True)
```

imsegm.classification.**eval_classif_cross_val_scores**(*clf_name*, *classif*, *features*, *labels*, *cross_val=10*, *path_out=None*, *scorings=('f1_macro', 'accuracy', 'precision_macro', 'recall_macro')*)

compute statistic on cross-validation schema

http://scikit-learn.org/stable/modules/generated/sklearn.model_selection.cross_val_score.html

Parameters

- **clf_name** (*str*) – name of selected classifier
- **classif** (*obj*) – sklearn classifier
- **features** (*ndarray*) – features in dimension nb_samples x nb_features
- **labels** (*list(int)*) – annotation for samples
- **cross_val** (*object*) –
- **path_out** (*str*) – path for exporting statistic
- **scorings** (*list(str)*) – list of used scorings

Return DF

```
>>> labels = np.array([0] * 150 + [1] * 100 + [2] * 50)
>>> data = np.tile(labels, (6, 1)).T.astype(float)
>>> data += 0.5 - np.random.random(data.shape)
>>> data.shape
(300, 6)
>>> from sklearn.model_selection import StratifiedKFold
>>> cv = StratifiedKFold(n_splits=5, random_state=0, shuffle=True)
>>> classif = create_classifiers()[DEFAULT_CLASSIF_NAME]
>>> df = eval_classif_cross_val_scores(DEFAULT_CLASSIF_NAME, classif, data,␣
↪labels, cv)
>>> df.round(decimals=1)
   f1_macro  accuracy  precision_macro  recall_macro
0       1.0       1.0              1.0           1.0
1       1.0       1.0              1.0           1.0
2       1.0       1.0              1.0           1.0
3       1.0       1.0              1.0           1.0
4       1.0       1.0              1.0           1.0
>>> labels[labels == 1] = 2
>>> cv = StratifiedKFold(n_splits=3, random_state=0, shuffle=True)
>>> df = eval_classif_cross_val_scores(DEFAULT_CLASSIF_NAME, classif, data,␣
↪labels, cv, path_out='.')
>>> df.round(decimals=1)
   f1_macro  accuracy  precision_macro  recall_macro
0       1.0       1.0              1.0           1.0
1       1.0       1.0              1.0           1.0
2       1.0       1.0              1.0           1.0
>>> import glob
>>> p_files = glob.glob(NAME_CSV_CLASSIF_CV_SCORES.replace('{}', '*'))
>>> sorted(p_files)
['classif_RandForest_cross-val_scores-all-folds.csv',
 'classif_RandForest_cross-val_scores-statistic.csv']
>>> [os.remove(p) for p in p_files]
[...]
```

imsegm.classification.**export_results_clf_search**(*path_out*, *clf_name*, *clf_search*)

do the final testing and save all results

Parameters

- **path_out** (*str*) – path to directory for exporting classifier
- **clf_name** (*str*) – name of selected classifier
- **clf_search** (*object*) –

imsegm.classification.**feature_scoring_selection**(*features*, *labels*, *names=None*, *path_out=''*)

find the best features and retrun the indexes http://scikit-learn.org/stable/auto_examples/linear_model/plot_sparse_recovery.html http://scikit-learn.org/stable/auto_examples/feature_selection/plot_feature_selection.html

Parameters

- **features** (*ndarray*) – np.array<nb_samples, nb_features>
- **labels** (*ndarray*) – np.array<nb_samples, 1>
- **names** (*list(str)*) –
- **path_out** (*str*) –

Return tuple(list(int),DF) indices, Dataframe with scoring

```
>>> from sklearn.datasets import make_classification
>>> features, labels = make_classification(
...     n_samples=250, n_features=5, n_informative=3, n_redundant=0, n_repeated=0,
...     n_classes=2, random_state=0, shuffle=False)
>>> indices, df_scoring = feature_scoring_selection(features, labels)
>>> indices
array([1, 0, 2, 3, 4]...)
>>> df_scoring.sort_index(axis=1)
         ExtTree    F-test    k-Best variance
feature
1        0.24...   0.75...   0.75...  2.49...
2        0.33...  58.94...  58.94...  1.85...
3        0.22...   2.24...   2.24...  1.54...
4        0.10...   4.02...   4.02...  0.96...
5        0.09...   0.02...   0.02...  1.01...
>>> features[:, 2] = 1
>>> path_out = 'test_fts-select'
>>> os.mkdir(path_out)
>>> indices, df_scoring = feature_scoring_selection(features.tolist(), labels.
↪tolist(), path_out=path_out)
>>> indices
array([1, 0, 3, 4, 2]...)
>>> import shutil
>>> shutil.rmtree(path_out, ignore_errors=True)
```

imsegm.classification.**load_classifier**(*path_classif*)

estimate classifier for all data and export it

Parameters **path_classif** (*str*) – path to the exported classifier

Return dict

```
>>> load_classifier('none.abc')
```

imsegm.classification.**relabel_sequential**(*labels*, *uq_labels=None*)

relabel sequential vector staring from 0

Parameters

- **labels** (*list(int)*) – all labels
- **uq_labels** (*list(int)*) – unique labels

Return []

```
>>> relabel_sequential([0, 0, 0, 5, 5, 5, 0, 5])
[0, 0, 0, 1, 1, 1, 0, 1]
```

imsegm.classification.**save_classifier**(*path_out*, *classif*, *clf_name*, *params*, *feature_names=None*, *label_names=None*)

estimate classif for all data and export it

Parameters

- **path_out** (*str*) – path for exporting trained classofier
- **classif** – sklearn classif.
- **clf_name** (*str*) – name of selected classifier
- **feature_names** (*list(str)*) – list of string names

- **params** (*dict*) – extra parameters
- **label_names** (*list(str)*) – list of string names of label_names

Return str

```
>>> clf = create_classifiers()['RandForest']
>>> p_clf = save_classifier('.', clf, 'TESTINNG', {})
>>> os.path.basename(p_clf)
'classifier_TESTINNG.pkl'
>>> d_clf = load_classifier(p_clf)
>>> sorted(d_clf.keys())
['clf_pipeline', 'features', 'label_names', 'name', 'params']
>>> d_clf['clf_pipeline']
RandomForestClassifier(...)
>>> d_clf['name']
'TESTINNG'
>>> os.remove(p_clf)
```

imsegm.classification.**search_params_cut_down_max_nb_iter**(*clf_parameters*, *nb_iter*)
create parameters list and count number of possible combination in case they are they are limited

Parameters

- **clf_parameters** (*dict*) – dictionary with parameters
- **nb_iter** (*int*) – nb of random tryes

Return int

```
>>> clf_params = create_clf_param_search_grid(DEFAULT_CLASSIF_NAME)
>>> search_params_cut_down_max_nb_iter(clf_params, 100)
100
>>> search_params_cut_down_max_nb_iter(clf_params, 1e6)
1450
```

imsegm.classification.**shuffle_features_labels**(*features*, *labels*)
take the set of features and labels and shuffle them together while keeping link between feature and its label

Parameters

- **features** (*ndarray*) – features in dimension nb_samples x nb_features
- **labels** (*list(int)*) – annotation for samples

Returns np.array<nb_samples, nb_features>, np.array<nb_samples>

```
>>> np.random.seed(0)
>>> fts = np.random.random((5, 2))
>>> lbs = np.random.randint(0, 2, 5)
>>> fts_new, lbs_new = shuffle_features_labels(fts, lbs)
>>> np.array_equal(fts, fts_new)
False
>>> np.array_equal(lbs, lbs_new)
False
```

imsegm.classification.**unique_rows**(*data*)
with matrix detect unique row and return only them

Parameters **data** (*ndarray*) – np.array

Return ndarray np.array

imsegm.classification.**DEFAULT_CLASSIF_NAME = 'RandForest'**
default (recommended) classifier for supervised segmentation

imsegm.classification.**DEFAULT_CLUSTERING = 'kMeans'**
default (recommended) clustering for unsupervised segmentation

imsegm.classification.**DICT_SCORING = {'accuracy': sklearn.metrics.accuracy_score, 'f1': sk**
mapping of metrics names to used functions

imsegm.classification.**METRIC_AVERAGES = ('macro', 'weighted')**
default types of computed metrics

imsegm.classification.**METRIC_SCORING = ('f1_macro', 'accuracy', 'precision_macro', 'recall_**
default computed metrics

imsegm.classification.**NAME_CSV_CLASSIF_CV_ROC = 'classif_{}_cross-val_ROC-{}.csv'**
exporting partial results about trained classifier - Receiver Operating Characteristics

imsegm.classification.**NAME_CSV_CLASSIF_CV_SCORES = 'classif_{}_cross-val_scores-{}.csv'**
exporting partial results about trained classifier

imsegm.classification.**NAME_CSV_FEATURES_SELECT = 'feature_selection.csv'**
file name of exported evaluation on feature quality

imsegm.classification.**NAME_TXT_CLASSIF_CV_AUC = 'classif_{}_cross-val_AUC-{}.txt'**
exporting partial results about trained classifier - Area Under Curve

imsegm.classification.**NB_WORKERS_SERACH = 1**
default number of workers

imsegm.classification.**ROUND_UNIQUE_FTS_DIGITS = 3**
rounding unique features, in case to detail precision

imsegm.classification.**TEMPLATE_NAME_CLF = 'classifier_{}.pkl'**
name template forexporting trained classifier (adding classifier name and version)

imsegm.descriptors module

Framework for feature extraction

- color and gray 3D images
- color and texture features
- Ray features
- label histogram

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imsegm.descriptors.**_check_color_image**(*image*)
verify proper image

Parameters **image** (*ndarray*) –

Return bool

```
>>> _check_color_image(np.zeros((200, 250, 1)))
Traceback (most recent call last):
...
ValueError: image is not RGB with dims (200, 250, 1)
```

imsegm.descriptors.**_check_color_image_segm**(*image*, *segm*)
verify image - segmentation compatibility

Parameters

- **image** (*ndarray*) – image
- **segm** (*ndarray*) – segmentation

Return bool

```
>>> _check_color_image_segm(np.zeros((125, 150, 3)), np.zeros((150, 125)))
Traceback (most recent call last):
...
ValueError: ndarrays - image and segmentation do not match (125, 150, 3) vs (150,␣
↪125)
```

imsegm.descriptors.**_check_gray_image_segm**(*image*, *segm*)
verify image - segmentation compatibility

Parameters

- **image** (*ndarray*) – image
- **segm** (*ndarray*) – segmentation

Return bool

```
>>> _check_gray_image_segm(np.zeros((125, 150)), np.zeros((150, 125)))
Traceback (most recent call last):
...
ValueError: ndarrays - image and segmentation do not match (125, 150) vs (150,␣
↪125)
```

imsegm.descriptors.**_check_unrecognised_feature_group**(*feature_flags*)
search for not defined flags

Parameters **feature_flags** (*dict*) – input

Return list(str) unrecognised

```
>>> _check_unrecognised_feature_group({'color': [], 'texture': []})
['texture']
```

imsegm.descriptors.**_check_unrecognised_feature_names**(*feature_flags*)
search for not defined flags

Parameters **feature_flags** (*list(str)*) – input

Return list(str) unrecognised

```
>>> _check_unrecognised_feature_names(['mean', 'average'])
['average']
```

imsegm.descriptors.**adjust_bounding_box_crop**(*image_size*, *bbox_size*, *position*)
adjust the bounding box according image sizes and position

Parameters

- **int] image_size** (*tuple(int,int) | [int,]*) – image size
- **int] bbox_size** (*tuple(int,int) | [int,]*) – size of the bounding box
- **int] position** (*tuple(int,int) | [int,]*) – position in yhe image

Return (), (), (), () im_begin, im_end, bb_begin, bb_end

```
>>> adjust_bounding_box_crop((50, 50), (7, 7), (20, 20))
((17, 17), (24, 24), (0, 0), (7, 7))
>>> adjust_bounding_box_crop((50, 50), (15, 15), (20, 45))
((13, 38), (28, 50), (0, 0), (15, 12))
>>> adjust_bounding_box_crop((50, 50), (15, 15), (5, 5))
((0, 0), (13, 13), (2, 2), (15, 15))
>>> adjust_bounding_box_crop((50, 50), (80, 80), (20, 20))
((0, 0), (50, 50), (20, 20), (70, 70))
```

imsegm.descriptors.**compute_image2d_color_statistic**(*image*, *segm*, *feature_flags=('mean', 'std', 'energy', 'median', 'meanGrad')*, *color_name='color'*)

compute complete descriptors / statistic on color (2D) images

Parameters

- **image** (*ndarray*) –
- **segm** (*ndarray*) – segmentation
- **feature_flags** (*list(str)*) –
- **color_name** (*str*) – channel name

Return tuple(ndarray,list(str)) np.ndarray<nb_samples, nb_features>

```
>>> image = np.zeros((2, 10, 3))
>>> image[:, 2:6, 0] = 1
>>> image[:, 3:7, 1] = 3
>>> image[:, 4:9, 2] = 2
>>> segm = np.array([[0, 0, 0, 0, 0, 1, 1, 1, 1, 1],
...                  [0, 0, 0, 0, 0, 1, 1, 1, 1, 1]])
>>> features, names = compute_image2d_color_statistic(image, segm)
>>> names
['color-ch1_mean', 'color-ch2_mean', 'color-ch3_mean',
 'color-ch1_std', 'color-ch2_std', 'color-ch3_std',
 'color-ch1_energy', 'color-ch2_energy', 'color-ch3_energy',
 'color-ch1_median', 'color-ch2_median', 'color-ch3_median',
 'color-ch1_meanGrad', 'color-ch2_meanGrad', 'color-ch3_meanGrad']
>>> features.shape
(2, 15)
>>> np.round(features, 1).tolist()
[[0.6, 1.2, 0.4, 0.5, 1.5, 0.8, 0.6, 3.6, 0.8, 1.0, 0.0, 0.0, 0.2, 0.6, 0.4],
 [0.2, 1.2, 1.6, 0.4, 1.5, 0.8, 0.2, 3.6, 3.2, 0.0, 0.0, 2.0, -0.2, -0.6, -0.6]]
```

imsegm.descriptors.**compute_image3d_gray_statistic**(*image*, *segm*, *feature_flags=('mean', 'std', 'energy', 'median', 'meanGrad')*, *ch_name='gray'*)

compute complete descriptors / statistic on gray (3D) images

Parameters

- **image** (*ndarray*) –
- **segm** (*ndarray*) – segmentation
- **feature_flags** (*list(str)*) –
- **ch_name** (*str*) – channel name

Return tuple(ndarray,list(str)) np.ndarray<nb_samples, nb_features>

```
>>> image = np.zeros((2, 3, 8))
>>> image[0, :, 2:6] = 1
>>> image[1, :, 3:7] = 3
>>> segm = np.array([[[0, 0, 0, 0, 1, 1, 1, 1]] * 3,
...                  [[2, 2, 2, 2, 5, 5, 5, 5]] * 3])
>>> segm.shape
(2, 3, 8)
>>> features, names = compute_image3d_gray_statistic(image, segm)
>>> features.shape
(6, 5)
>>> np.round(features, 3)
array([[ 0.5  ,  0.5  ,  0.5  ,  0.5  ,  0.25 ],
       [ 0.5  ,  0.5  ,  0.5  ,  0.5  , -0.25 ],
       [ 0.75 ,  1.299,  2.25 ,  0.   ,  0.75 ],
       [ 0.   ,  0.   ,  0.   ,  0.   ,  0.   ],
       [ 0.   ,  0.   ,  0.   ,  0.   ,  0.   ],
       [ 2.25 ,  1.299,  6.75 ,  3.   , -1.125]])
>>> names
['gray_mean',
 'gray_std',
 'gray_energy',
 'gray_median',
 'gray_meanGrad']
```

imsegm.descriptors.**compute_img_filter_response2d**(*img*, *filter_battery*)
compute image filter response in 2D

Parameters

- **img** (*[[float]]*) – image
- **filter_battery** (*[[[float]]]*) – filters

Return [[float]]

imsegm.descriptors.**compute_img_filter_response3d**(*img*, *filter_battery*)
compute image filter response in 3D

Parameters

- **img** (*ndarray*) –
- **filter_battery** (*ndarray*) –

Returns

imsegm.descriptors.**compute_label_hist_proba**(*segm*, *position*, *struc_elem*)
compute histogram of labels for set of centric annulus expecting that each label has own layer

Parameters

- **segm** (*ndarray*) – np.array<height, width>
- **position** (*tuple(float,float)*) –
- **struc_elem** (*ndarray*) – np.array<height, width>

Return list(float)

```
>>> seg = np.zeros((50, 50, 2), dtype=float)
>>> seg[15:35, 20:40, 1] = 1
```

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```
>>> seg[:, :, 0] = 1 - seg[:, :, 1]
>>> compute_label_hist_proba(seg, (15, 20), np.ones((12, 13), dtype=int))
(array([ 114.,   42.]), 156)
```

imsegm.descriptors.**compute_label_hist_segm**(*segm*, *position*, *struc_elem*, *nb_labels*)

compute histogram of labels for set of centric annulus

Parameters

- **segm** (*ndarray*) – np.array<height, width>
- **position** (*tuple(float,float)*) – position in the segmentation
- **struc_elem** (*ndarray*) – np.array<height, width>
- **nb_labels** (*int*) – total number of labels in the segmentation

Return list(float)

See also:

imsegm.descriptors.cython_label_hist_seg2d()

```
>>> segm = np.zeros((10, 10), dtype=int)
>>> segm[1:9, 2:8] = 1
>>> segm[3:7, 4:6] = 2
>>> segm
array([[0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 1, 1, 1, 1, 1, 1, 0, 0],
       [0, 0, 1, 1, 1, 1, 1, 1, 0, 0],
       [0, 0, 1, 1, 2, 2, 1, 1, 0, 0],
       [0, 0, 1, 1, 2, 2, 1, 1, 0, 0],
       [0, 0, 1, 1, 2, 2, 1, 1, 0, 0],
       [0, 0, 1, 1, 2, 2, 1, 1, 0, 0],
       [0, 0, 1, 1, 1, 1, 1, 1, 0, 0],
       [0, 0, 1, 1, 1, 1, 1, 1, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0]])
>>> compute_label_hist_segm(segm, [6, 6], np.ones((3, 3)), 3)
(array([ 0.,  7.,  2.]), 9.0)
>>> compute_label_hist_segm(segm, [4, 4], np.ones((5, 5)), 3)
(array([  0.,  17.,   8.]), 25.0)
```

imsegm.descriptors.**compute_label_histograms_positions**(*segm*, *positions*, *diameters=(10, 20, 30, 40, 50)*, *nb_labels=None*)

compute the histogram features doe consecutive growing diameter of inter circle neighbouring around given points in the segmentation

Parameters

- **segm** (*ndarray*) – np.array<height, width>
- **int)] positions** (*[(int,*) – list of positions
- **diameters** (*list(int)*) – circular diameters
- **nb_labels** (*int*) –

Return tuple(ndarray,list(str)) ndarray<nb_samples, nb_features>, names

```
>>> segm = np.zeros((10, 10), dtype=int)
>>> segm[1:9, 2:8] = 1
>>> segm[3:7, 4:6] = 2
>>> points = [[3, 3], [4, 4], [2, 7], [6, 6]]
>>> hists, names = compute_label_histograms_positions(segm, points, [1, 2, 4])
>>> names
['hist-d_1-lb_0', 'hist-d_1-lb_1', 'hist-d_1-lb_2',      'hist-d_2-lb_0', 'hist-d_
↪2-lb_1', 'hist-d_2-lb_2',      'hist-d_4-lb_0', 'hist-d_4-lb_1', 'hist-d_4-lb_2
↪']
>>> hists.shape
(4, 9)
>>> np.round(hists, 2)
array([[ 0.  ,  0.8 ,  0.2 ,  0.12,  0.62,  0.25,  0.44,  0.41,  0.15],
       [ 0.  ,  0.2 ,  0.8 ,  0.  ,  0.62,  0.38,  0.22,  0.75,  0.03],
       [ 0.2 ,  0.8 ,  0.  ,  0.5 ,  0.5 ,  0.  ,  0.46,  0.33,  0.21],
       [ 0.  ,  0.8 ,  0.2 ,  0.12,  0.62,  0.25,  0.44,  0.41,  0.15]])
>>> segm = np.zeros((10, 10, 2), dtype=int)
>>> segm[3:7, 4:6, 1] = 1
>>> segm[:, :, 0] = 1 - segm[:, :, 0]
>>> points = [[3, 3], [4, 4], [2, 7], [6, 6]]
>>> hists, names = compute_label_histograms_positions(segm, points, [1, 2, 4])
>>> np.round(hists, 2)
array([[ 1.  ,  0.2 ,  1.  ,  0.25,  1.  ,  0.15],
       [ 1.  ,  0.8 ,  1.  ,  0.38,  1.  ,  0.03],
       [ 1.  ,  0.  ,  1.  ,  0.  ,  1.  ,  0.21],
       [ 1.  ,  0.2 ,  1.  ,  0.25,  1.  ,  0.15]])
```

imsegm.descriptors.**compute_ray_features_positions**(*segm*, *list_positions*, *angle_step=5.0*, *border_labels=None*, *segm_open=None*, *smooth_ray=None*, *shifting=True*, *edge='up'*)

compute ray features fo multiple points in the segmentation with given boundary labels and step angle

Parameters

- **segm** (*ndarray*) – np.array<height, width>
- **int)] list_positions** (*[(int,)*) –
- **angle_step** (*float*) –
- **border_labels** (*list(int)*) – all labels to be set as boundaries
- **segm_open** (*int*) –
- **smooth_ray** (*float*) –
- **shifting** (*bool*) –
- **edge** (*str*) – type of edge up/down

Returns

Note: for more examples, see unittests

```
>>> from skimage import draw
>>> np.random.seed(0)
>>> seg = np.zeros((100, 100), dtype=int)
```

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```
>>> x, y = draw.circle(45, 55, 30, shape=seg.shape)
>>> seg[x, y] = 1
>>> x, y = draw.circle(55, 45, 10, shape=seg.shape)
>>> seg[x, y] = 2
>>> points = [(50, 50), (60, 40), (44, 55)]
>>> ray_dist, shift, _ = compute_ray_features_positions(seg, points, 20)
>>> shift
[314.3..., 314.7..., 90.0...]
>>> ray_dist.astype(int).tolist()
[[37, 37, 35, 32, 30, 27, 25, 24, 23, 23, 24, 25, 26, 30, 31, 33, 35, 38],
 [50, 47, 41, 31, 23, 17, 13, 10, 9, 9, 9, 11, 14, 19, 27, 37, 45, 50],
 [31, 31, 31, 30, 30, 29, 30, 30, 29, 29, 30, 30, 29, 30, 30, 31, 31, 31]]
>>> noise_pos = np.random.randint(10, 80, (2, 300))
>>> seg[noise_pos[0], noise_pos[1]] = 0  # add random noise
>>> ray_dist, shift, names = compute_ray_features_positions(seg, points, 45,
...                                                         segm_open=10)
>>> names
['ray-lb_0-agl_0', 'ray-lb_0-agl_45', 'ray-lb_0-agl_90',
 'ray-lb_0-agl_135', 'ray-lb_0-agl_180', 'ray-lb_0-agl_225',
 'ray-lb_0-agl_270', 'ray-lb_0-agl_315']
>>> shift
[315.0..., 315.0..., 90.0...]
>>> ray_dist.astype(int)
array([[38, 35, 29, 25, 24, 25, 29, 35],
       [52, 41, 21, 11,  9, 11, 21, 41],
       [31, 31, 30, 29, 29, 29, 30, 31]])
```

imsegm.descriptors.**compute_ray_features_segm_2d**(*seg_binary*, *position*, *angle_step=5.0*, *smooth_coef=0*, *edge='up'*)

compute ray features vector , shift them to be starting from larges and smooth_coef them by gauss filter (from given point the close distance to boundary)

Parameters

- **seg_binary** (*ndarray*) – np.array<height, width>
- **position** (*tuple(int,int)*) – integer position in the segmentation
- **angle_step** (*float*) – angular step for ray features
- **edge** (*str*) – pointing to the up of down edge of an boundary
- **smooth_coef** (*int*) – smoothing the final ray features

Return list(float) ray distances

See also:

imsegm.descriptors.compute_ray_features_segm_2d_vectors()

Note: for more examples, see unittests

```
>>> seg_empty = np.zeros((100, 150), dtype=bool)
>>> compute_ray_features_segm_2d(seg_empty, (50, 75), 90)
array([-1., -1., -1., -1.]...)
>>> from skimage import draw
>>> seg = np.ones((100, 150), dtype=bool)
>>> x, y = draw.circle(50, 75, 40, shape=seg.shape)
```

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```
>>> seg[x, y] = False
>>> np.round(compute_ray_features_segm_2d(seg, (50, 75), 45))
array([ 40.,  41.,  40.,  41.,  40.,  41.,  40.,  41.]...)
>>> np.round(compute_ray_features_segm_2d(seg, (60, 40), 30, smooth_coef=1)).
↪tolist()
[66.0, 52.0, 32.0, 16.0, 8.0, 5.0, 5.0, 8.0, 16.0, 33.0, 53.0, 67.0]
>>> ray_fts = compute_ray_features_segm_2d(seg, (40, 60), 20)
>>> np.round(ray_fts).tolist()
[54.0, 57.0, 59.0, 55.0, 51.0, 44.0, 38.0, 31.0, 27.0, 24.0, 22.0, 22.0,
 23.0, 26.0, 29.0, 35.0, 42.0, 49.0]
```

imsegm.descriptors.**compute_ray_features_segm_2d_vectors**(*seg_binary*, *position*, *angle_step=5.0*, *smooth_coef=0*, *edge='up'*)

USES WHOLE IMAGE ROTATION SO IT IS VERY SLOW compute ray features vector , shift them to be startig from larges and smooth_coef them by gauss filter (from fiven point the close distance to boundary)

Parameters

- **edge** (*str*) – pointing to the up of down edge o
- **smooth_coef** (*int*) –
- **seg_binary** (*ndarray*) – np.array<height, width>
- **position** (*tuple(int,int)*) –
- **angle_step** (*float*) –

Return list(float)

See also:

imsegm.descriptors.compute_ray_features_segm_2d()

Note: for more examples, see unittests

```
>>> from skimage import draw
>>> seg = np.ones((100, 100), dtype=bool)
>>> x, y = draw.circle(45, 55, 30, shape=seg.shape)
>>> seg[x, y] = False
>>> compute_ray_features_segm_2d_vectors(seg, (50, 50), 45)
array([35, 29, 25, 23, 24, 29, 34, 36])
>>> compute_ray_features_segm_2d_vectors(seg, (60, 40), 30, smooth_coef=1)
array([35, 27, 18, 12, 10,  9, 12, 18, 27, 37, 45, 49])
>>> compute_ray_features_segm_2d_vectors(seg, (40, 60), 20).tolist()
[25, 27, 29, 32, 34, 35, 37, 36, 36, 34, 32, 29, 27, 25, 24, 23, 24, 24]
```

imsegm.descriptors.**compute_selected_features_color2d**(*img*, *segments*, *feature_flags={'color': ('mean', 'std', 'energy', 'median', 'meanGrad'), 'tLM': ('mean', 'std', 'energy', 'median', 'meanGrad')}*)

compute selected features color image 2D

Parameters

- **img** (*ndarray*) – image
- **segments** (*ndarray*) – segmentation
- **feature_flags** (*dict(list(str))*) – dictionary of feature flags

Return tuple(np.ndarray<nb_samples, nb_features>, list(str))

```
>>> image = np.zeros((2, 10, 3))
>>> image[:, 2:6, 0] = 1
>>> image[:, 3:7, 1] = 3
>>> image[:, 4:9, 2] = 2
>>> segm = np.array([[0, 0, 0, 0, 0, 1, 1, 1, 1, 1],
...                  [0, 0, 0, 0, 0, 1, 1, 1, 1, 1]])
>>> features, names = compute_selected_features_color2d(image, segm,
...                                     {'color': ('mean', 'std', 'median')})
>>> np.round(features, 3)
array([[ 0.6 ,  1.2 ,  0.4 ,  0.49,  1.47,  0.8 ,  1.  ,  0.  ,  0.  ],
       [ 0.2 ,  1.2 ,  1.6 ,  0.4 ,  1.47,  0.8 ,  0.  ,  0.  ,  2.  ]])
>>> features, names = compute_selected_features_color2d(image, segm,
...                                     {'color_hsv': ('mean', 'std')})
>>> np.round(features, 3)
array([[ 0.139,  0.533,  1.4  ,  0.176,  0.452,  1.356],
       [ 0.439,  0.733,  2.   ,  0.244,  0.389,  1.095]])
>>> _ = compute_selected_features_color2d(image, segm,
...                                     {'tLM': ('mean', 'std', 'energy')})
>>> features, names = compute_selected_features_color2d(image, segm,
...                                     {'tLM_short': ('mean', 'energy')})
>>> features.shape
(2, 90)
>>> features, names = compute_selected_features_color2d(image, segm)
>>> features.shape
(2, 315)
```

imsegm.descriptors.**compute_selected_features_gray2d**(*img*, *segments*, *features_flags={'color': ('mean', 'std', 'energy', 'median', 'meanGrad'), 'tLM': ('mean', 'std', 'energy', 'median', 'meanGrad')}*)

compute selected features for gray image 2D

Parameters

- **img** (*ndarray*) – image
- **segments** (*ndarray*) – segmentation
- **feature_flags** (*dict(list(str))*) – dictionary of feature flags

Return tuple(np.ndarray<nb_samples, nb_features>, list(str))

```
>>> image = np.zeros((2, 10))
>>> image[0, 2:6] = 1
>>> image[1, 3:7] = 3
>>> segm = np.array([[0, 0, 0, 0, 0, 1, 1, 1, 1, 1],
...                  [0, 0, 0, 0, 0, 1, 1, 1, 1, 1]])
>>> features, names = compute_selected_features_gray2d(
...     image, segm, {'color': ('mean', 'std', 'median')})
>>> np.round(features, 3)
array([[ 0.9  ,  1.136,  0.5  ],
```

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```
       [ 0.7  ,  1.187,  0.   ]])
>>> _ = compute_selected_features_gray2d(
...     image, segm, {'tLM': ('mean', 'std', 'median')})
>>> features, names = compute_selected_features_gray2d(
...     image, segm, {'tLM_short': ('mean', 'std', 'energy')})
>>> features.shape
(2, 45)
>>> features, names = compute_selected_features_gray2d(image, segm)
>>> features.shape
(2, 105)
```

imsegm.descriptors.**compute_selected_features_gray3d**(*img*, *segments*, *feature_flags={'color': ('mean', 'std', 'energy')}*)

compute selected features on gray 3D image

Parameters

- **img** (*ndarray*) – image
- **segments** (*ndarray*) – segmentation
- **feature_flags** (*dict(list(str))*) – dictionary of feature flags

Return tuple(np.ndarray<nb_samples, nb_features>, list(str))

```
>>> np.random.seed(0)
>>> img = np.random.random((2, 10, 15))
>>> slic = np.zeros((2, 10, 15), dtype=int)
>>> slic[:, :, :7] += 1
>>> slic[1, :, :] += 2
>>> fts, names = compute_selected_features_gray3d(
...     img, slic, {'color': ('mean', 'std', 'median')})
>>> fts.shape
(4, 3)
>>> names
['gray_mean', 'gray_std', 'gray_median']
>>> _ = compute_selected_features_gray3d(
...     img, slic, {'tLM': ('median', 'std', 'energy')})
>>> fts, names = compute_selected_features_gray3d(
...     img, slic, {'tLM_short': ('mean', 'std', 'energy')})
>>> fts.shape
(4, 45)
>>> names
['tLM_sigma1.4-edge_mean', ..., 'tLM_sigma4.0-GaussLap2_energy']
```

imsegm.descriptors.**compute_selected_features_img2d**(*image*, *segm*, *features_flags={'color': ('mean', 'std', 'energy')}*)

compute features

Parameters

- **img** (*ndarray*) – image
- **segments** (*ndarray*) – segmentation
- **feature_flags** (*dict(list(str))*) – dictionary of feature flags

Returns

imsegm.descriptors.**compute_texture_desc_lm_img2d_clr**(*img*, *seg*, *feature_flags*, *bank_type='normal'*)

compute texture descriptors via Lewen-Malik filter response

Parameters

- **img** (*ndarray*) – image
- **seg** (*ndarray*) – segmentation
- **feature_flags** (*list(str)*) –
- **bank_type** (*str*) – define used LM filter bank [‘short’, ‘normal’]

Return tuple(np.ndarray<nb_samples, nb_features>, list(str))

See also:

imsegm.descriptors.compute_texture_desc_lm_img3d_val()

```
>>> h, w, step = 30, 20, 5
>>> np.random.seed(0)
>>> seg = np.zeros((h, w), dtype=int)
>>> for i in range(int(np.ceil(h / float(step)))):
...     for j in range(int(np.ceil(w / float(step)))):
...         val = i * (w / step) + j
...         i_step, j_step = int(i * step), int(j * step)
...         seg[i_step:int(i_step + step), j_step:int(j_step + step)] = val
>>> img = np.random.random((h, w, 3))
>>> features, names = compute_texture_desc_lm_img2d_clr(img, seg,
...                            ['mean', 'std', 'median'], bank_type='short')
>>> features.shape
(24, 135)
>>> names
['tLM_sigma1.4-edge-ch1_mean', ..., 'tLM_sigma1.4-edge-ch3_mean',
 'tLM_sigma1.4-edge-ch1_std', ..., 'tLM_sigma1.4-edge-ch3_std',
 'tLM_sigma1.4-edge-ch1_median', ..., 'tLM_sigma1.4-edge-ch3_median',
 'tLM_sigma1.4-bar-ch1_mean', ..., 'tLM_sigma1.4-bar-ch3_median',
 'tLM_sigma1.4-Gauss-ch1_mean', ..., 'tLM_sigma1.4-Gauss-ch3_median',
 'tLM_sigma1.4-GaussLap-ch1_mean', ..., 'tLM_sigma1.4-GaussLap-ch3_median',
 'tLM_sigma1.4-GaussLap2-ch1_mean', ..., 'tLM_sigma1.4-GaussLap2-ch3_median',
 'tLM_sigma2.0-edge-ch1_mean', ..., 'tLM_sigma2.0-GaussLap2-ch3_median',
 'tLM_sigma4.0-edge-ch1_mean', ..., 'tLM_sigma4.0-GaussLap2-ch3_median']
```

imsegm.descriptors.**compute_texture_desc_lm_img3d_val**(*img*, *seg*, *feature_flags*, *bank_type='normal'*)

compute texture descriptors as mean / std / ... on Lewen-Malik filter bank response

Parameters

- **img** (*[[[float]]]*) – image
- **seg** (*[[[int]]]*) – segmentation
- **feature_flags** (*list(str)*) – list of feature flags
- **bank_type** (*str*) – define used LM filter bank [‘short’, ‘normal’]

Return tuple(ndarray,list(str)) np.ndarray<nb_samples, nb_features>, names

See also:

imsegm.descriptors.compute_texture_desc_lm_img2d_clr()

imsegm.descriptors.**create_filter_bank_lm_2d**(*radius=16*, *sigmas=(1.4142135623730951, 2, 2.8284271247461903, 4)*, *nb_orient=8*)

create filter bank with rotation, Gaussian, Laplace-Gaussian, ...

Parameters

- **radius** –
- **sigmas** –
- **nb_orient** –

Return np.ndarray<nb_samples, nb_features>, list(str)

```
>>> filters, names = create_filter_bank_lm_2d(6, SHORT_FILTERS_SIGMAS, 2)
>>> [f.shape for f in filters]
[(2, 13, 13), (2, 13, 13), (1, 13, 13), (1, 13, 13), (1, 13, 13),
 (2, 13, 13), (2, 13, 13), (1, 13, 13), (1, 13, 13), (1, 13, 13),
 (2, 13, 13), (2, 13, 13), (1, 13, 13), (1, 13, 13), (1, 13, 13)]
>>> names
['sigma1.4-edge', 'sigma1.4-bar',
 'sigma1.4-Gauss', 'sigma1.4-GaussLap', 'sigma1.4-GaussLap2',
 'sigma2.0-edge', 'sigma2.0-bar',
 'sigma2.0-Gauss', 'sigma2.0-GaussLap', 'sigma2.0-GaussLap2',
 'sigma4.0-edge', 'sigma4.0-bar',
 'sigma4.0-Gauss', 'sigma4.0-GaussLap', 'sigma4.0-GaussLap2']
```

imsegm.descriptors.**cython_img2d_color_energy**(*img*, *seg*)

wrapper for fast implementation of colour features

Parameters

- **img** (*ndarray*) – input RGB image
- **seg** (*ndarray*) – segmentation og the image

Returns np.array<nb_lbs, 3> matrix features per segment

See also:

imsegm.descriptors.numpy_img2d_color_energy()

```
>>> image = np.zeros((2, 10, 3))
>>> image[:, 2:6, 0] = 1
>>> image[:, 3:7, 1] = 3
>>> image[:, 4:9, 2] = 2
>>> segm = np.array([[0, 0, 0, 0, 0, 1, 1, 1, 1, 1],
...                  [0, 0, 0, 0, 0, 1, 1, 1, 1, 1]])
>>> cython_img2d_color_energy(image, segm)
array([[ 0.6,  3.6,  0.8],
       [ 0.2,  3.6,  3.2]])
```

imsegm.descriptors.**cython_img2d_color_mean**(*img*, *seg*)

wrapper for fast implementation of colour features

Parameters

- **img** (*ndarray*) – input RGB image
- **seg** (*ndarray*) – segmentation og the image

Returns np.array<nb_lbs, 3> matrix features per segment

See also:

imsegm.descriptors.numpy_img2d_color_mean()

```
>>> image = np.zeros((2, 10, 3))
>>> image[:, 2:6, 0] = 1
>>> image[:, 3:7, 1] = 3
>>> image[:, 4:9, 2] = 2
>>> segm = np.array([[0, 0, 0, 0, 0, 1, 1, 1, 1, 1],
...                  [0, 0, 0, 0, 0, 1, 1, 1, 1, 1]])
>>> cython_img2d_color_mean(image, segm)
array([[ 0.6,  1.2,  0.4],
       [ 0.2,  1.2,  1.6]])
```

imsegm.descriptors.**cython_img2d_color_std**(*img*, *seg*, *means=None*)

wrapper for fast implementation of colour features

Parameters

- **img** (*ndarray*) – input RGB image
- **seg** (*ndarray*) – segmentation og the image
- **means** (*ndarray*) – precomputed feature means

Returns np.array<nb_lbs, 3> matrix features per segment

See also:

imsegm.descriptors.numpy_img2d_color_std()

```
>>> image = np.zeros((2, 10, 3))
>>> image[:, 2:6, 0] = 1
>>> image[:, 3:7, 1] = 3
>>> image[:, 4:9, 2] = 2
>>> segm = np.array([[0, 0, 0, 0, 0, 1, 1, 1, 1, 1],
...                  [0, 0, 0, 0, 0, 1, 1, 1, 1, 1]])
>>> cython_img2d_color_std(image, segm)
array([[ 0.48989794,  1.46969383,  0.80000003],
       [ 0.40000001,  1.46969383,  0.80000001]])
```

imsegm.descriptors.**cython_img3d_gray_energy**(*img*, *seg*)

wrapper for fast implementation of colour features

WARNING: the Z dimension is parallel and without sync, multiple equal labels across Z dim may lead to not mistakes in summing

Parameters

- **img** (*ndarray*) – input RGB image
- **seg** (*ndarray*) – segmentation og the image

Returns np.array<nb_lbs, 1> vector of mean colour per segment

See also:

imsegm.descriptors.numpy_img3d_gray_energy()

```
>>> image = np.zeros((2, 3, 8))
>>> image[0, :, 2:6] = 1
>>> image[1, :, 3:7] = 3
>>> segm = np.array([[[0, 0, 0, 0, 1, 1, 1, 1]] * 3,
```

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```
...                   [[2, 2, 2, 2, 3, 3, 3, 3]] * 3])
>>> cython_img3d_gray_energy(image, segm)
array([ 0.5 ,  0.5 ,  2.25,  6.75])
```

imsegm.descriptors.**cython_img3d_gray_mean**(*img*, *seg*)

wrapper for fast implementation of colour features

WARNING: the Z dimension is parallel and without sync, multiple equal labels across Z dim may lead to not mistakes in summing

Parameters

- **img** (*ndarray*) – input RGB image
- **seg** (*ndarray*) – segmentation og the image

Returns np.array<nb_lbs, 1> vector of mean colour per segment

See also:

imsegm.descriptors.numpy_img3d_gray_mean()

```
>>> image = np.zeros((2, 3, 8))
>>> image[0, :, 2:6] = 1
>>> image[1, :, 3:7] = 3
>>> segm = np.array([[[0, 0, 0, 0, 1, 1, 1, 1]] * 3,
...                  [[2, 2, 2, 2, 3, 3, 3, 3]] * 3])
>>> segm.shape
(2, 3, 8)
>>> cython_img3d_gray_mean(image, segm)
array([ 0.5 ,  0.5 ,  0.75,  2.25])
```

imsegm.descriptors.**cython_img3d_gray_std**(*img*, *seg*, *mean=None*)

wrapper for fast implementation of colour features

WARNING: the Z dimension is parallel and without sync, multiple equal labels across Z dim may lead to not mistakes in summing

Parameters

- **img** (*ndarray*) – input RGB image
- **seg** (*ndarray*) – segmentation og the image
- **mean** (*ndarray*) – precomputed feature means

Returns np.array<nb_lbs, 1> vector of mean colour per segment

See also:

imsegm.descriptors.numpy_img3d_gray_std()

```
>>> image = np.zeros((2, 3, 8))
>>> image[0, :, 2:6] = 1
>>> image[1, :, 3:7] = 3
>>> segm = np.array([[[0, 0, 0, 0, 1, 1, 1, 1]] * 3,
...                  [[2, 2, 2, 2, 3, 3, 3, 3]] * 3])
>>> cython_img3d_gray_std(image, segm)
array([ 0.5       ,  0.5       ,  1.29903811,  1.29903811])
```

imsegm.descriptors.**cython_label_hist_seg2d**(*segm_select*, *struc_elem*, *nb_labels*)

compute histogram of labels for set of centric annulus

Parameters

- **segm_select** (*ndarray*) – np.array<height, width>
- **struc_elem** (*ndarray*) – np.array<height, width>
- **nb_labels** (*int*) – total number of labels in the segmentation

Return list(float)

See also:

imsegm.descriptors.compute_label_hist_segm()

Note: output of this function should be equal to

```
for lb in range(nb_labels):
    hist[lb] = np.sum(np.logical_and(segm_select == lb, struc_elem == 1))
```

```
>>> segm = np.zeros((10, 10), dtype=int)
>>> segm[1:9, 2:8] = 1
>>> segm[3:7, 4:6] = 2
>>> cython_label_hist_seg2d(segm[2:5, 4:7], np.ones((3, 3)), 3)
array([ 0.,  5.,  4.])
>>> cython_label_hist_seg2d(segm[1:6, 3:8], np.ones((5, 5)), 3)
array([  0.,  19.,   6.])
```

imsegm.descriptors.**cython_ray_features_seg2d**(*seg_binary*, *position*, *angle_step=5.0*, *edge='up'*)

computing the Ray features from a segmentation and given position

Parameters

- **seg_binary** (*ndarray*) – np.array<height, width>
- **position** (*tuple(int,int)*) – integer position in the segmentation
- **angle_step** (*float*) – angular step for ray features
- **edge** (*str*) – pointing to the up of down edge of an boundary

Return list(float) ray distances

See also:

imsegm.descriptors.numpy_ray_features_seg2d()

```
>>> seg_empty = np.zeros((100, 150), dtype=bool)
>>> cython_ray_features_seg2d(seg_empty, (50, 75), 90)
array([-1., -1., -1., -1.]...)
>>> from skimage import draw
>>> seg = np.ones((100, 150), dtype=bool)
>>> x, y = draw.circle(50, 75, 40, shape=seg.shape)
>>> seg[x, y] = False
>>> cython_ray_features_seg2d(seg, (50, 75), 45).astype(int)
array([40, 41, 40, 41, 40, 41, 40, 41]...)
>>> cython_ray_features_seg2d(seg, (60, 40), 30).astype(int).tolist()
[74, 55, 28, 10, 5, 4, 4, 5, 9, 30, 57, 75]
>>> cython_ray_features_seg2d(seg, (40, 60), 20).astype(int).tolist()
[54, 57, 58, 55, 50, 43, 38, 31, 26, 24, 22, 22, 23, 26, 29, 34, 41, 48]
```

imsegm.descriptors.**image_subtract_gauss_smooth**(*img*, *sigma*)
smoothing by fist dimension assuming the in dim 0. image is independent

Parameters

- **img** (*ndarray*) –
- **sigma** –

Returns

imsegm.descriptors.**interpolate_ray_dist**(*ray_dists*, *order='spline'*)
interpolate ray distances

Parameters

- **ray_dists** (*list(float)*) –
- **order** (*str|int*) – degree of interpolation

Return list(float)

```
>>> interpolate_ray_dist([-1] * 5)
array([-1, -1, -1, -1, -1])
>>> vals = np.sin(np.linspace(0, 2 * np.pi, 20)) * 10
>>> np.round(vals).astype(int).tolist()
[0, 3, 6, 8, 10, 10, 9, 7, 5, 2, -2, -5, -7, -9, -10, -10, -8, -6, -3, 0]
>>> vals[3:7] = -1
>>> vals[16:] = -1
>>> vals_interp = interpolate_ray_dist(vals, order=3)
>>> np.round(vals_interp).astype(int).tolist()
[0, 3, 6, 9, 10, 10, 8, 7, 5, 2, -2, -5, -7, -9, -10, -10, -10, -8, -4, 1]
>>> vals_interp = interpolate_ray_dist(vals, order='spline')
>>> np.round(vals_interp).astype(int).tolist()
[0, 3, 6, 8, 9, 10, 9, 7, 5, 2, -2, -5, -7, -9, -10, -10, -9, -7, -5, -3]
>>> vals_interp = interpolate_ray_dist(vals, order='cos')
>>> np.round(vals_interp).astype(int).tolist()
[0, 3, 6, 8, 10, 10, 9, 7, 5, 2, -2, -5, -7, -9, -10, -10, -8, -6, -3, 0]
```

imsegm.descriptors.**make_edge_filter2d**(*sig*, *phase*, *points*, *sup*)

imsegm.descriptors.**make_gaussian_filter1d**(*vals*, *sigma*, *order=0*)

imsegm.descriptors.**norm_features**(*features*, *scaler=None*)
normalise features to be in range(0;1)

Parameters

- **features** (*ndarray*) – vector of features
- **scaler** (*obj*) –

Return list(list(float))

imsegm.descriptors.**numpy_img2d_color_energy**(*img*, *seg*)
compute color energy by numpy

Parameters

- **img** (*ndarray*) – input RGB image
- **seg** (*ndarray*) – segmentation og the image

Returns np.array<nb_lbs, 3> matrix features per segment

See also:

imsegm.descriptors.cython_img2d_color_energy()

```
>>> image = np.zeros((2, 10, 3))
>>> image[:, 2:6, 0] = 1
>>> image[:, 3:8, 1] = 3
>>> image[:, 4:9, 2] = 2
>>> segm = np.array([[0, 0, 0, 0, 0, 1, 1, 1, 1, 1],
...                  [0, 0, 0, 0, 0, 1, 1, 1, 1, 1]])
>>> numpy_img2d_color_energy(image, segm)
array([[ 0.6,  3.6,  0.8],
       [ 0.2,  5.4,  3.2]])
```

imsegm.descriptors.**numpy_img2d_color_mean**(*img*, *seg*)

compute color means by numpy

Parameters

- **img** (*ndarray*) – input RGB image
- **seg** (*ndarray*) – segmentation og the image

Returns np.array<nb_lbs, 3> matrix features per segment

See also:

imsegm.descriptors.cython_img2d_color_mean()

```
>>> image = np.zeros((2, 10, 3))
>>> image[:, 2:6, 0] = 1
>>> image[:, 3:8, 1] = 3
>>> image[:, 4:9, 2] = 2
>>> segm = np.array([[0, 0, 0, 0, 0, 1, 1, 1, 1, 1],
...                  [0, 0, 0, 0, 0, 1, 1, 1, 1, 1]])
>>> numpy_img2d_color_mean(image, segm)
array([[ 0.6,  1.2,  0.4],
       [ 0.2,  1.8,  1.6]])
```

imsegm.descriptors.**numpy_img2d_color_median**(*img*, *seg*)

compute color median by numpy

Parameters

- **img** (*ndarray*) – input RGB image
- **seg** (*ndarray*) – segmentation og the image

Returns np.array<nb_lbs, 3> matrix features per segment

See also:

imsegm.descriptors.cython_img2d_color_median()

```
>>> image = np.zeros((2, 10, 3))
>>> image[:, 2:6, 0] = 1
>>> image[:, 3:8, 1] = 3
>>> image[:, 4:9, 2] = 2
>>> segm = np.array([[0, 0, 0, 0, 1, 1, 1, 1, 1, 1],
...                  [0, 0, 0, 0, 1, 1, 1, 1, 1, 1]])
>>> numpy_img2d_color_median(image, segm)
array([[ 0.5,  0. ,  0. ],
       [ 0. ,  3. ,  2. ]])
```

imsegm.descriptors.**numpy_img2d_color_std**(*img*, *seg*, *means=None*)
compute color STD by numpy

Parameters

- **img** (*ndarray*) – input RGB image
- **seg** (*ndarray*) – segmentation og the image
- **means** (*ndarray*) – precomputed feature means

Returns np.array<nb_lbs, 3> matrix features per segment

See also:

imsegm.descriptors.cython_img2d_color_std()

```
>>> image = np.zeros((2, 10, 3))
>>> image[:, 2:6, 0] = 1
>>> image[:, 3:8, 1] = 3
>>> image[:, 4:9, 2] = 2
>>> segm = np.array([[0, 0, 0, 0, 0, 1, 1, 1, 1, 1],
...                  [0, 0, 0, 0, 0, 1, 1, 1, 1, 1]])
>>> numpy_img2d_color_std(image, segm)
array([[ 0.48989795,  1.46969385,  0.8       ],
       [ 0.4       ,  1.46969385,  0.8       ]])
```

imsegm.descriptors.**numpy_img3d_gray_energy**(*img*, *seg*)
compute gray (3D) energy by numpy

Parameters

- **img** – input RGB image
- **seg** – segmentation og the image

Returns np.array<nb_lbs, 3> matrix features per segment

See also:

imsegm.descriptors.cython_img3d_gray_energy()

```
>>> image = np.zeros((2, 3, 8))
>>> image[0, :, 2:6] = 1
>>> image[1, :, 3:7] = 3
>>> segm = np.array([[[0, 0, 0, 0, 1, 1, 1, 1]] * 3,
...                  [[2, 2, 2, 2, 3, 3, 3, 3]] * 3])
>>> numpy_img3d_gray_energy(image, segm)
array([ 0.5 ,  0.5 ,  2.25,  6.75])
```

imsegm.descriptors.**numpy_img3d_gray_mean**(*img*, *seg*)
compute gray (3D) means by numpy

Parameters

- **img** (*ndarray*) – input RGB image
- **seg** (*ndarray*) – segmentation og the image

Returns np.array<nb_lbs, 3> matrix features per segment

See also:

imsegm.descriptors.cython_img3d_gray_mean()

```
>>> image = np.zeros((2, 3, 8))
>>> image[0, :, 2:6] = 1
>>> image[1, :, 3:7] = 3
>>> segm = np.array([[[0, 0, 0, 0, 1, 1, 1, 1]] * 3,
...                  [[2, 2, 2, 2, 3, 3, 3, 3]] * 3])
>>> numpy_img3d_gray_mean(image, segm)
array([ 0.5 ,  0.5 ,  0.75,  2.25])
```

imsegm.descriptors.**numpy_img3d_gray_median**(*img*, *seg*)
compute gray (3D) median by numpy

Parameters

- **img** (*ndarray*) – input RGB image
- **seg** (*ndarray*) – segmentation og the image

Returns np.array<nb_lbs, 3> matrix features per segment

See also:

imsegm.descriptors.cython_img3d_gray_median()

```
>>> image = np.zeros((2, 3, 8))
>>> image[0, :, 2:6] = 1
>>> image[1, :, 3:7] = 3
>>> segm = np.array([[[0, 0, 0, 0, 1, 1, 1, 1]] * 3,
...                  [[2, 2, 2, 2, 3, 3, 3, 3]] * 3])
>>> numpy_img3d_gray_median(image, segm)
array([ 0.5,  0.5,  0. ,  3. ])
```

imsegm.descriptors.**numpy_img3d_gray_std**(*img*, *seg*, *means=None*)
compute gray (3D) STD by numpy

Parameters

- **img** (*ndarray*) – input RGB image
- **seg** (*ndarray*) – segmentation og the image
- **means** (*ndarray*) – precomputed feature means

Returns np.array<nb_lbs, 3> matrix features per segment

See also:

imsegm.descriptors.cython_img3d_gray_std()

```
>>> image = np.zeros((2, 3, 8))
>>> image[0, :, 2:6] = 1
>>> image[1, :, 3:7] = 3
>>> segm = np.array([[[0, 0, 0, 0, 1, 1, 1, 1]] * 3,
...                  [[2, 2, 2, 2, 3, 3, 3, 3]] * 3])
>>> numpy_img3d_gray_std(image, segm)
array([ 0.5       ,  0.5       ,  1.29903811,  1.29903811])
```

imsegm.descriptors.**numpy_ray_features_seg2d**(*seg_binary*, *position*, *angle_step=5.0*, *edge='up'*)
computing the Ray features from a segmentation and given position

Parameters

- **seg_binary** (*ndarray*) – np.array<height, width>

- **position** (*tuple(int, int)*) – integer position in the segmentation
- **angle_step** (*float*) – angular step for ray features
- **edge** (*str*) – pointing to the up of down edge of an boundary

Return list(float) ray distances

See also:

imsegm.descriptors.cython_ray_features_seg2d()

```
>>> seg_empty = np.zeros((100, 150), dtype=bool)
>>> numpy_ray_features_seg2d(seg_empty, (50, 75), 90)
array([-1., -1., -1., -1.]...)
>>> from skimage import draw
>>> seg = np.ones((100, 150), dtype=bool)
>>> x, y = draw.circle(50, 75, 40, shape=seg.shape)
>>> seg[x, y] = False
>>> numpy_ray_features_seg2d(seg, (50, 75), 45).astype(int)
array([40, 41, 40, 41, 40, 41, 40, 41]...)
>>> numpy_ray_features_seg2d(seg, (60, 40), 30).astype(int).tolist()
[74, 55, 28, 10, 5, 4, 4, 5, 9, 30, 57, 75]
>>> numpy_ray_features_seg2d(seg, (40, 60), 20).astype(int).tolist()
[54, 57, 58, 55, 50, 43, 38, 31, 26, 24, 22, 22, 23, 26, 29, 34, 41, 48]
```

imsegm.descriptors.**reconstruct_ray_features_2d**(*position*, *ray_features*, *shift=0*)

reconstruct ray features for 2D image

Parameters

- **position** (*tuple(int, int)|tuple(float, float)*) –
- **ray_features** (*list(float)*) –
- **shift** (*float*) –

Return [[float, float]]

Note: for more examples, see unittests

```
>>> reconstruct_ray_features_2d((10., 10), np.array([1] * 4))
array([[ 10.,  11.],
       [ 11.,  10.],
       [ 10.,   9.],
       [  9.,  10.]])
>>> reconstruct_ray_features_2d((10., 10), np.array([-1, 0, 1, np.inf]))
array([[ 10.,  10.],
       [ 10.,   9.]])
```

imsegm.descriptors.**reduce_close_points**(*points*, *dist_thr*)

reduce remove points with smaller internal distance then treshold assumption, the points are in sequence geometrically ordered)

Parameters

- **float]] points** (*[[float,*) –
- **dist_thr** (*float*) – distance threshold

Return [[float, float]]

```
>>> points = np.array([range(10), range(10)]).T
>>> reduce_close_points(points, 2)
array([[0, 0],
       [2, 2],
       [4, 4],
       [6, 6],
       [8, 8]])
>>> points = np.array([[0, 0], [1, 1], [0, 2]])
>>> reduce_close_points(points, 2)
array([[0, 0],
       [0, 2]])
>>> reduce_close_points(np.ones((10, 2)), 2)
array([[ 1.,  1.]])
```

imsegm.descriptors.**shift_ray_features**(*ray_dist*, *method='phase'*)
shift Ray features ti the global maxim to be rotation invariant

Parameters

- **ray_dist** (*list(float)*) – array of features
- **method** (*str*) – use method for estimate shift maxima (phase or max)

Return list(float)

```
>>> vec = np.array([43, 46, 44, 39, 28, 18, 12, 10,  9, 12, 22, 28])
>>> ray, shift = shift_ray_features(vec)
>>> shift
41.50...
>>> ray
array([46, 44, 39, 28, 18, 12, 10,  9, 12, 22, 28, 43])
>>> ray2, shift = shift_ray_features(ray)
>>> shift
11.50...
>>> np.array_equal(ray, ray2)
True
>>> ray, shift = shift_ray_features(vec, method='max')
>>> shift
30.0...
```

imsegm.descriptors.**DEFAULT_FILTERS_SIGMAS = (1.4142135623730951, 2, 2.8284271247461903, 4)**
define sigmas for Lewen-Malik filter bank

imsegm.descriptors.**FEATURES_SET_ALL = {'color': ('mean', 'std', 'energy', 'median', 'meanG**
define the richest version of computed superpixel features

imsegm.descriptors.**FEATURES_SET_COLOR = {'color': ('mean', 'std', 'energy')}**
define basic color features for supepixels

imsegm.descriptors.**FEATURES_SET_TEXTURE = {'tLM': ('mean', 'std', 'energy')}**
define basic texture features (complete LM filter bank) for supepixels

imsegm.descriptors.**FEATURES_SET_TEXTURE_SHORT = {'tLM_short': ('mean', 'std', 'energy')}**
define basic color features for (small LM filter bank) supepixels

imsegm.descriptors.**HIST_CIRCLE_DIAGONALS = (10, 20, 30, 40, 50)**
define circular diamters for computing label histogram

imsegm.descriptors.**MAX_SIGNAL_RESPONSE = 1000000.0**
maximal response is bounded by fix number to prevent overflowing (for LM filer bank)

imsegm.descriptors.**NAMES_FEATURE_FLAGS = ('mean', 'std', 'energy', 'median', 'meanGrad')**
define all available statistic computed on superpixels

imsegm.descriptors.**SHORT_FILTERS_SIGMAS = (1.4142135623730951, 2, 4)**
define small list/range of sigmas for Lewen-Malik filter bank

imsegm.ellipse_fitting module

Framework for ellipse fitting

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class imsegm.ellipse_fitting.**EllipseModelSegm**(**args: Any*, ***kwargs: Any*)
Bases: skimage.measure.fit.EllipseModel

Total least squares estimator for 2D ellipses.

The functional model of the ellipse is:

```
xt = xc + a*cos(theta)*cos(t) - b*sin(theta)*sin(t)
yt = yc + a*sin(theta)*cos(t) + b*cos(theta)*sin(t)
d = sqrt((x - xt)**2 + (y - yt)**2)
```

where `(xt, yt)` is the closest point on the ellipse to `(x, y)`. Thus d is the shortest distance from the point to the ellipse.

The estimator is based on a least squares minimization. The optimal solution is computed directly, no iterations are required. This leads to a simple, stable and robust fitting method.

The `params` attribute contains the parameters in the following order:

```
xc, yc, a, b, theta
```

Example

```
>>> from imsegm.utilities.drawing import ellipse_perimeter
>>> params = 20, 30, 12, 16, np.deg2rad(30)
>>> rr, cc = ellipse_perimeter(*params)
>>> xy = np.array([rr, cc]).T
>>> ellipse = EllipseModelSegm()
>>> ellipse.estimate(xy)
True
>>> np.round(ellipse.params, 2)
array([ 19.5 ,  29.5 ,  12.45,  16.52,   0.53])
>>> xy = EllipseModelSegm().predict_xy(np.linspace(0, 2 * np.pi, 25), params)
>>> ellipse = EllipseModelSegm()
>>> ellipse.estimate(xy)
True
>>> np.round(ellipse.params, 2)
array([ 20.  ,  30.  ,  12.  ,  16.  ,   0.52])
>>> np.round(abs(ellipse.residuals(xy)), 5)
array([ 0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,
        0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.])
>>> ellipse.params[2] += 2
>>> ellipse.params[3] += 2
>>> np.round(abs(ellipse.residuals(xy)))
array([ 2.,  2.,  2.,  2.,  2.,  2.,  2.,  2.,  2.,  2.,  2.,  2.,  2.,
        2.,  2.,  2.,  2.,  2.,  2.,  2.,  2.,  2.,  2.,  2.,  2.])
```

criterion (*points*, *weights*, *labels*, *table_prob=(0.1, 0.9)*)
Determine residuals of data to model.

Parameters

- **points** – points coordinates
- **weights** – weight for each point represent the region size
- **labels** – vector of labels for each point
- **table_prob** – is a vector or foreground probabilities for each class and being background is supplement to 1. Another option is define a matrix with number of columns related to number of classes and the first row denote probability being foreground and second being background

Returns

Example

```
>>> seg = np.zeros((10, 15), dtype=int)
>>> r, c = np.meshgrid(range(seg.shape[1]), range(seg.shape[0]))
>>> el = EllipseModelSegm()
>>> el.params = [4, 7, 3, 6, np.deg2rad(10)]
>>> weights = np.ones(seg.ravel().shape)
>>> seg[4:5, 6:8] = 1
>>> table_prob = [[0.1, 0.9]]
>>> el.criterion(np.array([r.ravel(), c.ravel()]).T, weights, seg.ravel(),␣
↪table_prob)
87.888...
>>> seg[2:7, 4:11] = 1
>>> el.criterion(np.array([r.ravel(), c.ravel()]).T, weights, seg.ravel(),␣
↪table_prob)
17.577...
>>> seg[1:9, 1:14] = 1
>>> el.criterion(np.array([r.ravel(), c.ravel()]).T, weights, seg.ravel(),␣
↪table_prob)
-70.311...
```

imsegm.ellipse_fitting.**add_overlap_ellipse**(*segm*, *ellipse_params*, *label*, *thr_overlap=1.0*)
add to existing image ellipse with specific label if the new ellipse does not ouvelap with already existing object / ellipse

Parameters

- **segm** (*ndarray*) – segmentation
- **ellipse_params** (*tuple*) – parameters
- **label** (*int*) – selected label
- **thr_overlap** (*float*) – relative overlap with existing objects

Return ndarray

```
>>> seg = np.zeros((15, 20), dtype=int)
>>> ell_params = 7, 10, 5, 8, np.deg2rad(30)
>>> ell = add_overlap_ellipse(seg, ell_params, 1)
>>> ell
```

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```
array([[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0],
       [0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0],
       [0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0],
       [0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0],
       [0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0],
       [0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0],
       [0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0]])
>>> ell2_params = 4, 5, 2, 3, np.deg2rad(-30)
>>> add_overlap_ellipse(ell, ell2_params, 2)
array([[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 2, 2, 2, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0],
       [0, 0, 0, 2, 2, 2, 2, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0],
       [0, 0, 0, 2, 2, 2, 2, 2, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0],
       [0, 0, 0, 0, 2, 2, 2, 2, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0],
       [0, 0, 0, 0, 1, 2, 2, 2, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0],
       [0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0],
       [0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0],
       [0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0],
       [0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0]])
```

imsegm.ellipse_fitting.**filter_boundary_points**(*segm*, *slic*)

imsegm.ellipse_fitting.**get_slic_points_labels**(*segm*, *img=None*, *slic_size=20*, *slic_regul=0.1*)

run SLIC on image or supepixels and return superpixels, their centers and also lebels (label from segmentation in position of superpixel centre)

Parameters

- **segm** (*ndarray*) – segmentation
- **img** (*ndarray*) – input image
- **slic_size** (*int*) – superpixel size
- **slic_regul** (*float*) – regularisation in range (0, 1)

Return tuple

imsegm.ellipse_fitting.**prepare_boundary_points_close**(*seg*, *centers*, *sp_size=25*, *relative_compact=0.3*)

extract some point around foreground boundaries

Parameters

- **seg** (*ndarray*) – input segmentation
- **int)] centers** (*[(int,*) – list of centers

- **sp_size** (*int*) – superpixel size

Return [ndarray]

```
>>> seg = np.zeros((100, 200), dtype=int)
>>> ell_params = 50, 100, 40, 60, np.deg2rad(30)
>>> seg = add_overlap_ellipse(seg, ell_params, 1)
>>> pts = prepare_boundary_points_close(seg, [(40, 90)])
>>> pts
[array([[  6,  85],
        [  8, 150],
        ...
        [ 92, 118]])]
```

imsegm.ellipse_fitting.**prepare_boundary_points_ray_dist**(*seg*, *centers*, *close_points=1*, *sel_bg=15*, *sel_fg=5*)

extract some point around foreground boundaries

Parameters

- **seg** (*ndarray*) – input segmentation
- **int)] centers** (*[(int,*) – list of centers
- **close_points** (*float*) – remove closest point then a given threshold
- **sel_bg** (*int*) – smoothing background with morphological operation
- **sel_fg** (*int*) – smoothing foreground with morphological operation

Return [ndarray]

```
>>> seg = np.zeros((10, 20), dtype=int)
>>> ell_params = 5, 10, 4, 6, np.deg2rad(30)
>>> seg = add_overlap_ellipse(seg, ell_params, 1)
>>> pts = prepare_boundary_points_ray_dist(seg, [(4, 9)], 2, sel_bg=0, sel_fg=0)
>>> np.round(pts, 2).tolist()
[[[4.0, 16.0],
  [6.8, 15.0],
  [9.0, 5.5],
  [4.35, 5.0],
  [1.0, 6.9],
  [1.0, 9.26],
  [0.0, 11.31],
  [0.5, 14.0],
  [1.45, 16.0]]]
```

imsegm.ellipse_fitting.**prepare_boundary_points_ray_edge**(*seg*, *centers*, *close_points=5*, *min_diam=25.0*, *sel_bg=15*, *sel_fg=5*)

extract some point around foreground boundaries

Parameters

- **seg** (*ndarray*) – input segmentation
- **int)] centers** (*[(int,*) – list of centers
- **close_points** (*float*) – remove closest point then a given threshold
- **min_diam** (*int*) – minimal size of expected objest

- **sel_bg** (*int*) – smoothing background with morphological operation
- **sel_fg** (*int*) – smoothing foreground with morphological operation

Return [ndarray]

```
>>> seg = np.zeros((10, 20), dtype=int)
>>> ell_params = 5, 10, 4, 6, np.deg2rad(30)
>>> seg = add_overlap_ellipse(seg, ell_params, 1)
>>> pts = prepare_boundary_points_ray_edge(seg, [(4, 9)], 2.5, 3, sel_bg=1, sel_
↪fg=0)
>>> np.round(pts).tolist()
[[[4.0, 16.0],
  [7.0, 15.0],
  [9.0, 5.0],
  [4.0, 5.0],
  [1.0, 7.0],
  [0.0, 14.0]]]
```

imsegm.ellipse_fitting.**prepare_boundary_points_ray_join**(*seg*, *centers*, *close_points=5*, *min_diam=25.0*, *sel_bg=15*, *sel_fg=5*)

extract some point around foreground boundaries

Parameters

- **seg** (*ndarray*) – input segmentation
- **int)] centers** (*[(int,*) – list of centers
- **close_points** (*float*) – remove closest point then a given threshold
- **min_diam** (*int*) – minimal size of expected objest
- **sel_bg** (*int*) – smoothing background with morphological operation
- **sel_fg** (*int*) – smoothing foreground with morphological operation

Return [ndarray]

```
>>> seg = np.zeros((10, 20), dtype=int)
>>> ell_params = 5, 10, 4, 6, np.deg2rad(30)
>>> seg = add_overlap_ellipse(seg, ell_params, 1)
>>> pts = prepare_boundary_points_ray_join(seg, [(4, 9)], 5., 3, sel_bg=1, sel_
↪fg=0)
>>> np.round(pts).tolist()
[[[4.0, 16.0],
  [7.0, 10.0],
  [9.0, 5.0],
  [4.0, 16.0],
  [7.0, 10.0]]]
```

imsegm.ellipse_fitting.**prepare_boundary_points_ray_mean**(*seg*, *centers*, *close_points=5*, *min_diam=25.0*, *sel_bg=15*, *sel_fg=5*)

extract some point around foreground boundaries

Parameters

- **seg** (*ndarray*) – input segmentation

- **int)] centers** ([(*int*,) – list of centers
- **close_points** (*float*) – remove closest point then a given threshold
- **min_diam** (*int*) – minimal size of expected objest
- **sel_bg** (*int*) – smoothing background with morphological operation
- **sel_fg** (*int*) – smoothing foreground with morphological operation

Return [ndarray]

```
>>> seg = np.zeros((10, 20), dtype=int)
>>> ell_params = 5, 10, 4, 6, np.deg2rad(30)
>>> seg = add_overlap_ellipse(seg, ell_params, 1)
>>> pts = prepare_boundary_points_ray_mean(seg, [(4, 9)], 2.5, 3, sel_bg=1, sel_
↪fg=0)
>>> np.round(pts).tolist()
[[[4.0, 16.0],
  [7.0, 15.0],
  [9.0, 5.0],
  [4.0, 5.0],
  [1.0, 7.0],
  [0.0, 14.0]]]
```

imsegm.ellipse_fitting.**ransac_segm**(*points*, *model_class*, *points_all*, *weights*, *labels*, *table_prob*, *min_samples*, *residual_threshold=1*, *max_trials=100*)

Fit a model to points with the RANSAC (random sample consensus).

Parameters

- **points** (*[list, tuple of] (N, D) array*) – Data set to which the model is fitted, where N is the number of points points and D the dimensionality of the points. If the model class requires multiple input points arrays (e.g. source and destination coordinates of `skimage.transform.AffineTransform`), they can be optionally passed as tuple or list. Note, that in this case the functions `estimate(*points)`, `residuals(*points)`, `is_model_valid(model, *random_data)` and `is_data_valid(*random_data)` must all take each points array as separate arguments.
- **model_class** (*class*) – Object with the following object methods:

  – `success = estimate(*points)`

  – `residuals(*points)`

  where *success* indicates whether the model estimation succeeded (*True* or *None* for success, *False* for failure).
- **points_all** (*list*) –
- **weights** (*list*) –
- **labels** (*list*) –
- **table_prob** (*list*) –
- **min_samples** (*int float*) – The minimum number of points points to fit a model to.
- **residual_threshold** (*float*) – Maximum distance for a points point to be classified as an inlier.

- **max_trials** (*int, optional*) – Maximum number of iterations for random sample selection.

Returns

- **model** (*object*) – Best model with largest consensus set.
- **inliers** (*(N,) array*) – Boolean mask of inliers classified as `True`.

Examples

```
>>> seg = np.zeros((120, 150), dtype=int)
>>> ell_params = 60, 75, 40, 65, np.deg2rad(30)
>>> seg = add_overlap_ellipse(seg, ell_params, 1)
>>> slic, points_all, labels = get_slic_points_labels(seg, slic_size=10, slic_
↪regul=0.3)
>>> points = prepare_boundary_points_ray_dist(seg, [(40, 90)], 2, sel_bg=1, sel_
↪fg=0)[0]
>>> table_prob = [[0.01, 0.75, 0.95, 0.9], [0.99, 0.25, 0.05, 0.1]]
>>> weights = np.bincount(slic.ravel())
>>> ransac_model, _ = ransac_segm(
...     points, EllipseModelSegm, points_all, weights, labels, table_prob, 0.6, 3,
↪ max_trials=15)
>>> np.round(ransac_model.params[:4]).astype(int)
array([60, 75, 41, 65])
>>> np.round(ransac_model.params[4], 1)
0.5
```

imsegm.ellipse_fitting.**split_segm_background_foreground**(*seg*, *sel_bg=15*, *sel_fg=5*)

smoothing segmentation with morphological operation

Parameters

- **seg** (*ndarray*) – input segmentation
- **sel_bg** (*int / float*) – smoothing background with morphological operation
- **sel_fg** (*int*) – smoothing foreground with morphological operation

Return tuple(ndarray,ndarray)

```
>>> seg = np.zeros((10, 20), dtype=int)
>>> ell_params = 5, 10, 4, 6, np.deg2rad(30)
>>> seg = add_overlap_ellipse(seg, ell_params, 1)
>>> seg_bg, seg_fc = split_segm_background_foreground(seg, 1.5, 0)
>>> seg_bg.astype(int)
array([[1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1],
       [1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1],
       [1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1],
       [1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1],
       [1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1],
       [1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1],
       [1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1],
       [1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1],
       [1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1],
       [1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1]])
>>> seg_fc.astype(int)
array([[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0],
```

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```
        [0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0],
        [0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0],
        [0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0],
        [0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0],
        [0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0],
        [0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0],
        [0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0],
        [0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0]])
```

imsegm.ellipse_fitting.**MAX_FIGURE_SIZE = 14**
define maximal Figure size in larger dimension

imsegm.ellipse_fitting.**MIN_ELLIPSE_DAIM = 25.0**
define minimal size of estimated ellipse

imsegm.ellipse_fitting.**STRUC_ELEM_BG = 15**
smoothing background with morphological operation

imsegm.ellipse_fitting.**STRUC_ELEM_FG = 5**
smoothing foreground with morphological operation

imsegm.features_cython module

imsegm.graph_cuts module

Framework for GraphCut

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imsegm.graph_cuts.**compute_edge_model**(*edges*, *proba*, *metric='l_T'*)
compute the edge weight from the feature space

small differences are large weights, diff close 0 appears to be 1 setting min weight ~ max difference in proba as weight meaning if two vertexes have same proba to all classes the diff is 0 and weights are 1 on the other hand if there is [0.7, 0.1, 0.2] and [0.2, 0.7, 0.1] gives large diff [0.5, 0.6, 0.1] in 1. and 2. diff and zero in 3 leading to weights [0.5, 0.4, 0.9] and so we take the min values

Parameters

- **int)] edges** (*[(int,*) – edges
- **proba** (*[[float]]*) – probablilitirs
- **metric** (*str*) – define metric

Return list(float)

```
>>> segments = np.array([[0] * 3 + [1] * 5 + [2] * 4,
...                      [4] * 4 + [5] * 5 + [6] * 3])
>>> edges = np.array(get_vertexes_edges(segments)[1], dtype=int)
>>> np.random.seed(0)
>>> img = np.random.random(segments.shape + (3,)) * 255
>>> proba = np.random.random((segments.max() + 1, 2))
>>> weights = compute_edge_model(edges, proba, metric='l1')
>>> np.round(weights, 3).tolist()
[0.002, 0.015, 0.001, 0.002, 0.0, 0.002, 0.015, 0.034, 0.001]
>>> weights = compute_edge_model(edges, proba, metric='l2')
```

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```
>>> np.round(weights, 3).tolist()
[0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.002, 0.005, 0.0]
>>> weights = compute_edge_model(edges, proba, metric='lT')
>>> np.round(weights, 3).tolist()
[0.0, 0.002, 0.0, 0.005, 0.0, 0.0, 0.101, 0.092, 0.001]
```

imsegm.graph_cuts.**compute_edge_weights**(*segments*, *image=None*, *features=None*, *proba=None*, *edge_type=''*)

pp 32, http://www.coe.utah.edu/~cs7640/readings/graph_cuts_intro.pdf exp(- norm value diff) * (geom dist vertex)**-1

Parameters

- **segments** (*ndarry*) – superpixels
- **image** (*ndarry*) – input image
- **features** (*ndarry*) – features for each segment (superpixel)
- **proba** (*ndarry*) – probability of each superpixel and class
- **edge_type** (*str*) – contains edge type, if 'model', after '_' you can specify the metric, eg. 'model_l2'

Return [[int, int]], [float]

```
>>> segments = np.array([[0] * 3 + [1] * 5 + [2] * 4,
...                      [4] * 4 + [5] * 5 + [6] * 3])
>>> np.random.seed(0)
>>> img = np.random.random(segments.shape + (3,)) * 255
>>> features = np.random.random((segments.max() + 1, 15)) * 10
>>> proba = np.random.random((segments.max() + 1, 2))
>>> edges, weights = compute_edge_weights(segments)
>>> edges.tolist()
[[0, 1], [1, 2], [0, 4], [1, 4], [1, 5], [2, 5], [4, 5], [2, 6], [5, 6]]
>>> np.round(weights, 2).tolist()
[1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0]
>>> edges, weights = compute_edge_weights(segments, image=img, edge_type='spatial
↪')
>>> np.round(weights, 3).tolist()
[0.776, 0.69, 2.776, 0.853, 2.194, 0.853, 0.69, 2.776, 0.776]
>>> edges, weights = compute_edge_weights(segments, image=img, edge_type='color')
>>> np.round(weights, 3).tolist()
[0.06, 0.002, 0.001, 0.001, 0.001, 0.009, 0.001, 0.019, 0.044]
>>> edges, weights = compute_edge_weights(segments, features=features, edge_type=
↪'features')
>>> np.round(weights, 3).tolist()
[0.031, 0.005, 0.051, 0.032, 0.096, 0.013, 0.018, 0.033, 0.013]
>>> edges, weights = compute_edge_weights(segments, proba=proba, edge_type='model
↪')
>>> np.round(weights, 3).tolist()
[0.001, 0.028, 1.122, 0.038, 0.117, 0.688, 0.487, 1.152, 0.282]
```

imsegm.graph_cuts.**compute_multivarian_otsu**(*features*)

compute otsu individually over each sample dimension WARNING: this compute only localy and since it does compare all combinations of orienting the asign for tight cases it may not decide

Parameters **features** (*ndarray*) –

Return list(bool)

```
>>> np.random.seed(0)
>>> fts = np.row_stack([np.random.random((5, 3)) - 1,
...                     np.random.random((5, 3)) + 1])
>>> fts[:, 1] = - fts[:, 1]
>>> compute_multivarian_otsu(fts).astype(int)
array([0, 0, 0, 0, 0, 1, 1, 1, 1, 1])
```

imsegm.graph_cuts.**compute_pairwise_cost**(*gc_regul*, *proba_shape*, *max_pairwise_cost=100000.0*)

wrapper for creating GC pairwise cost

Parameters

- **gc_regul** –
- **proba_shape** (*tuple(int,int)*) –
- **max_pairwise_cost** (*float*) –

Return ndarray

imsegm.graph_cuts.**compute_pairwise_cost_from_transitions**(*trans*, *min_prob=1e-09*)

compute pairwise cost from segments-label transitions

Parameters

- **trans** (*ndarray*) –
- **min_prob** (*float*) – minimal probability

Return ndarray

```
>>> trans = np.array([[ 25.,   5.,  0.],
...                   [  5.,  10.,  8.],
...                   [  0.,   8.,  30.]])
>>> np.round(compute_pairwise_cost_from_transitions(trans), 3)
array([[  0.182,   1.526,  20.723],
       [  1.526,   0.833,   1.056],
       [ 20.723,   1.056,   0.236]])
>>> np.round(compute_pairwise_cost_from_transitions(np.ones(3)), 2)
array([[ 1.1,  1.1,  1.1],
       [ 1.1,  1.1,  1.1],
       [ 1.1,  1.1,  1.1]])
>>> np.round(compute_pairwise_cost_from_transitions(np.eye(3)), 2)
array([[  0.  ,  20.72,  20.72],
       [ 20.72,   0.  ,  20.72],
       [ 20.72,  20.72,   0.  ]])
```

imsegm.graph_cuts.**compute_spatial_dist**(*centres*, *edges*, *relative=False*)

compute spatial distance between all neighbouring segments

Parameters

- **int]] centres** (*[[int,*) – superpixel centres
- **int]] edges** (*[[int,*) –
- **relative** (*bool*) – normalise the distances to mean distance

Returns

```
>>> from imsegm.superpixels import superpixel_centers
>>> segments = np.array([[0] * 3 + [1] * 2 + [2] * 5,
...                      [4] * 4 + [5] * 2 + [6] * 4])
>>> centres = superpixel_centers(segments)
>>> edges = [[0, 1], [1, 2], [4, 5], [5, 6], [0, 4], [1, 5], [2, 6]]
>>> np.round(compute_spatial_dist(centres, edges), 2)
array([ 2.5 ,  3.5 ,  3.  ,  3.  ,  1.12,  1.41,  1.12])
>>> np.round(compute_spatial_dist(centres, edges, relative=True), 2)
array([ 1.12,  1.57,  1.34,  1.34,  0.5 ,  0.63,  0.5 ])
```

imsegm.graph_cuts.**compute_unary_cost**(*proba*, *min_prob=0.01*)
compute the GC unary cost with some threshold on minimal values

Parameters

- **proba** (*ndarray*) –
- **min_prob** (*float*) –

Return ndarray

```
>>> compute_unary_cost(np.random.random((50, 2))).shape
(50, 2)
```

imsegm.graph_cuts.**count_label_transitions_connected_segments**(*dict_slics*, *dict_labels*, *nb_labels=None*)
count transitions among labeled segment in between connected segments

Parameters

- **dict_slics** (*dict(list(list(int)))*) – image name: ndarray
- **dict_labels** (*dict(list(int))*) – image name: ndarray
- **nb_labels** (*int*) –

Return ndarray matrix of shape nb_labels x nb_labels

```
>>> dict_slics = {'a':
...        np.array([[0] * 3 + [1] * 3 + [2] * 3 + [3] * 3 + [4] * 3,
...                  [5] * 3 + [6] * 3 + [7] * 3 + [8] * 3 + [9] * 3])}
>>> dict_labels = {'a': np.array([0, 0, 1, 1, 2, 0, 1, 1, 0, 2])}
>>> dict_slics['a']
array([[0, 0, 0, 1, 1, 1, 2, 2, 2, 3, 3, 3, 4, 4, 4],
       [5, 5, 5, 6, 6, 6, 7, 7, 7, 8, 8, 8, 9, 9, 9]])
>>> dict_labels['a'][dict_slics['a']]
array([[0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 2, 2, 2],
       [0, 0, 0, 1, 1, 1, 1, 1, 1, 0, 0, 0, 2, 2, 2]])
>>> count_label_transitions_connected_segments(dict_slics, dict_labels)
array([[ 2.,  5.,  1.],
       [ 5.,  3.,  1.],
       [ 1.,  1.,  1.]])
```

imsegm.graph_cuts.**create_pairwise_matrix**(*gc_regul*, *nb_classes*)
wrapper for create pairwise matrix - uniform or specific

Parameters

- **gc_regul** –
- **nb_classes** (*int*) –

Returns np.array<nb_classes, nb_classes>

```
>>> create_pairwise_matrix(0.6, 3)
array([[ 0. ,  0.6,  0.6],
       [ 0.6,  0. ,  0.6],
       [ 0.6,  0.6,  0. ]])
>>> create_pairwise_matrix([((1, 2), 0.5), ((0, 2), 0.7)], 3)
array([[ 0. ,  1. ,  0.7],
       [ 1. ,  0. ,  0.5],
       [ 0.7,  0.5,  0. ]])
>>> trans = np.array([[ 341.,   31.,   22.],
...                   [  31.,   12.,   21.],
...                   [  22.,   21.,   44.]])
>>> gc_regul = compute_pairwise_cost_from_transitions(trans)
>>> np.round(create_pairwise_matrix(gc_regul, len(gc_regul)), 2)
array([[ 0.  ,  0.58,  1.23],
       [ 0.58,  1.53,  0.97],
       [ 1.23,  0.97,  0.54]])
```

imsegm.graph_cuts.**create_pairwise_matrix_specif**(*pos_weights*, *nb_classes=None*)

create GC pairwise matrix wih specific values on particular positions

Parameters

- **int), float)] pos_weights** (*[((int,*) – pair of coord in matrix and values
- **nb_classes** (*int*) – initialise as empty matrix

Returns np.array<nb_classes, nb_classes>

```
>>> create_pairwise_matrix_specif([((1, 2), 0.5), ((1, 0), 0.7)], 4)
array([[ 0. ,  0.7,  1. ,  1. ],
       [ 0.7,  0. ,  0.5,  1. ],
       [ 1. ,  0.5,  0. ,  1. ],
       [ 1. ,  1. ,  1. ,  0. ]])
>>> create_pairwise_matrix_specif([((1, 2), 0.5), ((0, 2), 0.7)])
array([[ 0. ,  1. ,  0.7],
       [ 1. ,  0. ,  0.5],
       [ 0.7,  0.5,  0. ]])
```

imsegm.graph_cuts.**create_pairwise_matrix_uniform**(*gc_reg*, *nb_classes*)

create GC pairwise matrix - uniform with zeros on diagonal

Parameters

- **gc_reg** (*float*) –
- **nb_classes** (*int*) –

Return ndarray

```
>>> create_pairwise_matrix_uniform(0.2, 3)
array([[ 0. ,  0.2,  0.2],
       [ 0.2,  0. ,  0.2],
       [ 0.2,  0.2,  0. ]])
```

imsegm.graph_cuts.**estim_class_model**(*features*, *nb_classes*, *estim_model='GMM'*, *pca_coef=None*, *use_scaler=True*, *max_iter=99*)

create pipeline (scaler, PCA, model) over several options how to cluster samples and fit it on data

Parameters

- **features** (*ndarray*) –
- **nb_classes** (*int*) – number of expected classes
- **pca_coef** (*float*) – range (0, 1) or None
- **use_scaler** (*bool*) – whether use a scaler
- **estim_model** (*str*) – used model
- **max_iter** (*int*) –

Returns

```
>>> np.random.seed(0)
>>> fts = np.row_stack([np.random.random((50, 3)) - 1,
...                     np.random.random((50, 3)) + 1])
>>> mm = estim_class_model(fts, 2)
>>> mm.predict_proba(fts).shape
(100, 2)
>>> mm = estim_class_model(fts, 2, estim_model='GMM_kmeans', pca_coef=0.95, max_
↪iter=3)
>>> mm.predict_proba(fts).shape
(100, 2)
>>> mm = estim_class_model(fts, 2, estim_model='GMM_Otsu', max_iter=3)
>>> mm.predict_proba(fts).shape
(100, 2)
>>> mm = estim_class_model(fts, 2, estim_model='kmeans_quantiles', use_
↪scaler=False, max_iter=3)
>>> mm.predict_proba(fts).shape
(100, 2)
>>> mm = estim_class_model(fts, 2, estim_model='BGM', max_iter=3)
>>> mm.predict_proba(fts).shape
(100, 2)
>>> mm = estim_class_model(fts, 2, estim_model='Otsu', max_iter=3)
>>> mm.predict_proba(fts).shape
(100, 2)
```

imsegm.graph_cuts.**estim_class_model_gmm**(*features*, *nb_classes*, *init='kmeans'*)

from all features estimate Gaussian Mixture Model and assuming each cluster is a single class compute probability that each feature belongs to each class

Parameters

- **features** (*[[float]]*) – list of features per segment
- **nb_classes** (*int*) – number of classes
- **init** (*int*) – initialisation

Return [[float]] probabilities that each feature belongs to each class

```
>>> np.random.seed(0)
>>> fts = np.row_stack([np.random.random((50, 3)) - 1,
...                     np.random.random((50, 3)) + 1])
>>> mm = estim_class_model_gmm(fts, 2)
>>> mm.predict_proba(fts).shape
(100, 2)
```

imsegm.graph_cuts.**estim_class_model_kmeans**(*features*, *nb_classes*, *init_type='k-means++'*, *max_iter=99*)

from all features estimate Gaussian from k-means clustering

Parameters

- **features** (*[[float]]*) – list of features per segment
- **nb_classes** (*int*) – number of classes
- **init_type** (*str*) – initialization
- **max_iter** (*int*) – maximal number of iterations

Return [[float]] probabilities that each feature belongs to each class

```
>>> np.random.seed(0)
>>> fts = np.row_stack([np.random.random((50, 3)) - 1,
...                     np.random.random((50, 3)) + 1])
>>> mm, y = estim_class_model_kmeans(fts, 2, max_iter=9)
>>> y.shape
(100,)
>>> mm.predict_proba(fts).shape
(100, 2)
```

imsegm.graph_cuts.**estim_gmm_params**(*features*, *prob*)
with given soft labeling (take the maxim) get the GMM parameters

Parameters

- **features** (*ndarray*) –
- **prob** (*ndarray*) –

Returns

```
>>> np.random.seed(0)
>>> prob = np.array([[1, 0]] * 30 + [[0, 1]] * 40)
>>> fts = prob + np.random.random(prob.shape)
>>> mm = estim_gmm_params(fts, prob)
>>> mm['weights']
[0.42857142857142855, 0.5714285714285714]
>>> mm['means']
array([[ 1.49537196,  0.53745455],
       [ 0.54199936,  1.42606497]])
```

imsegm.graph_cuts.**get_vertexes_edges**(*segments*)
wrapper - get list of vertexes edges for 2D / 3D images

Parameters **segments** (*ndarray*) –

Returns

imsegm.graph_cuts.**insert_gc_debug_images**(*debug_visual*, *segments*, *graph_labels*, *unary_cost*, *edges*, *edge_weights*)
wrapper for placing intermediate variable to a dictionary

imsegm.graph_cuts.**segment_graph_cut_general**(*segments*, *proba*, *image=None*, *features=None*, *gc_regul=1.0*, *edge_type='model'*, *edge_cost=1.0*, *debug_visual=None*)
segment the image segmented via superpixels and estimated features

Parameters

- **features** (*ndarray*) – features sor each instance
- **segments** (*ndarray*) – segmentation mapping each pixel into a class

- **image** (*ndarray*) – image
- **proba** (*ndarray*) – probabilities that each feature belongs to each class
- **edge_type** (*str*) –
- **edge_cost** (*str*) –
- **gc_regul** – regularisation for GrphCut
- **debug_visual** (*dict*) –

Return list(int) labelling by resulting classes

```
>>> np.random.seed(0)
>>> segments = np.array([[0] * 3 + [2] * 3 + [4] * 3 + [6] * 3 + [8] * 3,
...                      [1] * 3 + [3] * 3 + [5] * 3 + [7] * 3 + [9] * 3])
>>> proba = np.array([[0.1] * 6 + [0.9] * 4, [0.9] * 6 + [0.1] * 4], dtype=float).
↪T
>>> proba += (0.5 - np.random.random(proba.shape)) * 0.2
>>> compute_unary_cost(proba)
array([[ 2.40531242,  0.15436155],
       [ 2.53266106,  0.11538463],
       [ 2.1604864 ,  0.13831863],
       [ 2.18495711,  0.19644636],
       [ 4.60517019,  0.0797884 ],
       [ 3.17833405,  0.11180231],
       [ 0.12059702,  4.20769207],
       [ 0.0143091 ,  1.70059894],
       [ 0.01005034,  3.39692559],
       [ 0.16916609,  3.64975219]])
>>> segment_graph_cut_general(segments, proba, gc_regul=0., edge_type='')
array([1, 1, 1, 1, 1, 1, 0, 0, 0, 0]...)
>>> labels = segment_graph_cut_general(segments, proba, gc_regul=1., edge_type=
↪'spatial')
>>> labels[segments]
array([[1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0],
       [1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0]], dtype=int32)
>>> slic = np.array([[0] * 4 + [1] * 6 + [2] * 4,
...                  [3] * 5 + [4] * 4 + [5] * 5])
>>> proba = np.array([[1] * 3 + [0] * 3, [0] * 3 + [1] * 3], dtype=float).T
>>> proba += np.random.random(proba.shape) / 2.
>>> np.argmax(proba, axis=1)
array([0, 0, 0, 1, 1, 1]...)
>>> debug_visual = dict()
>>> segment_graph_cut_general(
...     slic, proba, gc_regul=0., edge_type='', debug_visual=debug_visual)
array([0, 0, 0, 1, 1, 1]...)
>>> sorted(debug_visual.keys())
['edge_weights', 'edges', 'img_graph_edges', 'img_graph_segm',
 'imgs_unary_cost', 'segments']
```

imsegm.graph_cuts.**DEFAULT_GC_ITERATIONS = 25**
define munber of iteration in Grap-Cut optimization

imsegm.graph_cuts.**MAX_PAIRWISE_COST = 100000.0**
define maximal value of parwise (smoothness) term in Graph-Cut

imsegm.graph_cuts.**MIN_MAX_EDGE_WEIGHT = 1000.0**
max is this value and min is inverse (1 / val)

imsegm.graph_cuts.**MIN_UNARY_PROB = 0.01**
define minimal value of unary (being a class) term in Graph-Cut

imsegm.labeling module

Framework for labeling

imsegm.labeling.**assign_label_by_max**(*label_hist*)
assign label according maximal label count in particular region

Parameters **label_hist** (*dict(list(int))*) – mapping of label to histogram

Return list(int) resulting LookUpTable

```
>>> slic = np.array([[0] * 4 + [1] * 3 + [2] * 3 + [3] * 3] * 4 +
...                 [[4] * 3 + [5] * 3 + [6] * 3 + [7] * 4] * 4)
>>> segm = np.zeros(slic.shape, dtype=int)
>>> segm[4:, 6:] = 1
>>> lb_hist = segm_labels_assignment(slic, segm)
>>> assign_label_by_max(lb_hist)
array([0, 0, 0, 0, 0, 0, 1, 1])
```

imsegm.labeling.**assign_label_by_threshold**(*dict_label_hist*, *thresh=0.75*)
assign label if the purity reach certain threshold

Parameters

- **dict_label_hist** (*dict(list(int))*) – mapping of label to histogram
- **thresh** (*float*) – threshold for region purity

Return list(int) resulting LookUpTable

```
>>> slic = np.array([[0] * 4 + [1] * 3 + [2] * 3 + [3] * 3] * 4 +
...                 [[4] * 3 + [5] * 3 + [6] * 3 + [7] * 4] * 4)
>>> segm = np.zeros(slic.shape, dtype=int)
>>> segm[4:, 6:] = 1
>>> lb_hist = segm_labels_assignment(slic, segm)
>>> assign_label_by_threshold(lb_hist)
array([0, 0, 0, 0, 0, 0, 1, 1])
```

imsegm.labeling.**assume_bg_on_boundary**(*segm*, *bg_label=0*, *boundary_size=1*)
swap labels such that the background label will be mostly on image boundary

Parameters

- **segm** (*ndarray*) – segmentation
- **bg_label** (*int*) – background label
- **boundary_size** (*float*) –

Returns

```
>>> segm = np.zeros((6, 12), dtype=int)
>>> segm[1:4, 4:] = 2
>>> assume_bg_on_boundary(segm, boundary_size=1)
array([[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 2, 2, 2, 2, 2, 2, 2, 2],
```

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```
       [0, 0, 0, 0, 2, 2, 2, 2, 2, 2, 2, 2],
       [0, 0, 0, 0, 2, 2, 2, 2, 2, 2, 2, 2],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0]])
>>> segm[segm == 0] = 1
>>> assume_bg_on_boundary(segm, boundary_size=1)
array([[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 2, 2, 2, 2, 2, 2, 2, 2],
       [0, 0, 0, 0, 2, 2, 2, 2, 2, 2, 2, 2],
       [0, 0, 0, 0, 2, 2, 2, 2, 2, 2, 2, 2],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0]])
```

imsegm.labeling.**binary_image_from_coords**(*coords*, *size*)

create binary image just from point contours

Parameters

- **coords** (*ndarray*) –
- **size** (*tuple(int,int)*) –

Return ndarray

```
>>> img = np.zeros((6, 6), dtype=int)
>>> img[1:5, 2:] = 1
>>> coords = contour_coords(img)
>>> binary_image_from_coords(coords, img.shape)
array([[0, 0, 0, 0, 0, 0],
       [0, 0, 1, 1, 1, 0],
       [0, 0, 1, 0, 0, 0],
       [0, 0, 1, 0, 0, 0],
       [0, 0, 1, 1, 1, 0],
       [0, 0, 0, 0, 0, 0]])
```

imsegm.labeling.**compute_boundary_distances**(*segm_ref*, *segm*)

compute distances among boundaries of two segmentation

Parameters

- **segm_ref** (*ndarray*) – reference segmentation
- **segm** (*ndarray*) – input segmentation

Return ndarray

```
>>> segm_ref = np.zeros((6, 10), dtype=int)
>>> segm_ref[3:4, 4:5] = 1
>>> segm = np.zeros((6, 10), dtype=int)
>>> segm[:, 2:9] = 1
>>> pts, dist = compute_boundary_distances(segm_ref, segm)
>>> pts
array([[2, 4],
       [3, 3],
       [3, 4],
       [3, 5],
       [4, 4]])
>>> dist.tolist()
[2.0, 1.0, 2.0, 3.0, 2.0]
```

imsegm.labeling.**compute_distance_map**(*seg*, *label=1*)
compute distance from label boundaries

Parameters

- **seg** (*ndarray*) – integer images, typically a segmentation
- **label** (*int*) – selected singe label in segmentation

Return ndarray

```
>>> img = np.zeros((6, 6), dtype=int)
>>> img[1:5, 2:] = 1
>>> dist = compute_distance_map(img)
>>> np.round(dist, 2)
array([[ 2.24,  1.41,  1.  ,  1.  ,  1.  ,  1.41],
       [ 2.  ,  1.  ,  0.  ,  0.  ,  0.  ,  1.  ],
       [ 2.  ,  1.  ,  0.  ,  1.  ,  1.  ,  1.41],
       [ 2.  ,  1.  ,  0.  ,  1.  ,  1.  ,  1.41],
       [ 2.  ,  1.  ,  0.  ,  0.  ,  0.  ,  1.  ],
       [ 2.24,  1.41,  1.  ,  1.  ,  1.  ,  1.41]])
```

imsegm.labeling.**compute_labels_overlap_matrix**(*seg1*, *seg2*)
compute overlap between tho segmentation atlasess) with same sizes

Parameters

- **seg1** (*ndarray*) – np.array<height, width>
- **seg2** (*ndarray*) – np.array<height, width>

Return ndarray np.array<height, width>

```
>>> seg1 = np.zeros((7, 15), dtype=int)
>>> seg1[1:4, 5:10] = 3
>>> seg1[5:7, 6:13] = 2
>>> seg2 = np.zeros((7, 15), dtype=int)
>>> seg2[2:5, 7:12] = 1
>>> seg2[4:7, 7:14] = 3
>>> compute_labels_overlap_matrix(seg1, seg1)
array([[76,  0,  0,  0],
       [ 0,  0,  0,  0],
       [ 0,  0, 14,  0],
       [ 0,  0,  0, 15]])
>>> compute_labels_overlap_matrix(seg1, seg2)
array([[63,  4,  0,  9],
       [ 0,  0,  0,  0],
       [ 2,  0,  0, 12],
       [ 9,  6,  0,  0]])
```

imsegm.labeling.**contour_binary_map**(*seg*, *label=1*, *include_boundary=False*)
get object boundaries

Parameters

- **seg** (*ndarray*) – integer images, typically a segmentation
- **label** (*int*) – selected singe label in segmentation
- **include_boundary** (*bool*) – assume that the object end with image boundary

Return ndarray

```
>>> img = np.zeros((6, 6), dtype=int)
>>> img[1:5, 2:] = 1
>>> contour_binary_map(img)
array([[0, 0, 0, 0, 0, 0],
       [0, 0, 1, 1, 1, 0],
       [0, 0, 1, 0, 0, 0],
       [0, 0, 1, 0, 0, 0],
       [0, 0, 1, 1, 1, 0],
       [0, 0, 0, 0, 0, 0]])
>>> contour_binary_map(img, include_boundary=True)
array([[0, 0, 0, 0, 0, 0],
       [0, 0, 1, 1, 1, 1],
       [0, 0, 1, 0, 0, 1],
       [0, 0, 1, 0, 0, 1],
       [0, 0, 1, 1, 1, 1],
       [0, 0, 0, 0, 0, 0]])
```

imsegm.labeling.**contour_coords**(*seg*, *label=1*, *include_boundary=False*)

get object boundaries

Parameters

- **seg** (*ndarray*) – integer images, typically a segmentation
- **label** (*int*) – selected singe label in segmentation
- **include_boundary** (*bool*) – assume that the object end with image boundary

Return [[int, int]]

```
>>> img = np.zeros((6, 6), dtype=int)
>>> img[1:5, 2:] = 1
>>> contour_coords(img)
[[1, 2], [1, 3], [1, 4], [2, 2], [3, 2], [4, 2], [4, 3], [4, 4]]
>>> contour_coords(img, include_boundary=True)
[[1, 2], [1, 3], [1, 4], [2, 2], [3, 2], [4, 2], [4, 3], [4, 4],
 [1, 5], [2, 5], [3, 5], [4, 5]]
```

imsegm.labeling.**convert_segms_2_list**(*segms*)

convert segmentation to a list tha can be simpy user for standard evaluation (classification or clustering metrics)

Parameters **segms** ([*ndarray*]) – list of segmentation

Return list(int)

```
>>> seg_pipe = np.ones((2, 3), dtype=int)
>>> convert_segms_2_list([seg_pipe, seg_pipe * 0, seg_pipe * 2])
[1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 2, 2, 2, 2, 2, 2]
```

imsegm.labeling.**histogram_regions_labels_counts**(*slic*, *segm*)

histogram or overlaping region between two segmentations, the typical usage is label superpixel from annotation

Parameters

- **slic** (*ndarray*) – input superpixel segmenatation
- **segm** (*ndarray*) – reference segmentation

Return ndarray

```
>>> slic = np.array([[0] * 3 + [1] * 3 + [2] * 3] * 4 +
...                 [[4] * 3 + [5] * 3 + [6] * 3] * 4)
>>> segm = np.zeros(slic.shape, dtype=int)
>>> segm[4:, 5:] = 2
>>> histogram_regions_labels_counts(slic, segm)
array([[ 12.,   0.,   0.],
       [ 12.,   0.,   0.],
       [ 12.,   0.,   0.],
       [  0.,   0.,   0.],
       [ 12.,   0.,   0.],
       [  8.,   0.,   4.],
       [  0.,   0.,  12.]])
```

imsegm.labeling.**histogram_regions_labels_norm**(*slic*, *segm*)

normalised histogram or overlapping region between two segmentation, the typical usage is label superpixel from annotation - relative overlap

Parameters

- **slic** (*ndarray*) – input superpixel segmentation
- **segm** (*ndarray*) – reference segmentation

Return ndarray

```
>>> slic = np.array([[0] * 3 + [1] * 3 + [2] * 3] * 4 +
...                 [[4] * 3 + [5] * 3 + [6] * 3] * 4)
>>> segm = np.zeros(slic.shape, dtype=int)
>>> segm[4:, 5:] = 2
>>> histogram_regions_labels_norm(slic, segm)
array([[ 1.        ,  0.        ,  0.        ],
       [ 1.        ,  0.        ,  0.        ],
       [ 1.        ,  0.        ,  0.        ],
       [ 0.        ,  0.        ,  0.        ],
       [ 1.        ,  0.        ,  0.        ],
       [ 0.66666667,  0.        ,  0.33333333],
       [ 0.        ,  0.        ,  1.        ]])
```

imsegm.labeling.**mask_segm_labels**(*img_labeling*, *labels*, *mask_init=None*)

with given labels image and list of desired labels it create mask finding all labels in the list (perform logical or on image with a list of labels)

Parameters

- **im_labeling** (*ndarray*) – np.array<height, width> input labeling
- **labels** (*list(int)*) – list of wanted labels to be detected in image
- **mask_init** (*ndarray*) – np.array<height, width> initial bool mask on the beginning

Return ndarray np.array<height, width> bool mask

```
>>> img = np.zeros((4, 6))
>>> img[:-1, 1:] = 1
>>> img[1:2, 2:4] = 2
>>> mask_segm_labels(img, [1])
array([[False,  True,  True,  True,  True,  True],
       [False,  True, False, False,  True,  True],
       [False,  True,  True,  True,  True,  True],
       [False, False, False, False, False, False]], dtype=bool)
```

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```
>>> mask_segm_labels(img, [2], np.full(img.shape, True, dtype=bool))
array([[ True,  True,  True,  True,  True,  True],
       [ True,  True,  True,  True,  True,  True],
       [ True,  True,  True,  True,  True,  True],
       [ True,  True,  True,  True,  True,  True]], dtype=bool)
```

imsegm.labeling.**merge_probab_labeling_2d**(*proba*, *dict_labels*)
merging probability labeling

Parameters

- **proba** (*ndarray*) – probabilities
- **dict_labels** (*dict(list(int))*) – mapping of label to histogram

Return ndarray

```
>>> p = np.ones((5, 5))
>>> proba = np.array([p * 0.3, p * 0.4, p * 0.2])
>>> proba = np.rollaxis(proba, 0, 3)
>>> proba.shape
(5, 5, 3)
>>> proba_new = merge_probab_labeling_2d(proba, {0: [1, 2], 1: [0]})
>>> proba_new.shape
(5, 5, 2)
>>> proba_new[0, 0]
array([ 0.6,  0.3])
```

imsegm.labeling.**neighbour_connect4**(*seg*, *label*, *pos*)
check incoherent part of the segmentation

Parameters

- **seg** (*ndarray*) – segmentation
- **label** (*int*) – selected label
- **pos** (*tuple(int,int)*) – position

Returns

```
>>> neighbour_connect4(np.eye(5), 1, (2, 2))
True
>>> neighbour_connect4(np.ones((5, 5)), 1, (3, 3))
False
```

imsegm.labeling.**relabel_by_dict**(*labels*, *dict_labels*)
relabel according given dictionary of new - old labels

Parameters

- **labels** (*ndarray*) –
- **dict_labels** (*dict(list(int))*) – mapping of label to histogram

Return ndarray

```
>>> labels = np.array([2, 1, 0, 3, 3, 0, 2, 3, 0, 0])
>>> relabel_by_dict(labels, {0: [1, 2], 1: [0, 3]}).tolist()
[0, 0, 1, 1, 1, 1, 0, 1, 1, 1]
```

imsegm.labeling.**relabel_max_overlap_merge**(*seg_ref*, *seg_relabel*, *keep_bg=False*)
relabel the second segmentation cu that maximise relative overlap for each pattern (object), if one pattern in reference atlas is likely composed from multiple patterns in relabel atlas, it merge them

Note: it skips background class - 0

Parameters

- **seg_ref** (*ndarray*) – reference segmentation
- **seg_relabel** (*ndarray*) – segmentation for relabeling
- **keep_bg** (*bool*) – the label 0 holds

Return ndarray resulting segentation

```
>>> atlas1 = np.zeros((7, 15), dtype=int)
>>> atlas1[1:4, 5:10] = 1
>>> atlas1[5:7, 3:13] = 2
>>> atlas2 = np.zeros((7, 15), dtype=int)
>>> atlas2[0:3, 7:12] = 1
>>> atlas2[3:7, 1:7] = 2
>>> atlas2[4:7, 7:14] = 3
>>> atlas2[:2, :3] = 5
>>> relabel_max_overlap_merge(atlas1, atlas2, keep_bg=True)
array([[1, 1, 1, 0, 0, 0, 0, 1, 1, 1, 1, 1, 0, 0, 0],
       [1, 1, 1, 0, 0, 0, 0, 1, 1, 1, 1, 1, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 0, 0, 0],
       [0, 2, 2, 2, 2, 2, 2, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 0],
       [0, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 0],
       [0, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 0]])
>>> relabel_max_overlap_merge(atlas2, atlas1, keep_bg=True)
array([[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 0, 0],
       [0, 0, 0, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 0, 0]])
>>> relabel_max_overlap_merge(atlas1, atlas2, keep_bg=False)
array([[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 2, 2, 2, 2, 2, 2, 2, 0],
       [0, 0, 0, 0, 0, 0, 0, 2, 2, 2, 2, 2, 2, 2, 0],
       [0, 0, 0, 0, 0, 0, 0, 2, 2, 2, 2, 2, 2, 2, 0]])
```

imsegm.labeling.**relabel_max_overlap_unique**(*seg_ref*, *seg_relabel*, *keep_bg=False*)
relabel the second segmentation cu that maximise relative overlap for each pattern (object), the relation among patterns is 1-1

Note: it skips background class - 0

Parameters

- **seg_ref** (*ndarray*) – reference segmentation
- **seg_relabel** (*ndarray*) – segmentation for relabeling
- **keep_bg** (*bool*) – keep the background

Return ndarray resulting segentation

```
>>> atlas1 = np.zeros((7, 15), dtype=int)
>>> atlas1[1:4, 5:10] = 1
>>> atlas1[5:7, 3:13] = 2
>>> atlas2 = np.zeros((7, 15), dtype=int)
>>> atlas2[0:3, 7:12] = 1
>>> atlas2[3:7, 1:7] = 2
>>> atlas2[4:7, 7:14] = 3
>>> atlas2[:2, :3] = 5
>>> relabel_max_overlap_unique(atlas1, atlas2, keep_bg=True)
array([[5, 5, 5, 0, 0, 0, 0, 1, 1, 1, 1, 1, 0, 0, 0],
       [5, 5, 5, 0, 0, 0, 0, 1, 1, 1, 1, 1, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 0, 0, 0],
       [0, 3, 3, 3, 3, 3, 3, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 3, 3, 3, 3, 3, 3, 2, 2, 2, 2, 2, 2, 2, 0],
       [0, 3, 3, 3, 3, 3, 3, 2, 2, 2, 2, 2, 2, 2, 0],
       [0, 3, 3, 3, 3, 3, 3, 2, 2, 2, 2, 2, 2, 2, 0]])
>>> relabel_max_overlap_unique(atlas2, atlas1, keep_bg=True)
array([[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 0, 0],
       [0, 0, 0, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 0, 0]])
>>> relabel_max_overlap_unique(atlas1, atlas2, keep_bg=False)
array([[5, 5, 5, 0, 0, 0, 0, 1, 1, 1, 1, 1, 0, 0, 0],
       [5, 5, 5, 0, 0, 0, 0, 1, 1, 1, 1, 1, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 0, 0, 0],
       [0, 3, 3, 3, 3, 3, 3, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 3, 3, 3, 3, 3, 3, 2, 2, 2, 2, 2, 2, 2, 0],
       [0, 3, 3, 3, 3, 3, 3, 2, 2, 2, 2, 2, 2, 2, 0],
       [0, 3, 3, 3, 3, 3, 3, 2, 2, 2, 2, 2, 2, 2, 0]])
>>> atlas2[0, 0] = -1
>>> relabel_max_overlap_unique(atlas1, atlas2, keep_bg=True)
array([[-1,  5,  5,  0,  0,  0,  0,  1,  1,  1,  1,  1,  0,  0,  0],
       [ 5,  5,  5,  0,  0,  0,  0,  1,  1,  1,  1,  1,  0,  0,  0],
       [ 0,  0,  0,  0,  0,  0,  0,  1,  1,  1,  1,  1,  0,  0,  0],
       [ 0,  3,  3,  3,  3,  3,  3,  0,  0,  0,  0,  0,  0,  0,  0],
       [ 0,  3,  3,  3,  3,  3,  3,  2,  2,  2,  2,  2,  2,  2,  0],
       [ 0,  3,  3,  3,  3,  3,  3,  2,  2,  2,  2,  2,  2,  2,  0],
       [ 0,  3,  3,  3,  3,  3,  3,  2,  2,  2,  2,  2,  2,  2,  0]])
```

imsegm.labeling.**segm_labels_assignment**(*segm*, *segm_gt*)

create labels assign to the particular regions

Parameters

- **segm** (*ndarray*) – input segmentation
- **segm_gt** (*ndarray*) – true segmentation

Returns

```
>>> slic = np.array([[0] * 3 + [1] * 3 + [2] * 3 + [3] * 3] * 4 +
...                 [[4] * 3 + [5] * 3 + [6] * 3 + [7] * 3] * 4)
>>> segm = np.zeros(slic.shape, dtype=int)
>>> segm[4:, 6:] = 1
>>> segm_labels_assignment(slic, segm)
{0: [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
 1: [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
 2: [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
 3: [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
 4: [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
 5: [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
 6: [1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1],
 7: [1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1]}
```

imsegm.labeling.**sequence_labels_merge**(*labels_stack*, *dict_colors*, *labels_free*, *change_label=-1*)

the input is time series of labeled images and output idx labeled image with labels that was constant for all the time the special case is using free labels which can be assumed as any labeled

Example if labels series, {0, 1, 2} and 0 is free label: - 11111111 -> 1 - 11211211 -> CHANGE_LABEL - 10111100 -> 1 - 00000000 -> CHANGE_LABEL

Parameters

- **labels_stack** (*ndarray*) – np.array<date, height, width> input stack of labeled images
- **{int** – (int, int, int)} dict_colors: dictionary of labels-colors
- **labels_free** (*list(int)*) – list of free labels
- **change_label** (*int*) – label that is set for non constant time series

Return ndarray np.array<height, width>

```
>>> dict_colors = {0: [], 1: [], 2: []}
>>> sequence_labels_merge(np.zeros((8, 1, 1)), dict_colors, [0])
array([[-1]])
>>> sequence_labels_merge(np.ones((8, 1, 1)), dict_colors, [0])
array([[1]])
>>> sequence_labels_merge(np.array([[1], [1], [2], [1], [1], [1], [2], [1]]),␣
↪dict_colors, [0])
array([-1])
>>> sequence_labels_merge(np.array([[1], [0], [1], [1], [1], [1], [0], [0]]),␣
↪dict_colors, [0])
array([1])
```

imsegm.pipelines module

Pipelines for supervised and unsupervised segmentation

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imsegm.pipelines.**compute_color2d_superpixels_features**(*image*, *dict_features*, *sp_size=30*, *sp_regul=0.2*)

segment image into superpixels and estimate features per superpixel

Parameters

- **image** (*ndarray*) – input RGB image
- **dict_features** (*dict(list(str))*) – list of features to be extracted
- **sp_size** (*int*) – initial size of a superpixel(meaning edge length)
- **sp_regul** (*float*) – regularisation in range(0;1) where "0" gives elastic and "1" nearly square segments

Return list(list(int)), [[floats]] superpixels and related of features

imsegm.pipelines.**estim_model_classes_group**(*list_images*, *nb_classes*, *dict_features*, *sp_size=30*, *sp_regul=0.2*, *use_scaler=True*, *pca_coef=None*, *model_type='GMM'*, *nb_workers=1*)

estimate a model from sequence of input images and return it as result

Parameters

- **list_images** (*[ndarray]*) –
- **nb_classes** (*int*) – number of classes
- **sp_size** (*int*) – initial size of a superpixel(meaning edge lenght)
- **sp_regul** (*float*) – regularisation in range(0;1) where "0" gives elastic and "1" nearly square slic
- **dict_features** (*dict(list(str))*) – list of features to be extracted
- **pca_coef** (*float*) – range (0, 1) or None
- **use_scaler** (*bool*) – whether use a scaler
- **model_type** (*str*) – model type
- **nb_workers** (*int*) – number of jobs running in parallel

Returns

imsegm.pipelines.**pipe_color2d_slic_features_model_graphcut**(*image*, *nb_classes*, *dict_features*, *sp_size=30*, *sp_regul=0.2*, *pca_coef=None*, *use_scaler=True*, *estim_model='GMM'*, *gc_regul=1.0*, *gc_edge_type='model'*, *debug_visual=None*)

complete pipe-line for segmentation using superpixels, extracting features and graphCut segmentation

Parameters

- **image** (*ndarray*) – input RGB image
- **nb_classes** (*int*) – number of classes to be segmented(indexing from 0)
- **sp_size** (*int*) – initial size of a superpixel(meaning edge length)
- **sp_regul** (*float*) – regularisation in range(0,1) where 0 gives elastic and 1 nearly square slic
- **dict_features** (*dict*) – {clr: list(str)}
- **pca_coef** (*float*) – range (0, 1) or None

- **estim_model** (*str*) – estimating model
- **gc_regul** (*float*) – GC regularisation
- **gc_edge_type** (*str*) – graphCut edge type
- **use_scaler** (*bool*) – using scaler block in pipeline
- **debug_visual** – dict

Return list(list(int)) segmentation matrix maping each pixel into a class

```
>>> np.random.seed(0)
>>> image = np.random.random((125, 150, 3)) / 2.
>>> image[:, :75] += 0.5
>>> segm, seg_soft = pipe_color2d_slic_features_model_graphcut(image, 2, {'color':
↪ ['mean']})
>>> segm.shape
(125, 150)
>>> seg_soft.shape
(125, 150, 2)
```

imsegm.pipelines.**pipe_gray3d_slic_features_model_graphcut**(*image*, *nb_classes*, *dict_features*, *spacing=(12, 1, 1)*, *sp_size=15*, *sp_regul=0.2*, *gc_regul=0.1*)

complete pipe-line for segmentation using superpixels, extracting features and graphCut segmentation

Parameters

- **image** (*ndarray*) – input RGB image
- **sp_size** (*int*) – initial size of a superpixel(meaning edge lenght)
- **sp_regul** (*float*) – regularisation in range(0;1) where “0” gives elastic and “1” nearly square segments
- **nb_classes** (*int*) – number of classes to be segmented(indexing from 0)
- **spacing** (*tuple(int,int,int)*) –
- **gc_regul** (*float*) – regularisation for GC

Return list(list(int)) segmentation matrix maping each pixel into a class

```
>>> np.random.seed(0)
>>> image = np.random.random((5, 125, 150)) / 2.
>>> image[:, :, :75] += 0.5
>>> segm = pipe_gray3d_slic_features_model_graphcut(image, 2, {'color': ['mean']})
>>> segm.shape
(5, 125, 150)
```

imsegm.pipelines.**segment_color2d_slic_features_model_graphcut**(*image*, *model_pipeline*, *dict_features*, *sp_size=30*, *sp_regul=0.2*, *gc_regul=1.0*, *gc_edge_type='model'*, *debug_visual=None*)

complete pipe-line for segmentation using superpixels, extracting features and graphCut segmentation

Parameters

- **image** (*ndarray*) – input RGB image
- **model_pipeline** (*obj*) –
- **sp_size** (*int*) – initial size of a superpixel(meaning edge lenght)
- **sp_regul** (*float*) – regularisation in range(0;1) where "0" gives elastic and "1" nearly square slic
- **dict_features** (*dict(list(str))*) – list of features to be extracted
- **gc_regul** (*float*) – GC regularisation
- **gc_edge_type** (*str*) – select the GC edge type
- **debug_visual** – dict

Return list(list(int)) segmentation matrix mapping each pixel into a class

Examples

```
>>> # UnSupervised:
>>> import imsegm.descriptors as seg_fts
>>> np.random.seed(0)
>>> seg_fts.USE_CYTHON = False
>>> image = np.random.random((125, 150, 3)) / 2.
>>> image[:, :75] += 0.5
>>> model, _ = estim_model_classes_group([image], 2, {'color': ['mean']})
>>> segm, seg_soft = segment_color2d_slic_features_model_graphcut(image, model, {
↪'color': ['mean']})
>>> segm.shape
(125, 150)
>>> seg_soft.shape
(125, 150, 2)
```

```
>>> # Supervised:
>>> import imsegm.descriptors as seg_fts
>>> np.random.seed(0)
>>> seg_fts.USE_CYTHON = False
>>> image = np.random.random((125, 150, 3)) / 2.
>>> image[:, 75:] += 0.5
>>> annot = np.zeros(image.shape[:2], dtype=int)
>>> annot[:, 75:] = 1
>>> clf, _, _, _ = train_classif_color2d_slic_features([image], [annot], {'color':
↪ ['mean']})
>>> segm, seg_soft = segment_color2d_slic_features_model_graphcut(image, clf, {
↪'color': ['mean']})
>>> segm.shape
(125, 150)
>>> seg_soft.shape
(125, 150, 2)
```

imsegm.pipelines.**train_classif_color2d_slic_features**(*list_images*, *list_annots*, *dict_features*, *sp_size=30*, *sp_regul=0.2*, *clf_name='RandForest'*, *label_purity=0.9*, *feature_balance='unique'*, *pca_coef=None*, *nb_classif_search=1*, *nb_hold_out=2*, *nb_workers=1*)

train classifier on list of annotated images

Parameters

- **list_images** (*[ndarray]*) –
- **list_annots** (*[ndarray]*) –
- **sp_size** (*int*) – initial size of a superpixel(meaning edge lenght)
- **sp_regul** (*float*) – regularisation in range(0;1) where "0" gives elastic and "1" nearly square segments
- **dict_features** (*dict(list(str))*) – list of features to be extracted
- **clf_name** (*str*) – selet udsed classifier
- **label_purity** (*float*) – set the sample-labels purity for training
- **feature_balance** (*str*) – set how to balance datasets
- **pca_coef** (*float*) – select PCA coef or None
- **nb_classif_search** (*int*) – number of tries for hyper-parameters seach
- **nb_hold_out** (*int*) – cross-val leave out
- **nb_workers** (*int*) – parallelism

Returns

imsegm.pipelines.**wrapper_compute_color2d_slic_features_labels**(*img_annot*, *sp_size*, *sp_regul*, *dict_features*, *label_purity*)

imsegm.pipelines.**CLASSIF_NAME = 'RandForest'**
select default Classifier for supervised segmentation

imsegm.pipelines.**CLUSTER_METHOD = 'kMeans'**
select default Modeling/clustering for unsupervised segmentation

imsegm.pipelines.**CROSS_VAL_LEAVE_OUT = 2**
define how many images will be left out during cross-validation training

imsegm.pipelines.**FTS_SET_SIMPLE = {'color': ('mean', 'std', 'energy')}**
select basic features extracted from superpixels

imsegm.pipelines.**NB_WORKERS = 1**
default number of workers

imsegm.region_growing module

Framework for region growing

- general GraphCut segmentation with and without shape model
- region growing with shape prior - greedy & GraphCut

imsegm.region_growing.**compute_centre_moment_points**(*points*)
compute centre and moment from set of points

Parameters **float)] points**(*[(float,)* –

Returns

```
>>> points = list(zip([0] * 10, np.arange(10))) + [(0, 0)] * 5
>>> compute_centre_moment_points(points)
(array([ 0.,  3.]), 0.0)
>>> points = list(zip(np.arange(10), [0] * 10)) + [(10, 0)]
>>> compute_centre_moment_points(points)
(array([ 5.,  0.]), 90.0)
>>> points = list(zip(-np.arange(10), -np.arange(10))) + [(0, 0)] * 5
>>> compute_centre_moment_points(points)
(array([-3., -3.]), 45.0)
>>> points = list(zip(-np.arange(10), np.arange(10))) + [(-10, 10)]
>>> compute_centre_moment_points(points)
(array([-5.,  5.]), 135.0)
```

imsegm.region_growing.**compute_cumulative_distrib**(*means*, *stds*, *weights*, *max_dist*)
compute invers cumulative distribution based given means, covariance and weights for each segment

Parameters

- **means**(*[[float]]*) – mean values for each model and ray direction
- **stds**(*[[float]]*) – STD for each model and ray direction
- **weights**(*[float]*) – model wights
- **max_dist**(*float*) – maxim distance for shape model

Return [[float]]

```
>>> cdist = compute_cumulative_distrib(
...     np.array([[1, 2]]), np.array([[1.5, 0.5], [0.5, 1]]), np.array([0.5]), 6)
>>> np.round(cdist, 2)
array([[ 1.  ,  0.67,  0.34,  0.12,  0.03,  0.  ,  0.  ],
       [ 1.  ,  0.98,  0.5 ,  0.02,  0.  ,  0.  ,  0.  ]])
```

imsegm.region_growing.**compute_data_costs_points**(*slic*, *slic_prob_fg*, *centres*, *labels*)
compute Look up Table ro date term costs

Parameters

- **slic**(*nadarray*) – superpixel segmentation
- **slic_prob_fg**(*list(float)*) – weight for particular pixel belongs to FG
- **int]] centres**(*[[int,)* – actual centre position
- **labels**(*list(int)*) – labels for points to be assigned to an object

Returns

imsegm.region_growing.**compute_object_shapes**(*list_img_objects*, *ray_step=5*, *interp_order=3*, *smooth_coef=0*, *shift_method='phase'*)

for all object in all images compute gravity center and Ray beatures (if object are not split already by different label is made here)

Parameters

- **list_img_objects** ([*nadarray*]) – list of binary segmentation
- **ray_step** (*int*) – select the angular step for Ray features
- **interp_order** (*int*) – if None, no interpolation is performed
- **smooth_coef** (*float*) – smoothing the ray features
- **shift_method** (*str*) – use method for estimate shift maxima (phase or max)

Return tuple(list(list(int)),list(int))

```
>>> img1 = np.zeros((100, 100))
>>> img1[20:50, 30:60] = 1
>>> img1[40:80, 50:90] = 2
>>> img2 = np.zeros((100, 100))
>>> img2[10:40, 20:50] = 1
>>> img2[50:80, 20:50] = 1
>>> img2[50:80, 60:90] = 1
>>> list_imgs = [img1, img2]
>>> list_rays, list_shifts = compute_object_shapes(list_imgs, ray_step=45)
>>> np.array(list_rays).astype(int)
array([[19, 17,  9, 17, 19, 14, 19, 14],
       [29, 21, 28, 20, 28, 20, 28, 21],
       [22, 16, 21, 15, 21, 15, 21, 16],
       [22, 16, 21, 15, 21, 15, 21, 16],
       [22, 16, 21, 15, 21, 15, 21, 16]])
>>> np.array(list_shifts) % 180
array([ 135.,   45.,   45.,   45.,   45.])
```

imsegm.region_growing.**compute_pairwise_penalty**(*edges*, *labels*, *prob_bg_fg=0.05*, *prob_fg1_fg2=0.01*)

compute cost of neighboring labels pionts

Parameters

- **int)] edges** ([(*int*,) – graph edges, connectivity
- **labels** ([*int*]) – labels for vertexes
- **prob_bg_fg** (*float*) – penalty between background and foreground
- **prob_fg1_fg2** (*float*) – penaly between two different foreground classes

Returns

```
>>> edges = np.array([[0, 1], [1, 2], [0, 3], [2, 3], [2, 4]])
>>> labels = np.array([0, 0, 1, 2, 1])
>>> compute_pairwise_penalty(edges, labels, 0.05, 0.01)
array([ 0.        ,  2.99573227,  2.99573227,  4.60517019,  0.        ])
```

imsegm.region_growing.**compute_rg_crit**(*labels*, *lut_data_cost*, *lut_shape_cost*, *slic_weights*, *edges*, *coef_data*, *coef_shape*, *coef_pairwise*, *prob_label_trans*)

imsegm.region_growing.**compute_segm_object_shape**(*img_object*, *ray_step=5*, *interp_order=3*, *smooth_coef=0*, *shift_method='phase'*)

assuming single object in image and compute gravity centre and for this point compute Ray features and optionally: - interpolate missing values - smooth the Ray features

Parameters

- **img_object** (*ndarray*) – binary segmentation of single object
- **ray_step** (*int*) – select the angular step for Ray features
- **interp_order** (*int*) – if None, no interpolation is performed
- **smooth_coef** (*float*) – smoothing the ray features
- **shift_method** (*str*) – use method for estimate shift maxima (phase or max)

Return tuple(list(int), int)

```
>>> img = np.zeros((100, 100))
>>> img[20:70, 30:80] = 1
>>> rays, shift = compute_segm_object_shape(img, ray_step=45)
>>> rays
[36.7..., 26.0..., 35.3..., 25.0..., 35.3..., 25.0..., 35.3..., 26.0...]
```

imsegm.region_growing.**compute_segm_prob_fg**(*slic*, *segm*, *labels_prob*)

compute probability being forground from input segmentation

Parameters

- **slic** (*ndarray*) –
- **segm** (*ndarray*) –
- **labels_prob** (*list(float)*) –

Returns

```
>>> slic = np.array([[0, 0, 0, 0, 1, 1, 1, 1], [2, 2, 2, 2, 3, 3, 3, 3]])
>>> segm = np.array([0, 1, 1, 0])[slic]
>>> compute_segm_prob_fg(slic, segm, [0.3, 0.8])
array([ 0.3,  0.8,  0.8,  0.3])
```

imsegm.region_growing.**compute_shape_prior_table_cdf**(*point*, *cum_distribution*, *centre*, *angle_shift=0*)

compute shape prior for a point based on centre, rotation shift and cumulative histogram

Parameters

- **point** (*tuple(int,int)*) – single points
- **centre** (*tuple(int,int)*) – center of model
- **cum_distribution** (*[[float]]*) – cumulative histogram
- **angle_shift** (*float*) –

Return float

```
>>> chist = [[1.0, 1.0, 0.8, 0.7, 0.6, 0.5, 0.3, 0.0, 0.0],
...          [1.0, 1.0, 0.9, 0.8, 0.7, 0.3, 0.2, 0.2, 0.0],
...          [1.0, 1.0, 1.0, 0.7, 0.6, 0.5, 0.3, 0.1, 0.1],
...          [1.0, 1.0, 0.6, 0.5, 0.4, 0.3, 0.2, 0.0, 0.0]]
```

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```
>>> centre = (1, 1)
>>> compute_cdf = compute_shape_prior_table_cdf
>>> compute_cdf([1, 1], chist, centre)
1.0
>>> compute_cdf([10, 10], chist, centre)
0.0
>>> compute_cdf([10, -10], chist, centre)
0.100...
>>> compute_cdf([2, 3], chist, centre)
0.805...
>>> compute_cdf([-3, -2], chist, centre)
0.381...
>>> compute_cdf([3, -2], chist, centre)
0.676...
>>> compute_cdf([2, 3], chist, centre, angle_shift=270)
0.891...
```

imsegm.region_growing.**compute_update_shape_costs_points_close_mean_cdf**(*lut_shape_cost*, *slic*, *points*, *labels*, *init_centres*, *centres*, *shifts*, *volumes*, *shape_model_cdfs*, *selected_idx=None*, *swap_shift=False*, *dict_thresholds=None*)

update the shape prior for given segmentation (new centre is computed), set of points and cumulative histogram representing the shape model

Parameters

- **lut_shape_cost** – look-up-table for shape cost for GC
- **slic** (*ndarray*) – superpixel segmentation
- **int]] points** (*[[int,]*) – subsample space, points = superpixel centres
- **labels** (*list (int)*) – labels for points to be assigned to an object
- **int]] init_centres** (*[[int,]*) – initial centre position for compute center shift during the iterations
- **int]] centres** (*[[int,]*) – actual centre position
- **shifts** (*list (int)*) – orientation for each region / object
- **volumes** (*list (int)*) – size / volume for each region
- **shape_model_cdfs** – represent the shape prior and histograms
- **selected_idx** (*list (int)*) – selected object for update

- **swap_shift** (*bool*) – allow swapping orientation by 90 degree, try to get out from local optimal
- **dict_thresholds** (*dict | None*) – configuration with thresholds
- **dict_thresholds** – set some threshold updating shape prior

Return tuple(list(float),list(int))

```
>>> np.random.seed(0)
>>> h, w, step = 8, 8, 2
>>> slic = np.array([[ 0,  0,  1,  1,  2,  2,  3,  3],
...                  [ 0,  0,  1,  1,  2,  2,  3,  3],
...                  [ 4,  4,  5,  5,  6,  6,  7,  7],
...                  [ 4,  4,  5,  5,  6,  6,  7,  7],
...                  [ 8,  8,  9,  9, 10, 10, 11, 11],
...                  [ 8,  8,  9,  9, 10, 10, 11, 11],
...                  [12, 12, 13, 13, 14, 14, 15, 15],
...                  [12, 12, 13, 13, 14, 14, 15, 15]])
>>> points = np.array([(0, 0), (0, 2), (0, 4), (0, 6), (2, 0), (2, 2),
...                    (2, 4), (2, 6), (4, 0), (4, 2), (4, 4), (4, 6),
...                    (6, 0), (6, 2), (6, 4), (6, 6)])
>>> labels = np.array([0] * 4 + [0, 1, 1, 0, 0, 1, 1, 0] + [0] * 4)
>>> cdf1, cdf2 = np.zeros((8, 10)),  np.zeros((8, 7))
>>> cdf1[:7] = 0.5
>>> cdf1[:4] = 1.0
>>> cdf2[:6] = 1.0
>>> set_m_cdf = [([4] * 8, cdf1), ([5] * 8, cdf2)]
>>> s_costs = np.zeros((len(points), 2))
>>> mm = mixture.GaussianMixture(2).fit(np.random.random((100, 8)))
>>> s_costs, centres, shifts, _ = compute_update_shape_costs_points_close_mean_
↪cdf(
...                         s_costs, slic, points, labels, [(0, 0)],
...                         [(np.Inf, np.Inf)], [0], [0], (mm, set_m_cdf))
>>> centres
array([[3, 3]])
>>> shifts
array([ 90.])
>>> np.round(s_costs, 3)
array([[ 0.   , -0.01 ],
       [ 0.   , -0.01 ],
       [ 0.   , -0.01 ],
       [ 0.   , -0.01 ],
       [ 0.   , -0.01 ],
       [ 0.   , -0.01 ],
       [ 0.   , -0.01 ],
       [ 0.   ,  0.868],
       [ 0.   , -0.01 ],
       ...
       [ 0.   ,  4.605]])
```

imsegm.region_growing.**compute_update_shape_costs_points_table_cdf**(*lut_shape_cost*, *points*, *labels*, *init_centres*, *centres*, *shifts*, *volumes*, *shape_chist*, *selected_idx=None*, *swap_shift=False*, *dict_thresholds=None*)

update the shape prior for given segmentation (new centre is computed), set of points and cumulative histogram representing the shape model

Parameters

- **lut_shape_cost** – look-up-table for shape cost for GC
- **int]] points** (*[[int,*) – subsample space, points = superpixel centres
- **labels** (*list(int)*) – labels for points to be assigned to an object
- **int]] init_centres** (*[[int,*) – initial centre position for compute center shift during the iteretions
- **int]] centres** (*[[int,*) – actual centre postion
- **shifts** (*list(int)*) – orientation for each region / object
- **volumes** (*list(int)*) – size / volume for each region
- **shape_chist** – represent the shape prior and histograms
- **selected_idx** (*list(int)*) – selected object for update
- **swap_shift** (*bool*) – allow swapping orientation by 90 degree, try to get out from local optimal
- **dict_thresholds** (*dict|None*) – configuration with thresholds
- **dict_thresholds** – set some threshold updating shape prior

Return tuple(list(float),list(int))

```
>>> cdf = np.zeros((8, 20))
>>> cdf[:10] = 0.5
>>> cdf[:4] = 1.0
>>> points = np.array([[13, 16], [1, 5], [10, 15], [15, 25], [10, 5]])
>>> labels = np.ones(len(points))
>>> s_costs = np.zeros((len(points), 2))
>>> s_costs, centres, shifts, _ = compute_update_shape_costs_points_table_cdf(
...     s_costs, points, labels, [(0, 0)], [(np.Inf, np.Inf)], [0], [0], (None,␣
↪cdf))
>>> centres
array([[10, 13]])
>>> shifts
array([ 209.])
>>> np.round(s_costs, 3)
array([[ 0.   ,  0.673],
       [ 0.   , -0.01 ],
       [ 0.   ,  0.184],
```

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```
       [ 0.   ,  0.543],
       [ 0.   ,  0.374]])
>>> dict_thrs = RG2SP_THRESHOLDS
>>> dict_thrs['centre_init'] = 1
>>> _, centres, _, _ = compute_update_shape_costs_points_table_cdf(
...     s_costs, points, labels, [(7, 18)], [(np.Inf, np.Inf)], [0], [0], (None,␣
↪cdf),
...     dict_thresholds=dict_thrs)
>>> np.round(centres, 1)
array([[  7.5,  17.1]])
```

imsegm.region_growing.**enforce_center_labels**(*slic*, *labels*, *centres*)

force the labels to hold label of the center, prevention of desepearing labels of any center in list

Parameters

- **slic** –
- **labels** –
- **centres** –

Returns

imsegm.region_growing.**get_neighboring_candidates**(*slic_neighbours*, *labels*, *object_idx*, *use_other_obj=True*)

get neighboring candidates from background and optionally also from foreground if it is allowed

Parameters

- **slic_neighbours** (*[[int]]*) – list of neighboring superpixel for each one
- **labels** (*[int]*) – labels for each superpixel
- **object_idx** (*int*) –
- **use_other_obj** (*bool*) – allowing use another foreground object

Return [int]

```
>>> neighbours = [[1], [0, 2, 3], [1, 3], [1, 2]]
>>> labels = np.array([0, 0, 1, 1])
>>> get_neighboring_candidates(neighbours, labels, 1)
[1]
```

imsegm.region_growing.**object_segmentation_graphcut_pixels**(*segm*, *centres*, *labels_fg_prob=(0.1, 0.9)*, *gc_regul=1*, *seed_size=0*, *coef_shape=0.0*, *shape_mean_std=(50.0, 10.0)*, *debug_visual=None*)

object segmentation using Graph Cut directly on pixel level

Parameters

- **centres** (*ndarray*) –
- **segm** (*ndarray*) – input structure segmentation
- **int)] centres** (*[(int,*) – superpixel centres

- **labels_fg_prob** (*list(float)*) – set how much particular label belongs to foreground
- **gc_regul** (*float*) – regularisation for GC
- **seed_size** (*int*) – create circular neighborhood around initial centre
- **coef_shape** (*float*) – set the weight of shape prior
- **shape_mean_std** – mean and STD for shape prior
- **debug_visual** (*dict*) – dictionary with some intermediate results

Return list(list(int))

```
>>> segm = np.array([[0] * 10,
...                  [1] * 5 + [0] * 5, [1] * 4 + [0] * 6,
...                  [0] * 6 + [1] * 4, [0] * 5 + [1] * 5,
...                  [0] * 10])
>>> centres = [(1, 2), (4, 8)]
>>> object_segmentation_graphcut_pixels(segm, centres, gc_regul=0., coef_shape=0.
↪5)
array([[0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [2, 2, 1, 2, 2, 0, 0, 0, 0, 0],
       [2, 2, 2, 2, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 2, 2, 2, 2],
       [0, 0, 0, 0, 0, 2, 2, 2, 2, 2],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0]], dtype=int32)
>>> object_segmentation_graphcut_pixels(segm, centres, gc_regul=.5, seed_size=1)
array([[0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [1, 1, 1, 1, 1, 0, 0, 0, 0, 0],
       [1, 1, 1, 1, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 2, 2, 2, 2],
       [0, 0, 0, 0, 0, 2, 2, 2, 2, 2],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0]], dtype=int32)
```

imsegm.region_growing.**object_segmentation_graphcut_slic**(*slic*, *segm*, *centres*, *labels_fg_prob=(0.1, 0.9)*, *gc_regul=1*, *edge_coef=0.5*, *edge_type='model'*, *coef_shape=0.0*, *shape_mean_std=(50.0, 10.0)*, *add_neighbours=False*, *debug_visual=None*)

object segmentation using Graph Cut directly on super-pixel level

Parameters

- **slic** (*ndarray*) – superpixel pre-segmentation
- **segm** (*ndarray*) – input structure segmentation
- **int)] centres** (*[(int,*) – superpixel centres
- **labels_fg_prob** (*list(float)*) – weight for particular label belongs to FG
- **gc_regul** (*float*) – regularisation for GC
- **edge_coef** (*float*) – weight og edges on GC
- **edge_type** (*str*) – select the egde weights on graph

- **coef_shape** (*float*) – set the weight of shape prior
- **shape_mean_std** – mean and STD for shape prior
- **add_neighbours** (*bool*) – add also neighboring supepixels to the center
- **debug_visual** (*dict*) – dictionary with some intermediate results

Return list(list(int))

```
>>> slic = np.array([[0] * 3 + [1] * 3 + [2] * 3 + [3] * 3 + [4] * 3,
...                  [5] * 3 + [6] * 3 + [7] * 3 + [8] * 3 + [9] * 3])
>>> segm = np.array([[0] * 15, [1] * 12 + [0] * 3])
>>> object_segmentation_graphcut_slic(slic, segm, [(1, 7)], gc_regul=0., edge_
↪coef=1., coef_shape=1.)
array([0, 0, 0, 0, 0, 1, 1, 1, 1, 0], dtype=int32)
>>> object_segmentation_graphcut_slic(slic, segm, [(1, 7)], gc_regul=1., edge_
↪coef=1., debug_visual={})
array([0, 0, 0, 0, 0, 1, 1, 1, 1, 0], dtype=int32)
```

imsegm.region_growing.**prepare_graphcut_variables**(*candidates*, *slic_points*, *slic_neighbours*, *slic_weights*, *labels*, *nb_centres*, *lut_data_cost*, *lut_shape_cost*, *coef_data*, *coef_shape*, *coef_pairwise*, *prob_label_trans*)

for boundary get connected points in BG and FG construct graph and set potentials and hard connect BG and FG in unary

Parameters

- **candidates** (*[int]*) – list of candidates, neighbours of actual objects
- **int)] slic_points** (*[(int,)* –
- **slic_neighbours** (*[[int]]*) – list of neighboring superpixel for each one
- **slic_weights** (*list(float)*) – weight for each superpixel
- **labels** (*[int]*) – labels for each superpixel
- **nb_centres** (*int*) – number of centres - classes
- **lut_data_cost** (*ndarray*) – look-up-table for data cost for each object (class) with superpixel as first index
- **lut_shape_cost** (*ndarray*) – look-up-table for shape cost for each object (class) with superpixel as first index
- **coef_data** (*float*) – weight for data priors
- **coef_shape** (*float*) – weight for shape priors
- **coef_pairwise** (*float*) – CG pairwise coeficient
- **prob_label_trans** – probability transition between background (first) and objects and among objects (second)

Returns

imsegm.region_growing.**region_growing_shape_slic_graphcut**(*slic, slic_prob_fg, centres, shape_model, shape_type='cdf', coef_data=1.0, coef_shape=1, coef_pairwise=2, prob_label_trans=(0.1, 0.03), optim_global=True, allow_obj_swap=True, dict_thresholds=None, nb_iter=999, debug_history=None*)

Region growing method with given shape prior on pre-segmented images it uses the GraphCut strategy on neigbouring superpixels

Parameters

- **slic** (*ndarray*) – superpixel segmentation
- **slic_prob_fg** (*list (float)*) – weight for particular superpixel belongs to FG
- **int)] centres** (*[(int,*) – list of initial centres
- **shape_model** – represent the shape prior and histograms
- **shape_type** (*str*) – identification of used shape model
- **coef_data** (*float*) – weight for data prior
- **coef_shape** (*float*) – weight for shape prior
- **coef_pairwise** (*float*) – setting for pairwise cost
- **prob_label_trans** – probability transition between background (first) and objects and among objects (second)
- **optim_global** (*bool*) – optimise the GC as global or per object
- **allow_obj_swap** (*bool*) – allow swapping foreground object labels
- **dict_thresholds** (*dict | None*) – configuration with thresholds
- **nb_iter** (*int*) – maximal number of iterations
- **dict_thresholds** – set some threshold updating shape prior

```
>>> h, w, step = 15, 20, 2
>>> segm = np.zeros((h, w), dtype=int)
>>> segm[3:12, 5:17] = 1
>>> segm
array([[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0],
       [0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0],
       [0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0],
       [0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0],
       [0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0],
       [0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0],
       [0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0],
       [0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0],
```

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```
        [0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0],
        [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
        [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
        [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0]])
>>> slic = np.zeros((h, w), dtype=int)
>>> for i in range(int(np.ceil(h / float(step)))):
...     for j in range(int(np.ceil(w / float(step)))):
...         val = i * (w / step) + j
...         i_step, j_step = int(i * step), int(j * step)
...         slic[i_step:int(i_step + step), j_step:int(j_step + step)] = val
>>> centres = [(7.5, 10)]
>>> chist = [[1.] * 3 + [0.8, 0.7, 0.6, 0.5, 0.3, 0.1, 0.0],
...          [1.] * 3 + [0.9, 0.8, 0.7, 0.3, 0.2, 0.2, 0.1],
...          [1.] * 3 + [1.0, 0.7, 0.6, 0.5, 0.3, 0.1, 0.1],
...          [1.] * 3 + [0.6, 0.5, 0.4, 0.3, 0.2, 0.1, 0.0]]
>>> dict_debug = {}
>>> slic_prob_fg = compute_segm_prob_fg(slic, segm, [0.1, 0.9])
>>> labels = region_growing_shape_slic_graphcut(slic, slic_prob_fg, centres,
...                                            (None, chist), coef_pairwise=0,
...                                            debug_history=dict_debug)
>>> np.round(dict_debug['criteria']).astype(int)
array([397, 325, 206, 111,  81,  81])
>>> labels[slic]
array([[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0]])
>>> labels = region_growing_shape_slic_graphcut(slic, slic_prob_fg, centres,
...                                            (None, chist), coef_pairwise=2,
...                                            debug_history=dict_debug)
>>> np.round(dict_debug['criteria']).astype(int)
array([415, 380, 289, 193, 164, 164])
>>> labels[slic]
array([[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
```

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```
        [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
        [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0]])
>>> segm = np.ones((h, w), dtype=int)
>>> chist = np.zeros((16, 9))
>>> chist[:, :5] = 1.
>>> dict_debug = {}
>>> slic_prob_fg = compute_segm_prob_fg(slic, segm, [0.1, 0.9])
>>> labels = region_growing_shape_slic_graphcut(slic, slic_prob_fg, [(6.5, 9)],
...                                                  (None, chist), coef_shape=10.,
...                                                  coef_pairwise=1,
...                                                  debug_history=dict_debug)
>>> np.round(dict_debug['criteria']).astype(int)
array([7506, 7120, 6328, 5719, 5719])
>>> labels[slic]
array([[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0]])
```

imsegm.region_growing.**region_growing_shape_slic_greedy**(*slic, slic_prob_fg, centres, shape_model, shape_type='cdf', coef_data=1.0, coef_shape=1, coef_pairwise=1, prob_label_trans=(0.1, 0.01), allow_obj_swap=True, greedy_tol=0.001, dict_thresholds=None, nb_iter=999, debug_history=None*)

Region growing method with given shape prior on pre-segmented images it uses the Greedy strategy and set some stopping criterion

Parameters

- **slic** (*ndarray*) – superpixel segmentation
- **slic_prob_fg** (*list(float)*) – weight for particular superpixel belongs to FG
- **int)] centres** (*[(int,*) – list of initial centres
- **shape_model** – represent the shape prior and histograms
- **shape_type** (*str*) – identification of used shape model
- **coef_data** (*float*) – weight for data prior

- **coef_shape** (*float*) – weight for shape prior
- **coef_pairwise** (*float*) – setting for pairwise cost
- **prob_label_trans** – probability transition between background (first) and objects and among objects (second)
- **allow_obj_swap** (*bool*) – allow swapping foreground object labels
- **greedy_tol** (*float*) – stopping criterion - energy change between inters
- **dict_thresholds** (*dict | None*) – configuration with thresholds
- **nb_iter** (*int*) – maximal number of iterations
- **dict_thresholds** – set some threshold updating shape prior

Returns

```
>>> np.random.seed(0)
>>> h, w, step = 15, 20, 2
>>> segm = np.zeros((h, w), dtype=int)
>>> segm[3:12, 5:17] = 1
>>> segm
array([[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0],
       [0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0],
       [0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0],
       [0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0],
       [0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0],
       [0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0],
       [0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0],
       [0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0],
       [0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0]])
>>> slic = np.zeros((h, w), dtype=int)
>>> for i in range(int(np.ceil(h / float(step)))):
...     for j in range(int(np.ceil(w / float(step)))):
...         val = i * (w / step) + j
...         i_step, j_step = int(i * step), int(j * step)
...         slic[i_step:int(i_step + step), j_step:int(j_step + step)] = val
>>> centres = [(7.5, 10)]
>>> chist = [[1.] * 3 + [0.8, 0.7, 0.6, 0.5, 0.3, 0.1, 0.0],
...          [1.] * 3 + [0.9, 0.8, 0.7, 0.3, 0.2, 0.2, 0.1],
...          [1.] * 3 + [1.0, 0.7, 0.6, 0.5, 0.3, 0.1, 0.1],
...          [1.] * 3 + [0.6, 0.5, 0.4, 0.3, 0.2, 0.1, 0.0]]
>>> dict_debug = {}
>>> slic_prob_fg = compute_segm_prob_fg(slic, segm, [0.1, 0.9])
>>> labels = region_growing_shape_slic_greedy(slic, slic_prob_fg, centres,
...                                           (None, chist), coef_pairwise=0,
...                                           debug_history=dict_debug)
>>> np.round(dict_debug['criteria']).astype(int)
array([397, 325, 307, 289, 272, 238, 204, 188, 173, ..., 81,  81])
>>> labels[slic]
array([[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
```

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```
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0]])
>>> labels = region_growing_shape_slic_greedy(slic, slic_prob_fg, centres,
...                                  (None, chist), coef_pairwise=1,
...                                  debug_history=dict_debug)
>>> np.round(dict_debug['criteria']).astype(int)
array([406, 352, 334, 316, 300, 283, 270, 254, 238, 226, 210, ..., 123, 123])
>>> labels[slic]
array([[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0]])
>>> segm = np.ones((h, w), dtype=int)
>>> chist = np.zeros((16, 9))
>>> chist[:, :5] = 1.
>>> slic_prob_fg = compute_segm_prob_fg(slic, segm, [0.1, 0.9])
>>> labels = region_growing_shape_slic_greedy(slic, slic_prob_fg, [(6.5, 9)],
...                                  (None, chist), coef_shape=10,
...                                  coef_pairwise=1,
...                                  debug_history=dict_debug)
>>> np.round(dict_debug['criteria']).astype(int)
array([7506, 7120, 6715, 6328, 5719, 5719])
>>> labels[slic]
array([[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
```

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```
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0]])
```

imsegm.region_growing.**transform_rays_model_cdf_histograms**(*list_rays*, *nb_bins=10*)

from list of all measured rays create cumulative histogram for each ray

Parameters

- **list_rays** (*list (list (int))*) – list ray features (distances)
- **nb_bins** (*int*) – binarise histogram

Returns

```
>>> list_rays = [[9, 4, 9], [4, 9, 7], [9, 7, 11], [10, 8, 10],
...              [9, 11, 8], [4, 8, 5], [8, 10, 6], [9, 7, 11]]
>>> chist = transform_rays_model_cdf_histograms(list_rays, nb_bins=5)
>>> chist
[[1.0, 1.0, 1.0, 1.0, 0.75, 0.75, 0.75, 0.625, 0.625, 0.0, 0.0, 0.0],
 [1.0, 1.0, 1.0, 1.0, 0.875, 0.875, 0.875, 0.375, 0.25, 0.25, 0.0, 0.0],
 [1.0, 1.0, 1.0, 1.0, 1.0, 0.75, 0.625, 0.5, 0.375, 0.375, 0.0, 0.0]]
```

imsegm.region_growing.**transform_rays_model_cdf_kmeans**(*list_rays*, *nb_components=None*)

compute the mixture model and transform it into cumulative distribution

Parameters

- **list_rays** (*list (list (int))*) – list ray features (distances)
- **nb_components** (*int*) – number components in mixture model

Return any, list(list(int)) mixture model, list of stat/param of models

```
>>> np.random.seed(0)
>>> list_rays = [[9, 4, 9], [4, 9, 7], [9, 7, 11], [10, 8, 10],
...              [9, 11, 8], [4, 8, 5], [8, 10, 6], [9, 7, 11]]
>>> mm, cdist = transform_rays_model_cdf_kmeans(list_rays)
>>> np.round(cdist, 1).tolist()
[[1.0, 1.0, 1.0, 1.0, 0.9, 0.8, 0.7, 0.7, 0.6, 0.4, 0.2, 0.0, 0.0],
 [1.0, 1.0, 1.0, 1.0, 0.9, 0.9, 0.8, 0.7, 0.5, 0.3, 0.2, 0.1, 0.0],
 [1.0, 1.0, 1.0, 1.0, 1.0, 0.9, 0.8, 0.7, 0.5, 0.4, 0.2, 0.1, 0.0]]
>>> mm, cdist = transform_rays_model_cdf_kmeans(list_rays, nb_components=2)
```

imsegm.region_growing.**transform_rays_model_cdf_mixture**(*list_rays*, *coef_components=1*)

compute the mixture model and transform it into cumulative distribution

Parameters

- **list_rays** (*list (list (int))*) – list ray features (distances)
- **coef_components** (*int*) – multiplication for number of components

Return any, list(list(int)) mixture model, cumulative distribution

```
>>> np.random.seed(0)
>>> list_rays = [[9, 4, 9], [4, 9, 7], [9, 7, 11], [10, 8, 10],
...              [9, 11, 8], [4, 8, 5], [8, 10, 6], [9, 7, 11]]
>>> mm, cdist = transform_rays_model_cdf_mixture(list_rays)
>>> # the rounding variate a bit according GMM estimated model
```

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```
>>> np.round(np.array(cdist) * 4) / 4.
array([[ 1. , 1. , 1. , 1. , 1. , 1. , 0.75, 0.75, 0.5 , 0.25, 0. ],
       [ 1. , 1. , 1. , 1. , 1. , 1. , 1.  , 0.75, 0.5 , 0.25, 0. ],
       [ 1. , 1. , 1. , 1. , 1. , 1. , ...,  0.75, 0.5 , 0.25, 0. ]])
```

imsegm.region_growing.**transform_rays_model_cdf_spectral**(*list_rays*, *nb_components=5*)

compute the mixture model and transform it into cumulative distribution

Parameters

- **list_rays** (*list(list(int))*) – list ray features (distances)
- **nb_components** (*int*) – number components in mixture model

Return tuple(any,list(list(int))) mixture model, list of stat/param of models

```
>>> np.random.seed(0)
>>> list_rays = [[9, 4, 9], [4, 9, 7], [9, 7, 11], [10, 8, 10],
...              [9, 11, 8], [4, 8, 5], [8, 10, 6], [9, 7, 11]]
>>> mm, cdist = transform_rays_model_cdf_spectral(list_rays)
>>> np.round(cdist, 1).tolist()
[[1.0, 1.0, 1.0, 1.0, 1.0, 0.9, 0.8, 0.6, 0.5, 0.2, 0.0],
 [1.0, 1.0, 1.0, 1.0, 1.0, 0.9, 0.9, 0.7, 0.5, 0.2, 0.0],
 [1.0, 1.0, 1.0, 1.0, 1.0, 0.9, 0.8, 0.7, 0.5, 0.3, 0.0]]
```

imsegm.region_growing.**transform_rays_model_sets_mean_cdf_kmeans**(*list_rays*, *nb_components=5*)

compute the mixture model and transform it into cumulative distribution

Parameters

- **list_rays** (*list(list(int))*) – list ray features (distances)
- **nb_components** (*int*) – number components in mixture model

Return tuple(any,list(list(int))) mixture model, list of stat/param of models

```
>>> np.random.seed(0)
>>> list_rays = [[9, 4, 9], [4, 9, 7], [9, 7, 11], [10, 8, 10],
...              [9, 11, 8], [4, 8, 5], [8, 10, 6], [9, 7, 11]]
>>> mm, mean_cdf = transform_rays_model_sets_mean_cdf_kmeans(list_rays, 2)
>>> len(mean_cdf)
2
```

imsegm.region_growing.**transform_rays_model_sets_mean_cdf_mixture**(*list_rays*, *nb_components=5*, *slic_size=15*)

compute the mixture model and transform it into cumulative distribution

Parameters

- **list_rays** (*list(list(int))*) – list ray features (distances)
- **nb_components** (*int*) – number components in mixture model
- **slic_size** (*int*) – superpixel size

Return tuple(any,list(list(int))) mixture model, list of stat/param of models

```
>>> np.random.seed(0)
>>> list_rays = [[9, 4, 9], [4, 9, 7], [9, 7, 11], [10, 8, 10],
...              [9, 11, 8], [4, 8, 5], [8, 10, 6], [9, 7, 11]]
>>> mm, mean_cdf = transform_rays_model_sets_mean_cdf_mixture(list_rays, 2)
>>> len(mean_cdf)
2
```

imsegm.region_growing.**update_shape_costs_points**(*lut_shape_cost*, *slic*, *points*, *labels*, *init_centres*, *centres*, *shifts*, *volumes*, *shape_model*, *shape_type*, *selected_idx=None*, *swap_shift=False*, *dict_thresholds=None*)

update the shape prior for given segmentation (new centre is computed), set of points and shape model

Parameters

- **lut_shape_cost** – look-up-table for shape cost for GC
- **slic** (*nadarray*) – superpixel segmentation
- **int]] points** (*[[int,*) – subsample space, points = superpixel centres
- **labels** (*list(int)*) – labels for points to be assigned to an object
- **int]] init_centres** (*[[int,*) – initial centre position for compute center shift during the iteretions
- **int]] centres** (*[[int,*) – actual centre postion
- **shifts** (*list(int)*) – orientation for each region / object
- **volumes** (*[int]*) – size / volume for each region
- **shape_model** – represent the shape prior and histograms
- **shape_type** (*str*) – type or shape model
- **selected_idx** (*[int]*) – selected object for update
- **swap_shift** (*bool*) – allow swapping orientation by 90 degree, try to get out from local optima
- **dict_thresholds** (*dict | None*) – configuration with thresholds
- **dict_thresholds** – set some threshold updating shape prior

Return tuple(list(float),list(int))

imsegm.region_growing.**GC_REPLACE_INF = 100000.0**

all infinty values in Grah-Cut terms replace by this value

imsegm.region_growing.**MAX_UNARY_PROB = 0.99**

define maximal value of unary (being a class) term in Graph-Cut

imsegm.region_growing.**MIN_SHAPE_PROB = 0.01**

define minimal value for any vodel of shape prior term

imsegm.region_growing.**RG2SP_THRESHOLDS = {'centre': 30, 'centre_init': 50, 'shift': 15, 'v**

define thresholds parameters for iterative Region Growing

imsegm.superpixels module

Framework for superpixels

- wrapper over skimage.SLIC
- other related functions

SEE: * http://scikit-image.org/docs/dev/auto_examples/plot_segmentations.html

imsegm.superpixels.**get_neighboring_segments**(*edges*)
get the indexes of neighboring superpixels for each superpixel the input is list edges of all neighboring segments

Parameters **int]] edges** (*[[int,*) –

Return [[int]]

```
>>> get_neighboring_segments([[0, 1], [1, 2], [1, 3], [2, 3]])
[[1], [0, 2, 3], [1, 3], [1, 2]]
```

imsegm.superpixels.**get_segment_diffs_2d_conn4**(*grid*)
wrapper for getting 4-connected in 2D image plane

Parameters **grid** (*ndarray*) – segmentation

Return [(int, int)]

imsegm.superpixels.**get_segment_diffs_3d_conn6**(*grid*)
wrapper for getting 6-connected in 3D image plane

Parameters **grid** (*ndarray*) – segmentation

Return [(int, int, int)]

imsegm.superpixels.**make_graph_segm_connect_grid2d_conn4**(*grid*)
construct graph of connected components

Parameters **grid** (*ndarray*) – segmentation

Return [int], [(int, int)]

```
>>> grid = np.array([[0] * 5 + [1] * 5, [2] * 5 + [3] * 5])
>>> v, edges = make_graph_segm_connect_grid2d_conn4(grid)
>>> v
array([0, 1, 2, 3])
>>> edges
[[0, 1], [0, 2], [1, 3], [2, 3]]
```

imsegm.superpixels.**make_graph_segm_connect_grid3d_conn6**(*grid*)
construct graph of connected components

Parameters **grid** (*ndarray*) – segmentation

Return [int], [(int, int)]

```
>>> grid_2d = np.array([[0] * 5 + [1] * 5, [2] * 5 + [3] * 5])
>>> grid = np.array([grid_2d, grid_2d + 4])
>>> v, edges = make_graph_segm_connect_grid3d_conn6(grid)
>>> v
array([0, 1, 2, 3, 4, 5, 6, 7])
>>> edges
```

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```
[[0, 1], [0, 2], [1, 3], [2, 3], [0, 4], [1, 5], [4, 5], [2, 6], [4, 6],
[3, 7], [5, 7], [6, 7]]
```

imsegm.superpixels.**make_graph_segment_connect_edges**(*vertices*, *all_edges*)
make graph of connencted components SEE: http://peekaboo-vision.blogspot.cz/2011/08/region-connectivity-graphs-in-python.html

Parameters

- **vertices** (*ndarray*) –
- **all_edges** (*ndarray*) –

Return tuple(ndarray,ndarray)

imsegm.superpixels.**segment_slic_img2d**(*img*, *sp_size=50*, *relative_compact=0.1*, *slico=False*)
segmentation by SLIC superpixels using original SLIC implementation

Parameters

- **img** (*ndarray*) – input color image
- **sp_size** (*int*) – superpixel initial size
- **relative_compact** (*float*) – relative regularisation in range (0, 1) where 0 is for free form and 1 for nearly rectangular superpixels
- **slico** (*bool*) – whether use parameter free version ASLIC/SLICO

Return ndarray segmentation

```
>>> np.random.seed(0)
>>> img = np.random.random((100, 150, 3))
>>> slic = segment_slic_img2d(img, 20, 0.2)
>>> slic.shape
(100, 150)
>>> img = np.random.random((150, 100))
>>> slic = segment_slic_img2d(img, 20, 0.2)
>>> slic.shape
(150, 100)
```

imsegm.superpixels.**segment_slic_img3d_gray**(*im*, *sp_size=50*, *relative_compact=0.1*, *space=(1, 1, 1)*)
segmentation by SLIC superpixels using originla SLIC implementation

Parameters

- **im** (*ndarray*) – input 3D grascale image
- **sp_size** (*int*) – superpixel initial size
- **relative_compact** (*float*) – relative regularisation in range (0, 1) where 0 is for free form and 1 for nearly rectangular superpixels
- **space** (*tuple(int,int,int)*) – spacing in 3d image may not be equal

Return ndarray

```
>>> np.random.seed(0)
>>> img = np.random.random((100, 100, 10))
>>> slic = segment_slic_img3d_gray(img, 20, 0.2, (1, 1, 5))
>>> slic.shape
(100, 100, 10)
```

imsegm.superpixels.**superpixel_centers**(*segments*)
estimate centers of each superpixel

Parameters **segments** (*ndarray*) – segmentation np.array<height, width>

Return [(float, float)]

```
>>> segm = np.array([[0] * 6 + [1] * 5, [0] * 6 + [2] * 5])
>>> superpixel_centers(segm)
[(0.5, 2.5), (0.0, 8.0), (1.0, 8.0)]
>>> superpixel_centers(np.array([segm, segm, segm]))
[[1.0, 0.5, 2.5], [1.0, 0.0, 8.0], [1.0, 1.0, 8.0]]
```

imsegm.superpixels.**IMAGE_SPACING = (1, 1, 1)**
spacing among neighboring pixels in axies X, Y, Z

1.2.3 Module contents

General superpixel image segmentation: (un)supervised, center detection, region growing

1.3 Examples

1.3.1 Sample unsupervised segmentation on Color images

Image segmentation is widely used as an initial phase of many image processing tasks in computer vision and image analysis. Many recent segmentation methods use superpixels, because they reduce the size of the segmentation problem by an order of magnitude. In addition, features on superpixels are much more robust than features on pixels only. We use spatial regularization on superpixels to make segmented regions more compact. The segmentation pipeline comprises: (i) computation of superpixels; (ii) extraction of descriptors such as color and texture; (iii) soft classification, using the Gaussian Mixture Model for unsupervised learning; (iv) final segmentation using Graph Cut. We use this segmentation pipeline on four real-world applications in medical imaging. We also show that unsupervised segmentation is sufficient for some situations, and provides similar results to those obtained using trained segmentation.

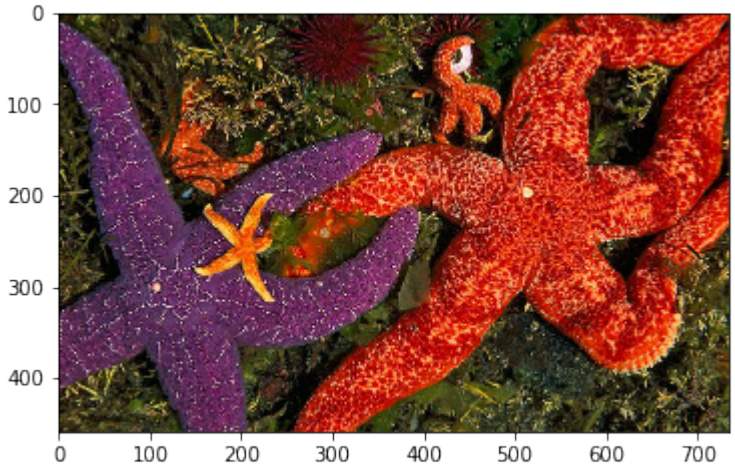
Borovec, J., Svihlik, J., Kybic, J., & Habart, D. (2017). **Supervised and unsupervised segmentation using superpixels, model estimation, and Graph Cut.** Journal of Electronic Imaging.

[1]:
```
%matplotlib inline
import os, sys, glob, time
import numpy as np
from PIL import Image
import matplotlib.pyplot as plt
from skimage.segmentation import mark_boundaries
sys.path += [os.path.abspath('.'), os.path.abspath('..')] # Add path to root
import imsegm.utilities.data_io as tl_data
import imsegm.pipelines as segm_pipe
```

Load image

[8]:
```
path_dir = os.path.join(tl_data.update_path('data-images'), 'others')
print ([os.path.basename(p) for p in glob.glob(os.path.join(path_dir, '*.jpg'))])
path_img = os.path.join(path_dir, 'sea_starfish-2.jpg')

img = np.array(Image.open(path_img))

FIG_SIZE = (8. * np.array(img.shape[:2]) / np.max(img.shape))[::-1]
_= plt.imshow(img)
```

```
['stars_nb2.jpg', 'star_nb1.jpg']
```



Segment Image

Set segmentation parameters:

[4]:
```
nb_classes = 3
sp_size = 25
sp_regul = 0.2
dict_features = {'color': ['mean', 'std', 'median']}
```

Estimate the model without any annotation

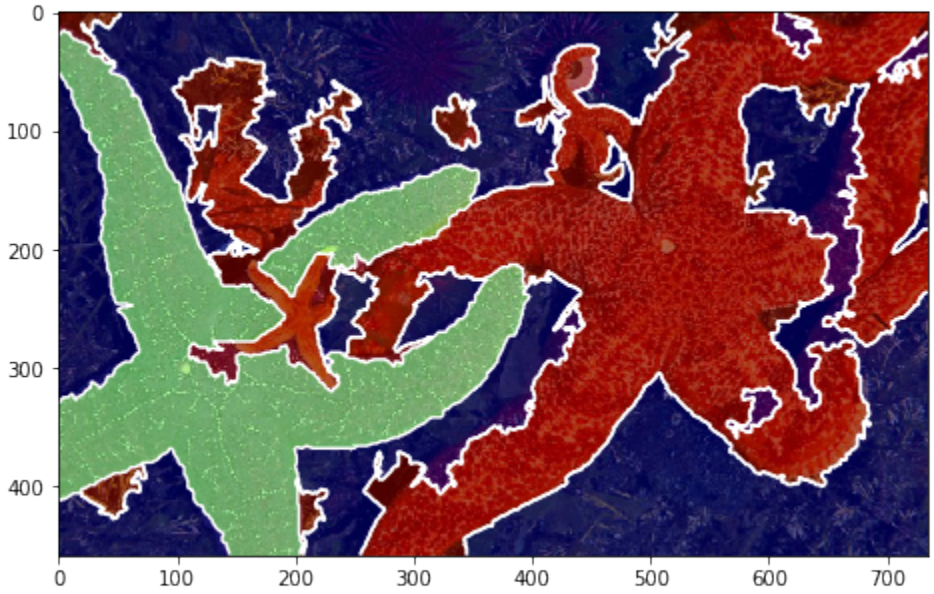
[5]:
```
model, _ = segm_pipe.estim_model_classes_group([img], nb_classes, sp_size=sp_size, sp_
↪regul=sp_regul,
                                               dict_features=dict_features, pca_
↪coef=None, model_type='GMM')
```

Perform segmentation with estimated model

[6]:
```
dict_debug = {}
seg, _ = segm_pipe.segment_color2d_slic_features_model_graphcut(img, model, sp_
↪size=sp_size, sp_regul=sp_regul,
                      dict_features=dict_features, gc_regul=5., gc_edge_type='color',␣
↪debug_visual=dict_debug)
```

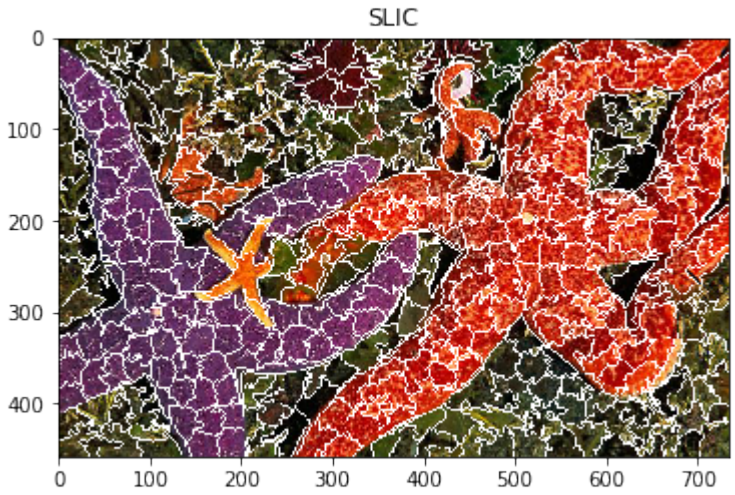
```
/usr/local/lib/python3.5/dist-packages/sklearn/mixture/base.py:237:␣
↪ConvergenceWarning: Initialization 1 did not converge. Try different init␣
↪parameters, or increase max_iter, tol or check for degenerate data.
  % (init + 1), ConvergenceWarning)
```

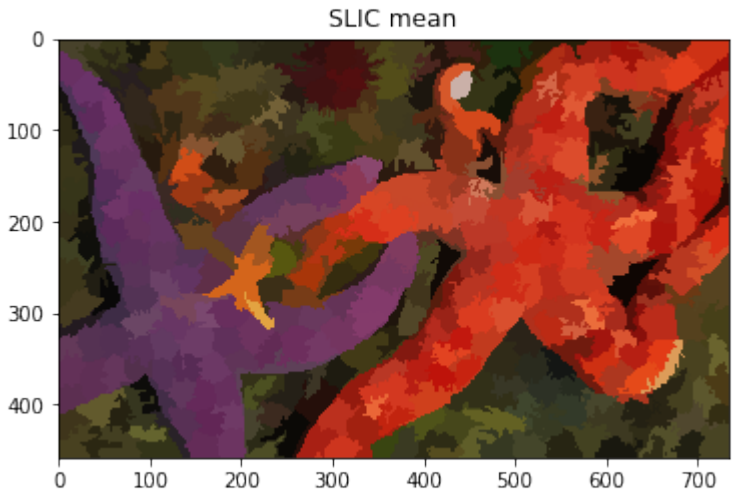
[9]:
```
fig = plt.figure(figsize=FIG_SIZE)
plt.imshow(img)
plt.imshow(seg, alpha=0.6, cmap=plt.cm.jet)
_= plt.contour(seg, levels=np.unique(seg), colors='w')
```

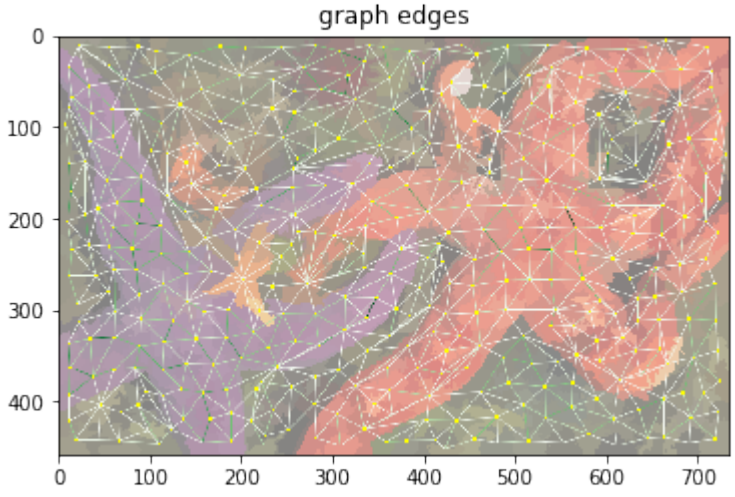


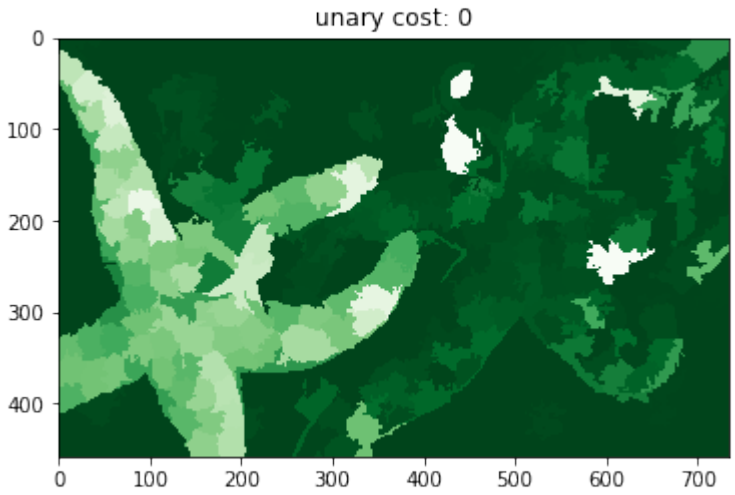
Visualise intermediate steps

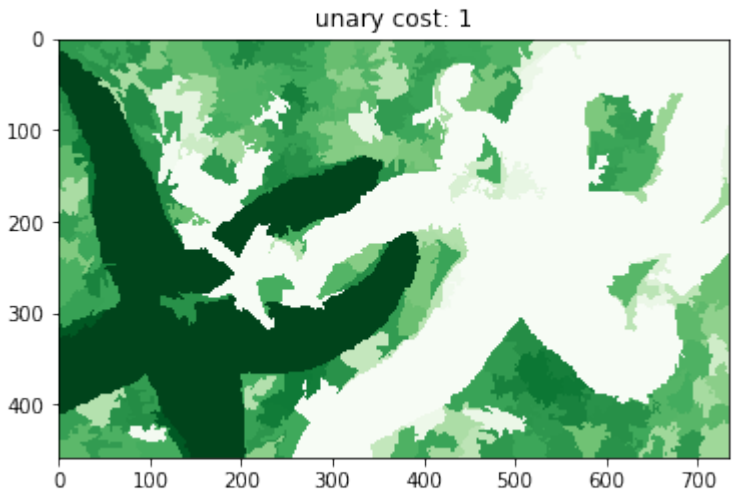
[12]:
```
plt.figure(), plt.imshow(mark_boundaries(img, dict_debug['slic'], color=(1, 1, 1))),␣
↪plt.title('SLIC')
plt.figure(), plt.imshow(dict_debug['slic_mean']), plt.title('SLIC mean')
plt.figure(), plt.imshow(dict_debug['img_graph_edges']), plt.title('graph edges')
for i, im_u in enumerate(dict_debug['imgs_unary_cost']):
    plt.figure(), plt.title('unary cost: %i' % i), plt.imshow(im_u)
# plt.figure(), plt.imshow(dict_debug['img_graph_segm'])
```

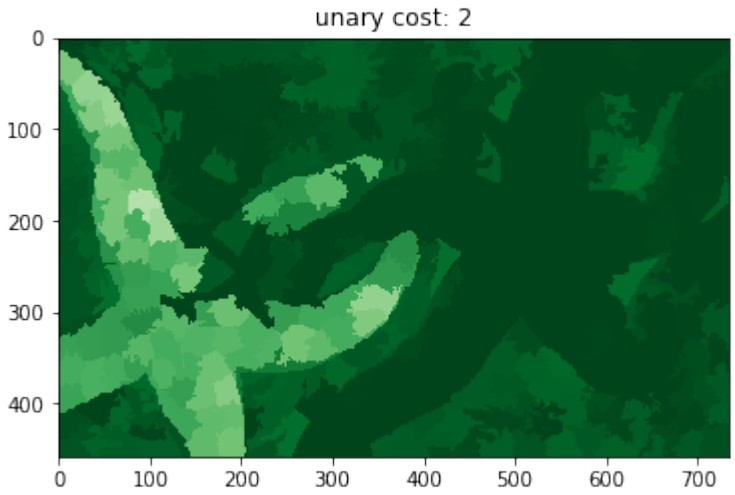

SLIC
0
100
200
300
400
0
100
200
300
400
500
600
700


SLIC mean
0
100
200
300
400
0
100
200
300
400
500
600
700


graph edges
0
100
200
300
400
0
100
200
300
400
500
600
700


unary cost: 0
0
100
200
300
400
0
100
200
300
400
500
600
700


unary cost: 1
0
100
200
300
400
0
100
200
300
400
500
600
700


unary cost: 2
0
100
200
300
400
0
100
200
300
400
500
600
700

[ ]:

1.3.2 Sample supervised segmentation on Gray images

Image segmentation is widely used as an initial phase of many image processing tasks in computer vision and image analysis. Many recent segmentation methods use superpixels, because they reduce the size of the segmentation problem by an order of magnitude. In addition, features on superpixels are much more robust than features on pixels only. We use spatial regularization on superpixels to make segmented regions more compact. The segmentation pipeline comprises: (i) computation of superpixels; (ii) extraction of descriptors such as color and texture; (iii) soft classification, using a standard classifier for supervised learning; (iv) final segmentation using Graph Cut. We use this segmentation pipeline on four real-world applications in medical imaging. We also show that unsupervised segmentation is sufficient for some situations, and provides similar results to those obtained using trained segmentation.

Borovec, J., Svihlik, J., Kybic, J., & Habart, D. (2017). **Supervised and unsupervised segmentation using superpixels, model estimation, and Graph Cut.** Journal of Electronic Imaging.

[1]:
```
%matplotlib inline
import os, sys, glob, time
import numpy as np
from PIL import Image
import matplotlib.pyplot as plt
from skimage.segmentation import mark_boundaries
sys.path += [os.path.abspath('.'), os.path.abspath('..')] # Add path to root
import imsegm.utilities.data_io as tl_data
import imsegm.pipelines as segm_pipe
```

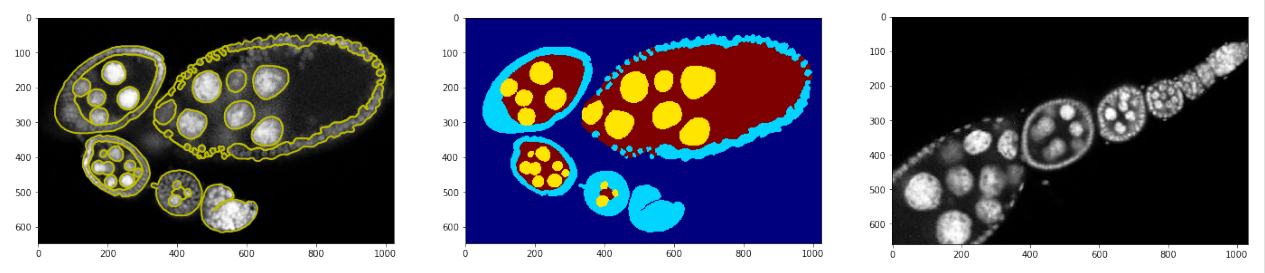
Load image

[2]:
```
path_dir = os.path.join(tl_data.update_path('data-images'), 'drosophila_ovary_slice')
path_images = os.path.join(path_dir, 'image')
print ([os.path.basename(p) for p in glob.glob(os.path.join(path_images, '*.jpg'))])
# loading images
path_img = os.path.join(path_images, 'insitu7545.jpg')
img = np.array(Image.open(path_img))[:, :, 0]
path_img = os.path.join(path_images, 'insitu4174.jpg')
img2 = np.array(Image.open(path_img))[:, :, 0]
# loading annotations
path_annots = os.path.join(path_dir, 'annot_struct')
path_annot = os.path.join(path_annots, 'insitu7545.png')
annot = np.array(Image.open(path_annot))
```

```
['insitu7331.jpg', 'insitu4174.jpg', 'insitu4358.jpg', 'insitu7545.jpg', 'insitu7544.
↪jpg']
```

Show that training example with annotation and testing image

[14]:
```
FIG_SIZE = (8. * np.array(img.shape[:2]) / np.max(img.shape))[::-1]
fig = plt.figure(figsize=FIG_SIZE * 3)
_= plt.subplot(1,3,1), plt.imshow(img, cmap=plt.cm.Greys_r), plt.contour(annot,␣
↪colors='y')
_= plt.subplot(1,3,2), plt.imshow(annot, cmap=plt.cm.jet)
_= plt.subplot(1,3,3), plt.imshow(img2, cmap=plt.cm.Greys_r)
```



Segment Image

Set segmentation parameters:

[4]:
```
sp_size = 25
sp_regul = 0.2
dict_features = {'color': ['mean', 'std', 'median'], 'tLM': ['mean']}
```

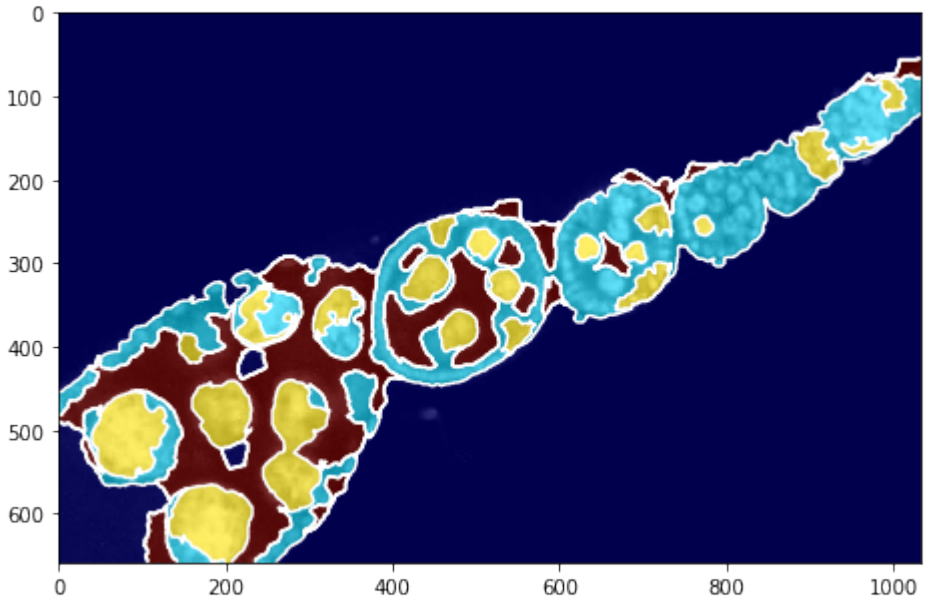
Train the classifier

[5]:
```
classif, list_slic, list_features, list_labels = segm_pipe.train_classif_color2d_slic_
↪features([img], [annot],
                sp_size=sp_size, sp_regul=sp_regul, dict_features=dict_features, pca_
↪coef=None)
```

Perform the segmentation with trained classifier

[6]:
```
dict_debug = {}
seg, _ = segm_pipe.segment_color2d_slic_features_model_graphcut(img2, classif, sp_
↪size=sp_size, sp_regul=sp_regul,
                    gc_regul=1., dict_features=dict_features, gc_edge_type='model',␣
↪debug_visual=dict_debug)
```

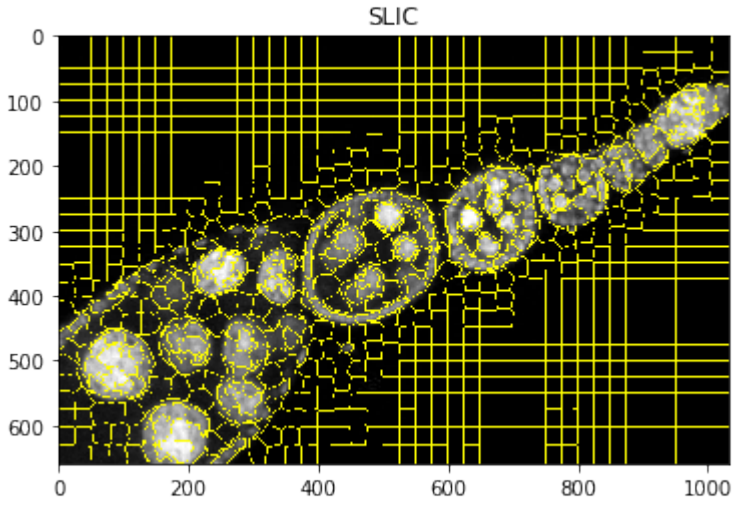
[15]:
```
fig = plt.figure(figsize=FIG_SIZE)
plt.imshow(img2, cmap=plt.cm.Greys_r)
plt.imshow(seg, alpha=0.6, cmap=plt.cm.jet)
_= plt.contour(seg, levels=np.unique(seg), colors='w')
```

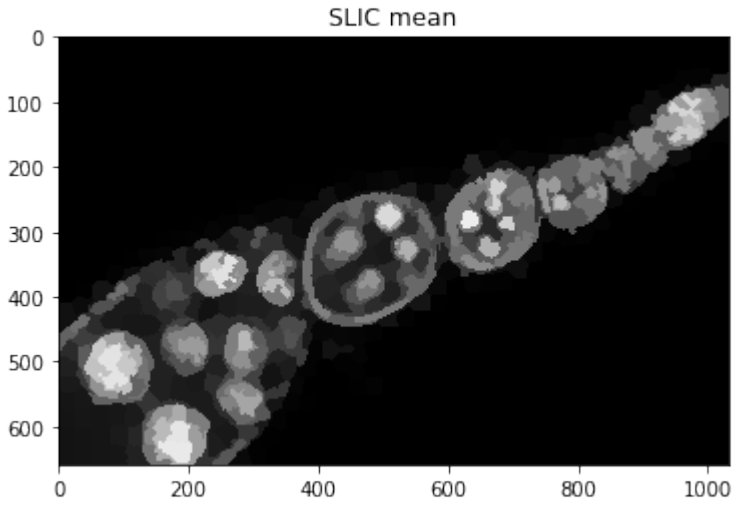


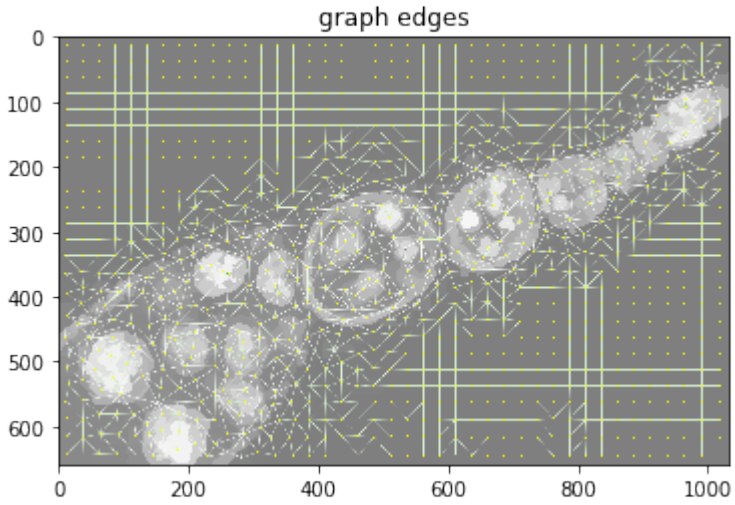
Visualise intermediate steps

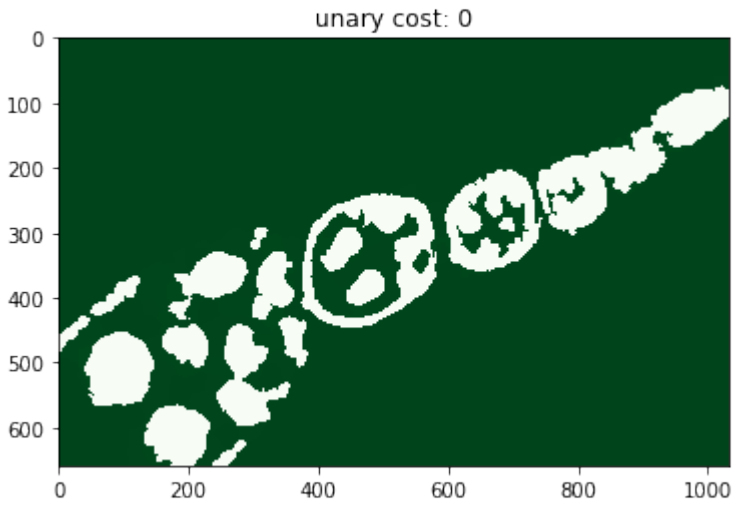
[13]:
```
print ('debug fields: %s' % repr(dict_debug.keys()))
plt.figure(), plt.imshow(mark_boundaries(img2, dict_debug['slic'])), plt.title('SLIC')
plt.figure(), plt.imshow(dict_debug['slic_mean']), plt.title('SLIC mean')
plt.figure(), plt.imshow(dict_debug['img_graph_edges']), plt.title('graph edges')
for i, im_u in enumerate(dict_debug['imgs_unary_cost']):
    plt.figure(), plt.title('unary cost: %i' % i), plt.imshow(im_u)
# plt.figure(), plt.imshow(dict_debug['img_graph_segm'])
```

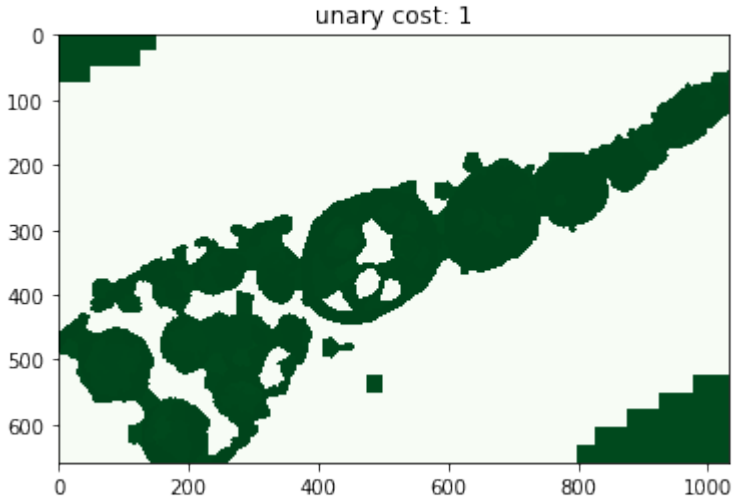
```
debug fields: dict_keys(['slic', 'img_graph_segm', 'slic_mean', 'segments', 'edge_
↪weights', 'imgs_unary_cost', 'img_graph_edges', 'image', 'edges'])
```

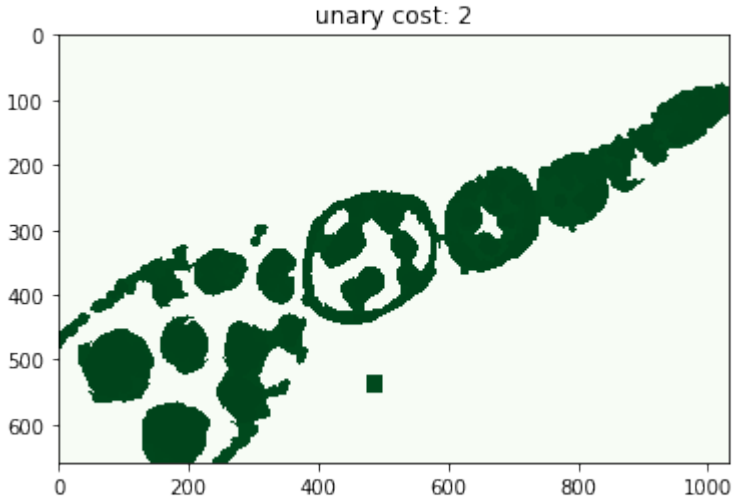


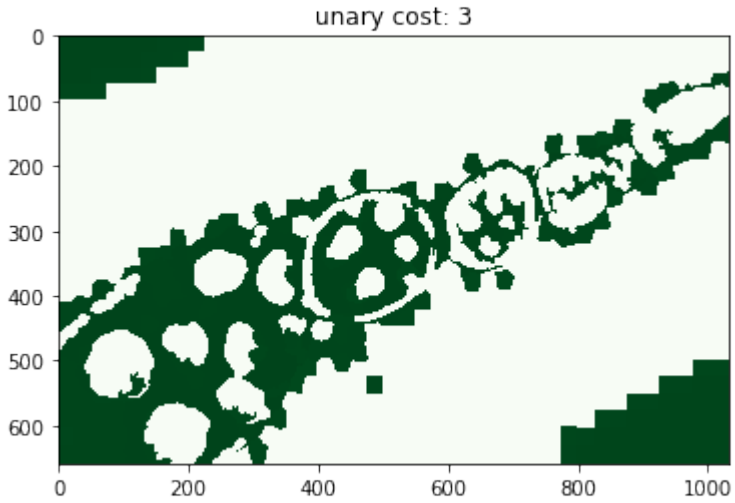

SLIC mean
0
100
200
300
400
500
600
0
200
400
600
800
1000


graph edges
0
100
200
300
400
500
600
0
200
400
600
800
1000


unary cost: 0
0
100
200
300
400
500
600
0
200
400
600
800
1000


unary cost: 1
0
100
200
300
400
500
600
0
200
400
600
800
1000


unary cost: 2
0
100
200
300
400
500
600
0
200
400
600
800
1000


unary cost: 3
0
100
200
300
400
500
600
0
200
400
600
800
1000

[ ]:

1.3.3 Object shape model - estimation

Measure ray features and estimate the model over whole dataset. We play a bit with different mixture strategies sich as GMM, Mean shift, Kmeans, etc.

[1]:
```
%matplotlib inline
import os, sys, glob
import numpy as np
import pandas as pd
from PIL import Image
import matplotlib.pylab as plt
from scipy import ndimage
```

[2]:
```
sys.path += [os.path.abspath('.'), os.path.abspath('..')] # Add path to root
import imsegm.utilities.data_io as tl_io
import imsegm.region_growing as tl_rg
import imsegm.descriptors as tl_fts
```

Loading ovary

[4]:
```
COLORS = 'bgrmyck'
PATH_IMAGES = tl_io.update_path(os.path.join('data-images', 'drosophila_ovary_slice'))
PATH_DATA = tl_io.update_path('data-images', absolute=True)
PATH_OUT = tl_io.update_path('output', absolute=True)
PATH_MEASURED_RAYS = os.path.join(PATH_IMAGES, 'eggs_ray-shapes.csv')
print ([os.path.basename(p) for p in glob.glob(os.path.join(PATH_IMAGES, '*')) if os.
↪path.isdir(p)])
dir_annot = os.path.join(PATH_IMAGES, 'annot_eggs')
# dir_annot = os.path.expanduser('/home/jirka/Dropbox/temp/mask_2d_slice_complete_ind_
↪egg')
```

```
['center_levels', 'image', 'annot_struct', 'ellipse_fitting', 'annot_eggs', 'segm_rgb
↪', 'segm', 'image_cut-stage-2']
```

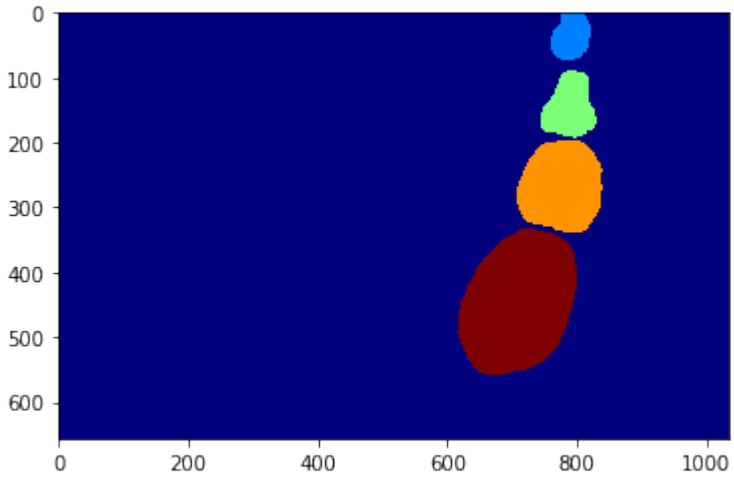
Loading...

[5]:
```
list_paths = sorted(glob.glob(os.path.join(dir_annot, '*.png')))
print ('nb images: %i SAMPLES: \n %s' % (len(list_paths), repr([os.path.basename(p)␣
↪for p in list_paths[:5]])))
list_segms = []
for path_seg in list_paths:
    seg = np.array(Image.open(path_seg))
    list_segms.append(seg)
```

```
nb images: 67 SAMPLES:
 ['insitu14807.png', 'insitu14808.png', 'insitu14809.png', 'insitu14810.png',
↪'insitu14811.png']
```

Randomly selected sample image from fiven dataset.

[6]:
```
seg = list_segms[np.random.randint(0, len(list_segms))]
_= plt.imshow(seg, cmap=plt.cm.jet)
```



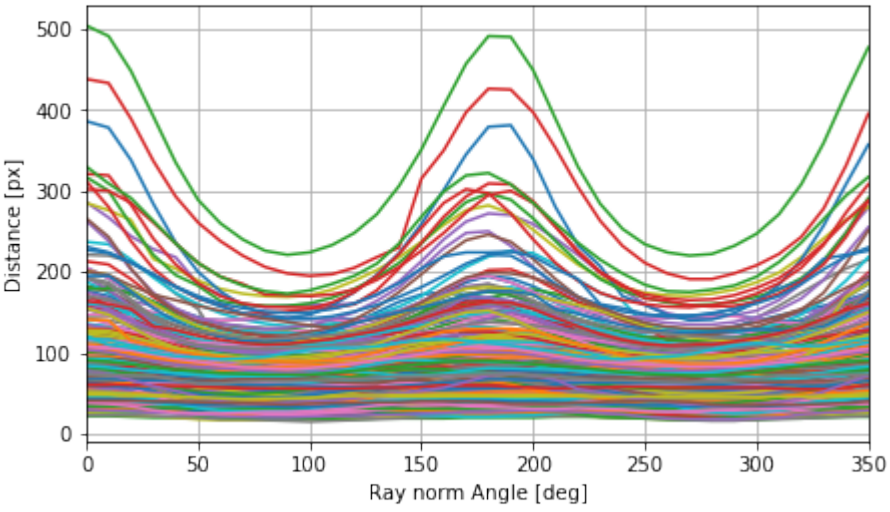
Compute Ray features

Simple statistic over measured normalised Ray features over whole dataset.

[7]:
```
list_rays, list_shifts = tl_rg.compute_object_shapes(list_segms, ray_step=10, interp_
↪order='spline', smooth_coef=1, shift_method='max')
print ('nb eggs: %i ; nb rays: %i' % (len(list_rays), len(list_rays[0])))
```

```
nb eggs: 241 ; nb rays: 36
```

[9]:
```
fig = plt.figure(figsize=(7, 4))
x_axis = np.linspace(0, 360, len(list_rays[0]), endpoint=False)
plt.plot(x_axis, np.array(list_rays).T, '-')
plt.grid(), plt.xlim([0, 350])
_= plt.xlabel('Ray norm Angle [deg]'), plt.ylabel('Distance [px]')
#fig.savefig(os.path.join(PATH_OUT, 'shape-rays_all.pdf'), bbox_inches='tight')
```

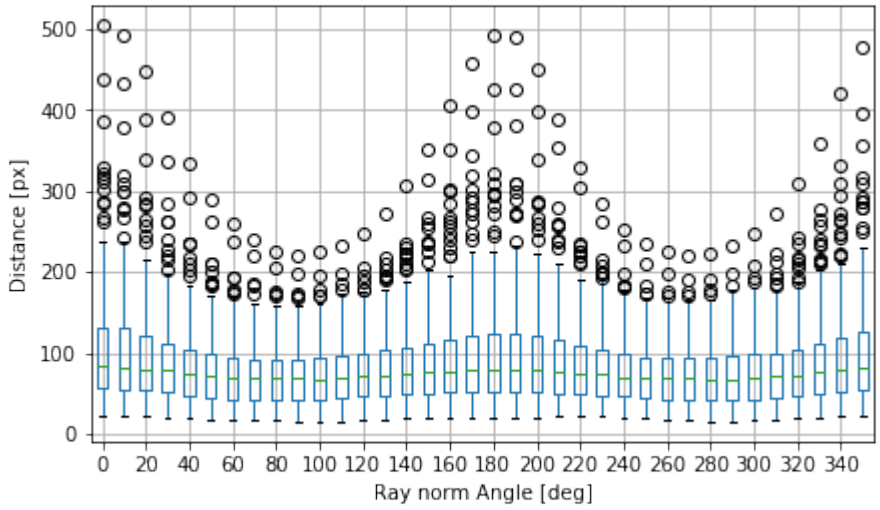


[10]:
```
df = pd.DataFrame(np.array(list_rays), columns=x_axis.astype(int))
df.to_csv(PATH_MEASURED_RAYS)
```

(continues on next page)

(continued from previous page)

```
df.plot.box(figsize=(7, 4), grid=True)
plt.plt.xticks(range(1, 37, 2), [str(i * 10) for i in range(0, 36, 2)])
_= plt.xlabel('Ray norm Angle [deg]'), plt.ylabel('Distance [px]')
#plt.savefig(os.path.join(PATH_OUT, 'shape-rays_statistic.pdf'), bbox_inches='tight')
```



Clustering

You can compte thre Ray features from segmentation or load precomputed vectors in CSV file.

[11]:
```
df = pd.read_csv(PATH_MEASURED_RAYS, index_col=0)
list_rays = df.values
x_axis = np.linspace(0, 360, list_rays.shape[1], endpoint=False)
```

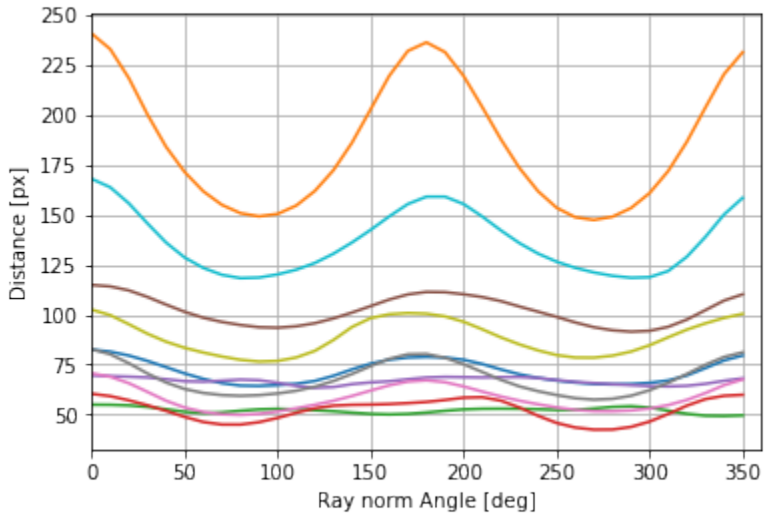
Spectral Clustering

[12]:
```
from sklearn import cluster

model = cluster.SpectralClustering(10)
model.fit(np.array(list_rays))
print ('label histogram: %s' % repr(np.bincount(model.labels_)))

list_ray_core = []
for lb in np.unique(model.labels_):
    mean_rays = np.mean(np.asarray(list_rays)[model.labels_ == lb], axis=0)
    mean_rays = ndimage.filters.gaussian_filter1d(mean_rays, 1)
    list_ray_core.append(mean_rays)
```

```
label histogram: array([  6,   2,   2,   2,   2,   2,   2,   2,   2, 219])
```

```
/usr/local/lib/python2.7/dist-packages/sklearn/manifold/spectral_embedding_.py:234:␣
↪UserWarning: Graph is not fully connected, spectral embedding may not work as␣
↪expected.
  warnings.warn("Graph is not fully connected, spectral embedding"
```

[18]:
```
#fig = plt.figure(figsize=(10, 5))
plt.plot(x_axis, np.array(list_ray_core).T, '-')
plt.grid(), plt.xlim([0, 360])
_= plt.xlabel('Ray norm Angle [deg]'), plt.ylabel('Distance [px]')
```

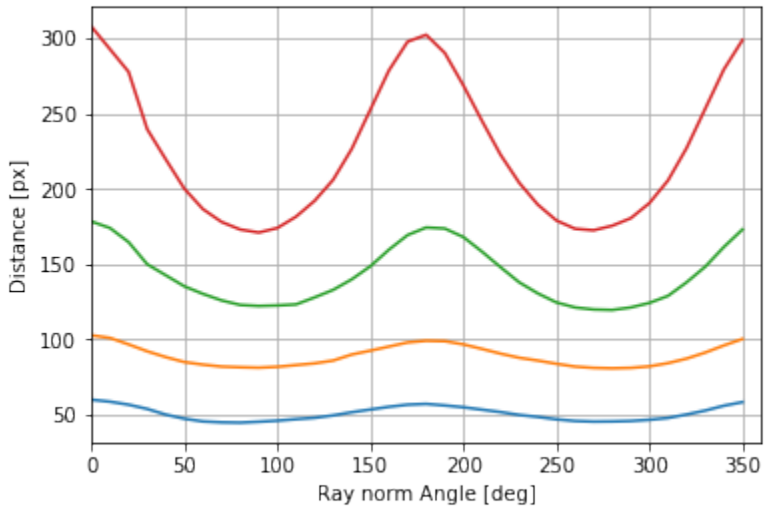


Mean Shift

[19]:
```
from sklearn import cluster

mean_shift = cluster.MeanShift()
mean_shift.fit(np.array(list_rays))
print ('label histogram: %s' % repr(np.bincount(mean_shift.labels_)))
```

```
[8 6 3 2]
```

[20]:
```
#fig = plt.figure(figsize=(10, 5))
plt.plot(x_axis, mean_shift.cluster_centers_.T, '-')
plt.grid(), plt.xlim([0, 360])
_= plt.xlabel('Ray norm Angle [deg]'), plt.ylabel('Distance [px]')
```

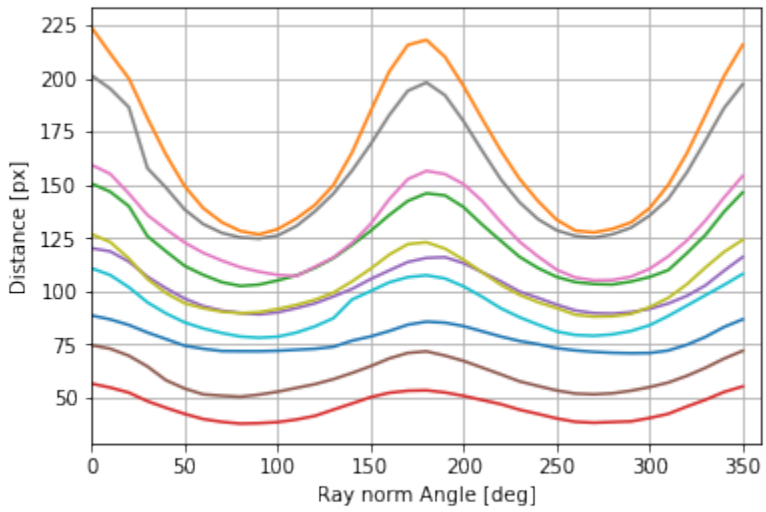


Gaussian Mixture Model

[21]:
```
from sklearn import mixture

gmm = mixture.BayesianGaussianMixture(n_components=10)
gmm.fit(np.array(list_rays))
# gmm.fit(np.array(list_rays), mean_shift_labels)
print ('weights:', gmm.weights_, 'means:', gmm.means_.shape, 'covariances:', gmm.
↪covariances_.shape)
```

```
weights: [0.19914697 0.09375047 0.1318912  0.16338295 0.11149782 0.16540886
 0.0531903  0.04021706 0.02724381 0.01427057] means: (10, 36) covariances: (10, 36,␣
↪36)
```

[22]:
```
#fig = plt.figure(figsize=(10, 5))
plt.plot(x_axis, gmm.means_.T, '-', label=' ')
plt.grid(), plt.xlim([0, 360])
_= plt.xlabel('Ray norm Angle [deg]'), plt.ylabel('Distance [px]')
```

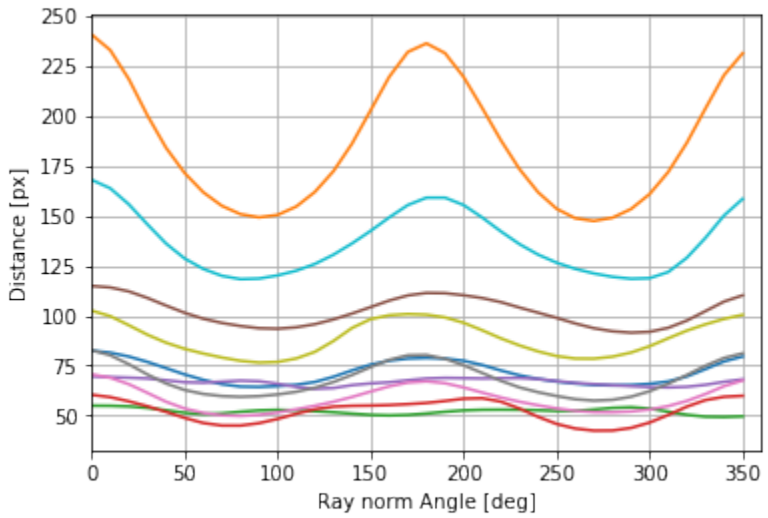


Agglomerative Clustering

[23]:
```
agg = cluster.AgglomerativeClustering(7)
agg.fit(np.array(list_rays))
# gmm.fit(np.array(list_rays), mean_shift_labels)
print ('label histogram: %s' % repr(np.bincount(agg.labels_)))

list_ray_core = []
for lb in np.unique(model.labels_):
    mean_rays = np.mean(np.asarray(list_rays)[model.labels_ == lb], axis=0)
    mean_rays = ndimage.filters.gaussian_filter1d(mean_rays, 1)
    list_ray_core.append(mean_rays)
```

```
[2 4 4 2 3 3 1]
```

[24]:
```
#plt.figure(figsize=(10, 5))
plt.plot(x_axis, np.array(list_ray_core).T, '-')
plt.grid(), plt.xlim([0, 360])
_= plt.xlabel('Ray norm Angle [deg]'), plt.ylabel('Distance [px]')
```



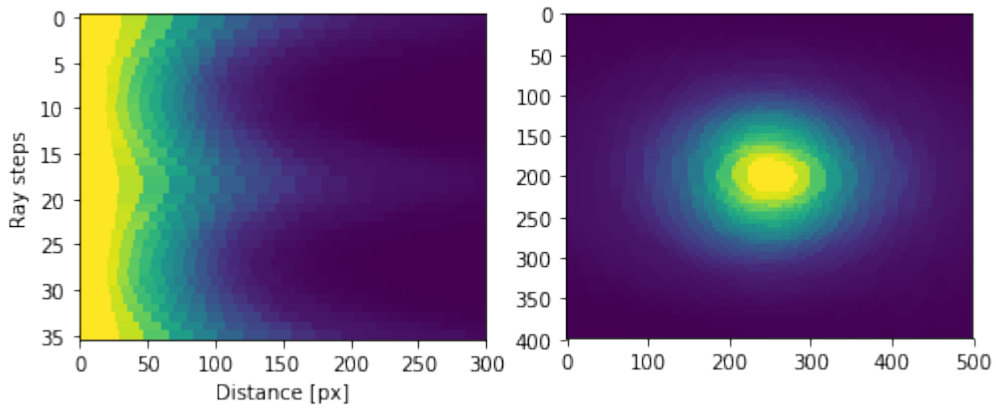
Cumulativ Priors

[13]:
```
df = pd.read_csv(PATH_MEASURED_RAYS, index_col=0)
list_rays = df.values
```

[14]:
```
def compute_prior_map(cdist, size=(500, 800), step=5):
    prior_map = np.zeros(size)
    centre = np.array(size) / 2
    for i in np.arange(prior_map.shape[0], step=step):
        for j in np.arange(prior_map.shape[1], step=step):
            prior_map[i:i+step, j:j+step] = \
                tl_rg.compute_shape_prior_table_cdf([i, j], cdist, centre, angle_
↪shift=0)
    return prior_map
```

Histogram

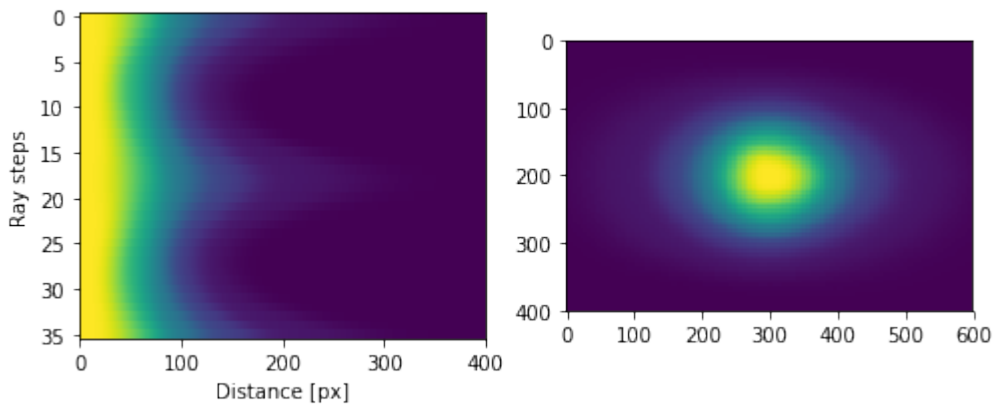
[15]:
```
list_cdf = tl_rg.transform_rays_model_cdf_histograms(list_rays, nb_bins=25)
cdist = np.array(list_cdf)

fig = plt.figure(figsize=(8, 3))
_= plt.subplot(1, 2, 1), plt.imshow(cdist[:, :300], aspect='auto'), plt.ylabel('Ray␣
↪steps'), plt.xlabel('Distance [px]')
_= plt.subplot(1, 2, 2), plt.imshow(compute_prior_map(cdist, size=(400, 500), step=5))
```



Mixture model

[16]:
```
mm, list_cdf = tl_rg.transform_rays_model_cdf_mixture(list_rays, coef_components=1)
cdist = np.array(list_cdf)
print (mm.weights_)

fig = plt.figure(figsize=(8, 3))
_= plt.subplot(1, 2, 1), plt.imshow(cdist[:, :], aspect='auto'), plt.ylabel('Ray steps
↪'), plt.xlabel('Distance [px]')
_= plt.subplot(1, 2, 2), plt.imshow(compute_prior_map(cdist, size=(400, 600), step=5))
# plt.savefig('shape-rays_gmm-cdf-proj.pdf')
```

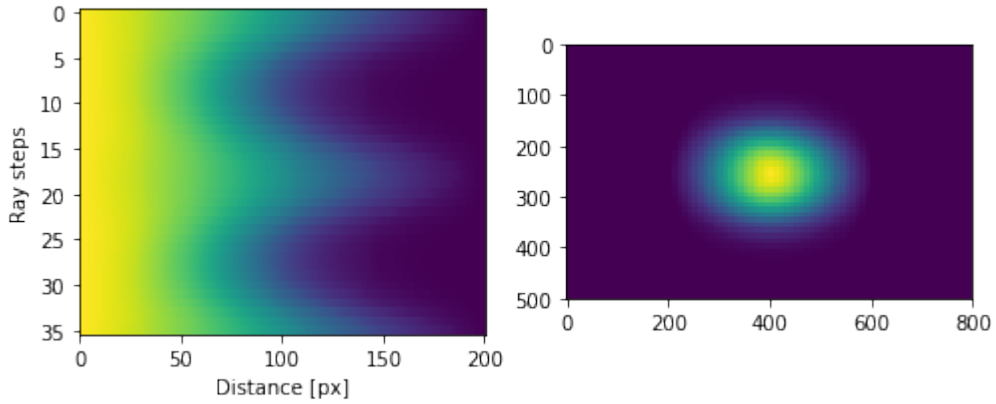
```
[ 0.21486968  0.05343626  0.17167657  0.13797019  0.01205806  0.1950365
  0.21495274]
```



Spectral Clustering

[17]:
```
sc, list_cdf = tl_rg.transform_rays_model_cdf_spectral(list_rays)
cdist = np.array(list_cdf)
print ('label histogram: %s' % repr(np.bincount(sc.labels_)))

fig = plt.figure(figsize=(8, 3))
_= plt.subplot(1, 2, 1), plt.imshow(cdist, aspect='auto'), plt.ylabel('Ray steps'),␣
↪plt.xlabel('Distance [px]')
_= plt.subplot(1, 2, 2), plt.imshow(compute_prior_map(cdist, step=10))
```

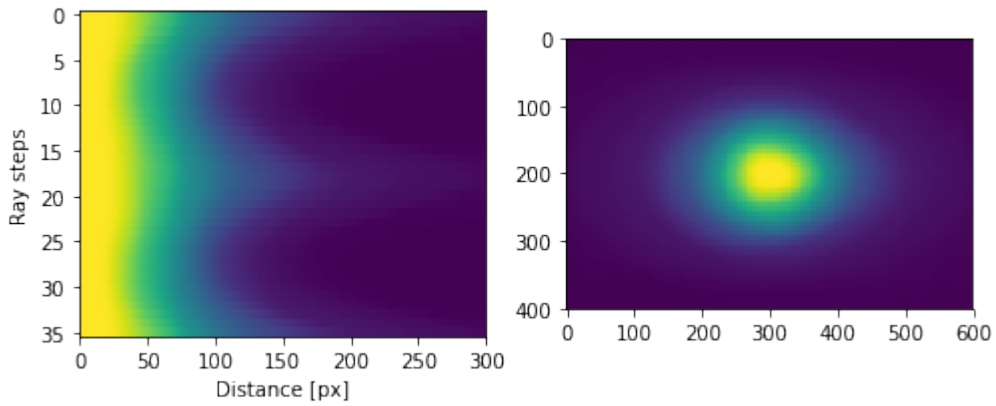
```
label histogram: array([233,   2,   2,   2,   2])
```



K-means

[18]:
```
km, list_cdf = tl_rg.transform_rays_model_cdf_kmeans(list_rays, 15)
cdist = np.array(list_cdf)
print ('label histogram: %s' % repr(np.bincount(km.labels_)))

fig = plt.figure(figsize=(8, 3))
_= plt.subplot(1, 2, 1), plt.imshow(cdist[:, :300], aspect='auto'), plt.ylabel('Ray␣
↪steps'), plt.xlabel('Distance [px]')
_= plt.subplot(1, 2, 2), plt.imshow(compute_prior_map(cdist, size=(400, 600), step=5))
```

```
label histogram: array([28,  5, 30, 12,  1, 32, 33,  7, 34,  7,  1, 19,  1,  1, 30])
```

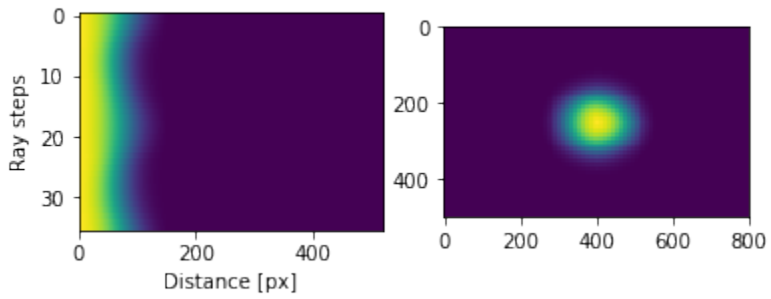


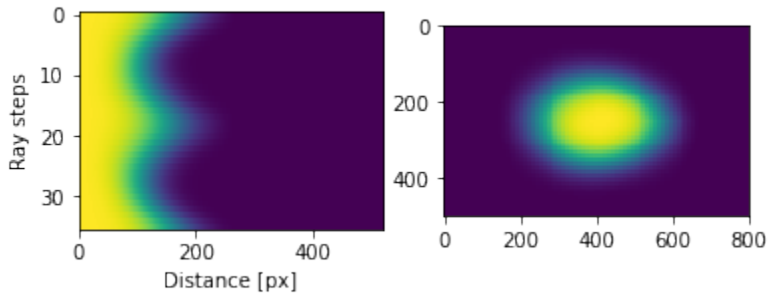
Mixture of Cumulativ Models

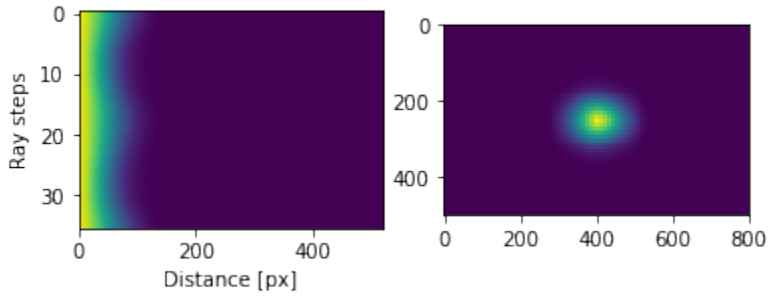
[19]:
```
df = pd.read_csv(PATH_MEASURED_RAYS, index_col=0)
list_rays = df.values
```

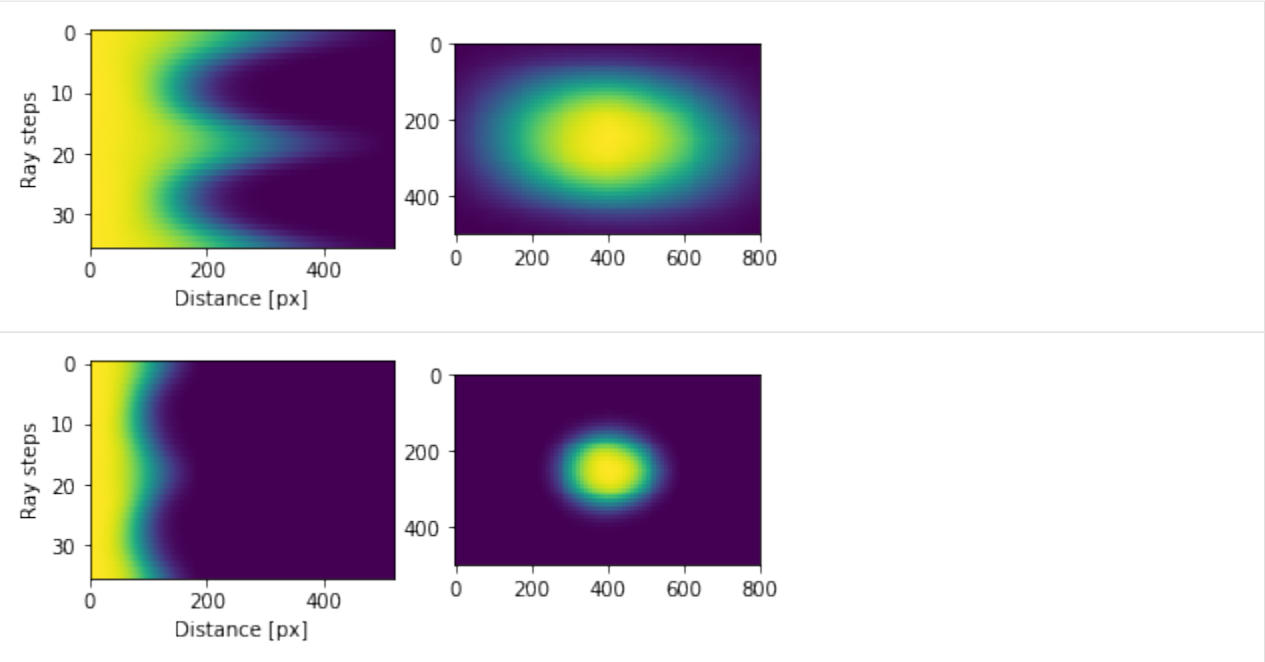
Gaussian mixture

[20]:
```
model, list_mean_cdf = tl_rg.transform_rays_model_sets_mean_cdf_mixture(list_rays, 5)
max_len = max([np.asarray(l_cdf).shape[1] for _, l_cdf in list_mean_cdf])

for i, (mean, list_cdf) in enumerate(list_mean_cdf):
    cdist = np.zeros((len(list_cdf), max_len))
    cdist[:, :len(list_cdf[0])] = np.array(list_cdf)
    plt.figure(figsize=(6, 2))
    plt.subplot(1, 2, 1), plt.imshow(cdist, aspect='auto'), plt.xlim([0, max_len]),␣
↪plt.ylabel('Ray steps'), plt.xlabel('Distance [px]')
    plt.subplot(1, 2, 2), plt.imshow(compute_prior_map(cdist, step=10))
    # plt.savefig('shape-rays_gmm-cdf-proj_%i.pdf' % (i + 1))
```



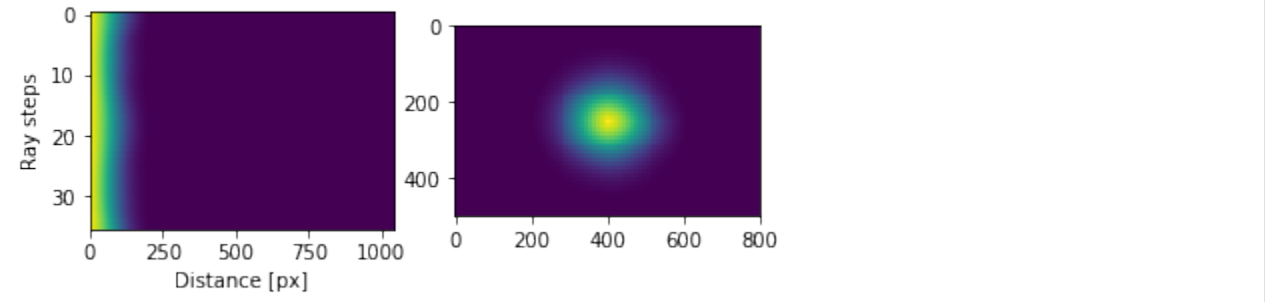


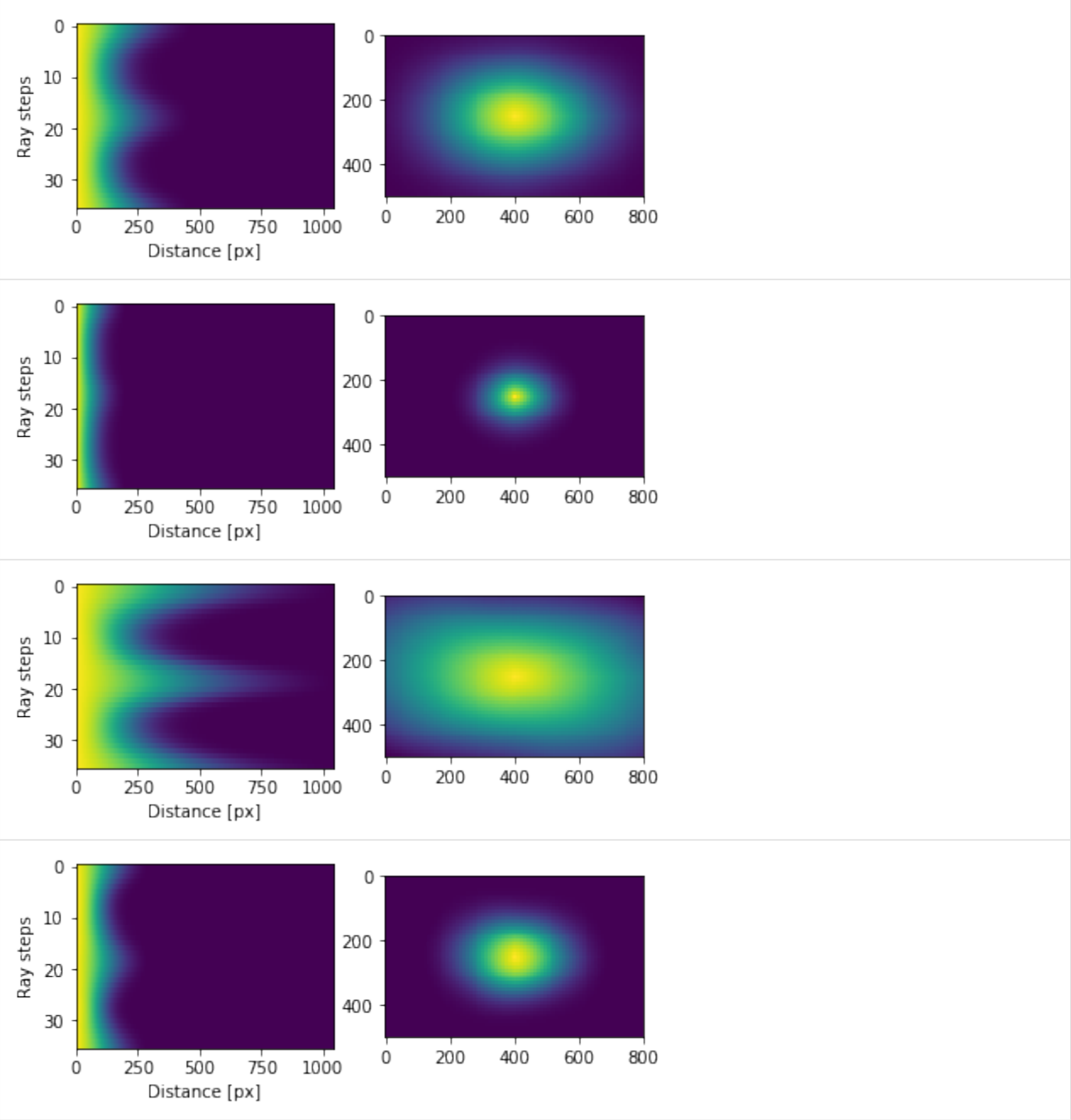




K-Means

[21]:
```
model, list_mean_cdf = tl_rg.transform_rays_model_sets_mean_cdf_kmeans(list_rays, 5)
max_len = max([np.asarray(l_cdf).shape[1] for _, l_cdf in list_mean_cdf])

for mean, list_cdf in list_mean_cdf:
    cdist = np.zeros((len(list_cdf), max_len))
    cdist[:, :len(list_cdf[0])] = np.array(list_cdf)
    plt.figure(figsize=(6, 2))
    plt.subplot(1, 2, 1), plt.imshow(cdist, aspect='auto'), plt.xlim([0, max_len]),␣
↪plt.ylabel('Ray steps'), plt.xlabel('Distance [px]')
    plt.subplot(1, 2, 2), plt.imshow(compute_prior_map(cdist, step=10))
```



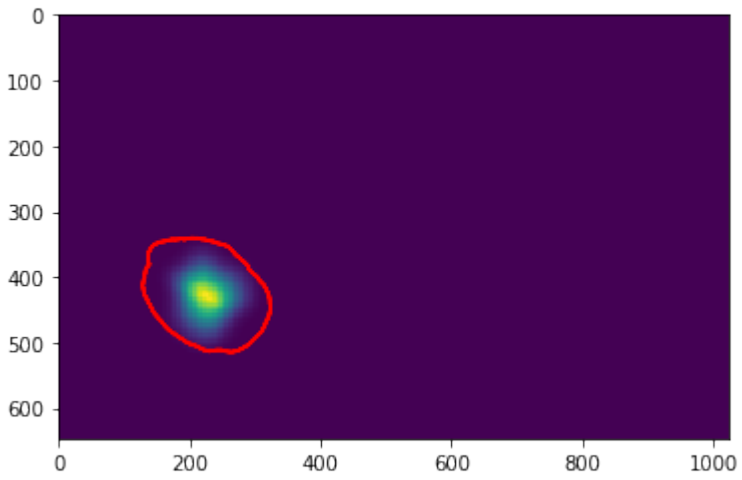


Show Shape prior with sample egg

[43]:
```
seg_object = (seg == 3)
centre = ndimage.measurements.center_of_mass(seg_object)
ray = tl_fts.compute_ray_features_segm_2d(seg_object, centre, edge='down')
_, shift = tl_fts.shift_ray_features(ray)
print ('centre: %s' % repr(centre))
print ('angle shift: %f' % shift)
```

```
centre: (426.3299148683429, 224.6435953276579)
angle shift: 220.0
```

[44]:
```
prior_map = np.zeros(seg_object.shape)
error_pos = []
for i in np.arange(prior_map.shape[0], step=5):
    for j in np.arange(prior_map.shape[1], step=5):
        prior_map[i:i+5, j:j+5] = tl_rg.compute_shape_prior_table_cdf([i, j], cdist,␣
↪centre, angle_shift=shift)

_= plt.imshow(prior_map), plt.contour(seg_object, colors='r')
```



[ ]:
```
```

1.3.4 Object segmentation with Region Growing with Shape Prior

Region growing is a classical image segmentation method based on hierarchical region aggregation using local similarity rules. Our proposed method differs from classical region growing in three important aspects. First, it works on the level of superpixels instead of pixels, which leads to a substantial speedup. Second, our method uses learned statistical shape properties which encourage growing leading to plausible shapes. In particular, we use ray features to describe the object boundary. Third, our method can segment multiple objects and ensure that the segmentations do not overlap. The problem is represented as an energy minimization and is solved either greedily, or iteratively using GraphCuts.

Borovec, J., Kybic, J., & Sugimoto, A. (2017). **Region growing using superpixels with learned shape prior.** Journal of Electronic Imaging. Dvorak, J. et al. (2018). *Volume estimation from single images: an application to pancreatic islets.* Image Analysis & Stereology.

[1]:
```
%matplotlib inline
import os, sys, glob
import pickle
import numpy as np
import pandas as pd
from PIL import Image
from scipy import ndimage
from skimage import segmentation as sk_segm
from skimage import io, measure
import matplotlib.pylab as plt
```

[2]:
```
sys.path += [os.path.abspath('.'), os.path.abspath('..')] # Add path to root
import imsegm.utilities.data_io as tl_io
import imsegm.utilities.drawing as tl_visu
import imsegm.superpixels as seg_spx
import imsegm.region_growing as seg_rg
import imsegm.graph_cuts as seg_gc
import imsegm.pipelines as seg_pipe
```

Loading data

[3]:
```
COLORS = 'bgrmyck'
PATH_IMAGES = os.path.join(tl_io.update_path('data-images'), 'langerhans_islets')
PATH_DATA = tl_io.update_path('data-images', absolute=True)
PATH_OUT = tl_io.update_path('output', absolute=True)
PATH_MEASURED_RAYS = os.path.join(PATH_IMAGES, 'islets_ray-shapes_1400x1050.csv')
print ([os.path.basename(p) for p in glob.glob(os.path.join(PATH_IMAGES, '*')) if os.
↪path.isdir(p)])
# dir_annot = os.path.expanduser('~/Dropbox/Workspace/segment_Medical/Ovary-eggs/mask_
↪2d_slice_complete_ind_egg')
```

```
['image_red', 'image', 'binary-masks_1400x', 'binary-masks', 'annot']
```

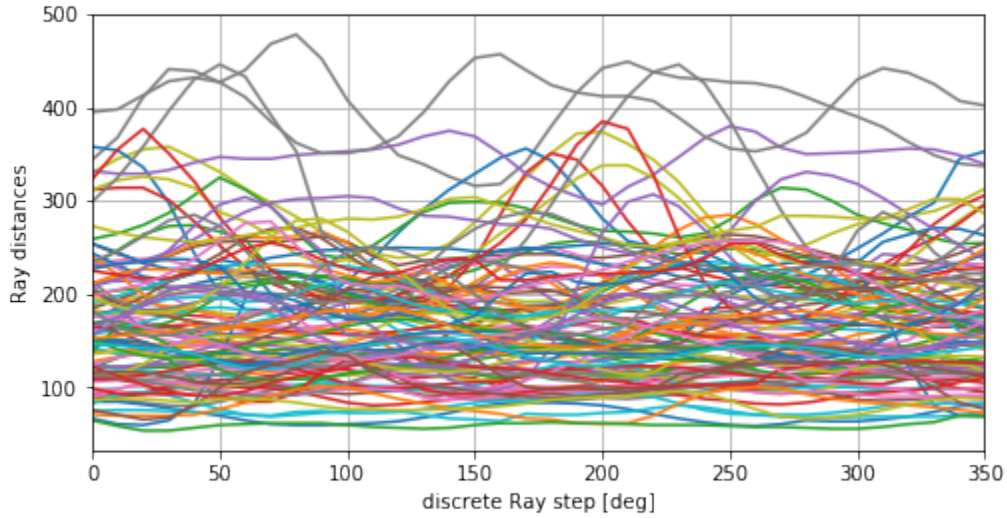
[4]:
```
DIR_IMAGES = os.path.join(PATH_IMAGES, 'image')
DIR_SEGMS = os.path.join(PATH_IMAGES, 'segm')
DIR_ANNOTS = os.path.join(PATH_IMAGES, 'annot')
```

Estimate shape models

[5]:
```
def compute_prior_map(cdist, size=(500, 800), step=5):
    prior_map = np.zeros(size)
    centre = np.array(size) / 2
    for i in np.arange(prior_map.shape[0], step=step):
        for j in np.arange(prior_map.shape[1], step=step):
            prior_map[i:i+step, j:j+step] = seg_rg.compute_shape_prior_table_cdf([i,␣
↪j], cdist, centre, angle_shift=0)
    return prior_map
```

Visualisation of all normalised Ray features with given angular step.

[7]:
```
df = pd.read_csv(PATH_MEASURED_RAYS, index_col=0)
list_rays = df.values.tolist()
fig = plt.figure(figsize=(8, 4))
plt.plot(np.linspace(0, 360, len(list_rays[0]) + 1)[:-1], np.array(list_rays).T, '-')
_= plt.xlim([0, 350]), plt.grid(), plt.xlabel('discrete Ray step [deg]'), plt.ylabel(
↪'Ray distances')
```



Computing shape prior model

Estimate and exporting model...

[8]:
```
model_rg, list_mean_cdf = seg_rg.transform_rays_model_sets_mean_cdf_mixture(list_rays,
↪ 5)
# model, list_mean_cdf = tl_rg.transform_rays_model_sets_mean_cdf_kmeans(list_rays,␣
↪25)
PATH_MODEL_MIXTURE = os.path.join(PATH_DATA, 'RG2SP_islets_single-model.pkl')

with open(PATH_MODEL_MIXTURE, 'w') as fp:
    pickle.dump({'name': 'set_cdfs', 'cdfs': list_mean_cdf, 'mix_model': model_rg},␣
↪fp)
```

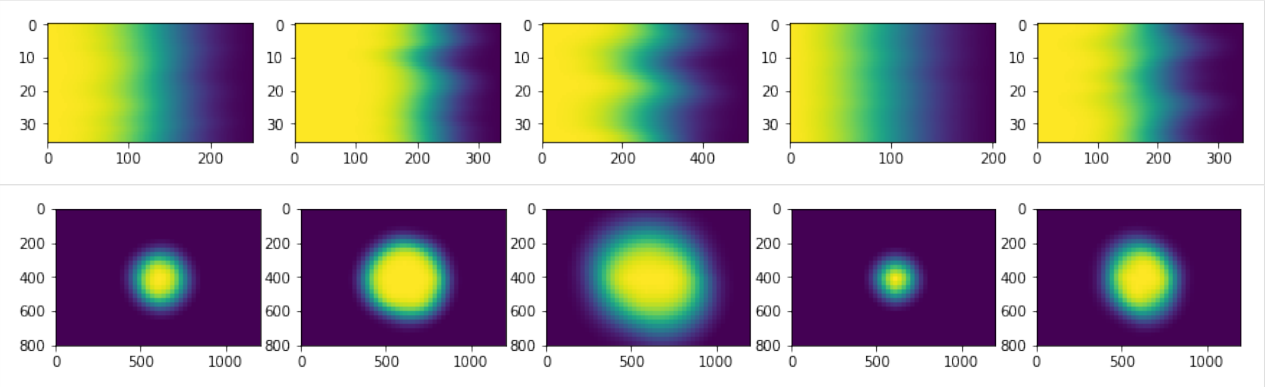
Try to load just exported model to verify that it is readeble.

[9]:
```
file_model = pickle.load(open(PATH_MODEL_MIXTURE, 'r'))
print (file_model.keys())
list_mean_cdf = file_model['cdfs']
model_rg = file_model['mix_model']
```

```
['mix_model', 'cdfs', 'name']
```

Visualise the set of components from Mixture model and their back reconstructions

[12]:
```
subfig_per_row = 8
subfig_per_col = int(np.ceil(len(list_mean_cdf) / float(subfig_per_row)))
fig = plt.figure(figsize=(3 * subfig_per_row, 1.5 * subfig_per_col))
for i in range(len(list_mean_cdf)):
    plt.subplot(subfig_per_col, subfig_per_row, i+1), plt.imshow(list_mean_cdf[i][1],␣
↪aspect='auto')
fig = plt.figure(figsize=(3 * subfig_per_row, 2 * subfig_per_col))
for i in range(len(list_mean_cdf)):
    plt.subplot(subfig_per_col, subfig_per_row, i+1)
    plt.imshow(compute_prior_map(list_mean_cdf[i][1], size=(800, 1200), step=25))
```

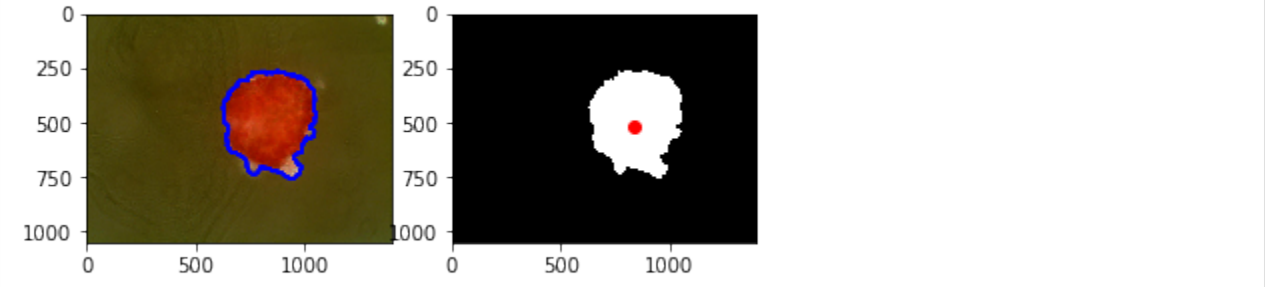


Loading Image

[13]:
```
name = 'Lh05-09'
img = io.imread(os.path.join(DIR_IMAGES, name + '.jpg'))
annot = measure.label(io.imread(os.path.join(DIR_ANNOTS, name + '.png')))
centers = np.array([ndimage.measurements.center_of_mass(annot == l) for l in range(1,␣
↪np.max(annot) + 1)])
centers += (np.random.random(centers.shape) - 0.5) * 100
print ('centres: %s' % repr(centers))
FIG_SIZE = (8. * np.array(img.shape[:2]) / np.max(img.shape))[::-1]
```

```
centres: array([[ 513.78095009,  837.2978496 ]])
```

[15]:
```
plt.subplot(1, 2, 1)
plt.imshow(img), plt.contour(annot, colors='b')
plt.subplot(1, 2, 2)
plt.imshow(annot, cmap=plt.cm.Greys_r)
plt.plot(centers[:, 1], centers[:, 0], 'or')
_= plt.xlim([0, img.shape[1]]),  plt.ylim([img.shape[0], 0])
```



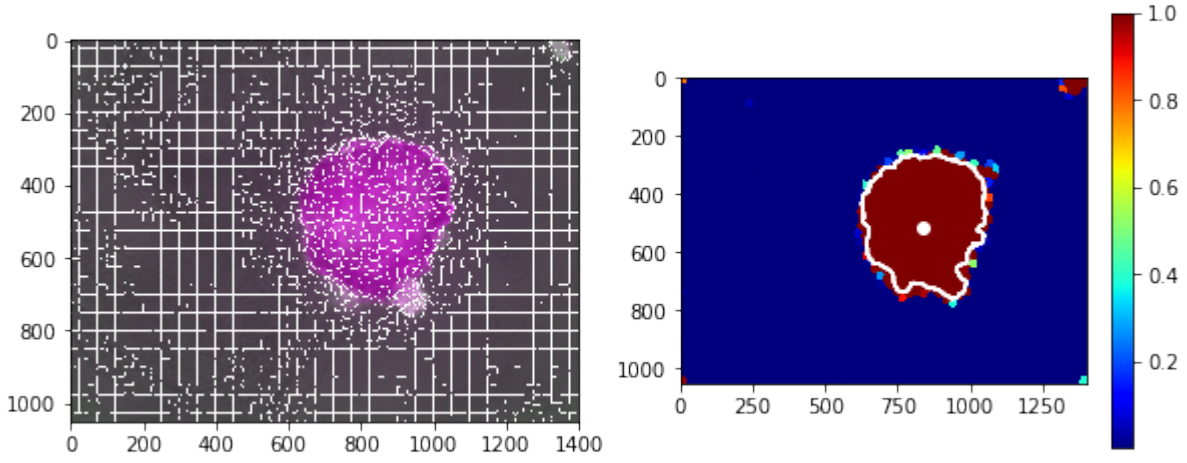
Compute superpixels and probabilities

[16]:
```
img_tf = img.copy()
img_tf[:, :, 2] = img_tf[:, :, 0]
SLIC_SIZE = 25
SLIC_REGUL = 0.2
DICT_FEATURES = {'color': ['mean', 'median']}
slic, features = seg_pipe.compute_color2d_superpixels_features(img_tf, dict_
↪features=DICT_FEATURES, sp_size=SLIC_SIZE, sp_regul=SLIC_REGUL)
features = np.nan_to_num(features)
print ('feature space: %s' % repr(features.shape))

model_seg = seg_gc.estim_class_model(features, 2, pca_coef=None, estim_model='GMM',␣
↪use_scaler=True)
slic_preds = model_seg.predict_proba(features)
print ('prediction shape: %s' % repr(slic_preds.shape))
```

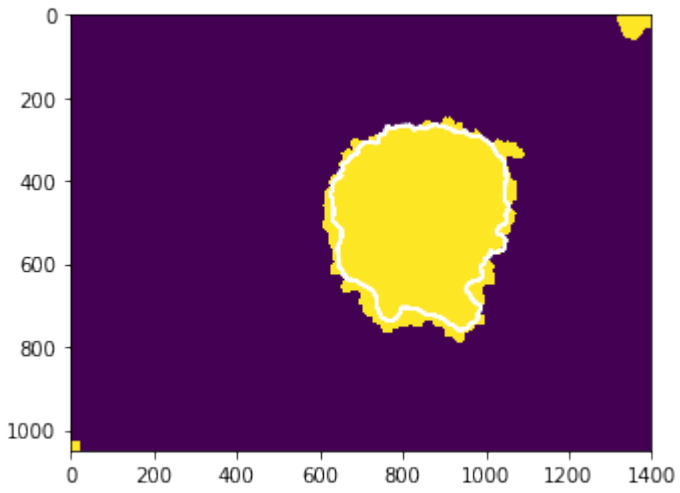
```
feature space: (2329, 6)
prediction shape: (2329, 2)
```

[17]:
```
grid_x, grid_y = np.mgrid[0:img.shape[0], 0:img.shape[1]]
grid_x -= int(img.shape[0] / 2.)
grid_y -= int(img.shape[1] / 2.)
dist_center = np.sqrt(grid_x ** 2 + grid_y ** 2)
img_bg_score = [np.mean(dist_center * slic_preds[:, i][slic]) for i in range(slic_
↪preds.shape[1])]
slic_prob_fg = slic_preds[:, np.argmin(img_bg_score)]
print ('image BG scores: %s' % repr(img_bg_score))

plt.figure(figsize=(10, 4))
plt.subplot(1, 2, 1), plt.imshow(sk_segm.mark_boundaries(img_tf, slic, color=(1, 1,␣
↪1)))

plt.subplot(1, 2, 2)
plt.imshow(slic_prob_fg[slic], cmap=plt.cm.jet), plt.colorbar()
plt.contour(annot, colors='w')
plt.plot(centers[:, 1], centers[:, 0], 'ow')
_= plt.xlim([0, img.shape[1]]),  plt.ylim([img.shape[0], 0])
```

```
image BG scores: [441.35775946597442, 30.228474053176999]
```



[29]:
```
# model_seg, _, _, _ = seg_pipe.train_classif_color2d_slic_features([img_red],␣
↪[annot], DICT_FEATURES, sp_size=SLIC_SIZE, sp_regul=SLIC_REGUL)
segm_gc, _ = seg_pipe.segment_color2d_slic_features_model_graphcut(img_tf, model_seg,␣
↪DICT_FEATURES, sp_size=SLIC_SIZE, sp_regul=SLIC_REGUL, gc_edge_type='color', gc_
↪regul=20.)

_= plt.imshow(segm_gc), plt.contour(annot, colors='w')
# plt.subplot(1, 2, 2), plt.imshow(seg_soft[:, :, 1])
```



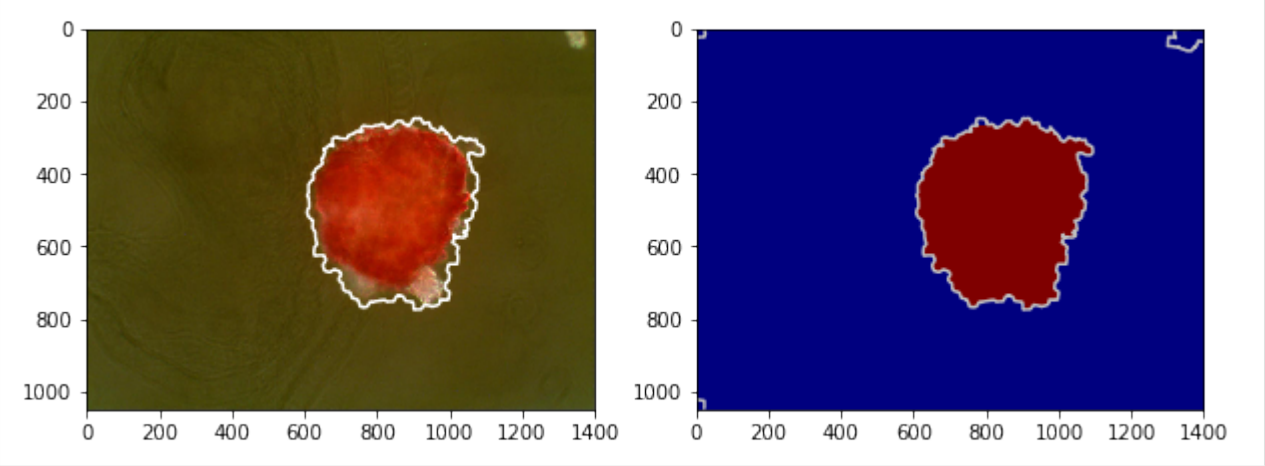
[24]:
```
from IPython.html import widgets
from IPython.display import display
```

```
:0: FutureWarning: IPython widgets are experimental and may change in the future.
```

Region growing - GraphCut

[26]:
```
debug_gc_mm = {}
labels_gc = seg_rg.region_growing_shape_slic_graphcut(slic, slic_prob_fg, centers,␣
↪(model_rg, list_mean_cdf), 'set_cdfs',
                  coef_shape=2., coef_pairwise=5., prob_label_trans=[0.1, 0.03], optim_
↪global=False,
                  allow_obj_swap=False, dict_thresholds=seg_rg.RG2SP_THRESHOLDS, nb_
↪iter=100, debug_history=debug_gc_mm)
segm_obj = labels_gc[slic]
print (debug_gc_mm.keys())

fig = plt.figure(figsize=(10, 4))
_= plt.subplot(1, 2, 1), plt.imshow(img), plt.contour(segm_obj, levels=np.unique(segm_
↪obj), colors='w')
_= plt.subplot(1, 2, 2), plt.imshow(segm_obj, cmap=plt.cm.jet), plt.contour(segm_gc,␣
↪levels=np.unique(segm_gc), colors='#bfbfbf')
```

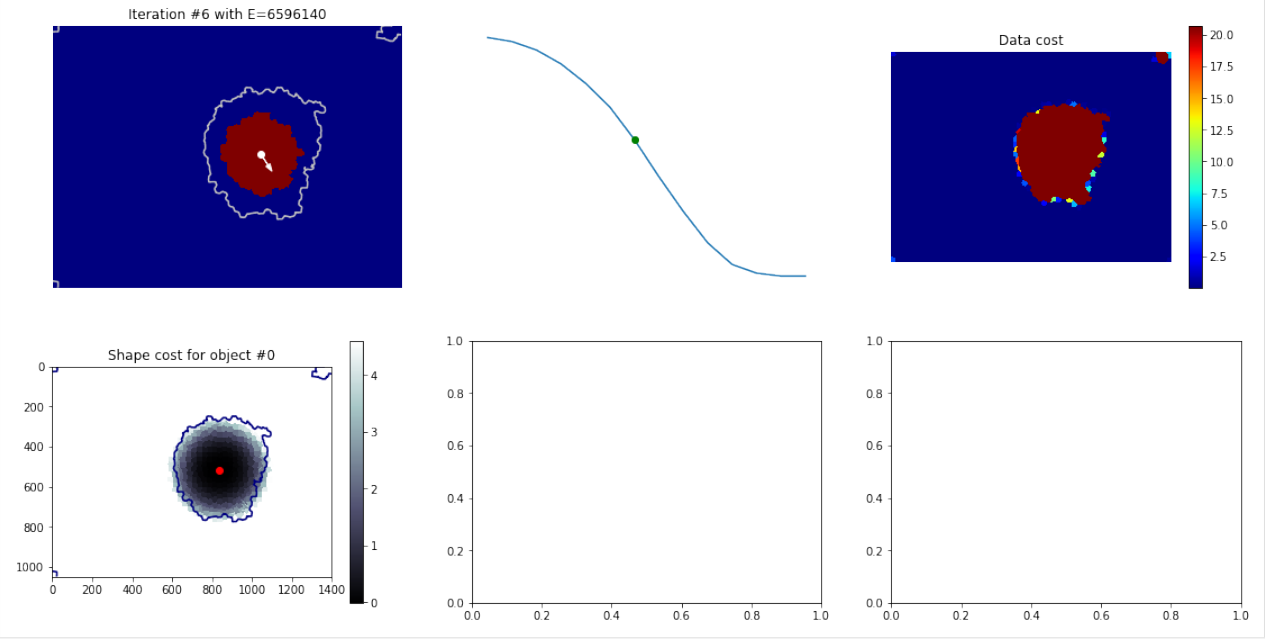
```
['shifts', 'lut_data_cost', 'lut_shape_cost', 'criteria', 'labels', 'centres']
```



Interastive visualisation - over iterations

[27]:
```
def show_partial(i):
    _= plt.close(), tl_visu.figure_rg2sp_debug_complete(segm_gc, slic, debug_gc_mm, i,
↪ max_size=5)
# show the interact
widgets.interact(show_partial, i=(0, len(debug_gc_mm['criteria']) -1))
```

[27]:
```
<function __main__.show_partial>
```



[ ]:

1.3.5 Object segmentation with Region Growing with Shape Prior

Region growing is a classical image segmentation method based on hierarchical region aggregation using local similarity rules. Our proposed method differs from classical region growing in three important aspects. First, it works on the level of superpixels instead of pixels, which leads to a substantial speedup. Second, our method uses learned statistical shape properties which encourage growing leading to plausible shapes. In particular, we use ray features to describe the object boundary. Third, our method can segment multiple objects and ensure that the segmentations do not overlap. The problem is represented as an energy minimization and is solved either greedily, or iteratively using GraphCuts.

Borovec, J., Kybic, J., & Sugimoto, A. (2017). **Region growing using superpixels with learned shape prior.** Journal of Electronic Imaging.

[1]:
```
%matplotlib inline
import os, sys, glob
import pickle
import numpy as np
import pandas as pd
from PIL import Image
# from scipy import spatial, ndimage
from skimage import segmentation as sk_segm
import matplotlib.pylab as plt
```

[2]:
```
sys.path += [os.path.abspath('.'), os.path.abspath('..')] # Add path to root
import imsegm.utilities.data_io as tl_io
import imsegm.utilities.drawing as tl_visu
import imsegm.superpixels as seg_spx
import imsegm.region_growing as seg_rg
```

Loading data

[3]:
```
COLORS = 'bgrmyck'
RG2SP_THRESHOLDS = seg_rg.RG2SP_THRESHOLDS
PATH_IMAGES = os.path.join(tl_io.update_path('data-images'), 'drosophila_ovary_slice')
PATH_DATA = tl_io.update_path('data-images', absolute=True)
PATH_OUT = tl_io.update_path('output', absolute=True)
PATH_MEASURED_RAYS = os.path.join(PATH_IMAGES, 'eggs_ray-shapes.csv')
print ([os.path.basename(p) for p in glob.glob(os.path.join(PATH_IMAGES, '*')) if os.
↪path.isdir(p)])
```

```
['center_levels', 'image', 'annot_struct', 'ellipse_fitting', 'annot_eggs', 'segm_rgb
↪', 'segm', 'image_cut-stage-2']
```

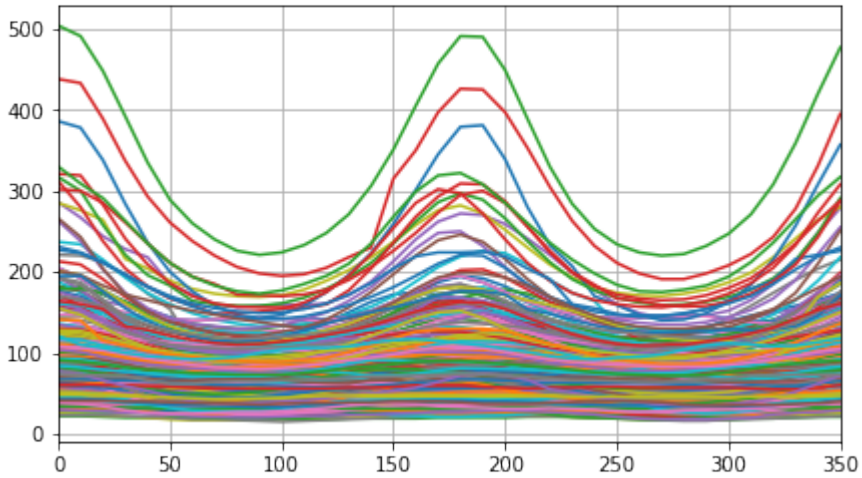
[4]:
```
DIR_IMAGES = os.path.join(PATH_IMAGES, 'image')
DIR_SEGMS = os.path.join(PATH_IMAGES, 'segm')
DIR_ANNOTS = os.path.join(PATH_IMAGES, 'annot_eggs')
DIR_CENTERS = os.path.join(PATH_IMAGES, 'center_levels')
```

Estimate shape models

[5]:
```
def compute_prior_map(cdist, size=(500, 800), step=5):
    prior_map = np.zeros(size)
    centre = np.array(size) / 2
    for i in np.arange(prior_map.shape[0], step=step):
        for j in np.arange(prior_map.shape[1], step=step):
            prior_map[i:i+step, j:j+step] = seg_rg.compute_shape_prior_table_cdf([i,␣
↪j], cdist, centre, angle_shift=0)
    return prior_map
```

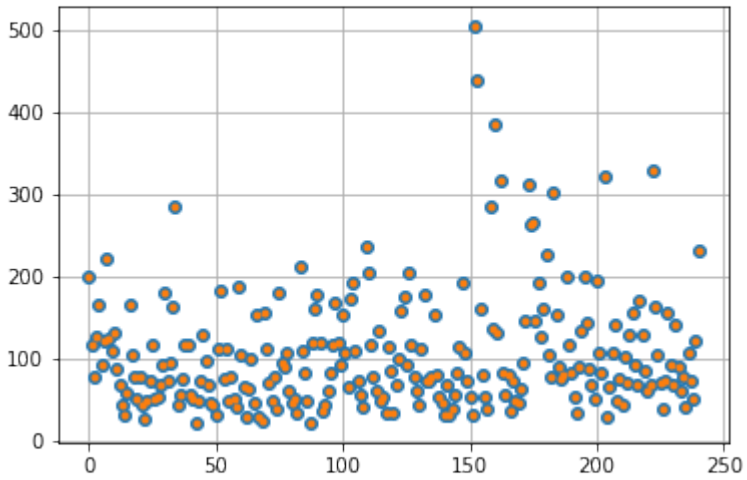
Visualisation of all normalised Ray features with given angular step.

[7]:
```
df = pd.read_csv(PATH_MEASURED_RAYS, index_col=0)
list_rays = df.values.tolist()
fig = plt.figure(figsize=(7, 4))
plt.plot(np.linspace(0, 360, len(list_rays[0]) + 1)[:-1], np.array(list_rays).T, '-')
_= plt.xlim([0, 350]), plt.grid()
```



Visualise the maxima for each egg of measured Ray features.

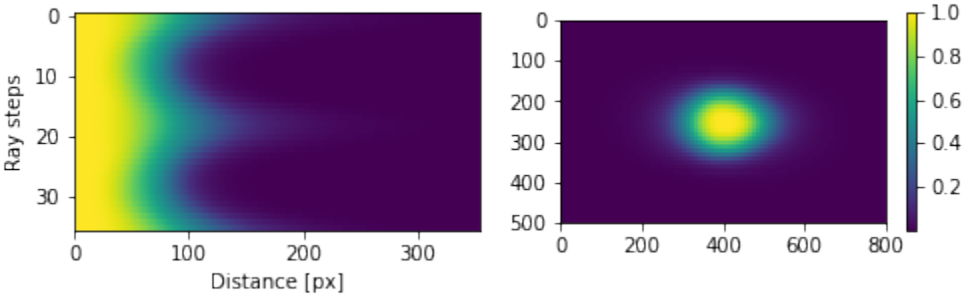
[8]:
```
maxima = np.max(list_rays, axis=1)
plt.plot(maxima, 'o'), plt.grid()
# list_rays += [ray * (1 + np.random.random() / 10.) for ray in np.array(list_
↪rays)[maxima > 250]]
# list_rays += [ray * (1 + np.random.random() / 10.) for ray in np.array(list_
↪rays)[maxima > 250]]
_= plt.plot(np.max(list_rays, axis=1), '.')
```



Estimate and exporting model...

[9]:
```
# list_cdf = tl_rg.transform_rays_model_cdf_histograms(list_rays, nb_bins=15)
mm, list_cdf = seg_rg.transform_rays_model_cdf_mixture(list_rays, 15)
cdf = np.array(np.array(list_cdf))
PATH_MODEL_SINGLE = os.path.join(PATH_DATA, 'RG2SP_eggs_single-model.pkl')

with open(PATH_MODEL_SINGLE, 'w') as fp:
    pickle.dump({'name': 'cdf', 'cdfs': cdf, 'mix_model': mm}, fp)
```

[11]:
```
fig = plt.figure(figsize=(8, 2))
plt.subplot(1, 2, 1), plt.imshow(cdf, aspect='auto'), plt.ylabel('Ray steps'), plt.
↪xlabel('Distance [px]')
_= plt.subplot(1, 2, 2), plt.imshow(compute_prior_map(cdf, step=10)), plt.colorbar()
# fig.savefig(os.path.join(PATH_OUT, 'shape-prior.pdf'), bbox_inches='tight')
```



Computing shape prior model

Estimate and exporting model...

[16]:
```
model, list_mean_cdf = seg_rg.transform_rays_model_sets_mean_cdf_mixture(list_rays,␣
↪15)
# model, list_mean_cdf = tl_rg.transform_rays_model_sets_mean_cdf_kmeans(list_rays,␣
↪25)
PATH_MODEL_MIXTURE = os.path.join(PATH_DATA, 'RG2SP_eggs_mixture-model.pkl')
```

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```
with open(PATH_MODEL_MIXTURE, 'w') as fp:
    pickle.dump({'name': 'set_cdfs', 'cdfs': list_mean_cdf, 'mix_model': model}, fp)
```

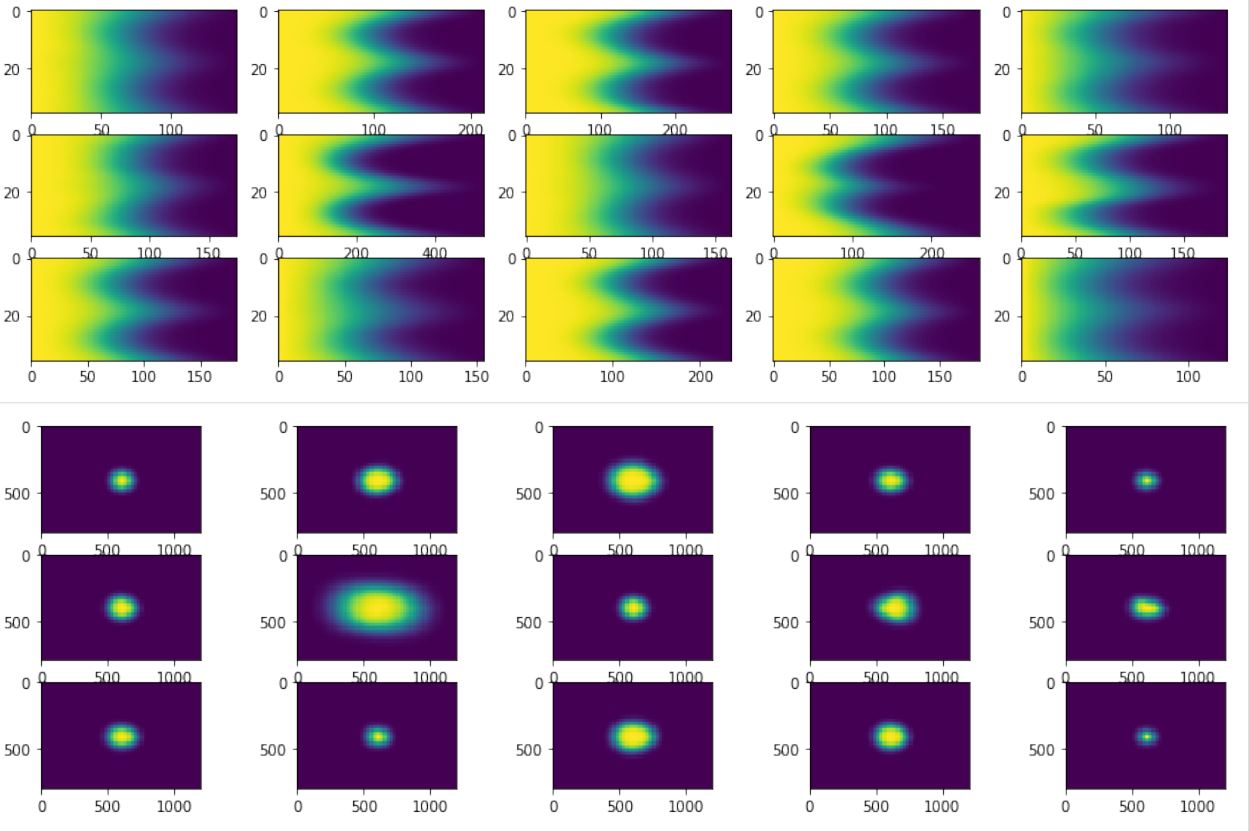
Try to load just exported model to verify that it is readeble.

[17]:
```
file_model = pickle.load(open(PATH_MODEL_MIXTURE, 'r'))
print (file_model.keys())
list_mean_cdf = file_model['cdfs']
model = file_model['mix_model']
```

```
['mix_model', 'cdfs', 'name']
```

Visualise the set of components from Mixture model and their back reconstructions

[19]:
```
subfig_per_row = 5
subfig_per_col = int(np.ceil(len(list_mean_cdf) / float(subfig_per_row)))
fig = plt.figure(figsize=(3 * subfig_per_row, 1.5 * subfig_per_col))
for i in range(len(list_mean_cdf)):
    plt.subplot(subfig_per_col, subfig_per_row, i+1), plt.imshow(list_mean_cdf[i][1],␣
↪aspect='auto')
fig = plt.figure(figsize=(3 * subfig_per_row, 1.5 * subfig_per_col))
for i in range(len(list_mean_cdf)):
    plt.subplot(subfig_per_col, subfig_per_row, i+1)
    plt.imshow(compute_prior_map(list_mean_cdf[i][1], size=(800, 1200), step=25))
```



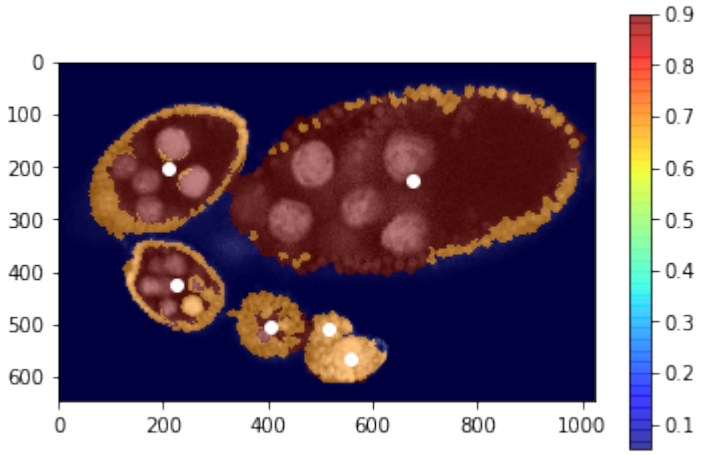
Loading Image

[20]:
```
name = 'insitu7545'
# name = 'insitu4200'
img = np.array(Image.open(os.path.join(DIR_IMAGES, name + '.jpg')))
seg = np.array(Image.open(os.path.join(DIR_SEGMS, name + '.png')))
# seg = np.array(Image.open(os.path.join(DIR_SEGMS, name + '_gc.png')))
centers = pd.read_csv(os.path.join(DIR_CENTERS, name + '.csv'), index_col=0).values
centers[:, [0, 1]] = centers[:, [1, 0]]
FIG_SIZE = (6. * np.array(img.shape[:2]) / np.max(img.shape))[::-1]
# print centers
```

Project the structure segmentation with probabbilties for each class

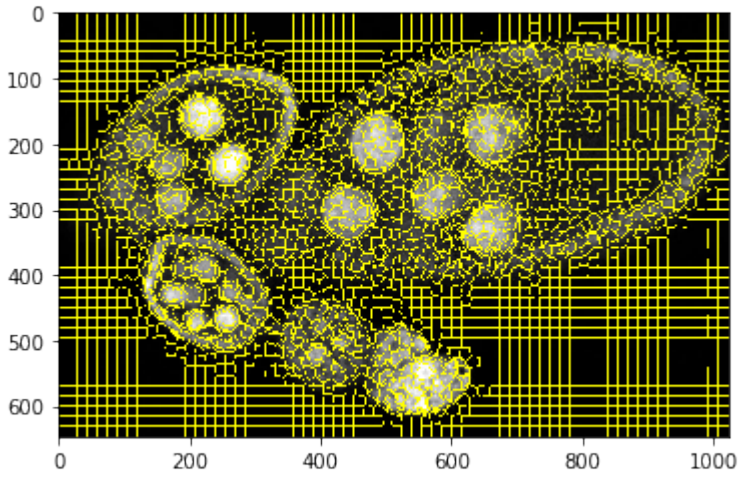
[21]:
```
labels_fg_prob = [0.05, 0.7, 0.9, 0.9]
# labels_fg_prob = [0.05, 0.8, 0.95, 0.95]

# plt.figure(figsize=FIG_SIZE)
plt.imshow(img[:, :, 0], cmap=plt.cm.Greys_r)
plt.imshow(np.array(labels_fg_prob)[seg], alpha=0.5, cmap=plt.cm.jet), plt.colorbar()
plt.plot(centers[:, 1], centers[:, 0], 'ow')
_= plt.xlim([0, img.shape[1]]),  plt.ylim([img.shape[0], 0])
```



Compute superpixels

[22]:
```
slic = seg_spx.segment_slic_img2d(img, sp_size=15, relative_compact=0.35)
# plt.figure(figsize=FIG_SIZE[:-1])
_= plt.imshow(sk_segm.mark_boundaries(img[:, :, 0], slic))
```



Loading ipython (interactive) visualisation functions

[23]:
```
from IPython.html import widgets
from IPython.display import display
```

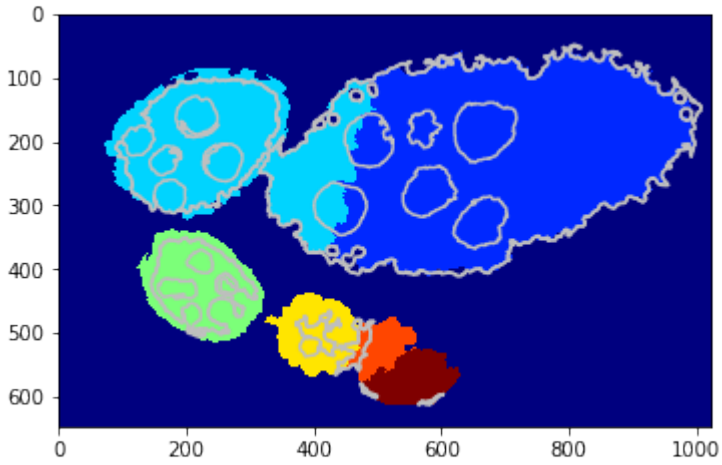
```
:0: FutureWarning: IPython widgets are experimental and may change in the future.
```

Region growing - Greedy

Single model

[24]:
```
debug_gd_1m = {}
slic_prob_fg = seg_rg.compute_segm_prob_fg(slic, seg, labels_fg_prob)
labels_greedy = seg_rg.region_growing_shape_slic_greedy(slic, slic_prob_fg, centers,␣
↪(None, cdf), 'cdf',
                    coef_shape=1., coef_pairwise=5., prob_label_trans=[0.1, 0.01],␣
↪greedy_tol=2e-1,
                    allow_obj_swap=True, dict_thresholds=RG2SP_THRESHOLDS, nb_
↪iter=250, debug_history=debug_gd_1m)
segm_obj = labels_greedy[slic]
print (debug_gd_1m.keys())
fig = plt.figure(figsize=FIG_SIZE)
_= plt.imshow(segm_obj, cmap=plt.cm.jet), plt.contour(seg, levels=np.unique(seg),␣
↪colors='#bfbfbf')
```

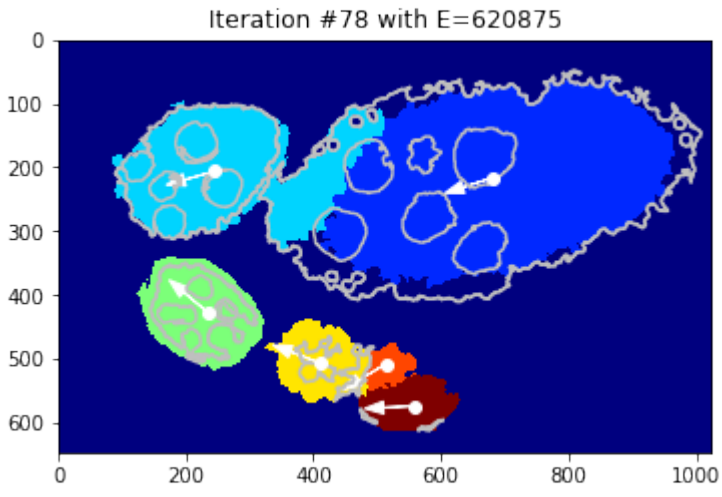
```
['shifts', 'lut_data_cost', 'lut_shape_cost', 'criteria', 'labels', 'centres']
```



Interastive visualisation - over iterations

[25]:
```
def show_partial(i):
    _= plt.close(), tl_visu.draw_rg2sp_results(plt.figure(figsize=FIG_SIZE).gca(),␣
↪seg, slic, debug_gd_1m, i)
# show the interact
widgets.interact(show_partial, i=(0, len(debug_gd_1m['criteria']) -1))
```

[25]:
```
<function __main__.show_partial>
```



Mixture model

[26]:
```
debug_gd_mm = {}
slic_prob_fg = seg_rg.compute_segm_prob_fg(slic, seg, labels_fg_prob)
labels_greedy = seg_rg.region_growing_shape_slic_greedy(slic, slic_prob_fg, centers,␣
↪(model, list_mean_cdf), 'set_cdfs',
                    coef_shape=5., coef_pairwise=15., prob_label_trans=[0.1, 0.03],␣
↪greedy_tol=3e-1,
                    allow_obj_swap=True, dict_thresholds=RG2SP_THRESHOLDS, nb_
↪iter=250, debug_history=debug_gd_mm)
```

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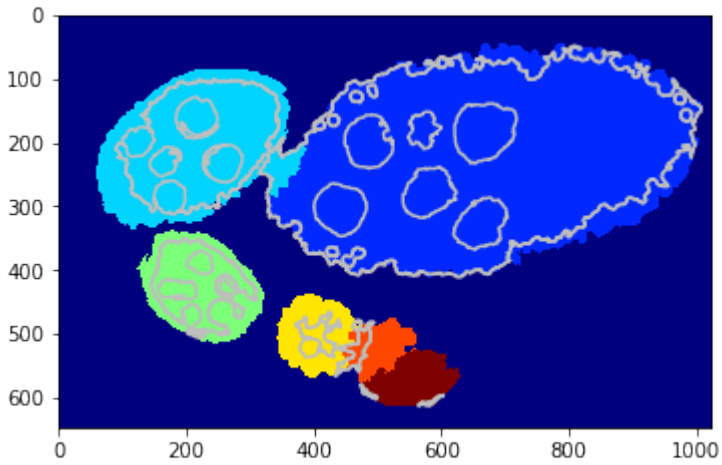
```
segm_obj = labels_greedy[slic]
print (debug_gd_mm.keys())
fig = plt.figure(figsize=FIG_SIZE)
_= plt.imshow(segm_obj, cmap=plt.cm.jet), plt.contour(seg, levels=np.unique(seg),␣
↪colors='#bfbfbf')
```

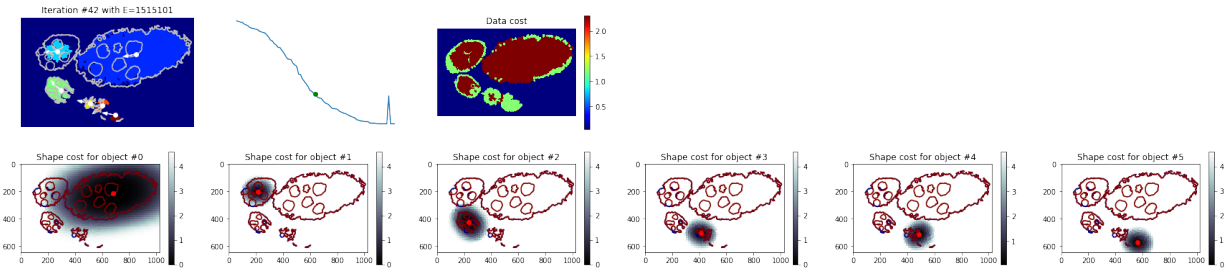
```
['shifts', 'lut_data_cost', 'lut_shape_cost', 'criteria', 'labels', 'centres']
```



Interastive visualisation - over iterations

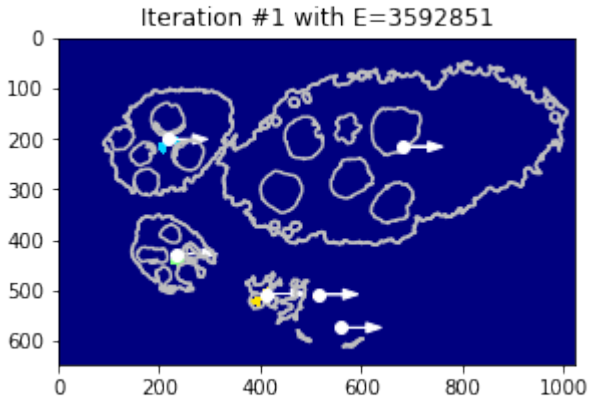
[27]:
```
def show_partial(i):
    _= plt.close(), tl_visu.figure_rg2sp_debug_complete(seg, slic, debug_gd_mm, i,␣
↪max_size=4)
# show the interact
widgets.interact(show_partial, i=(0, len(debug_gd_mm['criteria']) - 1))
```

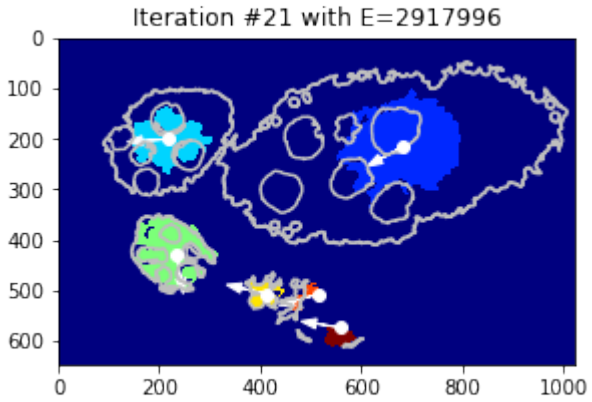
[27]:
```
<function __main__.show_partial>
```

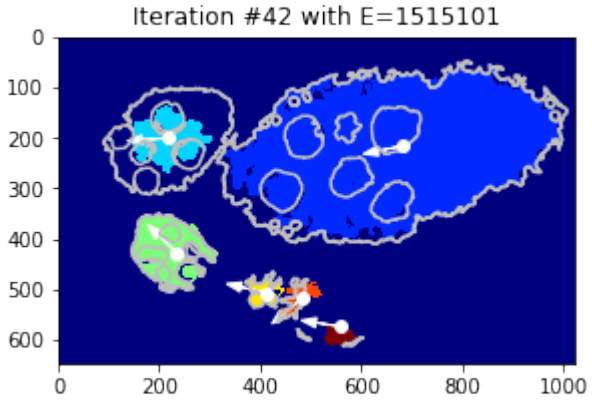


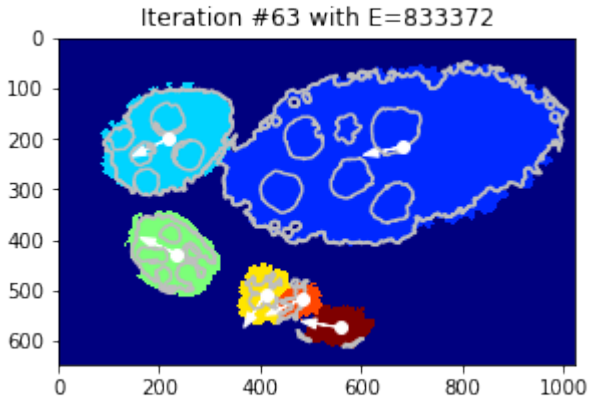
Visualise some iterations

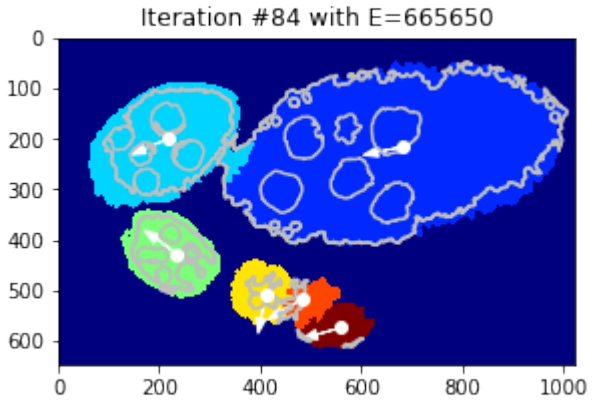
[28]:
```
nb_iter = len(debug_gd_mm['criteria'])
for i in np.linspace(1, nb_iter - 1, 5):
    _= tl_visu.draw_rg2sp_results(plt.figure(figsize=(6, 3)).gca(), seg, slic, debug_
↪gd_mm, int(i))
```


Iteration #1 with E=3592851
0
100
200
300
400
500
600
0
200
400
600
800
1000


Iteration #21 with E=2917996
0
100
200
300
400
500
600
0
200
400
600
800
1000


Iteration #42 with E=1515101
0
100
200
300
400
500
600
0
200
400
600
800
1000





Exporting iterations

[35]:
```
nb_iter = len(debug_gd_mm['criteria'])
fig_size = np.array(FIG_SIZE) * np.array([debug_gd_mm['lut_data_cost'].shape[1] - 1,␣
↪2]) / 2.
for i in range(nb_iter):
    fig = plt.figure(figsize=fig_size)
    tl_visu.draw_rg2sp_results(fig.gca(), seg, slic, debug_gd_mm, int(i))
    plt.savefig(os.path.join(PATH_OUT, 'debug-gd-mm_iter-%03d' % i))
    plt.close(fig)
```

Region growing - GraphCut

Single model

[29]:
```
debug_gc_1m = {}
slic_prob_fg = seg_rg.compute_segm_prob_fg(slic, seg, labels_fg_prob)
labels_gc = seg_rg.region_growing_shape_slic_graphcut(slic, slic_prob_fg, centers,␣
↪(None, cdf), 'cdf',
                coef_shape=5., coef_pairwise=25., prob_label_trans=[0.1, 0.03], optim_
↪global=True,
                allow_obj_swap=True, dict_thresholds=RG2SP_THRESHOLDS, nb_iter=65,␣
↪debug_history=debug_gc_1m)
```

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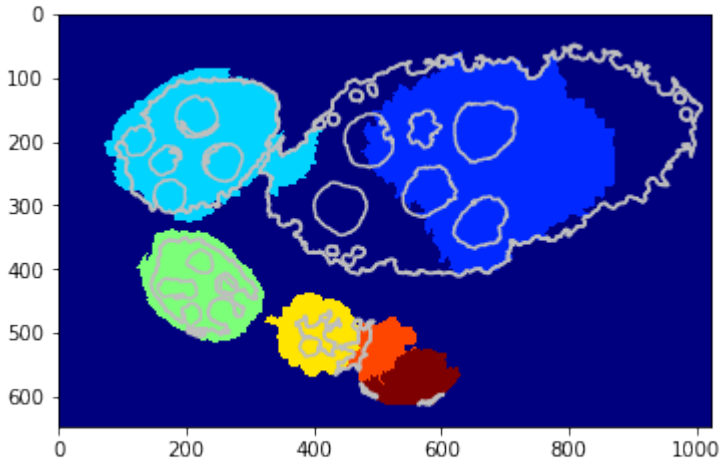
```
segm_obj = labels_gc[slic]
print (debug_gc_1m.keys())
fig = plt.figure(figsize=FIG_SIZE)
_= plt.imshow(segm_obj, cmap=plt.cm.jet), plt.contour(seg, levels=np.unique(seg),␣
↪colors='#bfbfbf')
# print debug_gc_1m.keys(), debug_gc_1m['centres']
```

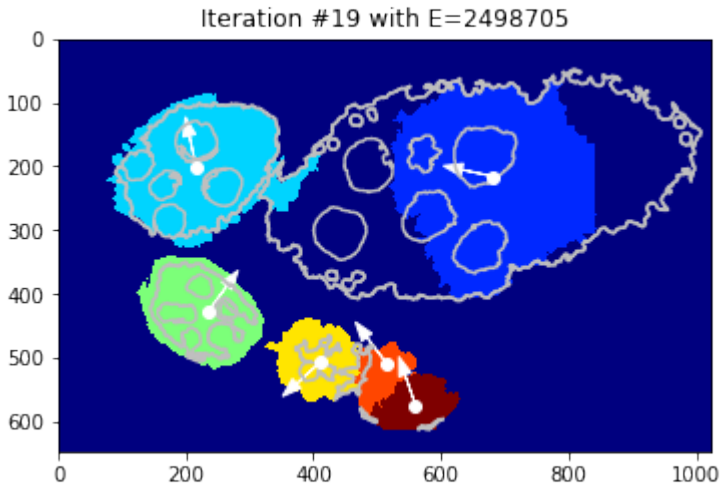
```
['shifts', 'lut_data_cost', 'lut_shape_cost', 'criteria', 'labels', 'centres']
```



Interastive visualisation - over iterations

[30]:
```
def show_partial(i):
    _= plt.close(), tl_visu.draw_rg2sp_results(plt.figure(figsize=FIG_SIZE).gca(),␣
↪seg, slic, debug_gc_1m, i)
# show the interact
widgets.interact(show_partial, i=(0, len(debug_gc_1m['criteria']) -1))
```

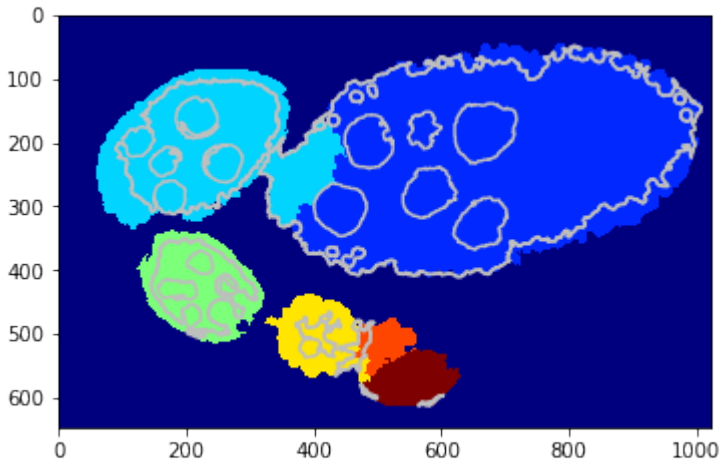
[30]:
```
<function __main__.show_partial>
```



Mixture model

[31]:
```
debug_gc_mm = {}
slic_prob_fg = seg_rg.compute_segm_prob_fg(slic, seg, labels_fg_prob)
labels_gc = seg_rg.region_growing_shape_slic_graphcut(slic, slic_prob_fg, centers,␣
↪(model, list_mean_cdf), 'set_cdfs',
                coef_shape=5., coef_pairwise=15., prob_label_trans=[0.1, 0.03], optim_
↪global=False,
                allow_obj_swap=False, dict_thresholds=RG2SP_THRESHOLDS, nb_iter=65,␣
↪debug_history=debug_gc_mm)
segm_obj = labels_gc[slic]
print (debug_gc_mm.keys())
fig = plt.figure(figsize=FIG_SIZE)
_= plt.imshow(segm_obj, cmap=plt.cm.jet), plt.contour(seg, levels=np.unique(seg),␣
↪colors='#bfbfbf')
```

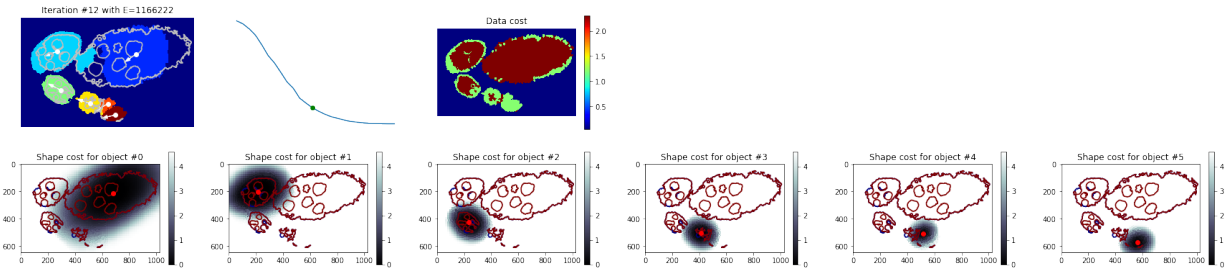
```
['shifts', 'lut_data_cost', 'lut_shape_cost', 'criteria', 'labels', 'centres']
```



Interastive visualisation - over iterations

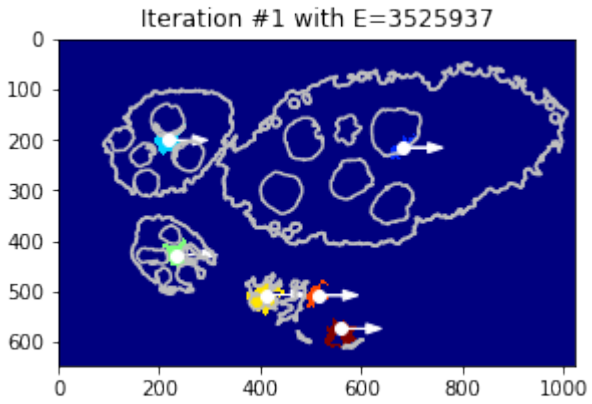
[32]:
```
def show_partial(i):
    _= plt.close(), tl_visu.figure_rg2sp_debug_complete(seg, slic, debug_gc_mm, i,␣
↪max_size=4)
# show the interact
widgets.interact(show_partial, i=(0, len(debug_gc_mm['criteria']) -1))
```

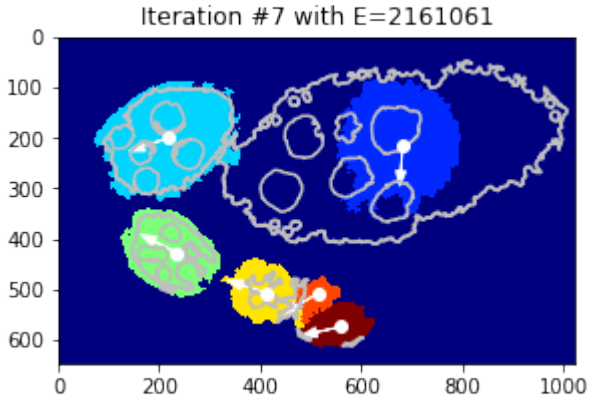
[32]:
```
<function __main__.show_partial>
```

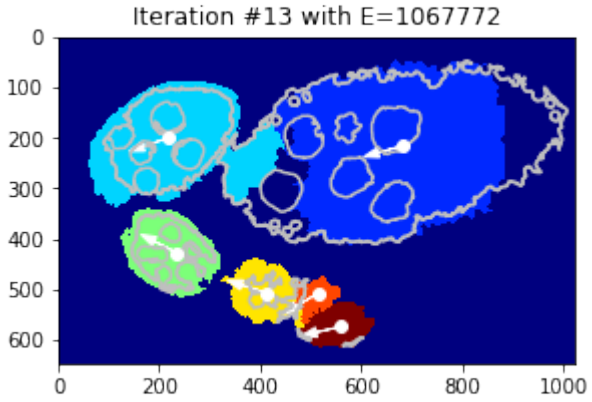


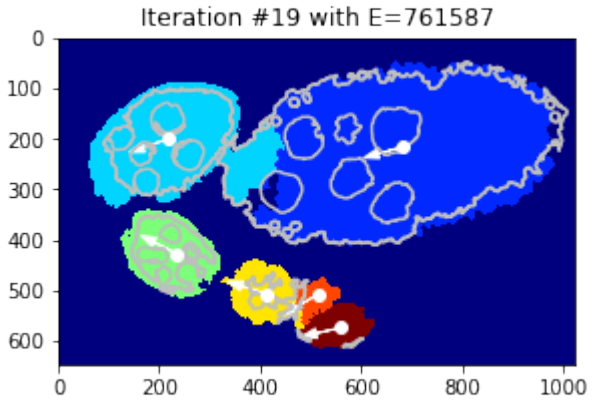
Visualise some iterations

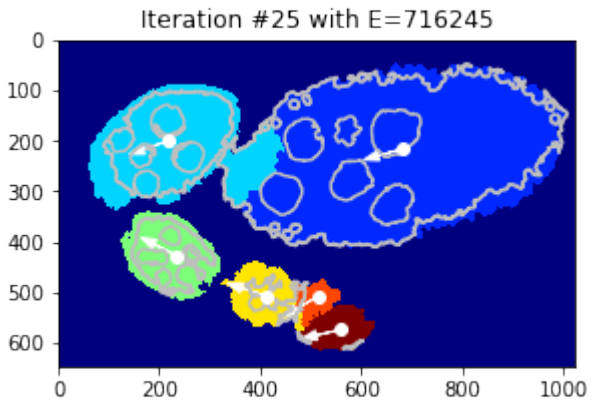
[34]:
```
nb_iter = len(debug_gc_mm['criteria'])
for i in np.linspace(1, nb_iter - 1, 5):
    _= tl_visu.draw_rg2sp_results(plt.figure(figsize=(6, 3)).gca(), seg, slic, debug_
↪gc_mm, int(i))
```











Exporting iteretions

[44]:
```
nb_iter = len(debug_gc_mm['criteria'])
path_out = tl_io.find_path_bubble_up('output')
fig_size = np.array(FIG_SIZE) * np.array([debug_gc_mm['lut_data_cost'].shape[1] - 1,␣
↪2]) / 2.
for i in range(nb_iter):
    fig = plt.figure(figsize=fig_size)
    tl_visu.draw_rg2sp_results(fig.gca(), seg, slic, debug_gc_mm, int(i))
    plt.savefig(os.path.join(path_out, 'debug-gc-mm_iter-%03d' % i))
    plt.close(fig)
```

Compare GC and Greedy

Comparing the energy evolving for all strategies

[31]:
```
fig = plt.figure(figsize=(7, 4))
plt.plot(debug_gd_1m['criteria'], 'g--', label='Grredy - single model')
plt.plot(debug_gd_mm['criteria'], 'g-.', label='Grredy - mixture model')
plt.plot(debug_gc_1m['criteria'], 'r:', label='GraphCut - single model')
plt.plot(debug_gc_mm['criteria'], 'r-', label='GraphCut - mixture model')
_= plt.ylabel('Energy'), plt.xlabel('iteration'), plt.grid(), plt.legend(loc='upper␣
↪right')
```

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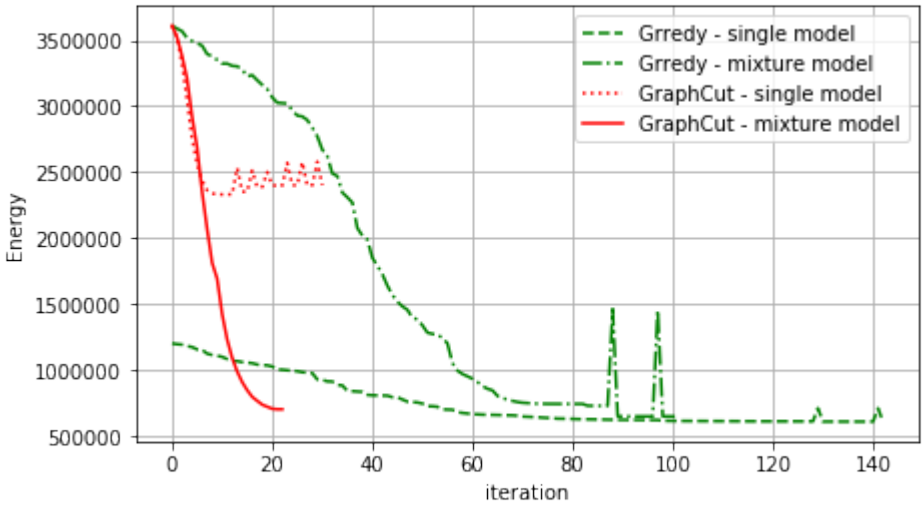
```
# fig.subplots_adjust(left=0.15, bottom=0.12, right=0.99, top=0.9)
# fig.savefig(os.path.join(PATH_OUT, 'figure_RG-energy-iter.pdf'))
```



[ ]:

1.3.6 Egg segm. from centre with GraphCut

A simple obejct segmentation method using Graph Cut over whole image initilised from a few initial seeds.

[1]:
```
%matplotlib inline
import os, sys, glob
import numpy as np
import pandas as pd
from PIL import Image
# from scipy import spatial, ndimage
from skimage import segmentation as sk_segm
import matplotlib.pylab as plt
```

[3]:
```
sys.path += [os.path.abspath('.'), os.path.abspath('..')] # Add path to root
import imsegm.utilities.data_io as tl_io
import imsegm.superpixels as tl_spx
import imsegm.region_growing as tl_rg
```

Loading data

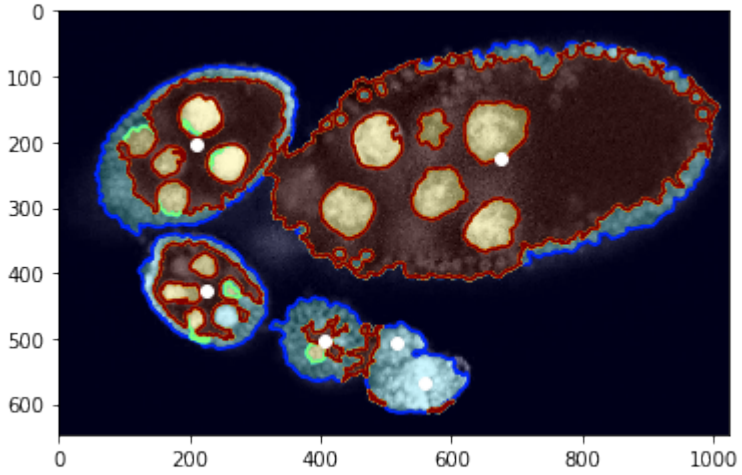
[4]:
```
COLORS = 'bgrmyck'
PATH_IMAGES = tl_io.update_path(os.path.join('data-images', 'drosophila_ovary_slice'))
print ([os.path.basename(p) for p in glob.glob(os.path.join(PATH_IMAGES, '*')) if os.
↪path.isdir(p)])
dir_img = os.path.join(PATH_IMAGES, 'image')
dir_segm = os.path.join(PATH_IMAGES, 'segm')
dir_annot = os.path.join(PATH_IMAGES, 'annot_eggs')
dir_center = os.path.join(PATH_IMAGES, 'center_levels')
```

```
['center_levels', 'image', 'annot_struct', 'annot_eggs', 'segm_rgb', 'segm']
```

[5]:
```
name = 'insitu7545'
img = np.array(Image.open(os.path.join(dir_img, name + '.jpg')))
seg = np.array(Image.open(os.path.join(dir_segm, name + '.png')))
centers = pd.read_csv(os.path.join(dir_center, name + '.csv'), index_col=0).values
centers[:, [0, 1]] = centers[:, [1, 0]]
FIG_SIZE = (8. * np.array(img.shape[:2]) / np.max(img.shape))[::-1]
```

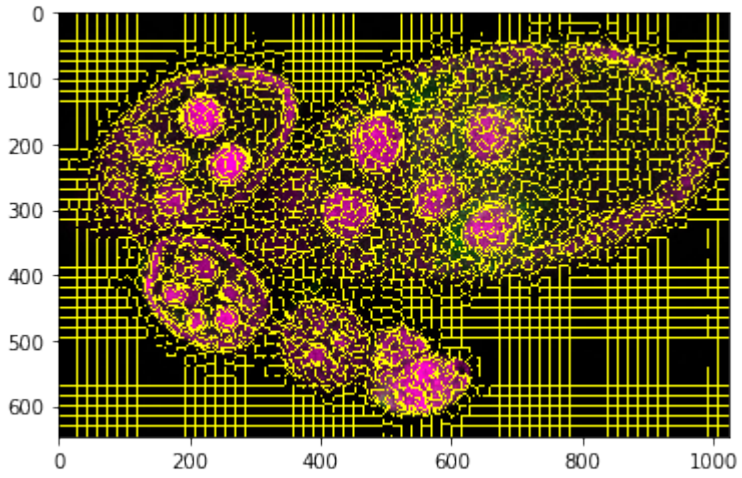
```
/usr/local/lib/python3.5/dist-packages/IPython/kernel/__main__.py:4: FutureWarning:␣
↪from_csv is deprecated. Please use read_csv(...) instead. Note that some of the␣
↪default arguments are different, so please refer to the documentation for from_csv␣
↪when changing your function calls
```

[6]:
```
# plt.figure(figsize=FIG_SIZE)
plt.imshow(img[:, :, 0], cmap=plt.cm.Greys_r)
plt.imshow(seg, alpha=0.2, cmap=plt.cm.jet), plt.contour(seg, cmap=plt.cm.jet)
_= plt.plot(centers[:, 1], centers[:, 0], 'ow')
```



Superpixels

[7]:
```
slic = tl_spx.segment_slic_img2d(img, sp_size=15, relative_compact=0.3)
_= plt.imshow(sk_segm.mark_boundaries(img, slic))
```

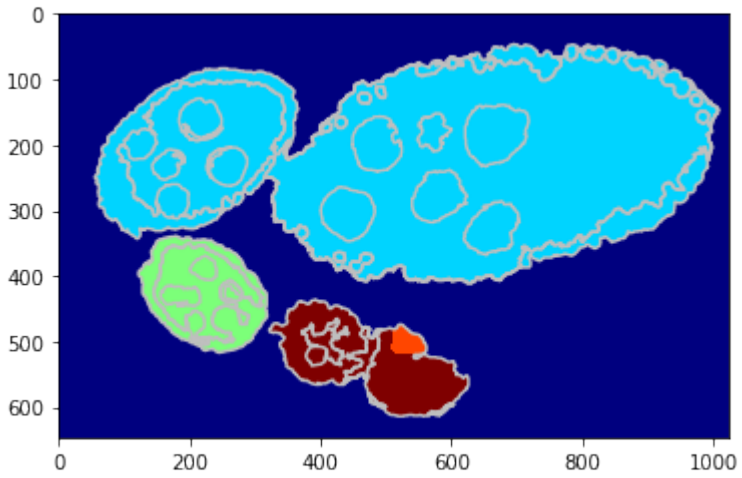


Obejct segmentation on pixel level

Estimating eggs with just single global GraphCut on probability according structure segmentation and annotated centre points.

[8]:
```
labels_fg_prob = [0.05, 0.7, 0.9, 0.9]
```

[10]:
```
debug_visual = dict()
segm_obj = tl_rg.object_segmentation_graphcut_pixels(seg, centers, labels_fg_prob, gc_
↪regul=1.,
                                                     seed_size=10, debug_visual=debug_
↪visual)
#fig = plt.figure(figsize=FIG_SIZE)
plt.imshow(segm_obj, cmap=plt.cm.jet)
_= plt.contour(seg, levels=np.unique(seg), colors='#bfbfbf')
```



Visualise the unary potential as maxima over join matrix U.

[11]:
```
unary = np.array([u.tolist() for u in debug_visual['unary_imgs']])
print ('shape: %s and unique labels %s' % (repr(unary.shape), repr(np.unique(np.
↪argmin(unary, axis=0)))))
```

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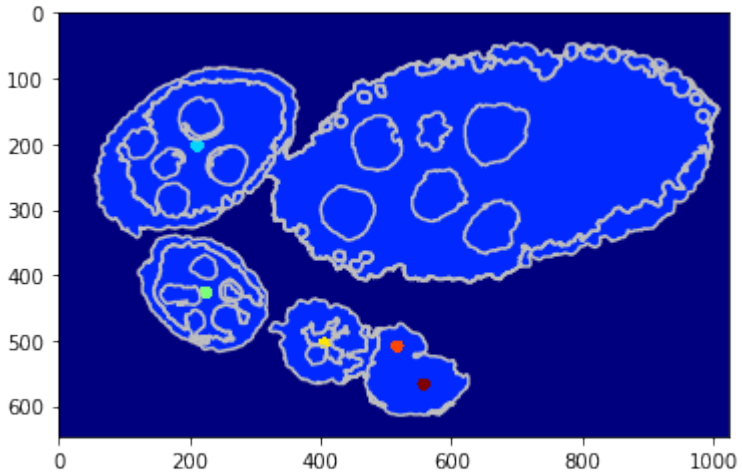
```
#fig = plt.figure(figsize=FIG_SIZE)
plt.imshow(np.argmin(unary, axis=0), cmap=plt.cm.jet)
_ = plt.contour(seg, levels=np.unique(seg), colors='#bfbfbf')
```

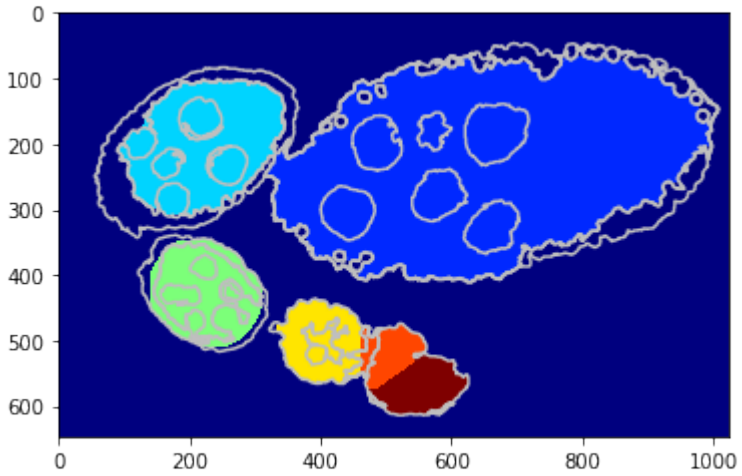
```
(7, 647, 1024) [0 1 2 3 4 5 6]
```



Using a shape prior

Similar scenarion as berore but in this case we draw a cicrcular shaper prior around each center wchich helps beter egg identification.

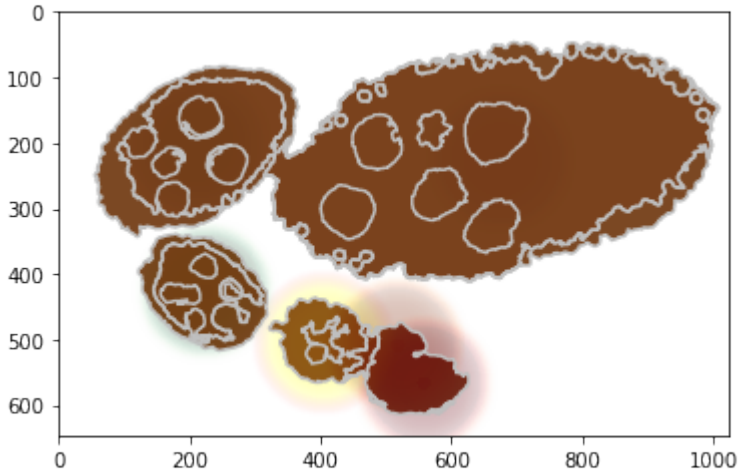
[12]:
```
debug_visual = dict()
segm_obj = tl_rg.object_segmentation_graphcut_pixels(seg, centers, labels_fg_prob, gc_
↪regul=2., seed_size=10,
                                                     coef_shape=0.1, shape_mean_
↪std=(50., 10.), debug_visual=debug_visual)
#fig = plt.figure(figsize=FIG_SIZE)
plt.imshow(segm_obj, cmap=plt.cm.jet)
_= plt.contour(seg, levels=np.unique(seg), colors='#bfbfbf')
```



Visualise the unary potential as maxima over join matrix U.

[13]:
```
unary = np.array([u.tolist() for u in debug_visual['unary_imgs']])
print ('shape: %s and unique labels %s' % (repr(unary.shape), repr(np.unique(np.
↪argmin(unary, axis=0)))))
#fig = plt.figure(figsize=FIG_SIZE)
plt.contour(seg, levels=np.unique(seg), colors='#bfbfbf')
CMAPS = [plt.cm.Greys, plt.cm.Purples, plt.cm.Blues, plt.cm.Greens, plt.cm.autumn,␣
↪plt.cm.Oranges, plt.cm.Reds]
for i in range(1, len(unary)):
    im = 1 - (unary[i, :, :] / np.max(unary[i, :, :]))
    im = (im * 1000).astype(int)
    lut = CMAPS[i](range(1001))
    lut[:, 3] = np.linspace(0, 0.7, 1001)
    plt.imshow(lut[im], alpha=1)
```

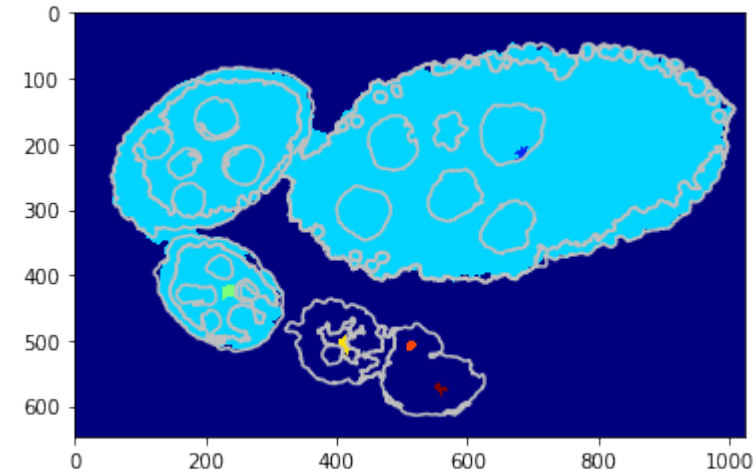
```
(7, 647, 1024) [0 1 2 3 4 5 6]
```



Obejct segmentation on SLIC level

We replicate the previous methods but apply on superpixels - flat unary potential.

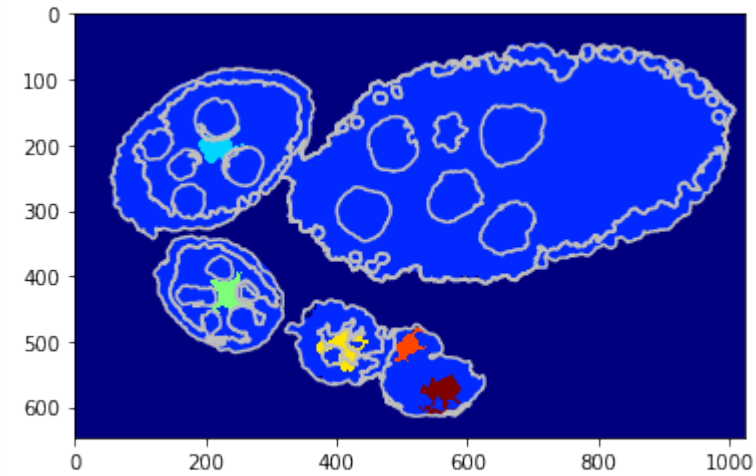
[15]:
```
debug_visual = dict()
gc_labels = tl_rg.object_segmentation_graphcut_slic(slic, seg, centers, labels_fg_
↪prob, gc_regul=2., edge_coef=1.,
                                                    edge_type='ones', add_
↪neighbours=True, debug_visual=debug_visual)
segm_obj = np.array(gc_labels)[slic]

#fig = plt.figure(figsize=FIG_SIZE)
plt.imshow(segm_obj, cmap=plt.cm.jet)
_ = plt.contour(seg, levels=np.unique(seg), colors='#bfbfbf')
```



Visualise the unary potential as maxima over join matrix U.

[16]:
```
unary = np.array([u.tolist() for u in debug_visual['unary_imgs']])
print ('shape: %s and unique labels %s' % (repr(unary.shape), repr(np.unique(np.
↪argmin(unary, axis=0)))))
#fig = plt.figure(figsize=FIG_SIZE)
plt.imshow(np.argmin(unary, axis=0), cmap=plt.cm.jet)
_ = plt.contour(seg, levels=np.unique(seg), colors='#bfbfbf')
```

```
(7, 647, 1024) [0 1 2 3 4 5 6]
```



Using a shape prior

We replicate the previous methods but apply on superpixels - unary potential with circular shape prior.

[17]:
```
debug_visual = dict()
gc_labels = tl_rg.object_segmentation_graphcut_slic(slic, seg, centers, labels_fg_
↪prob, gc_regul=1., edge_coef=1.,
                                                    edge_type='ones', coef_shape=0.1,␣
↪shape_mean_std=(50., 10.),
                                                    add_neighbours=False, debug_
↪visual=debug_visual)
```

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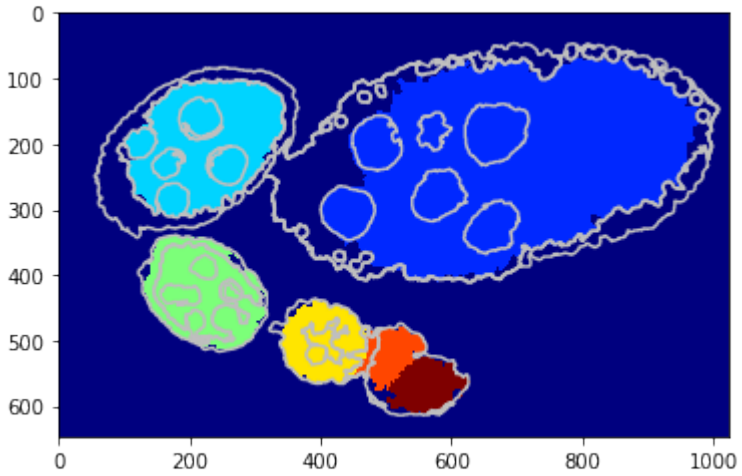
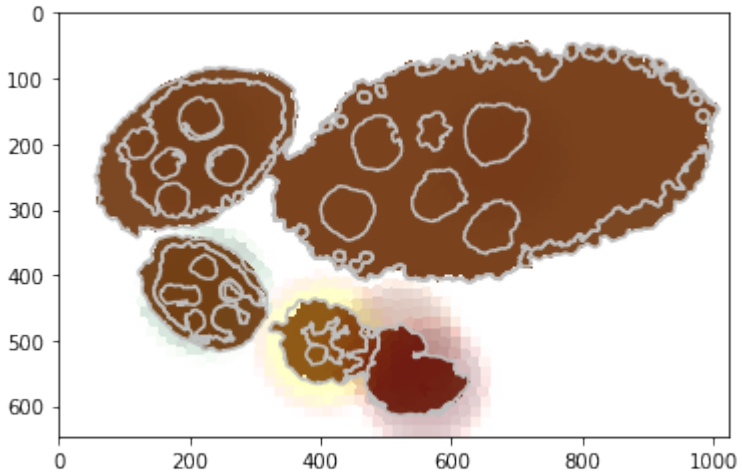
```
segm_obj = np.array(gc_labels)[slic]
#fig = plt.figure(figsize=FIG_SIZE)
plt.imshow(segm_obj, cmap=plt.cm.jet)
_= plt.contour(seg, levels=np.unique(seg), colors='#bfbfbf')
```



Visualise the unary potential as maxima over join matrix U.

[18]:
```
unary = np.array([u.tolist() for u in debug_visual['unary_imgs']])
print ('shape: %s and unique labels %s' % (repr(unary.shape), repr(np.unique(np.
↪argmin(unary, axis=0)))))
#fig = plt.figure(figsize=FIG_SIZE)
plt.contour(seg, levels=np.unique(seg), colors='#bfbfbf')
CMAPS = [plt.cm.Greys, plt.cm.Purples, plt.cm.Blues, plt.cm.Greens, plt.cm.autumn,␣
↪plt.cm.Oranges, plt.cm.Reds]
for i in range(1, len(unary)):
    im = 1 - (unary[i, :, :] / np.max(unary[i, :, :]))
    im = (im * 1000).astype(int)
    lut = CMAPS[i](range(1001))
    lut[:, 3] = np.linspace(0, 0.7, 1001)
    plt.imshow(lut[im], alpha=1)
```

```
(7, 647, 1024) [0 1 2 3 4 5 6]
```



[ ]:

1.3.7 Centre candidates and clustering

An image processing pipeline to detect and localize Drosophila egg chambers that consists of the following steps: (i) superpixel-based image imsegm into relevant tissue classes (see above); (ii) detection of egg center candidates using label histograms and ray features; (iii) clustering of center candidates. Prepare zones for training center candidates and perfom desity clustering.

Borovec, J., Kybic, J., & Nava, R. (2017). **Detection and Localization of Drosophila Egg Chambers in Microscopy Images.** In Q. Wang, Y. Shi, H.-I. Suk, & K. Suzuki (Eds.), Machine Learning in Medical Imaging, (pp. 19–26).

[1]:
```
%matplotlib inline
import os, sys
import numpy as np
from PIL import Image
from sklearn import cluster
import matplotlib.pylab as plt
```

[2]:
```
sys.path += [os.path.abspath('.'), os.path.abspath('..')] # Add path to root
import imsegm.utilities.data_io as tl_io
import imsegm.ellipse_fitting as seg_fit
import imsegm.descriptors as seg_fts
import imsegm.classification as seg_clf
```

```
WARNING:root:descriptors: using pure python libraries
/usr/local/lib/python3.5/dist-packages/sklearn/cross_validation.py:41:␣
↪DeprecationWarning: This module was deprecated in version 0.18 in favor of the␣
↪model_selection module into which all the refactored classes and functions are␣
↪moved. Also note that the interface of the new CV iterators are different from that␣
↪of this module. This module will be removed in 0.20.
  "This module will be removed in 0.20.", DeprecationWarning)
/usr/local/lib/python3.5/dist-packages/sklearn/grid_search.py:42: DeprecationWarning:␣
↪This module was deprecated in version 0.18 in favor of the model_selection module␣
↪into which all the refactored classes and functions are moved. This module will be␣
↪removed in 0.20.
  DeprecationWarning)
```

Load images

[3]:
```
name = 'insitu7545'
PATH_BASE = tl_io.update_path(os.path.join('data-images', 'drosophila_ovary_slice'))
PATH_IMAGES = os.path.join(PATH_BASE, 'image')
PATH_SEGM = os.path.join(PATH_BASE, 'segm')
PATH_ANNOT = os.path.join(PATH_BASE, 'annot_eggs')
PATH_CENTRE = os.path.join(PATH_BASE, 'center_levels')
COLORS = 'bgrcymk'
```

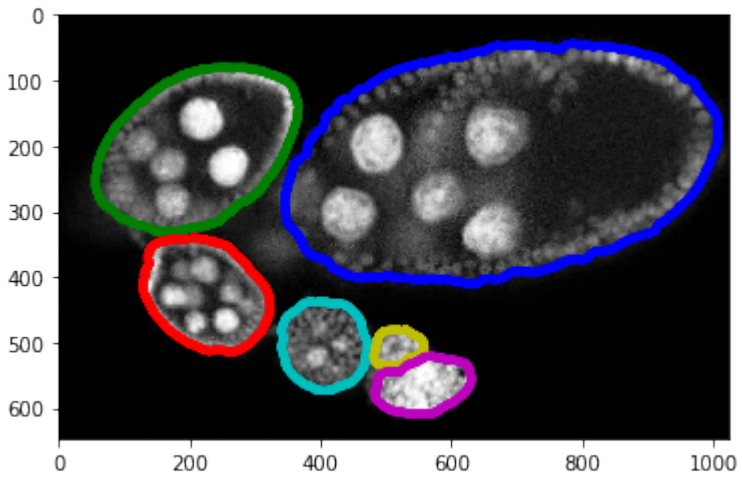
[4]:
```
img = np.array(Image.open(os.path.join(PATH_IMAGES, name + '.jpg')))
segm = np.array(Image.open(os.path.join(PATH_SEGM, name + '.png')))
annot = np.array(Image.open(os.path.join(PATH_ANNOT, name + '.png')))
levels = np.array(Image.open(os.path.join(PATH_CENTRE, name + '.png')))
FIG_SIZE = (10. * np.array(img.shape[:2]) / np.max(img.shape))[::-1]
```

Show training for center detection

In this part we discuss the procedure of preparing training data...

Individual egg annotation

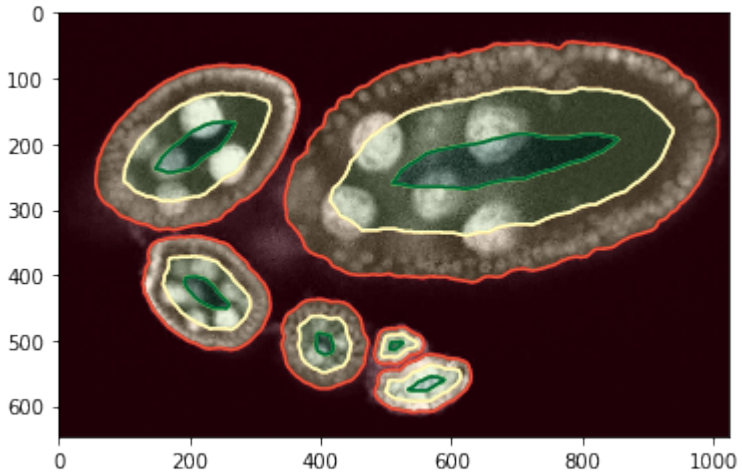
[5]:
```
#plt.figure(figsize=FIG_SIZE)
plt.imshow(img[:, :, 0], cmap=plt.cm.Greys_r)
# _= plt.contour(annot, levels=np.unique(annot), linewidths=(4,))
for i in range(1, np.max(annot) + 1):
    _= plt.contour(annot == i, colors=COLORS[(i-1) % len(COLORS)], linewidths=(4,))
```



Zones inside eggs

We have generated zones inside each objetc/egg such as we divide into 3 centric shapes. In fact this annotation can be automatly created by oour scipt and then manually adjasted.

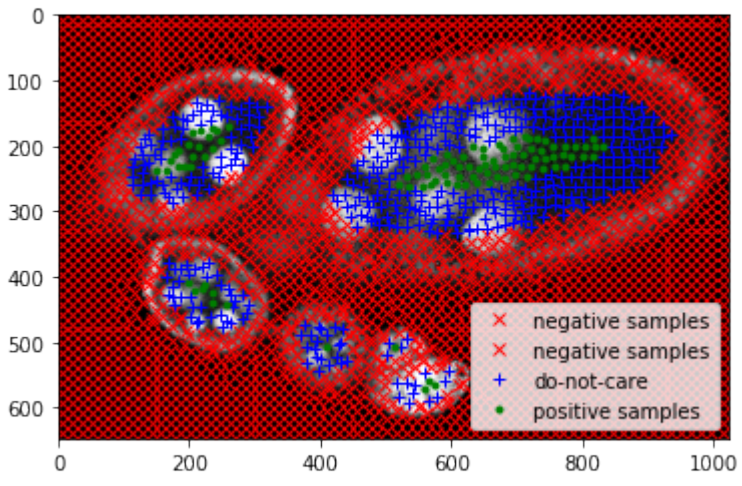
[6]:
```
#plt.figure(figsize=FIG_SIZE)
plt.imshow(img[:, :, 0], cmap=plt.cm.Greys_r)
_= plt.imshow(levels, alpha=0.2, cmap=plt.cm.RdYlGn), plt.contour(levels, cmap=plt.cm.
↪RdYlGn)
```



Training examples, points

We assume that the center zone is postive (green), background and near boundary is negative (red) and the zone in between we ignore (blue).

[8]:
```
slic, points, labels = seg_fit.get_slic_points_labels(levels, img, slic_size=15, slic_
↪regul=0.3)
#plt.figure(figsize=FIG_SIZE)
plt.imshow(img[:, :, 0], cmap=plt.cm.Greys_r)
plt.plot(points[labels == 0, 1], points[labels == 0, 0], 'xr', label='negative samples
↪')
plt.plot(points[labels == 1, 1], points[labels == 1, 0], 'xr', label='negative samples
↪')
plt.plot(points[labels == 2, 1], points[labels == 2, 0], '+b', label='do-not-care')
plt.plot(points[labels == 3, 1], points[labels == 3, 0], '.g', label='positive samples
↪')
_= plt.xlim([0, img.shape[1]]), plt.ylim([img.shape[0], 0]), plt.legend(loc='lower␣
↪right')
```



Feature extraction for each sample point.

[9]:
```
features_hist, names_hist = seg_fts.compute_label_histograms_positions(segm, points,␣
↪diameters=[25, 50, 100, 150, 200, 300])
features_ray, _, names_ray = seg_fts.compute_ray_features_positions(segm, points,␣
↪angle_step=15, edge='up', border_labels=[0], smooth_ray=0)
features = np.hstack((features_hist, features_ray))
```

Adjustment the annotation as we decribed before and train a classifier. . .

[10]:
```
clf_pipeline = seg_clf.create_clf_pipeline()
labels[labels == 1] = 0
labels[labels == 3] = 2
clf_pipeline.fit(features, labels)
```

[10]:
```
Pipeline(memory=None,
     steps=[('scaler', StandardScaler(copy=True, with_mean=True, with_std=True)), (
↪'reduce_dim', PCA(copy=True, iterated_power='auto', n_components=0.95, random_
↪state=None,
  svd_solver='auto', tol=0.0, whiten=False)), ('classif',␣
↪RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini'..._jobs=-
↪1,
            oob_score=False, random_state=None, verbose=0,
            warm_start=False))])
```

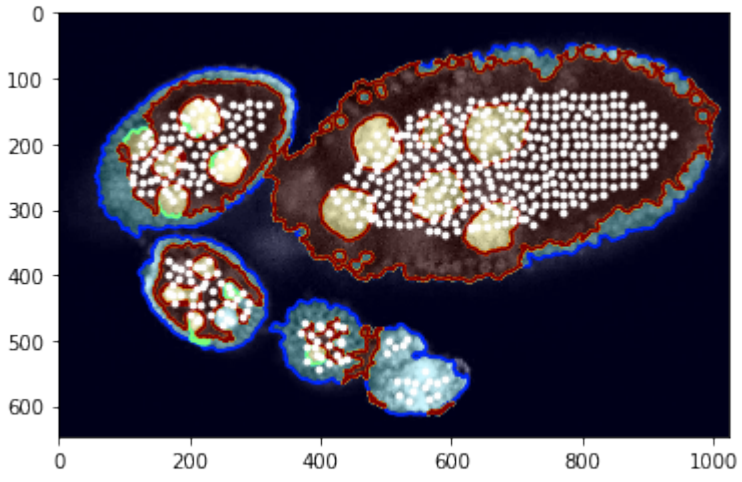
Predict lables for these sample points, note that overfitting may appeare.

[11]:
```
labels = clf_pipeline.predict(features)
candidates = points[labels == 2, :]
```

Center clustering

Visualisation of predicted positive sample points. . .

[12]:
```
# candidates = points[labels == 3, :]
#plt.figure(figsize=FIG_SIZE)
plt.imshow(img[:, :, 0], cmap=plt.cm.Greys_r)
plt.imshow(segm, alpha=0.2, cmap=plt.cm.jet), plt.contour(segm, cmap=plt.cm.jet)
_= plt.plot(candidates[:, 1], candidates[:, 0], '.w')
```



As you can see that potentila points inside egg are more less grouped together. We apply decity clustering which alloes us to identify individual eggs.

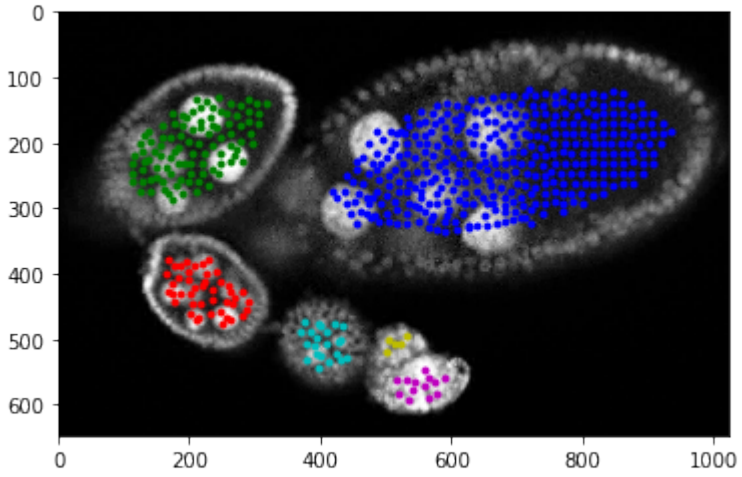
[17]:
```
dbscan = cluster.DBSCAN(eps=40, min_samples=1)
dbscan.fit(candidates)
```

[17]:
```
DBSCAN(algorithm='auto', eps=40, leaf_size=30, metric='euclidean',
    metric_params=None, min_samples=1, n_jobs=1, p=None)
```

[18]:
```
#fig = plt.figure(figsize=FIG_SIZE)
plt.imshow(img[:, :, 0], cmap=plt.cm.Greys_r)
# plt.imshow(seg, alpha=0.2), plt.contour(seg)
centers = []

for i in range(max(dbscan.labels_) + 1):
    select = candidates[dbscan.labels_ == i]
    centers.append(np.mean(select, axis=0))
    plt.plot(select[:, 1], select[:, 0], '.', color=COLORS[i % len(COLORS)])
centers = np.array(centers)

for i in range(len(centers)):
    fig.gca().scatter(centers[i, 1], centers[i, 0], s=300, c=COLORS[i % len(COLORS)])
    # plt.plot(centers[i, 1], centers[i, 0], 'o', color=COLORS[i % len(COLORS)])
_= plt.xlim([0, img.shape[1]]), plt.ylim([img.shape[0], 0])
```



[ ]:
```
```

1.3.8 Ellipse fitting from center

Having a center per egg and structural segmentation we want to aproximate the egg by an ellise fuct way that it maximise the expectation being single egg. Some ellipse fitting references: * Fitting an Ellipse to a Set of Data Points * Numerically Stable Direct Least Squares Fitting Of Ellipses * Non-linear fitting to an ellipse

Borovec, J., Kybic, J., & Nava, R. (2017). **Detection and Localization of Drosophila Egg Chambers in Microscopy Images.** In Q. Wang, Y. Shi, H.-I. Suk, & K. Suzuki (Eds.), Machine Learning in Medical Imaging, (pp. 19–26).

[1]:
```
%matplotlib inline
import os, sys
import numpy as np
import pandas as pd
```

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```
from PIL import Image
import matplotlib.pylab as plt
```

[2]:
```
sys.path += [os.path.abspath('.'), os.path.abspath('..')] # Add path to root
import imsegm.utilities.data_io as tl_io
import imsegm.utilities.drawing as tl_visu
import imsegm.ellipse_fitting as tl_fit
```

```
WARNING:root:descriptors: using pure python libraries
```

Loading data

[3]:
```
PATH_BASE = tl_io.update_path(os.path.join('data-images', 'drosophila_ovary_slice'))
PATH_IMAGES = os.path.join(PATH_BASE, 'image')
PATH_SEGM = os.path.join(PATH_BASE, 'segm')
PATH_ANNOT = os.path.join(PATH_BASE, 'annot_eggs')
PATH_CENTRE = os.path.join(PATH_BASE, 'center_levels')
COLORS = 'bgrmyck'
```

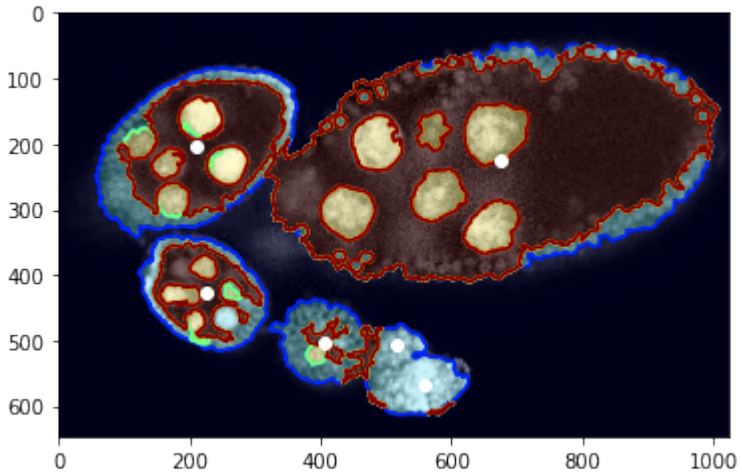
Loading images...

[4]:
```
name = 'insitu7545'
# name = 'insitu11151'
img = np.array(Image.open(os.path.join(PATH_IMAGES, name + '.jpg')))
seg = np.array(Image.open(os.path.join(PATH_SEGM, name + '.png')))
centers = pd.read_csv(os.path.join(PATH_CENTRE, name + '.csv'), index_col=0).values
centers = centers[:, [1, 0]]
FIG_SIZE = (8. * np.array(img.shape[:2]) / np.max(img.shape))[::-1]
```

```
/usr/local/lib/python3.5/dist-packages/IPython/kernel/__main__.py:5: FutureWarning:␣
↪from_csv is deprecated. Please use read_csv(...) instead. Note that some of the␣
↪default arguments are different, so please refer to the documentation for from_csv␣
↪when changing your function calls
```

Visualisation of structure segmentation overlped over input image and marked center points.

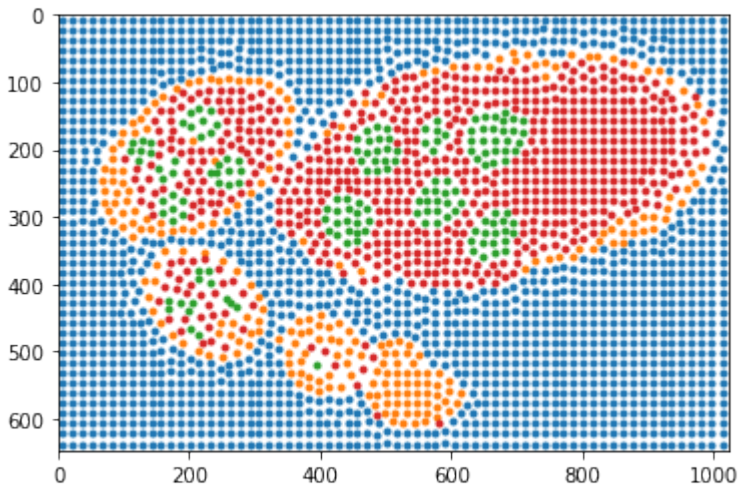
[5]:
```
#fig = plt.figure(figsize=FIG_SIZE)
plt.imshow(img[:, :, 0], cmap=plt.cm.Greys_r)
plt.imshow(seg, alpha=0.2, cmap=plt.cm.jet), plt.contour(seg, cmap=plt.cm.jet)
_= plt.plot(centers[:, 1], centers[:, 0], 'ow')
```



Preprocess - estimate boundary points

Visualisation of labeled sample points according structure segmentation / annotations.

[6]:
```
slic, points_all, labels = tl_fit.get_slic_points_labels(seg, slic_size=15, slic_
↪regul=0.3)
# points_all, labels = egg_segm.get_slic_points_labels(seg, img, size=15, regul=0.25)
for lb in np.unique(labels):
    plt.plot(points_all[labels == lb, 1], points_all[labels == lb, 0], '.')
_= plt.xlim([0, seg.shape[1]]), plt.ylim([seg.shape[0], 0])
weights = np.bincount(slic.ravel())
```

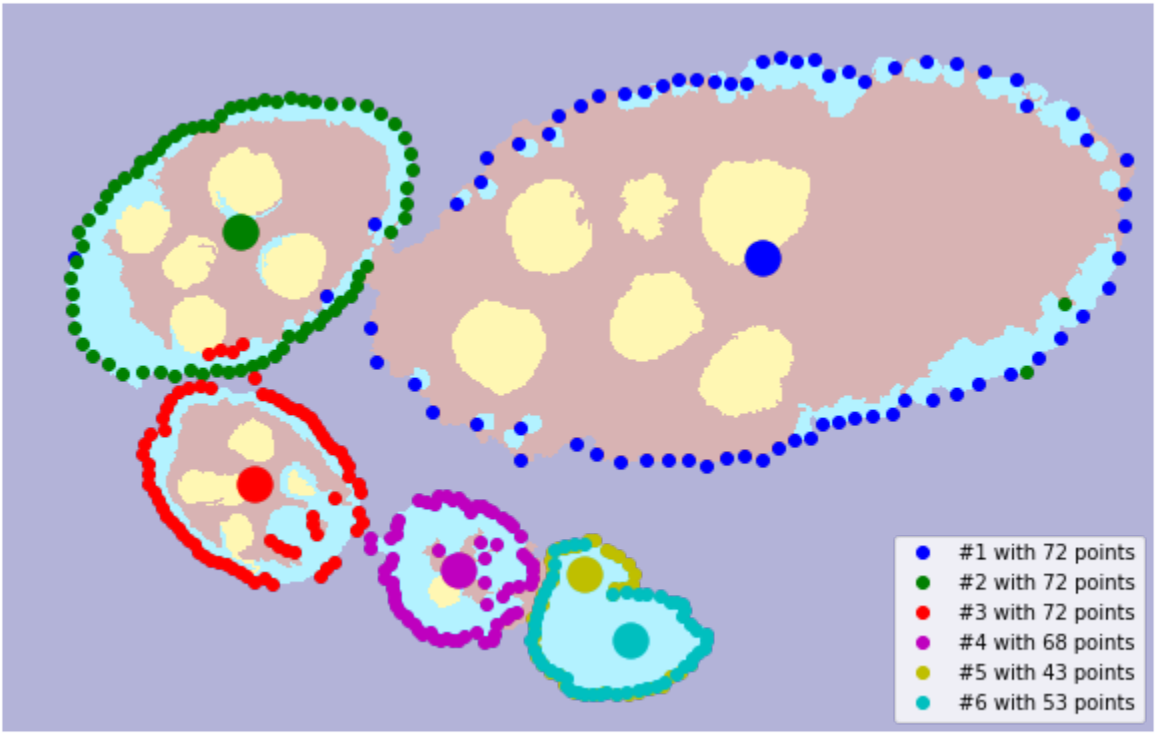


Reconstruction of boundary points using ray features from centers.

[7]:
```
points_centers = tl_fit.prepare_boundary_points_ray_edge(seg, centers, close_points=5)
# points_centers = tl_fit.prepare_boundary_points_ray_mean(seg, centers, close_
↪points=5)
# points_centers = tl_fit.prepare_boundary_points_dist(seg, centers)
```

[8]:
```
fig = plt.figure(figsize=FIG_SIZE)
plt.imshow(seg, alpha=0.3, cmap=plt.cm.jet)
for i, points in enumerate(points_centers):
    plt.plot(points[:, 1], points[:, 0], 'o', color=COLORS[i % len(COLORS)], label='#
↪%i with %i points' % ((i + 1), len(points)))
for i in range(len(centers)):
    # plt.plot(centers[i, 1], centers[i, 0], 'o', color=COLORS[i % len(COLORS)])
    plt.scatter(centers[i, 1], centers[i, 0], s=300, c=COLORS[i % len(COLORS)])
_= plt.legend(loc='lower right'), plt.axes().set_aspect('equal')
_= plt.xlim([0, seg.shape[1]]), plt.ylim([seg.shape[0], 0])
plt.axis('off'), fig.subplots_adjust(left=0, right=1, top=1, bottom=0)
# fig.savefig('fig1.pdf')
```

[8]:
```
((0.0, 1024.0, 647.0, 0.0), None)
```



Fit ellipse by RANDSAC and hypothesis

Set the probability of being egg for each class from initial segmentation.

[9]:
```
TABLE_FB_PROBA = [[0.01, 0.7, 0.95, 0.8],
                  [0.99, 0.3, 0.05, 0.2]]
print ('points: %i weights: %i labels: %i' % (len(labels), len(points_all),␣
↪len(weights)))
```

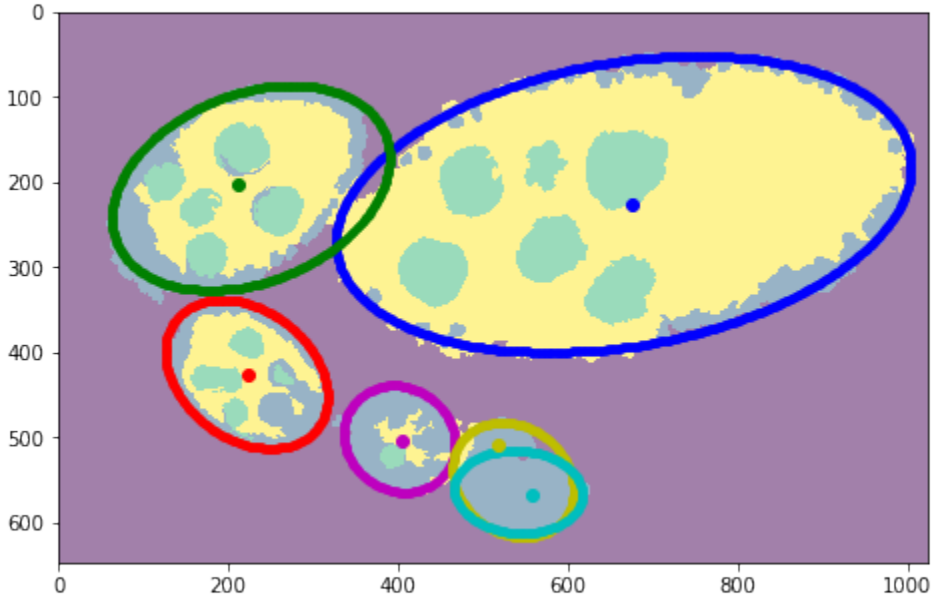
```
points: 2652 weights: 2652 labels: 2652
```

Fit the ellpse to maximise the hypoteses having single egg inside.

[10]:
```
plt.figure(figsize=FIG_SIZE)
plt.imshow(seg, alpha=0.5)
ellipses, crits = [], []
for i, points in enumerate(points_centers):
    model, _ = tl_fit.ransac_segm(points, tl_fit.EllipseModelSegm, points_all,␣
↪weights,  labels,
                                  TABLE_FB_PROBA, min_samples=0.4, residual_
↪threshold=10, max_trials=150)
    if model is None: continue
    c1, c2, h, w, phi = model.params
    ellipses.append(model.params)
    crit = model.criterion(points_all, weights, labels, TABLE_FB_PROBA)
    crits.append(np.round(crit))
    print ('model params: %s' % repr(int(c1), int(c2), int(h), int(w), phi))
    print ('-> crit: %f' % model.criterion(points_all, weights, labels, TABLE_FB_
↪PROBA))
    rr, cc = tl_visu.ellipse_perimeter(int(c1), int(c2), int(h), int(w), phi)
    plt.plot(cc, rr, '.', color=COLORS[i % len(COLORS)])

# plt.plot(centers[:, 1], centers[:, 0], 'o')
for i in range(len(centers)):
    plt.plot(centers[i, 1], centers[i, 0], 'o', color=COLORS[i % len(COLORS)])
_= plt.xlim([0, seg.shape[1]]), plt.ylim([seg.shape[0], 0])
```

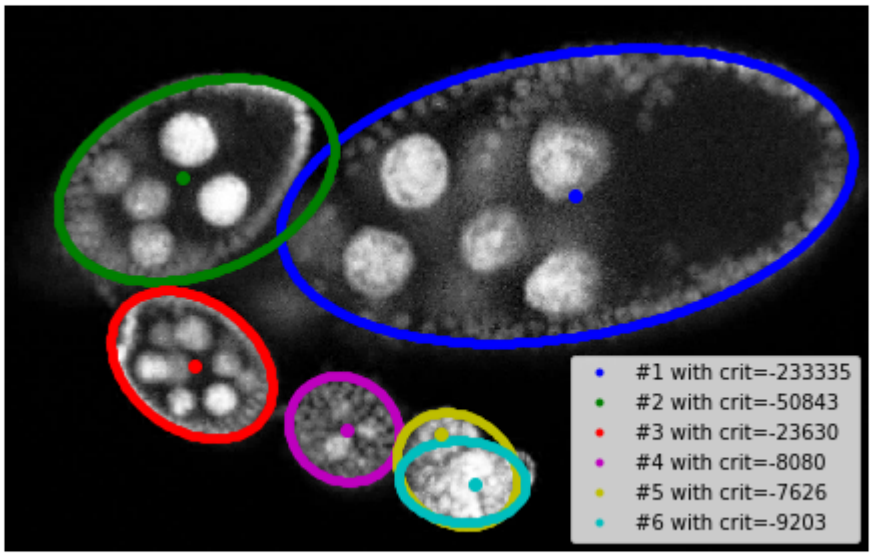
```
model params: (226, 666, 166, 342, 0.17135703308989025)
-> crit: -233334.76990445034
model params: (207, 227, 170, 110, 1.9451957515390759)
-> crit: -50842.71570683058
model params: (426, 222, 75, 104, -0.6423584612776315)
-> crit: -23629.744544518864
model params: (502, 402, 67, 60, 1.0308971690398319)
-> crit: -8080.076096030485
model params: (550, 536, 62, 75, -0.6448045520560932)
-> crit: -7626.153548780507
model params: (564, 542, 48, 75, -0.06859638756844778)
-> crit: -9202.723298924388
```



Visualizations

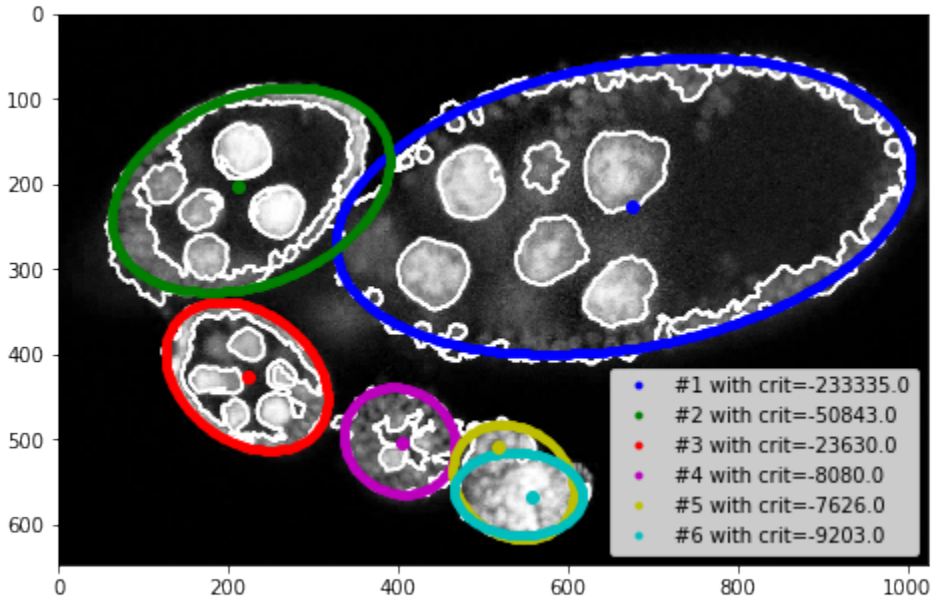
[12]:
```
#fig = plt.figure(figsize=FIG_SIZE)
# plt.imshow(img)
plt.imshow(img[:, :, 0], cmap=plt.cm.Greys_r)
for i, params in enumerate(ellipses):
    c1, c2, h, w, phi = params
    rr, cc = tl_visu.ellipse_perimeter(int(c1), int(c2), int(h), int(w), phi)
    plt.plot(cc, rr, '.', color=COLORS[i % len(COLORS)], label='#%i with crit=%d' %␣
↪((i + 1), int(crits[i])))
plt.legend(loc='lower right')

# plt.plot(centers[:, 1], centers[:, 0], 'ow')
for i in range(len(centers)):
    plt.plot(centers[i, 1], centers[i, 0], 'o', color=COLORS[i % len(COLORS)])
plt.xlim([0, seg.shape[1]]), plt.ylim([seg.shape[0], 0])
_= plt.axis('off'), fig.subplots_adjust(left=0, right=1, top=1, bottom=0)
# fig.savefig('fig2.pdf')
```



[14]:
```
plt.figure(figsize=FIG_SIZE)
plt.imshow(img[:, :, 0], cmap=plt.cm.Greys_r)
plt.contour(seg, colors='w') #, plt.imshow(seg, alpha=0.2)
for i, params in enumerate(ellipses):
    c1, c2, h, w, phi = params
    rr, cc = tl_visu.ellipse_perimeter(int(c1), int(c2), int(h), int(w), phi)
    plt.plot(cc, rr, '.', color=COLORS[i % len(COLORS)], label='#%i with crit=%.1f' %␣
↪((i + 1), crits[i]))
plt.legend(loc='lower right')

# plt.plot(centers[:, 1], centers[:, 0], 'ow')
for i in range(len(centers)):
    plt.plot(centers[i, 1], centers[i, 0], 'o', color=COLORS[i % len(COLORS)])
_= plt.xlim([0, seg.shape[1]]), plt.ylim([seg.shape[0], 0])
```


0
100
200
300
400
500
600
0
200
400
600
800
1000
#1 with crit=-233335.0
#2 with crit=-50843.0
#3 with crit=-23630.0
#4 with crit=-8080.0
#5 with crit=-7626.0
#6 with crit=-9203.0

[ ]:

CHAPTER

TWO

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CHAPTER

THREE

GENERAL SUPERPIXEL IMAGE SEGMENTATION: (UN)SUPERVISED, CENTER DETECTION, REGION GROWING

This package is aiming at (un/semi)supervised segmentation on superpixels withcomputing some basic colour and texture features. This general segmentationcan be followed by an object centre detection and proximate ellipse fittingto expected object boundaries. Last included method is region growingwith learned shape prior also running on superpixel grid. The package contains several low-level Cython implementation to speed up somefeature extraction methods. Overall the project/repository contains example codes with visualisationin ipython notebooks and experiments required for replicating all published results.

3.1 Superpixel segmentation with GraphCut regularisation

Image segmentation is widely used as an initial phase of many image processingtasks in computer vision and image analysis. Many recent segmentation methodsuse superpixels because they reduce the size of the segmentation problemby order of magnitude. Also, features on superpixels are much more robustthan features on pixels only. We use spatial regularisation on superpixelsto make segmented regions more compact. The segmentation pipeline comprises(i) computation of superpixels; (ii) extraction of descriptors such as colourand texture; (iii) soft classification, using a standard classifier for supervisedlearning, or the Gaussian Mixture Model for unsupervised learning; (iv) finalsegmentation using Graph Cut. We use this segmentation pipeline on real-worldapplications in medical imaging. We also show that unsupervised segmentationis sufficient for some situations, and provides similar results to those obtainedusing trained segmentation.

3.2 Object centre detection and Ellipse approximation

An image processing pipeline to detect and localize Drosophila egg chambers thatconsists of the following steps: (i) superpixel-based image segmentationinto relevant tissue classes (see above); (ii) detection of egg center candidatesusing label histograms and ray features; (iii) clustering of center candidates and;(iv) area-based maximum likelihood ellipse model fitting.

3.3 Superpixel Region Growing with Shape prior

Region growing is a classical image segmentation method based on hierarchicalregion aggregation using local similarity rules. Our proposed approach differsfrom standard region growing in three essential aspects. First, it workson the level of superpixels instead of pixels, which leads to a substantial speedup.Second, our method uses learned statistical shape properties which encourage growingleading to plausible shapes. In particular, we use ray features to describethe object boundary. Third, our method can segment multiple objects and ensurethat the segmentations do not overlap. The problem is represented as energyminimisation and is solved either greedily, or iteratively using GraphCuts.

3.4 References

- Borovec J., Svihlik J., Kybic J., Habart D. (2017). Supervised and unsupervisedsegmentation using superpixels, model estimation, and Graph Cut.SPIE Journal of Electronic Imaging 26(6), 061610. DOI: 10.1117/1.JEI.26.6.061610.
- Borovec J., Kybic J., Nava R. (2017) Detection and Localization of DrosophilaEgg Chambers in Microscopy Images. In: Wang Q., Shi Y., Suk HI., Suzuki K. (eds)Machine Learning in Medical Imaging. MLMI 2017. LNCS, vol 10541. Springer, Cham.DOI: 10.1007/978-3-319-67389-9_3.
- Borovec J., Kybic J., Sugimoto, A. (2017). Region growing using superpixelswith learned shape prior. SPIE Journal of Electronic Imaging 26(6), 061611.DOI: 10.1117/1.JEI.26.6.061611.

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