

Image segmentation & Region growing

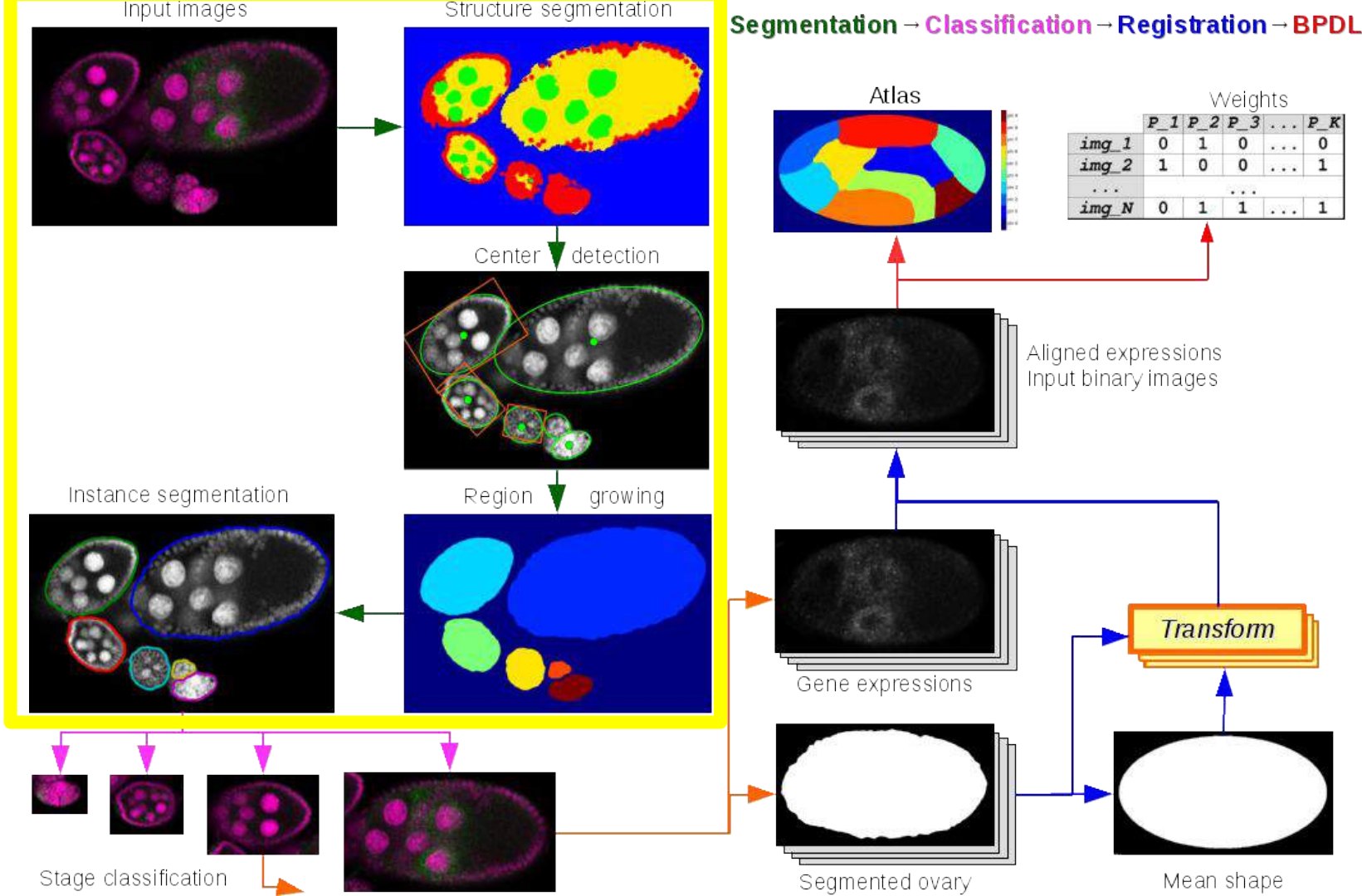
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23.11.2017

<http://cmp.felk.cvut.cz/~borovji3/>



Image analyses pipeline



Resources

- Publications:

- 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, <http://doi.org/10.1117/1.JEI.26.6.061610>
- Borovec J., Kybic J., Nava R. (2017) **Detection and Localization of Drosophila Egg Chambers in Microscopy Images**. In: Wang Q., Shi Y., Suk H.I., Suzuki K. (eds) Machine Learning in Medical Imaging. MLMI 2017. LNCS, vol 10541. Springer, Cham. http://doi.org/10.1007/978-3-319-67389-9_3
- Borovec J., Kybic J., Sugimoto, A. (2017). **Region growing using superpixels with learned shape prior**. SPIE Journal of Electronic Imaging 26(6), 061611, <http://doi.org/10.1117/1.JEI.26.6.061611>

- Implementation: <https://github.com/Borda/pyImSegm>

pyImSegm
Image segmentation - general superpixel segmentation & center detection & region growing

[View On GitHub](#)

Image segmentation toolbox

- Superpixel segmentation with GraphCut regularisation
- Object centre detection and Ellipse approximation
- Superpixel Region Growing with Shape prior
- Installation and configuration

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

build passing | codecov 92% | colicly A | run shippable | coverage 93% | PASSED

Supervised and unsupervised segmentation using superpixels, model estimation, and Graph Cut

Jiří Borovec, Jan Švihlík, Jan Kybic, David Habart, “**Supervised and unsupervised segmentation using superpixels, model estimation, and graph cut,**” *Journal Electron. Imaging* 26(6), 061610 (2017), DOI: 10.1117/1.JEI.26.6.061610.

Image analysis pipeline

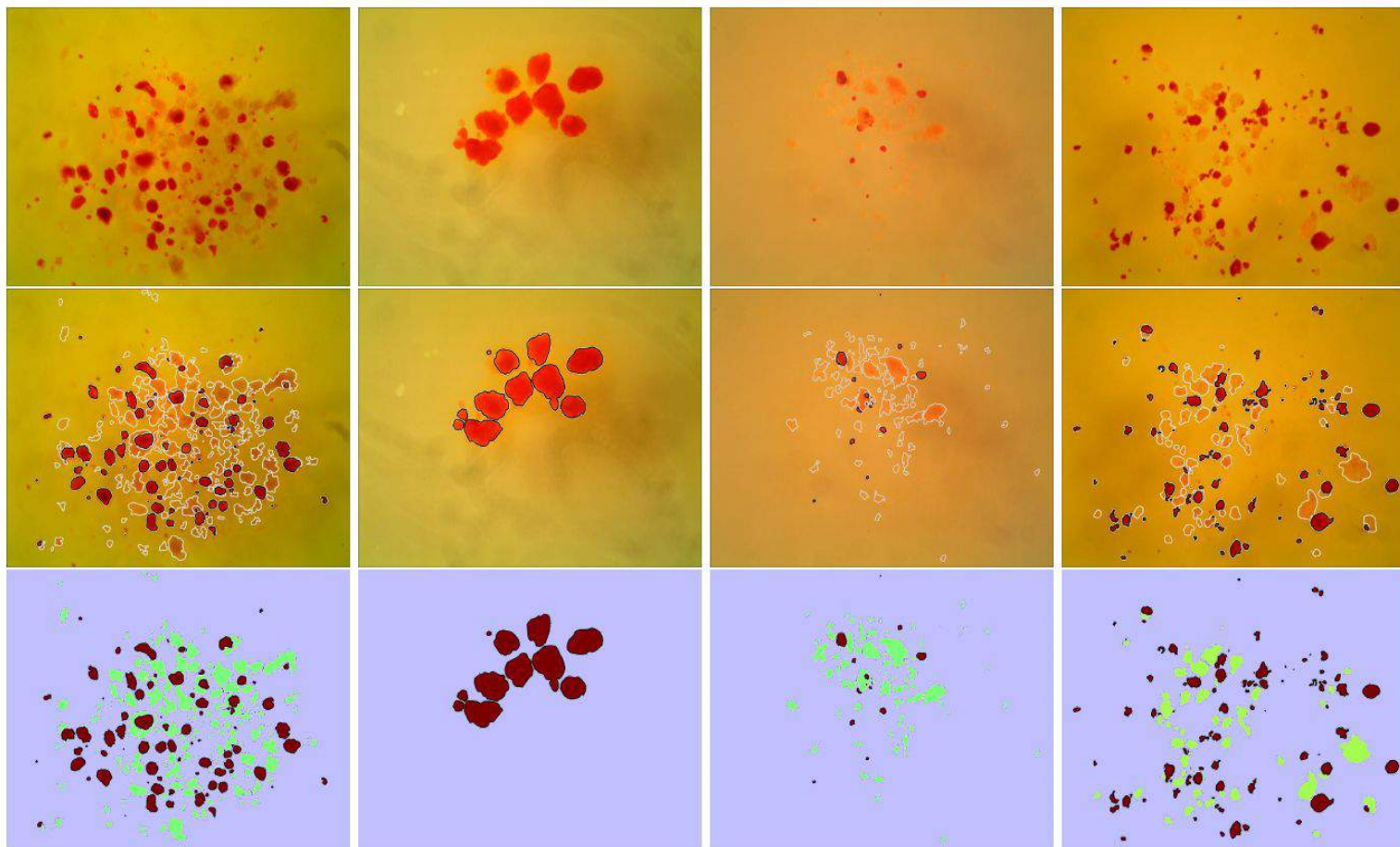
1. Structure (tissue) segmentation
 - a. computation of superpixels - SLIC
 - b. extraction of superpixel-based descriptors;
 - c. calculating image-based class probabilities;
 - d. spatial regularized superpixel classification using Graph Cut
2. Center detection
 - a. center candidate training & prediction
 - b. candidate clustering
 - c. ellipse fitting
3. Region growing
 - a. learning statistical model
 - b. region growing

Segmentation method overview

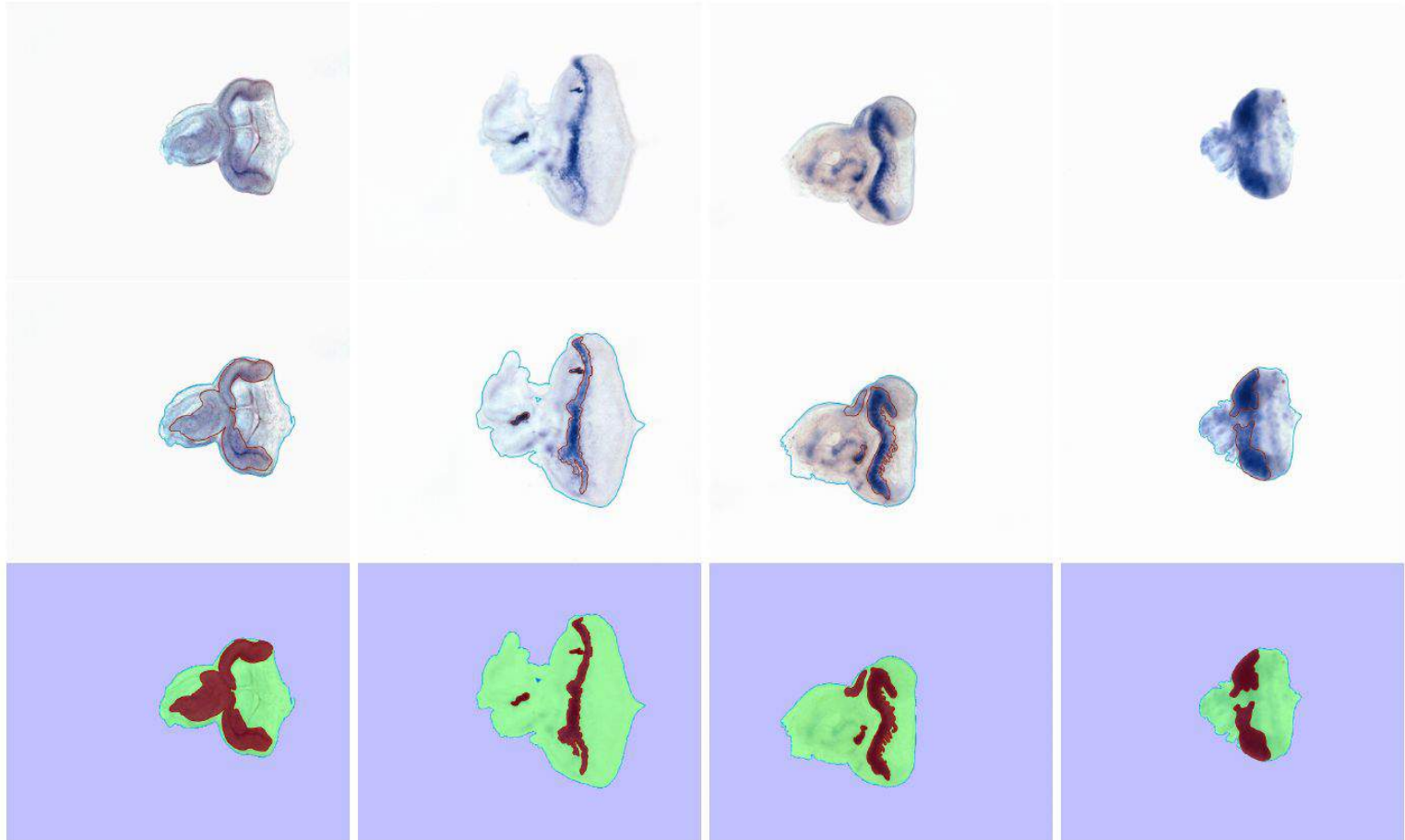
Image segmentation method consisting of the following steps:

1. Computation of superpixels - SLIC
2. Extraction of superpixel-based descriptors;
 - a. Color - mean, median, energy, STD
 - b. Texture - Leung-Malik filter bank
3. Calculating image-based class probabilities;
 - a. Supervised - Random Forest, k-NN, Adaboost, ...
 - b. Unsupervised - Gaussian Mixture Model
4. Spatial regularized superpixel classification using Graph Cut
 - a. Edge weights - color, features, model

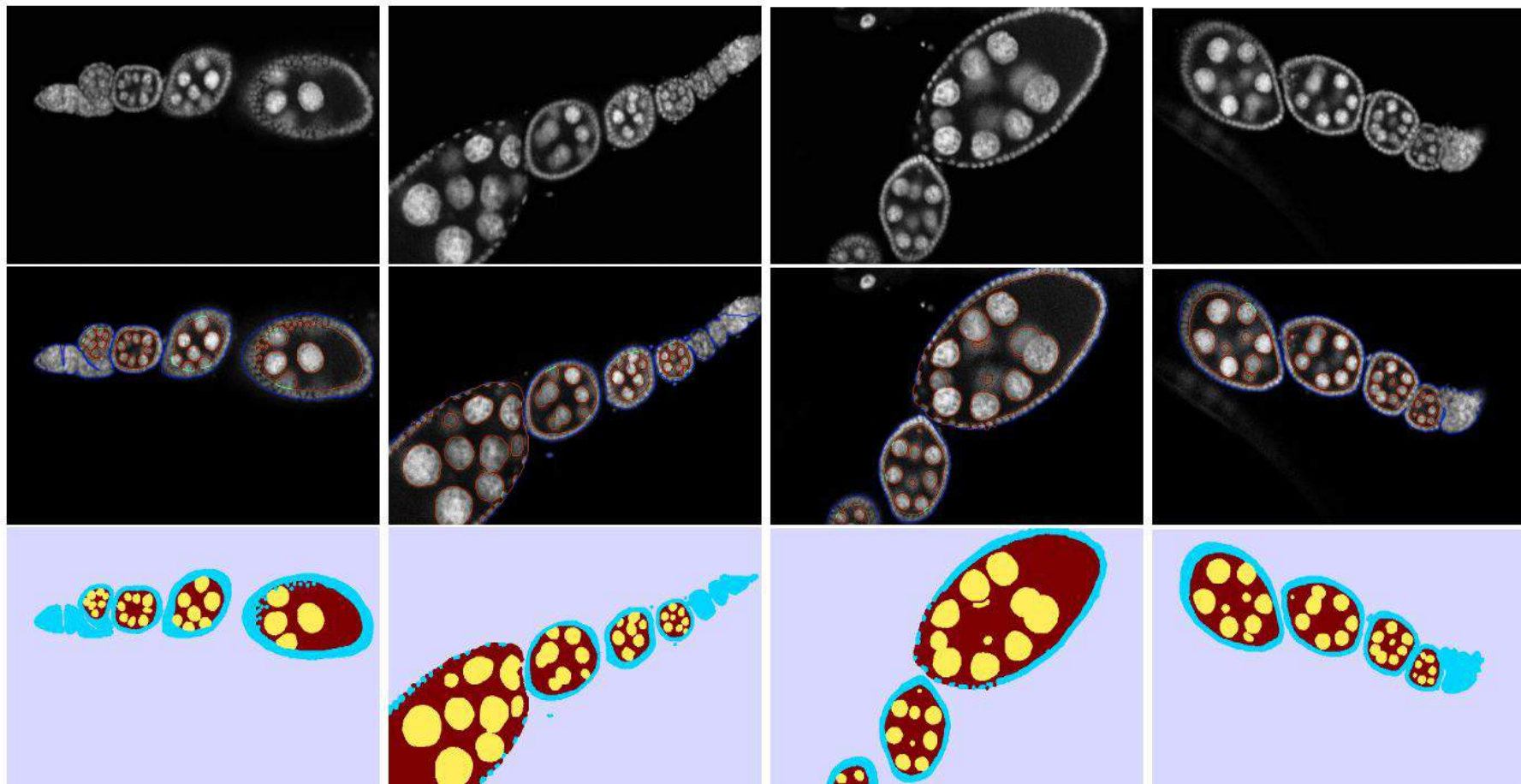
Used datasets - Langerhan islets

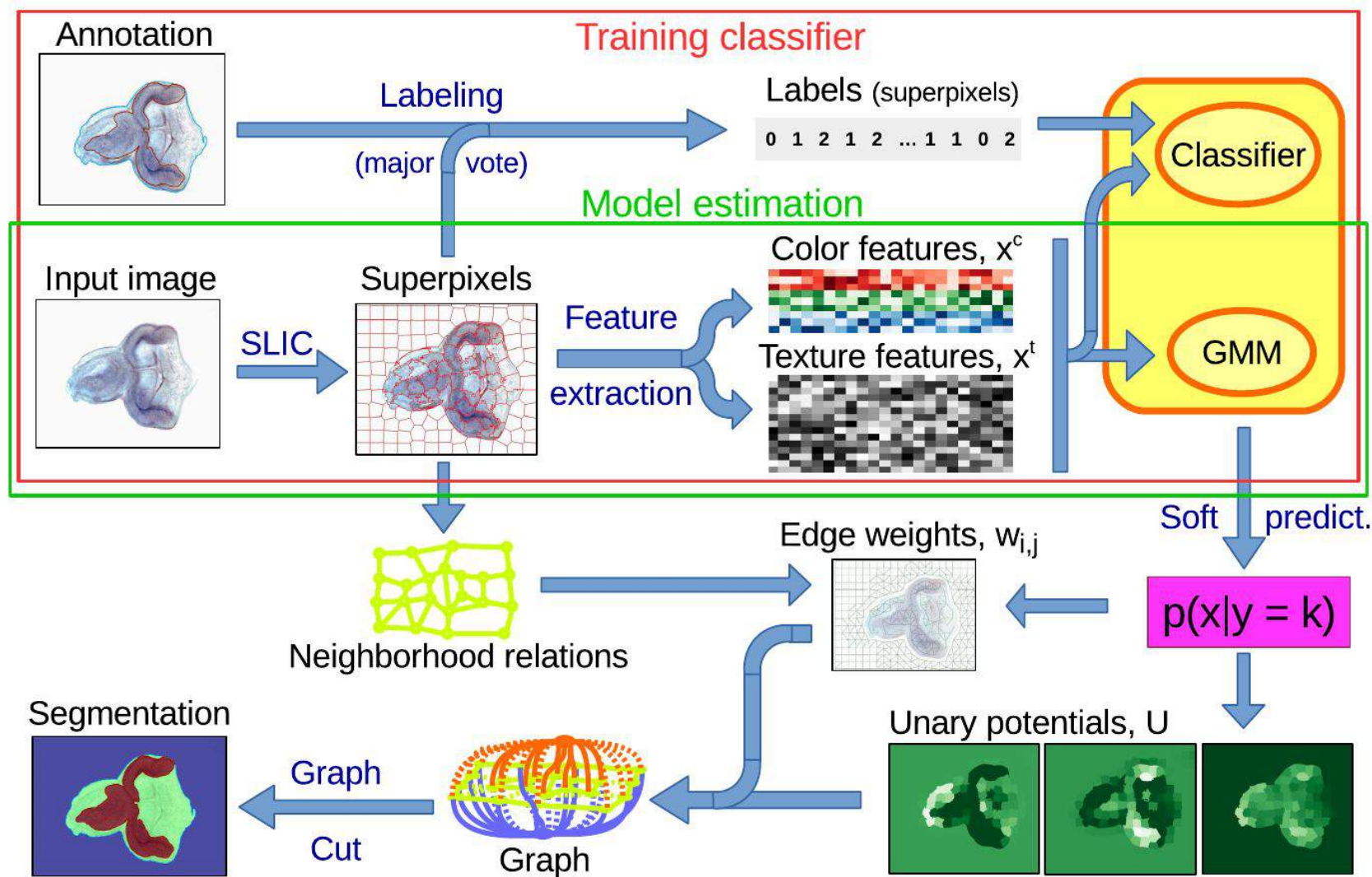


Used datasets - Drosophila imaginal discs



Used datasets - *Drosophila* ovary





Problem formulation

Formulation (standard) as

$$Y^* = \arg \max_Y P(Y|X) = \arg \max_Y \frac{p(X|Y) \cdot P(Y)}{p(X)}$$

$$P(Y) = \prod_{s \in S} h(y_s) \cdot \prod_{(i,j) \in \mathcal{N} \subseteq S^2} R(y_i, y_j)$$

$$Y^* = \arg \max_Y \prod_{i \in S} (p(\mathbf{x}_i | y_i) \cdot h(y_i)) \cdot \prod_{(i,j) \in \mathcal{N}} R(y_i, y_j)$$

Energy minimisation

$$Y^* = \arg \min_Y \sum_s \underbrace{-\log(p(\mathbf{x}_s | y_s) \cdot h(y_s))}_{U_s(y_s)} + \sum_{(i,j) \in \mathcal{N}} \underbrace{-\log R(y_i, y_j)}_{\beta w_{i,j} B(y_i, y_j)}$$

Graph Cut - Edge weight

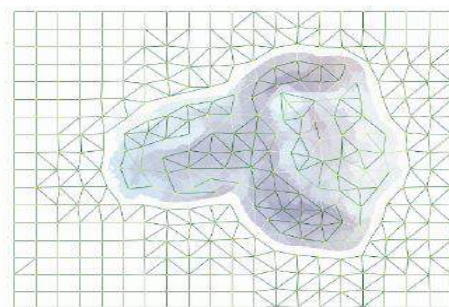
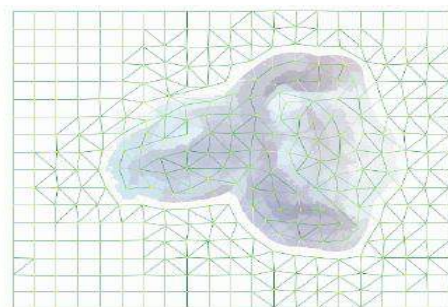
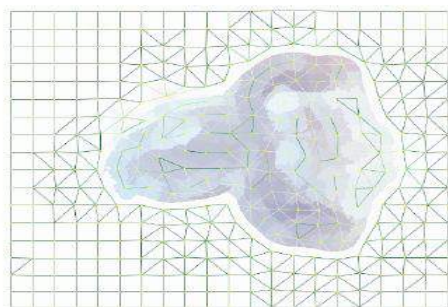
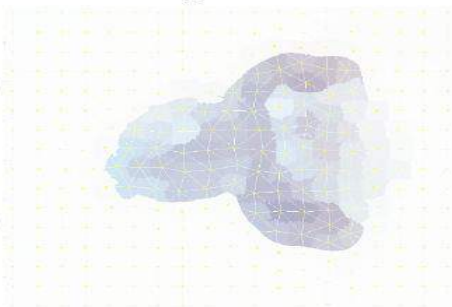
Spatial

Color

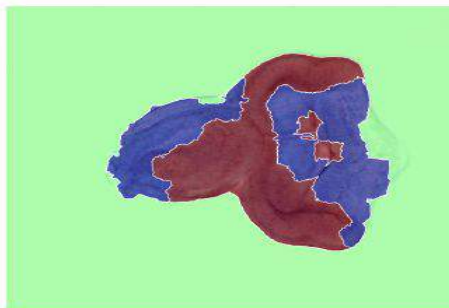
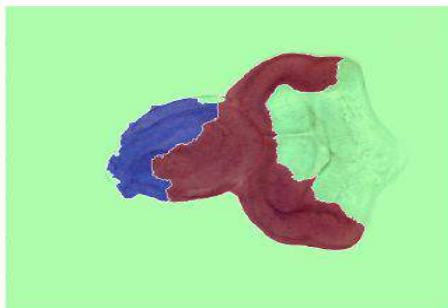
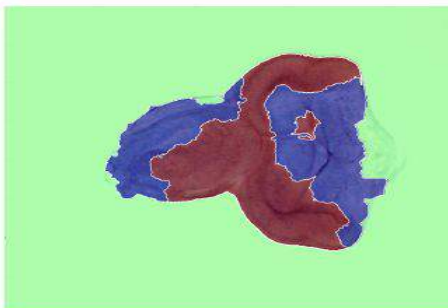
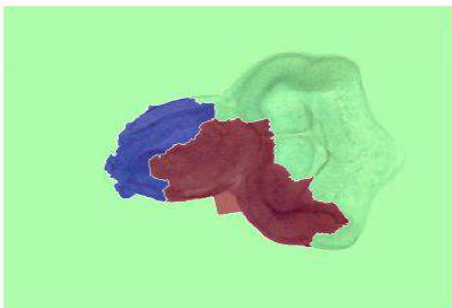
Features

Models

weighted edges



segmentation



$$w_{i,j} = \frac{d_E^{\bar{S}}}{d_E(i,j)}$$

$$\exp\left(-\frac{d_E(\bar{I}_i, \bar{I}_j)}{2\sigma_c^2}\right) \cdot \frac{d_E^{\bar{S}}}{d_E(i,j)}$$

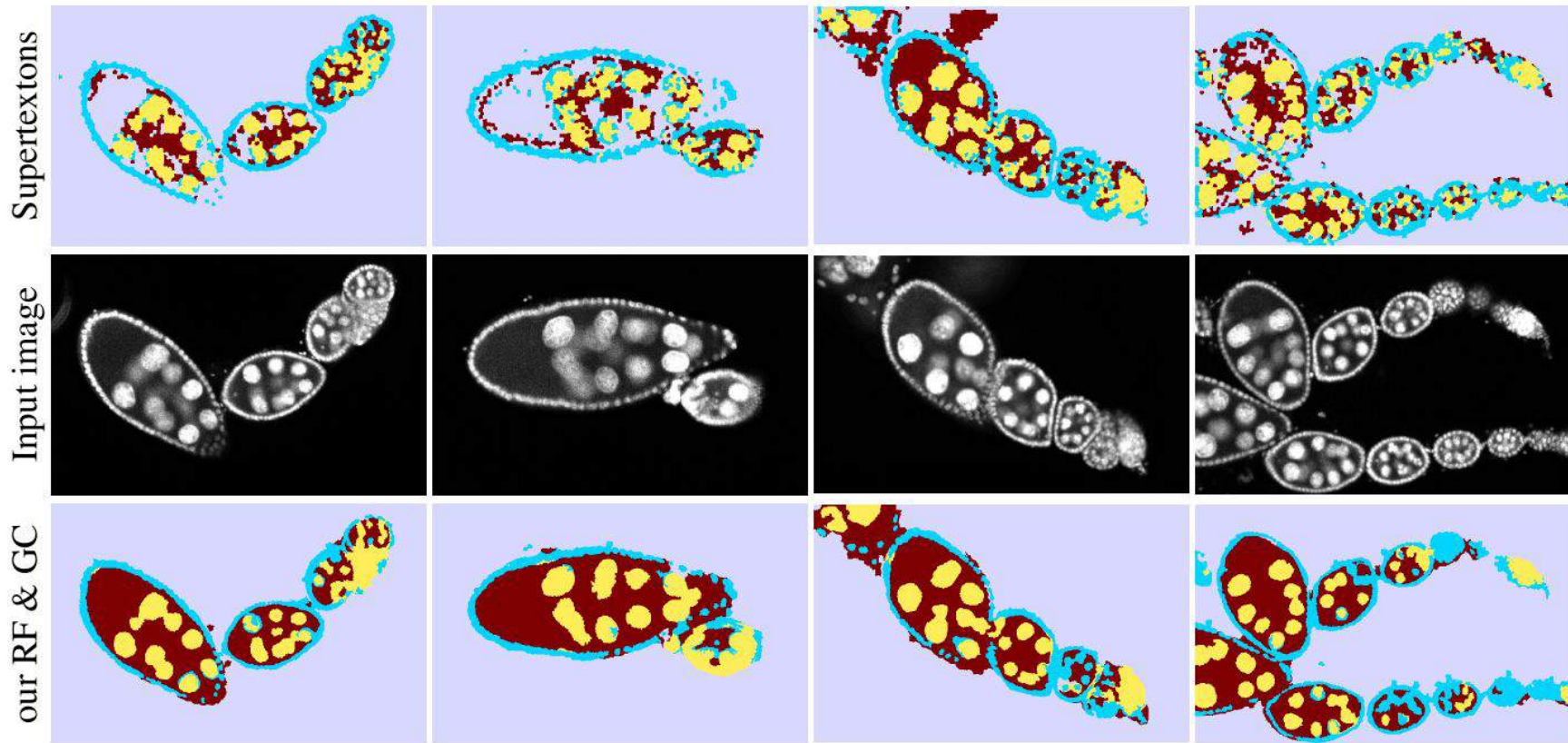
$$\exp\left(-\frac{d_M(\mathbf{x}_i, \mathbf{x}_j)}{2\sigma_X^2}\right) \cdot \frac{d_E^{\bar{S}}}{d_E(i,j)}$$

$$\exp\left(-\frac{d_T(p_i, p_j)}{2\sigma_p^2}\right) \cdot \frac{d_E^{\bar{S}}}{d_E(i,j)}$$

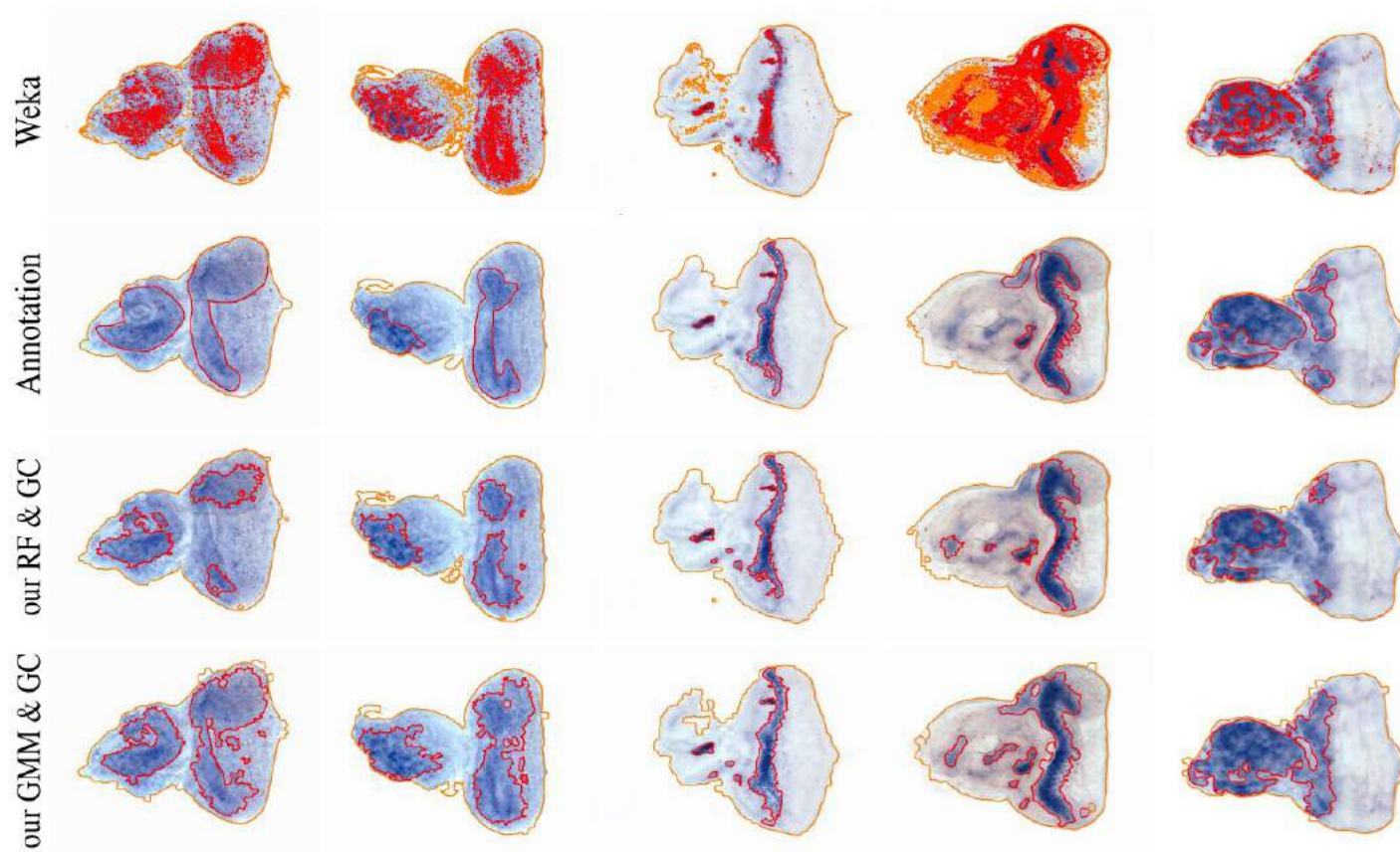
Segmentation results with SOA (F1-score)

		Method	Lang. islets	imaginal disc	ovary
Pixel-wise	Supervised	Weka ⁴⁴	0.7374	0.6923	0.5800
		Weka & GC(0, 100)	0.7373	0.6887	0.5810
		Weka & GC(1, 50)	0.7376	0.6887	0.5965
		Weka & GC(10, 50)	0.6935	0.6887	0.1395
		Weka & GC(50, 100)	0.6862	0.6850	0.6007
		NPA ³³	0.8420	-	-
Superpixels	Supervised	ideal segm. Y_A	0.8590	0.9696	0.9067
		Supertextons ¹⁷	-	-	0.7488
		our RF	0.8565	0.8181	0.8201
		our RF & GC	0.8570	0.8229	0.8600
	Unsuper.	our GMM	0.5358	0.7542	0.5967
		our GMM & GC	0.5465	0.7644	0.6039
		our GMM [gr]	0.5682	0.7301	0.6009
		our GMM [gr] & GC	0.5816	0.7564	0.6083

Advantage of using Graph Cut



Supervised vs Unsupervised



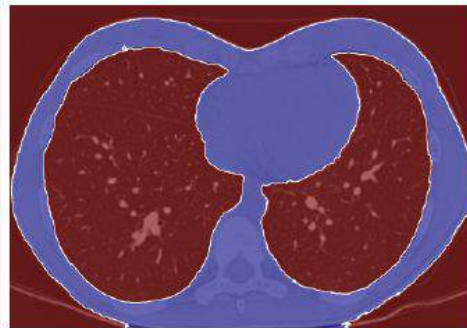
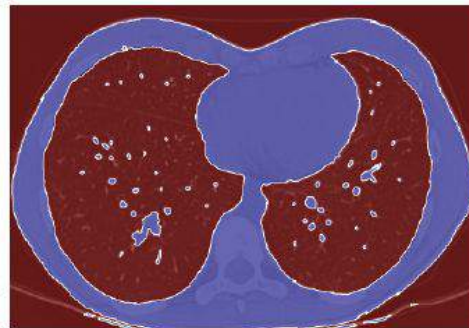
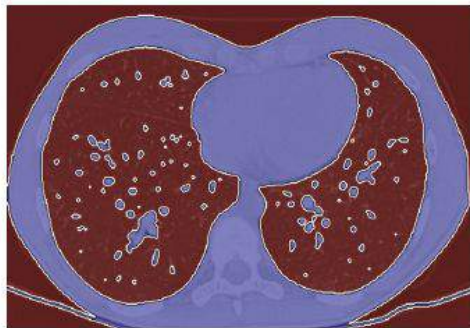
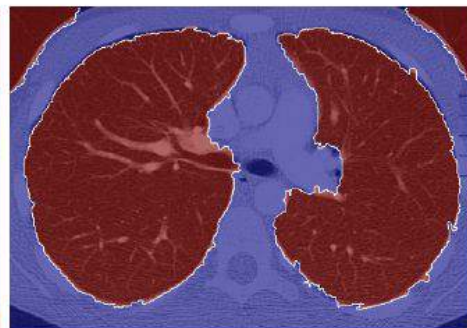
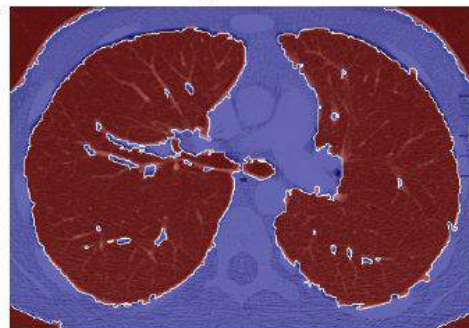
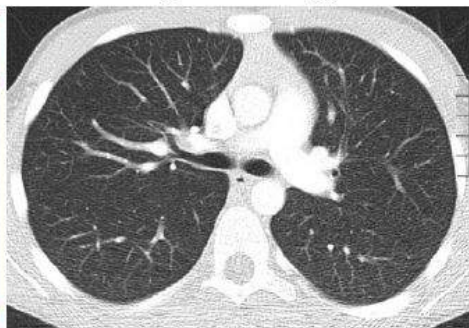
Unsupervised with Graph Cut

Weka segm. & CG

input image

our segm. GMM

our GMM & CG



Detection and localization of Drosophila egg chambers in microscopy images

Borovec J., Kybic J., Nava R. (2017) **Detection and Localization of Drosophila Egg Chambers in Microscopy Images**. In: Machine Learning in Medical Imaging. LNCS, vol 10541. Springer, DOI: 10.1007/978-3-319-67389-9_3

Image analysis pipeline

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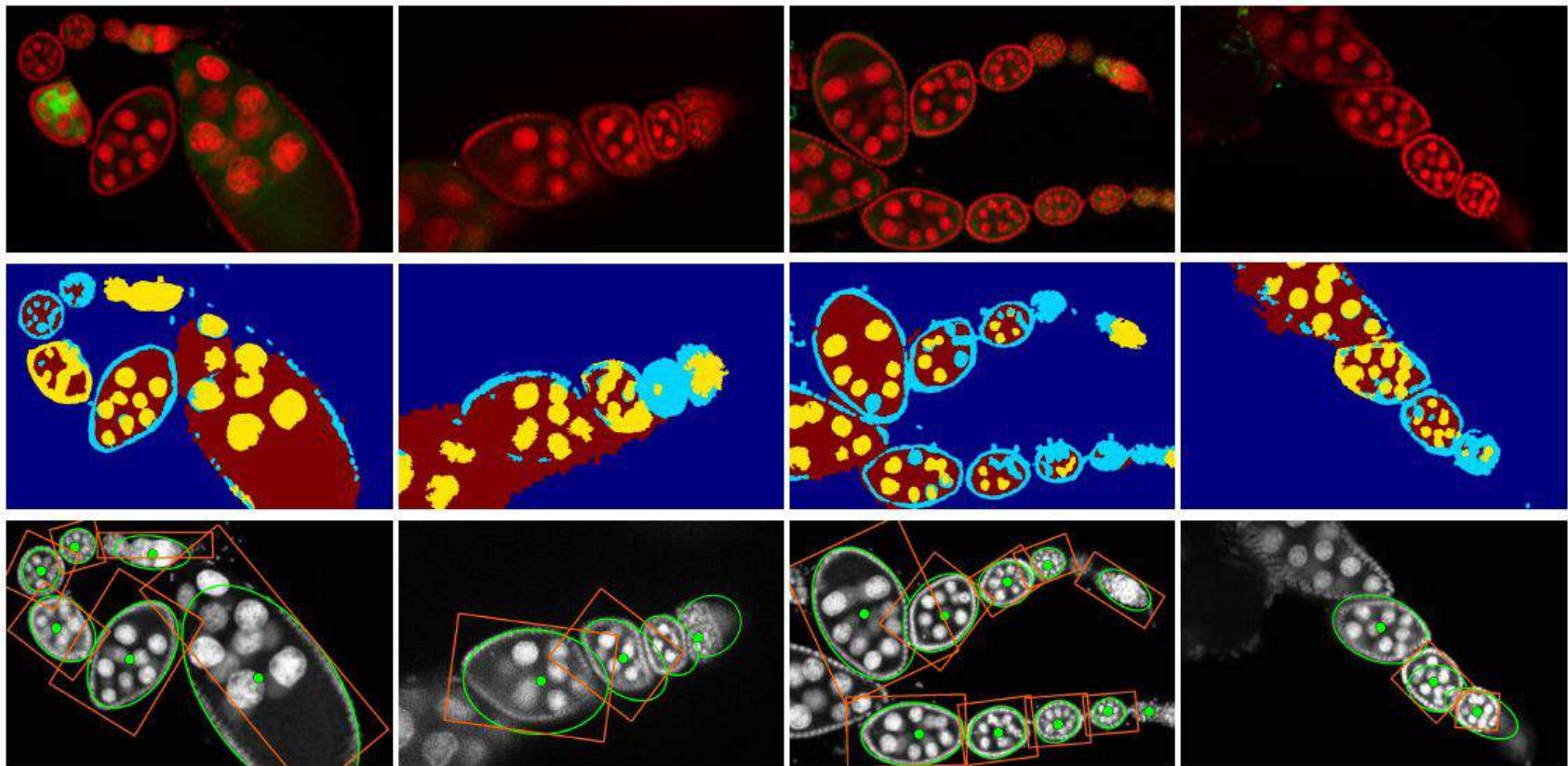
2. Center detection

- a. center candidate training & prediction
- b. candidate clustering
- c. ellipse fitting

3. Region growing

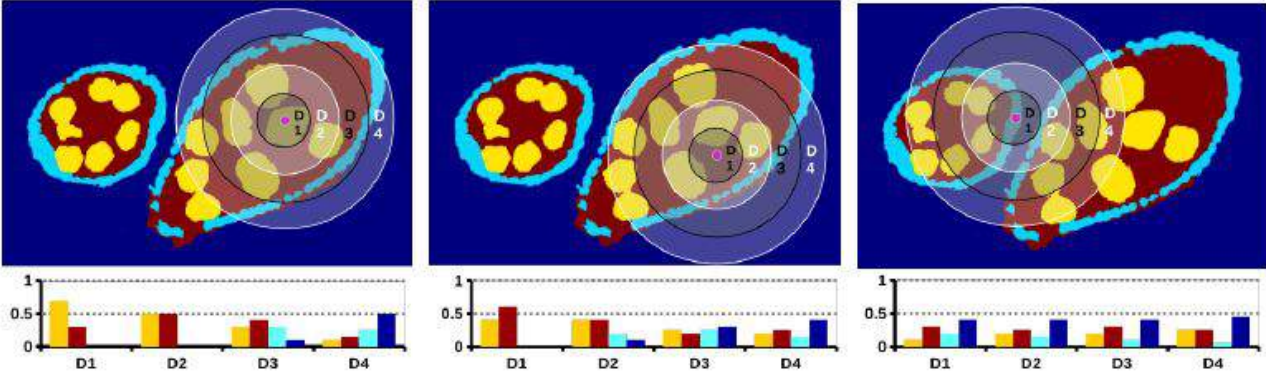
- a. learning statistical model
- b. region growing

Center detections

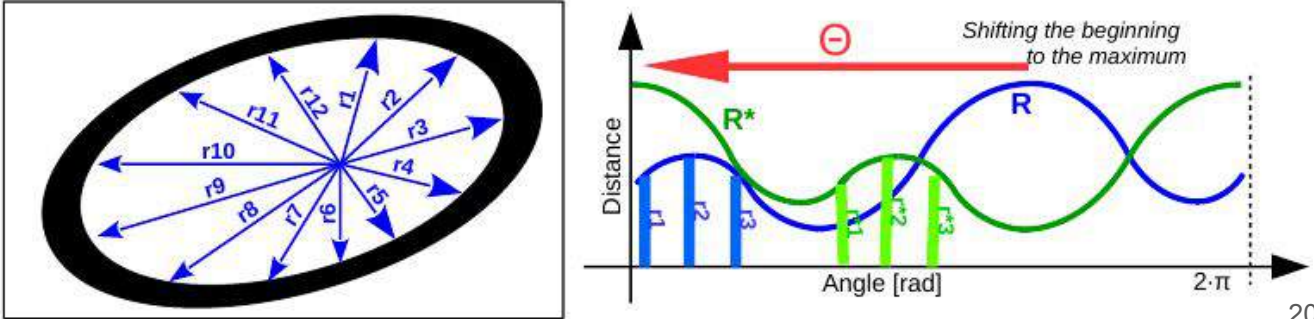


Features for center detection

- Label histogram



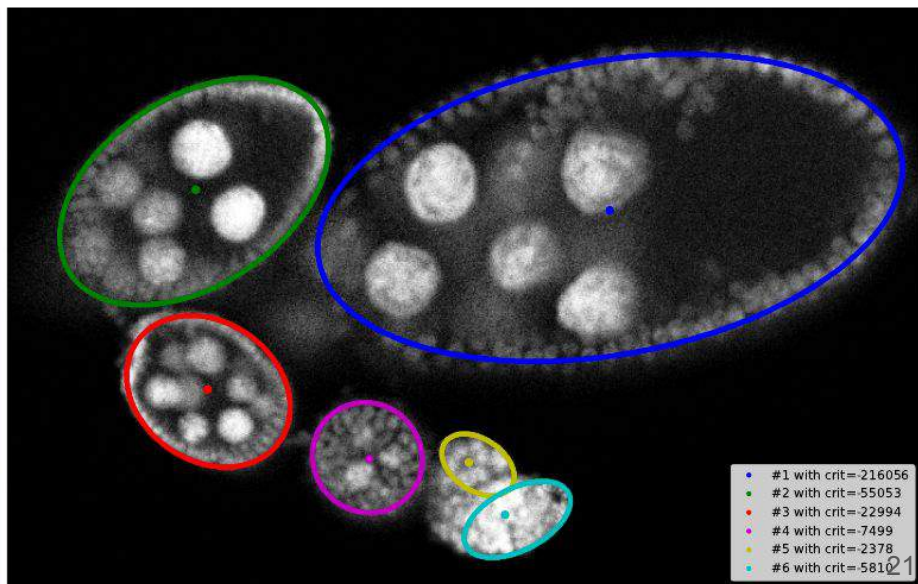
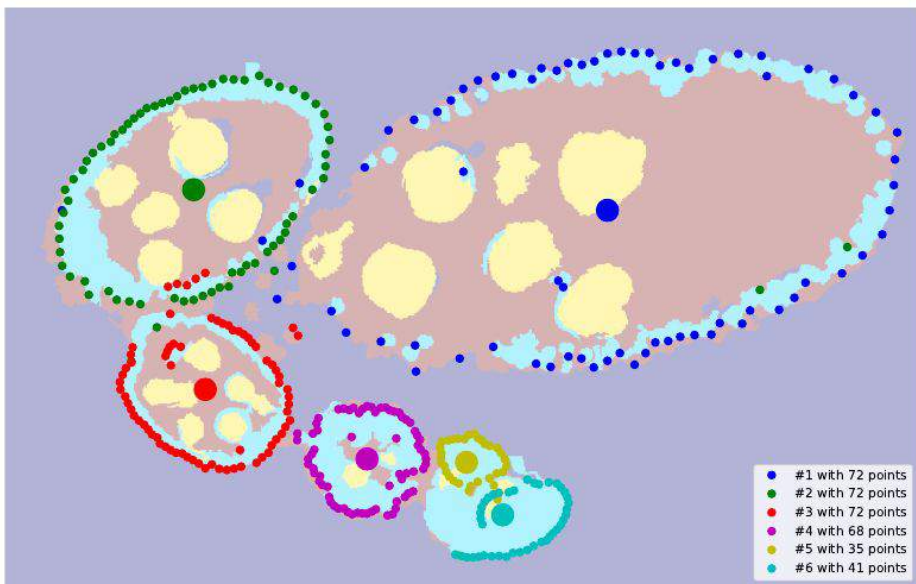
- Ray features

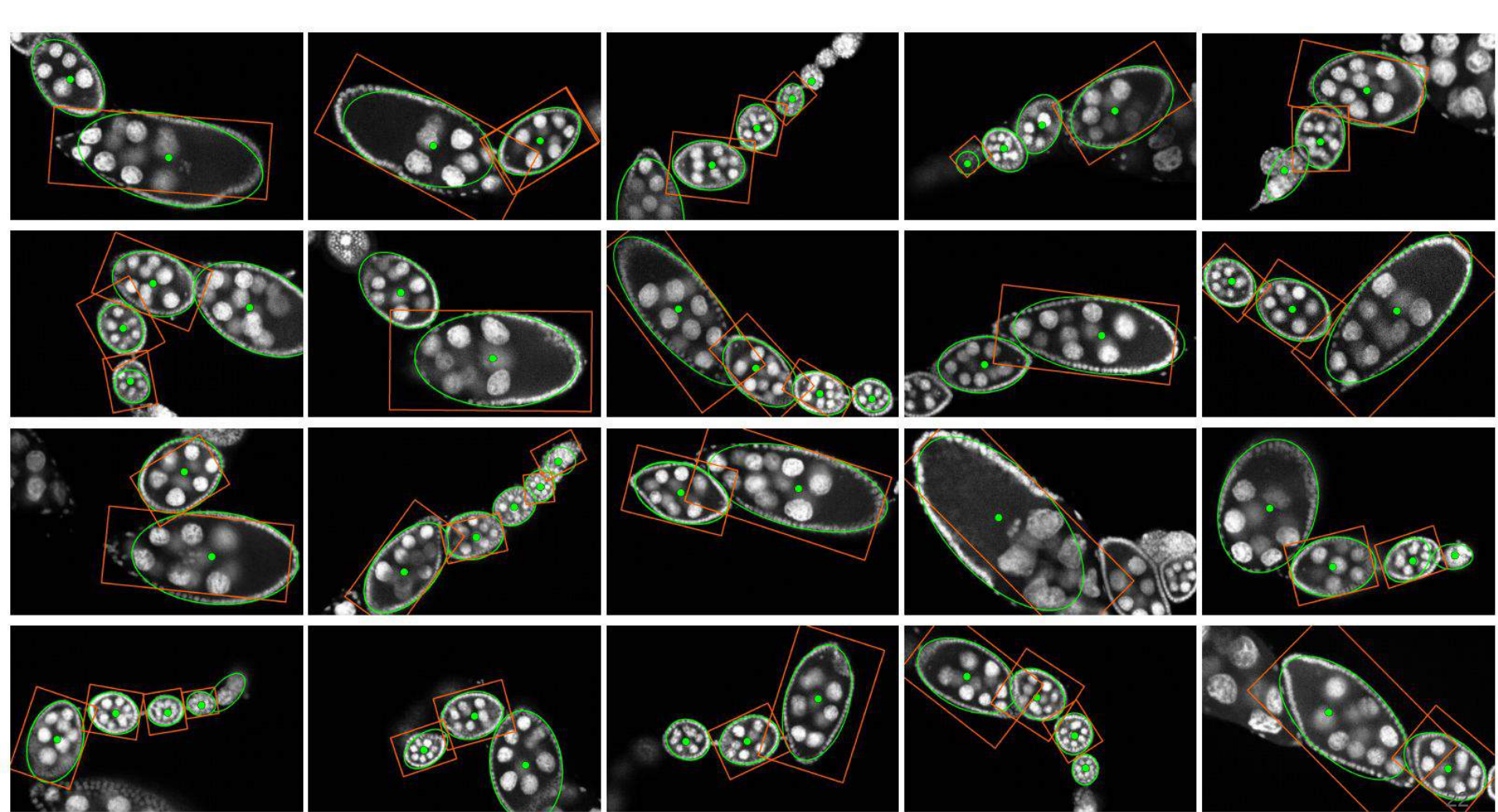


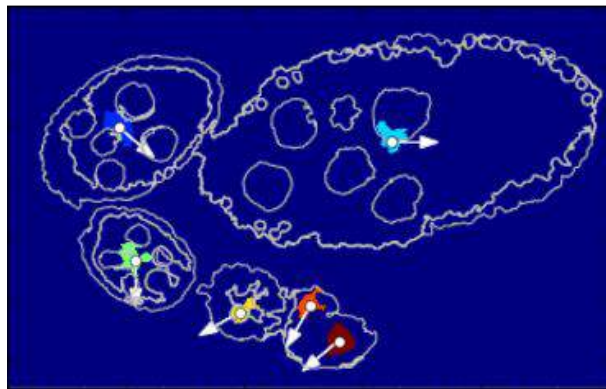
Ellipse fitting

Maximize likelihood

$$\prod_{i \in \Omega_F} P_F(Y_i) \cdot \prod_{i \in \Omega \setminus \Omega_F} P_B(Y_i)$$







Region growing using superpixels with learned shape prior

Jiří Borovec, Jan Kybic, Akihiro Sugimoto, “**Region growing using superpixels with learned shape prior**,” Journal Electron. Imaging 26(6), 061610 (2017), DOI: 10.1117/1.JEI.26.6.061611.

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- b. region growing

Region growing - variational framework

Formulated as:

$$P(g(s) | y, \mathbf{M}) = \frac{1}{Z(\mathbf{M}, y)} P_y(g | y) P_m(g | \mathbf{M}) P_R(g)$$

Where:

$$P_y(g | y) = \prod_{i \in \Omega} P_y(g(s(i)) | y(s(i))) = \prod_{s \in S} P_y(g(s) | y(s))^{|\Omega_s|}$$

$$P_m(g | \mathbf{M}) = \prod_{i \in \Omega} P_m(g(s(i)) | \mathbf{M}) = \prod_{s \in S} P_m(g(s) | \mathbf{M})^{|\Omega_s|}$$

$$P_R(g) = \prod_{(u,v) \in \mathcal{N}_S} H(g(u), g(v))$$

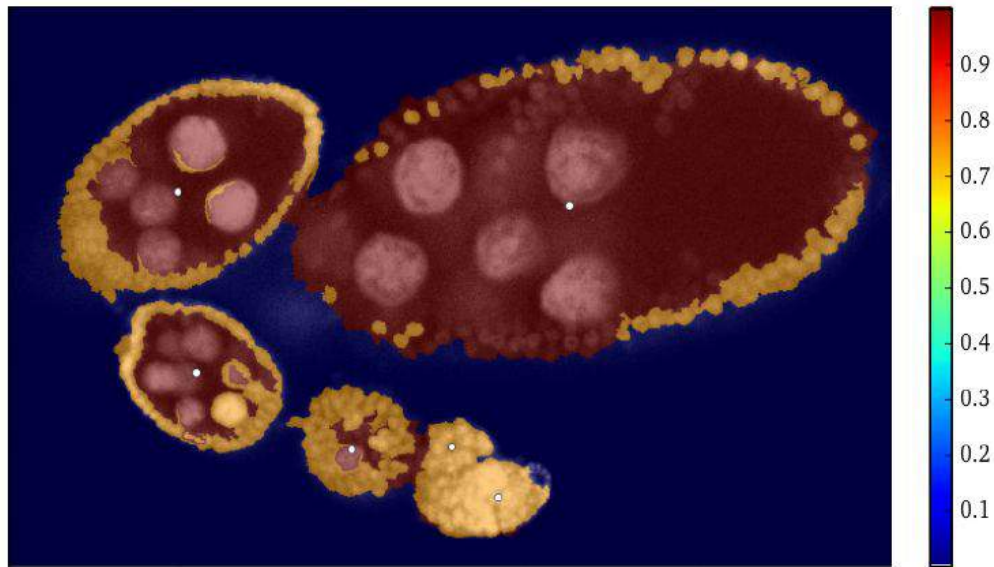
Resolves in energy minimisation:

$$E'(g) = \sum_{s \in S} |\Omega_s| [D_s(g(s)) + \beta V_s(g(s))] + \sum_{(u,v) \in \mathcal{N}_S} \gamma B(g(u), g(v))$$

Appearance model

Associating a probability for each pixel / superpixel whether it belongs to an object or not

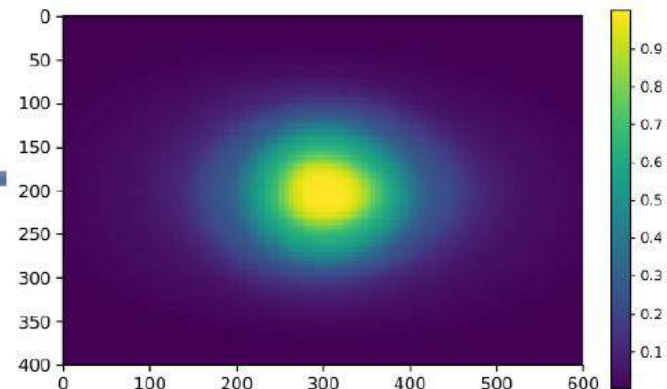
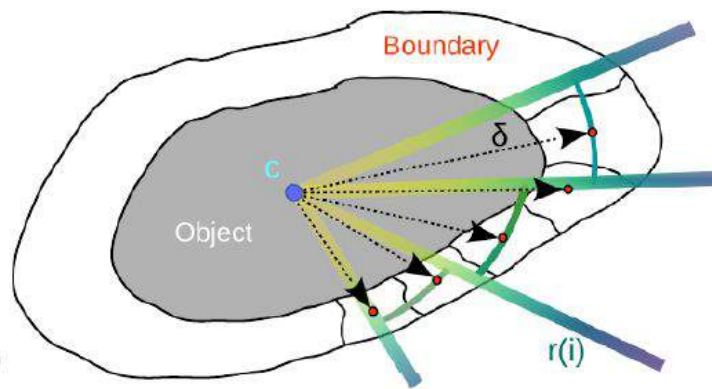
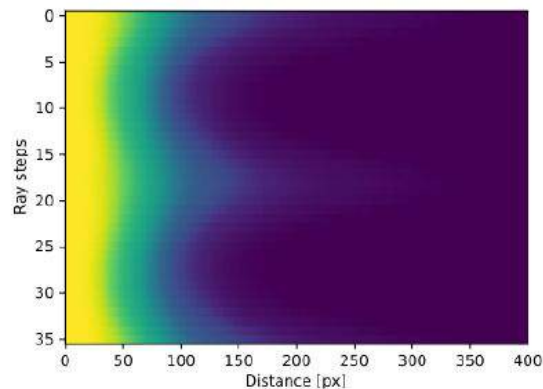
$$P_y(g(s)|y_s) = \begin{cases} P_y(y_s) & \text{for } g(s) \neq 0 \\ 1 - P_y(y_s) & \text{for } g(s) = 0 \end{cases}$$



Shape model & prior

$$p_r(\mathbf{r}) = \rho(\mathbf{r}) = \sum_{j=1}^M w_j f_j(\mathbf{r})$$

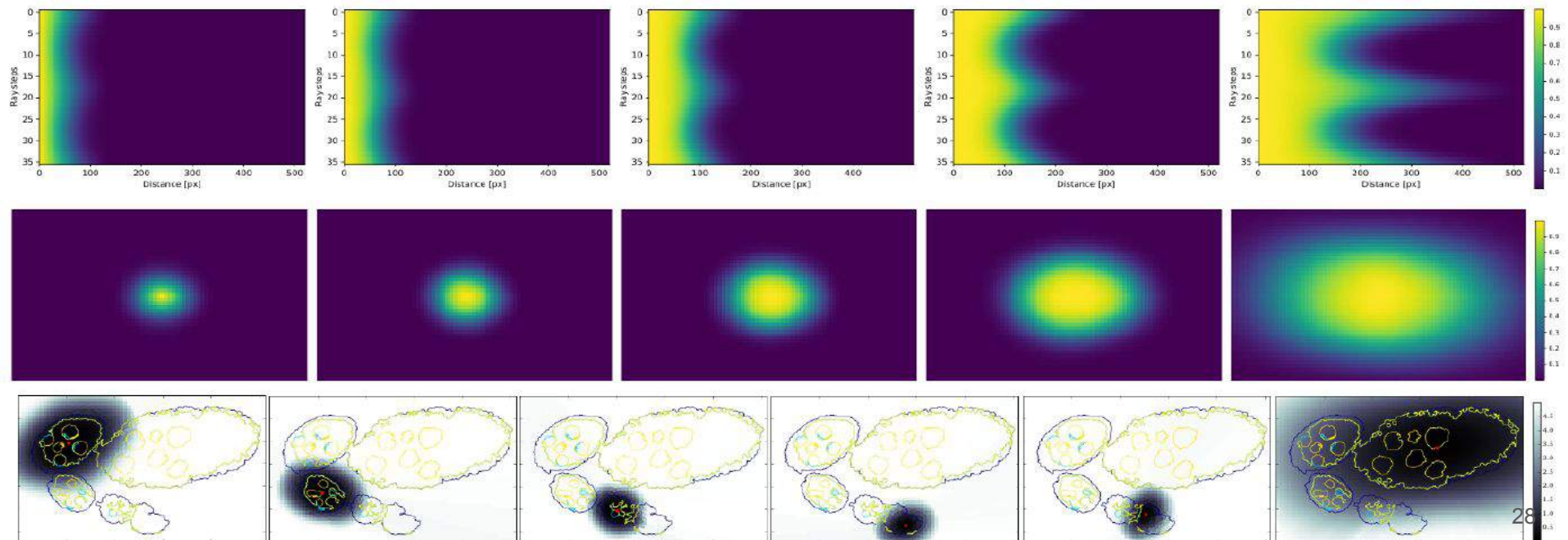
with $f_j(\mathbf{r}(i)) = \frac{1}{\sigma_{i,j} \sqrt{2\pi}} \exp\left(-\frac{(\mathbf{r}(i) - \mu_{i,j})^2}{2\sigma_{i,j}^2}\right)$ and $\sum_j w_j = 1$



$$q(s, \mathbf{m}_k) = \int_{\delta}^{\infty} \rho(r) dr = 1 - \int_0^{\delta} \rho(r) dr$$

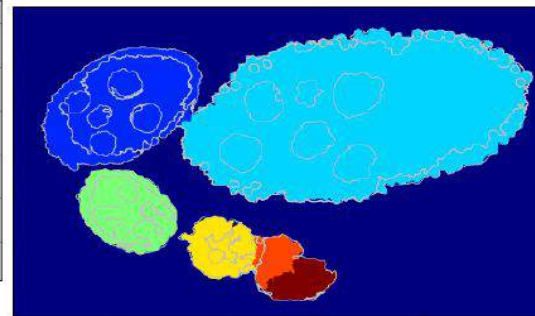
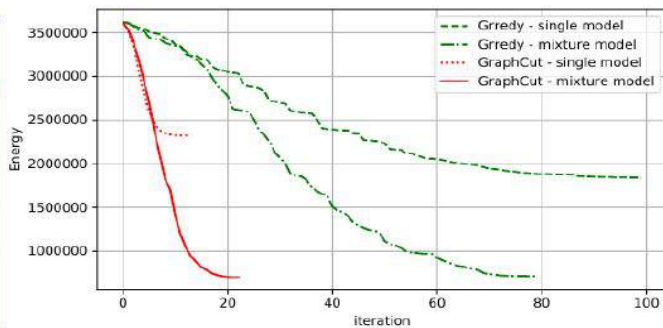
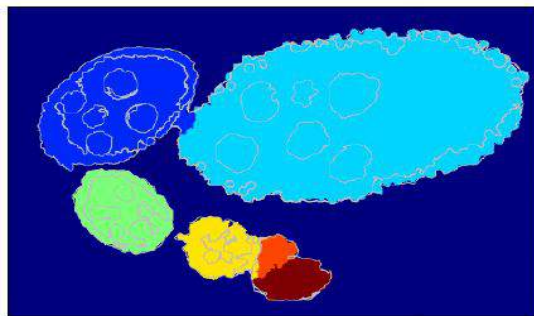
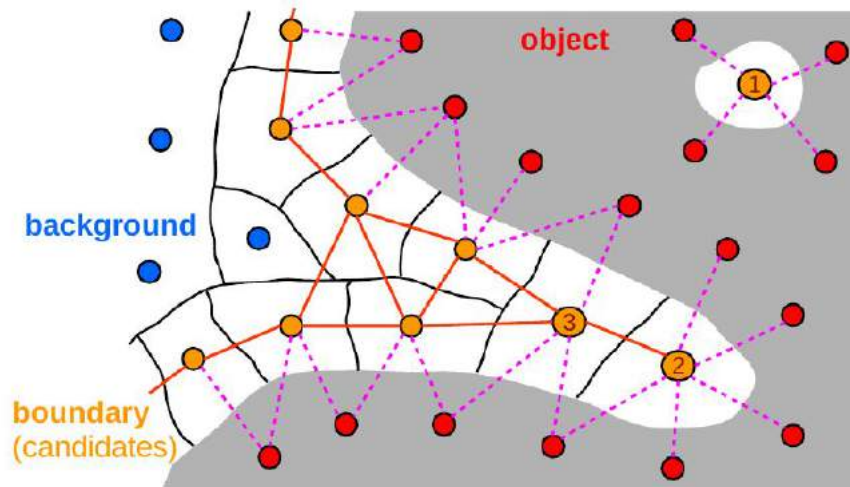
Mixture model

$$P_m(g(s) = k \mid \mathbf{M}) = \begin{cases} q(s, \mathbf{m}_k) & \text{for } k > 0 \\ \prod_l (1 - q(s, \mathbf{m}_l)) & \text{for } k = 0 \end{cases}$$



Region growing - optimisation

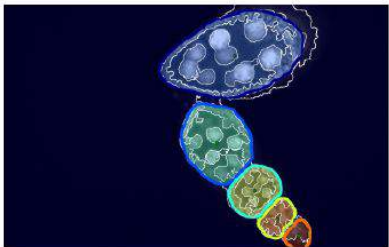
- Greedy
- Multi-class Graph Cut
- Binary Graph Cut
- Object swapping



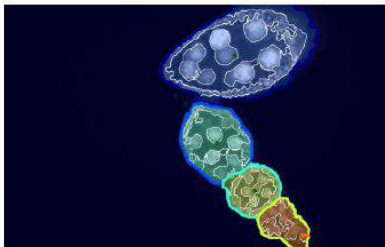
Result compare to SOA

	Jaccard	accuracy	F_1 score	precision	recall	time [s]
Watershed	0.5705	0.9246	0.9246	0.9246	0.9246	5
Watershed (w. morph.)	0.5705	0.9270	0.9198	0.9136	0.9327	7
Morph. snakes (image)	0.4251	0.8769	0.8070	0.9053	0.7987	784
Morph. snakes (P_y)	0.6494	0.8812	0.8812	0.8812	0.8812	968
Graph Cut (pixel-level)	0.7143	0.9204	0.9204	0.9204	0.9204	15
Graph Cut (superpixels)	0.3164	0.8643	0.8643	0.8643	0.8643	3
RG2Sp (greedy)	0.7527	0.9577	0.9577	0.9577	0.9577	72
RG2Sp (Graph Cut)	0.7544	0.9568	0.9568	0.9568	0.9568	9

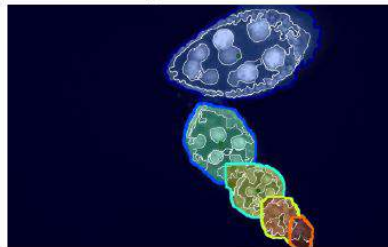
Annotation



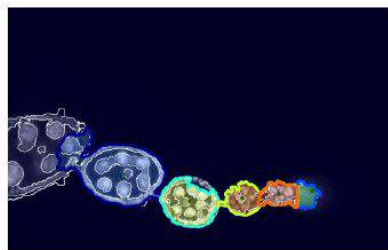
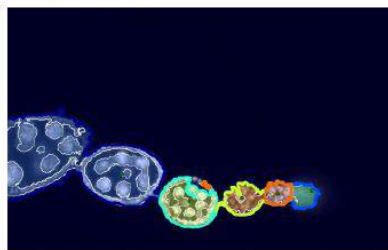
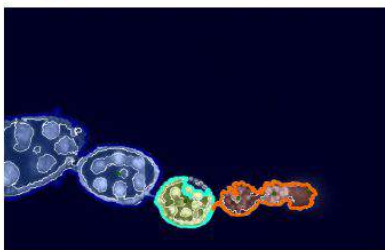
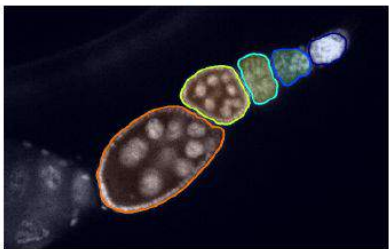
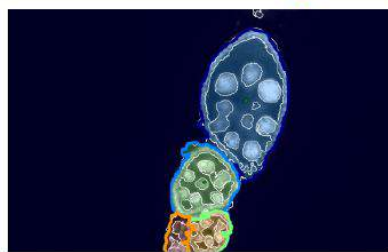
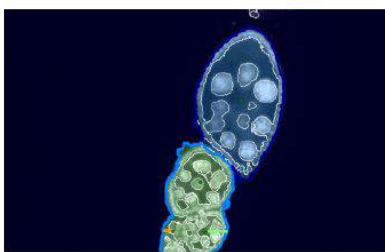
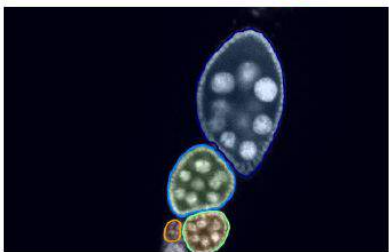
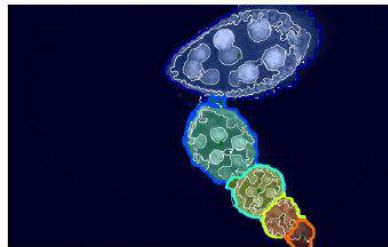
Watershed



GC (pixel-wise)



RG2Sp



Conclusion

- Presented 3 image methods
 - Image segmentation on superpixels
 - supervised
 - Partially-supervised
 - unsupervised
 - Center detection on segmented images
 - Region growing with shape prior
- Future work
 - Complete image analysis pipeline
 - Explore Instance segmentation with NN
 - ...

