Progress Report

ECE 435 Medical Image Processing

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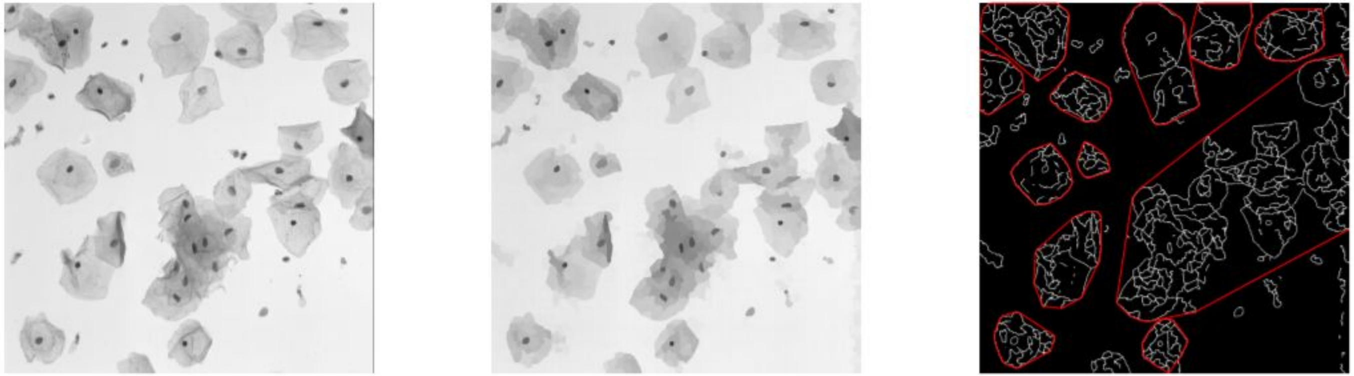
Chosen Paper and Dataset

Automated Nucleus and Cytoplasm segmentation of Overlapping Cervical Cells

Authors: Zhi Lu, Gustavo Carneiro, and Andrew P. Bradley
Publication: MICCAI 2013

ISBI 2014 Dataset Featuring:

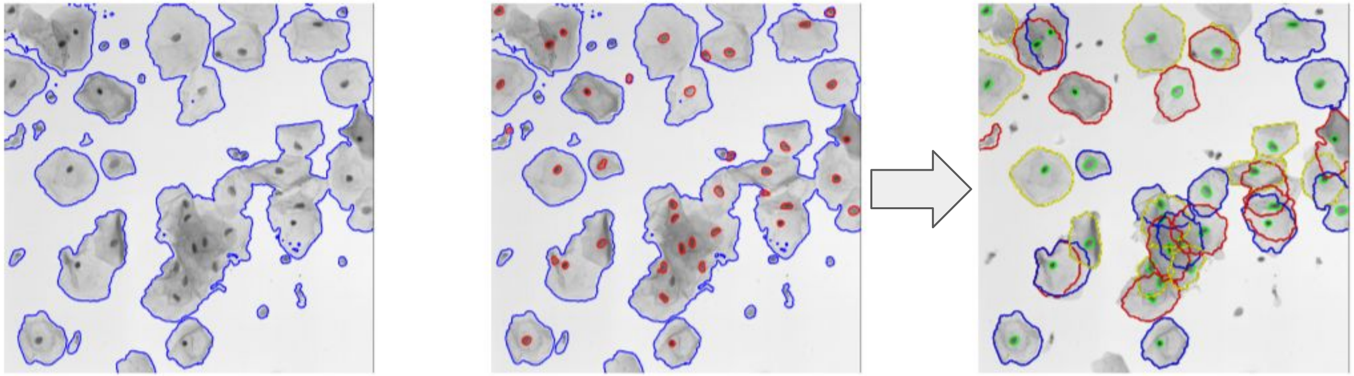
- 16 EDF real cervical cytology images
- 945 Synthetic images



(a) Pap smear image

(b) Super-pixel map

(c) Edge map (white) and Convex hulls (red)



(d) Clumps boundary

(e) Nuclei Segmentation

(f) Cell segmentation

Primary Contribution of the Chosen Paper

$$\mathcal{E}(\{\phi_i\}_{i=1}^{N}) = \sum_{i=1}^{N} \mathcal{E}_u(\phi_i) + \sum_{i=1}^{N} \sum_{j \in \mathcal{N}(i)} \mathcal{E}_b(\phi_i, \phi_j),$$

$$\mathcal{E}_u(\phi_i) = \mu \mathcal{R}(\phi_i) + \lambda \mathcal{L}(\phi_i) + \alpha \mathcal{A}(\phi_i) + \rho \mathcal{P}_p(\phi_i),$$

$$\mathcal{P}_p(\phi_i) = \int_{\Omega} g H(-p(\phi_i)) d\mathbf{x},$$

$$\begin{aligned}\mathcal{E}_b(\phi_i, \phi_j) = & \zeta f_a \left(\frac{\int_{\Omega} g H(-\phi_i) H(-\phi_j) d\mathbf{x}}{\int_{\Omega} g H(-\phi_i) d\mathbf{x}} \right) + \\ & \omega f_g \left(\frac{\int_{\Omega} v H(-\phi_i) d\mathbf{x}}{\int_{\Omega} g H(-\phi_i) d\mathbf{x}} - \frac{\int_{\Omega} v H(-\phi_i) H(-\phi_j) d\mathbf{x}}{\int_{\Omega} g H(-\phi_i) H(-\phi_j) d\mathbf{x}} \right),\end{aligned}$$

Level Set Method For Image Segmentation

Definition of Level Set…

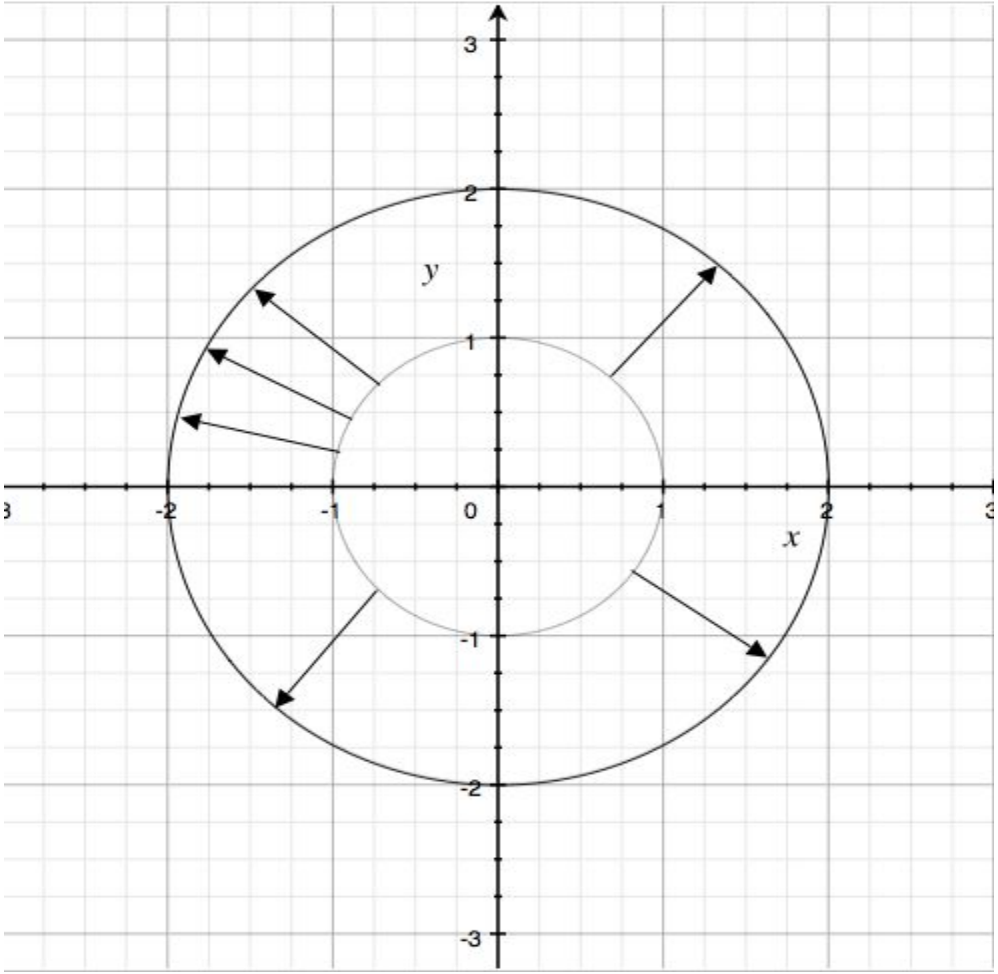
Recall MATH 100, 101...

$$L_c(f) = \{(x_1, \cdots, x_n) \mid f(x_1, \cdots, x_n) = c\} \ ,$$

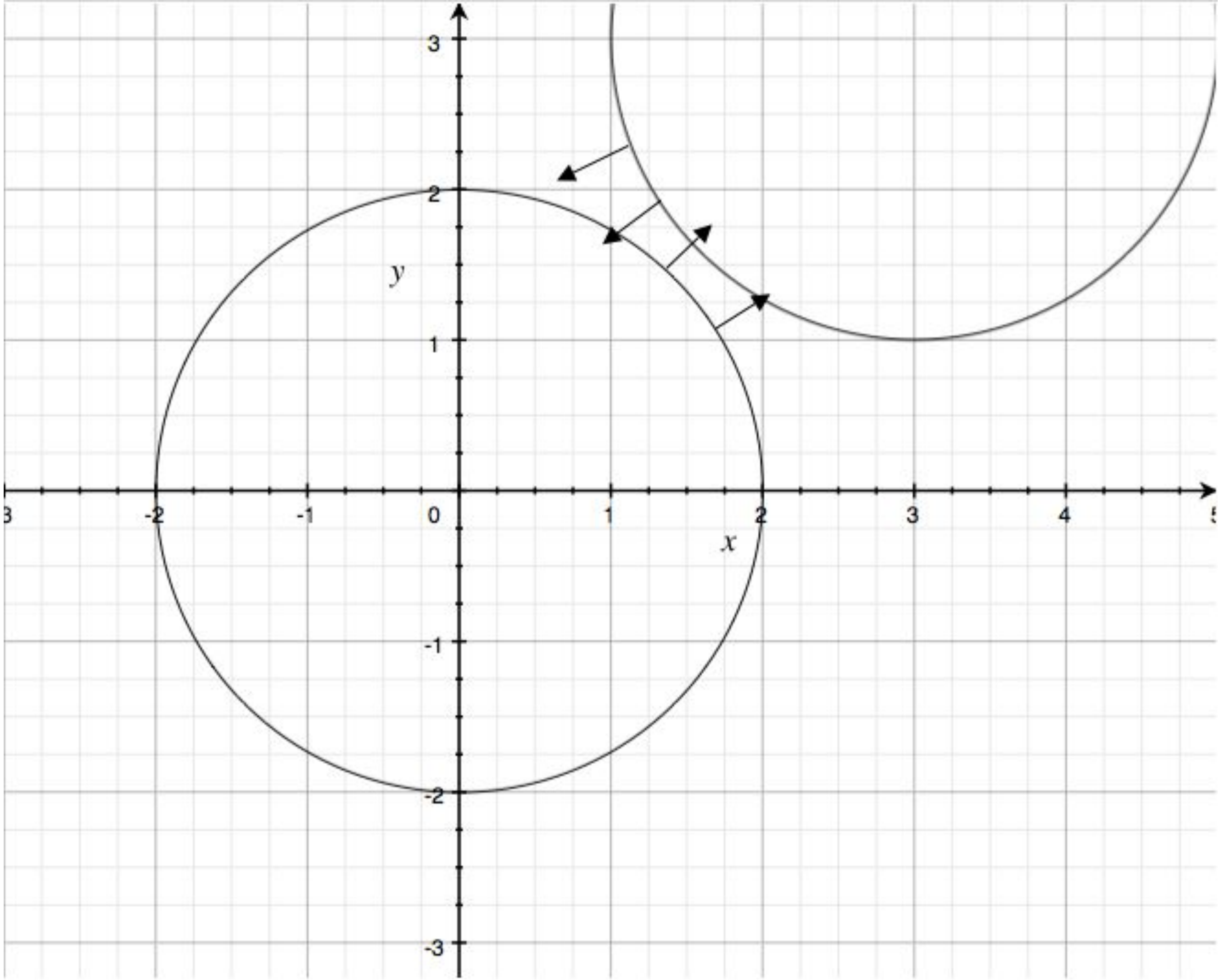
Mathematical Modeling

1. Throw a stone into the middle of a pond…
2. There would be a ripple of water…
3. Moving from the center, going wide until it hits the pond’s edge...

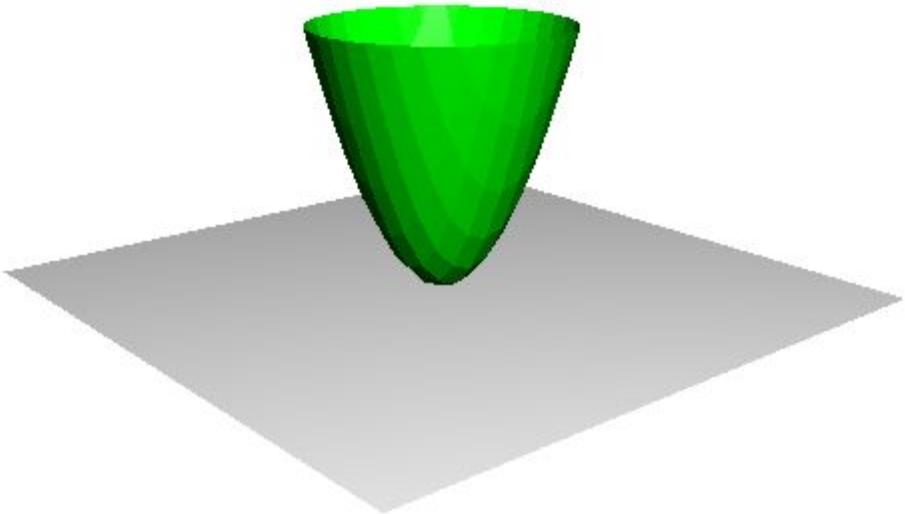
Modeling Explicitly

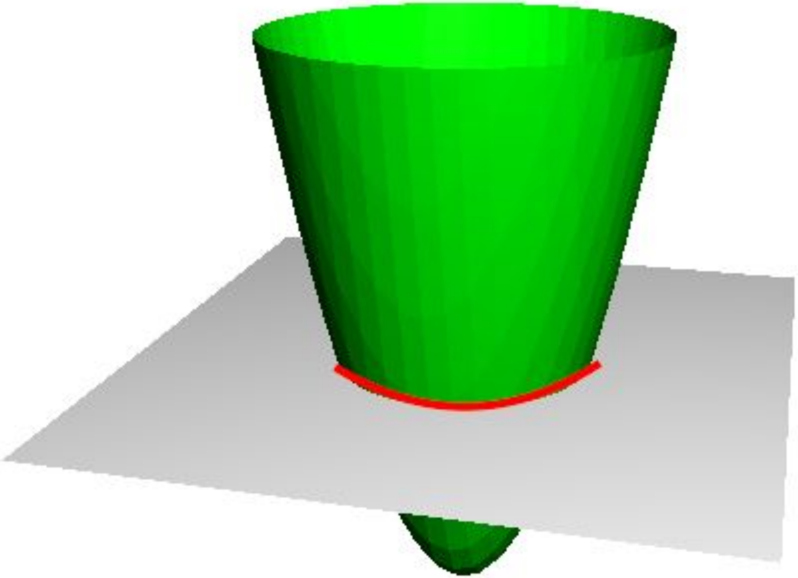


But… What if



Level Set Method Shines - Modeling Implicitly





Mathematical Derivation

$$\phi_t = -\boldsymbol{F}\|\nabla\phi\|$$

This gives us the propagation speed of the surface.

F can be thought as Force, drive the curve propagation / push the curve.

```
dphi = grad(phi)
dphi_norm = norm(dphi)
```

Finite Difference Method to Solve the PDE

$$\frac{\partial \phi(x(t), t)}{\partial t} = \frac{\phi(x(t), t + \Delta t) - \phi(x(t), t)}{\Delta t}$$

$$\phi' = \phi + \Delta t F \|\nabla \phi\|$$

```
for i in range(it):
    dphi = grad(phi)
    dphi_norm = norm(dphi)
    phi = phi + dt * F * dphi_norm
```

If you are familiar with Deep Learning...

$$x' = x + \alpha \nabla x$$

$$\phi' = \phi + \Delta t F \|\nabla \phi\|$$

Image Segmentation

$$\phi' = \phi + \Delta t F \|\nabla \phi\|$$

We can think F as velocity field, i.e., F is a vector field which tells us the direction and magnitude of the movement of our couture.

Since we are dealing with Image, F should be obtained from Image.

How?

Model-based Segmentation

Edge enhancement

- Computing the image gradient : vector composed of first-order partial derivatives

$$\nabla I = \left[\frac{\partial I}{\partial x} \quad \frac{\partial I}{\partial y} \right]^T$$

- The gradient magnitude gives the *amount* of the difference between pixels in the neighborhood (the *strength* of the edge).
- The gradient orientation gives the *direction* of the greatest change, which presumably is the direction across the edge (the edge normal).
- Derivatives are linear and shift invariant, thus the gradient can be computed with convolution

Model-based Segmentation

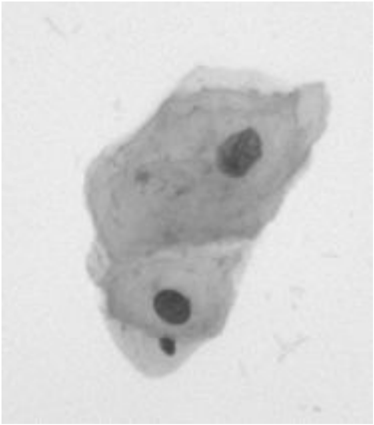
$$\phi' = \phi + \Delta t F \|\nabla \phi\|$$

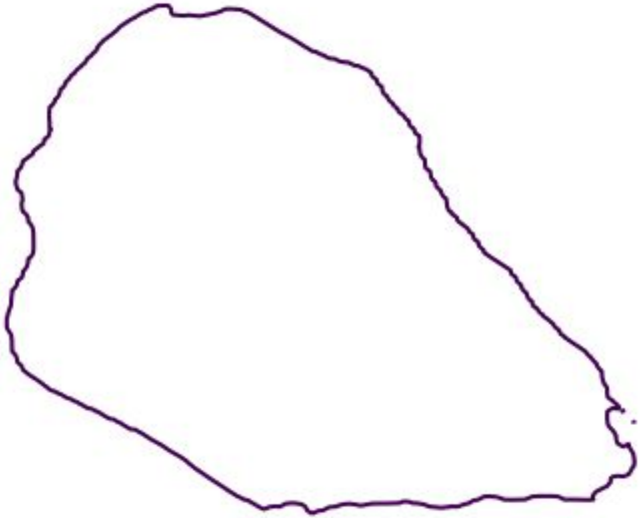
We want F to be high at all regions that are not the border (edge), low at the border (edge) of the object. Edge Detector, but inverse!

```
1. / (1. + norm(grad(x))**2)
```

$$g(I) = \frac{1}{1 + \|\nabla I\|^2}$$

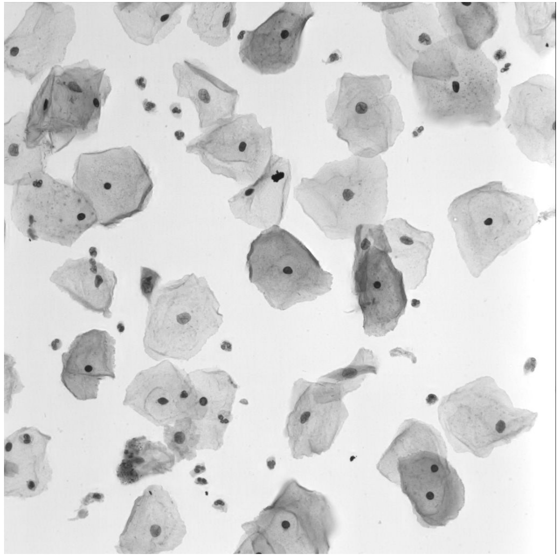
Result of Naive Level Set Method

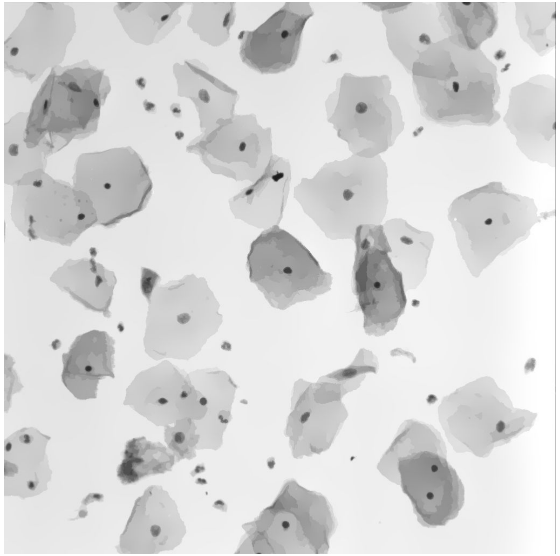




Preliminary Results

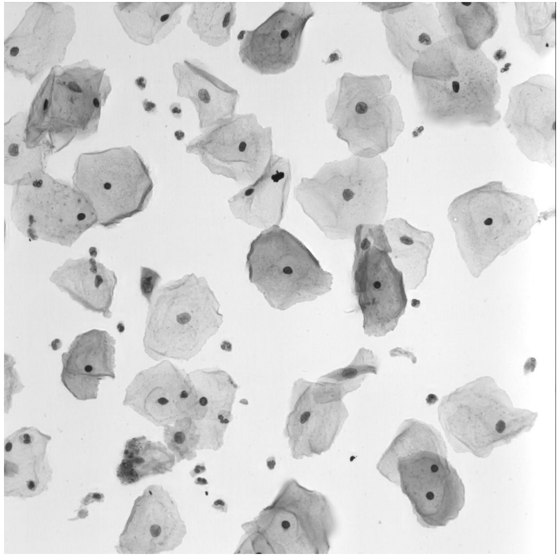
Mean Shift is used instead of Quick Shift to create a super-pixel map (right) from the original cervical cytology image from the ISBI 14 dataset (left).

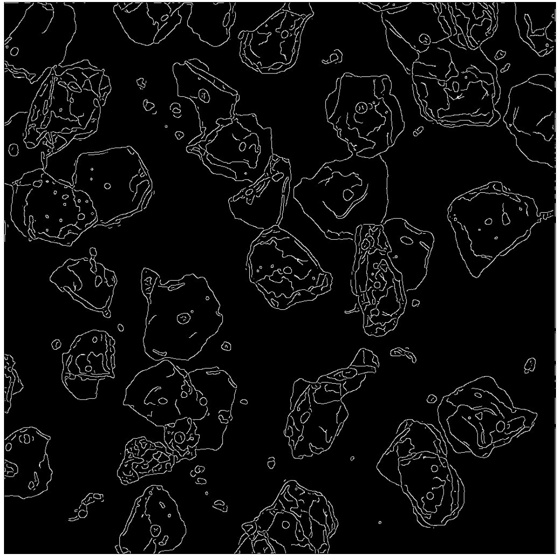




Preliminary Results

Canny edge detection is performed on the superpixel map to create of an edge map (right).





Expected Challenges

- Accuracy issues due to naive mean shift algorithm
- Implementation of binary classifier
- Implementation of Joint Level Set segmentation

Timeline and Work Distribution

Assignee	Tasks	Deadline
Yiping Wang	Unsupervised Binary Classifier	March 17th
Brian Pattie	Segmentation of Nuclei via MSER	March 17th
Both	Joint Level Set Segmentation of Overlapping Cells	March 24th
Both	Oral Presentation Slides	March 30th
Both	Finalize Code	April 6th
Both	Video Demo	April 8th
Both	Final Report	April 11th

Useful Tutorial Links

https://wiseodd.github.io/techblog/2016/11/05/levelset-method/

https://wiseodd.github.io/techblog/2016/11/20/levelset-segmentation/

https://profs.etsmtl.ca/hlombaert/levelset/