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Exploring the Addition of Boundary Energy to the Marked Point Process

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July 2019

Overview

- **Motivation**
  - Problem statement: MPP is limited to generic shapes
  - Illustrative dataset: Fiber reinforced composites
- **Marked Point Process (MPP)**
  - Set up: MPP = Point Process + Marks
  - Energy minimization using multiple birth and deaths
- **Part I: MPP and parametric Active Contours(AC)**
  - AC boundary energy: Smoothness and Curvature
  - Combination of MPP-AC: Disks with deformed boundaries
- **Part II: MPP and Level Sets(LS)**
  - LS boundary energy: Dark regions with strong edges
  - Object proposal: LS alone can guide the object proposal
- **Future Work**
  - Deep learning based approaches

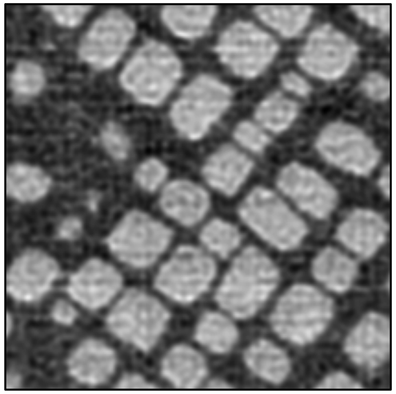
Motivation

Introduction

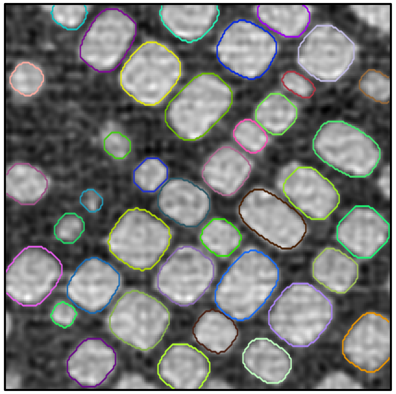
Motivation – Expand the limitations of the Marked Point Process(MPP)

What is the MPP?

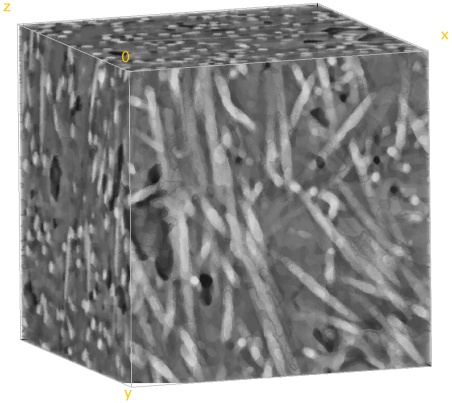
- Stochastic framework that models images as configuration of objects
- Considers:
  - Data in macroscopic scale
  - Object geometries
  - Relation between objects and prior knowledge
- **Problem**:
  - **MPP is limited to low-parametric geometries (disks/ellipses/tubes/lines)**



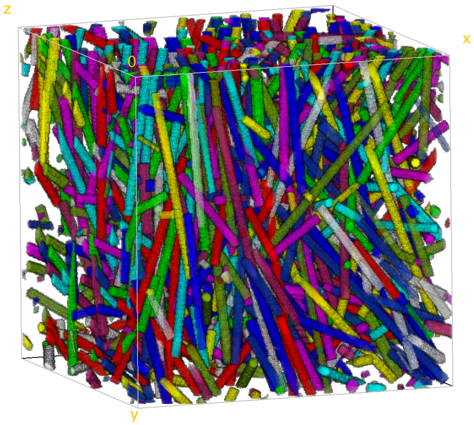
NiAlCr



Ellipse Model
[Zhao et al. 2016]



Fiber Reinforced Composite
[ACME Lab Purdue]



Connected Tube
[Li et al. 2018]

Illustrative dataset

Objective:

Characterization of glass fiber reinforced composite:

- **Structural Features**
  - Object location/orientation
  - Volume ratio
- **Mechanical Features**
  - Fiber breakout
  - Fiber pullout

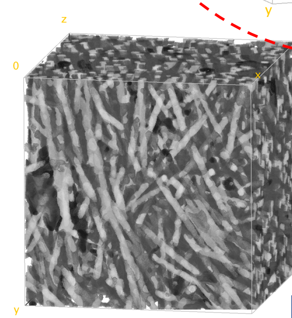
[Dupont]

Cone beam X-Ray tomography

[Argonne National Labs]

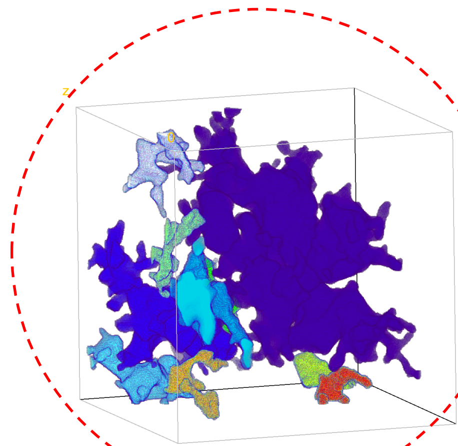
Reconstruction

[Tomopy by ACME Lab]

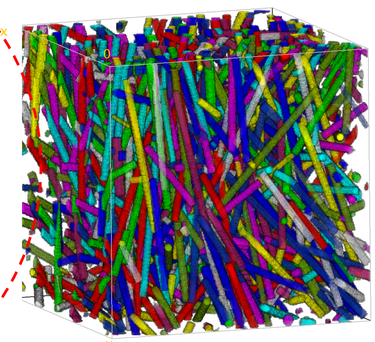


Raw Volume

MPP



Voids



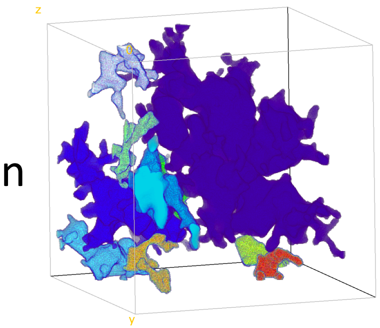
Fibers

The MPP approach models the underlying object distribution

Challenges

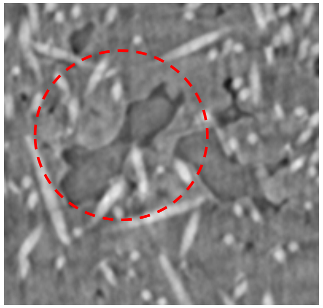
- Irregular shapes
  - ➢ Active Contour Modeling

➡ Void representation in composite:



- Low contrast
  - ➢ Balloon method (MPP-AC)
  - ➢ Hybrid LS method (MPP-LS)

➡ Composite cross section:



[ACME Lab Purdue]

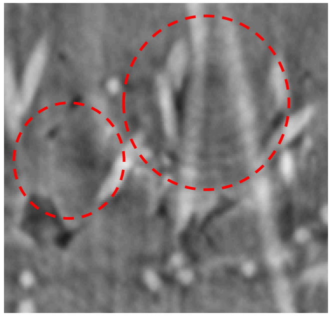
- Large datasets
  - ➢ Hybrid LS method

➡ Volume Size:

$2500 \times 2500 \times 1300$ voxels

- Imaging and reconstruction noise
  - ➢ 3D Filtering

➡ Composite cross section:



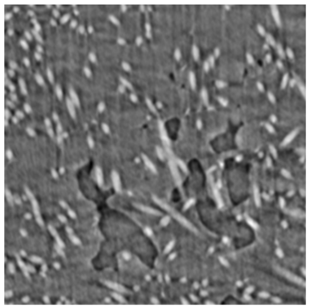
[ACME Lab Purdue]

Common Segmentation Approaches

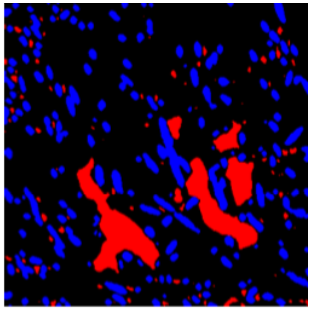
Machine Learning

Discriminative Dictionary Learning: Edge Classifier

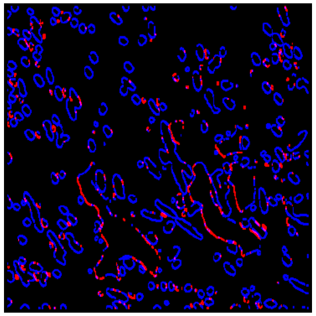
Sparse training data



Original Image



Labeled Image



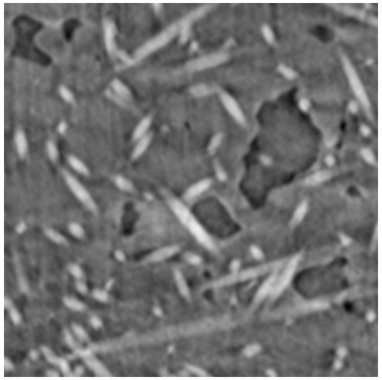
Classified Edges

[Mairal 2008]

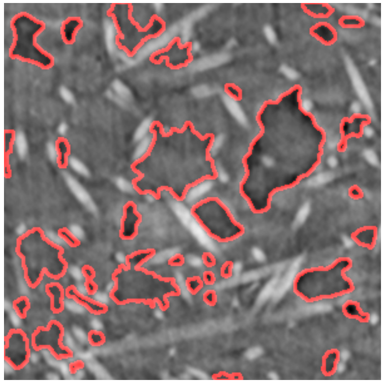
Active Contours only

Hybrid Level Sets

Initialization dependent



Original Image



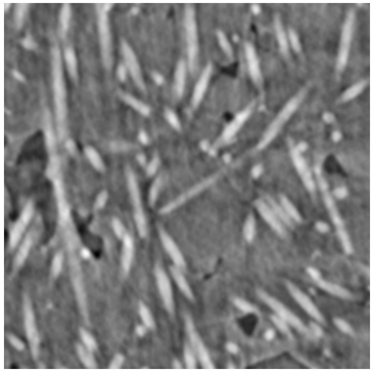
Detected Contours

[Yan 2008]

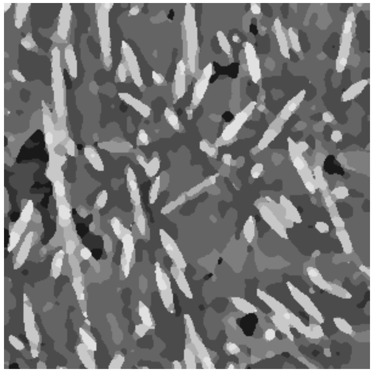
Markov Random Fields

EM/MPM

Pixelwise segmentation



Original Image



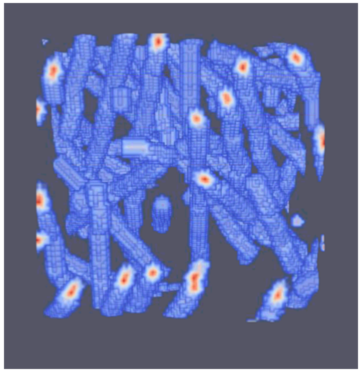
EMMPM. Labels = 9

[Comer 2000]

Watershed

Watershed by flooding

Requires careful energy/marker setting



Distance Transform

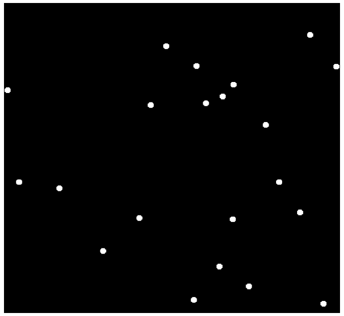
Watershed Segmentation

[Beucher 1979]

Marked Point Process

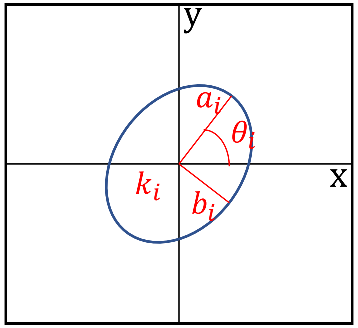
Marked Point Process

- Set up point process
  - Define a Point Process $\boldsymbol{x}$ on lattice $K \subset \mathbb{R}^d$
  - Each point k_i in $\boldsymbol{x} = \{k_1, \dots, k_n\}$ denotes a coordinate.
  - n is a random variable



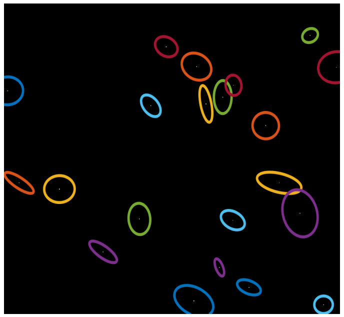
Realization of a Point Process

- Set up marks
  - A mark space M describes objects' parameters
  - Single marked object is $\omega_i = (k_i, m_i) \in K \times M$



Sample marked object
$\omega_i = (k_i, a_i, b_i, \theta_i)$

- MPP = point process + marks
  - An object configuration is $\boldsymbol{w} = \{\omega_1, \dots, \omega_n\}$
  - An MPP $\boldsymbol{w}$ is defined on space $\Omega = K \times M$



Realization of an MPP

MPP density

Density:

$$p(\boldsymbol{w}) = \frac{1}{z_\Omega} \exp(-\,U(\boldsymbol{w})\,)$$

$\boldsymbol{w}$: Marked object configuration
ω_i: Single Marked i^{th} object
z_Ω: Normalizing constant
$\omega_i \sim \omega_j$: Neighbor relation

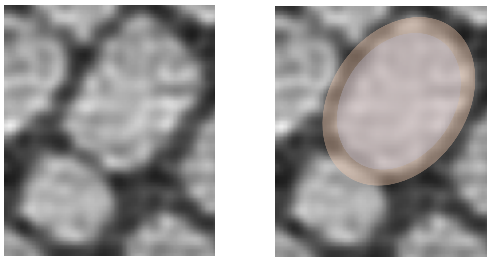
Gibbs Energy:

$$U(\boldsymbol{w}) = \underbrace{\sum_{\omega_i \in \boldsymbol{w}} U_d(\omega_i)}_{\text{data term}} + \underbrace{\sum_{\substack{\omega_i \sim \omega_j \\ \omega_i,\ \omega_j \in \boldsymbol{w}}} U_p\,(\omega_i\,, \omega_j)}_{\text{prior term}}$$

Data Term:

$U_d(\omega_i) \propto$ object fitting

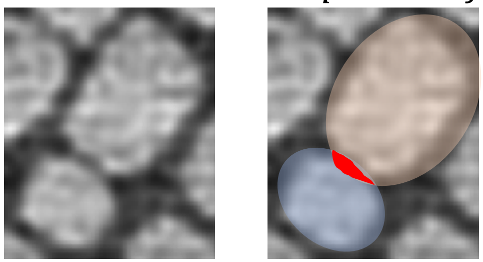
Data Term: $U_d(\omega_i)$



Prior Term:

$U_p(\omega_i, \omega_j) \propto$ overlap penalizer

Prior Term: $U_p(\omega_i, \omega_j)$



Energy Optimization

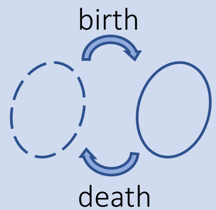
Goal: find optimal configuration

$$\hat{\boldsymbol{w}} = \arg\max_{\boldsymbol{w}\in\Omega} p(\boldsymbol{w}) = \arg\min_{\boldsymbol{w}\in\Omega} U(\boldsymbol{w})$$

Use Markov Chain Monte Carlo with stochastic annealing

Markov Chain on Ω needs to be:

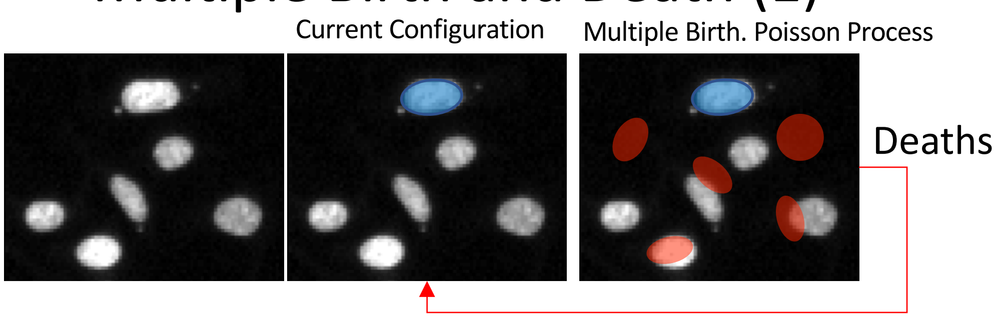
- Finite
- Aperiodic
- Irreducible
- Reversible



Annealing scheme:

$$T^{k+1} = T^{k}\,\alpha, \qquad \alpha \in (0, 1)$$

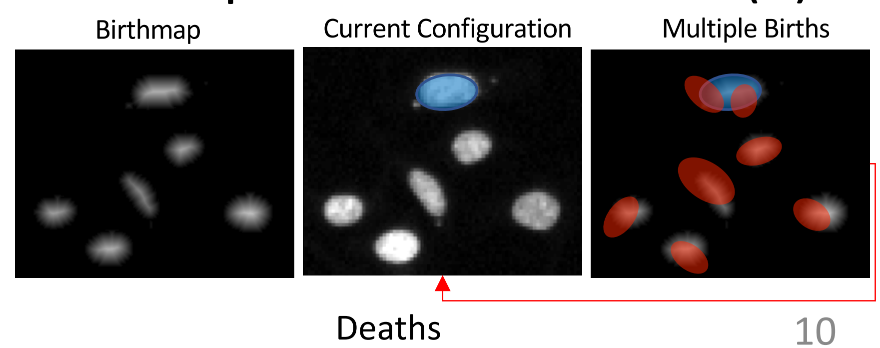
Multiple Birth and Death (1)



$\boldsymbol{w} = \{\omega_1\}$ $\quad$ $\boldsymbol{w}' = \{\omega'_1, \omega'_2 \dots \omega'_n\}$

[Descombes 09]

Multiple Birth and Death (2)



$\boldsymbol{w} = \{\omega_1\}$ $\quad$ $\boldsymbol{w}' = \{\omega'_1, \omega'_2 \dots \omega'_n\}$

[Kaggle Datascience Bowl 2018]

MPP-Active Contours

Active Contour Model

- Define curve: $C_t = \{(x_t, y_t)\}$, where $t \in [0, 2\pi]$
- Energy Function:

$$E(C_t) = \int_0^{2\pi} E_{\text{int}}(C_t) + E_{\text{ext}}(C_t)\, dt$$

- Internal Energy:

$$E_{\text{int}}(C_t) = \int_0^{2\pi} \frac{1}{2}[\alpha|C_t'|^2 + \beta|C_t''|^2 \ dt$$

Elastic Term Curvature Term

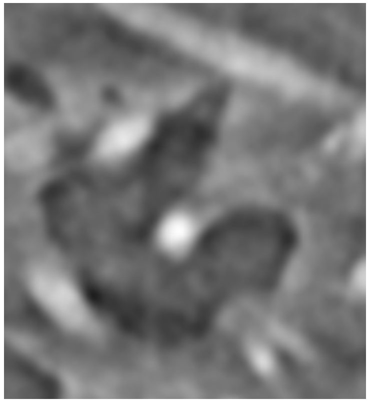
- External Energy:

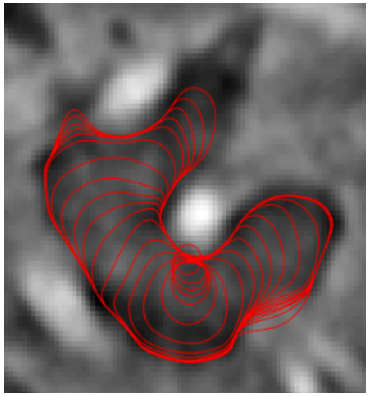
$$E_{\text{ext}}(C_t) = -\kappa_1|\nabla I(x_t, y_t)|^2 - \kappa_2|I_{\text{dark}}(x_t, y_t)| + \kappa_3\vec{n}_C(t)$$

Stop at edges Attract to dark regions Inflate the Contour

[Cohen 1993]

C_t: Parametric contour
C_t': First derivative w/r to t
C_t'': Second derivative w/r to t
x_t, y_t: Coordinates in contour
$\vec{n}_C$: Normal to the contour
I : Image Domain
I_{dark}: Image is 1 in pixels with low intensities

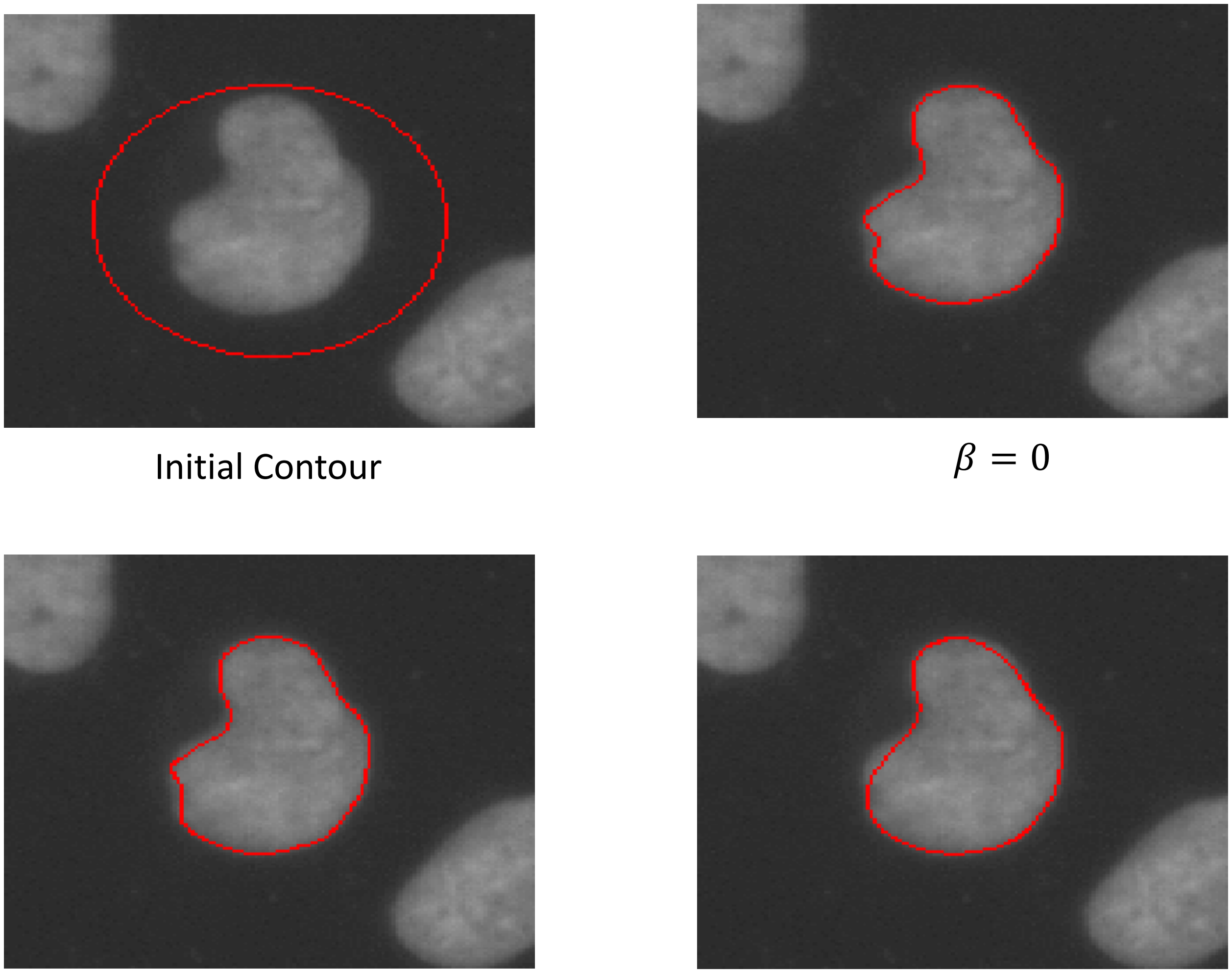




[Kass 1988]

Boundary Parameters

$$E(C_t) = \int_0^{2\pi} \frac{1}{2}[|C_t'|^2 + \beta|C_t''|^2 - 0.05\,|\nabla I(x_c, y_c)|^2 \;- 0.1\,\vec{n}_C(t)dt$$



Initial Contour

$\beta = 0$

$\beta = 10$

$\beta = 100$

Boundary Energies

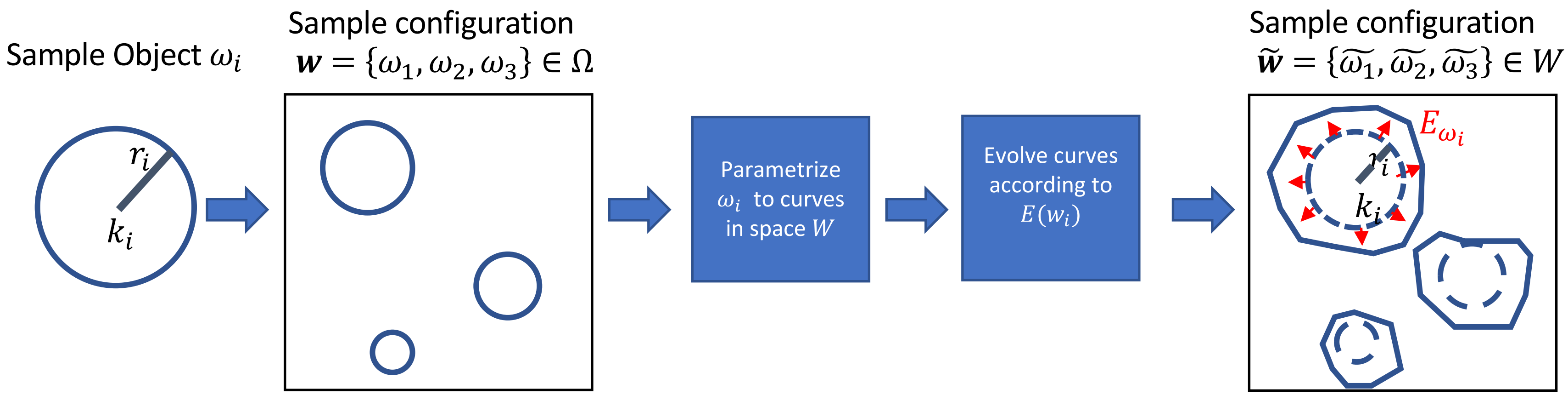
β	$C'(t)$	$C''(t)$
0	876.46	44.83
10	818.88	15.77
100	746.83	5.00

Active Contours in the MPP

K: Image lattice
Ω: Configuration space
W: Parametric space
$\boldsymbol{w}$: Marked object configuration
ω_i: Single marked i^{th} object
$\widetilde{\omega_i}$: Evolved marked i^{th} object
$\widetilde{\boldsymbol{w}}$: Evolved object configuration

- Initial Mark Object Field:
  - Disks with mark $\omega_i = \{k_i, m_i\} \in \Omega,\ \Omega \subset K \times M$
  - $M = [r_{\min}, r_{\max}]$
- Modified Marked Object Field:
  - Define energy functional $E(\omega_i)$ on space W
  - Parametrize curve $\omega_t \in$ W
  - Perform energy minimization on $E(\omega_t)$ to evolve ω_t into $\widetilde{\omega}_t \in$ W

[Kulikova, 2009]



Energies

MPP-AC Energy

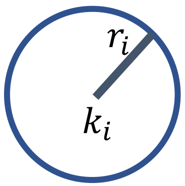
$\boldsymbol{w}$: Marked object configuration
ω_i: Single marked i^{th} object
$\widetilde{\omega_i}$: Evolved marked i^{th} object
$\widetilde{\boldsymbol{w}}$: Evolved object configuration
$\boldsymbol{z}$: Normalizing Constant
$\boldsymbol{\omega_i \sim \omega_j}$: Neighbor Relation

- Gibbs Process with probability density

$$p(\boldsymbol{w}) = \frac{1}{Z}\exp\{-U(\boldsymbol{w})\}$$

- Energy Function

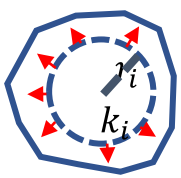
$$U(\boldsymbol{w}) = \sum_{\omega_i \in \boldsymbol{w}} U_d(\omega_i) + \sum_{\omega_i \sim \omega_j} U_p\left(\omega_i, \omega_j\right)$$



ω_i

- **Data Energy: Active Contour Energy**

$$U_d(\omega) = \min_{\omega_i}\left\{\int_0^1 E_{\text{int}}(\omega_t) + E_{\text{ext}}(\omega_t)dt\right\} = U_d(\widetilde{\omega_t})$$



$\widetilde{\omega}_i$

- Prior Energy

$$U_p(\omega_i, \omega_j) = \begin{cases} A_{\text{overlap}}\left(\widetilde{\omega_t}_i, \widetilde{\omega_t}_j\right) & \text{if } A_{\text{overlap}}\left(\widetilde{\omega_t}_i, \widetilde{\omega_t}_j\right) \leq T_{\text{overlap}} \\ \infty & \text{otherwise} \end{cases}$$

Simulation: Multiple Birth and Death

b_o: Birth Rate ∈ [0,1]
T: Process Temperature
σ: Process Intensity

Algorithm 1 Multiple Birth and Death Algorithm

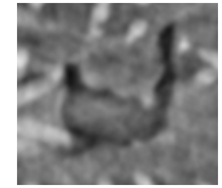
procedure MPP ENERGY MINIMIZATION
  Initialization:
    Create birthmap b_o
    Initialize $b_{rate} = b_o$, $T = T_o$, $\sigma = \sigma_o$.
  Birth Step:
    Visit pixels in raster order
    $\omega' \leftarrow$ draw a sample from space Ω
    Add ω' to configuration **w** with probability σb_{rate}
    Evolve ω' to $\tilde{\omega}'$
  Death Step:
    Sort all elements of **w** by decreasing energy.
    For every object ω_i in **w** calculate:

$$d_{rate}(w_i) = \frac{\sigma^{(k)} exp \frac{U(\mathbf{W}|Y)-U(\mathbf{W}-\omega_i|Y)}{T^k}}{1+\sigma^{(k)} exp \frac{U(\mathbf{W}|Y)-U(\mathbf{W}-\omega_i|Y)}{T^k}};$$

    Delete ω_i with probability $d_{rate}(\omega_i)$
  Convergence Test:
    if all the elements born during the birth step are killed during the death step
      terminate process
  else
      $T^{k+1} \leftarrow T^k \times \alpha$, $\sigma^{k+1} \leftarrow \sigma^k \times \alpha$ $\alpha \in (0,1)$
      goto Birth Step

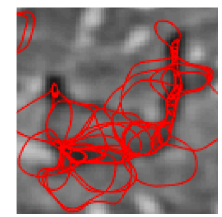
end procedure

Modified from [Descombes, 2009]

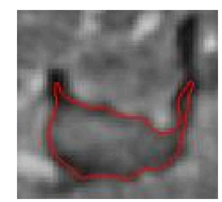


Initialization
(birth map)

Birth Step



Death Step



Multiple Birth and Death Algorithm

Simulation: Multiple Birth and Death

b_o: Birth Rate $\in [0,1]$
T: Process Temperature
σ: Process Intensity

Algorithm 1 Multiple Birth and Death Algorithm

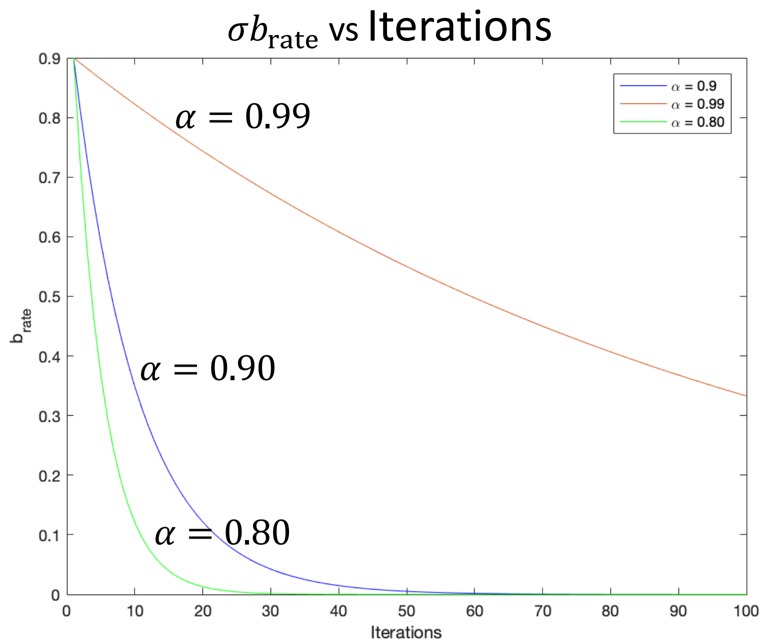
```
procedure MPP ENERGY MINIMIZATION
    Initialization:
    Create birthmap b_o
    Initialize b_rate = b_o, T = T_o, σ = σ_o.
    Birth Step:
        Visit pixels in raster order
        ω' ← draw a sample from space Ω
        Add ω' to configuration w with probability σb_rate
        Evolve ω' to ω̃'
    Death Step:
        Sort all elements of w by decreasing energy.
        For every object ω_i in w calculate:
        d_rate(w_i) = σ^(k) exp((U(W|Y)−U(W−ω_i|Y))/T^k) / (1+σ^(k) exp((U(W|Y)−U(W−ω_i|Y))/T^k));
        Delete ω_i with probability d_rate(ω_i)
    Convergence Test:
        if all the elements born during the birth step are killed
    during the death step
            terminate process
    else
            T^(k+1) ← T^k × α ,  σ^(k+1) ← σ^k × α  α ∈ (0,1)
            goto Birth Step

end procedure
```

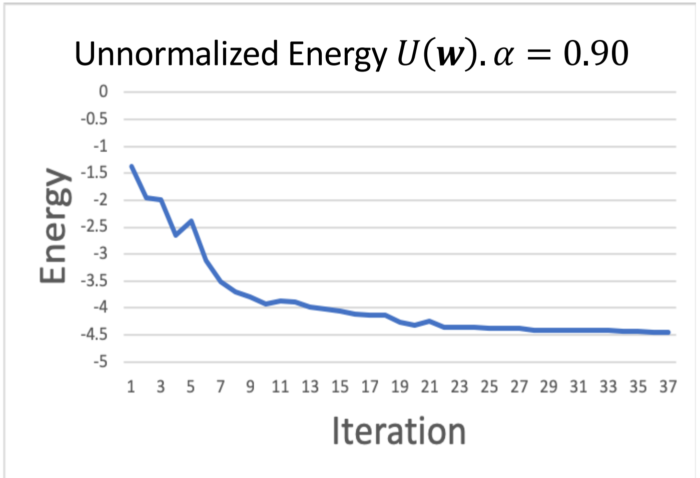
$$d_{rate}(w_i) = \frac{\sigma^{(k)} exp\frac{U(\mathbf{W}|Y)-U(\mathbf{W}-\omega_i|Y)}{T^k}}{1+\sigma^{(k)} exp\frac{U(\mathbf{W}|Y)-U(\mathbf{W}-\omega_i|Y)}{T^k}}$$

σ: Process Intensity

Energy Change
&
Temperature
dependent

Modified from [Descombes, 2009]

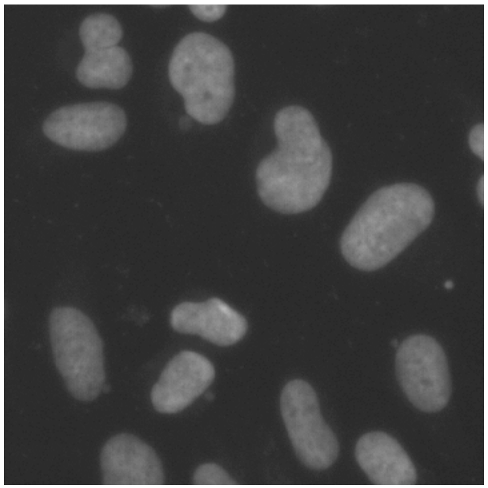




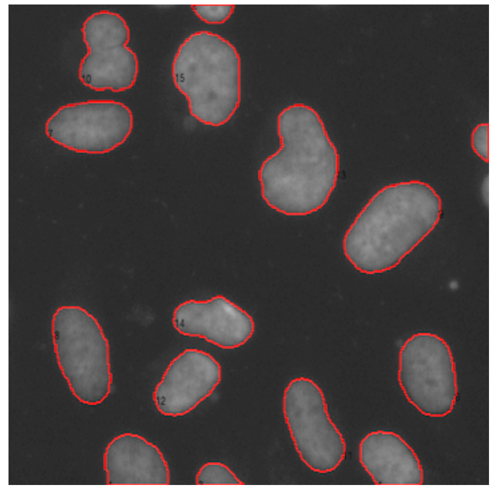
Sample Results I: Human Cells

$$E(C_t) = \int_0^{2\pi} \frac{1}{2}[|C_t'|^2 + \beta|C_t''|^2 - 0.05\,|\nabla I(x_c, y_c)|^2\,dt$$

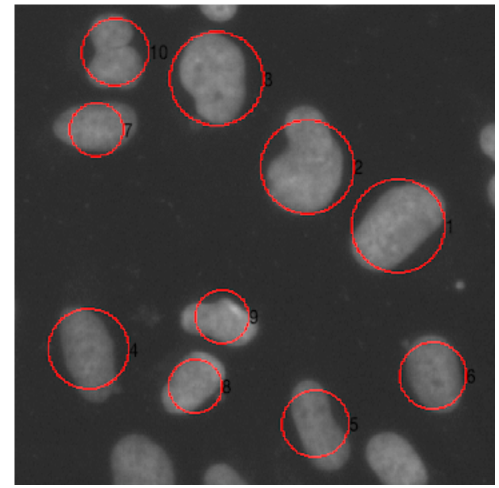
[Kaggle Datascience Bowl 2018]



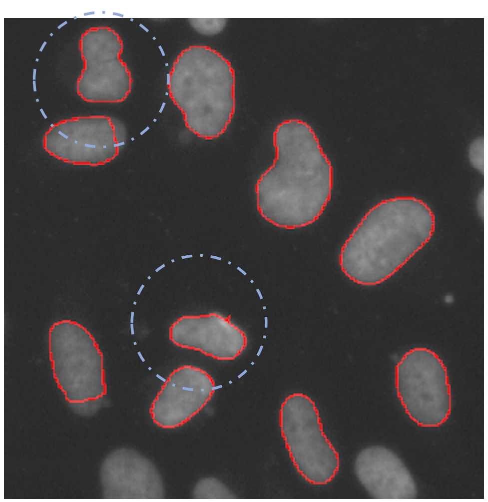
Original Image



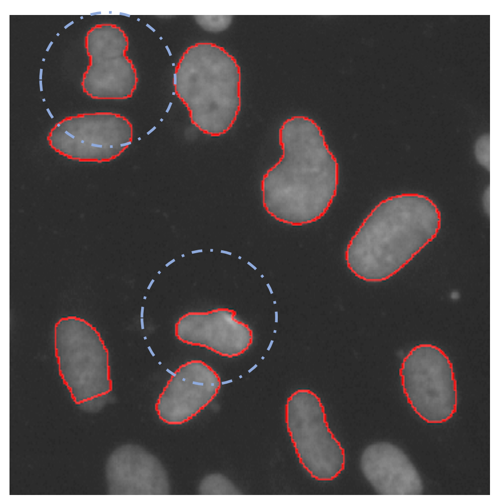
Ground Truth



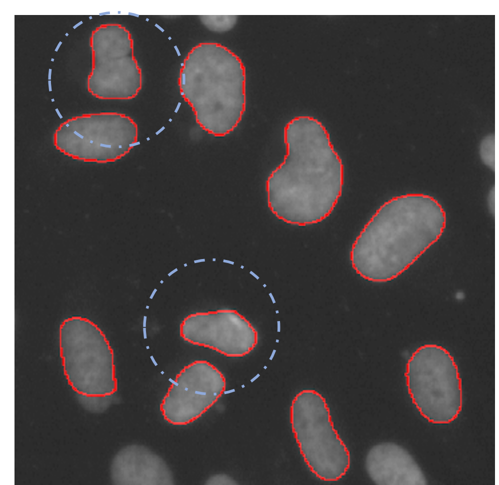
Marks



$\beta = 1$

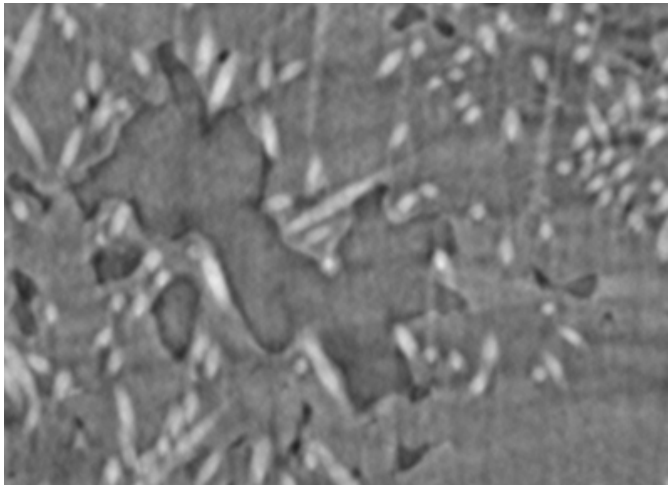


$\beta = 10$

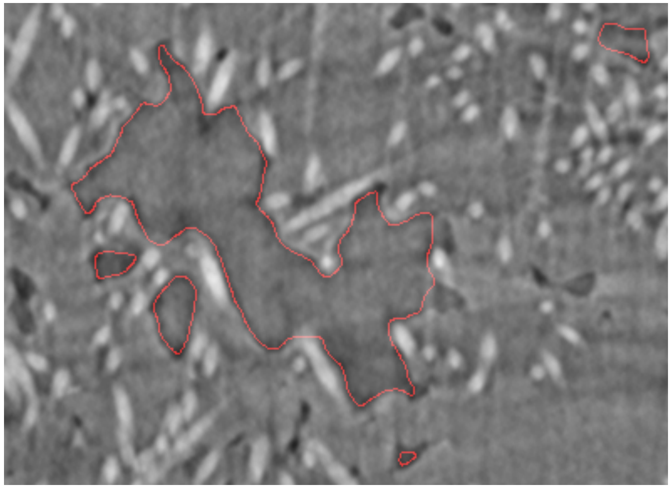


$\beta = 100$

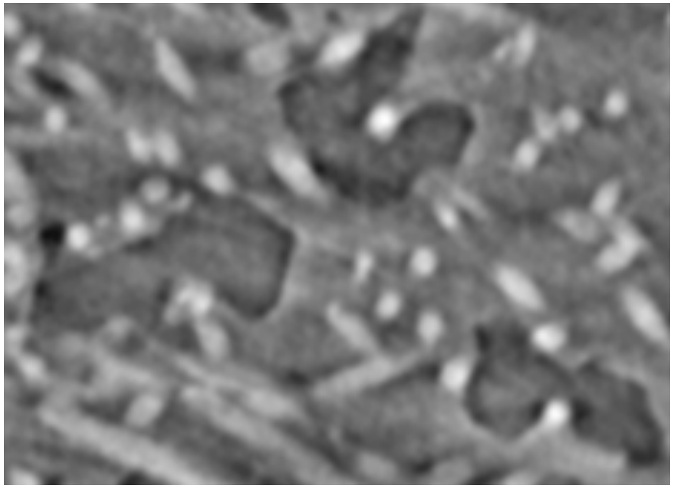
MPP-AC Results II: voids



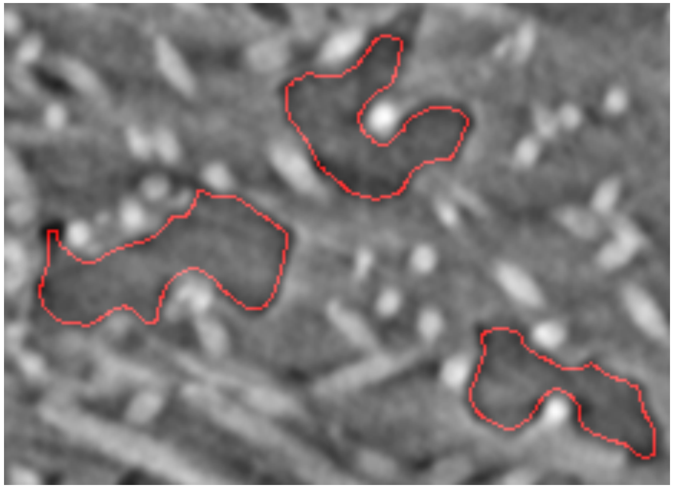
Original Image



MPP-AC

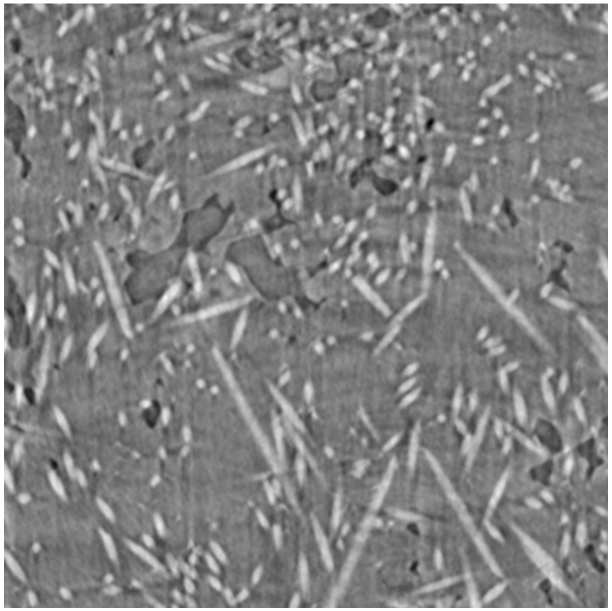


Original Image

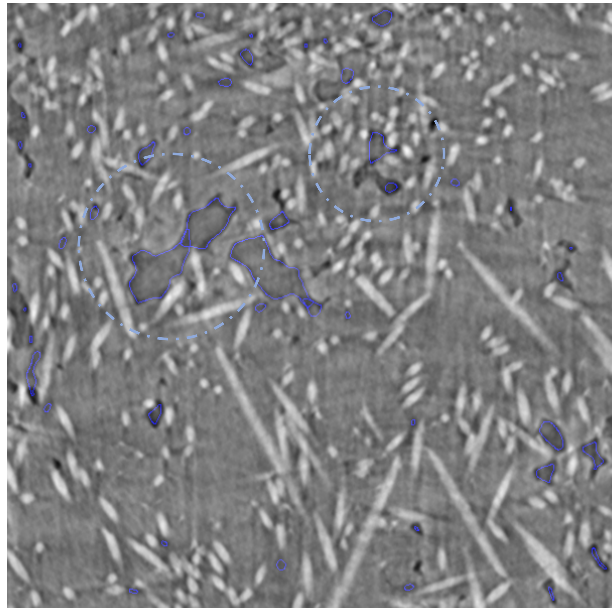


MPP-AC

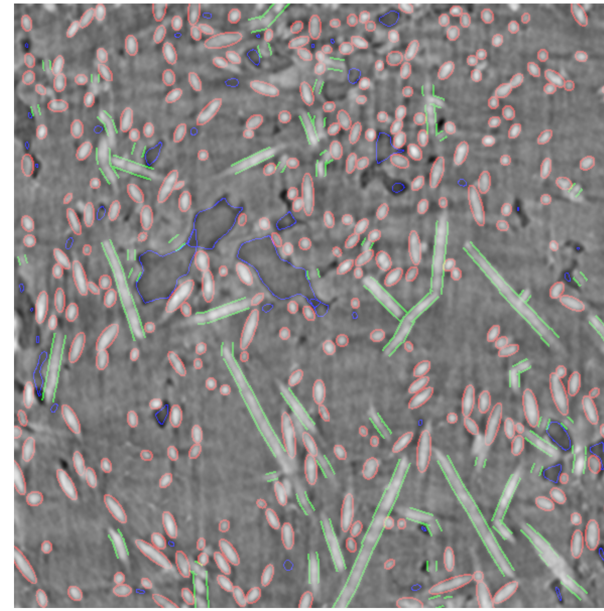
MPP-AC Results III: voids and fibers



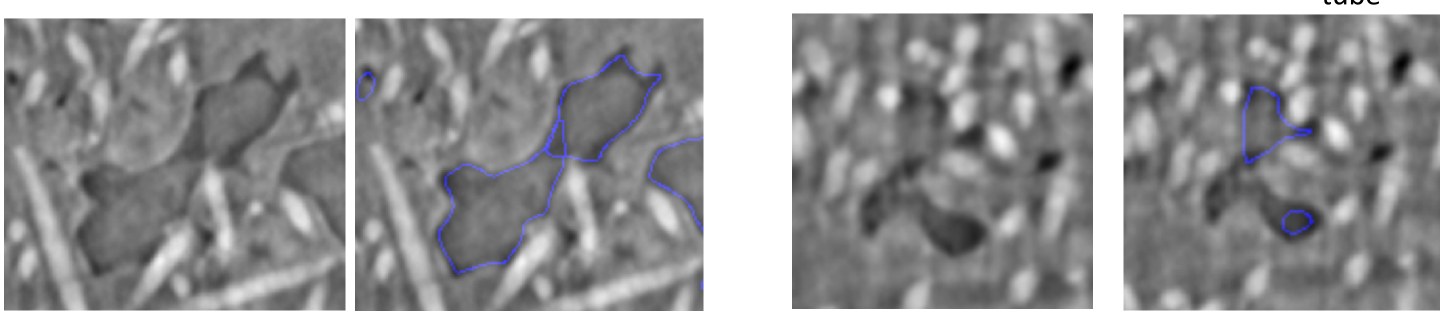
Original Image



MPP-AC for voids only



MPP-AC combined with MPP Connected tube



Parametrization Constrains

Contributions of this work

- Exploration of the MPP-AC to microscopy images
- Adaptation of the classic AC energy that involves smoothness and curvature.
  - Exploration of the curvature weighting effects
- Adaptation of the balloon force to capture objects with irregular shapes

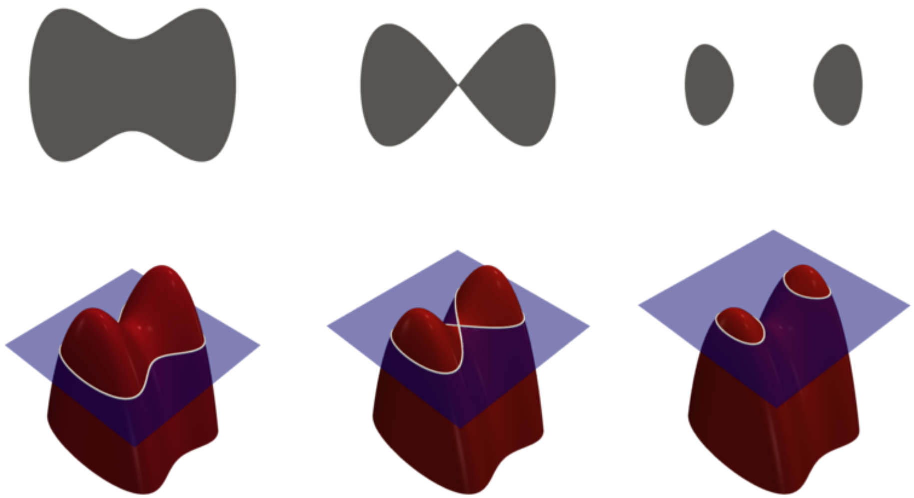
MPP-Level Sets

What is a level set?

Given a function $\phi: \mathbb{R}^d \to \mathbb{R}$

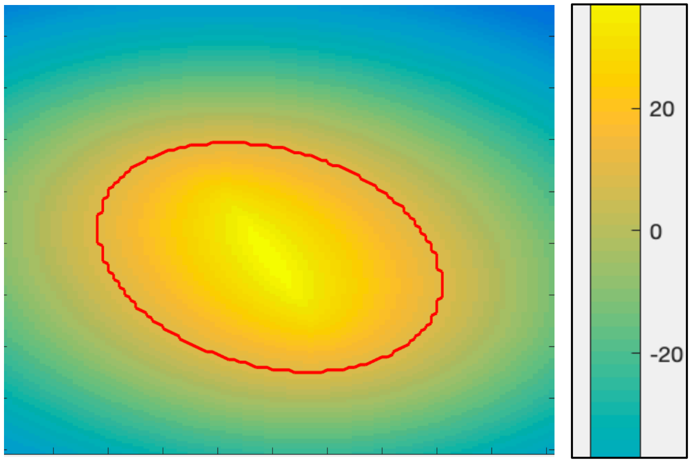
Curve: $C_t = \{k \in \mathbb{R}^d | \phi(k) = 0\}$ is the zeroth level set of ϕ

Example of level sets and object representations



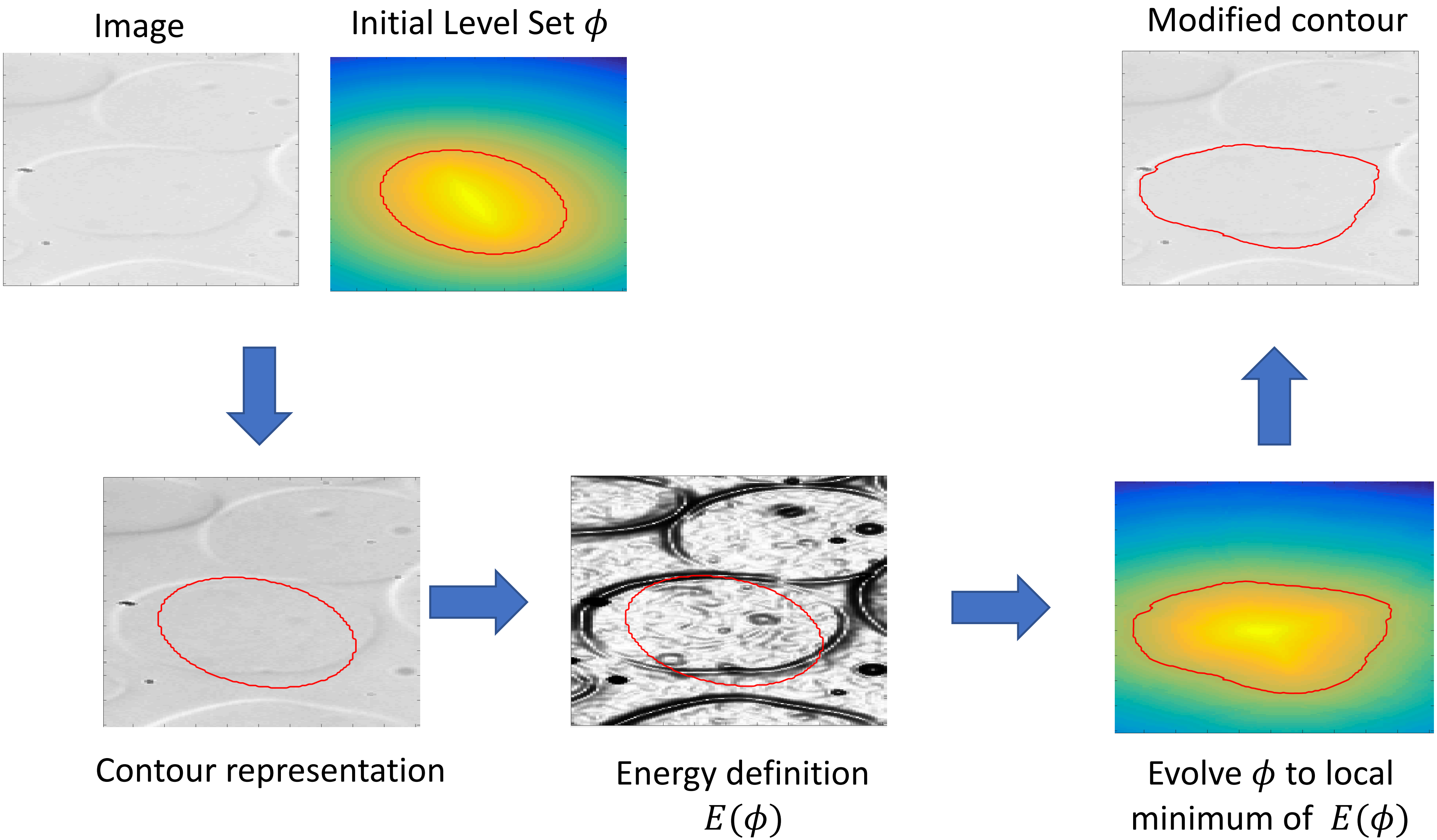
[Wikipedia]

Example of initial level set of ϕ



[Osher 1987]

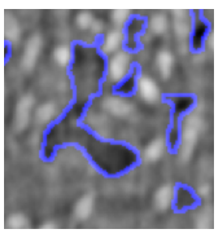
Summary of level sets approach



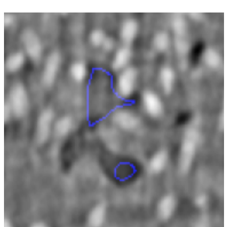
Advantages of LS vs parametric AC

- Level Sets can:
  - Adapt better to topological changes
  - Allow object merging and splitting
  - Facilitate the dimension increase

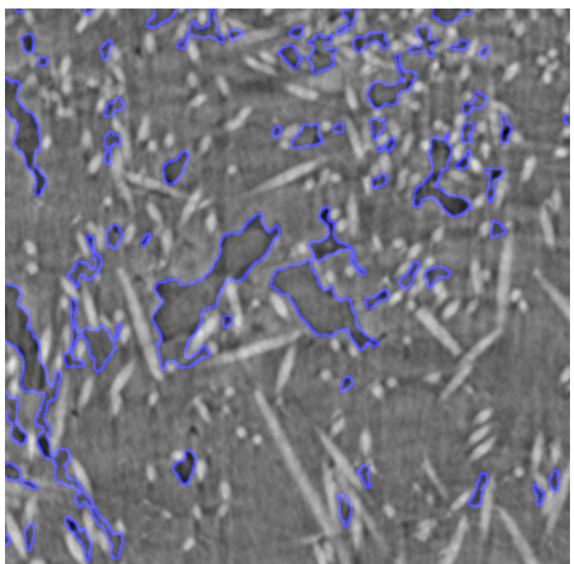
Level Sets



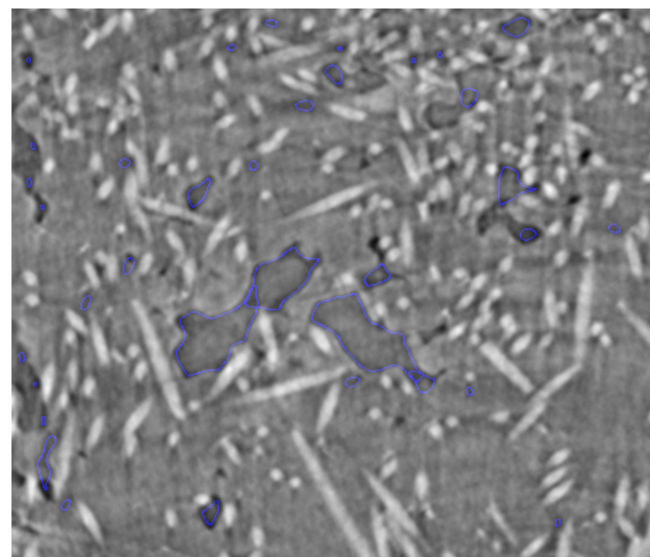
MPP-AC



Level Sets



MPP- AC



Hybrid Level Sets Energy + Shape prior

- Energy Function:

$$E(\phi) = \alpha E_{\text{region}}(\phi) + \beta E_{\text{edge}}(\phi) + \gamma E_{\text{shape}}(\phi)$$

[Yan 2008]

K: Image domain
ϕ: Embedding function
$H(\cdot)$: Heaviside function
$g(\cdot)$: Edge function
ϕ_o: Level set geometric prior

$$E_{\text{region}}(\phi) = \int_{k \in K} (k - \mu) H(\phi) dk$$

Attract to dark regions

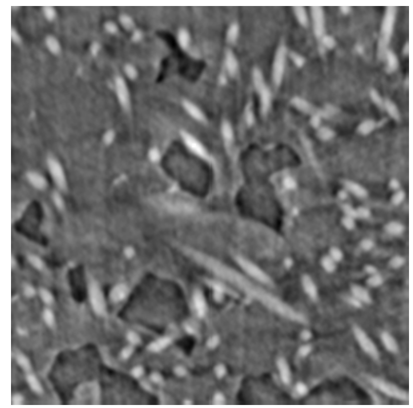
$$E_{\text{edge}}(\phi) = \int_{k \in K} g(k) |\nabla H(\phi)| dk$$

Attract to edges

$$E_{\text{prior}}(\phi) = \int_{k \in K} \left(H(\phi) - H(\phi_o)\right)^2 dk$$

Preserve shape

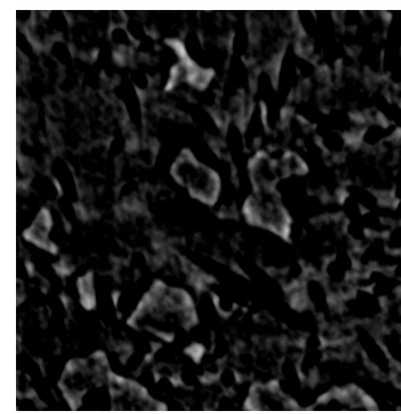
Preserve irreducible Markov Chain



Original Image

Manual label

E_{edge}

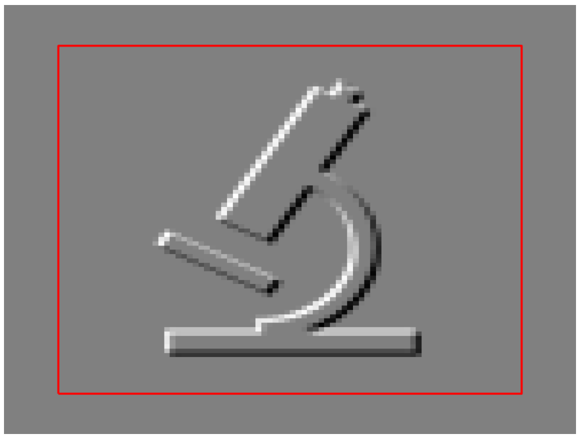


E_{region}

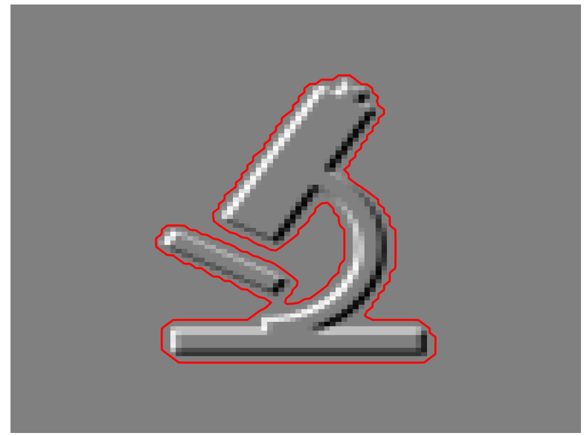
Hybrid Level Sets Boundary Penalizer

$$E(\phi) = \int_{k \in K} g(k) |\nabla H(\phi)| dk \qquad \phi_t = \beta \ \mathrm{div}(g(k) \nabla \phi) \qquad g(k) = \frac{1}{1 + c \,|\, \nabla \, f_\sigma * K |}$$

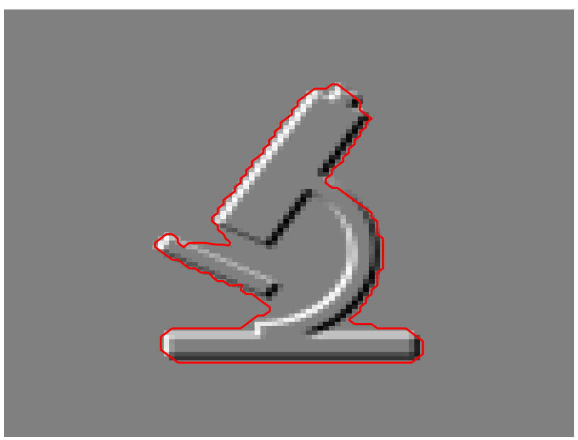
div: divergence operator
c: Slope constant
$\boldsymbol{f_\sigma}$: Gaussian filter
$*$: Convolution operator



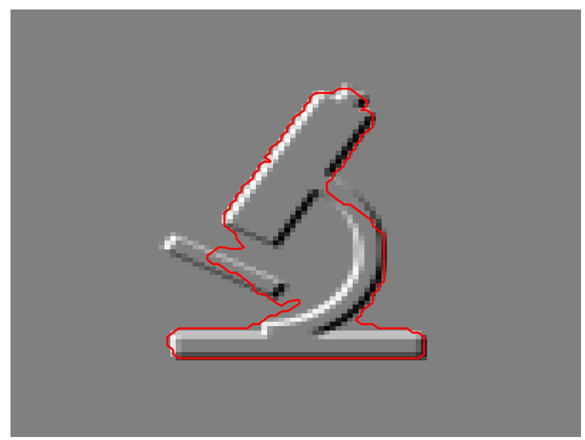
Initialization



$\beta = 1$



$\beta = 10$

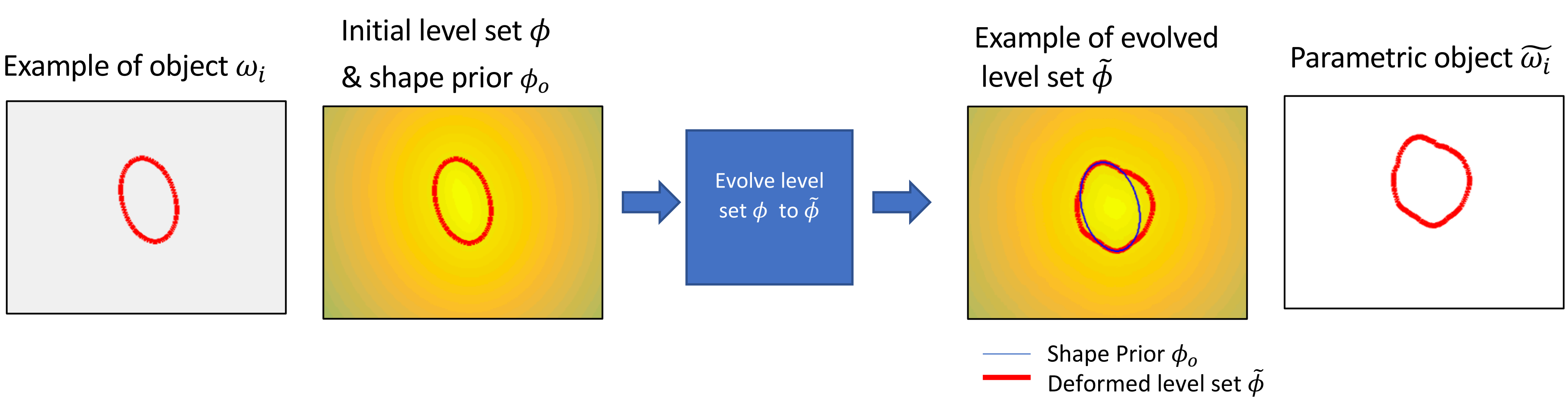


$\beta = 20$

Level Sets in the MPP

- MPP Object Field:
  - Ellipses with mark $\omega_i = (k_i, m_i) \in \Omega$
  - $M = [a_{\min}, a_{\max}] \times [b_{\min}, b_{\max}] \times [\theta_{\min}, \theta_{\max}]$

- Marked Object:
  - Use MPP object $\omega = (k_i, m_i)$ as initialization and shape prior ϕ_o
  - Evolve level set ϕ to $\tilde{\phi}$
  - Parametrize evolved level set $\tilde{\phi}$ to $\widetilde{\omega}$(t)



From LS to parametric energy

Level set energy:

$$E(\phi) = \int_{k\in K} \alpha(k-\mu)H(\phi) + \beta g_\sigma(k)|\nabla H(\phi)| + \gamma\big(H(\phi)-H(\phi_o)\big)^2\, dk$$

Parametric energy:

regions

edges

$$E(\omega_i) = \frac{1}{|D_{\widetilde{\omega}_i}|}\int_{t\in D_{\widetilde{\omega}_i}} \alpha\,(t-\mu)dA + \frac{1}{|d\widetilde{\omega}_i|}\int_{t\in d\widetilde{\omega}} \beta\, g_\sigma(t)dt$$

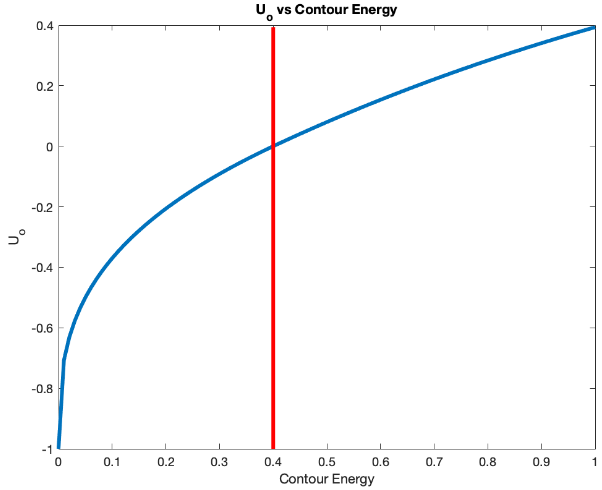
$D_{\widetilde{\omega}}$: Area inside $\widetilde{\omega}_i$

$d\widetilde{\omega}$: Line denoting contour $\widetilde{\omega}_i$

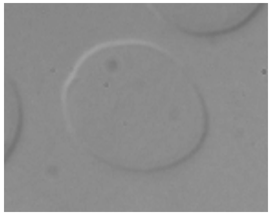
Quality Term:

$$U_d(\omega_i) = \begin{cases} 1 - \exp\left(-\dfrac{E(\widehat{\omega})-E_o}{3E_o}\right) & E(\widehat{\omega}) \geq E_o \\ \left(\dfrac{E(\widehat{\omega})}{E_o}\right)^{1/3} - 1 & \text{otherwise} \end{cases}$$

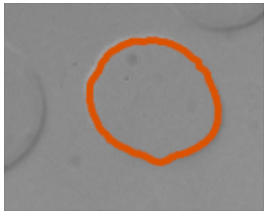
$E_o = 0.40$



Original Image

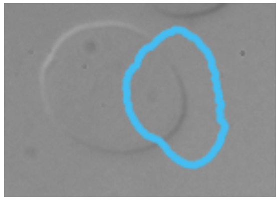


Good fit



$E(\omega) = 0.32$
$U_d(\omega) = -0.06$
$d_{\text{rate}}(\omega) = 0.33$

Bad fit



$E(\omega) = 0.76$
$U_d(\omega) = 0.26$
$d_{\text{rate}}(\omega) = 0.92$

MPP-LS Energy

$\boldsymbol{w}$: Marked Object Configuration
ω_i: Single Marked i^{th} Object
$\widetilde{\omega_i}$: Evolved Marked i^{th} Object
z: Normalizing Constant
$\omega_i \sim \omega_j$: Neighbor Relation
E_o : Contour energy parameter

- Gibbs Process with probability density

$$p(\boldsymbol{w}) = \frac{1}{Z} \exp\{-U(\boldsymbol{w})\}$$

- Energy Function

$$U(\boldsymbol{w}) = \sum_{\omega_i \in \boldsymbol{w}} U_d(\omega_i) + \sum_{\omega_i \sim \omega_j} U_p(\omega_i, \omega_j)$$

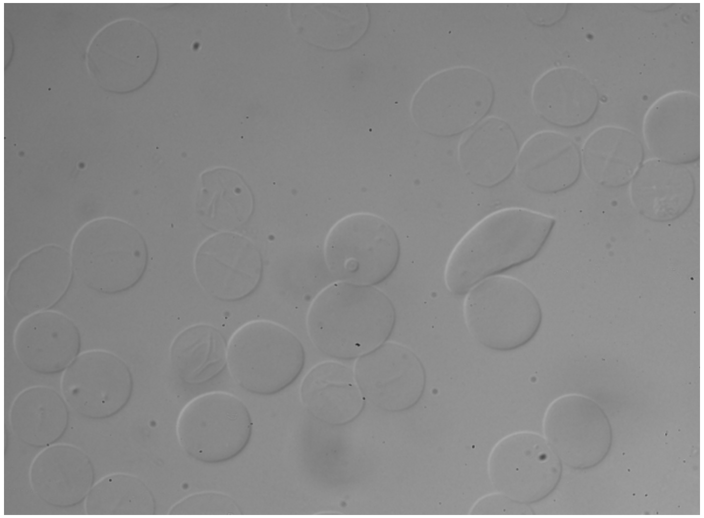
- Prior Energy

$$U_p(\omega_i, \omega_j) = \begin{cases} A_{\text{overlap}}(\widetilde{\omega_i}, \widetilde{\omega_j}) & \text{if } A_{\text{overlap}}(\widetilde{\omega}_i, \widetilde{\omega_j}) \le T_{\text{overlap}} \\ \infty & \text{otherwise} \end{cases}$$

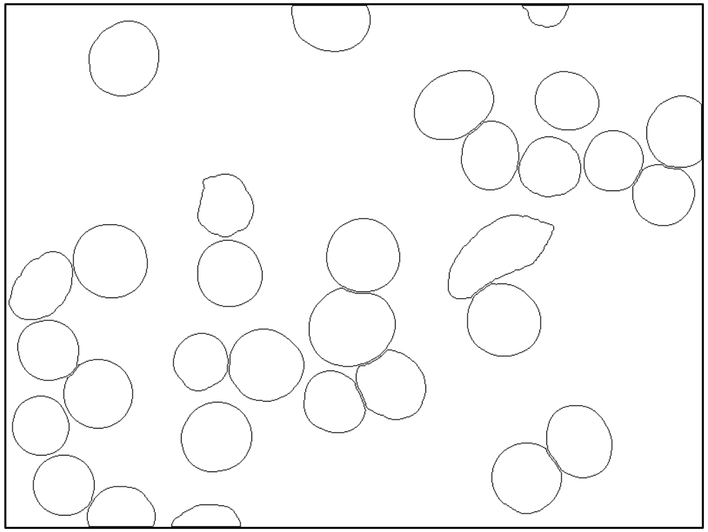
- Data Energy

$$U_d(\omega_i) = \begin{cases} 1 - \exp\left(-\frac{E(\widehat{\omega}) - E_o}{3E_o}\right) & E(\widehat{\omega}) \ge E_o \\ \left(\frac{E(\widehat{\omega})}{E_o}\right)^{\frac{1}{3}} - 1 & \text{otherwise} \end{cases}$$

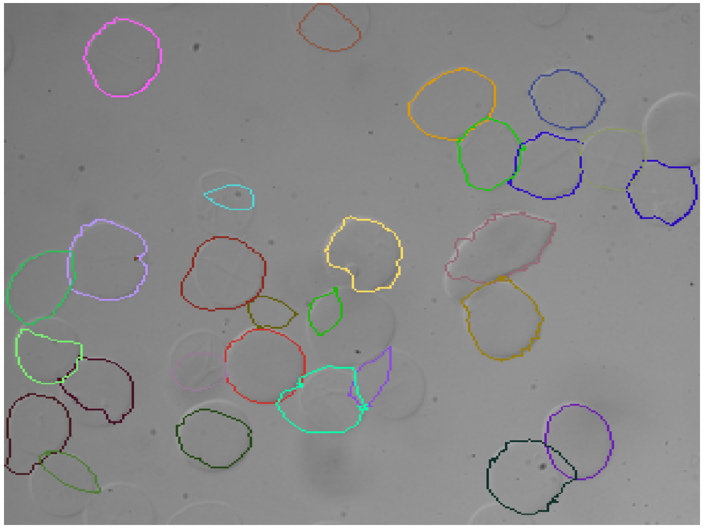
Human red blood cells



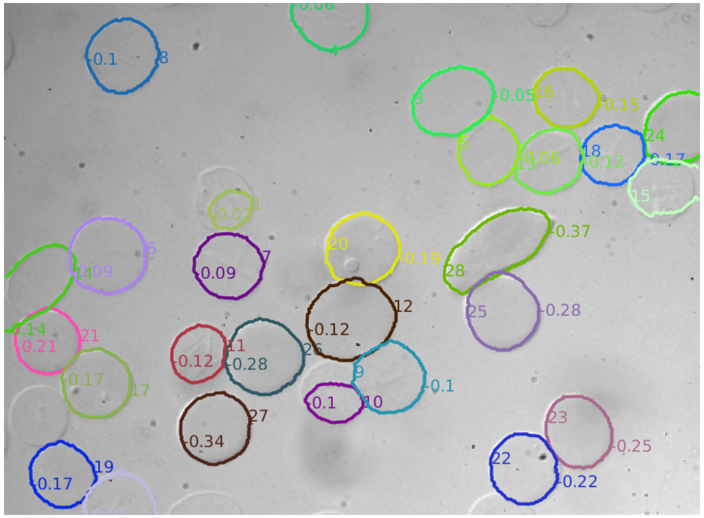
Original Image



Ground Truth



MPP-AC



MPP-LS

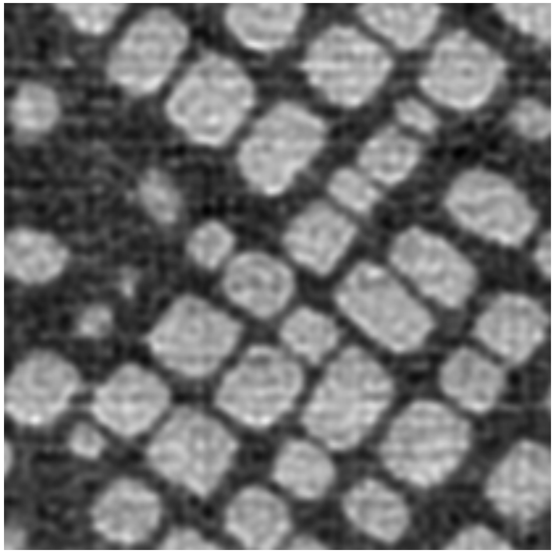
[Broad Bioimage Benchmark Collection]

F1 Scores

- Background
  - Pixelwise segmentation
- Outlines
  - Edges separated by a distance < 2 pixels
- Counts
  - Intersection over union IOU > 80%

Method	Background	Outlines	Counts
MPP-AC	0.790	0.680	0.829
MPP-LS	0.843	0.820	0.916
Hybrid-LS	0.432	0.784	-

NiCrAl Particles



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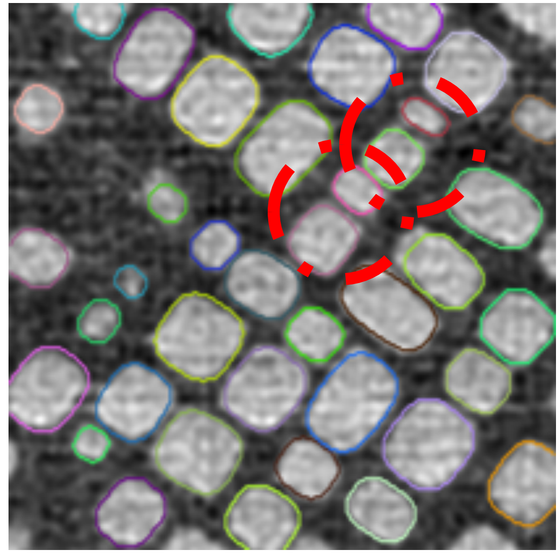
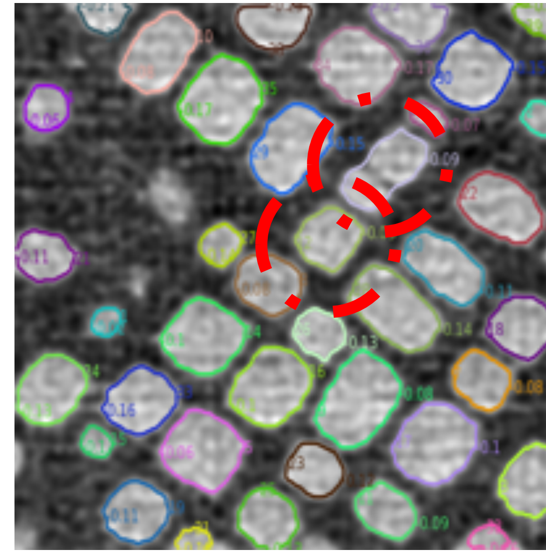
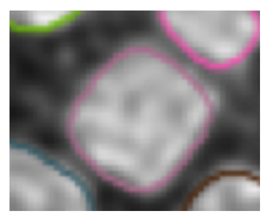
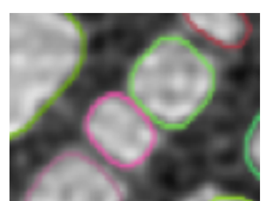


MPP



MPP-LS





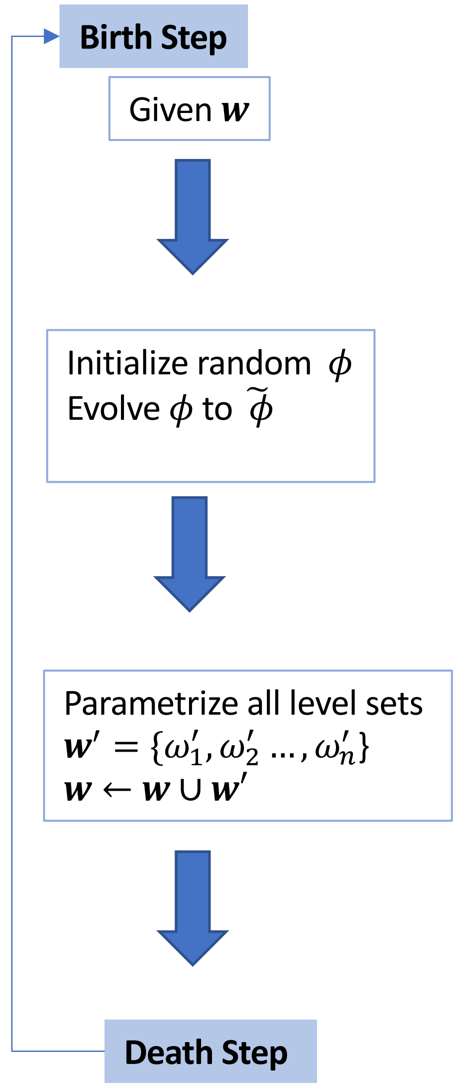
Multiple Object Level Set

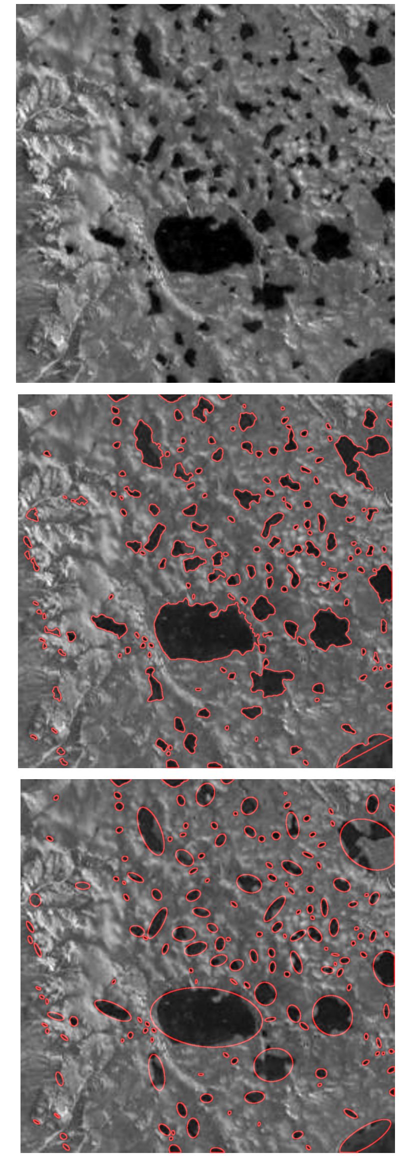
Goal: Use level sets to propose objects

Algorithm 2 Using Level Sets to simulate Multiple Births

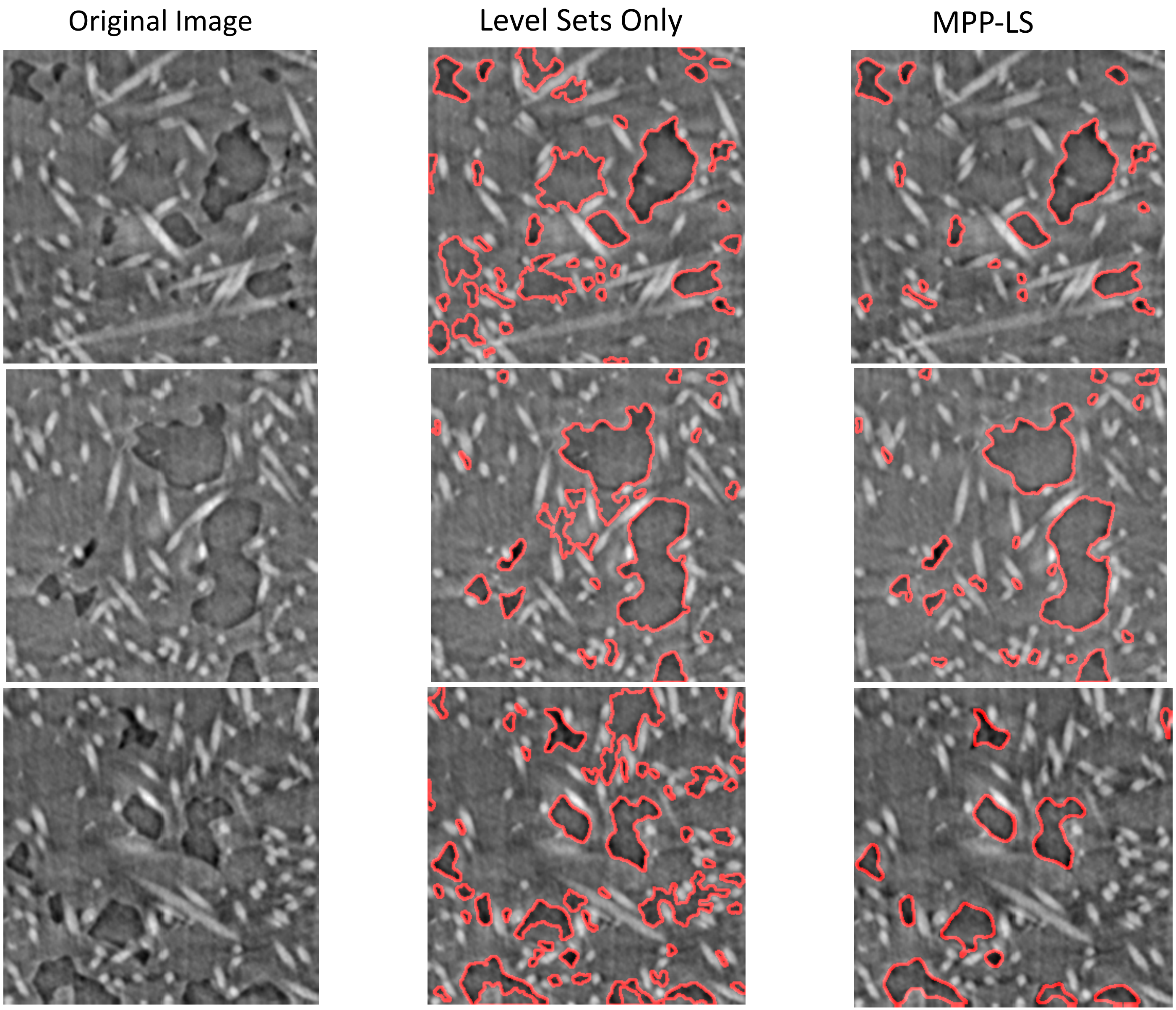
procedure MPP ENERGY MINIMIZATION IN IMAGE K
- **Initialization**:
- Initialize $b_{rate} = b_o$, $T = T_o$, $\sigma = \sigma_o$, $\mathbf{w} = \{\}$
- **Birth Step**:
  - Initialize a level set $\phi(k)$ at a random location
  - Evolve $\phi(k)$ to $\tilde{\phi(k)}$
  - Parametrize every closed contour $\tilde{\omega}'$ in $\tilde{\phi}(k)$
  - Calculate a best fitting marked object ω' for for each contour $\tilde{\omega}'$.
  - Call $\mathbf{w}' = \{\omega'_1, \omega'_2, ..., \omega'_n\}$ the new configuration.
  - Add the configuration to the current configuration $\mathbf{w} \leftarrow \mathbf{w} \cup \mathbf{w}'$
- **Death Step**
  - For every object ω in $\mathbf{w}$ calculate:
  - $a_\omega = \exp\left[\frac{U(\mathbf{w}) - U(\mathbf{w}-\omega)}{T^k}\right]$, draw p form a uniform distribution over $[0, 1]$
  - **if** $p < \frac{a_\omega \delta}{1 + a_\omega \delta}$
    - remove $\omega : \mathbf{w} \leftarrow \mathbf{w} - \omega$
- **if** $n < Max\ Iterations$
  - Update parameters: $T^{k+1} \leftarrow T^k \times \alpha$, $\sigma^{k+1} \leftarrow \sigma^k \times \alpha, n \leftarrow n + 1$
  - **goto Birth Step**

end procedure





Voids in fiber reinforced composites

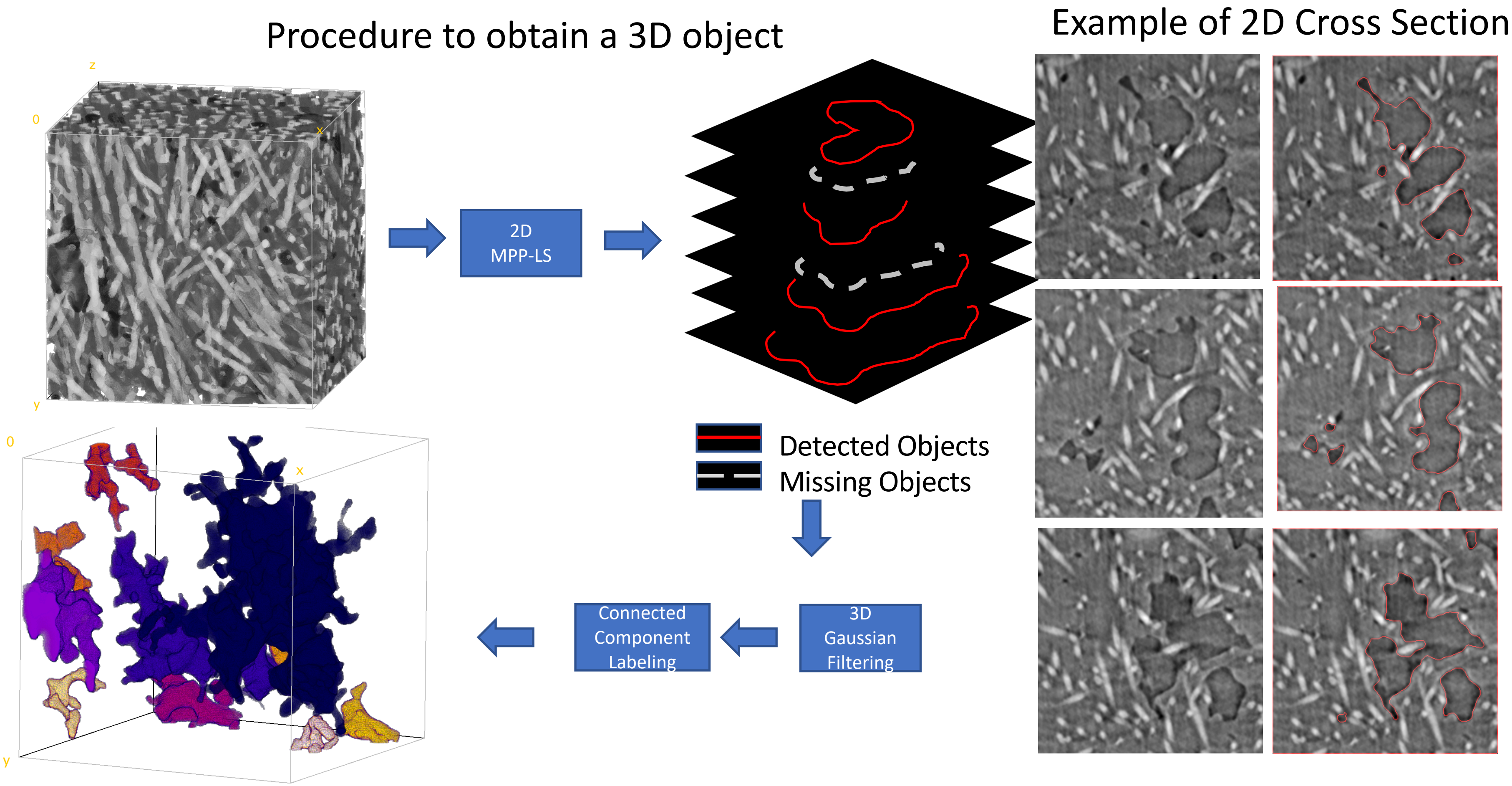


Contributions of this work

- Addition of the level sets method to the MPP model
- Extension of the a Hybrid level sets to incorporate a shape prior
- The use of level sets results to provide object proposals

Extension to 3D

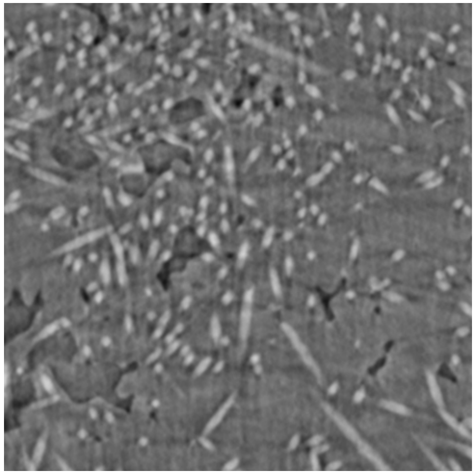
Use MPP-LS at each slice and filter



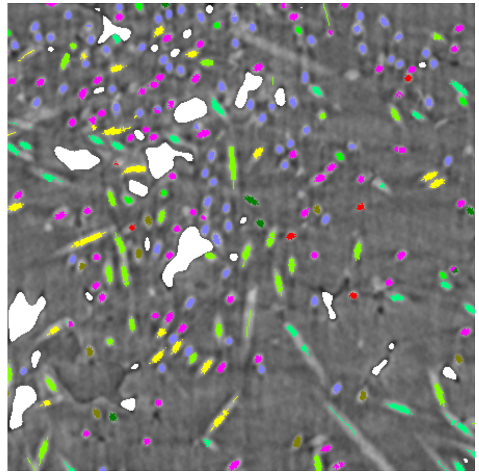
Towards Deep Learning

U-Net beats its training data

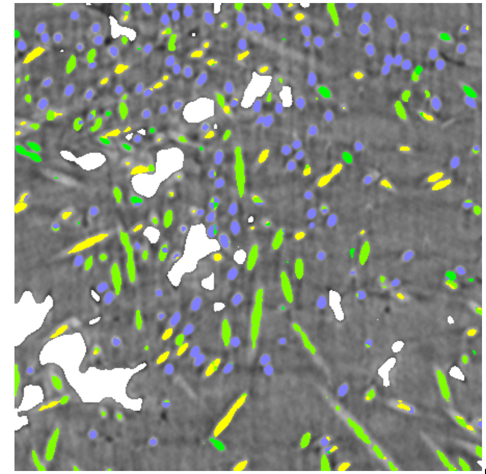
Original Image



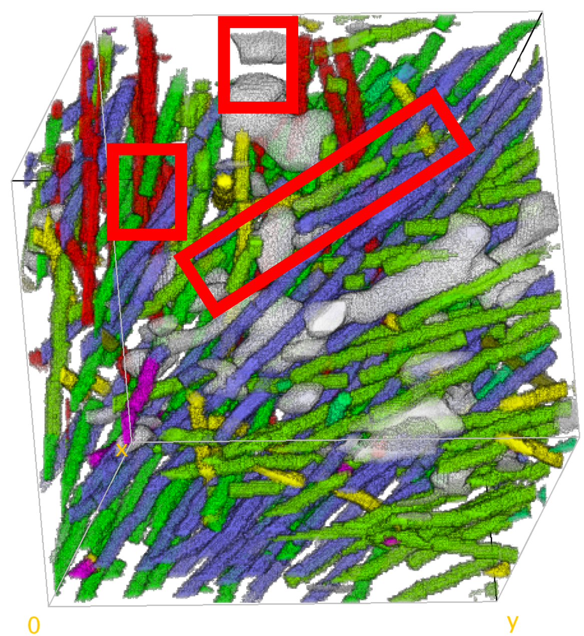
Training Data

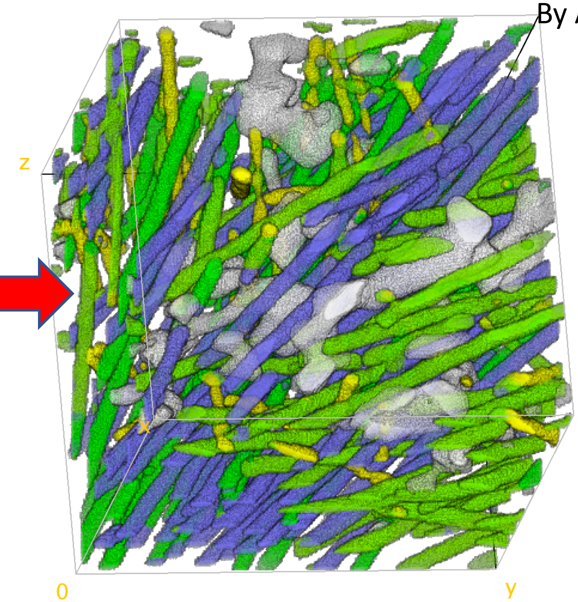


U-Net



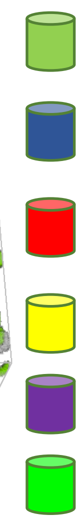
- 3D U-Net Generalizes data extremely well
- 3D U-Net improves the results of its training data
- The GPU setup makes it significantly faster than MPP-LS



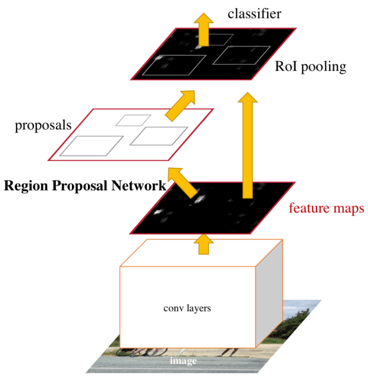


Corrections

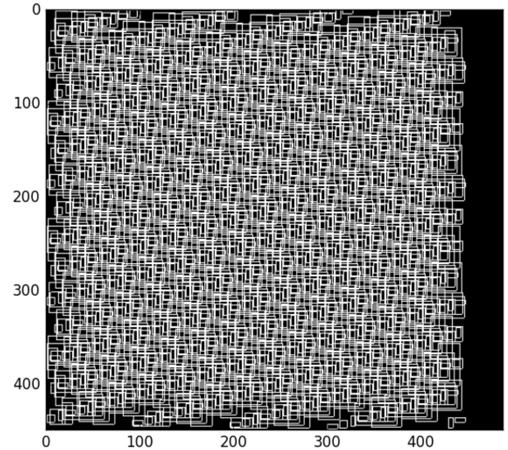
Fiber Class By Angles ϕ, θ



Faster RCNN could help guiding MCMC



Faster-RCNN

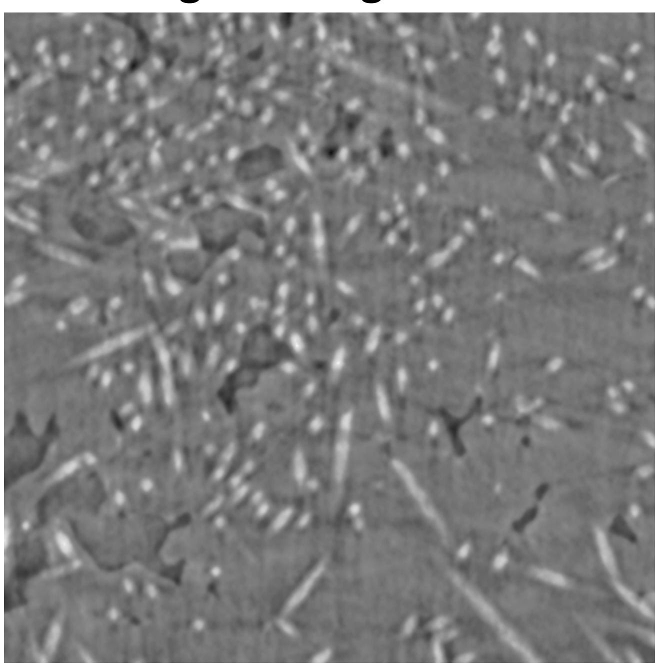


Anchor Proposals

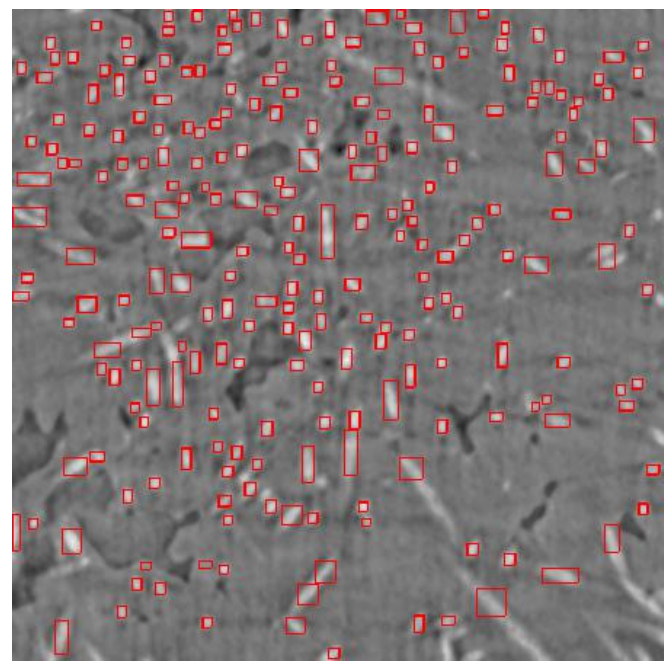
Fast RCNN has parallel relations with RJMCMC:

- Anchor Proposal ≡ birth death process
- Bounding Box Refinement ≡ perturbations

Original Image



Faster-RCNN Results



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- *(draft) C. Aguilar and M. Comer, “Combining Level sets in the Marked Point Process Framework,” International Symposium on Visual Computing (ISVC). July, 2019.

Summary of contributions

- Exploration of the MPP combined with:
  - Parametric active contours
  - Level sets
- We used multiple birth and death to sample our space but we also explored using only the level set results
- We obtained preliminary 3D data and trained Neural Networks with this data.

Thanks