Analysis of Local Image Statistics to Improve Medical Image Processing

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Proposal Exam
March 3, 2009

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Jeff Shamma	- Committee Member
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Outline

- Quick Background
- Localized Approach
- Preliminary Research
- Proposed Research

Background

Computer Vision

- Acquisition and Filtering
- Segmentation, Tracking, and Analysis
- Interpretation and Assigning Meaning

Segmentation

Segmentation

- Thresholding
- Region Growing
- Graph Cuts
- Snakes/Active Contours

Active Contours

Implementation

- Represent the contour
- Parametrized
- Non-parametrized

Level Sets

Definitions

- Image, $I:\mathbb{R}^n \rightarrow \mathbb{R}$ on the domain Ω
- Contour, C embedded in $\phi:\mathbb{R}^n \rightarrow \mathbb{R}$
- Such that: $C = \{x|\phi(x) = 0\}$

Sethian. Level Set Methods and Fast Marching Methods. 1999

Definitions

$$\mathcal{H}\phi = \begin{cases} 1 & \phi < -\epsilon \\ 0 & \phi > \epsilon \\ \text{smooth} & \text{otherwise} \end{cases}$$

$$\delta\phi = \begin{cases} 1 & \phi = 0 \\ 0 & |\phi| < \epsilon \\ \text{smooth} & \text{otherwise} \end{cases}$$

Define an Energy

- Make an assumption
- Craft an energy accordingly

Mumford and Shah "Boundary Detection by Minimizing Functionals," JIU, 1988

Uniform Mean Energy

Assumption: The foreground and background will be approximately constant.

$$E(\phi) = \int_\Omega \mathcal{H}\phi(I - \mu_{\text{in}})^2$$

$$+(1 - \mathcal{H}\phi)(I - \mu_{\text{out}})^2 dx$$

$$+\lambda \int_\Omega \delta\phi(x)\|\nabla\phi(x)\|dx$$

Chan and Vese. "Active contours without edges," TIP, 2001

Energy Minimization

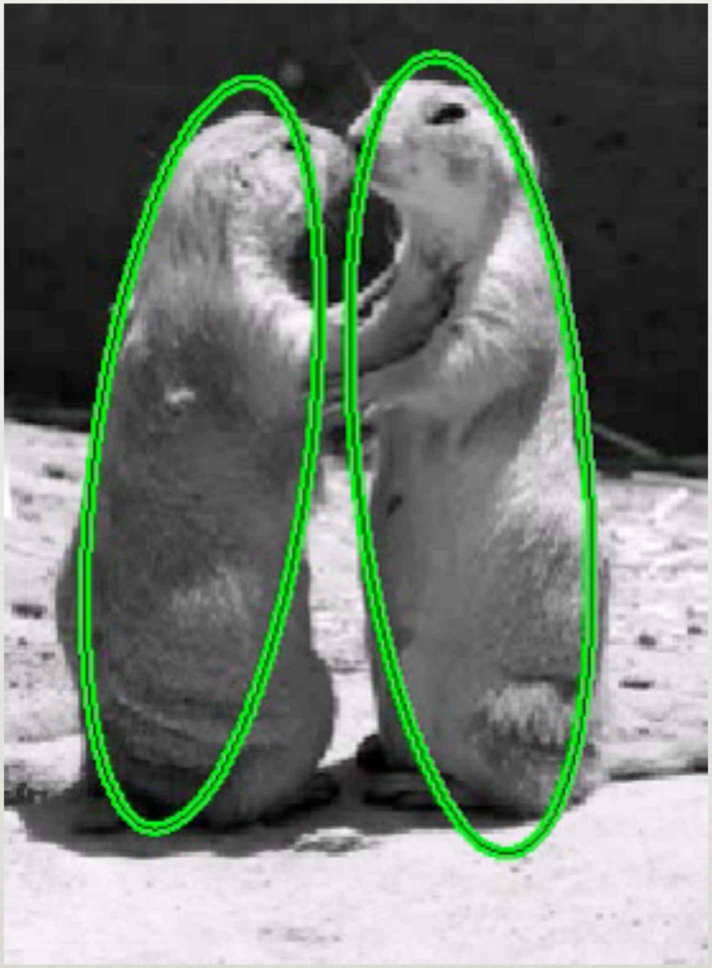
$$\frac{d\phi}{dt} = -\delta\phi\left((I-\mu_{\text{in}})^2 - (I-\mu_{\text{out}})^2 + \lambda\,\text{div}\left(\frac{\nabla\phi}{|\nabla\phi|}\right)\right)$$

$$\phi_{t+1} = \phi_t + dt \cdot \frac{d\phi}{dt}$$

Energy Minimization

- Global minima
- Almost-global minima
- Local minima

Things Get Harder



Localized Approach

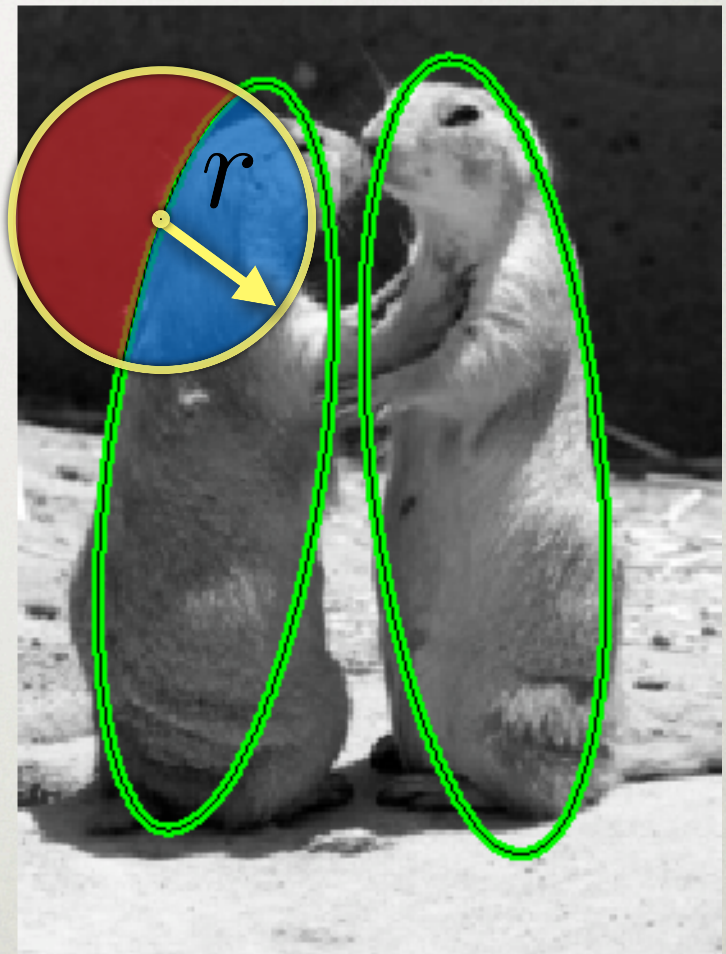
Localizing

$$x$$

$$\mathcal{B}(x,y)$$

$$\mathcal{B}(x,y)\cdot\mathcal{H}\phi(y)$$

$$\mathcal{B}(x,y)\cdot(1-\mathcal{H}\phi(y))$$



Lankton and Tannenbaum "Localized Region-Based Active Contours," TIP, 2008

Localized Contours

$$E(\phi) = \int_{\Omega_x} \delta\phi(x) \int_{\Omega_y} \mathcal{B}(x,y) \cdot F(I(y),\phi(y))dy \; dx$$

$$+ \lambda \int_{\Omega_x} \delta\phi(x) \|\nabla\phi(x)\| dx$$

$$\frac{\partial\phi}{\partial t}(x) = -\delta\phi(x) \int_{\Omega_u} \mathcal{B}(x,y) \cdot \nabla_{\phi(y)} F(I(y),\phi(y))dy + \lambda\delta\phi(x) \; \mathrm{div}\left(\frac{\nabla\phi(x)}{|\nabla\phi(x)|}\right)$$

Localized Means

$$\mu_{\text{in}} = \frac{\int_{\Omega_y} \mathcal{H}\phi(y) \cdot I(y)dy}{\int_{\Omega_y} \mathcal{H}\phi(y)dy}$$

$$\mu_{\text{out}} = \frac{\int_{\Omega_y} (1 - \mathcal{H}\phi(y)) \cdot I(y)dy}{\int_{\Omega_y} (1 - \mathcal{H}\phi(y))dy}$$

Localized Means

$$\mu_{\text{in}}(x) = \frac{\int_{\Omega_y} \mathcal{B}(x,y) \cdot \mathcal{H}\phi(y) \cdot I(y)dy}{\int_{\Omega_y} \mathcal{B}(x,y) \cdot \mathcal{H}\phi(y)dy}$$

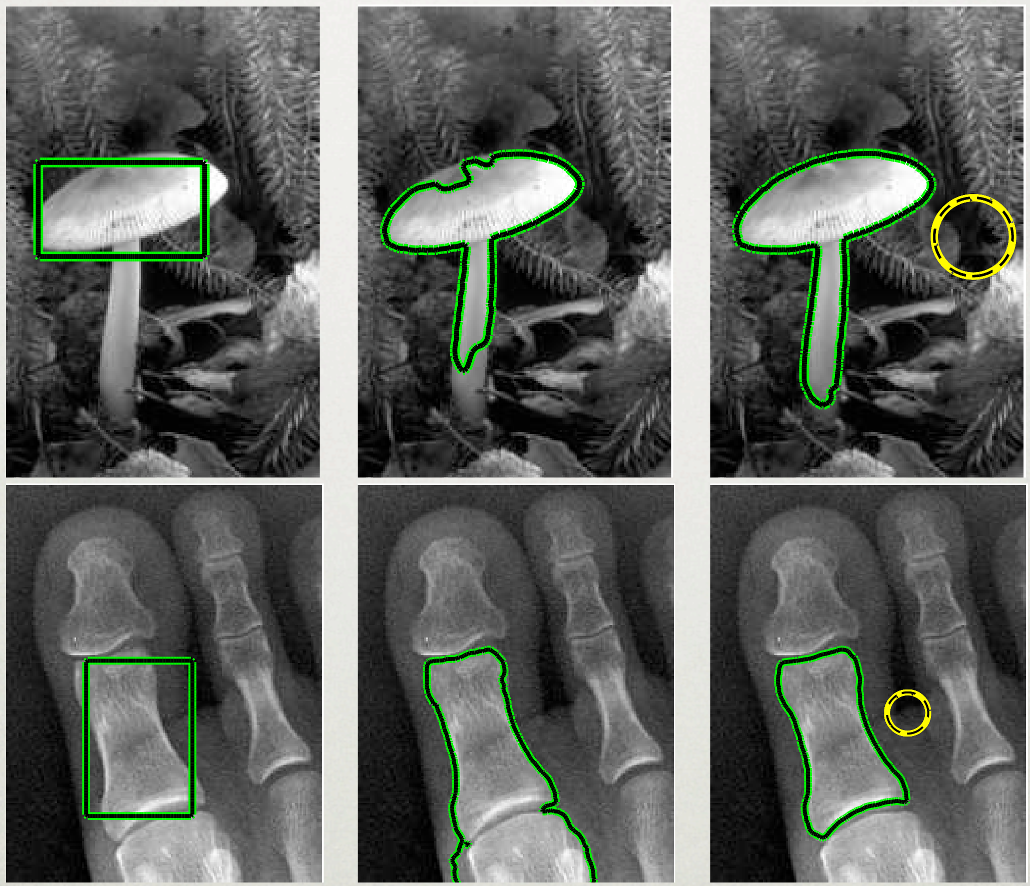
$$\mu_{\text{out}}(x) = \frac{\int_{\Omega_y} \mathcal{B}(x,y) \cdot (1 - \mathcal{H}\phi(y)) \cdot I(y)dy}{\int_{\Omega_y} \mathcal{B}(x,y) \cdot (1 - \mathcal{H}\phi(y))dy}$$

Uniform Mean Model

Assumption: The foreground and background will be approximately constant *locally*.

$$F_{\text{UM}} = \mathcal{H}\phi(y)(I(y) - \mu_{\text{in}}(x))^2 + (1 - \mathcal{H}\phi(y))(I(y) - \mu_{\text{out}}(x))^2$$

Uniform Mean Model



(a) Initialization (b) Global UM (c) Local UM

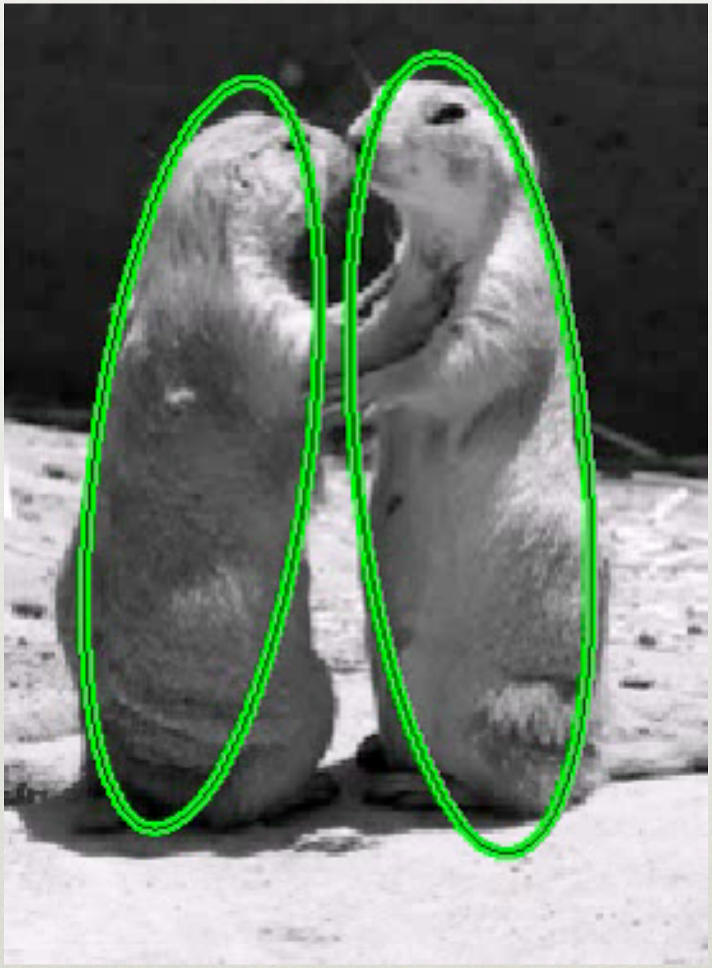
Mean Separation Model

Assumption: The foreground and background should be very different *locally*.

$$F_{\text{MS}} = -(\mu_{\text{in}}(x) - \mu_{\text{out}}(x))^2$$

Yezzi *et al*. "A Fully Global Approach to Image Segmentation... ," JVCIR 2002

Mean Separation Model



Preliminary Research

A Word on Localization
Fiber Bundles
Vessel Analysis

Benefits of Localization

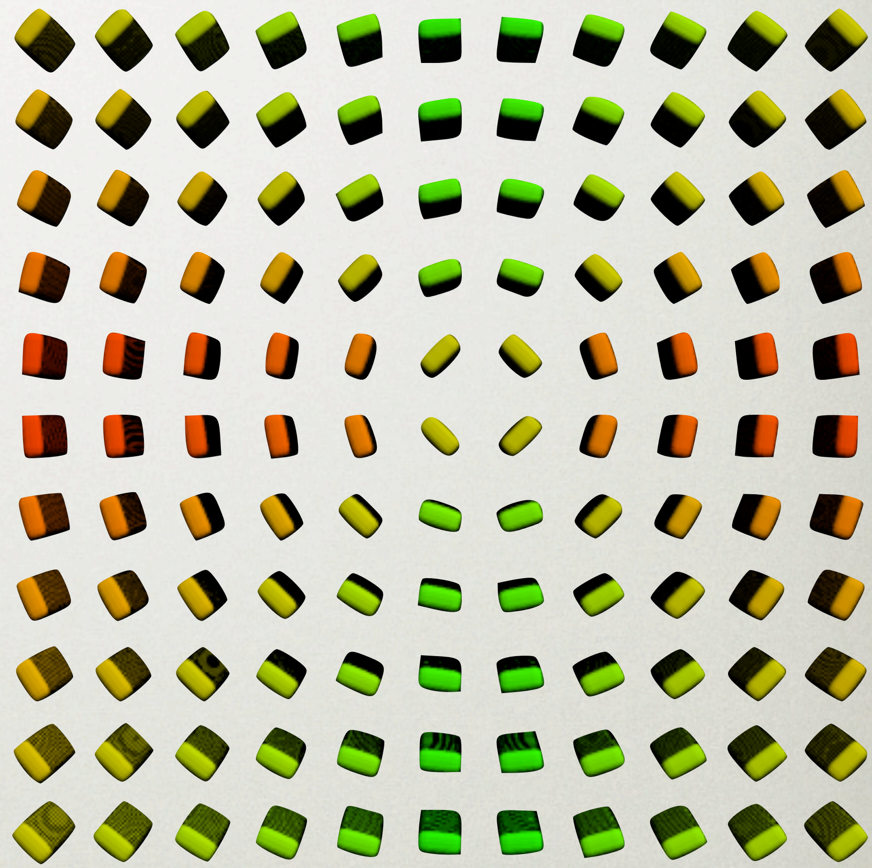
- Complex problems become simple
- Natural solution to many problems
- Scale is controllable

First Applications

- Fiber Bundle Segmentation
- Vessel Analysis

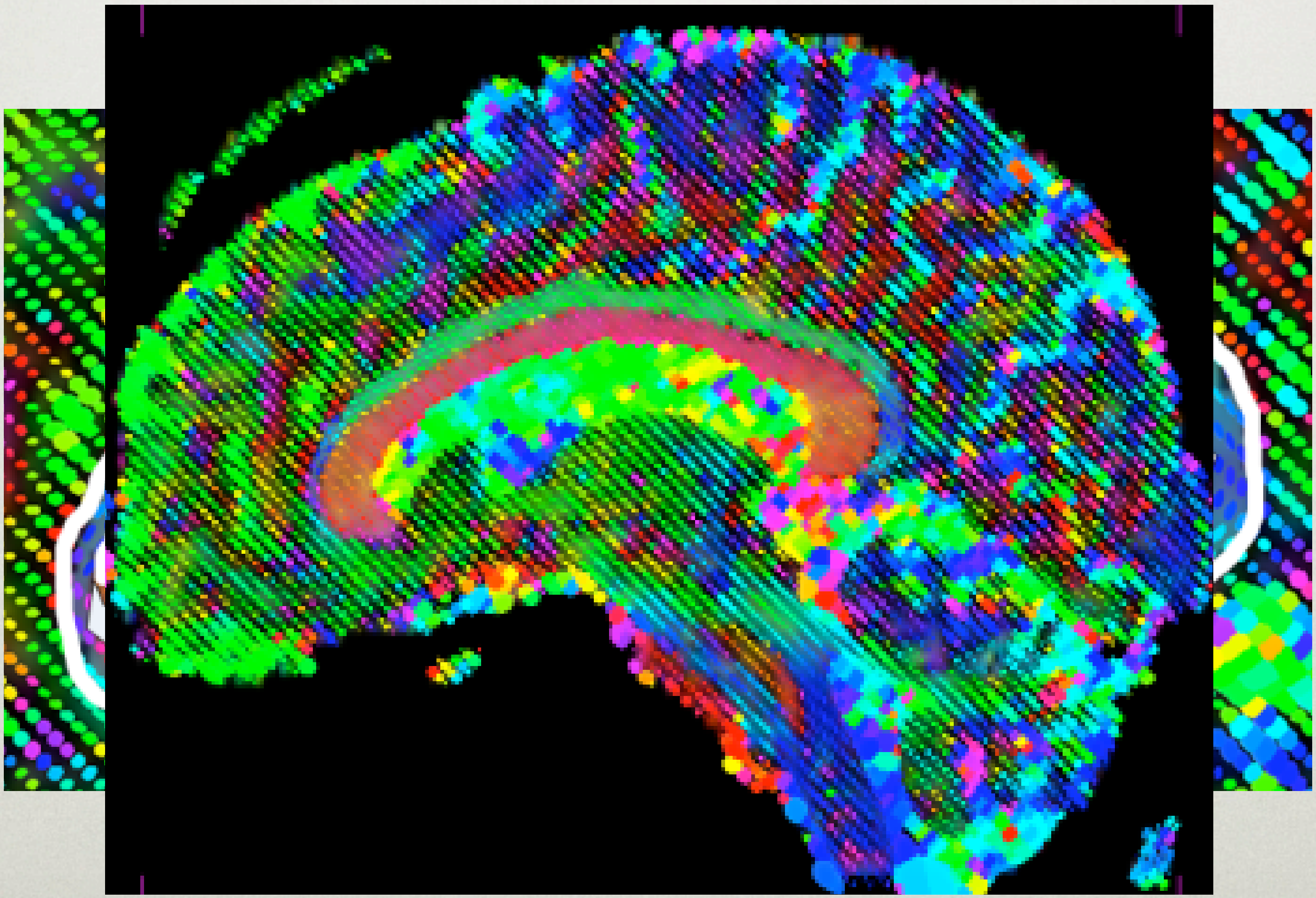
Fiber Bundles

- DW-MRI
- 3x3 Tensor Data
- Brain connectivity
- Analyze shape



Lankton *et al*. “Localized Statistics for DWI Fiber Bundle Segmentation,” MMBIA, 2008

Fiber Bundles



Fiber Bundles

- Initialized with single fiber
- Evolve to capture full bundle
- Uses "tensor uniform mean model"

Pichon. Novel Methods for Multidimensional Image Segmentation, Ph.D. Thesis, 2005

Fiber Bundles

Vessel Analysis

- Important
- Challenging
- Natural Solutions
- Segmentation
- Plaque Detection

Lankton *et al.* "Soft Plaque Detection...," MICCAI 2009 *(in submission)*

Vessel Segmentation

- CTA imagery
- Simple initialization
- No leaks
- Branch handling
- No shape information

Vessel Segmentation

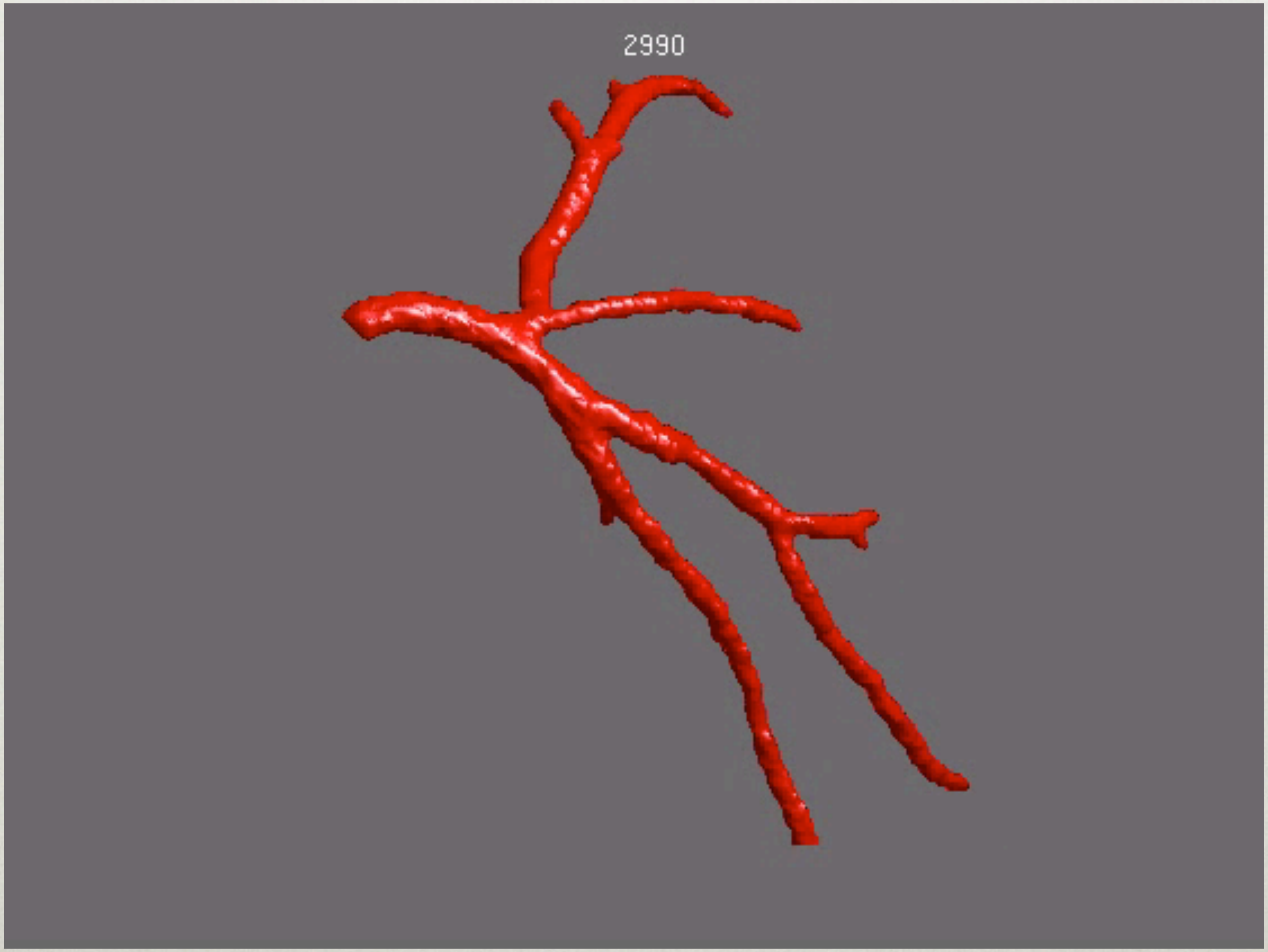
Localized Uniform Modeling Energy

$$F_{\text{UM}} = \mathcal{H}\phi(y)(I(y) - \mu_{\text{in}}(x))^2 + (1 - \mathcal{H}\phi(y))(I(y) - \mu_{\text{out}}(x))^2$$

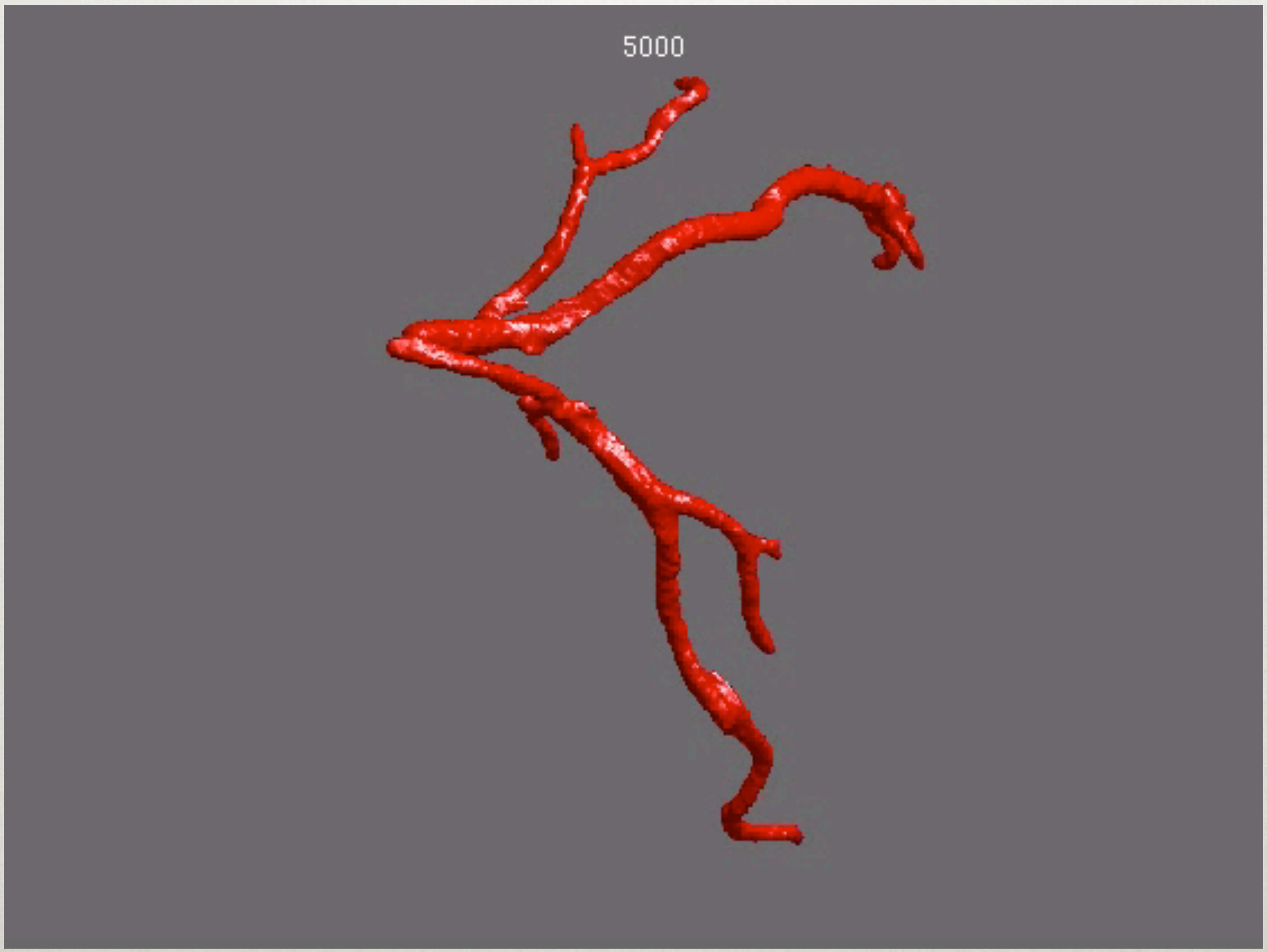
The Trick:

$$\tilde{\Omega} = \Omega \cap (I > \mu_{\text{HEART}} - 2\sigma_{\text{HEART}})$$

Vessel Segmentation

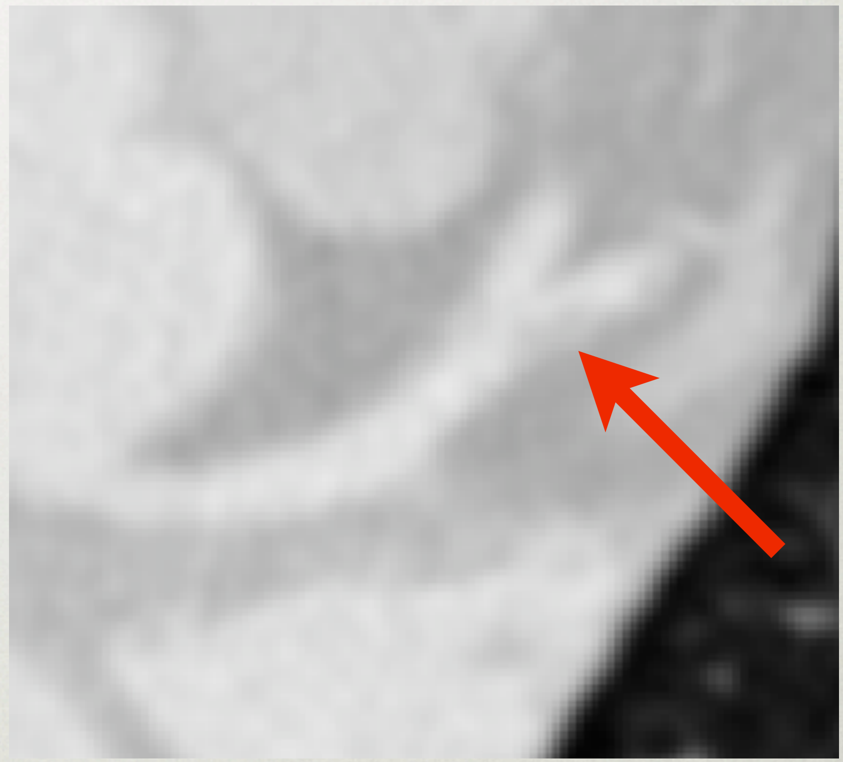


Vessel Segmentation



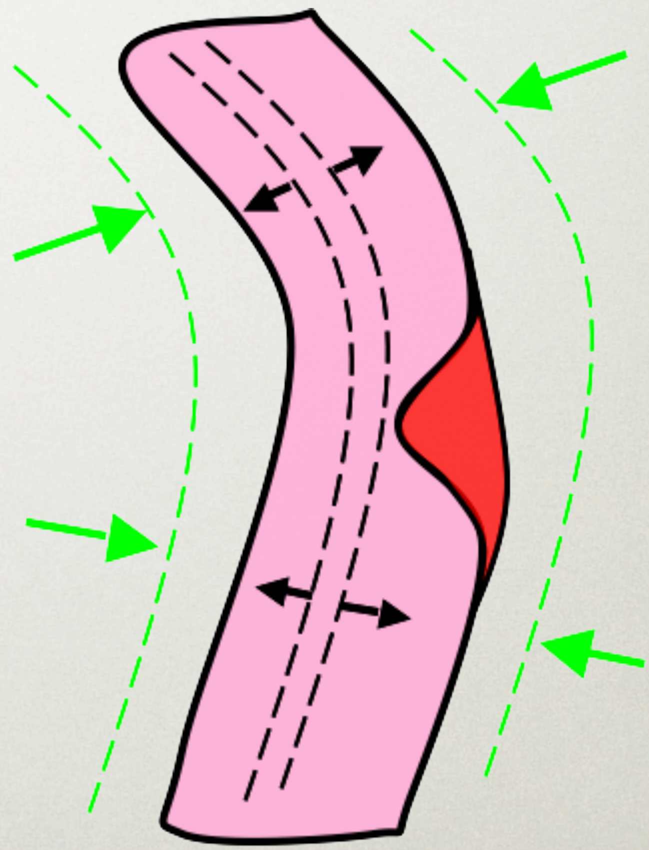
Soft Plaque Detection

- Hard to see
- Very dangerous
- No good tools



Soft Plaque Detection

- Two-front approach
- Inside moves out
- Outside moves in

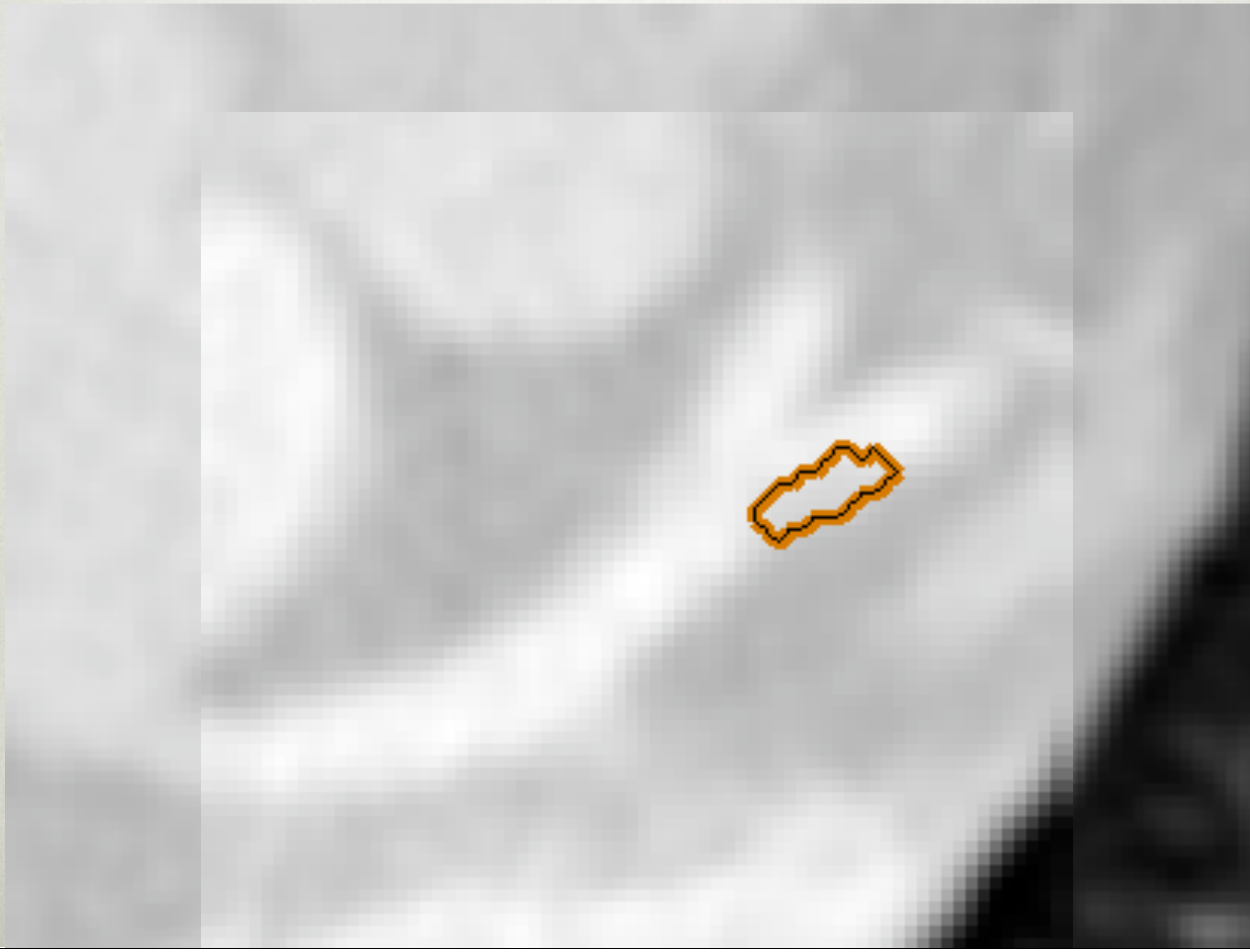


Detection Energy

Localized Means Separation Energy

$$F_{\mathrm{MS}} = -(\mu_{\mathrm{in}}(x) - \mu_{\mathrm{out}}(x))^2$$

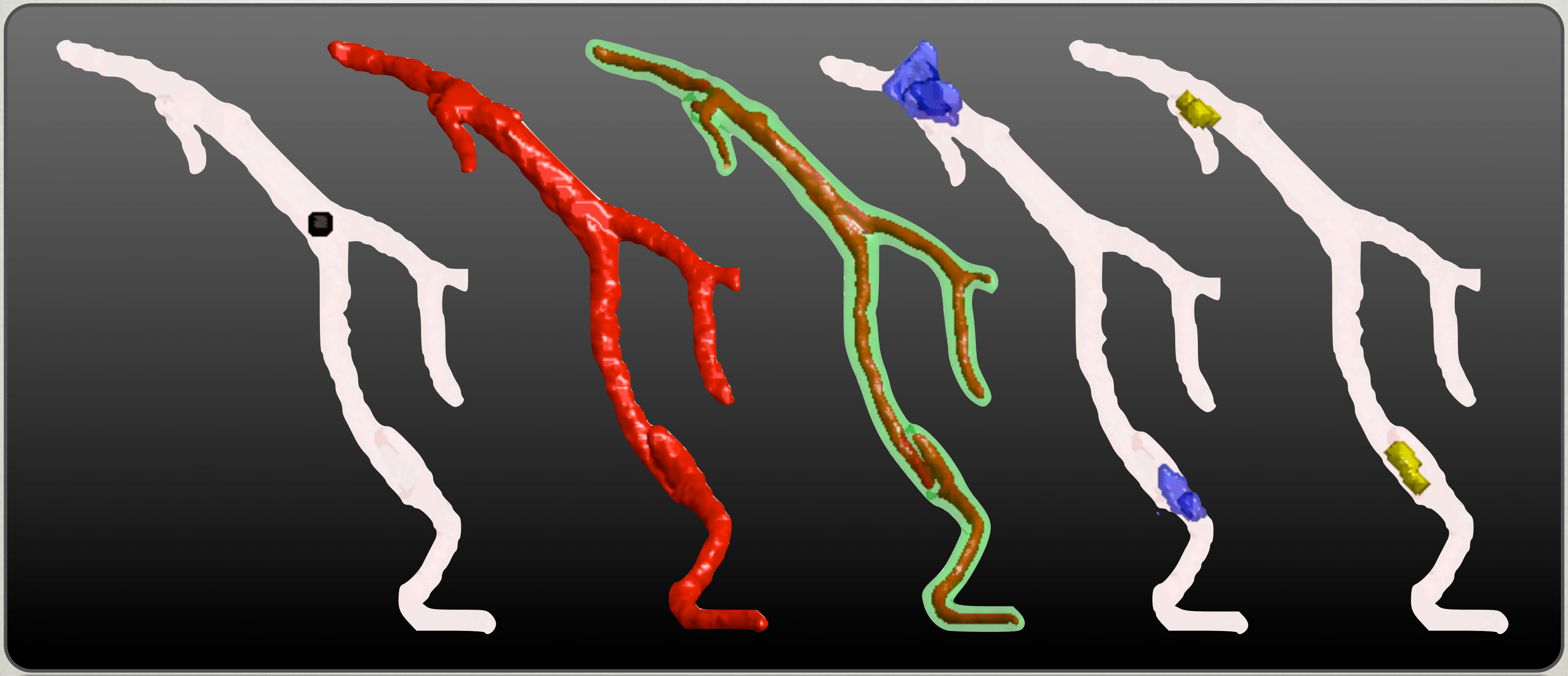
The Trick:
Clever Initializations



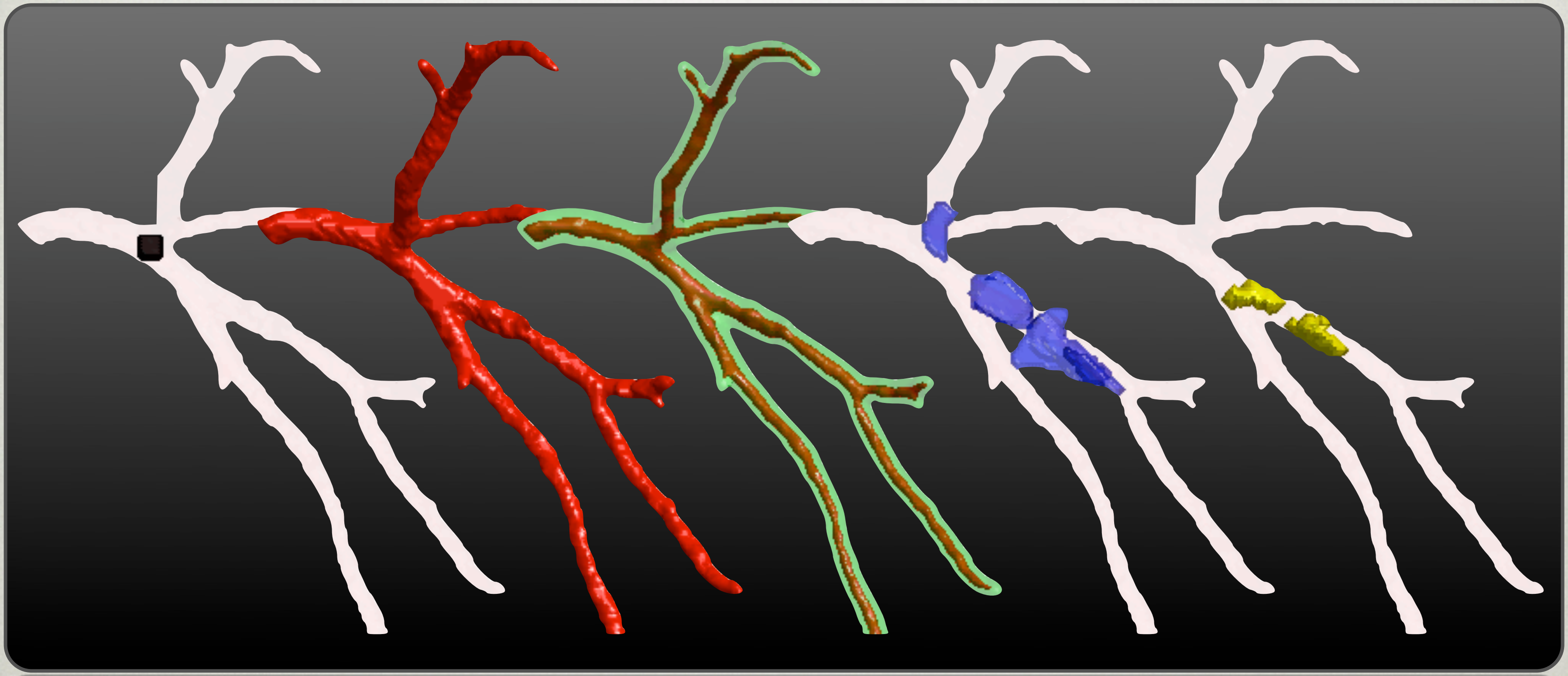
Steps for Detection

- Segment the Vessel
- Create Initialization
- Segment In to Out
- Segment Out to In
- Check for Differences

Naïve Results



Naïve Results

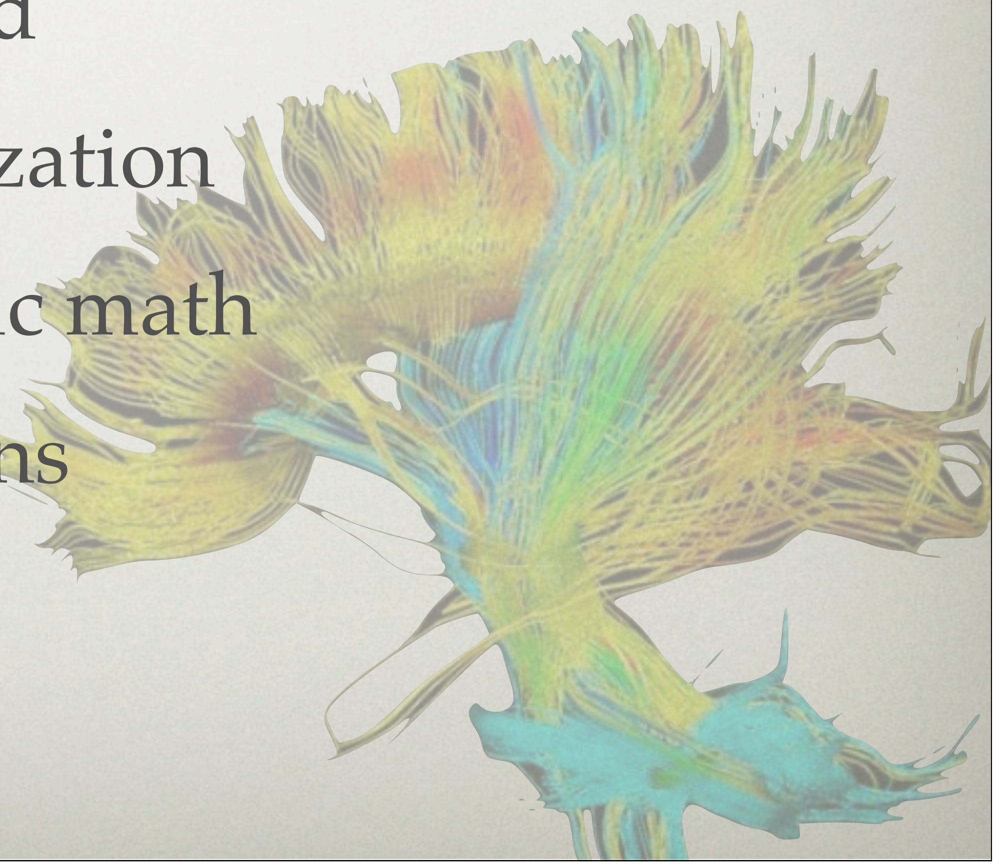


Proposed Research

Fiber Bundles
Soft Plaque Detection
Temporal Localization

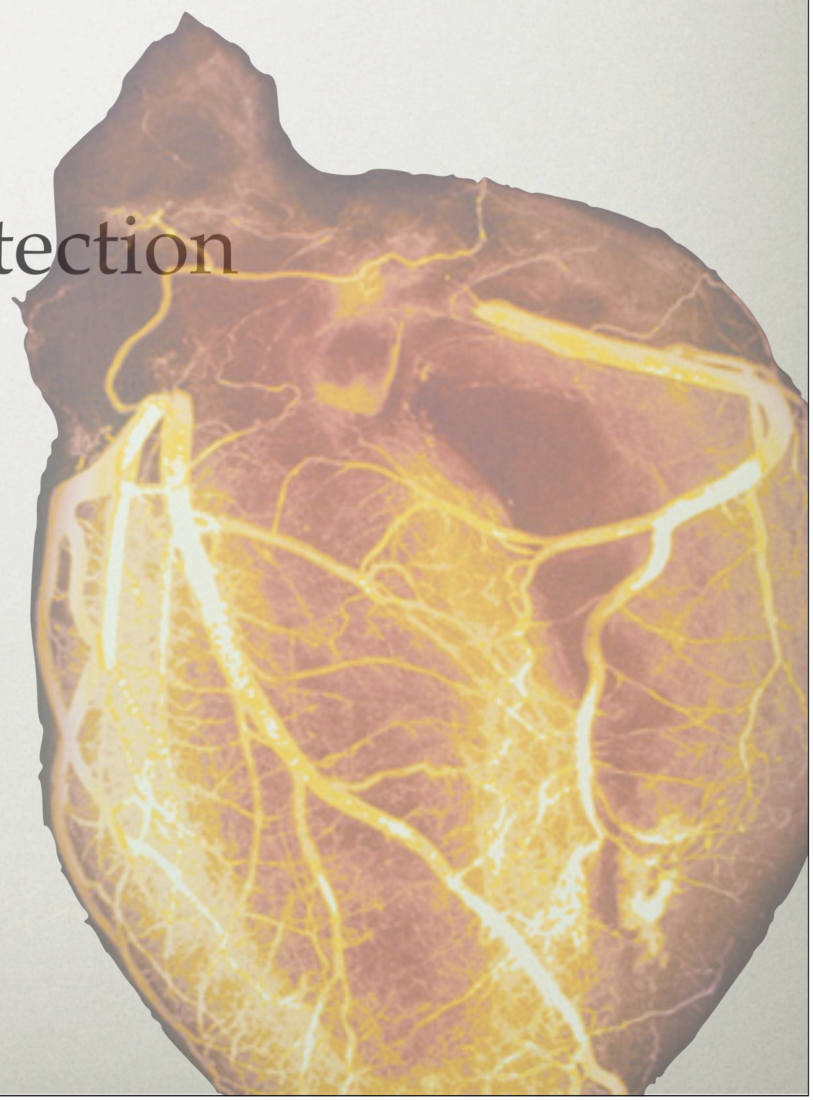
Fiber Bundles

- What we've learned
- Single-click Initialization
- More tensor-specific math
- Better segmentations



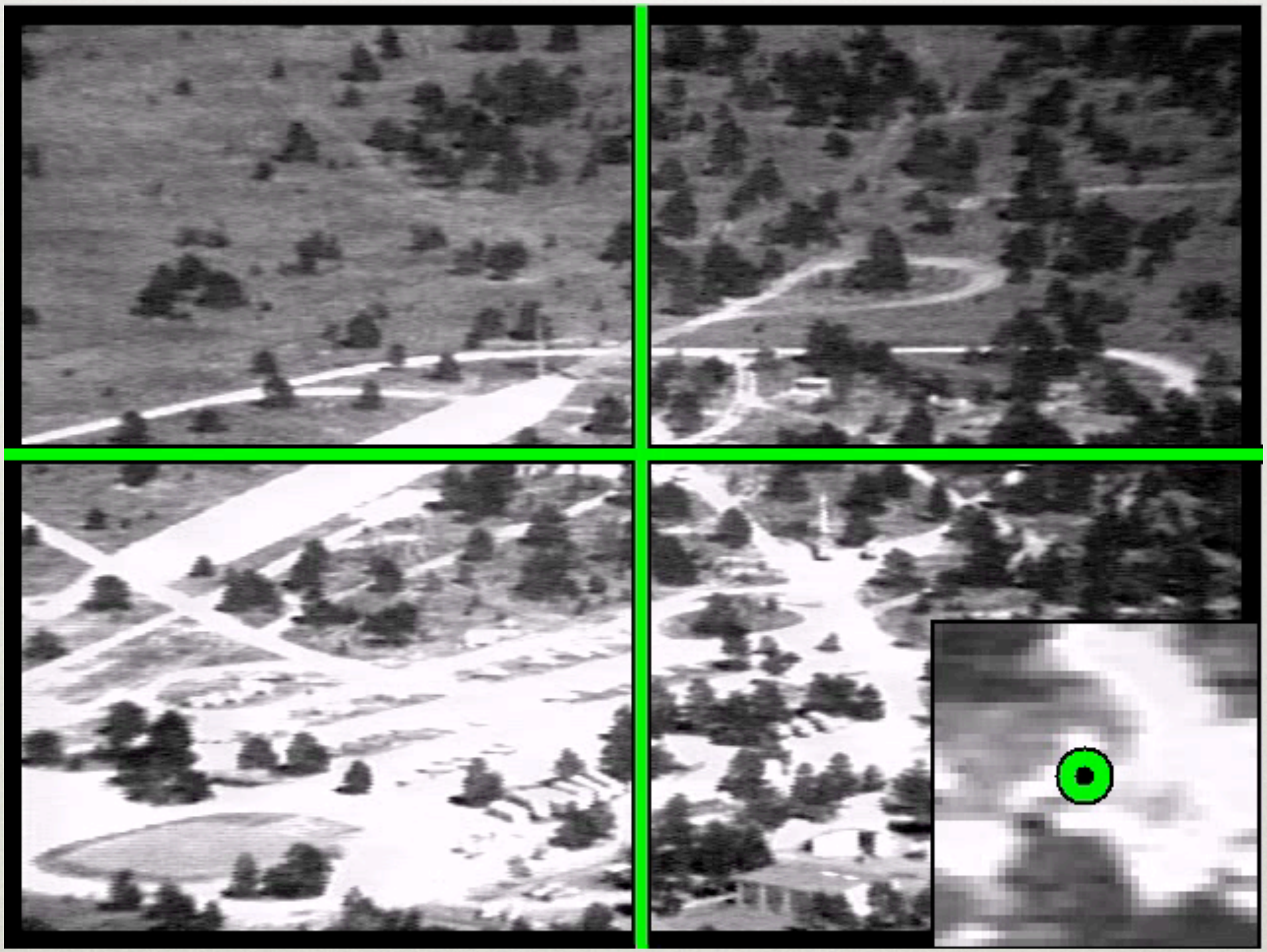
Soft Plaque Detection

- Problems with naïve detection
- Coupling contours
- Improve robustness
- Larger studies



Temporal Localization

Temporal Localization



Lankton *et al.* "Tracking Through Changes in Scale," ICIP 2008

Timeline and Deliverables

Key Publications

1. "**Localizing Region-Based Active Contours.**" S. Lankton and A. Tannenbaum. IEEE Transactions on Image Processing. Vol. 17, No. 11, pp 2029-2039, Nov. 2008.

2. "**Localized Statistics for DW-MRI Fiber Bundle Segmentation.**" S. Lankton, J. Melonakos, J. Malcolm, S. Dambreville, and A. Tannenbaum. Wkshp. Mathematical Methods in Biomedical Image Analysis. Jun. 2008.

3. **"Automatic Vessel Segmentation and Soft Plaque Detection."** S. Lankton, A. Stillman, P. Raggi, A. Tannenbaum. Medical Imaging and Computer Assisted Intervention. 2009. *(in submission)*

4. "**Tracking Through Changes in Scale.**" S. Lankton, J. Malcolm, A. Nakhmani, and A. Tannenbaum. IEEE International Conference on Image Processing. pp. 241 - 244, Oct. 2008

Additional Publications

1. **"Statistical Shape Learning for 3D Tracking."** R. Sandhu, S. Lankton, S. Dambreville, A. Tannenbaum. CDC, 2009. *(in submission)*

2. **"TAC: Thresholding Active Contours."** S. Dambreville, A. Yezzi, S. Lankton, and A. Tannenbaum. ICIP, 2008.

3. **"Improved Tracking by Decoupling Target and Camera Motion."** S. Lankton and A. Tannenbaum. SPIE Electronic Imaging, 2008.

4. **"Fast Optimal Mass Transport for Dynamic Active Contour Tracking on the GPU."** G. Pryor, T. Rehman, S. Lankton, P. Vela, and A. Tannenbaum. CDC, 2007.

5. **"Hybrid Geodesic Region-Based Curve Evolutions for Image Segmentation."** S. Lankton, D. Nain, A. Yezzi, A. Tannenbaum. SPIE Medical Imaging, 2007.

6. **"Fusion of IVUS and OCT Through Semi-Automatic Registration."** G. Unal, S. Lankton, S. Carlier, G. Slabuagh, and Y. Chen. MICCAI, 2006.

Planned Publications

1. **“Soft Plaque Detection and Vessel Analysis”**
   IEEE Trans. in Medical Imaging. May

2. “**Temporally Localized Models for Tracking**“
   IEEE Trans. in Pattern Recognition and Machine Intelligence. July

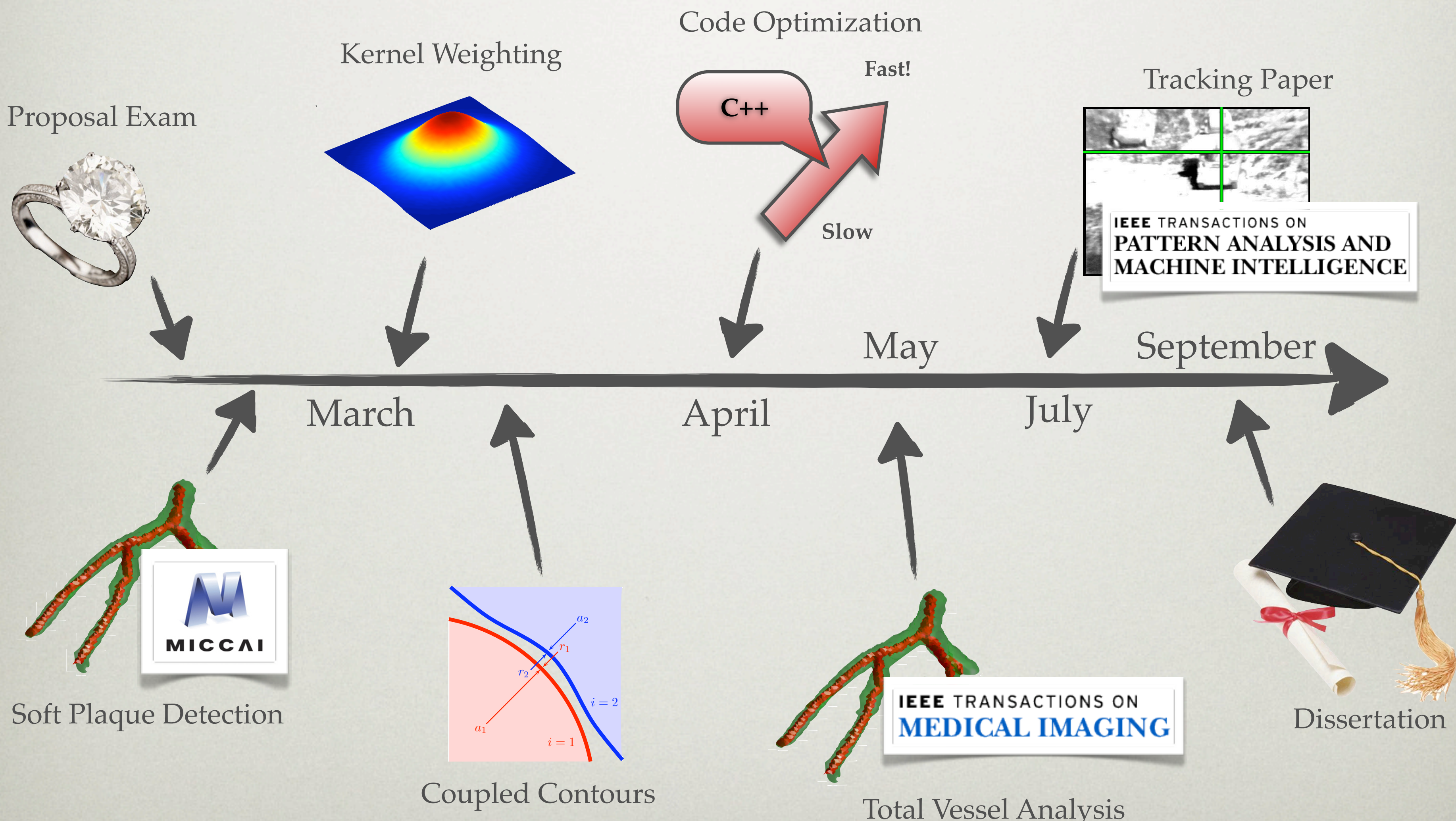
3. “**One-click Fiber Bundle Segmentation**“
   TBD

Research Timeline

Proposal Exam

Now

Research Timeline



Thank You.