



NA-MIC

National Alliance for Medical Image Computing

<http://na-mic.org>

Interactive Segmentation

EVERYONE!

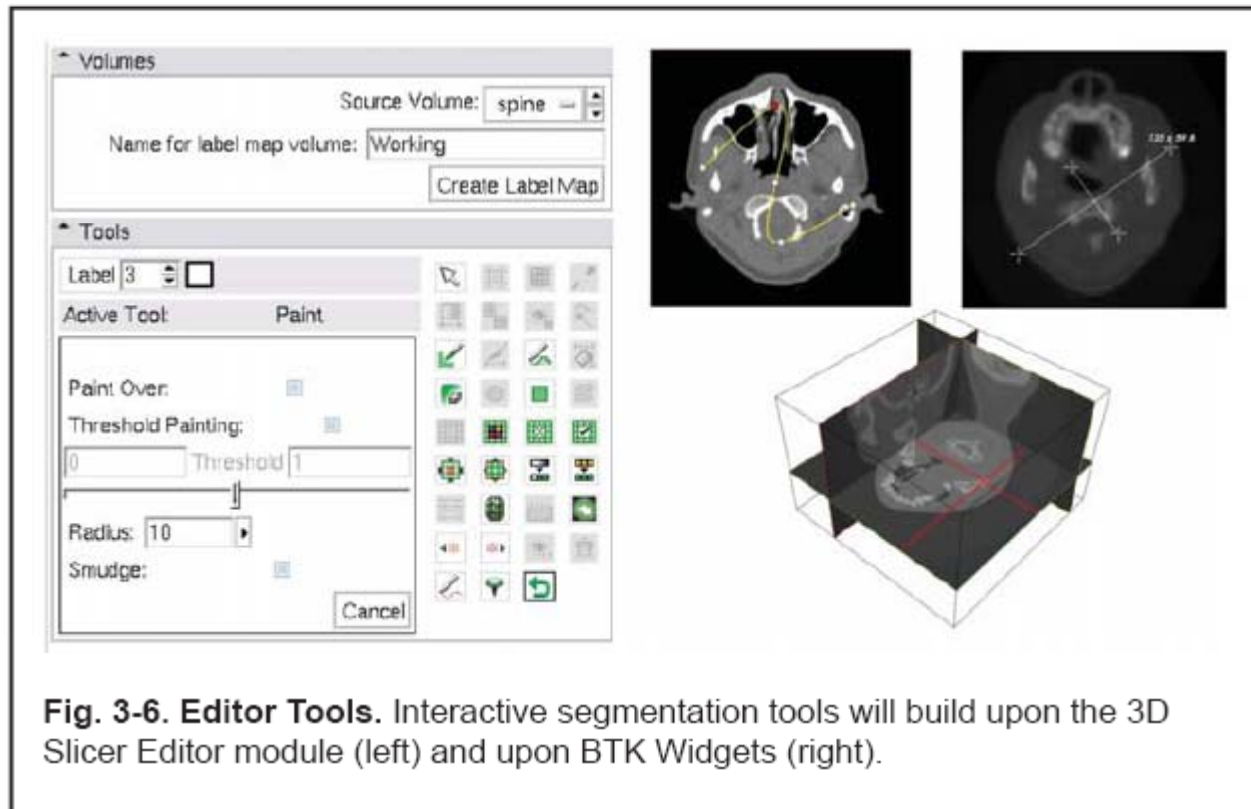


NA-MIC Interactive Segmentation

- Growcuts
- RSS
- Statistical/Geometric Active Contours
- Coupled Active Contours
- Preliminary Results

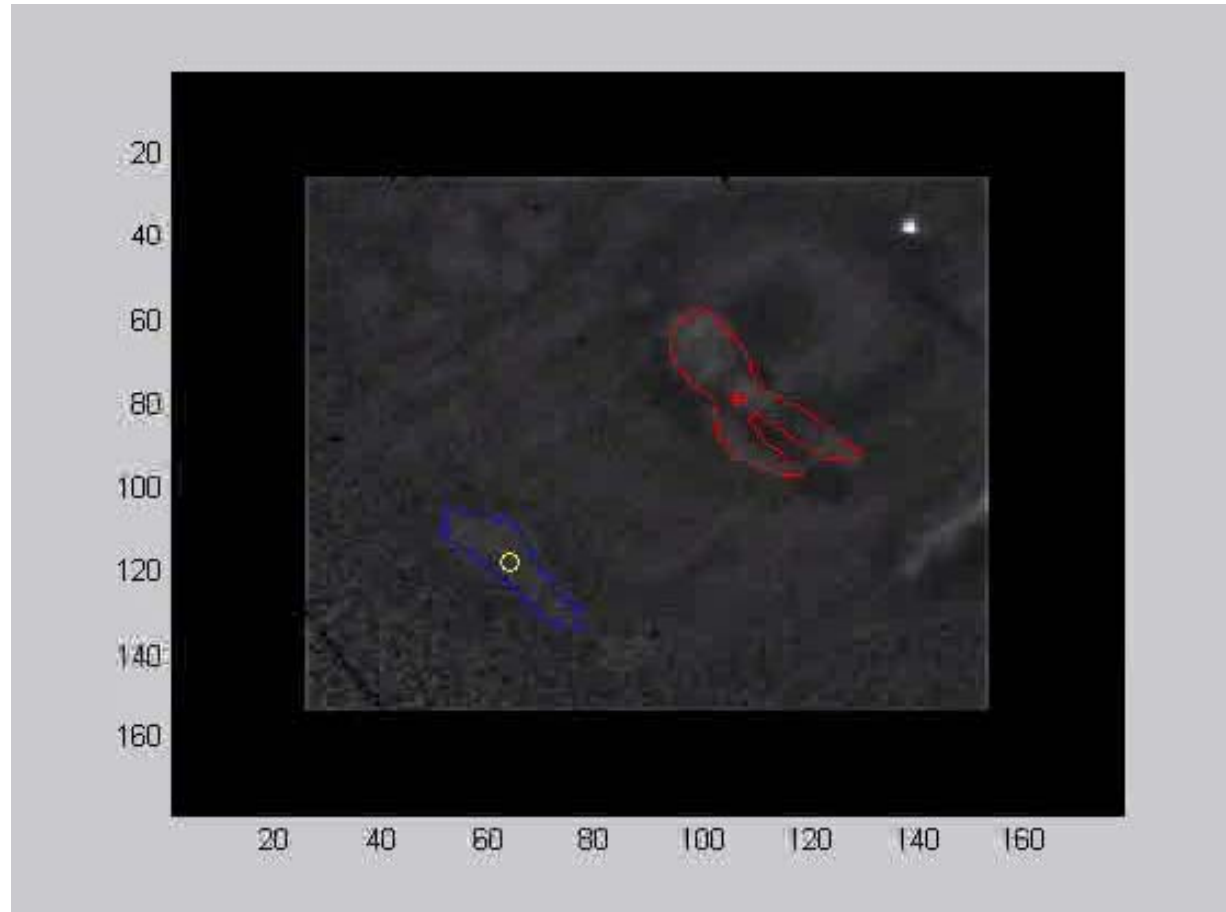


From the Proposal





Why Interactive





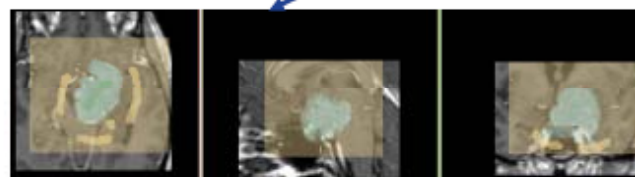
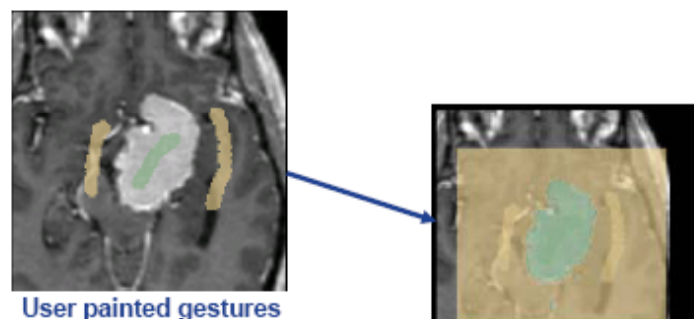
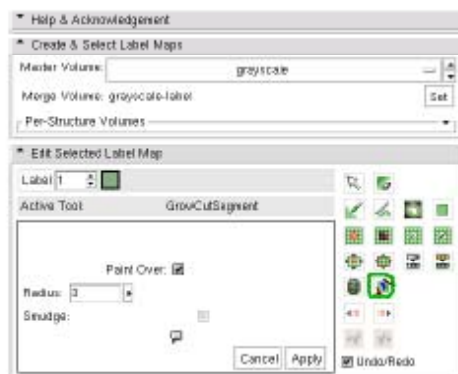
GrowCut: Jim Miller et al.

Given a small number of user-labeled pixels, the rest of the image is segmented automatically by a Cellular Automaton. The process is iterative, as the automaton labels the image, user can observe the segmentation evolution and guide the algorithm with human input where the segmentation is difficult to compute. In the areas, where the segmentation is reliably computed automatically no additional user effort is required.



Interactive Segmentation in Slicer3.6.2

- GrowCut image segmentation is in Slicer's Editor Effect
 - Incorporates paint tool interaction
 - Optionally interact using “draw”, “paint” Editor effect
- Supports simultaneous viewing of user inputs and segmentation
- Supports editing segmentation with additional gestures
- Simple user interface (no exposed parameters)

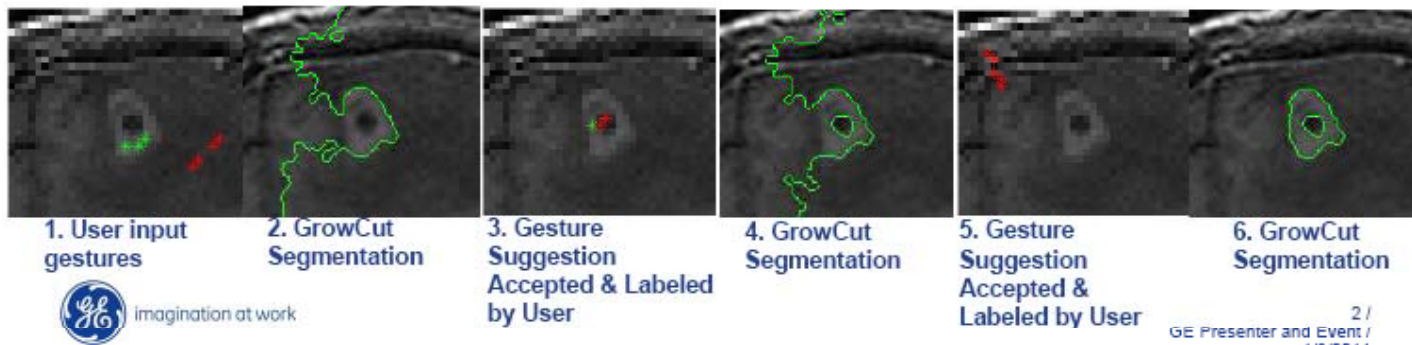
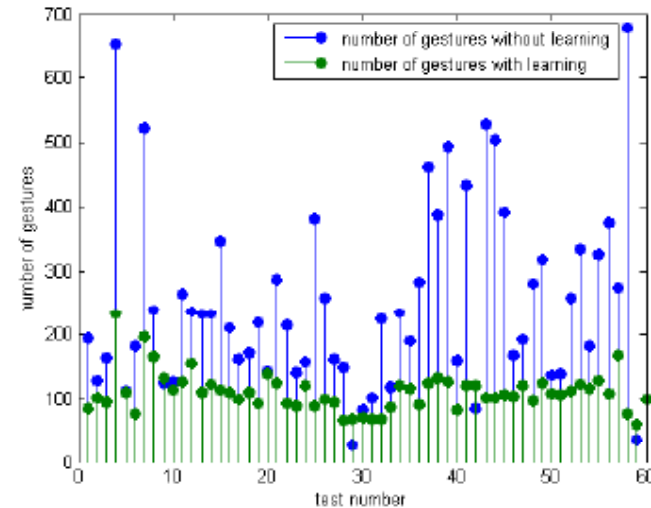


GE Presenter and Event /
1/3/2011



Active Learning For Guiding Gesture Placements

- **Gesture suggestions to user** combines GrowCut segmentation with active learning using SVM
 - Suggestions are selected using a two-step approach
 - **Step I** treats GrowCut segmentation and SVM classification as diverse ensembles to select query candidates
 - **Step II** employs SVM margin-based gesture selection on the query candidates
- Number of interactions required for novel image segmentation with learning is 50% less than without learning
- Algorithm guided interactions minimizes segmentation variability





Robust Statistics Segmentation(RSS)

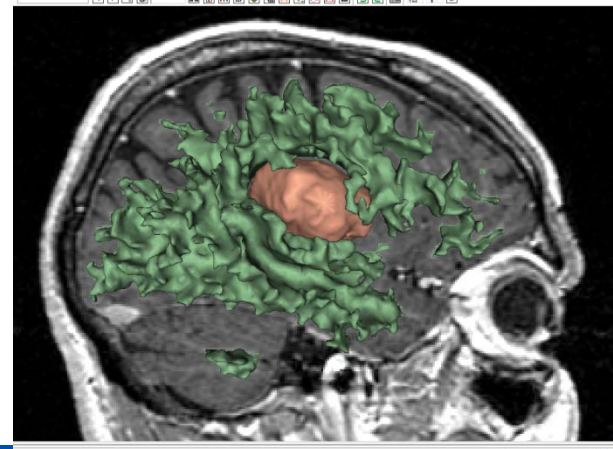
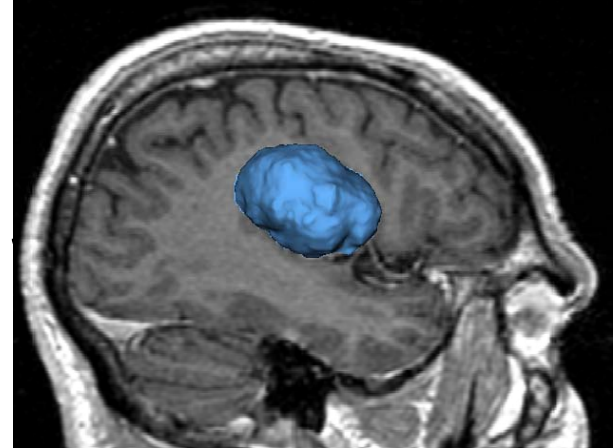
Yi Gao et al.



Single/multiple target(s)

- Single target RSS
 - *Segmentation module*

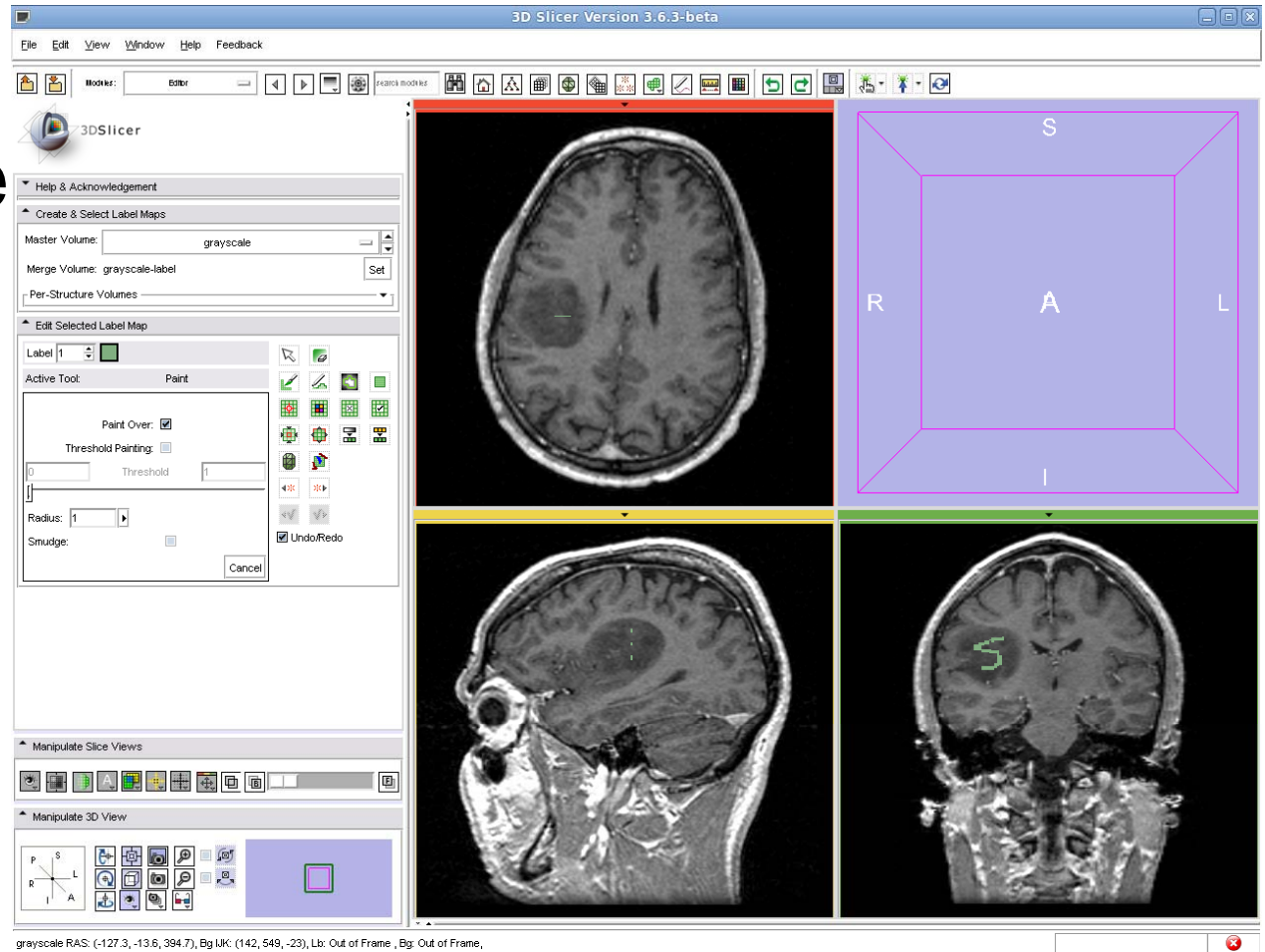
- Multiple target RSS
 - *Extension*





Single target RSS

1. Draw some seeds
2. “Apply”





Behind the Scenes

- Robust Statistics Feature Image

$$f(\mathbf{x}) = (MED(\mathbf{x}), IQR(\mathbf{x}), MAD(\mathbf{x}))^T \in \mathbb{R}^3$$

median (around \mathbf{x})

inter-quartile range

median absolute deviation

- For each pixel $I(\mathbf{x})$, compute $f(\mathbf{x})$ in a $3 \times 3 \times 3$ neighborhood.



Behind the Scenes, cont

- Robust Statistics Feature Image

$$\mathbf{f}(\mathbf{x}) = (MED(\mathbf{x}), IQR(\mathbf{x}), MAD(\mathbf{x}))^T \in \mathbb{R}^3$$

- Learn the features around Seeds

$$p_i(\mathbf{f}) = \frac{1}{|G_i|} \sum_{\mathbf{x} \in G_i} K_\eta(\mathbf{f} - \mathbf{f}(\mathbf{x}))$$

The i -th seed set

Gaussian kernel, stddev = η



Contour evolution

- Find optimal contour, minimizing:

$$E_i(C_i) := \int_{\mathbf{x} \text{ in } C_i} (p^c - p_i(\mathbf{f}(\mathbf{x}))) d\mathbf{x} + \lambda \int_{C_i} ds$$

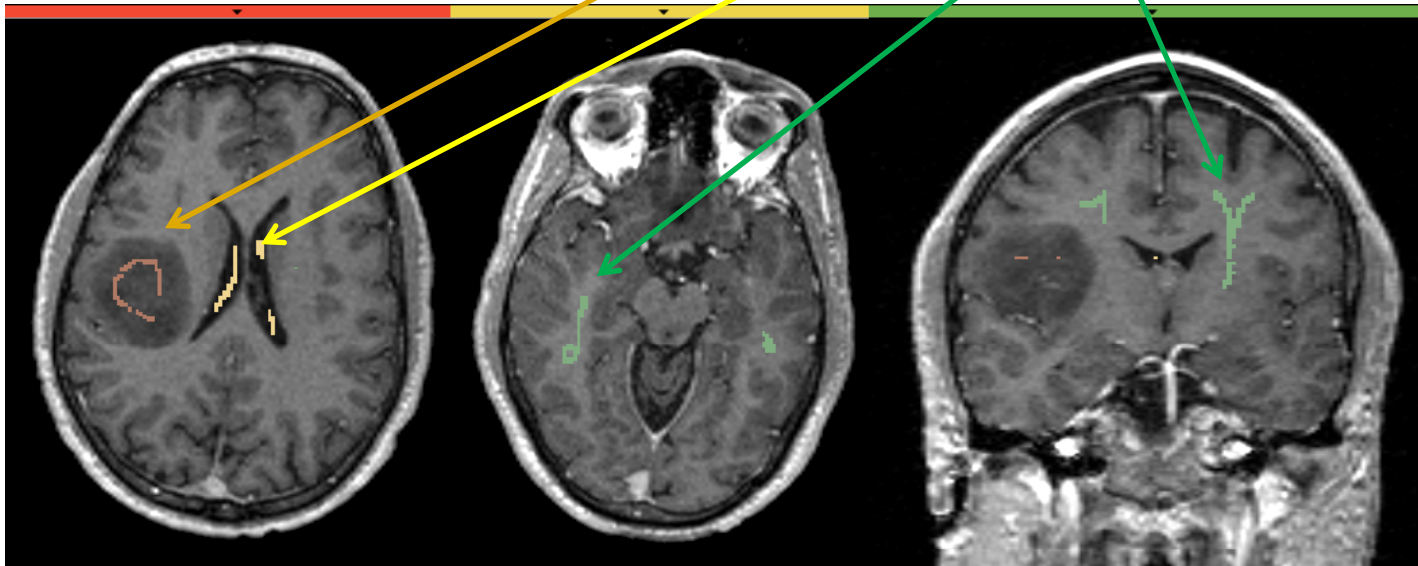
- Flow:

$$\frac{\partial C_i(q, t)}{\partial t} = [p^c - p_i(\mathbf{f}(C_i(q, t))) + \lambda \kappa_i(q, t)] \mathbf{N}_i(q, t)$$



Multiple target RSS

- Seeds:
 - Multiple seed groups
 - Different labels

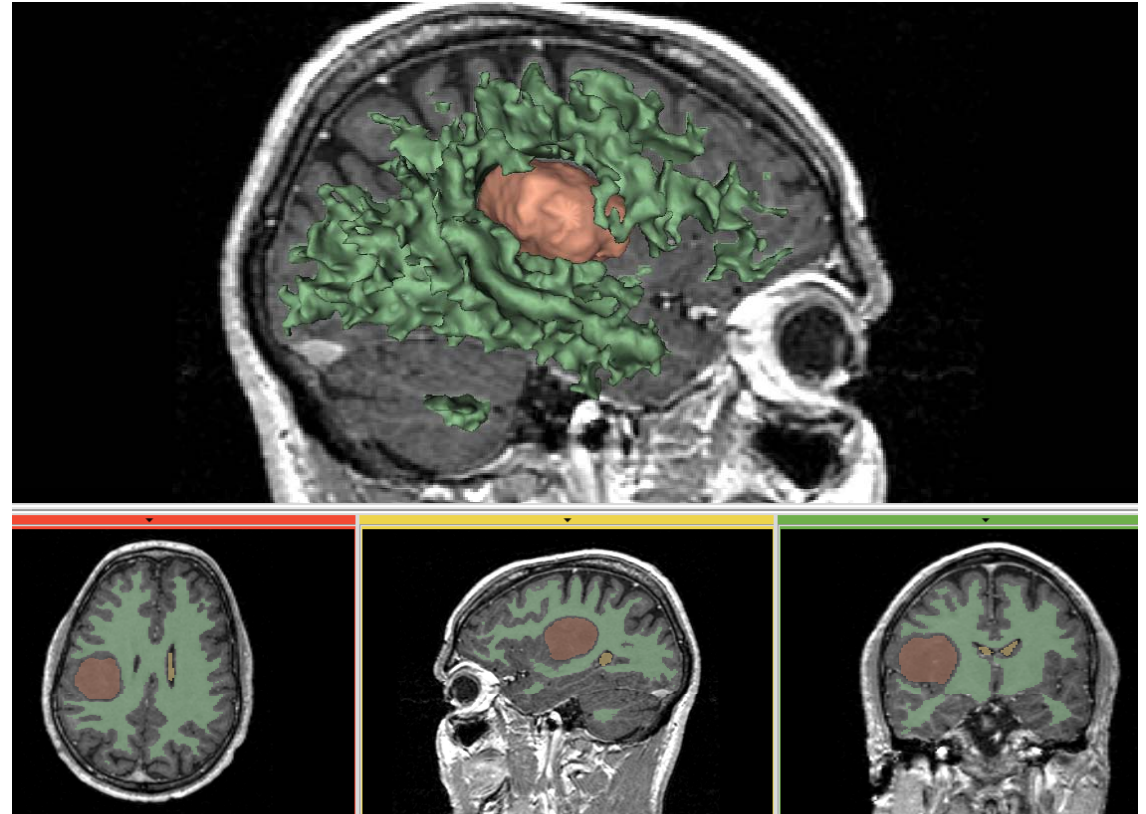




Multiple target RSS, cont.

Properties:

- 3D understanding of anatomy
- Non-overlapping





Behind the Scenes

- Contour interaction:
 - External force:

$$F_i^{ext}(\mathbf{p}) = - \sum_{j \neq i} \int_{C_j} e^{-|\mathbf{p} - C_j(w,t)|} (p_j(\mathbf{f}(\mathbf{p})) - p^c) \mathbf{N}_j(\mathbf{p}) dw$$

- Total force:

$$\frac{\partial C_i(q,t)}{\partial t} = [p_i(\mathbf{f}(C_i(q,t))) - p^c - \lambda \kappa_i(q,t)] \mathbf{N}_i(q,t) + F_i^{ext}(C_i(q,t))$$



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Segmentation for AFib

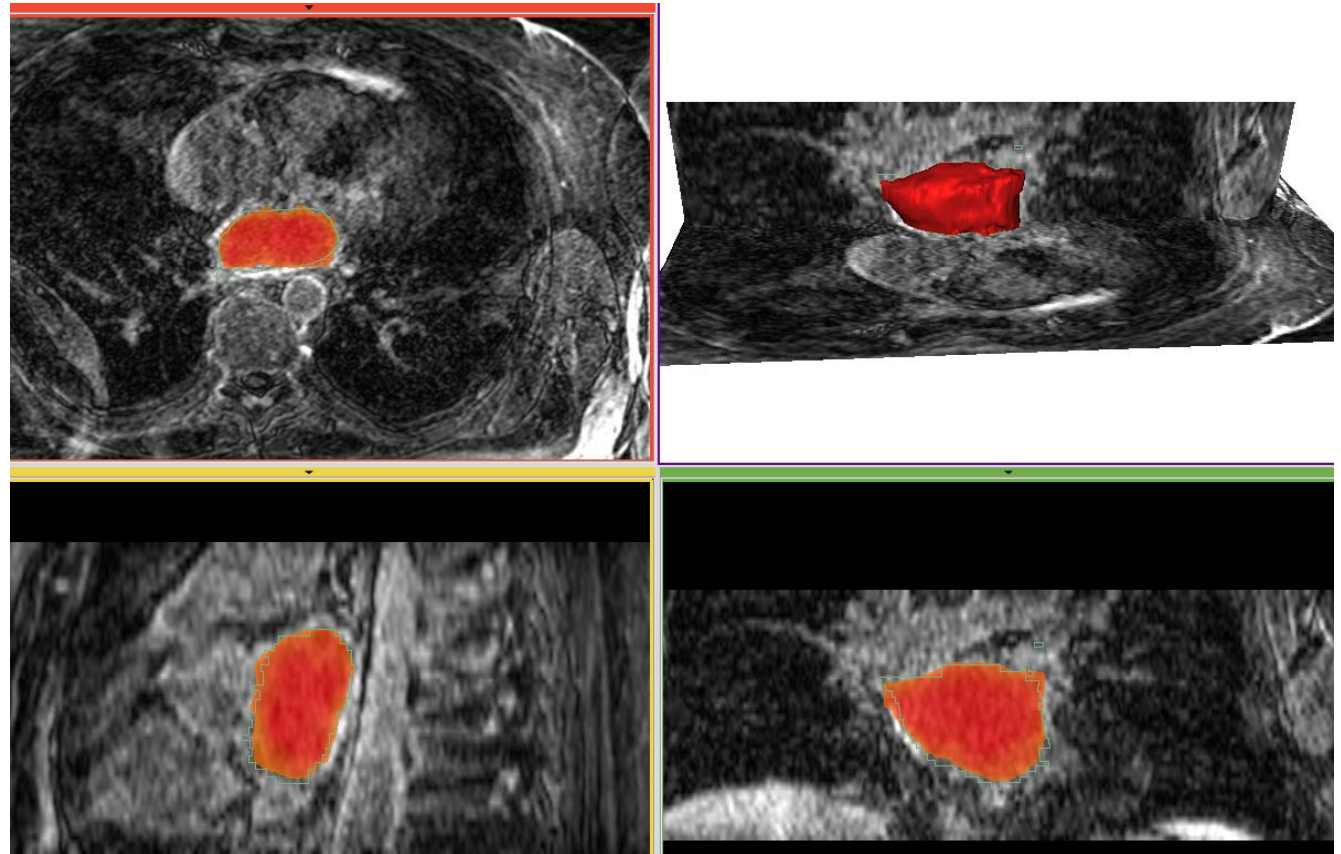
Yi Gao and Behnood Gholami et al.



Endocardium segmentation

Blood pool segmentation:
A combination
of multi-atlas
and active
contour

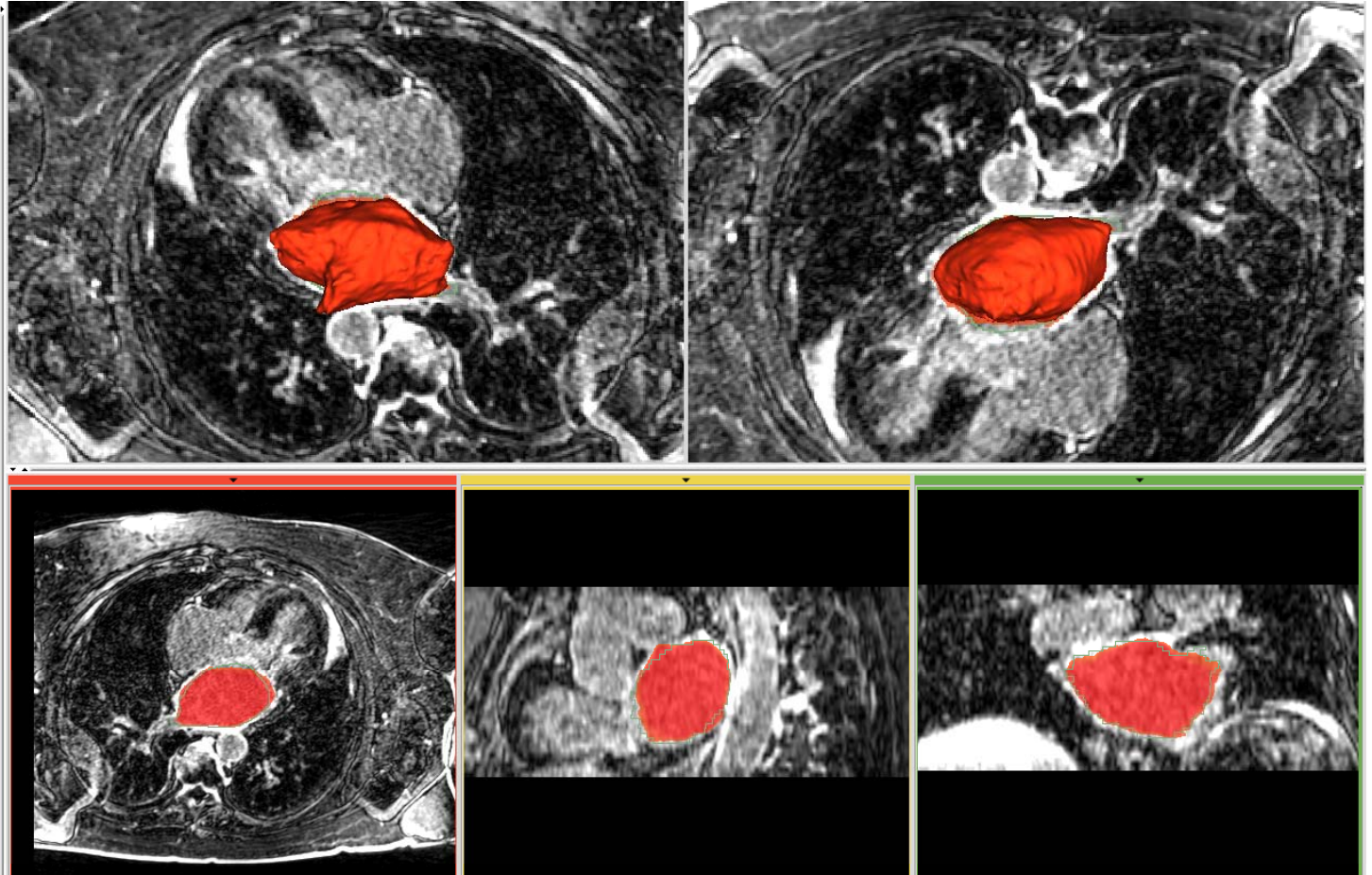
Axial	3D
Sagittal	Coronal





Endocardium segmentation

Blood pool segmentation:
A combination
of multi-atlas
and active
contour



3D		3D
Axl	Sagi	Coro

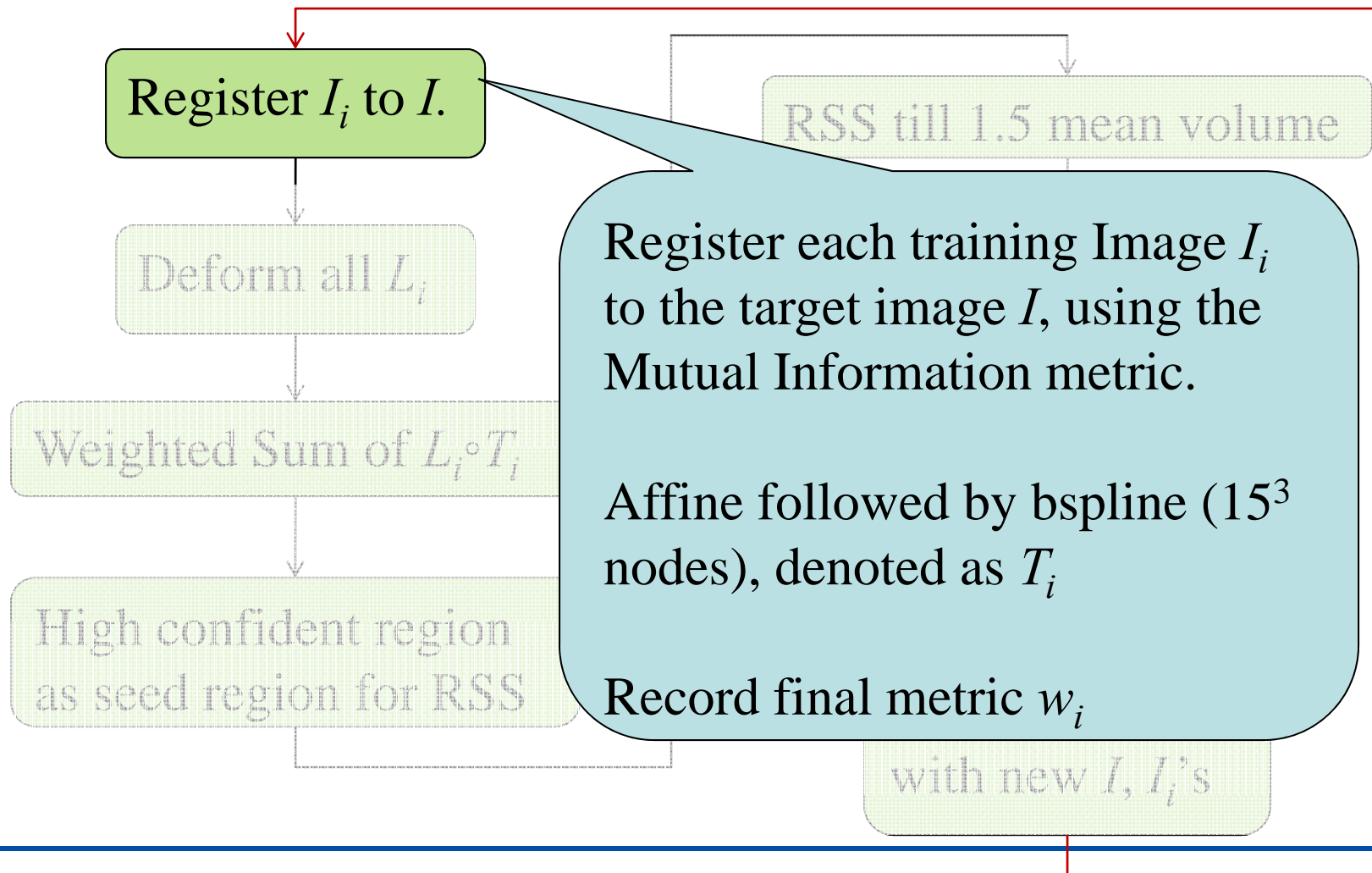


Segmentation method

- Notations:
 - Target image to be segmented: I
 - Training set:
 - Training MR images: $I_i, i=1, \dots, N$
 - Manual Endocardium mask: L_i

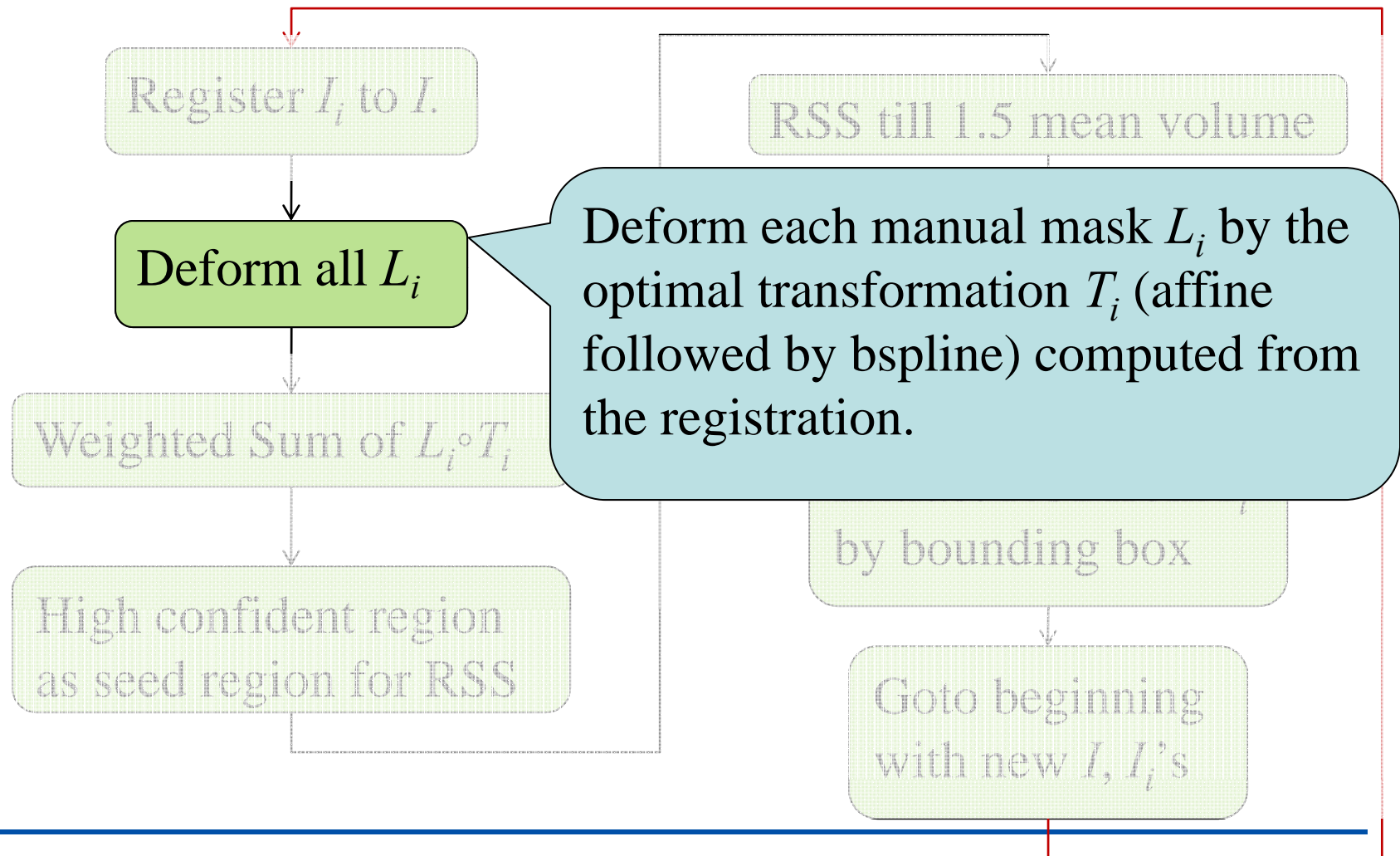


Segmentation method



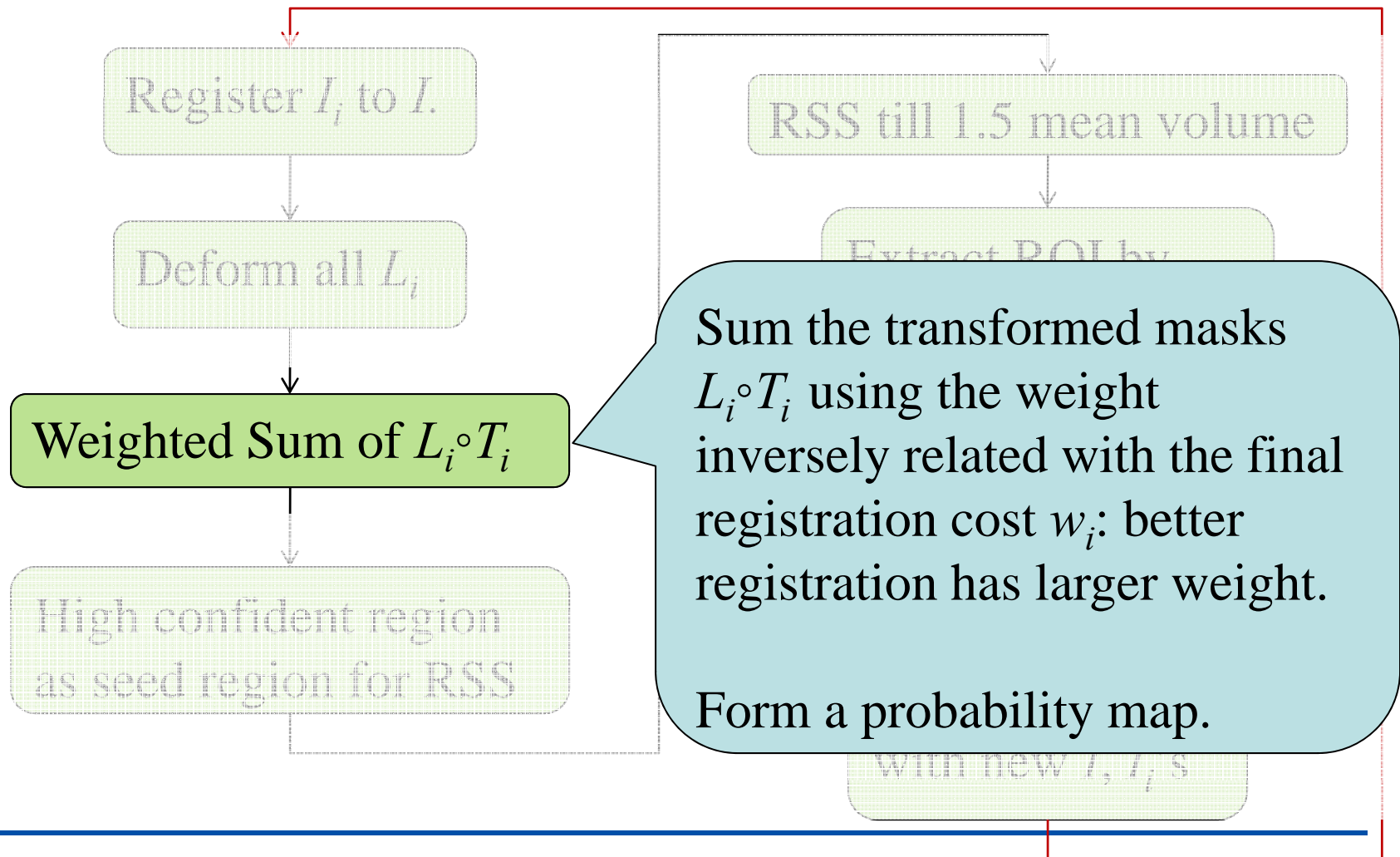


Segmentation method



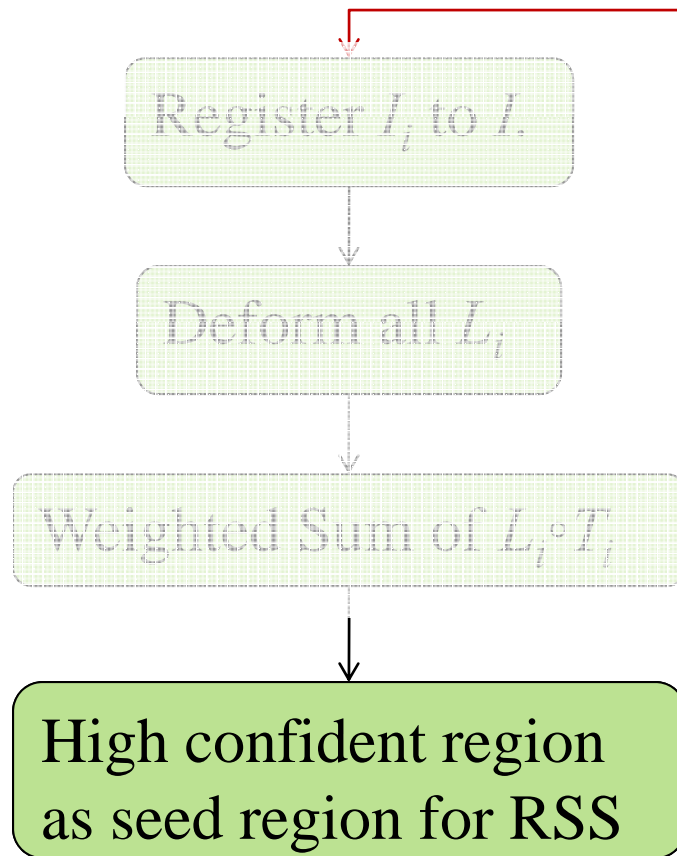


Segmentation method





Segmentation method



The probability map is NOT good enough. However, the high probability region are in the object.

Use those regions as seed for the RSS segmentation algorithm --- Learn the target feature on-line.

Go to beginning with new I, I_i 's



Segmentation method

The RSS is only used to extract the Region-Of-Interest around the target object, therefore the RSS is run till a little larger than the mean training volume.

Extract the ROI as the bounding box of current contour.

as seed region for RSS

RSS till 1.5 mean volume

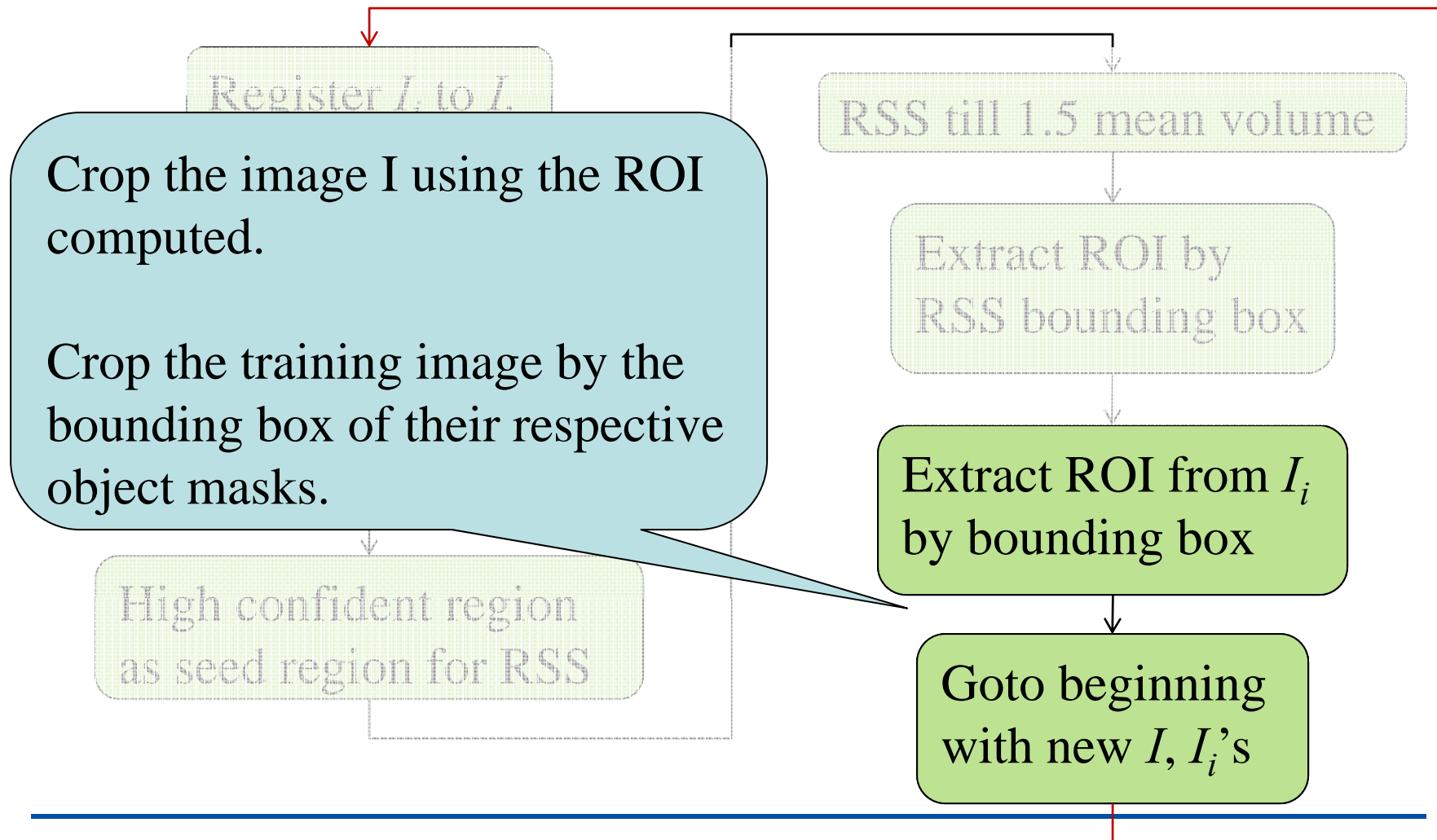
Extract ROI by
RSS bounding box

Extract ROI from I_i
by bounding box

Goto beginning
with new I_i 's

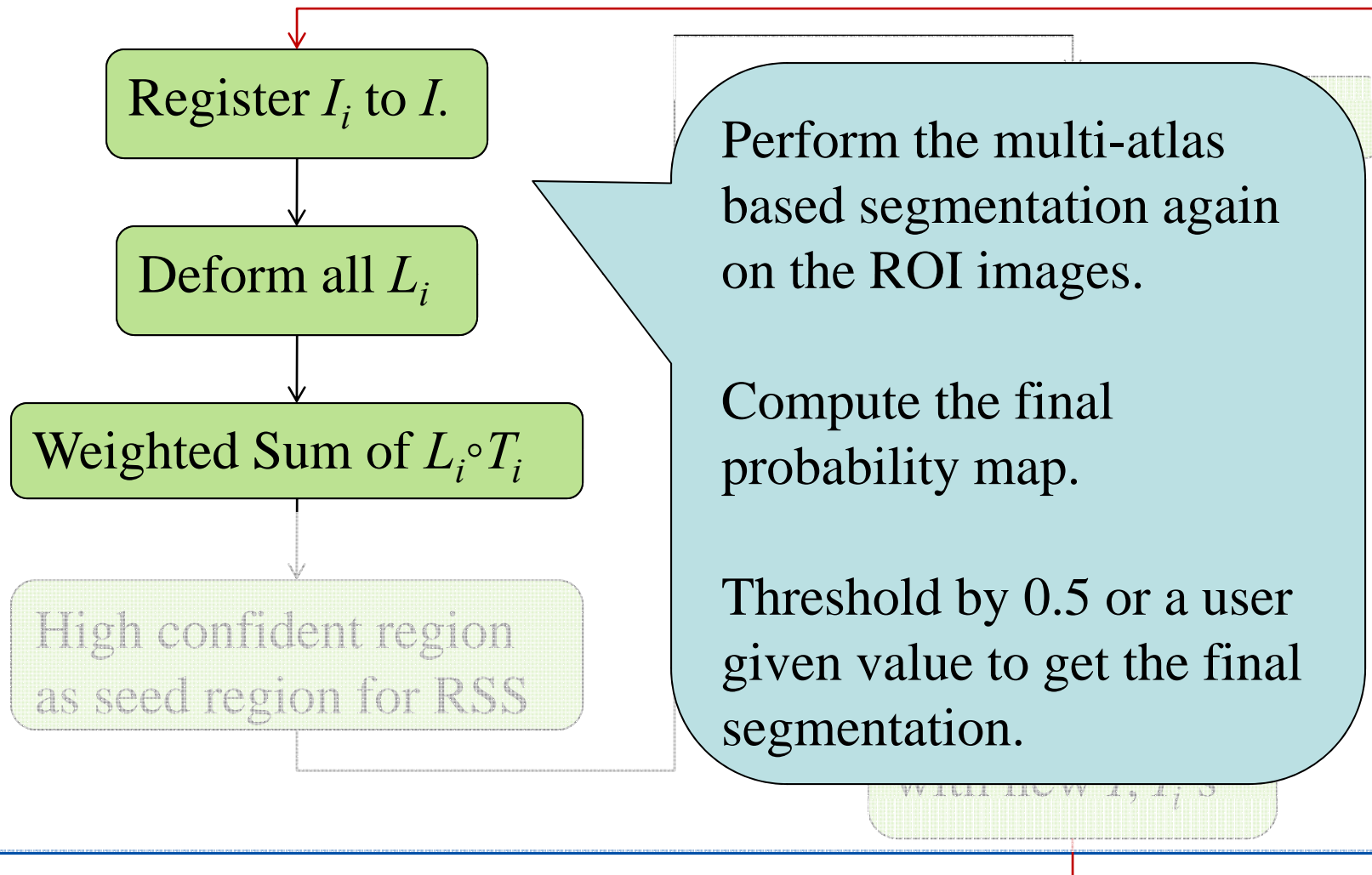


Segmentation method



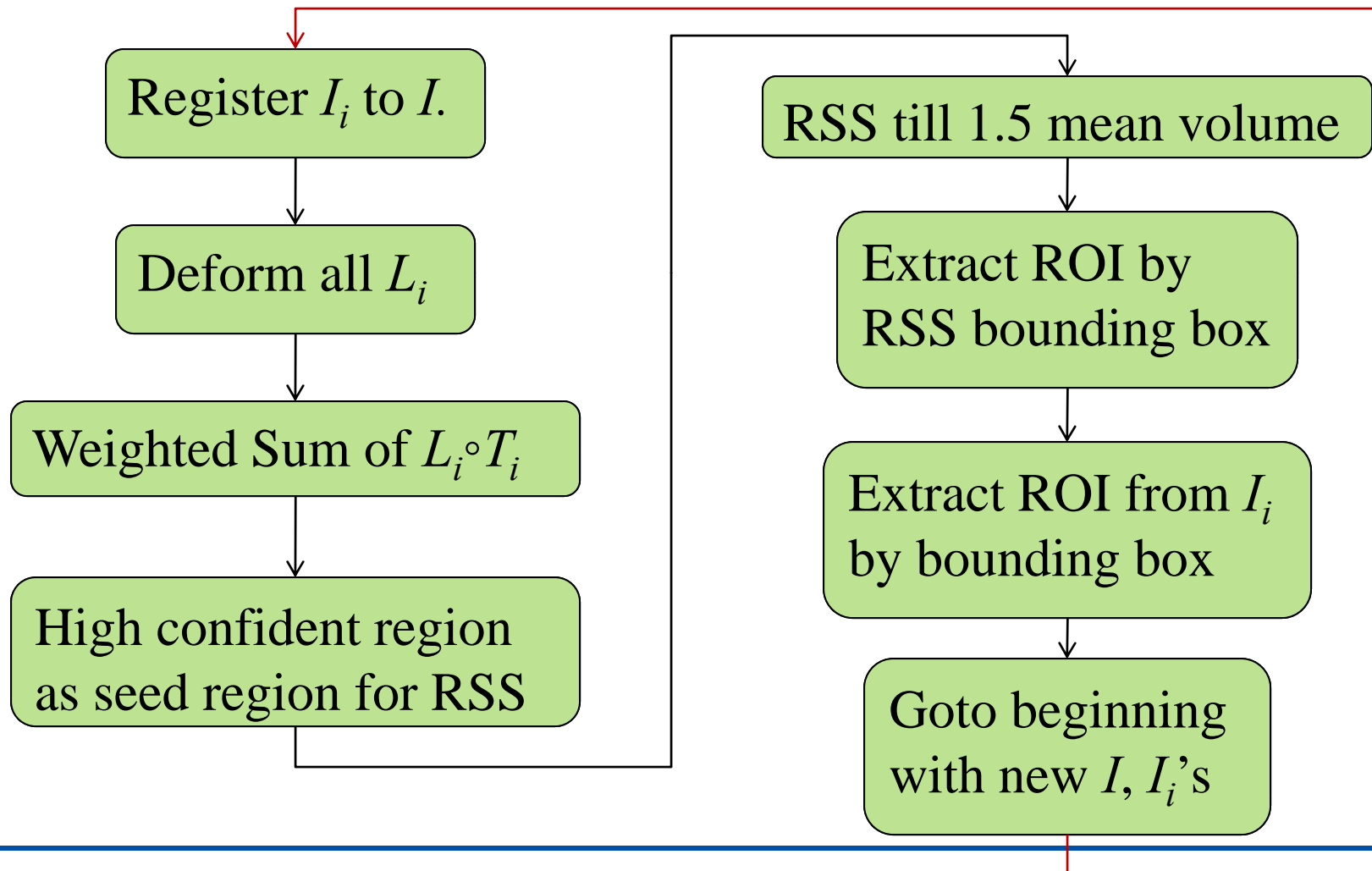


Segmentation method





Segmentation method





Wall segmentation

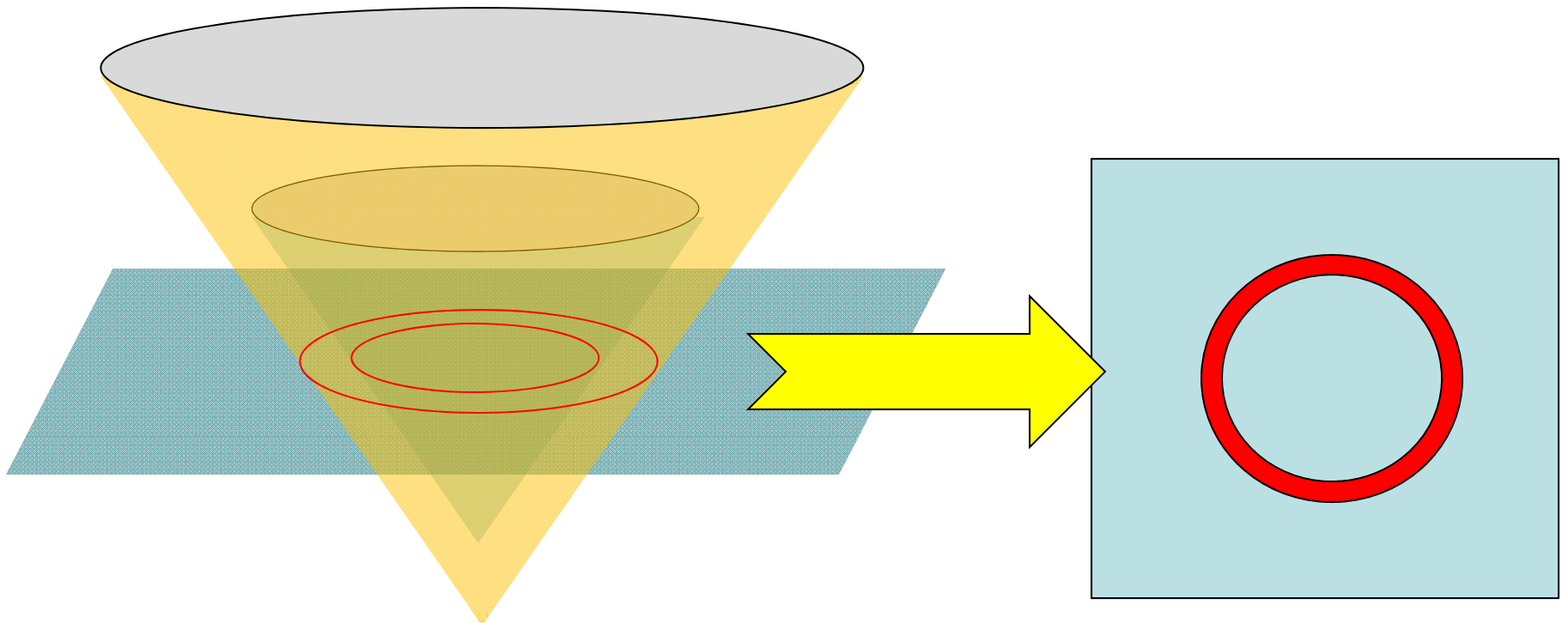


- Wall segmentation
 1. Coupled active contours
 2. Local Region Statistics between contours



Segmentation method

1. Coupled active contour





Coupled active contour

- ψ_1 and ψ_2 for inner/outer boundary of a ring/wall
- Wall region: $W = \{x \mid \psi_1(x) \geq 0, \psi_2(x) \leq 0\}$



Local Region Statistics between contours

- Evolve ψ_1 and ψ_2 so that the difference between $\mu(W)$ and $\mu(\overline{W})$ is maximized.

- Where:

$\mu(W)$ mean intensity in the wall

$\mu(\overline{W})$ mean intensity outside the wall, with in a layer same thickness as the wall



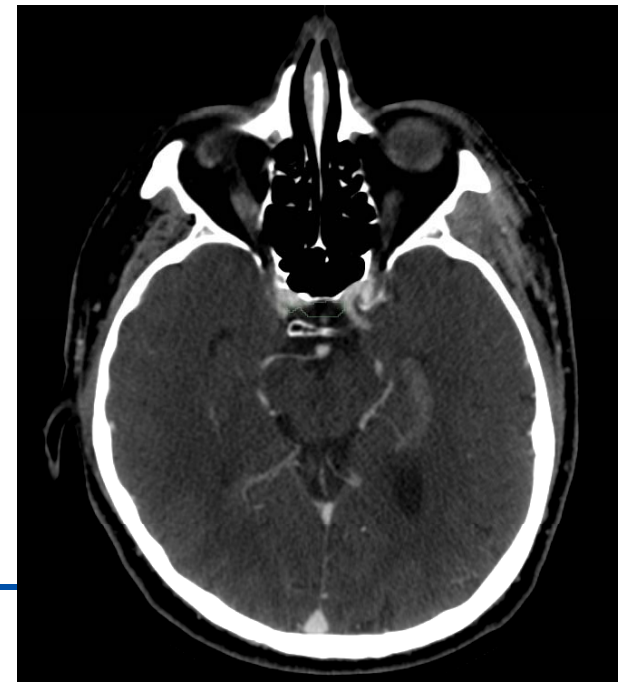
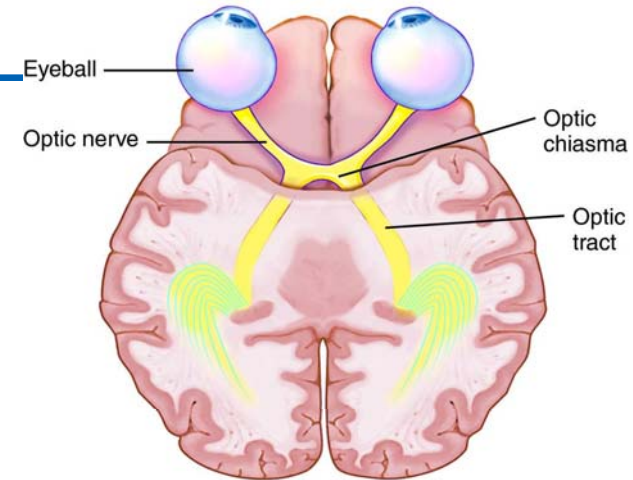
Adaptive Radiotherapy

Ivan Kolesov, Yi Gao et al.



Semi-automatic Segmentation

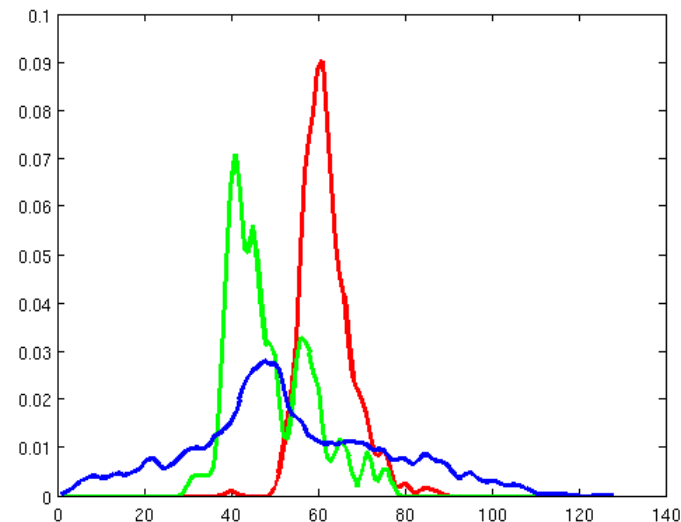
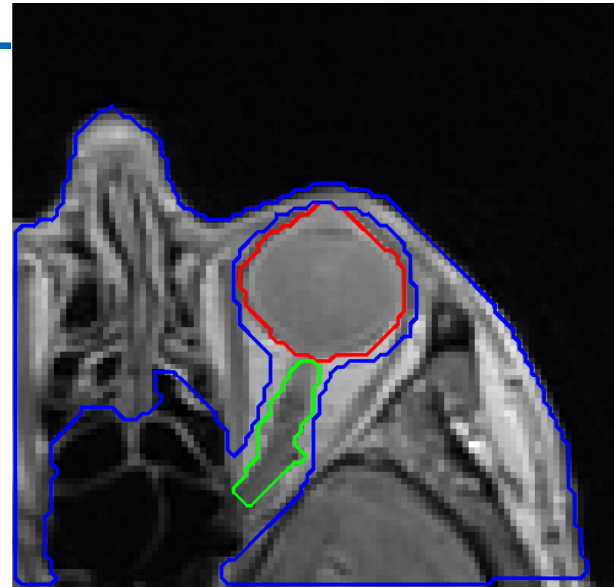
- First priority: segment eye structures
 - Eyeball
 - Lens
 - Optic Nerve
 - *Optic Chiasm
 - Above structures are highly sensitive to radiation





Segmentation Approach

- Organs have heterogeneous intensity profiles
- Structures are in close proximity to each other
- Intensity information not sufficient
- Need user input and/or shape constraint





User Constrained Segmentation

- Employ variational active contours
- Use local energies
- User seeds determine object of interest

$$E_{cv}(\phi) = \int_{\Omega_x} \delta\phi(x) \int_{\Omega_y} \mathcal{B}(x, y) \cdot (\mathcal{H}(\phi(y))(I(y) - u_l)^2 + (1 - \mathcal{H}(\phi(y)))(I(y) - v_l)^2) dy dx$$

$$E_{user}(\phi) = \int_{\Omega_x} \delta\phi(x) \int_{\Omega_y} \mathcal{B}(x, y) \cdot (\mathcal{H}(\phi(y))(I(y) - u_{seed})^2) dy dx$$

$$E_T(\phi(x)) = E_{cv}(\phi(x)) + \lambda E_{user}(\phi(x))$$

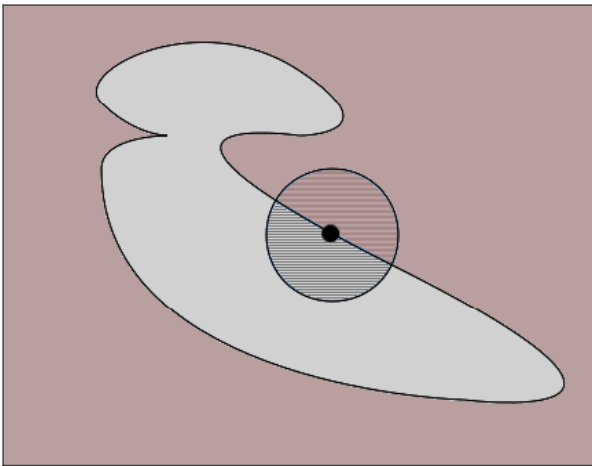


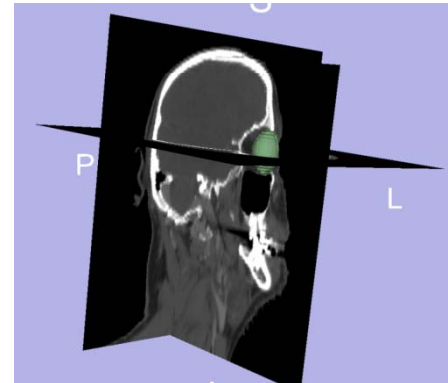
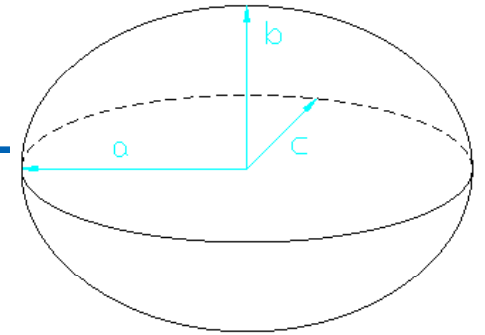
Image C





Eyeball Segmentation

- Roughly a sphere slightly elliptical
- Reduce dimensionality, impose shape constraint
- Heterogeneous intensity profile, look for edges



$$E(a, b, c, x_c, y_c, z_c) = \int_{\Omega} g(|\nabla I(C(q))|) dq + \alpha \left(\left(1 - \frac{a}{b}\right)^2 + \left(1 - \frac{c}{b}\right)^2 \right) - \lambda (a + b + c)$$

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<http://na-mit>

$$g(|\nabla I(C(a, b, c, x_c, y_c, z_c, q))|) = \frac{1}{1 + |\nabla I(C(q))|^2}$$



Conclusions

- Next year we hope to have substantial results with our DBP partners!