Joint Tumor Segmentation and Dense Deformable Registration of Brain MR Images

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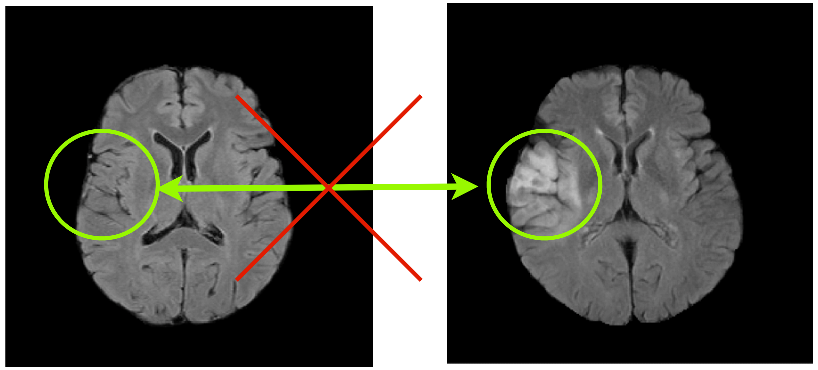
4. Département de Neurochirurgie, Hôpital Gui de Chauliac, Montpellier

Introduction

Brain Tumor Segmentation and Registration from healthy to pathological subject treated separately

- Fuzzy boundaries
- inhomogeneous appearances
- Various shapes
- intensity overlap with healthy tissue



- No correspondences in the tumor area: use of common methods impossible

Methods

- Classification techniques + pairwise smoothing
  Lee et al. MICCAI 2008
- Atlas based segmentation: dependent on registration quality
  Prastawa et al. Academic Radiology 2003

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- Growth models: computationally expensive/user interaction
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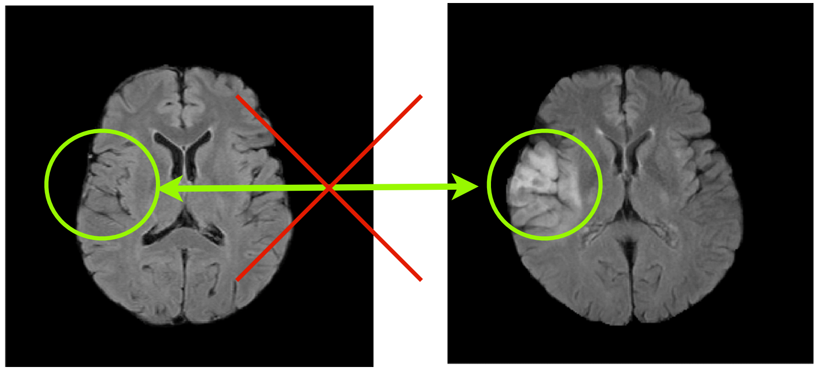

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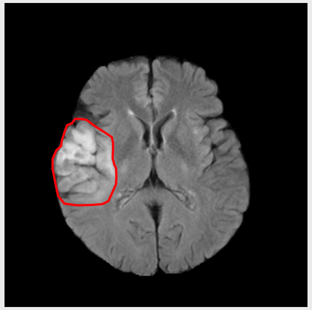
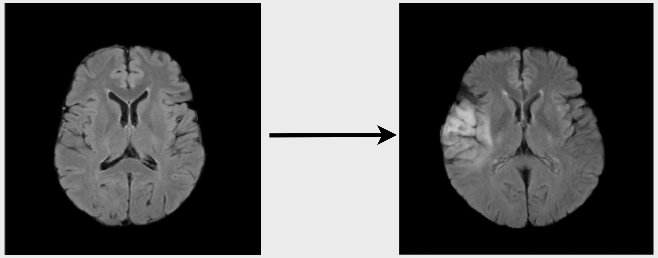
Method Overview

Simultaneously register a healthy subject to a diseased subject and find the tumor's segmentation map

Tumor segmentation



Healthy to diseased registration



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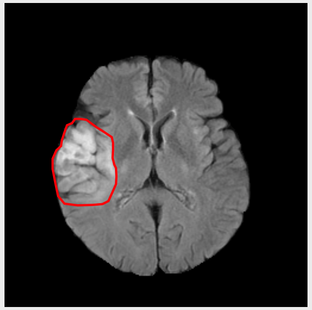

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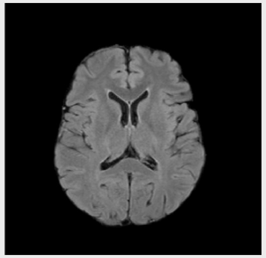

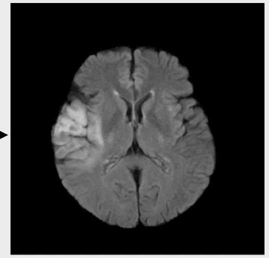

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Similarity criterion between the images
glocker et al. *Medical Image Analysis*, 2008

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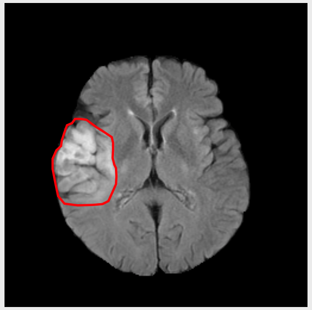
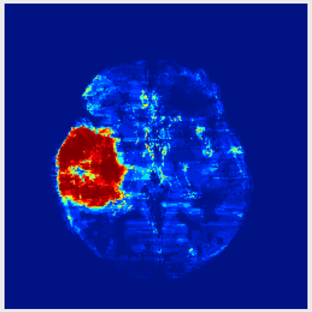


High score

Learned classifier

Friedman et al. *The Annals of Statistics* 2000



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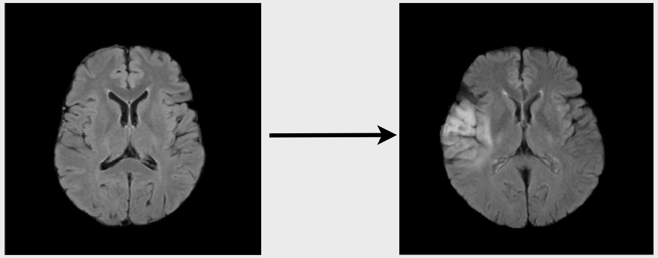

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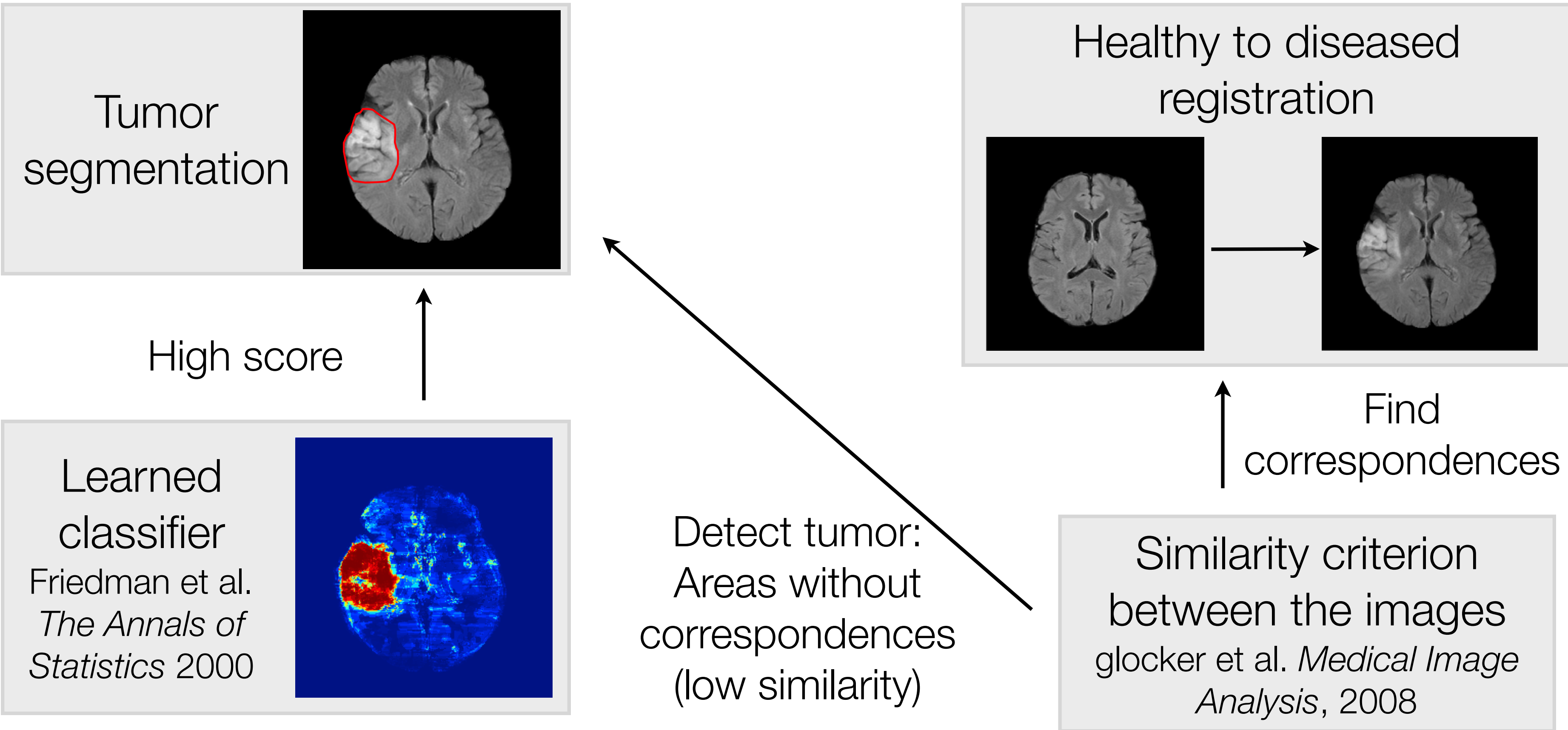

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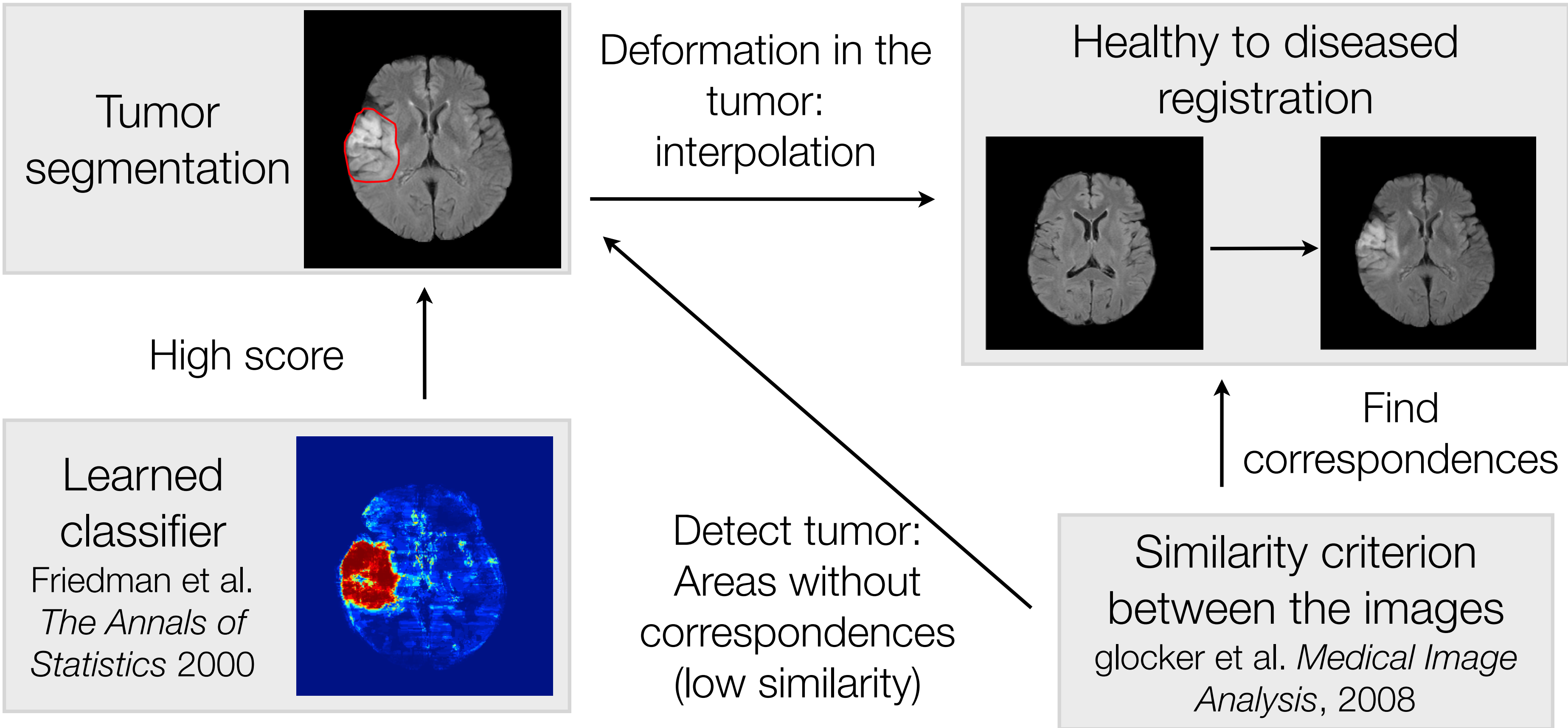

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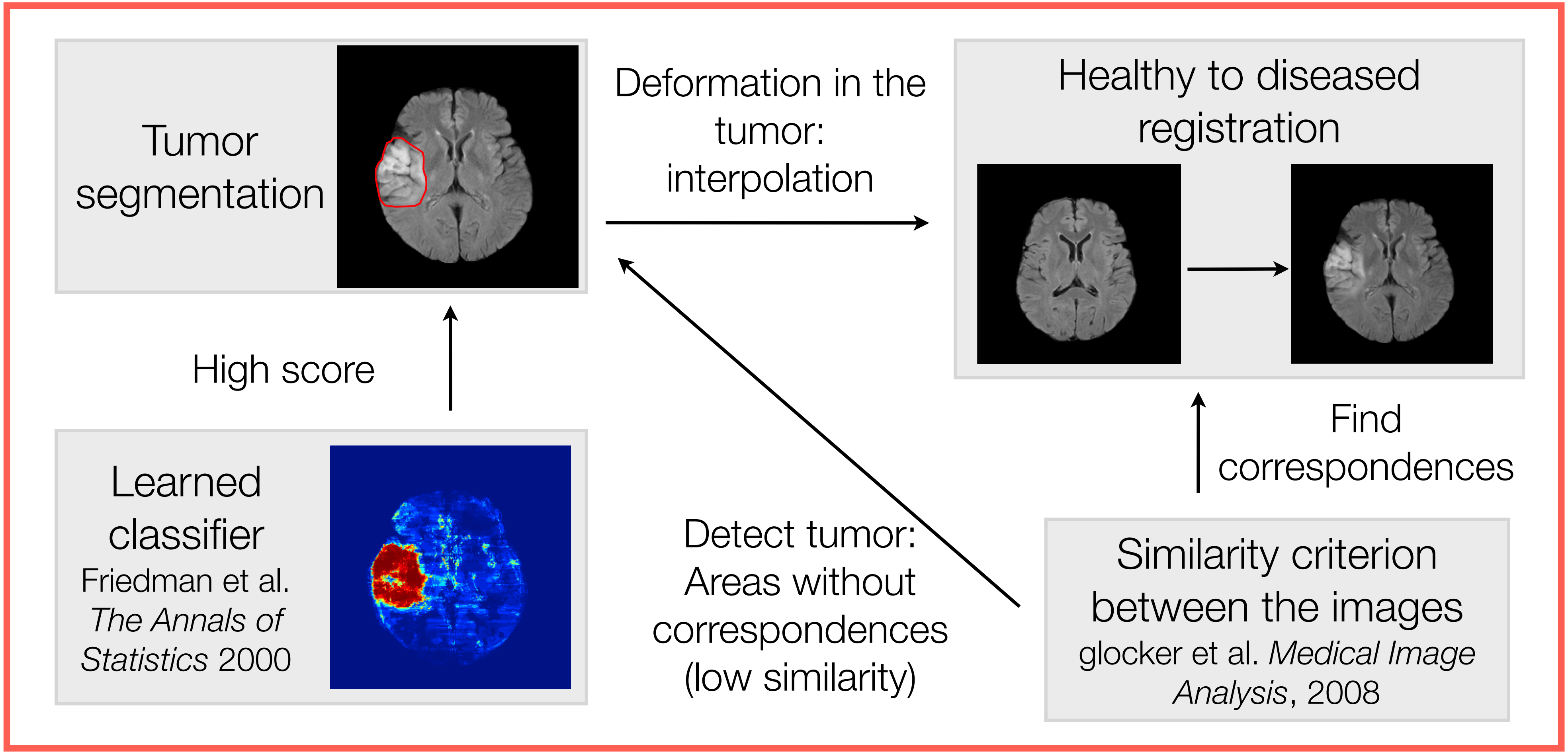
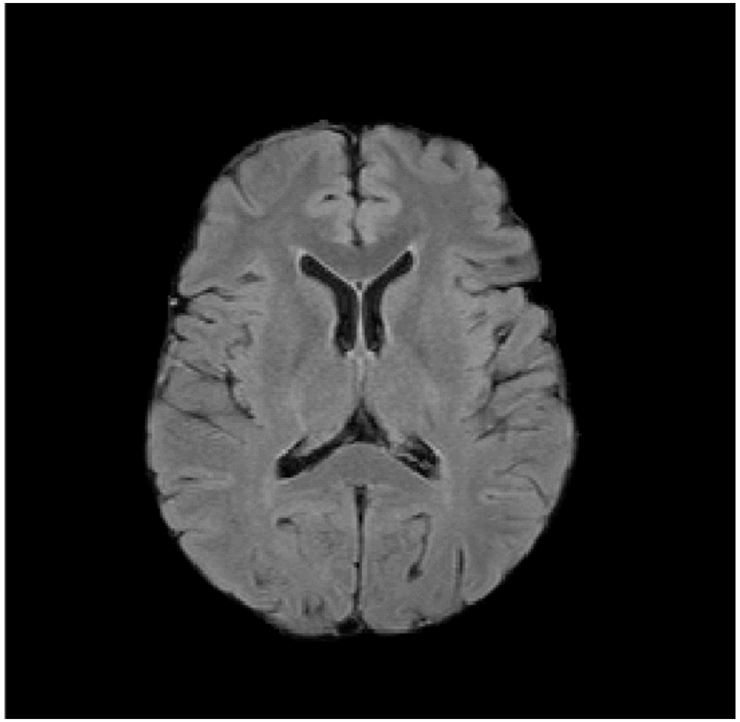


Discrete Markov Random Field Formulation

Parametrization

A



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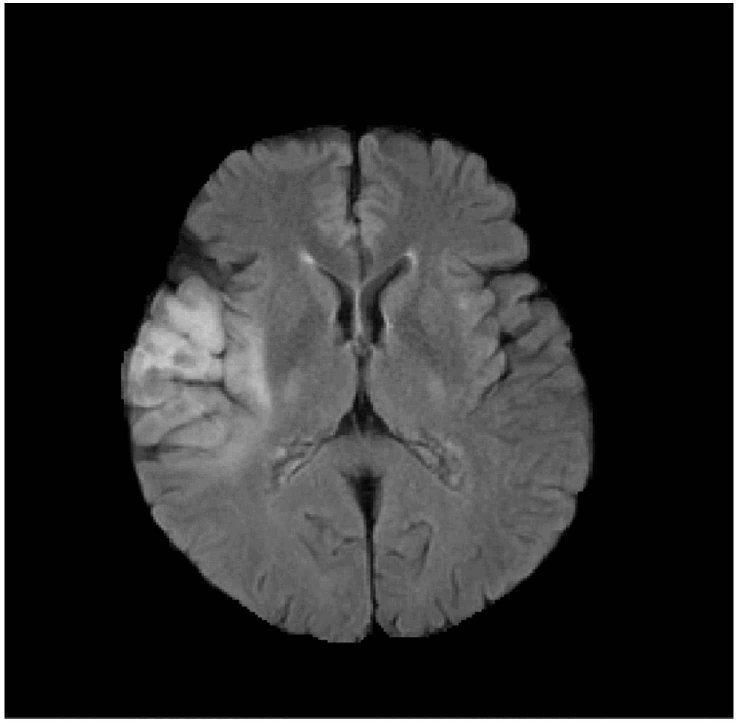

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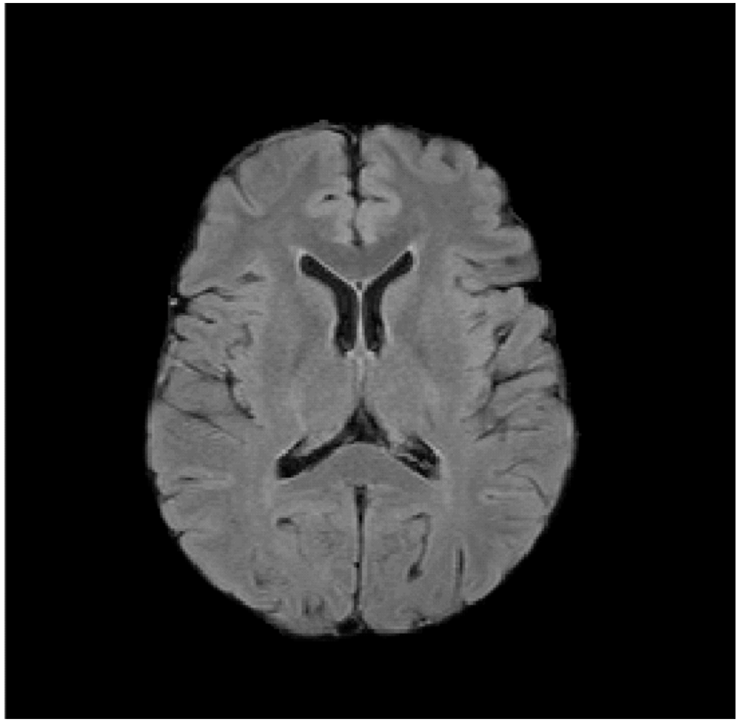

Deformation field

$$\mathcal{T}(\mathbf{x})$$

$$A \circ \mathcal{T}(\mathbf{x}) = I(\mathbf{x})$$

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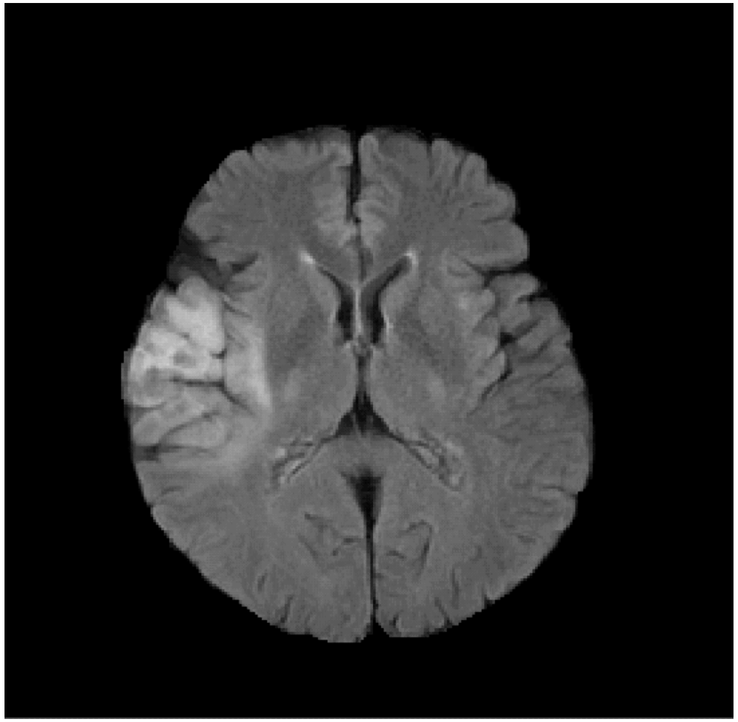

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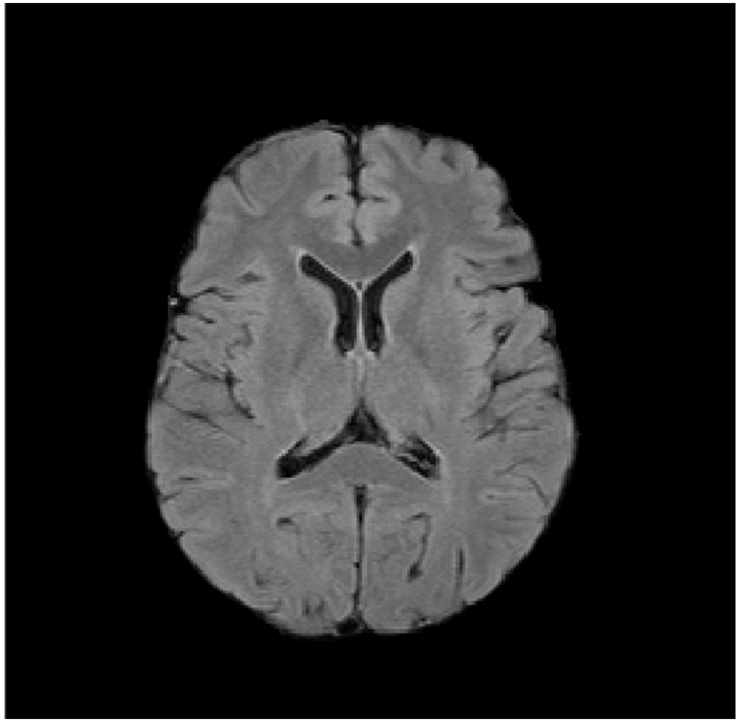

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$$\mathcal{S}(\mathbf{x})$$

Segmentation map

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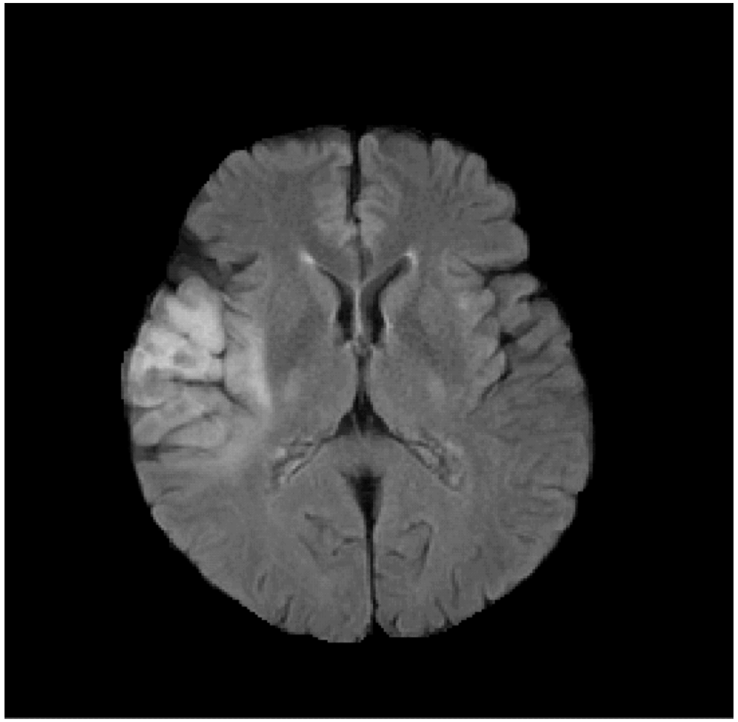

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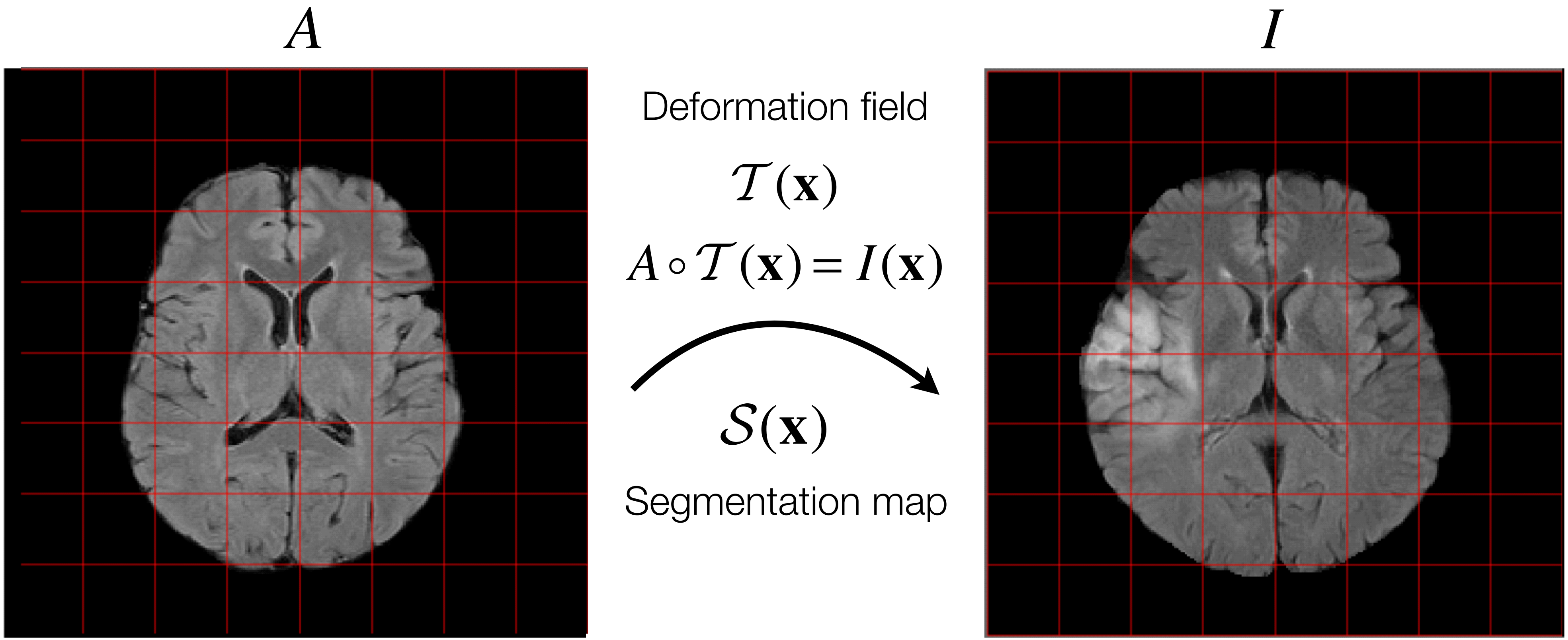

- *Free form deformation* approach:
  - Deformation and Segmentation estimated on a grid $\mathcal{G}$ superimposed to the images
  - Evaluation on the whole image by interpolation

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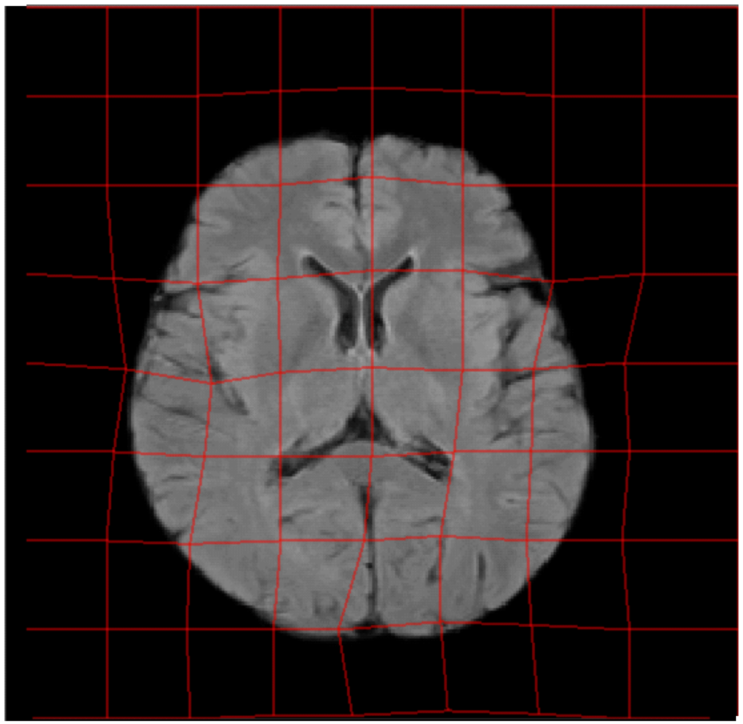

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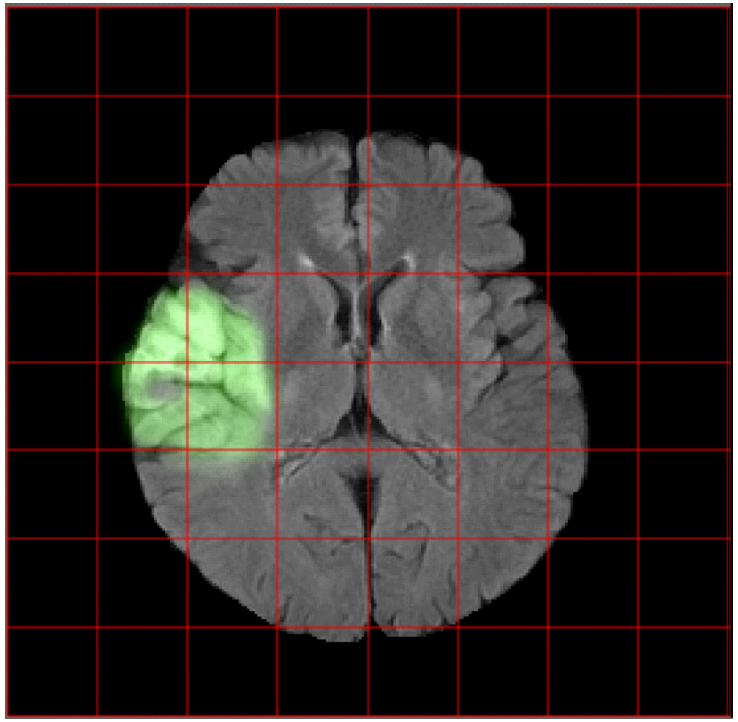

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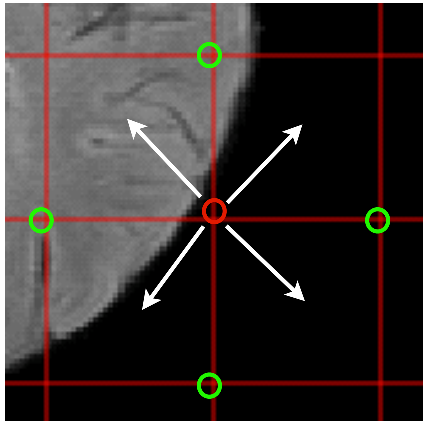
Markov Random Field Model

- Assign to each grid node p a label l_p corresponding to a pair segmentation (s^l) / displacement ($\mathbf{d}^l$)

$$l_p = \{s^{l_p}, \mathbf{d}^{l_p}\} \in \{0,1\} \times \{\mathbf{d}^1, \ldots, \mathbf{d}^k\}$$



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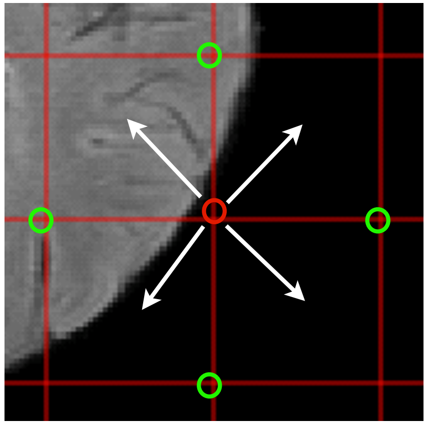
Discrete displacement set



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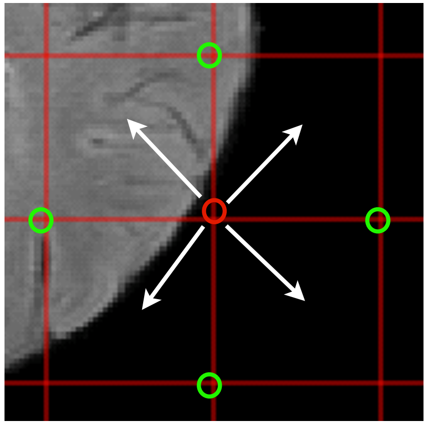
  Evaluate the optimal segmentation and displacement in a one shot optimization



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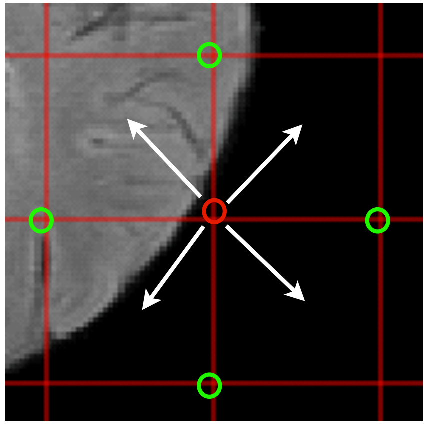

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- Markov Random Field Energy

$$E_{def,seg}(l) = \frac{1}{|\mathcal{G}|} \sum_{p \in \mathcal{G}} V_p(l_p) + \sum_{p \in \mathcal{G}} \sum_{q \in \mathcal{N}(p)} V_{pq}(l_p, l_q)$$

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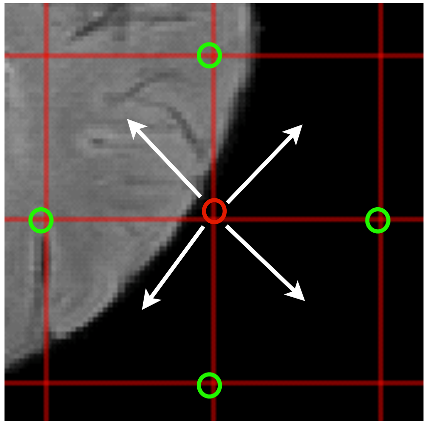

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- Pairwise term with neighbor nodes

Local consistency of the segmentation

Registration regularization

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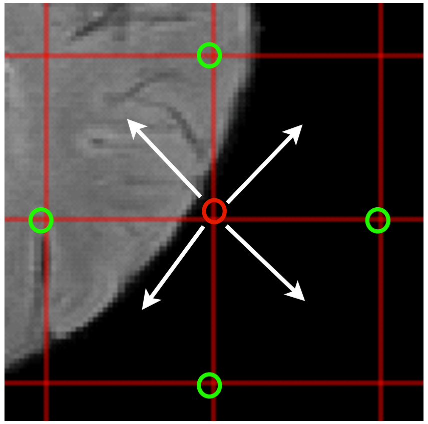

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- Unary term

$$V_p(l_p) = \alpha V_{def}(l_p) + (1-\alpha) V_{seg}(l_p)$$

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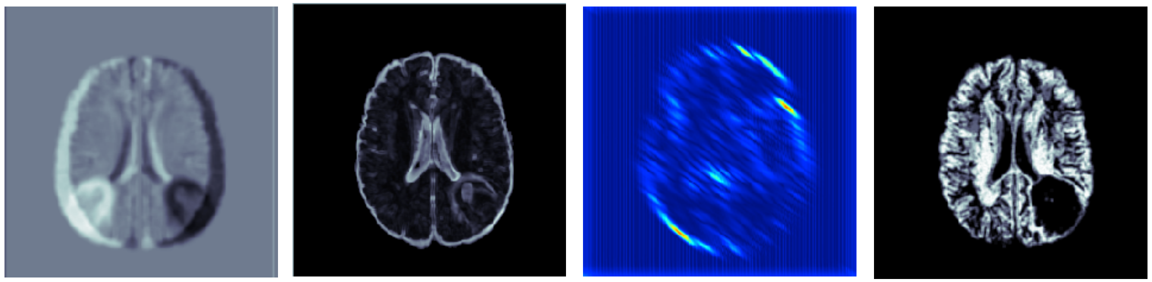
Unary Term: Segmentation

$$V_p(l_p) = \alpha V_{def}(l_p) + (1-\alpha)V_{seg}(l_p)$$

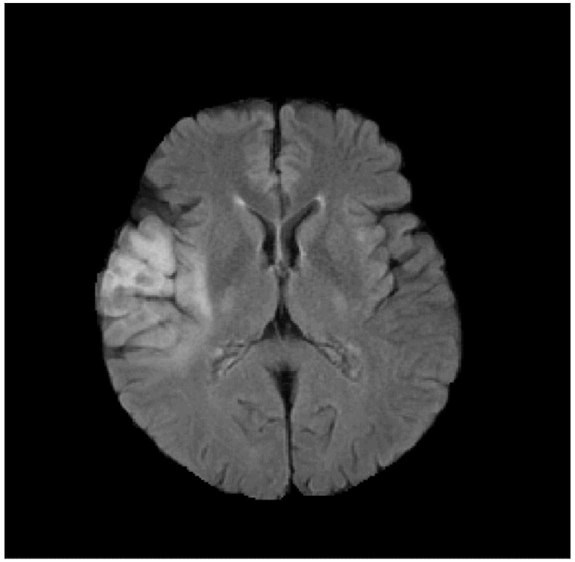
- Learning of a tumor vs background classifier
  - Features extracted from images

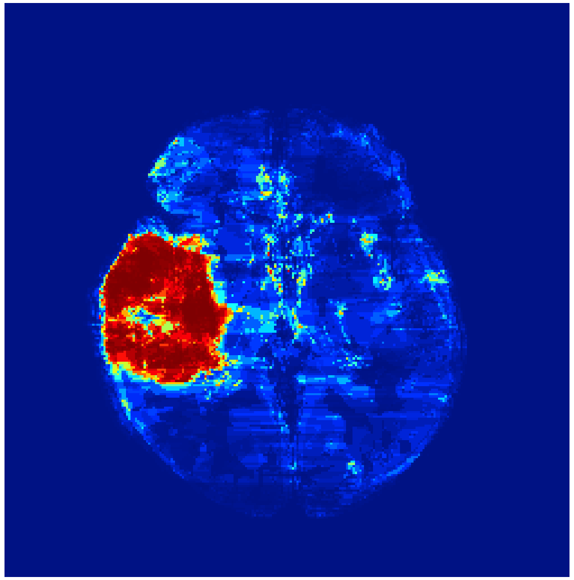


  - Gentle Adaboost algorithm

    Construction of a strong classifier as a combination of weak classifiers (decision stumps)

- Any classification technique can be used
- Nodes with high classification probability of being tumor should be labeled accordingly





Boosting probability map

Unary Term: Registration

$$V_p(l_p) = \alpha V_{def}(l_p) + (1-\alpha)V_{seg}(l_p)$$

$$\begin{cases} Sim\left(I(\mathbf{x}), A(\mathbf{x}+\mathbf{d}^{\mathbf{l_p}})\right) & \text{if } s^{l_p} = 0, \text{ Background} \\ C_{tm} & \text{if } s^{l_p} = 1, \text{Tumor} \end{cases}$$

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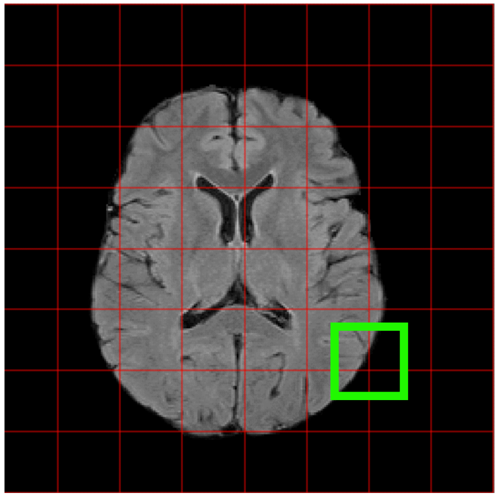
- Outside the tumor area: Find correspondences

Compute the similarity measure for all possible displacements



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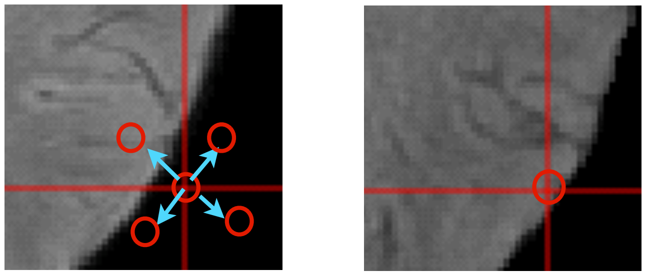

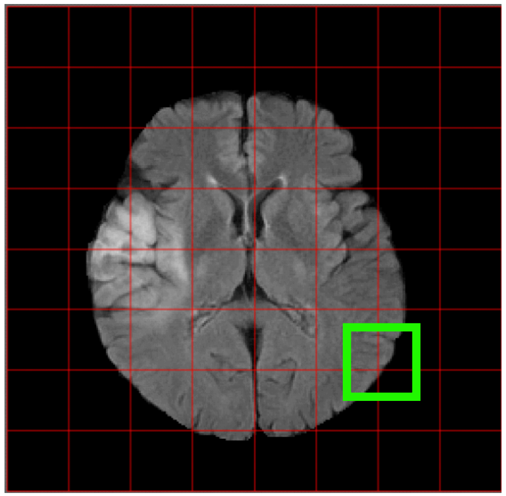

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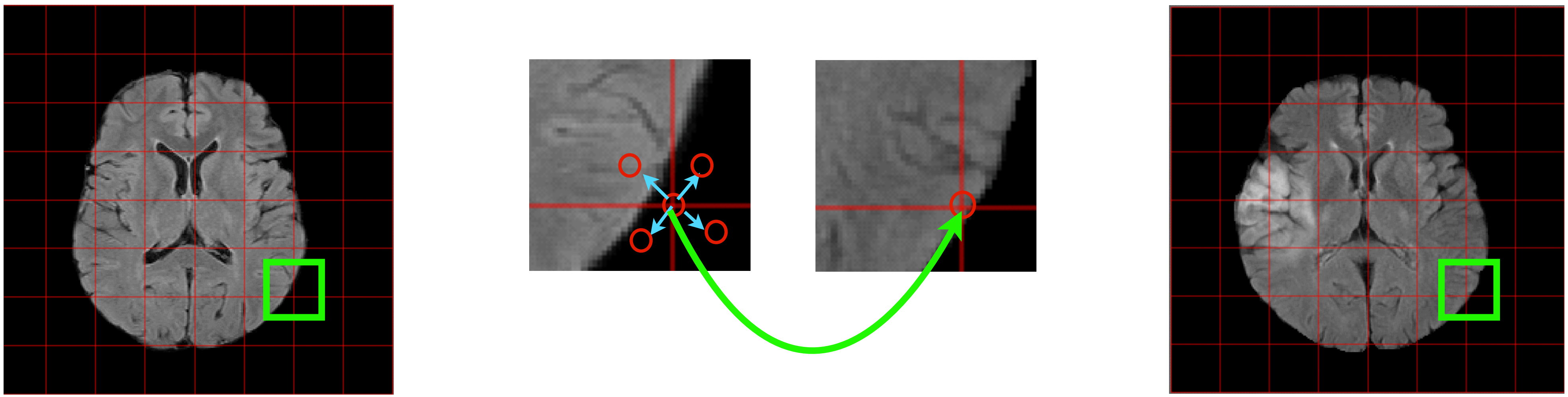

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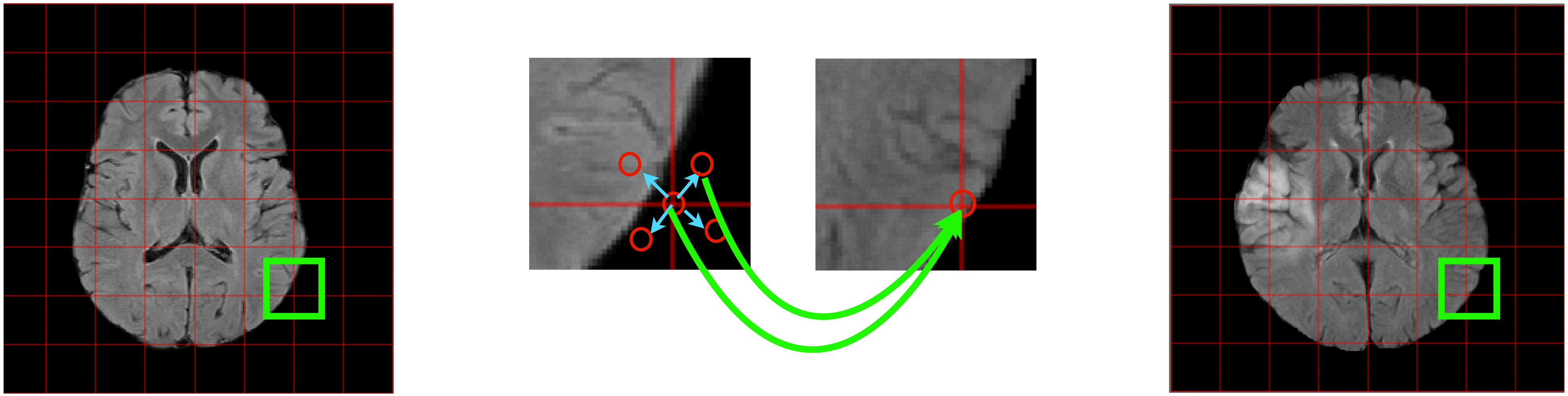

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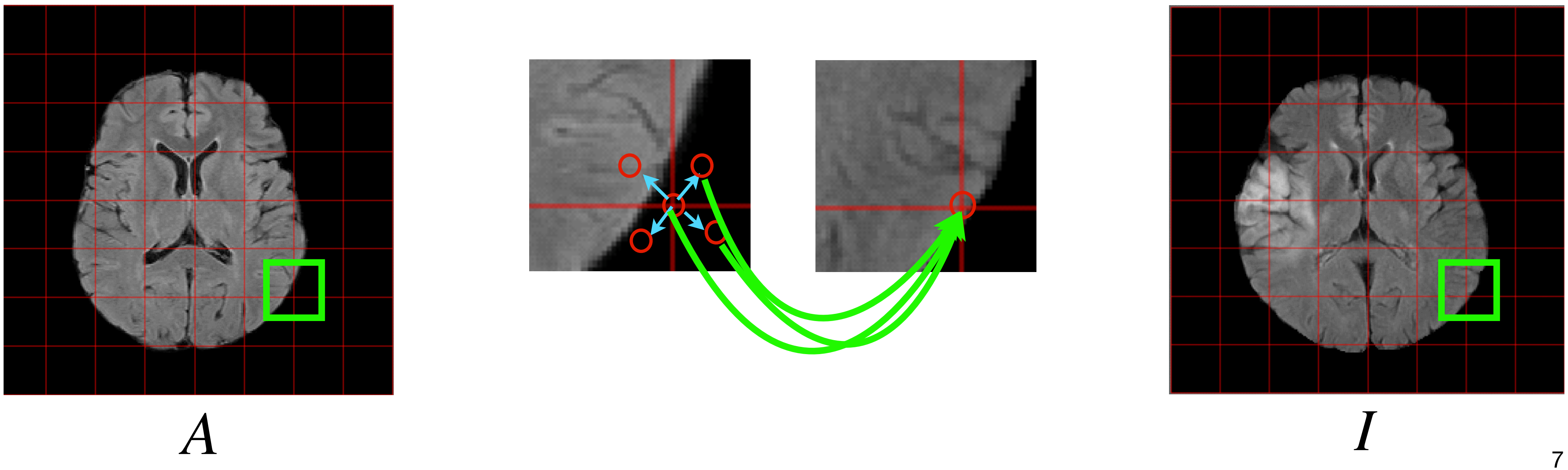

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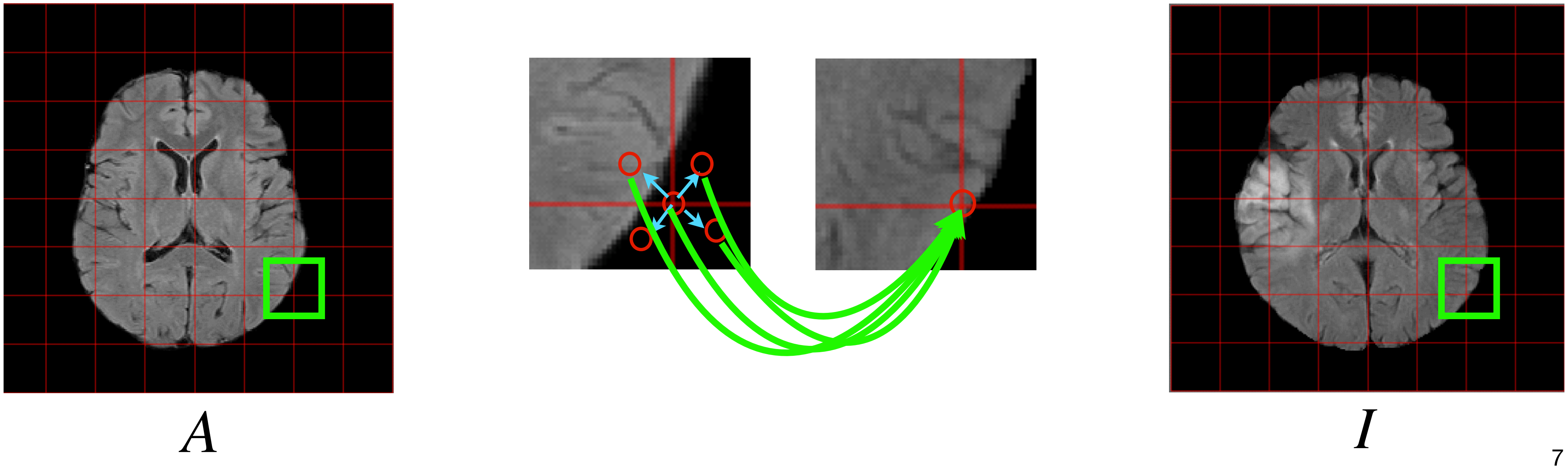

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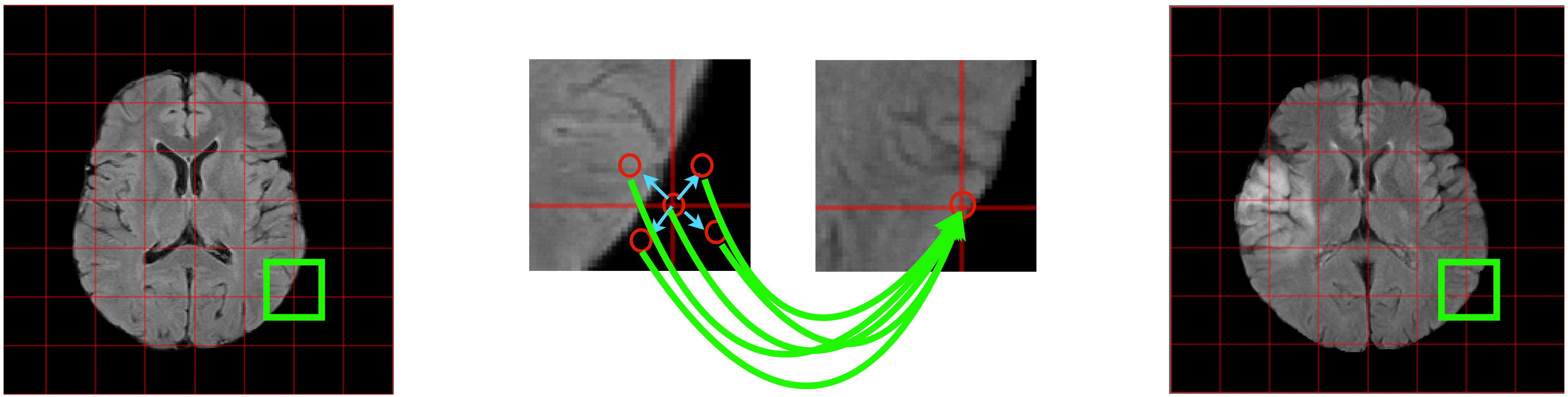

A

Similarity measure $Sim(I(\mathbf{x}), A(\mathcal{T}(\mathbf{x})))$

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Any kind of similarity criterion

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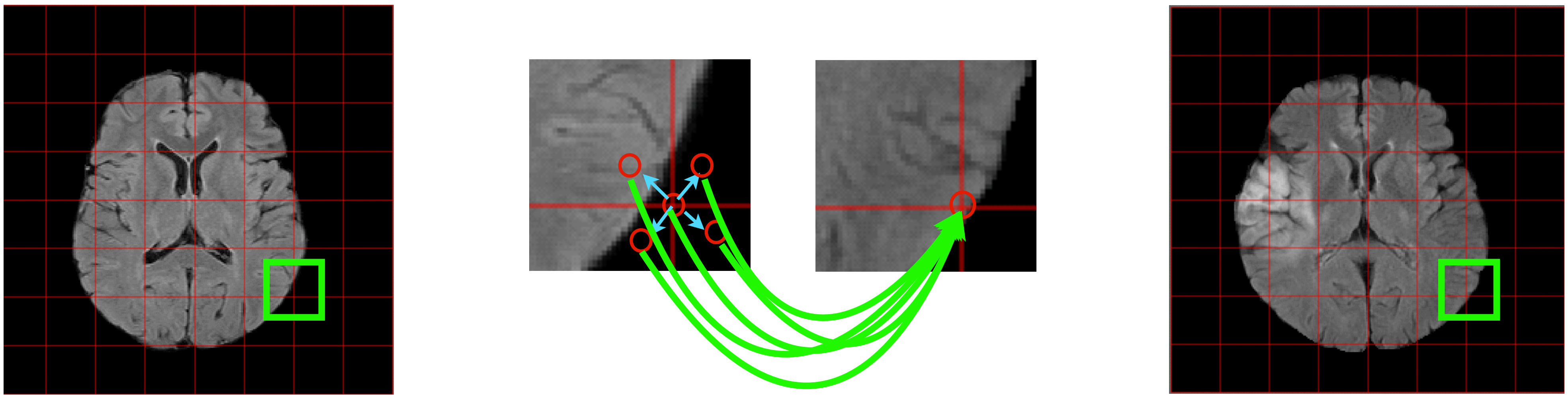

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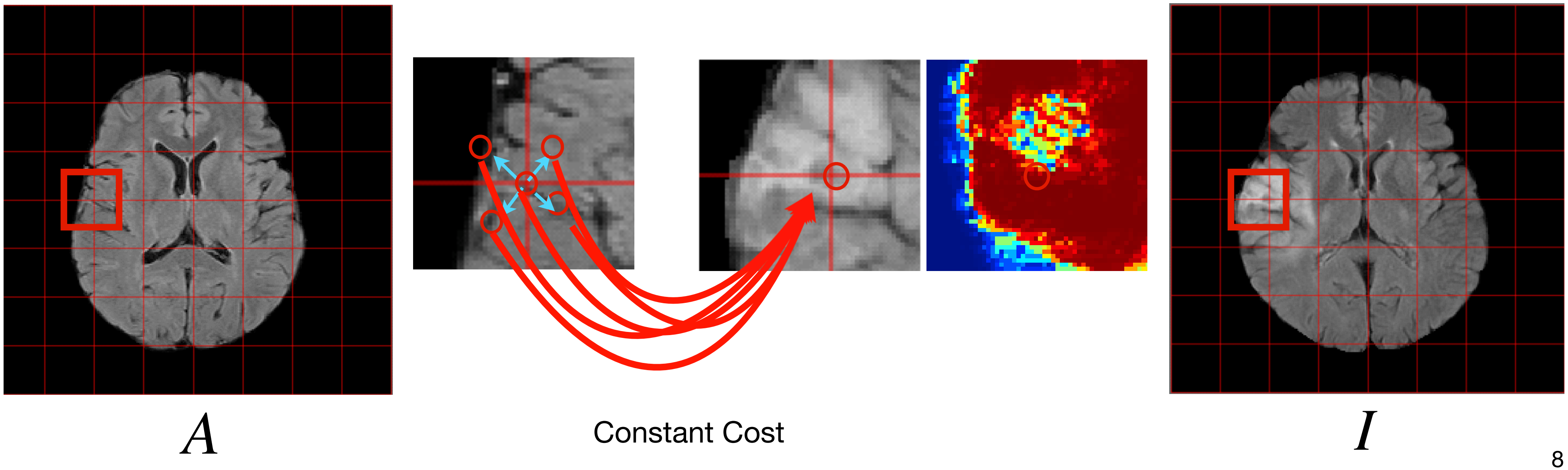
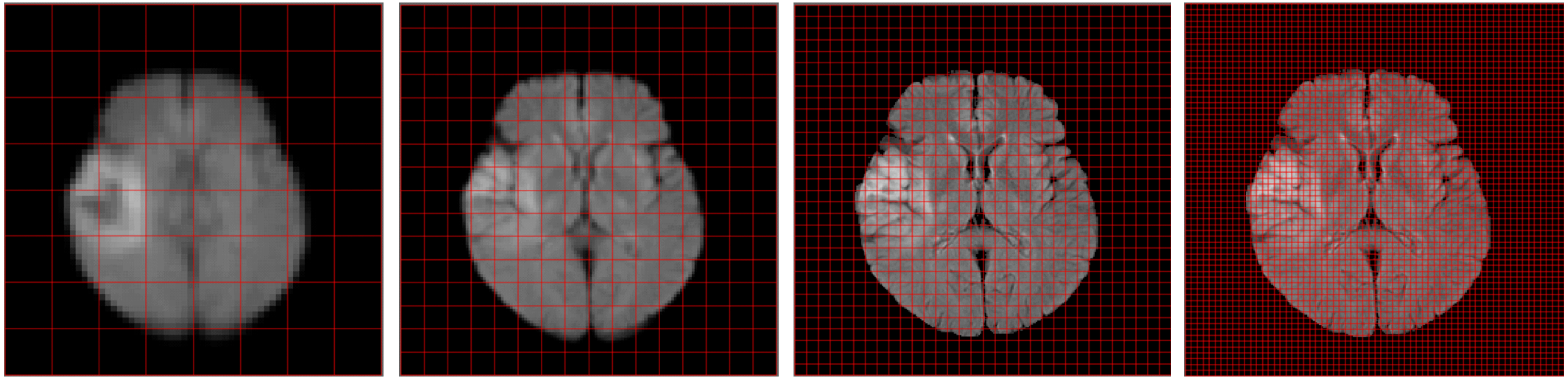
- In the tumor area: No correspondences

Constant cost independent of the displacement



Implementation

- Incremental Approach
    - 3 image levels, 4 grid resolutions

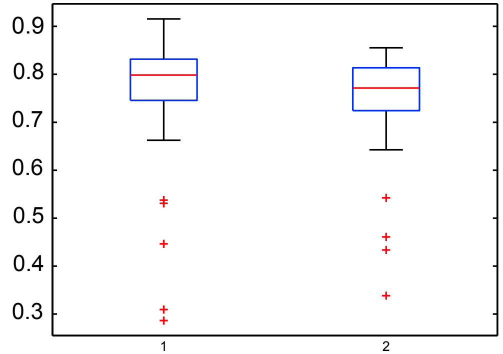


    - Increasing influence of the segmentation (progressive diminution of α value)
- Optimization
    - Linear programming (Komodakis et al. CVIU, 2008)
- Overall run time: 6 min (matlab implementation)

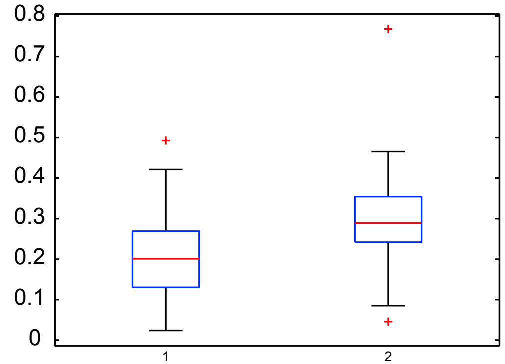
Experimental Validation

- Database: 97 T2 FLAIR volumes
  - Data likelihood learned on 40 volumes
  - Evaluation on 57 volumes
- Segmentation
  - Evaluated w.r.t manual segmentations
  - Compared with boosting classification with added pairwise smoothing (right on boxplots)
  - Median Dice: 77 to 80%, False positives: 30 to 20%, Mean Absolute Distance (MAD): 4.8 to 4.2mm
- Registration
  - Qualitative evaluation
  - Compared with Glocker et al. 2008, with masked pathology

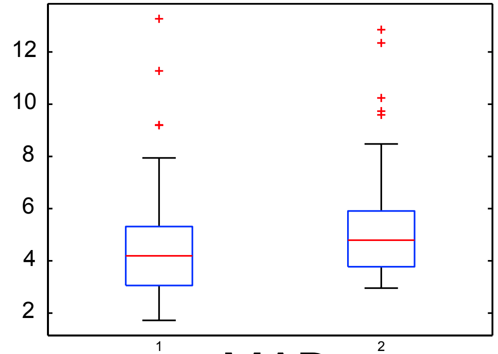
Our method Boosting



Dice Score



False positive rate



MAD

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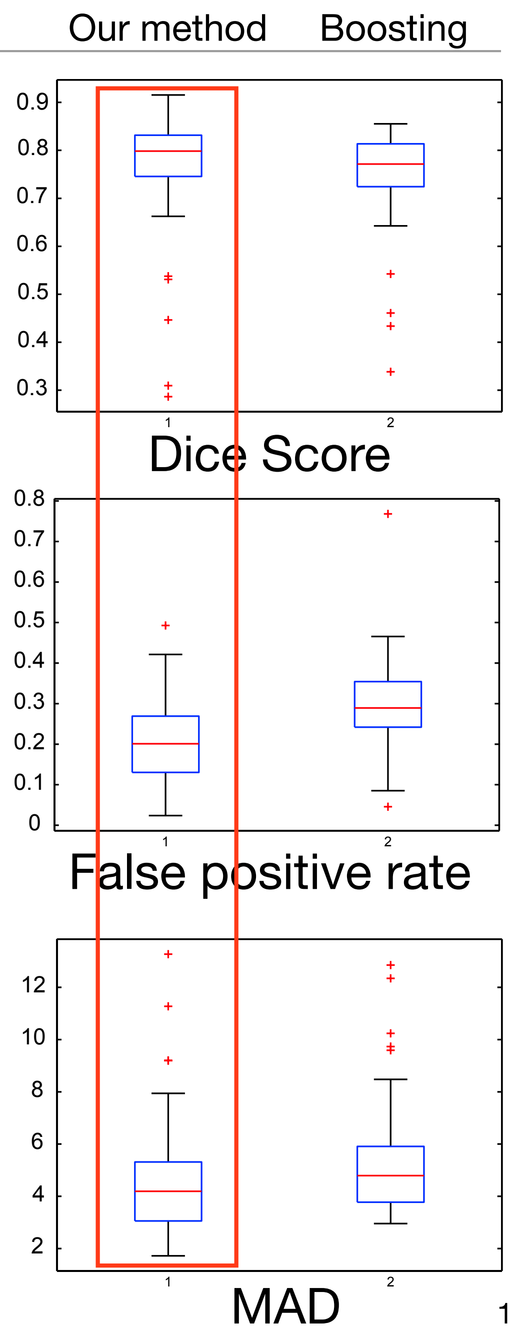
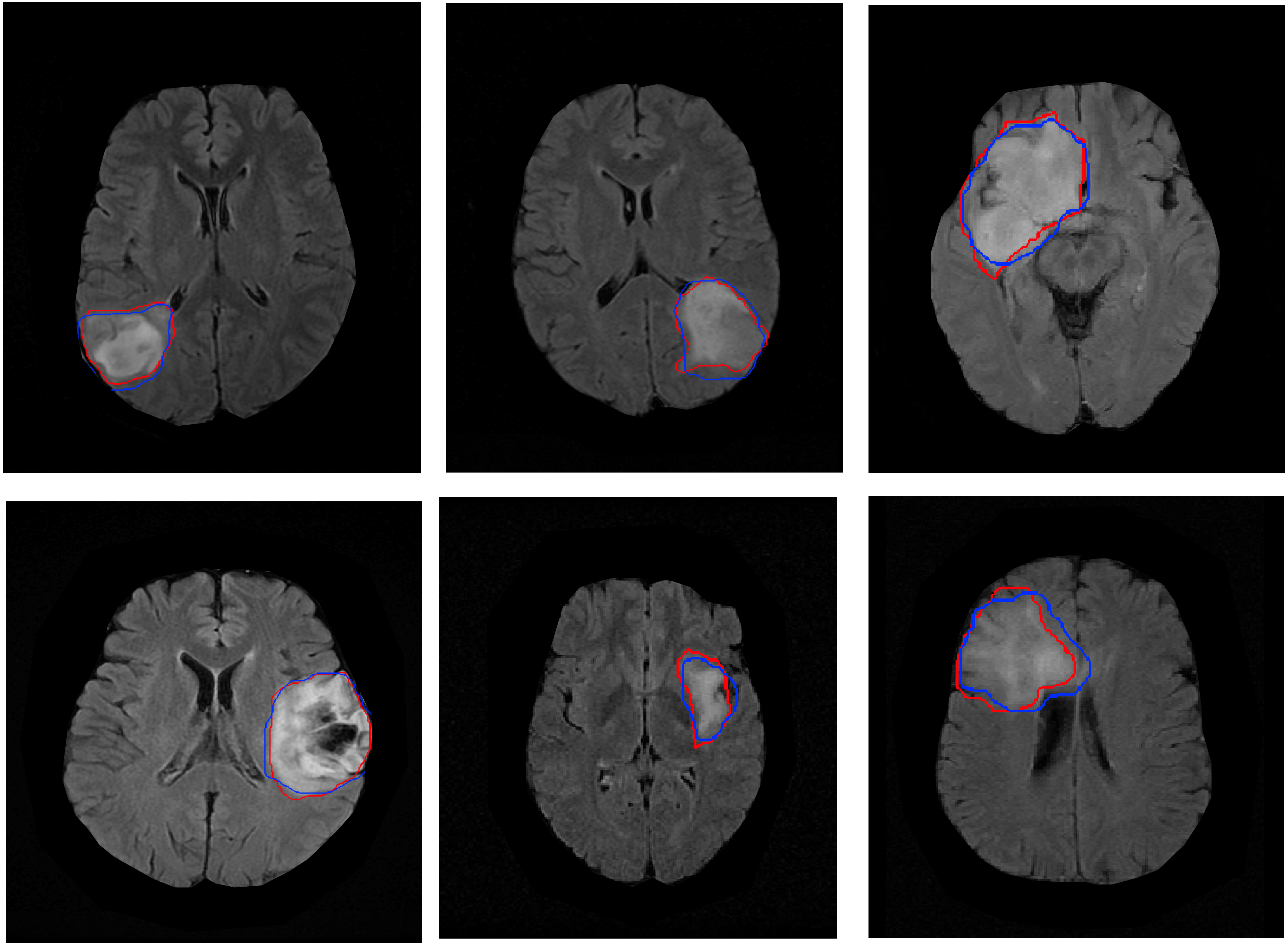
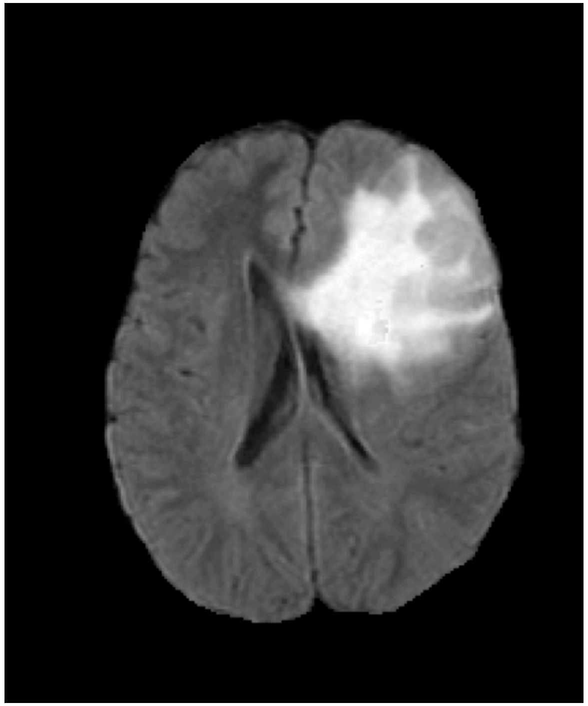
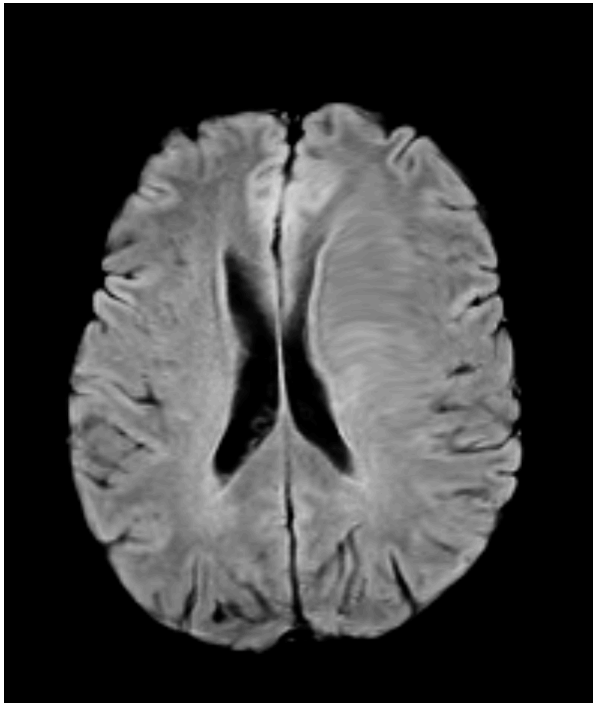




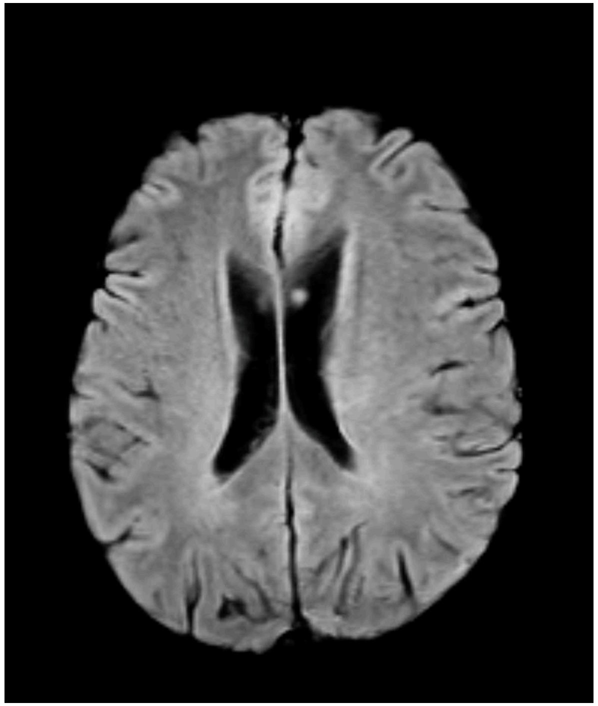
Red: Ground truth Blue: Automatic segmentation



Original image



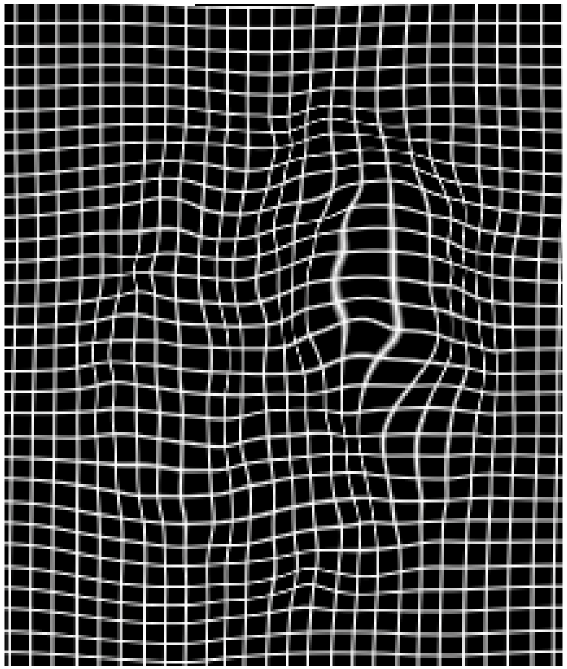
Glocker et al. 2008
Deformed image

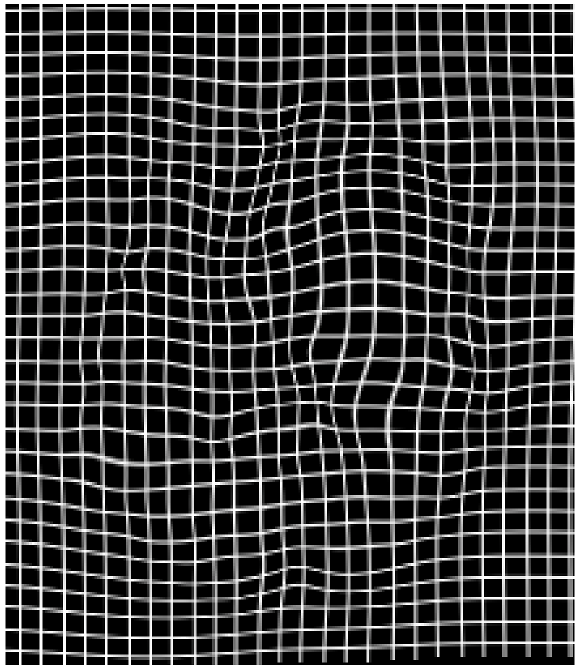


Our method
Deformed image

Left:
Glocker 08
Deformation field

Right
Our method
Deformation field





Conclusion

- Simultaneous registration and segmentation method
- Modular w.r.t image modality, similarity criterion and classification technique
- Can be adapted to any clinical context
- Fast and efficient optimization (ongoing work to reduce the run time to a few seconds)
- State of the art results
- Future work
  - Local spatial position prior information
  - Registration uncertainties
  - Adaptation to registration/segmentation before and during surgery with tumor resection

Poster *Th-1-AG-14*

Thursday 13:30-15:00

Thank you for your attention

Questions?