Non-rigid Registration with Missing Correspondences in Preoperative and Postresection Brain Images

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MICCAI

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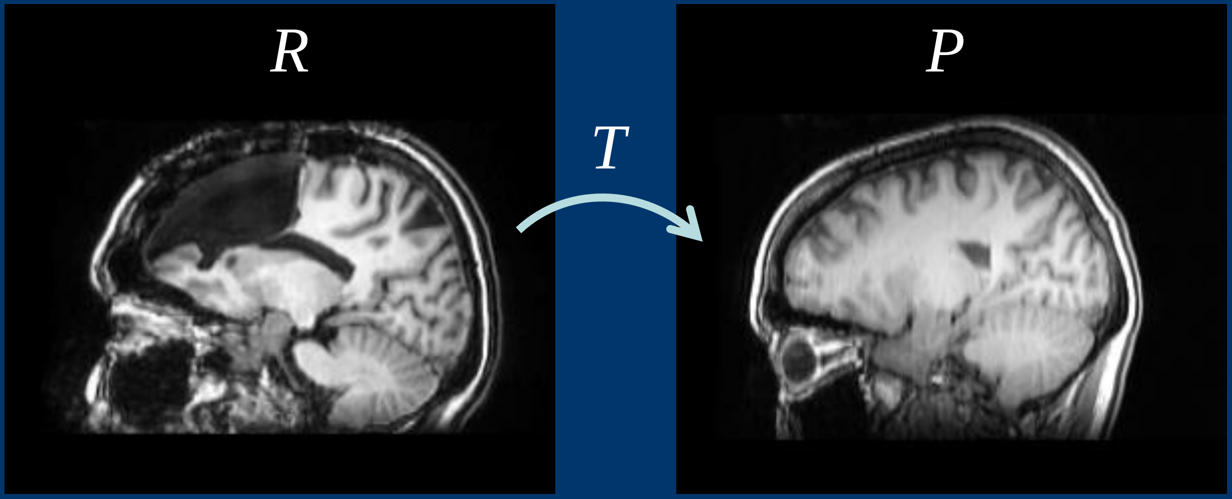
Image Registration Goal

- Align postresection and preoperative brain MRI of epilepsy patients



- Challenge: Missing Correspondences
  - Cause misalignment of other actual corresponding features

Approaches to Handle Missing Correspondences

Previous Methods

- Adapted demons registration + level set segmentation of resection[1]
- "De-enhance" DCE-MRI before registration[3]
- Estimate registration and missing data assuming equal chance of missing/valid label[4]
- Spatial prior on valid tissue/resection locations for post-resection images[5]

Our Approach

→ Jointly register and classify correspondence regions in statistical parameter estimation framework[2]

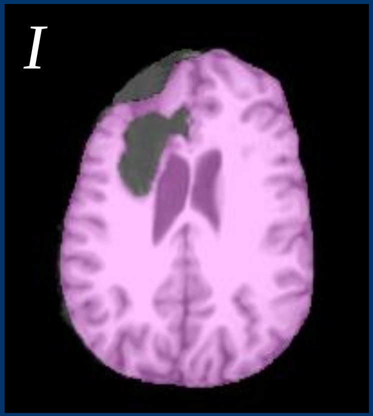
→ Put less weight on voxels believed to be missing correspondence

→ Include intensity prior on resection voxels

[1]Risholm et al., IPMI 2009; [2]Pohl et al., Neuroimage 2006; [3]Zheng et al., MICCAI 2007; [4]Periaswamy and Farid, MedIA 2006; [5]Chitphakdithai and Duncan, ISBI 2010

Registration and Indicator Map Estimation (RIME): Overview

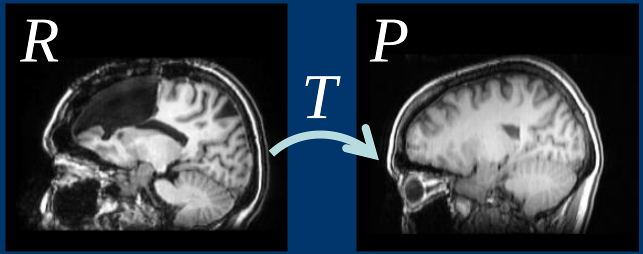
- Introduce "hidden" indicator map to segment valid tissue, resection, and background



  - Given indicator map
    → easier registration problem
  - Given correct alignment
    → easier to classify regions

- Maximum a posteriori framework:

$$\hat{T} = \arg\max_{T} \log \sum_{I} p(T, I \mid P, R)$$



Registration and Indicator Map Estimation (RIME): EM Algorithm

- E-Step: Indicator Map Estimation

$$\overbrace{p\left(I(\mathbf{x})=l \mid P,R,T^k\right)}^{\text{E-Step Weights}}=\frac{\overbrace{p\left(P\left(T^k(\mathbf{x})\right) \mid R, I(\mathbf{x})=l, T^k\right)}^{\text{Similarity Term}}\overbrace{p\left(R(\mathbf{x}) \mid I(\mathbf{x})=l\right)}^{\text{Intensity Prior}}}{\sum_{l'} p\left(P\left(T^k(\mathbf{x})\right) \mid R, I(\mathbf{x})=l', T^k\right) p\left(R(\mathbf{x}) \mid I(\mathbf{x})=l'\right)}$$

- M-Step: Registration

$$T^{k+1}=\arg\max_T \sum_{\mathbf{x}\in R}\sum_{l\in L}\overbrace{p\left(I(\mathbf{x})=l \mid P,R,T^k\right)}^{\text{E-Step Weights}}\Big[\log \overbrace{p\left(P\left(T(\mathbf{x})\right) \mid R, I(\mathbf{x})=l, T\right)}^{\text{Similarity Term}}$$

$$+\log \underbrace{p\left(R(\mathbf{x}) \mid I(\mathbf{x})=l\right)}_{\text{Intensity Prior}}\Big]+\log \underbrace{p(T)}_{\text{Transformation Prior}}$$

Probability Models: Likelihood

- Likelihood $p\left(P\left(T\left(\mathbf{x}\right)\right)|\,R,I\left(\mathbf{x}\right)=l,T\right)$ acts like the similarity metric
- Key: For different indicator values, can use different probability models

$$P\left(T\left(\mathbf{x}\right)\right)|\,R,T,I\left(\mathbf{x}\right)=l \sim \begin{cases} Unif\left(1/c\right) & ,l = \text{resection} \\ N\left(R\left(\mathbf{x}\right),\sigma_1\right) & ,l = \text{valid tissue} \\ N\left(R\left(\mathbf{x}\right),\sigma_2\right) & ,l = \text{background} \end{cases}$$

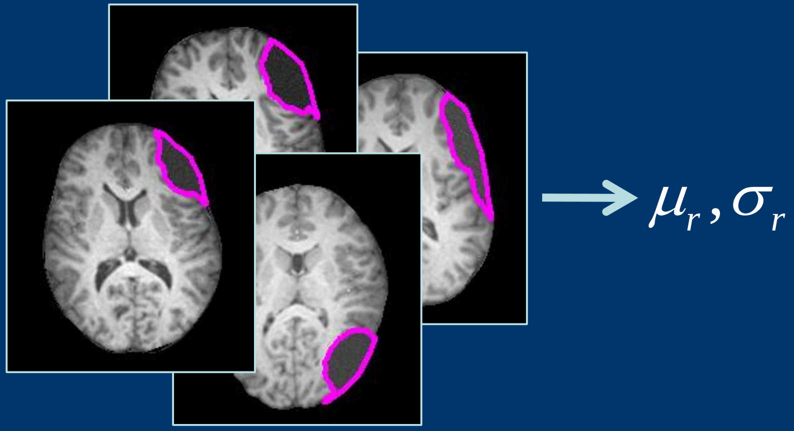
- Choose $c = \text{number of intensity levels}$
  $\sigma_2 > \sigma_1$

Probability Models: Intensity Prior

- $p\left(R(\mathbf{x}) \mid I(\mathbf{x}) = l\right)$ incorporates prior knowledge of intensities in postresection image

$$R(\mathbf{x}) \mid I(\mathbf{x}) = l \sim \begin{cases} N(\mu_r, \sigma_r) & , l = \text{resection} \\ Unif\left(\tfrac{1}{c}\right) & , l = \text{valid tissue} \\ N(0, \sigma_b) & , l = \text{background} \end{cases}$$

- Use training set of manually segmented postoperative images to estimate resection class parameters

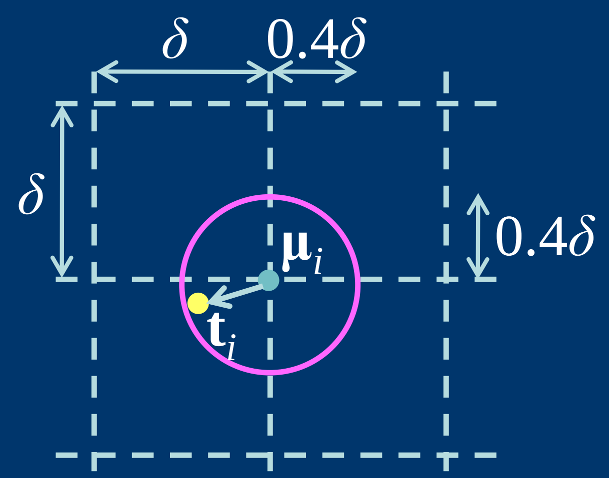


Probability Models: Transformation Prior

- Chose free form deformations (FFDs) based on uniform cubic B-splines
- Assume control points $\mathbf{t}_i$ and components $t_{i,j}$ independent with spacing δ

$$p(T) = \prod_i \prod_j p\left(t_{i,j}\right) \qquad t_{i,j} \sim N\left(\mu_{i,j}, \frac{0.4\delta}{3}\right)$$

- Restrict control points to lie within sphere of radius 0.4δ for injective transformation[1]



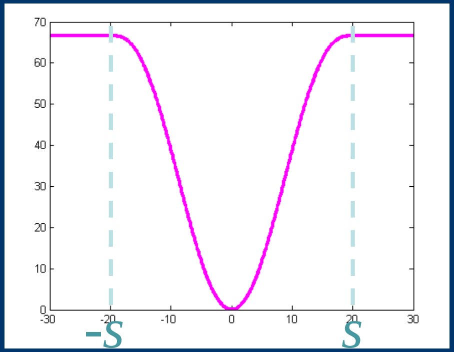
[1]Greene et al., MedIA 2009

Registration Methods for Comparison

- "Standard" non-rigid registration (SNRR) using
  - Uniform cubic B-spline FFDs[1]
  - Sum of squared differences (SSD) similarity
- Robust SSD similarity metric (RTR):

  $\rho_s\left(R(\mathbf{x}) - P\left(T(\mathbf{x})\right)\right) \sim N(0,\sigma)$, ρ is Tukey function

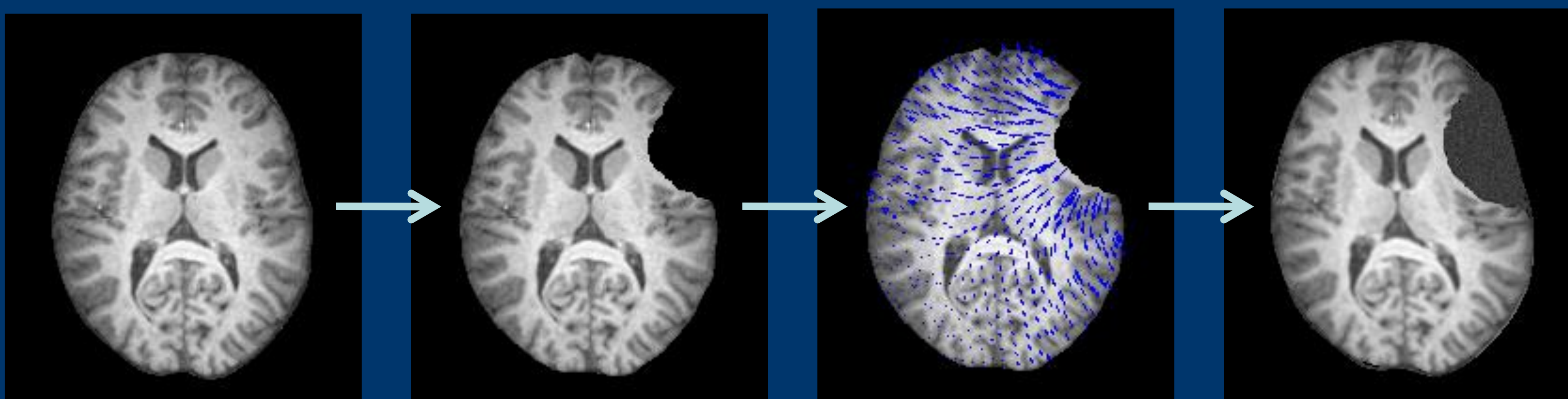
Tukey function with scaling parameter s



[1]Rueckert et al., TMI 1999

Synthetic Data: Experimental Setup

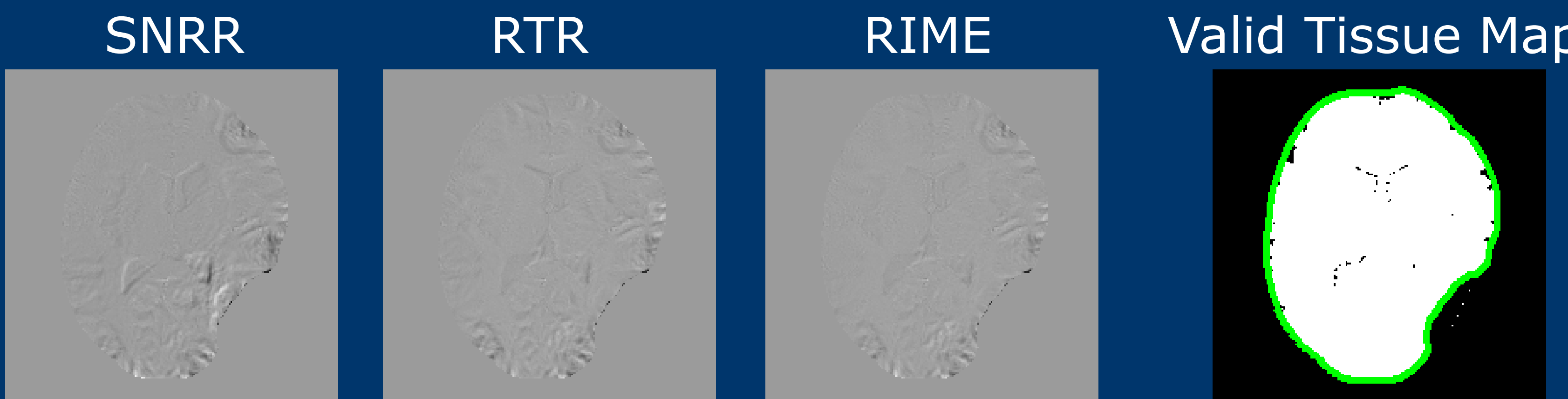
- Synthetic Image Creation:



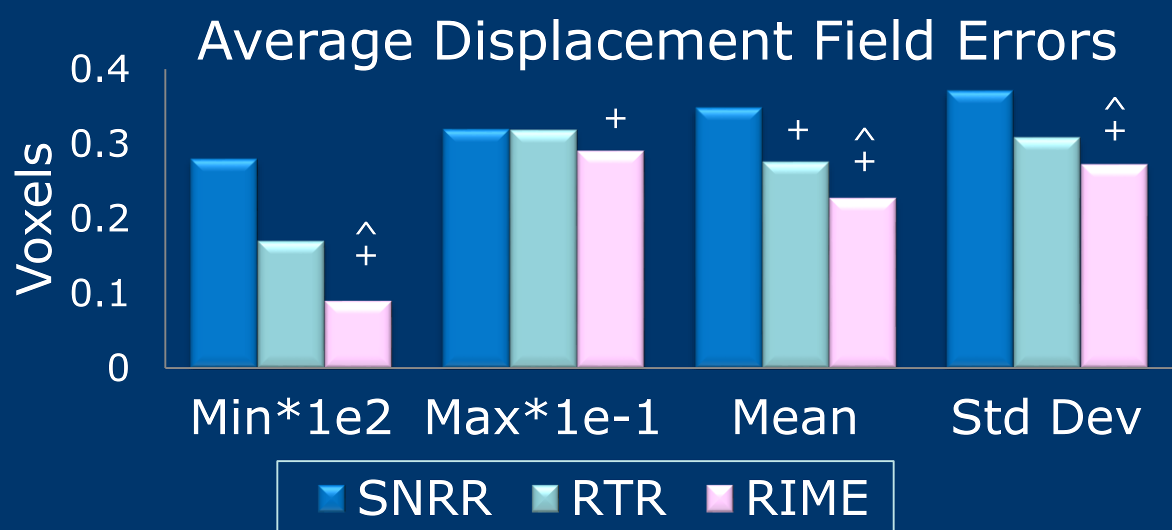
Preoperative (real image slice) | Voxels removed for “resection” | Simulated deformation field | Final Postresection

- Leave-one-out validation: train intensity prior on 10 images

Synthetic Data: Registration Results



Average dice: 0.98

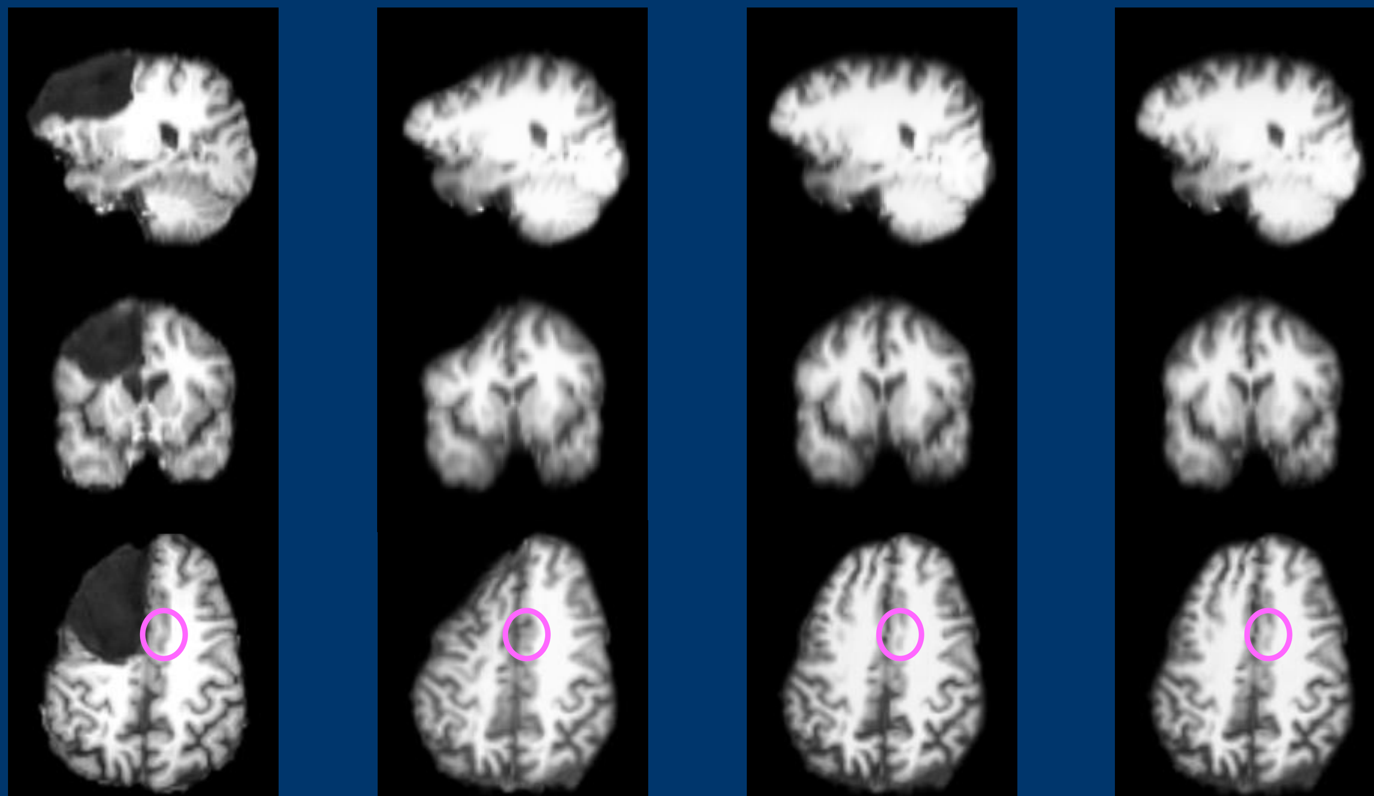


+ Significant compared to SNRR

^ Significant compared to RTR

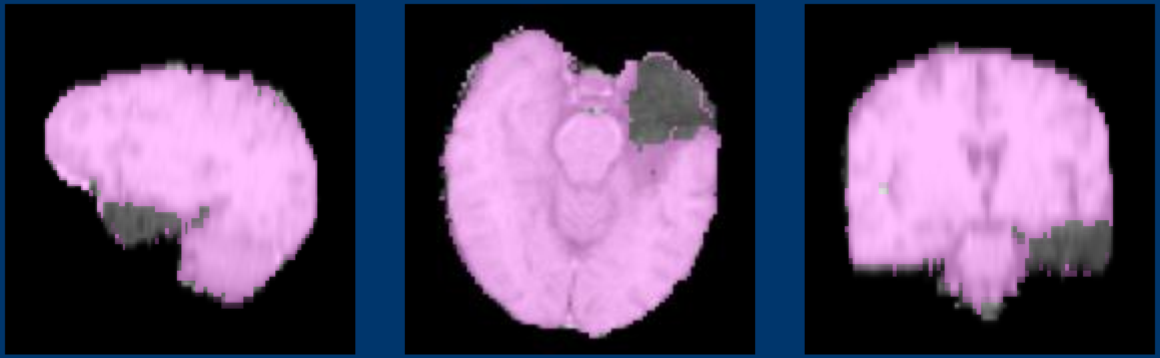
Real Data: Registration Results

Postresection	SNRR	RTR	RIME



Average Landmark Errors (6 datasets)	2.69 mm	2.16 mm	1.27 mm

Real Data: Indicator Map Estimation



Left temporal lobe resection
Pink = valid correspondences, Grey = resection

- Average dice coefficient for valid correspondence estimate: 0.92
- Some mislabeling of valid correspondence voxels as resection

Conclusions and Future Work

- Contributions
  - Registration handles missing correspondences by incorporating “hidden” indicator map
  - Probabilistic framework allowed inclusion of prior on postresection intensity given the label
- Future Work
  - Image histogram-based likelihood model
  - Improve estimate of indicator map by incorporating spatial prior
    - Include knowledge of resection location
    - Smooth map estimate

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