Pairwise Registration of Images with Missing Correspondences Due to Resection

Nicha Chitphakdithai and James S. Duncan
Image Processing and Analysis Group, Yale University

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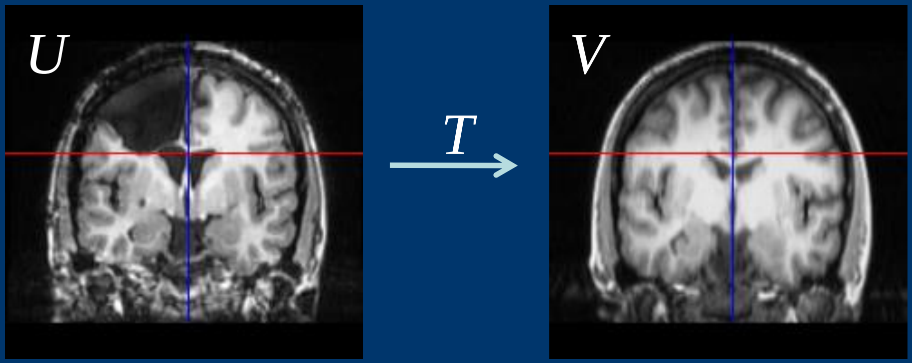
Yale University

The Image Registration Problem

- Goal: Find the transformation T to register postresection and preoperative brain images



- Motivation: Evaluation of epilepsy patients
- Why not use traditional registration methods?
  - Missing correspondences in resection volume
  - Possibly highly nonlinear deformations near resection site

Approaches to Handle Missing Correspondences

- Previous Methods
  - Hybrid similarity metric [Hartkens et al., MICCAI 2002; Papademetris et al., MICCAI 2004]
  - Directly model vast changes
    - Biomechanical models for brain deformation in tumor growth [Zacharaki et al., Trans BME 2008]
    - "De-enhance" contrast image [Zheng et al., MICCAI 2007]
    - Model for partial data [Periaswamy and Farid, MedIA 2006]
- Our Key Observations
  - Given valid correspondences, could use standard registration algorithm
  - Given registered images, could label missing correspondence regions

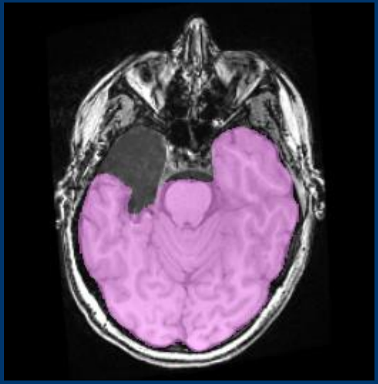
Jointly Estimate

MAP Registration Framework: Introducing the Indicator Map

- In maximum a posteriori framework, estimate

$$\hat{T} = \arg\max_{T} \log p\left(T \mid U, V\right)$$

- Consider “hidden” indicator map I on U
  - $I(\mathbf{x}) = 0$: no correspondence in V (resection voxel)
  - $I(\mathbf{x}) = 1$: valid tissue correspondence in V



- Marginalized MAP framework:

$$\hat{T} = \arg\max_{T} \log\left[\sum_{I} p\left(T, I \mid U, V\right)\right]$$

Applying the EM Algorithm: The M-Step

- Update the estimate for T using transformation T^k from the previous iteration:

$$T^{k+1} = \arg\max_T E_{I|U,V,T^k}\left[\log p\left(U,V \mid T,I\right) + \log p\left(T \mid I\right) + \log p\left(I\right)\right]$$

- Assume a set M of possible indicator maps I_m:

$$T^{k+1} = \arg\max_T \sum_{I_m \in M} p\left(I_m \mid U,V,T^k\right) \cdot \left[\log p\left(U,V \mid T,I_m\right) + \log p\left(T \mid I_m\right)\right]$$

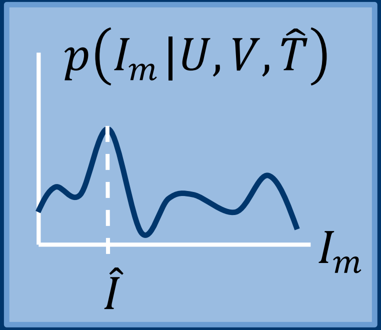
Applying the EM Algorithm: The E-Step

- Compute the probability of an indicator map given the images and current transformation estimate

$$p\left(I_m \mid U,V,T^k\right) = \frac{p\left(U,V \mid T^k, I_m\right) p\left(T^k \mid I_m\right) p\left(I_m\right)}{\sum_{I_{m'}} p\left(U,V \mid T^k, I_{m'}\right) p\left(T^k \mid I_{m'}\right) p\left(I_{m'}\right)}$$

- Final indicator map estimate:

$$\hat{I} = \arg\max_{I_m} p\left(I_m \mid U,V,\hat{T}\right)$$



Likelihood Models: Directly Comparing Intensities

- Assume voxels are independent
  → need models for $p\left(U(\mathbf{x}),V(T(\mathbf{x}))\mid T,I\right)$
- Probability distribution models
  - No correspondence: Uniform distribution
  - Valid correspondence: $U(\mathbf{x})-V(T(\mathbf{x})) \sim Normal(0,\sigma)$

$$p\left(U(\mathbf{x}),V(T(\mathbf{x}))\mid T,I\right)=\begin{cases} 1/c & ,\ I(\mathbf{x})=0 \\ \frac{1}{\sqrt{2\pi\sigma}}\exp\left(-\frac{\left[U(\mathbf{x})-V(T(\mathbf{x}))\right]^2}{2\sigma^2}\right) & ,\ I(\mathbf{x})=1 \end{cases}$$

where c = number of intensity levels

Likelihood Models: Correlation Coefficient (CC)

- Probability distribution models
  - No correspondence: no correlation, uniform distribution
  - Valid correspondence: higher probability with higher CC

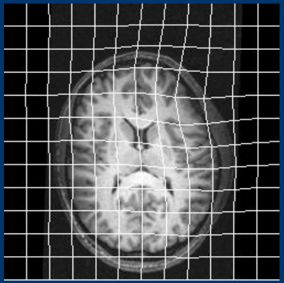
$$p\left(U(\mathbf{x}),V\left(T(\mathbf{x})\right)|T,I\right)=\begin{cases} k & ,I(\mathbf{x})=0 \\ \frac{1}{Z}\exp(\rho) & ,I(\mathbf{x})=1 \end{cases}$$

where $k=\frac{1}{Z}\exp(0)$

$Z=$ normalizing constant

$\rho=$ CC computed using only voxels where $I(\mathbf{x})=1$

Transformation Prior Given the Indicator Map



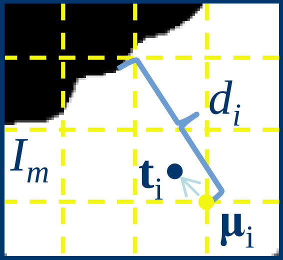
- Free-form deformation transformation model using uniform cubic B-Splines
- Assumptions
  - Control points $\mathbf{t}_i$ are independent
  - Control point components t are independent
  - Brain tissue may deform more near resection

→ Model $t \mid I_m \sim N\left(\mu, \sigma^2(d_i)\right)$

where $\mu =$ starting location of t on uniform grid

$\sigma^2(d_i) \propto \frac{1}{d_i}$

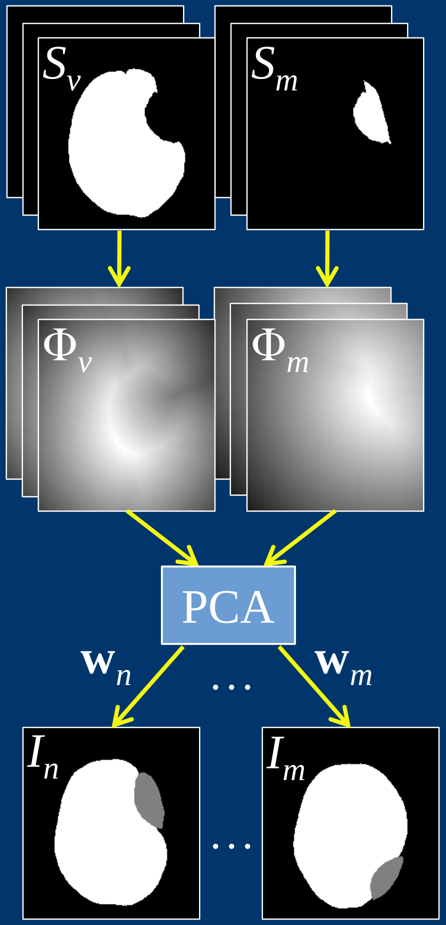
$d_i =$ distance between $\boldsymbol{\mu}_i$ and boundary of resection in I_m



Indicator Map Spatial Prior Model

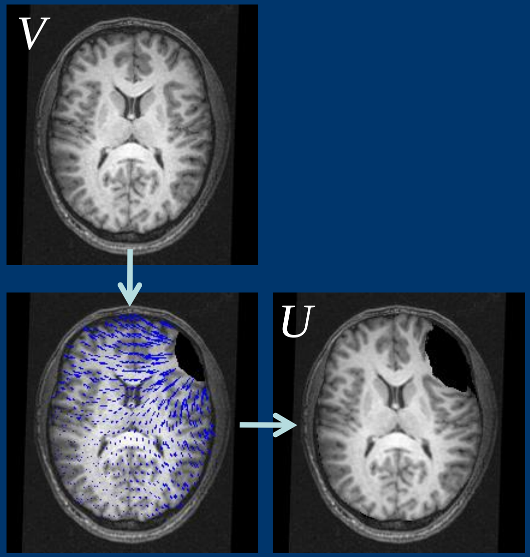
- Training Set Assumptions
  - Segmented valid (S_v) and missing (S_m) correspondence areas
  - Resections in similar area
- Use PCA to create shape model
  - Embed S in level set Φ
  - Model possible segmentations as
    $$\Phi = \bar{\Phi} + \sum_{i=1}^{q} w_i P_i$$
  - Represent map I by weights $\mathbf{w}$

  → Compute $p(I)$ using $\mathbf{w} \sim N\left(\mathbf{0}, \Sigma_q\right)$
- Indicator map library: constrain $\mathbf{w}$ to range governed by the eigenvalues



Results on Synthetic Data: Experimental Setup

- Synthetic Dataset Creation
  - Preoperative image
    - Slice from normal brain
  - Postoperative image
    - "Resected" tissue on left side
    - Warped using physical model
- Registration Setup
  - Likelihood model: direct intensity comparison
  - Leave-one-out cross-validation
- Compared to standard non-rigid registration (NRR) method [Rueckert et al., TMI 1999]
  - Implemented in BioImage Suite [Papademetris et al., www.bioimagesuite.org]

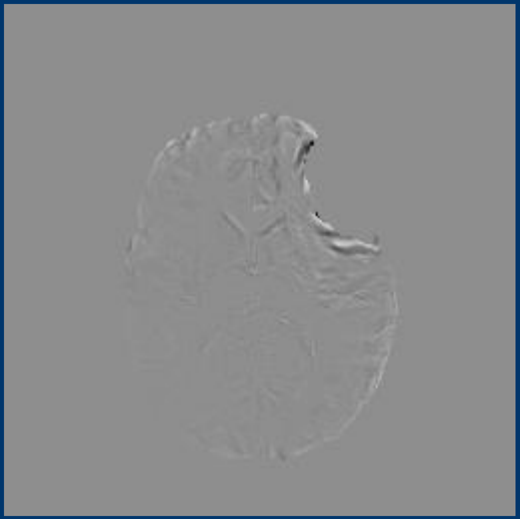


Results on Synthetic Data: Sample Difference Images

Standard NRR

- High errors especially near resection

Our Method



- Flatter overall
- Most improved near resection

Results on Synthetic Data: Displacement Field Errors

- Calculated error statistics between true displacements and displacements produced by registration algorithms
- Performed paired one-tailed t-tests

	Min	Max	Mean	Std Dev
Standard NRR	0.0022	4.2555	0.5361	0.6578
Our Method	0.0012	3.0010	0.3034	0.3360
p-value	< 0.03	< 0.0007	< 4E-5	< 2E-6

→ Our method reduced all displacement error statistics compared to standard NRR

Results on Real Data: Experimental Setup

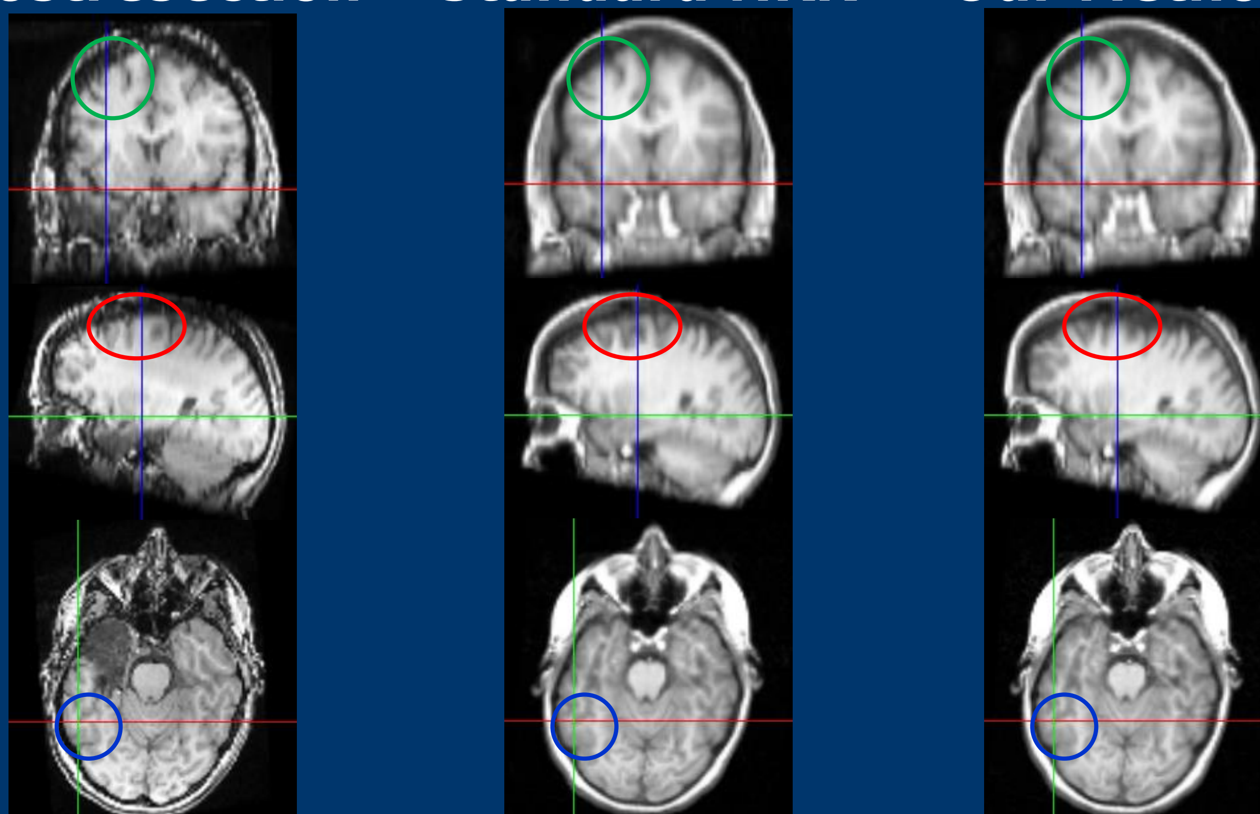
- 7 3D MR image pairs from epilepsy patients
- Likelihood model: correlated intensities
- Artificially enlarged training set
  - Shown to improve shape modeling capabilities [Koikkalainen et al., TMI 2008]
  - Only have small number of available images
  - Randomly warped true indicator using FFDs

True map Artificial maps

  - 30 images/training set

Results on Real Data: Registered Images

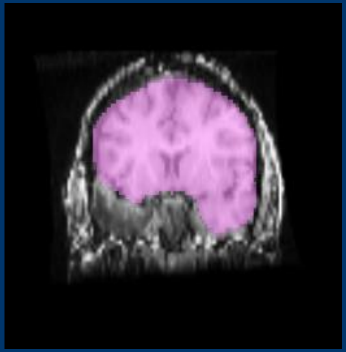
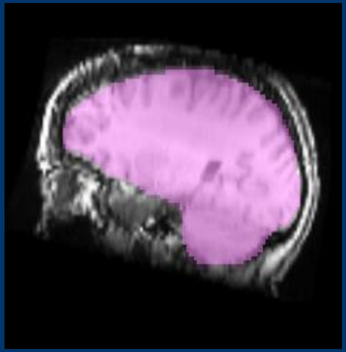
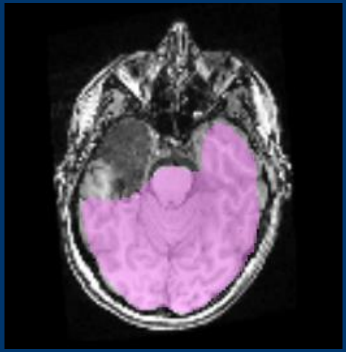
Postresection **Standard NRR** **Our Method**



Average CC in valid region: ↑19% ↑51%

Results on Real Data: Estimated Indicator Map

- Indicator map for valid correspondences

- Average dice coefficients (n = 7)
  - Between estimated and true maps: 0.91
  - Between best reconstruction using PCA components and true map: 0.92

→ Estimated indicator map limited by library of possible maps built using PCA on training data

Conclusions and Future Work

- Presented registration method for preoperative and postresection images
  - Handled missing correspondence problem by including a “hidden” indicator map
  - Simultaneously estimated registration parameters and correspondence regions
  - PCA spatial prior guided indicator map selection
- Future work
  - More discrete labels or continuous indicator map
  - Incorporate other similarity metrics (eg., MI)
  - Difficulty of spatial prior training data → consider intensity-based prior

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