Patch-Based Discrete Registration of Clinical Brain Images

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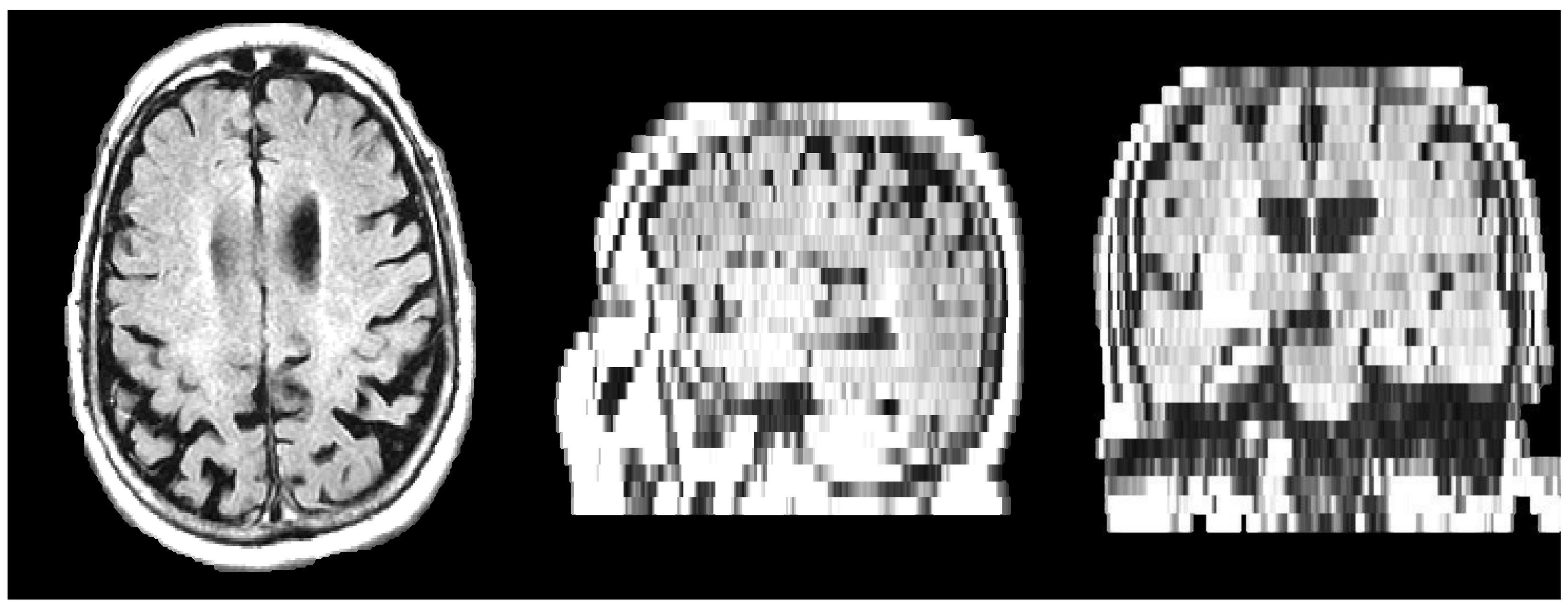
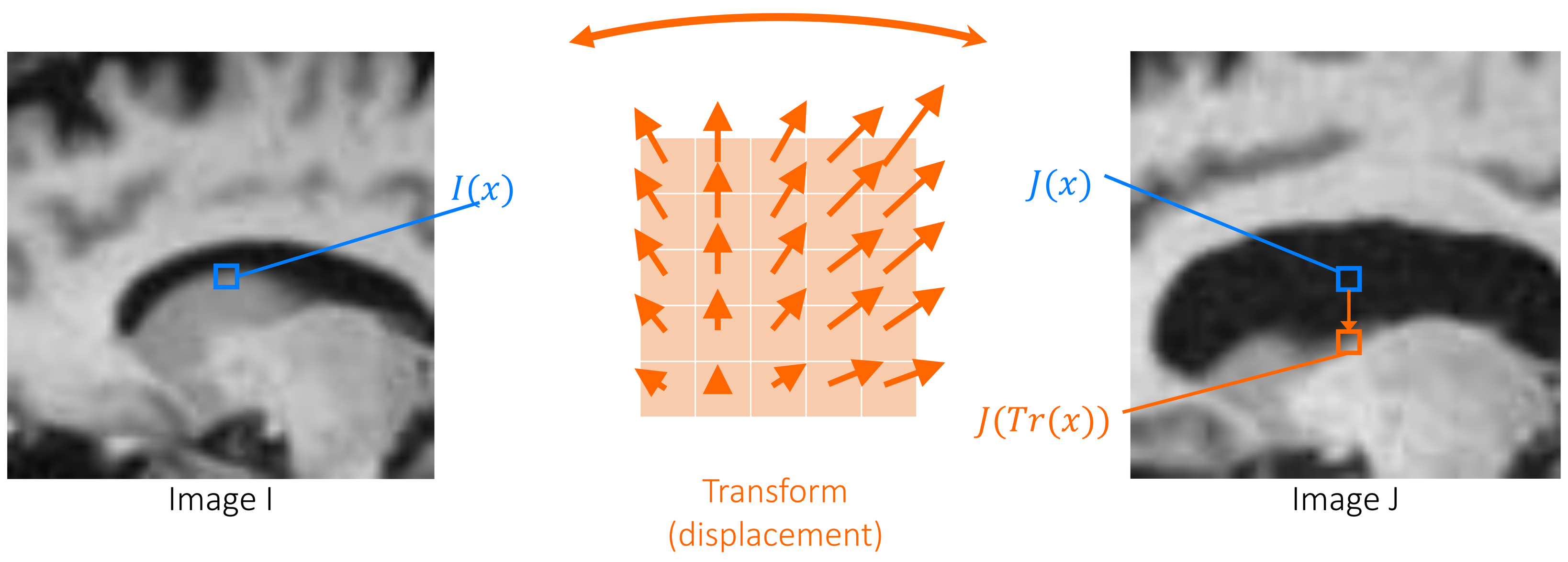
Background

Goal: deformable registration of low-quality brain images acquired in clinical settings

Problem
- Clinical images are sparse, with low resolution and artifacts
- Current registration algorithms fail on clinical images



Registration



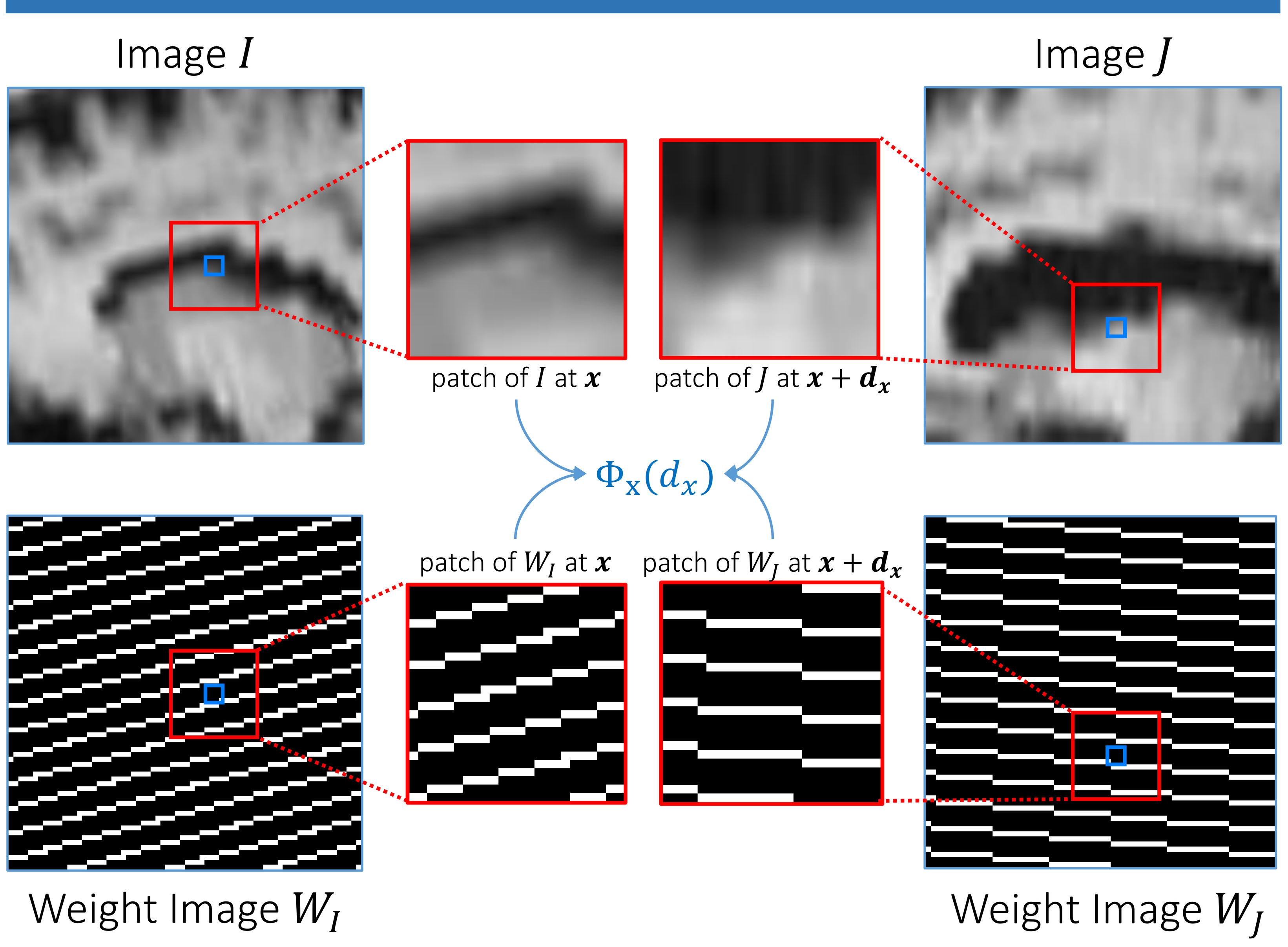
$$\text{Transform} = \underset{Tr}{argmin} \underbrace{\sum_{x \in \Omega} \|I(x) - J(Tr(x))\|_2^2}_{\text{data term}} + \underbrace{\lambda Reg(Tr)}_{\text{smoothness}}$$

Every voxel x in the scan

Typical registration frameworks
- Use continuity and smoothness assumptions
- Are voxel-based and need to take derivatives
- Require research quality images

Our solution: combine patches and sampling weights in a discrete registration framework

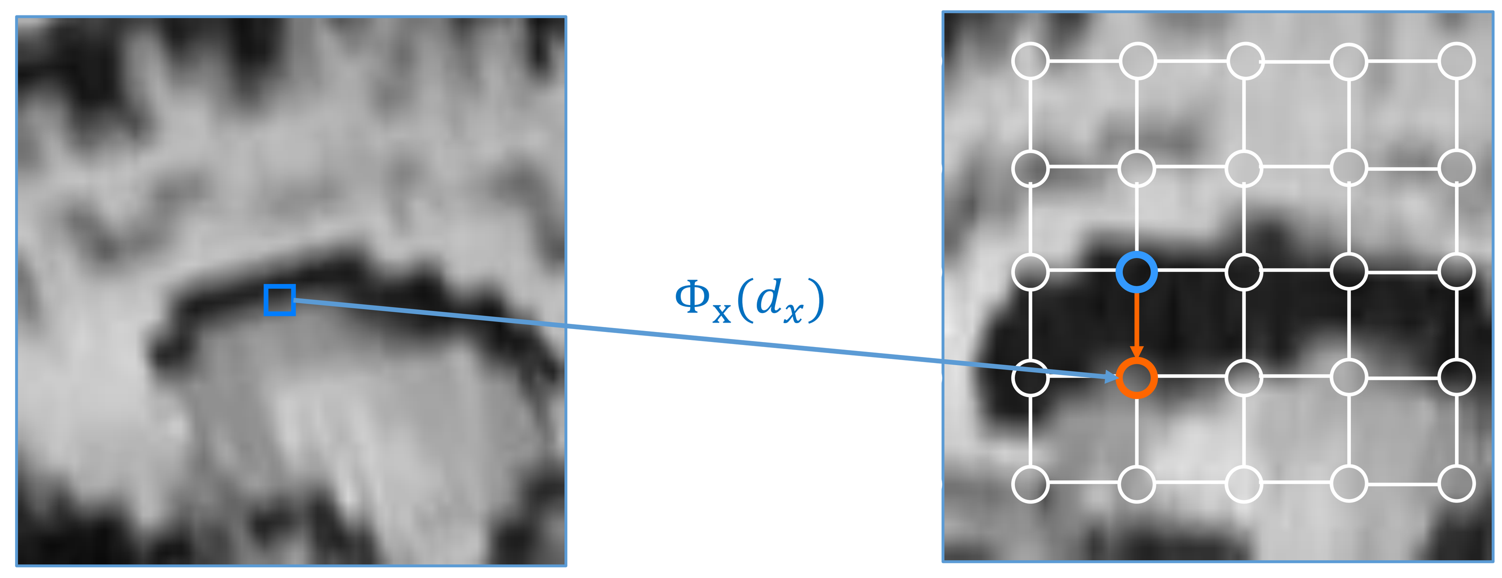
Patches

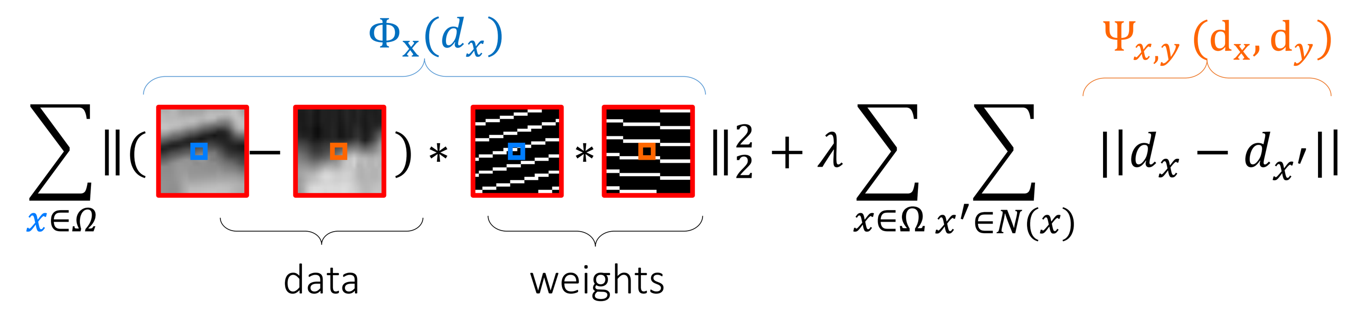


- Look at the context of a voxel by using patches
- Explicitly model known and missing information using sampling masks (weight images)
- Optimize patch-based registration efficiently in a discrete framework

Discrete Patch-Based Registration Methods

Model: undirected graph with node and edge weights
- nodes $x \in \Omega$ of the MRF = voxels in the moving image
- states at each node = possible displacements d_x of voxel x
- node potential $\Phi_x(d_x)$: score each displacement
- pairwise potential $\Psi_{x,y}(d_x, d_y)$: encourage similar neighbor displacements



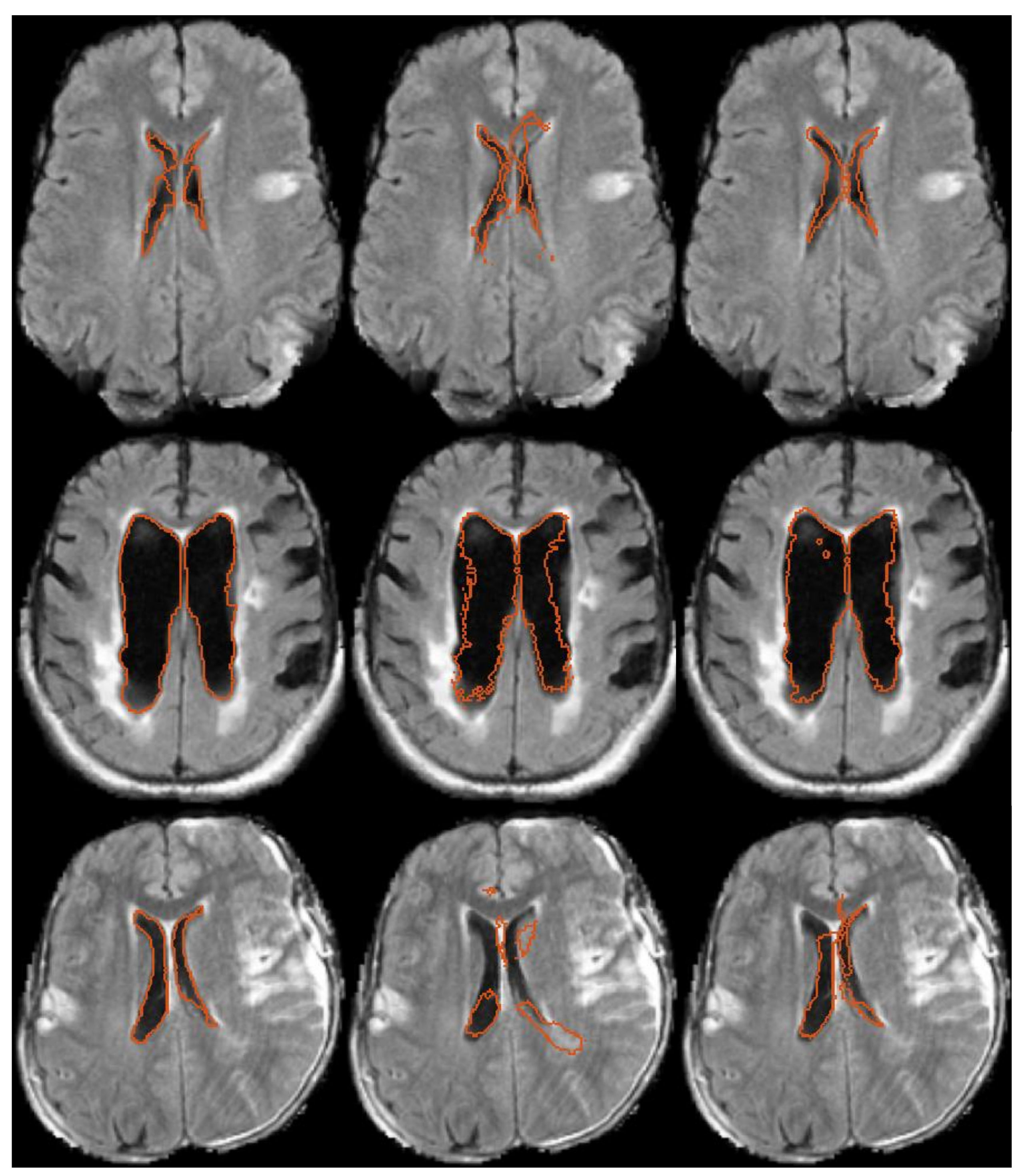


$$\Phi_x(d_x) = \frac{\sum_{z\in\Omega_x} W(x, d_x, z)\big(I(x+z) - J(x + d_x + z)\big)^2}{\sum_{z\in\Omega_x} W(x, d_x, z)}$$

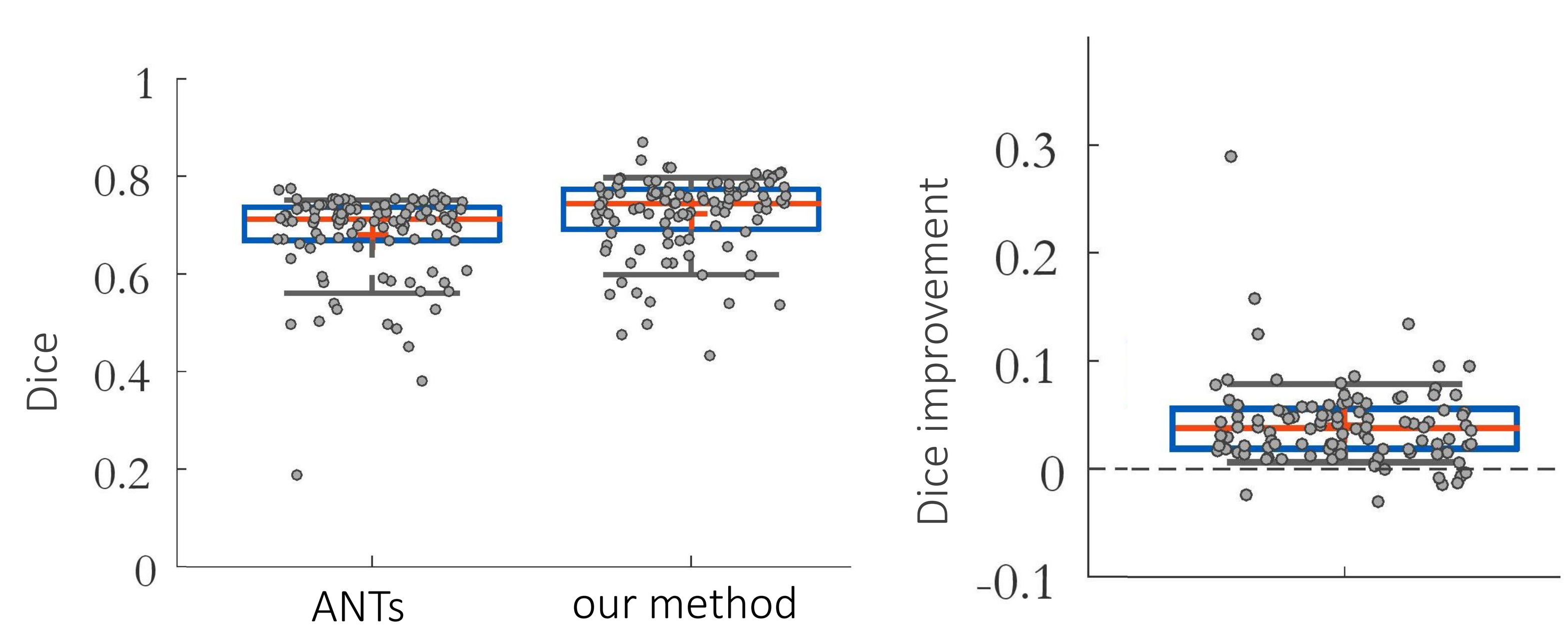
$$W(x, d_x, z) = W_I(x+z) W_J(x + d_x + z)$$

Freely available code:
http://github.com/adalca/patchRegistration

Results



Manual segmentation | Atlas based segmentation using ANTs | Atlas based segmentation using our method



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