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Joint T1 and brain fiber diffeomorphic registration using the demons

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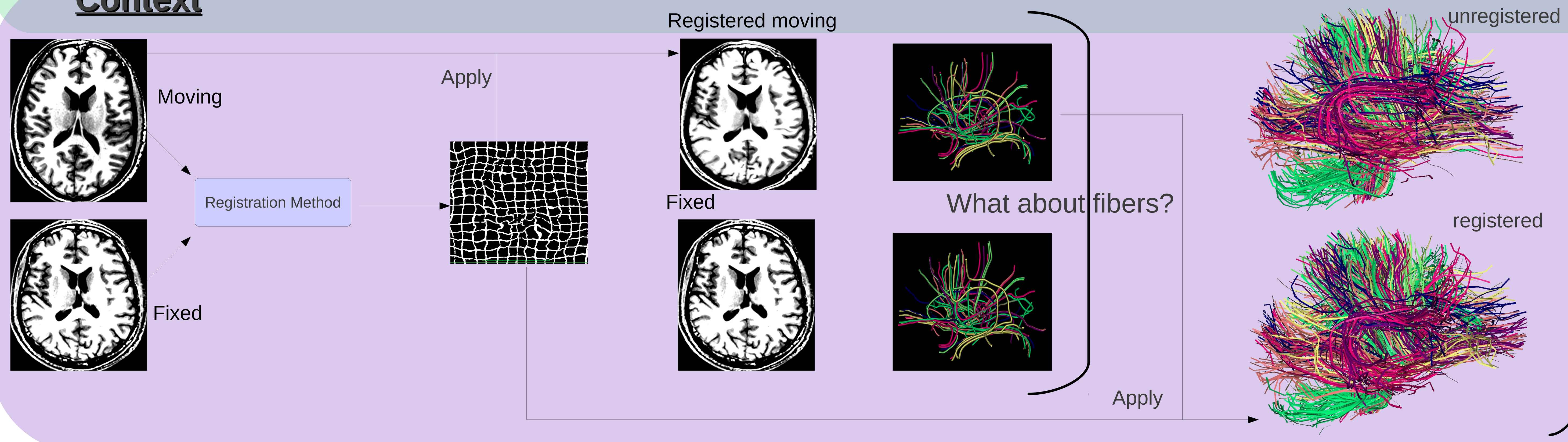
• Within inter-individual comparison, registration should align images as well as cortical and external structures such as sulcal lines and fibers in brain imaging.
• While using image-based registration, neural fibers appear uniformly white giving no information to the registration.
-Tensor-based registration improves white-matter alignment, however misregistration may also persist in regions where the tensor field appears uniform.
• We propose an hybrid approach by extending the Diffeomorphic Demons [1] registration to incorporate geometric constrains. Combining the image and the geometry, we define a mathematically sound framework to jointly register images and geometric descriptors of fibers.

Context



We have a set of predefined corresponding fibers obtained by [2]. We applied the transformation obtained by Diffeomorphic Demons, and we see that even though images are well align, internal structures are not.

Registration is not taking information from fiber, and T1 images does not contain relevant information from white-matter regions

Diffeomorphic Demons Registration

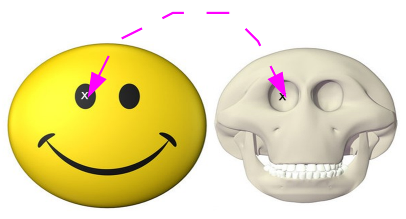
- We measure the similarity of the images $\mathrm{Sim}(F, M\circ s)=\frac{1}{2}\|F-M\circ s\|^2$

where F is the fixed image, M is the moving image and M∘s is the moving image after applying the transformation

- We minimize the following energy: $E(s,c)=\frac{1}{\sigma_i}\mathrm{Sim}(F,M\circ c)+\frac{1}{\sigma_x^2}\mathrm{dist}(s,c)^2+\frac{1}{\sigma_T^2}\mathrm{Reg}(s)$

where Reg is the regularization term

Where dist is the distance between the correspondences and the current transformation.



We minimize this distance, as we want small deformations at each step.

The minimization is done in 2 steps:
we first optimize for the correspondences
and then we take care of the regularization term.

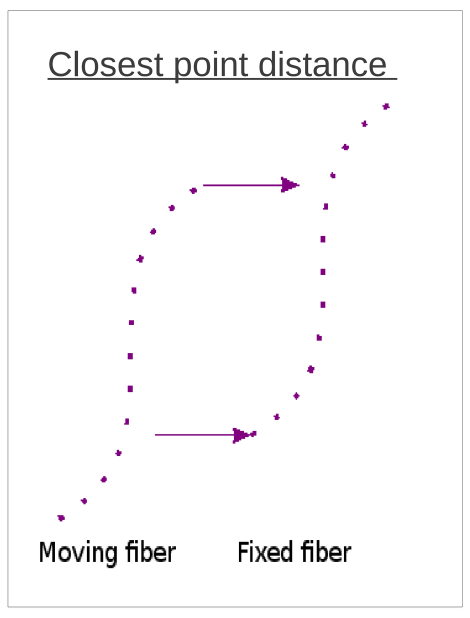
$$1-E_s^{corr}(u)=\|F-M\circ s\circ u\|^2+\|u\|^2\frac{\sigma_i^2}{\sigma_x^2}$$

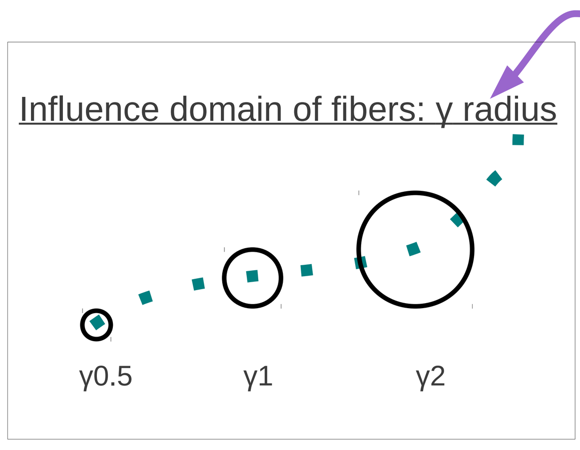
$$2-c\leftarrow s\circ u$$

$$3-s\leftarrow K*c$$

Repeat until the similarity between the images is small enough.

Incorporate the fibers as a set of points





Geometric Demons Registration

$$E(s,c)=\frac{1}{\sigma_i}\left(\mathrm{Sim}(F,M\circ c_I)+\mathrm{Sim}(X^F,X^M\circ c_P)\right)+\frac{1}{\sigma_x^2}\left(\mathrm{dist}(s,c_I)^2+\mathrm{dist}(s,c_P)\right)+\frac{1}{\sigma_T^2}\mathrm{Reg}(s)$$

where X^F is the set of points of all fibers in the fixed image
X^M is the set of points of all fibers in the moving image.
c^P are the correspondences between the moving points and the fixed points.

Update field for the image:

$$1-E_s^{corr}(u_I)=\|F-M\circ s\circ \exp(u_I)\|^2+\frac{\sigma_i^2}{\sigma_x^2}\,dist(s,s\circ\exp(u_I))^2$$

Update field for the fibers, where Sim is the closest point distance:

$$2-E_s^{corr}(u_P)=\mathrm{Sim}(X^F-X^M+u_P)+\frac{\sigma_i^2}{\sigma_x^2}\,dist(s,s\circ\exp(u_P))^2$$

Use RBF to extrapolate and convert the sparse update field from fiber to a dense one

$$3-u_P(x)=H(x).A^{-1}.U$$

Weight and combine the update fields, using fiber information close to where fiber points are defined.

$$4-u(x)=(1-w(x))u_I(x)+w(x)u_P(x)$$

Update the transformation

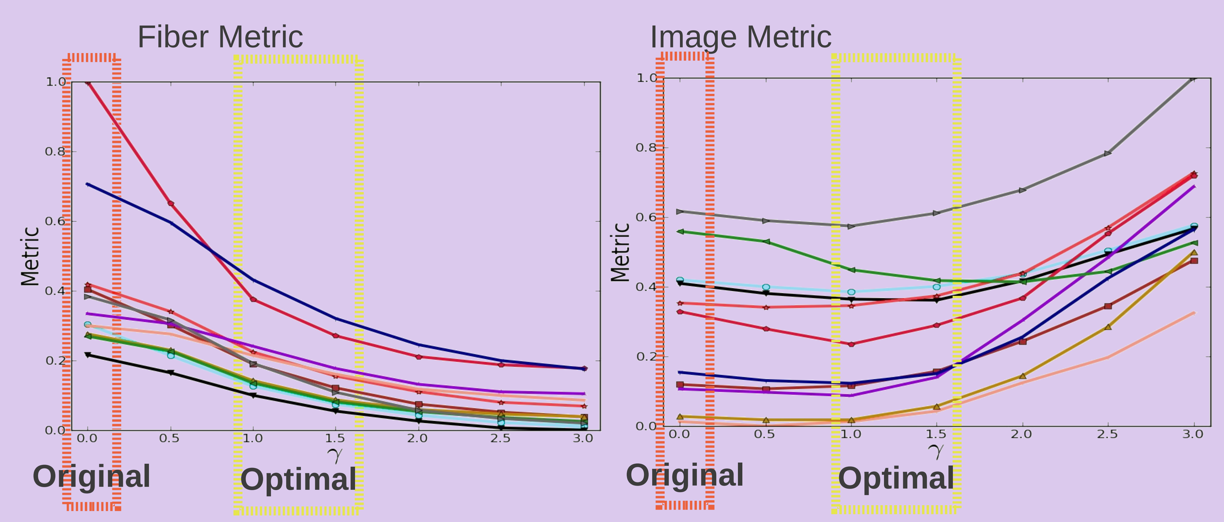
$$5-Let\ c\rightarrow s\circ\exp(u)$$

Take care of the regularization term (convolve with a Gaussian Kernel)

$$6-s\rightarrow K*c$$

Repeat until the similarity between the images and the set of points is small enough.

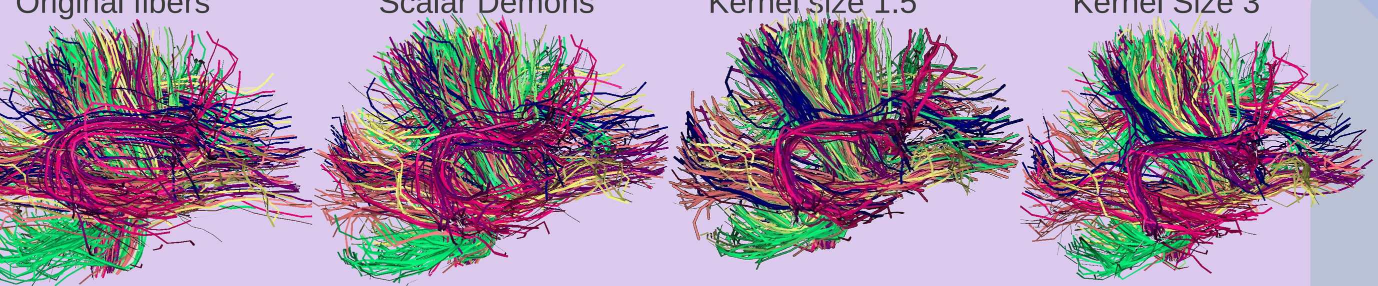
Optimal influence radius: γ



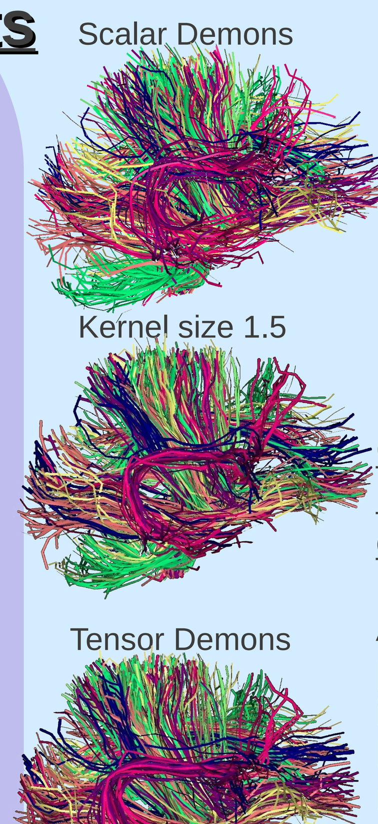
As we increase the radius the more the fibers influence the deformation field, therefore the fibers alignment improves at the expenses of image alignment.

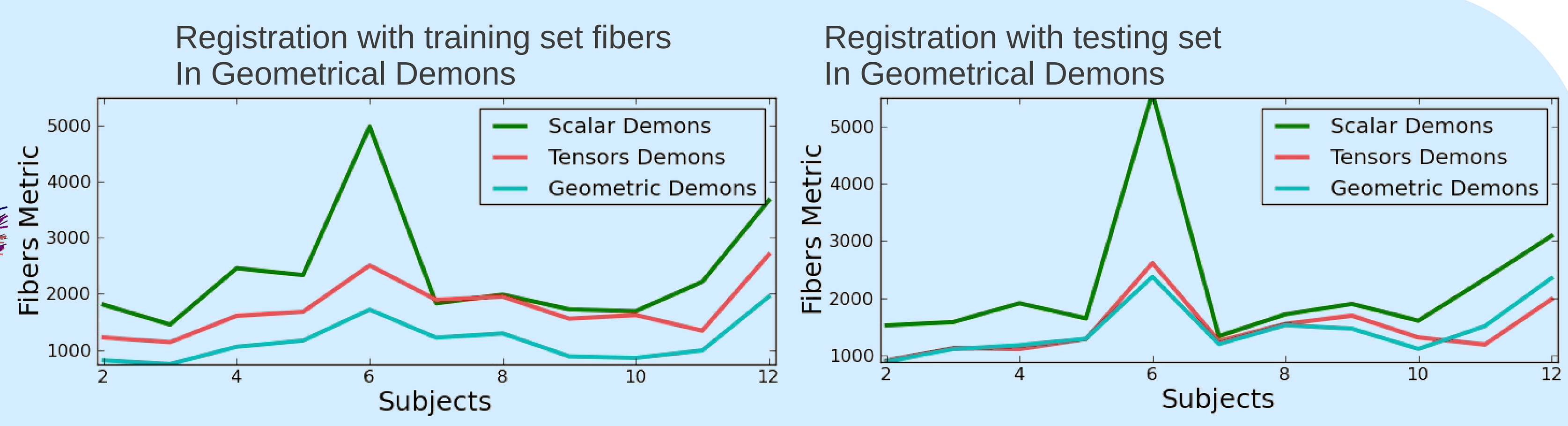
The optimal γ radius is between 1.0 and 1.5 where we are able to highly improve fibers alignment and also to maintain the image alignment.

Fiber alignment improvement from original to a high radius value



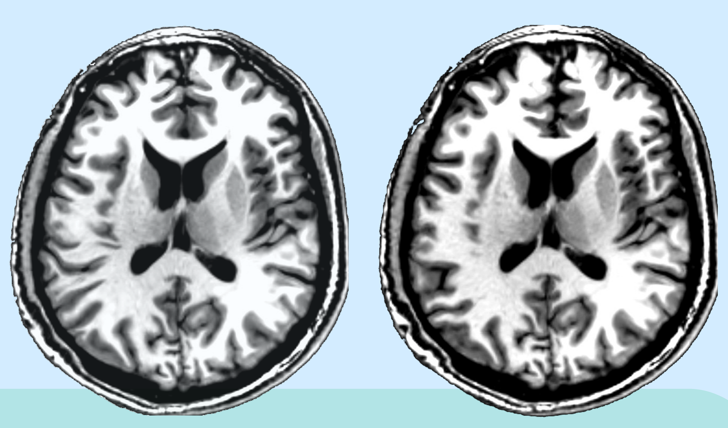
Results





Comparison between Scalar Demons, Tensor Demons, and Geometric Demons with the optimal value of γ.

Analysis was performed for 12 subjects of the NMR public database. 100 bundles were consistently identified in all subjects. The 50 longest (25 in each hemisphere) were used as training set, the the remaining 50 use for test the obtained deformation field. 11 subjects were registered to one.



For each subject registration we can see the metric improvement for the training set as for the test set.

Conclusions: We extended the well-stablished Demons registration algorithm to register jointly both, image and geometric descriptors. We were able to find a trade-off of parameters where a unique transformation is obtained well aligning both image and fibers. Future work consist in incorporating currents as the measure for fiber bundles.

[1] Vercauteren, T., , et al: Diffeomorphic demons: Efficient non-parametric image registration. NeuroImage 45(1, Sup. 1) (2009) S61–S72
[2] Guevara, P., et al.: Robust clustering of massive tractography datasets. Neuroimage 54(3) (2011) 1975–1993