Direct native space bundle alignment for group comparisons

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Diffusion Imaging in Python

http://dipy.org

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DIPY

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Declaration of Financial Interests or Relationships

Speaker Name: Eleftherios Garyfallidis

I have no financial interests or relationships to disclose with regard to the subject matter of this presentation.

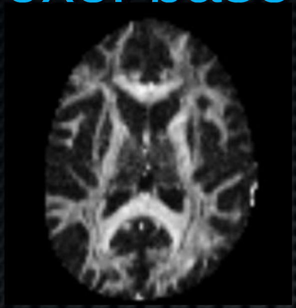
Problem: We want to study bundles across populations.

Question: What is the best way to register the bundles together so that we can calculate statistics, study their shape, etc.?

Picture: Courtesy of Flavio Dell' Acqua

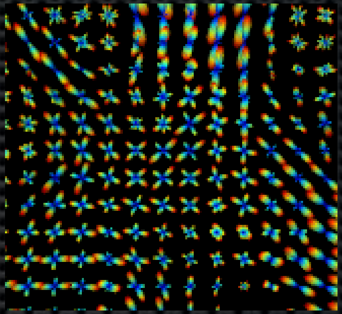
Current solutions

Voxel-based



Scalar e.g. FA[1]

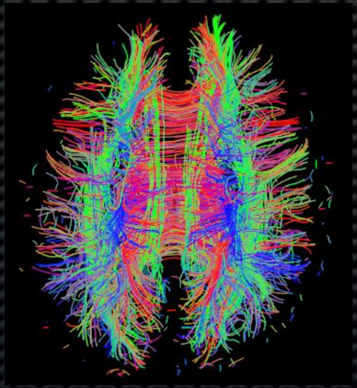
Tensors[2]



ODF/FOD[3]

Streamline-based[4,5]

full brain



same bundle

[1] Smith et al. Neuroimage 2006, [2] Zhang et al., IEEE TMI 2007, [3] Raffaelt et al. Neuroimage 2011, [4] Durrleman et al., Neuroimage 2011, [5] Mayer et al., IEEE TMI 2011.

Bundles of interest alignment

Let’s assume that we have already segmented our bundles.

Static Moving

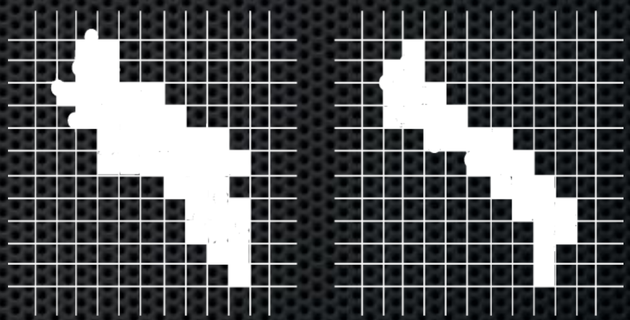
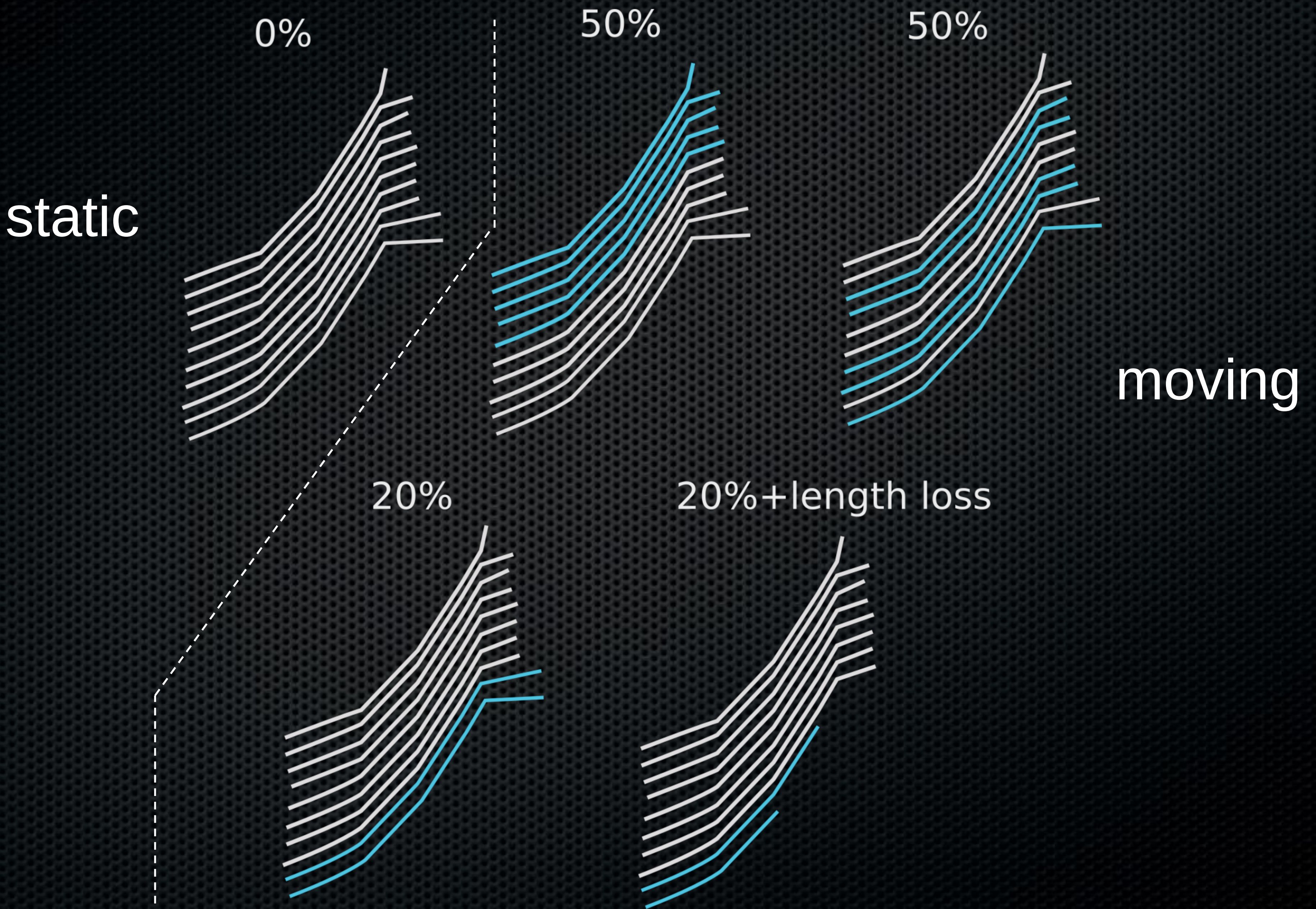


Image-based registration
- Mean Square Differences (MSD)
- Mutual Information
- Cross Correlation

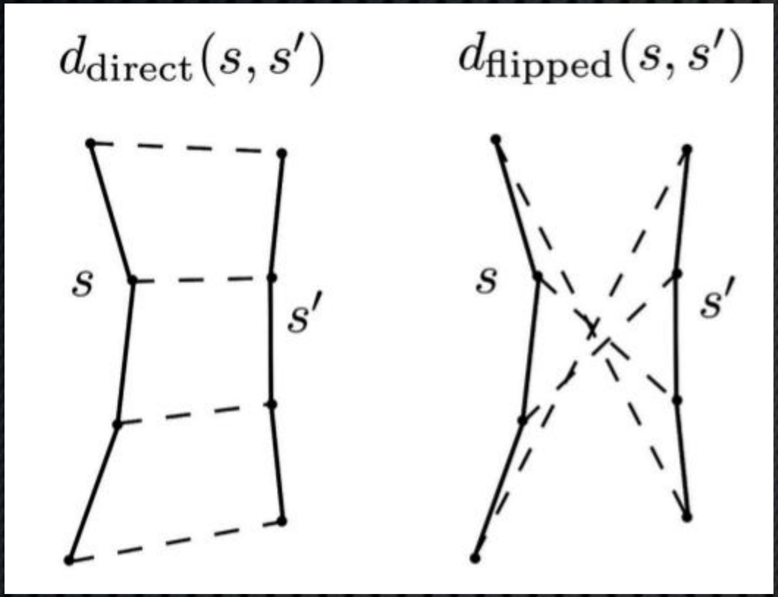
Point-based registration
- Iterative Closest Point ++

Streamline-based registration
- Which metric?
  - Shape, neighborhood, distance!

We need to resolve partial data



Distance metric



Minimum Direct Flipped[1,2] (MDF)

min(d_direct, d_flipped)

- Fast
- Symmetric
- Proper distance metric[2]

[1] Garyfallidis et al., OHBM 2010, [2] Garyfallidis et al., Frontiers 2012

Cost function

The squared sum of minimums along the rows and the columns of a distance matrix (D) created by the pairwise MDF distances.

Bundle Minimum distance (BMD)

$$\mathrm{BMD}(S_a, S_b) \rightarrow \frac{1}{4}\left(\frac{1}{A}\sum_{i}\min_{j} D(i,j) + \frac{1}{B}\sum_{j}\min_{i} D(i,j)\right)^{2}$$

Optimization method:

Streamline-based Linear Registration (SLR)

Cost function:	Bundle Min Distance (BMD)
Rigid :	6 parameters
Affine :	12 parameters
Optimizer :	Powell
	L-BFGS-B (bounded)

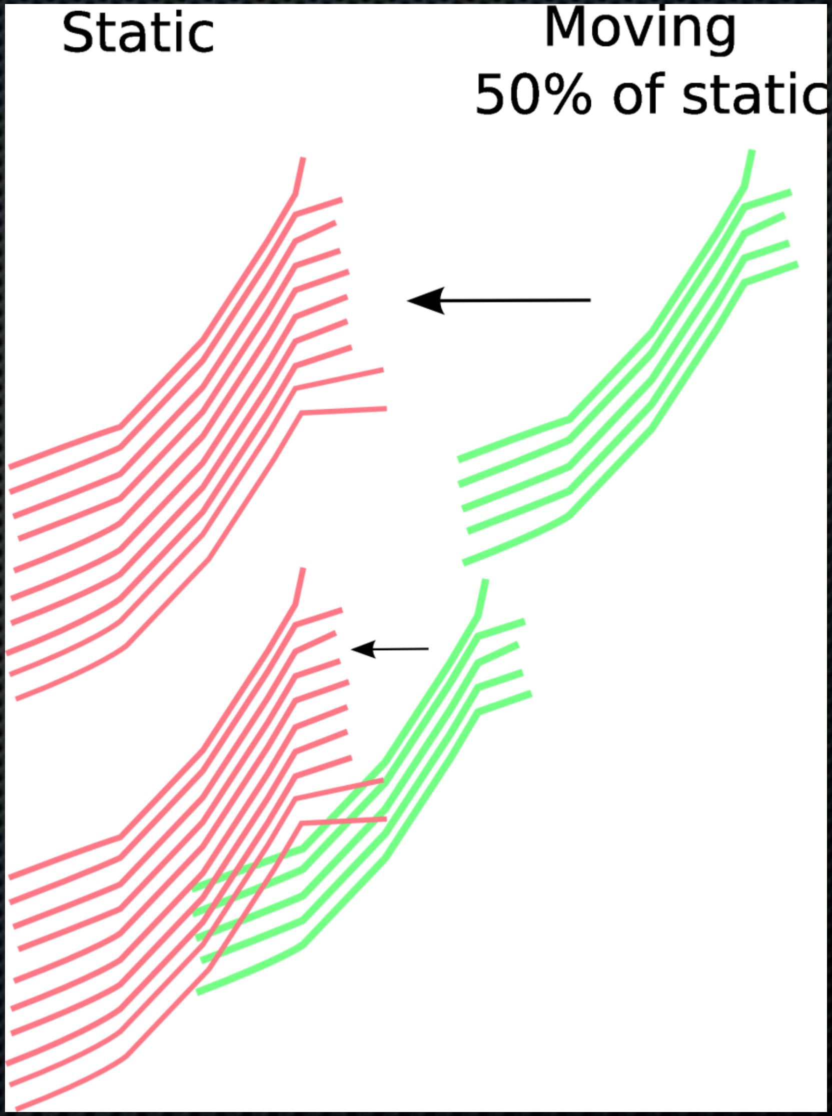
Basic optimization check experiment

For the same subject:

a) we take a bundle (static)

b) copy and transform one part of it (moving)

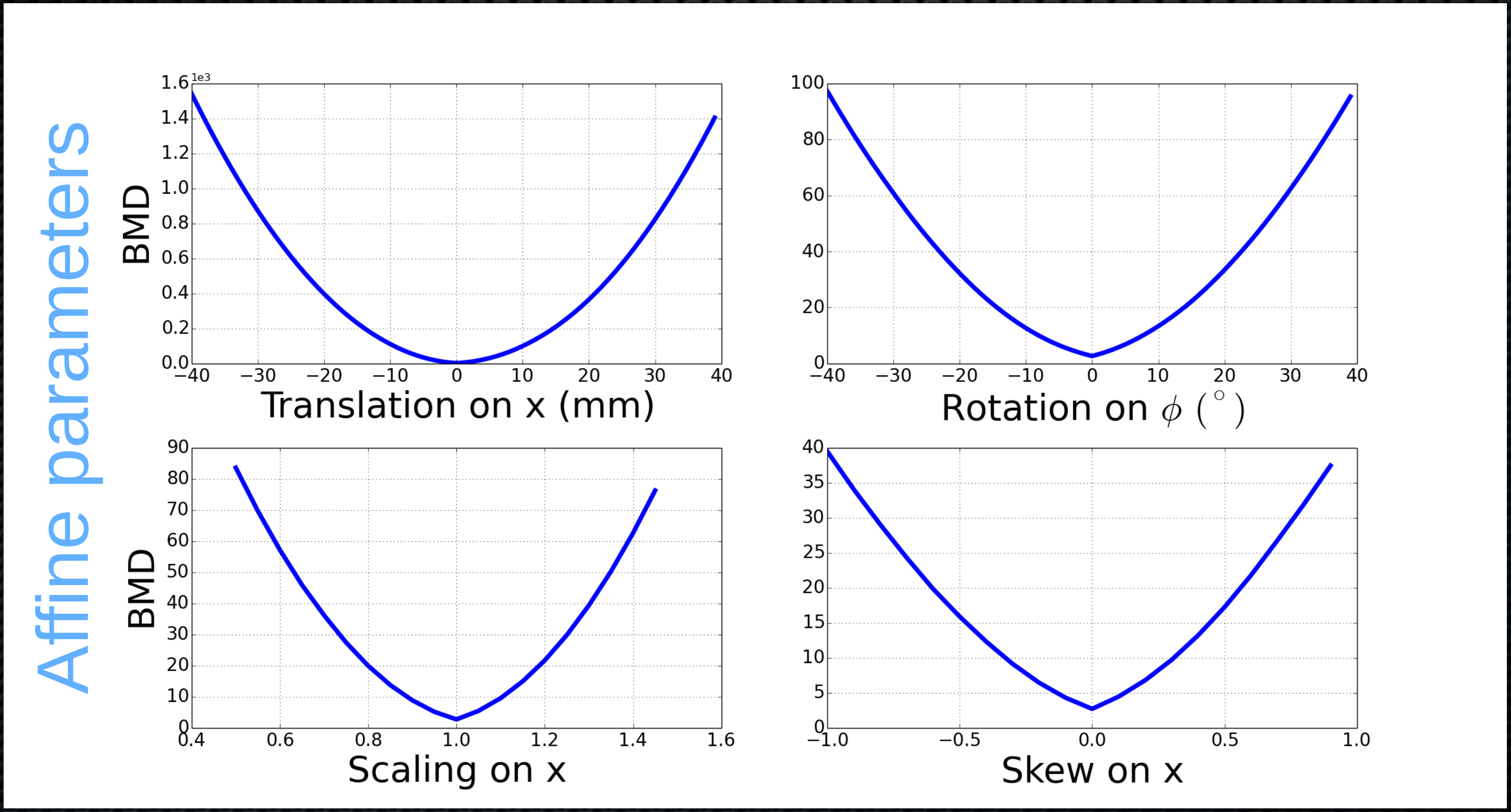
c) measure our cost function as we transform it back to its original place.



BMD is great for optimization

In this experiment we copied 33% of the left SLF bundle and started transforming it measuring BMD.

Our cost function is smooth and convex even with partial data!



Basic validation experiment

For the same subject:

a) we take a bundle (static)

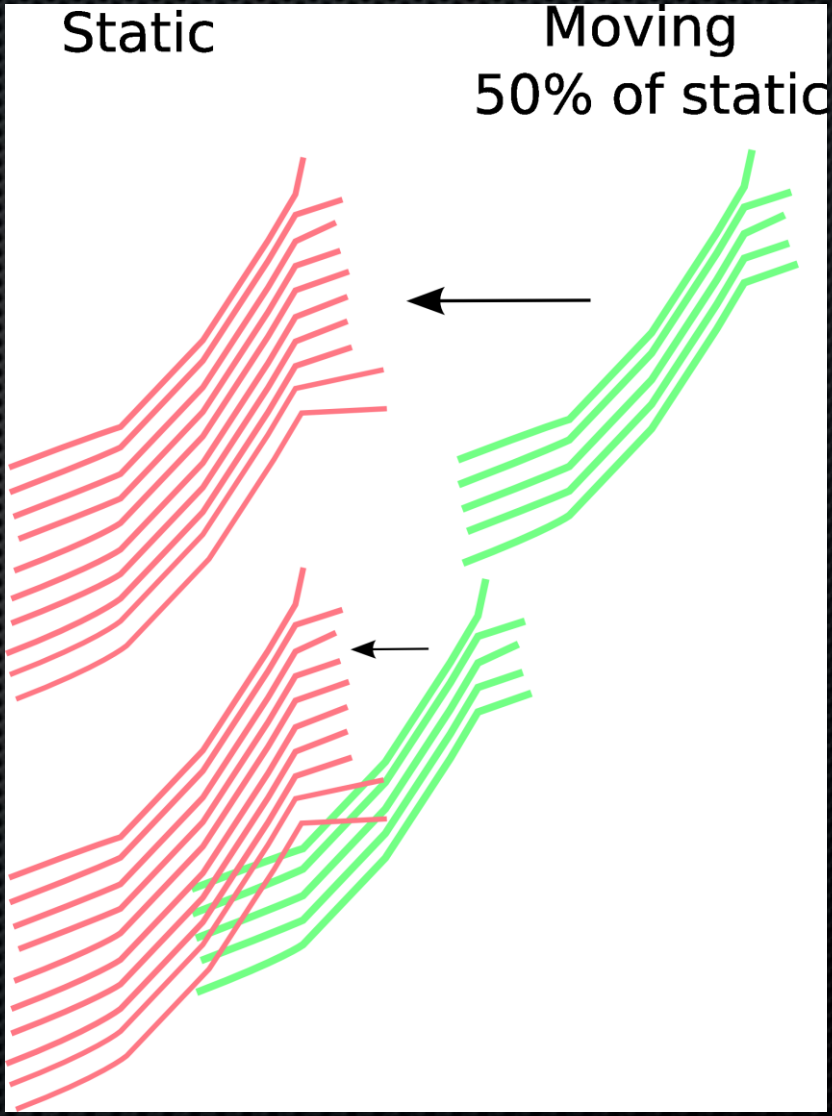
b) register the moving bundle

c) discretize the registered bundles

d) measure Jaccard Index

Jaccard index is a measure of overlap.

- 1 means perfect overlap
- 0 means no overlap



Results: Same subject comparison

Middle section of Corpus Callosum

Let’s compare the Jaccard indices of:

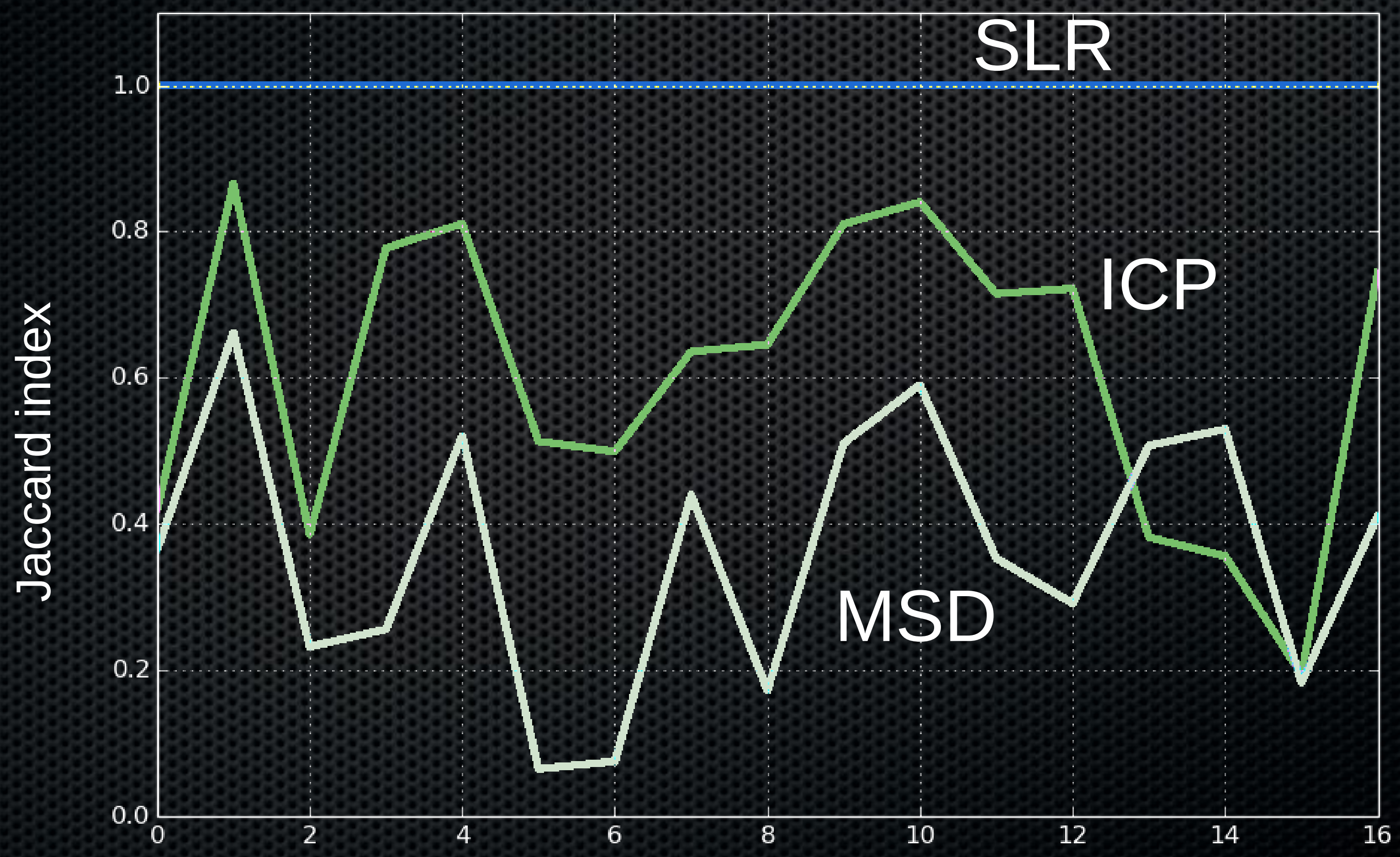
- SLR (streamlines)
- ICP (points)
- MSD (binarized bundle)

	SLR	ICP	MSD
0% missing	1.00	1.00	0.90

	SLR	ICP	MSD
50% missing	1.00	0.87	0.66

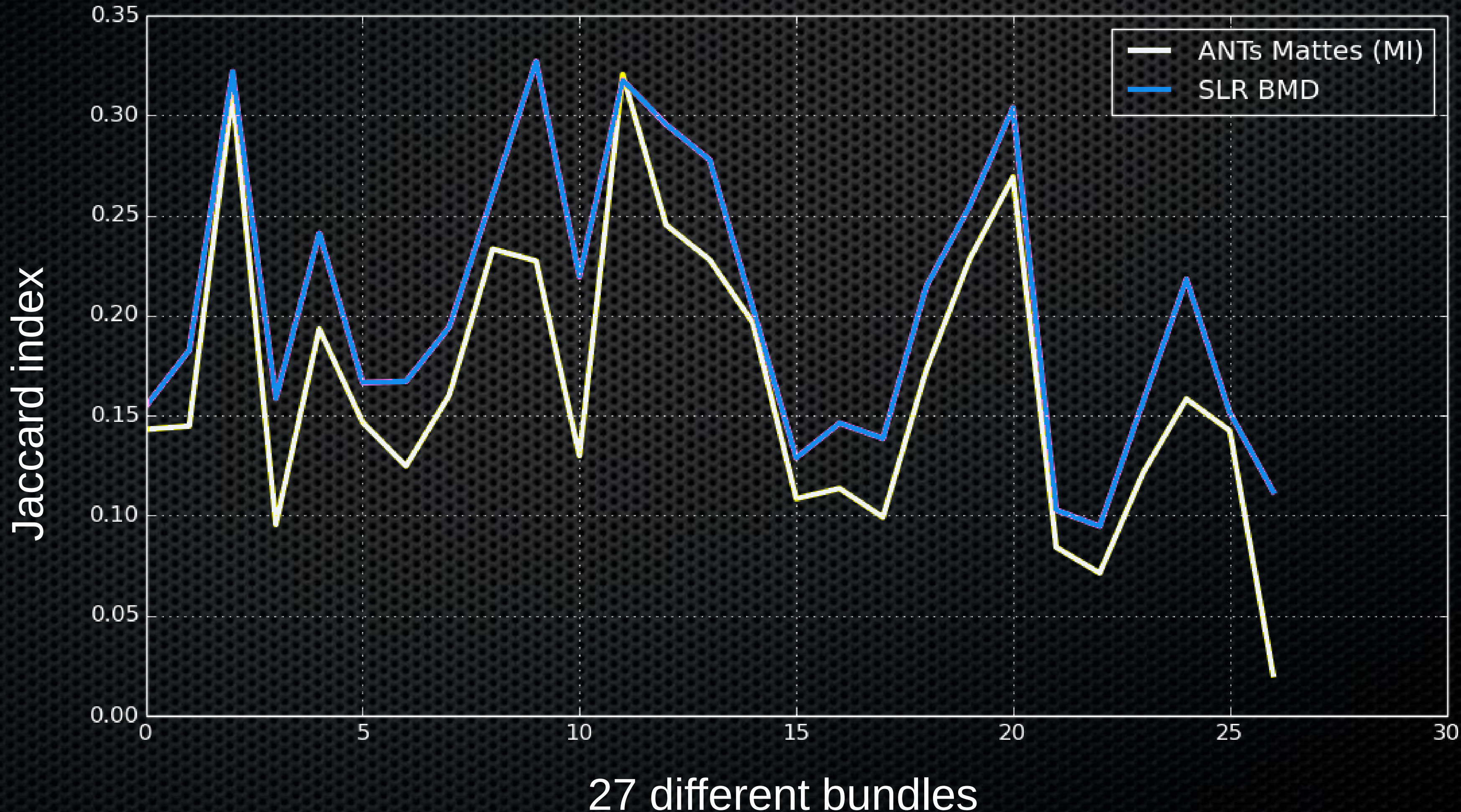
Results: Same subject comparison

17 different bundles



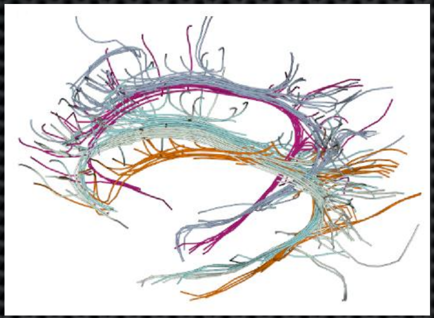
Results: FA-based full brain vs bundle-based SLR (2 subjects)

Rigid: Mutual Information (ANTs) vs SLR



Results: Example 5 subjects' CGs

5 cingulum bundles in native space

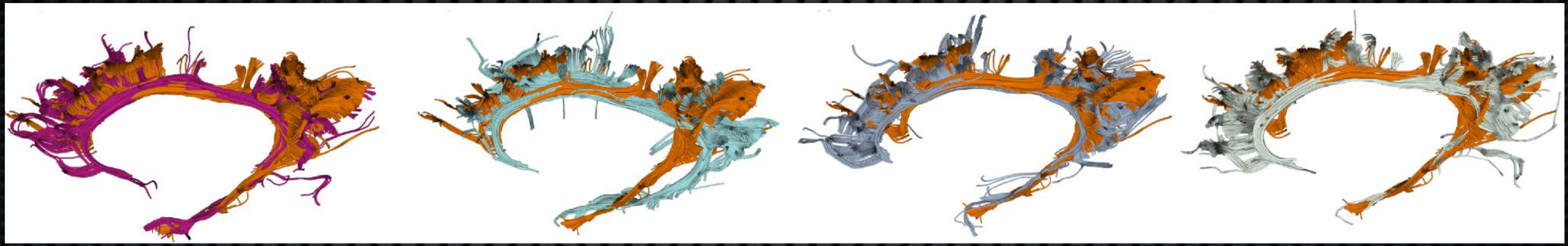


Cluster centroids e.g. from QuickBundles (optional)

4 bundles aligned with the orange bundle (static)

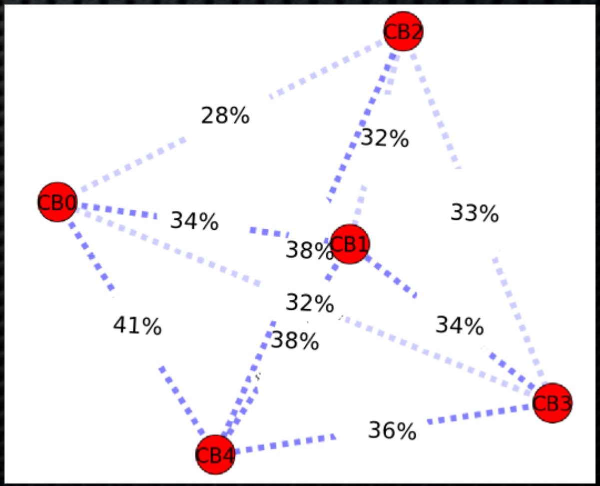
Results: Example 5 subjects' CGs

Apply the transformation matrix



Now if we repeat this procedure so that CG of every subject can be the static.

We can create a network showing the difference, e.g. % overlap, between every subject's bundle to any other subject's bundle.



Results: video

Demonstrations with rigid and affine registration.

- **Same subject**
- **Different subjects**

In the following video the static (reference) bundle will be always depicted with red and the moving will be green.

The bundles have been segmented using the tract-querier[1] with the white matter query language.

[1] Wassermann et al. MICCAI 2013
http://tract-querier.readthedocs.org

Conclusion

- The SLR uses streamline-only information to align bundles of interest.
- The BMD cost function used with the SLR has shown that is robust with partial and noisy real data.
- The code will be soon available in DIPY.
- Try it and give us feedback.

Thank you!

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TRACTOMETER

DIPY

http://tractometer.org

http://dipy.org

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