

ANTs: A retrospective

Brian (Penn) and Nick (UVa)

- 1 Retrospective**
- 2 Founding developers**
- 3 ANTs lineage**
- 4 Major papers**
- 5 ANTs and the perils of circularity**
- 6 Competitions**
- 7 ANTs: in summary**

This talk is online at <http://stnava.github.io/ANTs2015/> with colored **links** meant to be clicked for more information.

Retrospective

ANTs evolution



FreeSurfer, Bruce Fischl



NeuroImaging research as literature

“Contingency. AFNI is one result of unexpected events. I met a woman and fell in love.”

ANTs—*begotten in SyN*

WELCOME TO THE REALM
OF THE LEGEND

DOCTOR SYN

TERRY ANTHONY 85

Founding developers

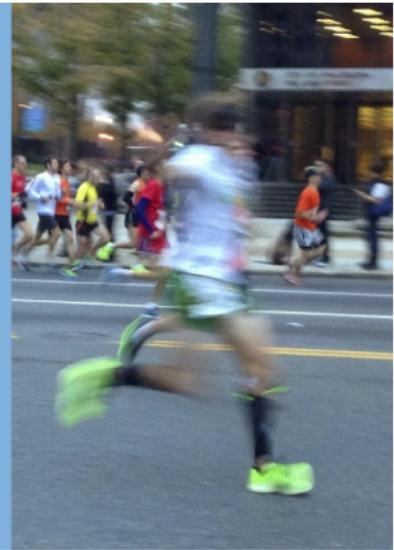
Brian and Edie



Nick and Bruce



Brian and Nick



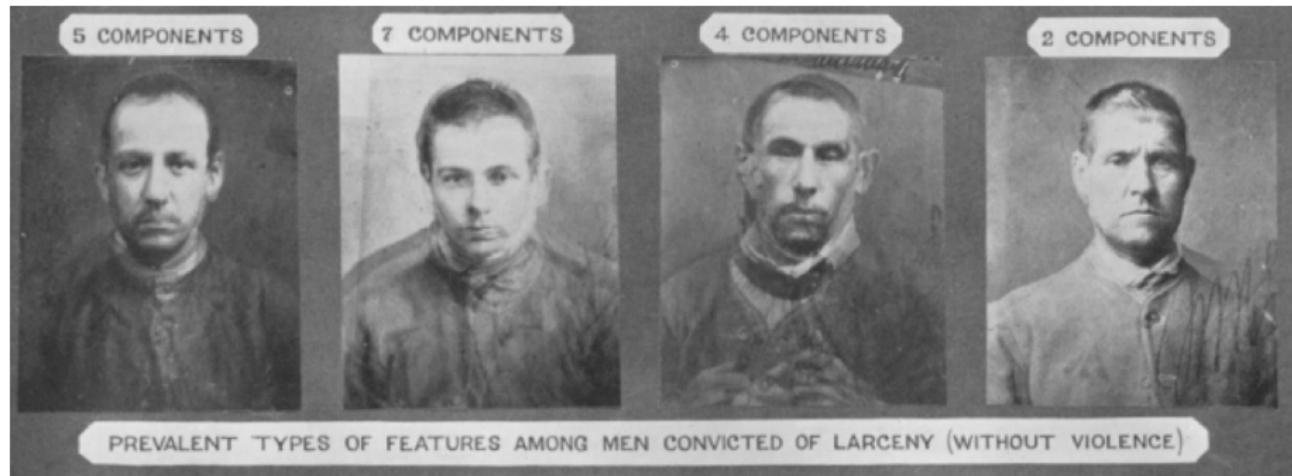
ANTs Long term collaborators



+ neurodebian, slicer, brainsfit, nipype, itk and more

Image mapping and perception: 1877

Francis Galton: *Can we see criminality in the face?*



What about syphilis, mental illness?

Speaking of criminality...

Can we say anything about the U.S. Congress?



Naive

Affine

SyN

Maybe he should have used **ANTs**?

Image mapping & biology: 1917

D'Arcy Thompson: *Comparison of related forms*

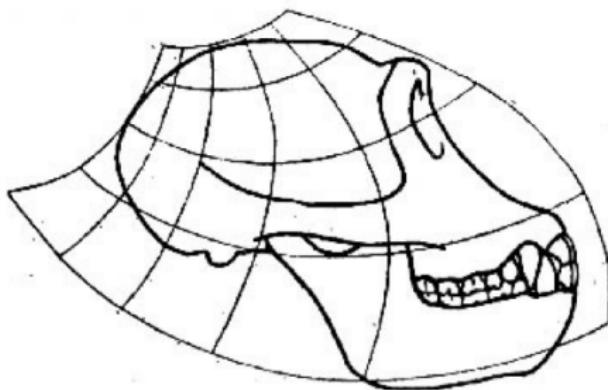


Fig. 550. Skull of chimpanzee.

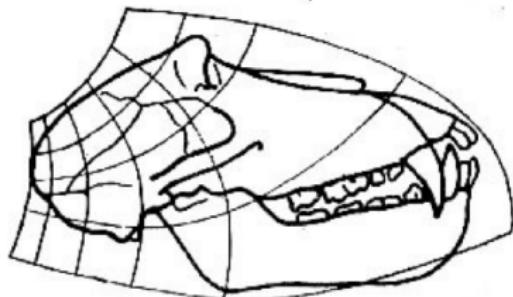
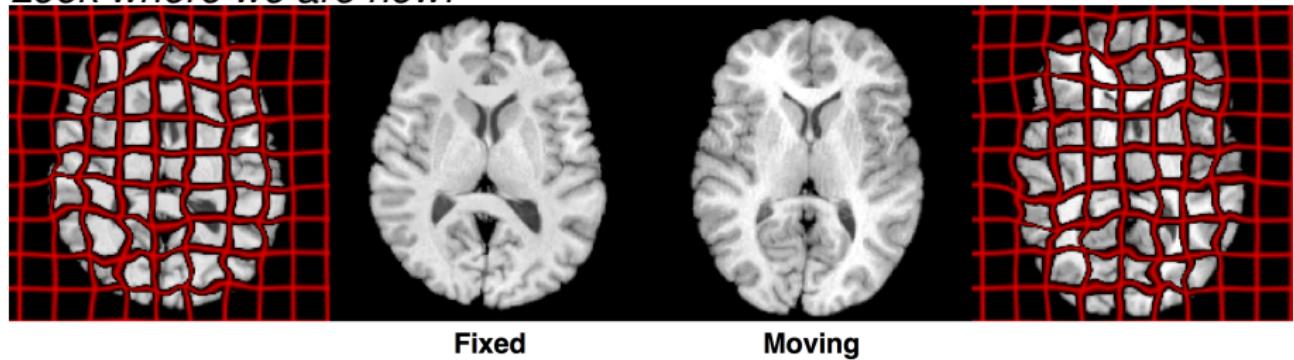


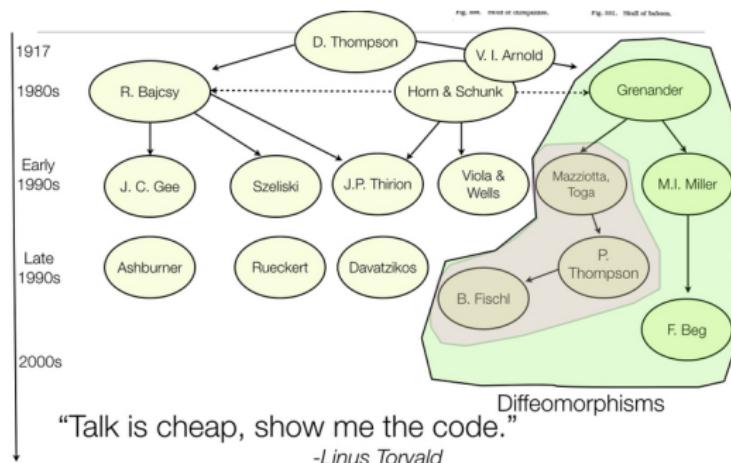
Fig. 551. Skull of baboon.

Image mapping & biology: Current

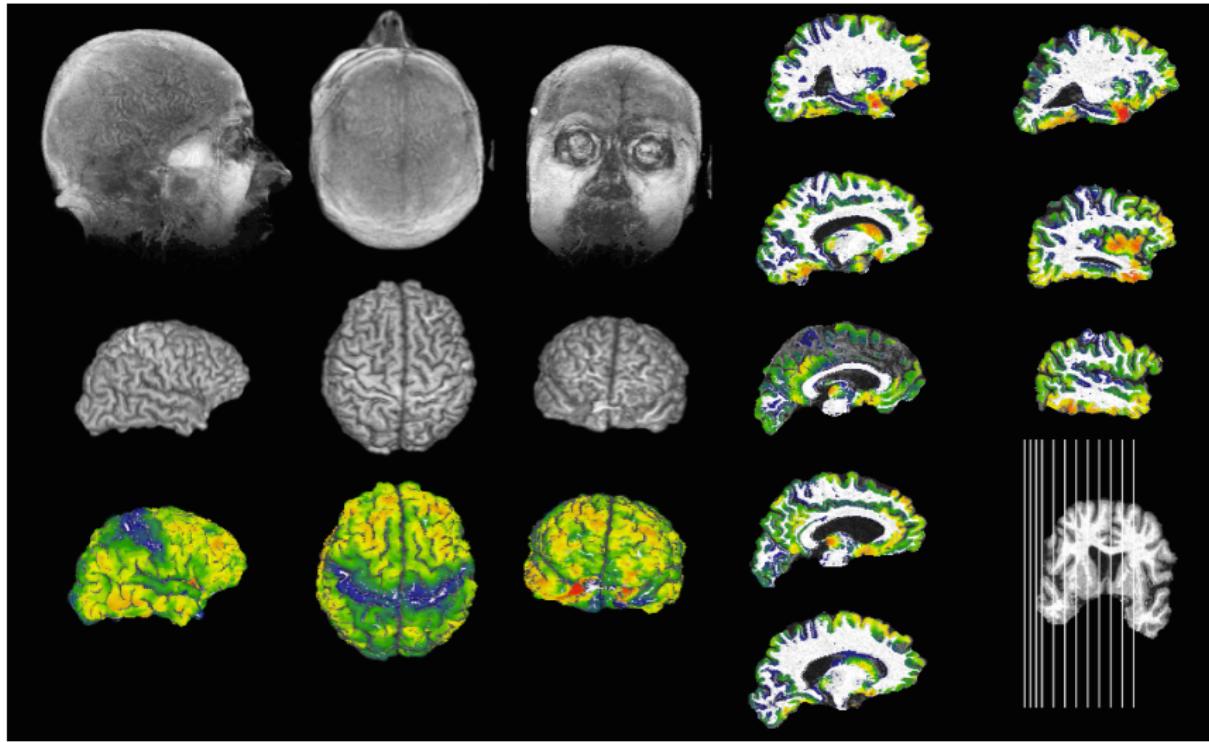
Look where we are now!



ANTs family tree



Initial scope

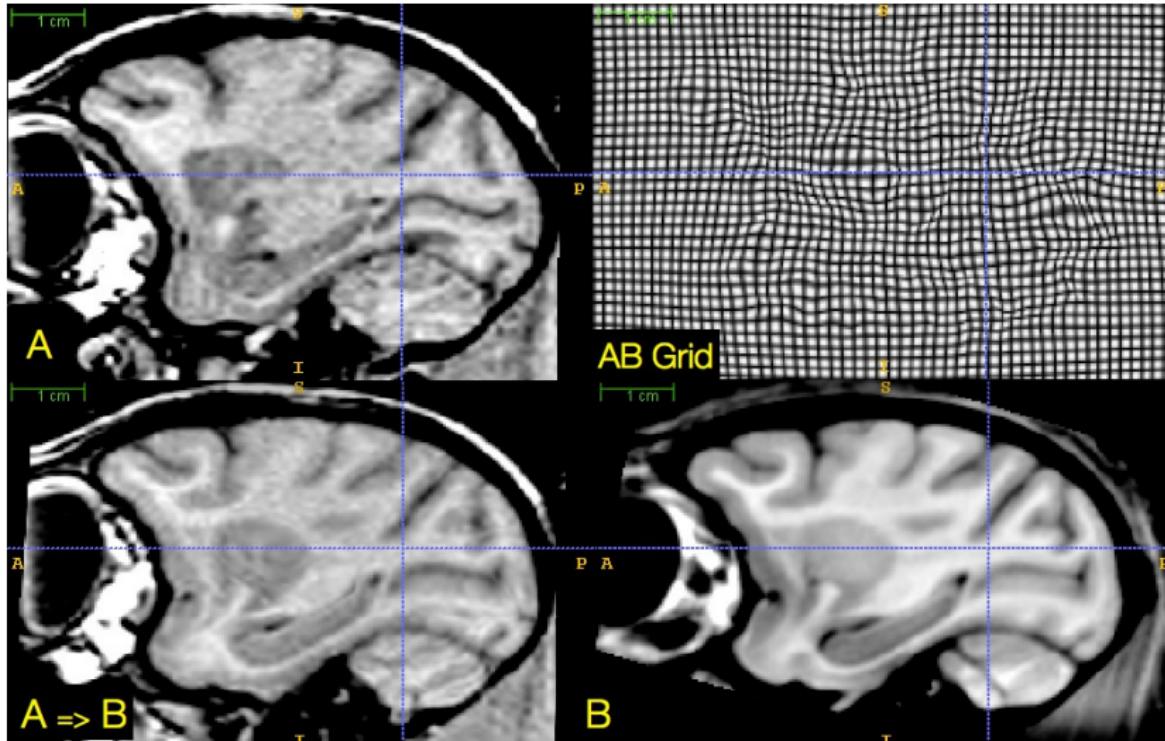


Diffeomorphisms: Occam's razor modeling

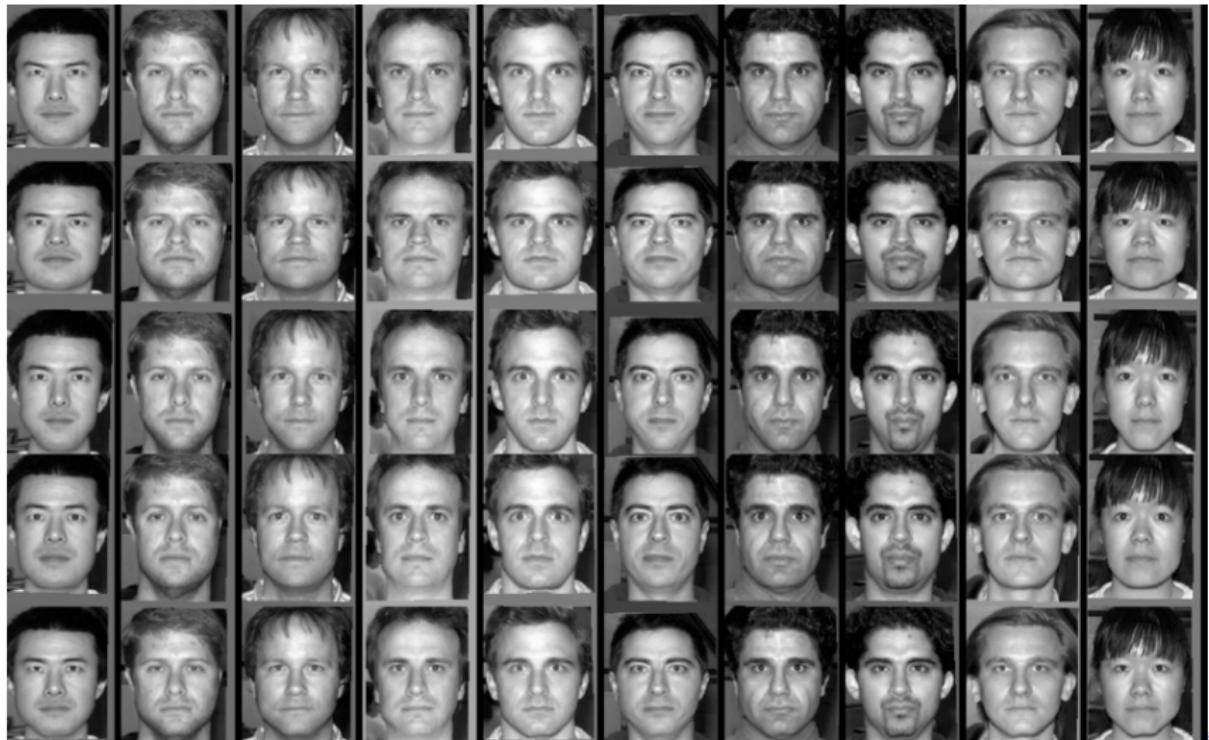


differentiable map with differentiable inverse

Diffeomorphisms: fine-grained and flexible maps



Diffeomorphisms: image parameterization in a metric space

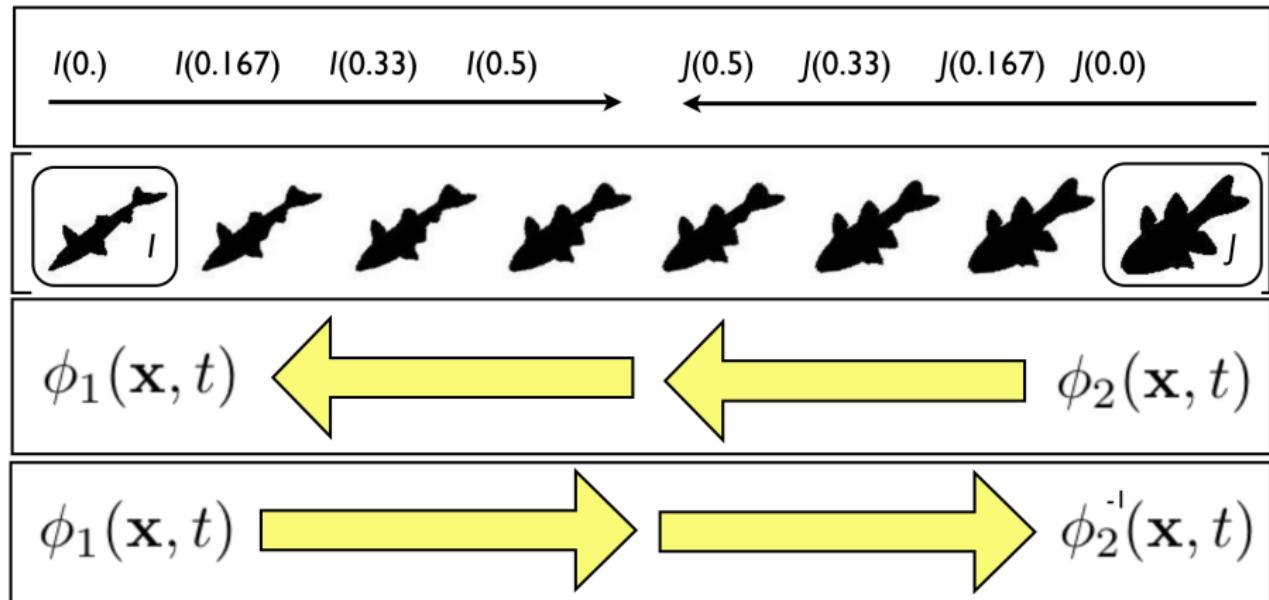


Donoho?

“Papers are just advertisements for the science.”

Symmetric Normalization (SyN)

$$\int_{t=0}^{0.5} (\|\mathbf{v}_1(x, t)\|_L^2 + \|\mathbf{v}_2(x, t)\|_L^2) dt + \|I(\phi_1(x, 0.5)) - J_i(\phi_2(x, 0.5))\|^2$$



Beyond original SyN

frontiers in
NEUROINFORMATICS

ORIGINAL RESEARCH ARTICLE

published: 28 April 2014

doi: 10.3389/fninf.2014.00044



The Insight ToolKit image registration framework

Brian B. Avants^{1*}, Nicholas J. Tustison², Michael Stauffer¹, Gang Song¹, Baohua Wu¹ and James C. Gee¹

¹ Penn Image Computing and Science Laboratory, Department of Radiology, University of Pennsylvania, Philadelphia, PA, USA

² Department of Radiology and Medical Imaging, University of Virginia, Charlottesville, VA, USA

frontiers in
NEUROINFORMATICS

METHODS ARTICLE

published: 23 December 2013

doi: 10.3389/fninf.2013.00039



Explicit B-spline regularization in diffeomorphic image registration

Nicholas J. Tustison^{1*} and Brian B. Avants²

antsRegistration

```
$ antsRegistration --help
```

COMMAND:

antsRegistration

This program is a user-level registration application. It consists of a transform; an image metric; and iterative smoothing sigmas for each level. Note that dimensionality output, convergence, shrink-factors and smoothing-sigma are mandatory.

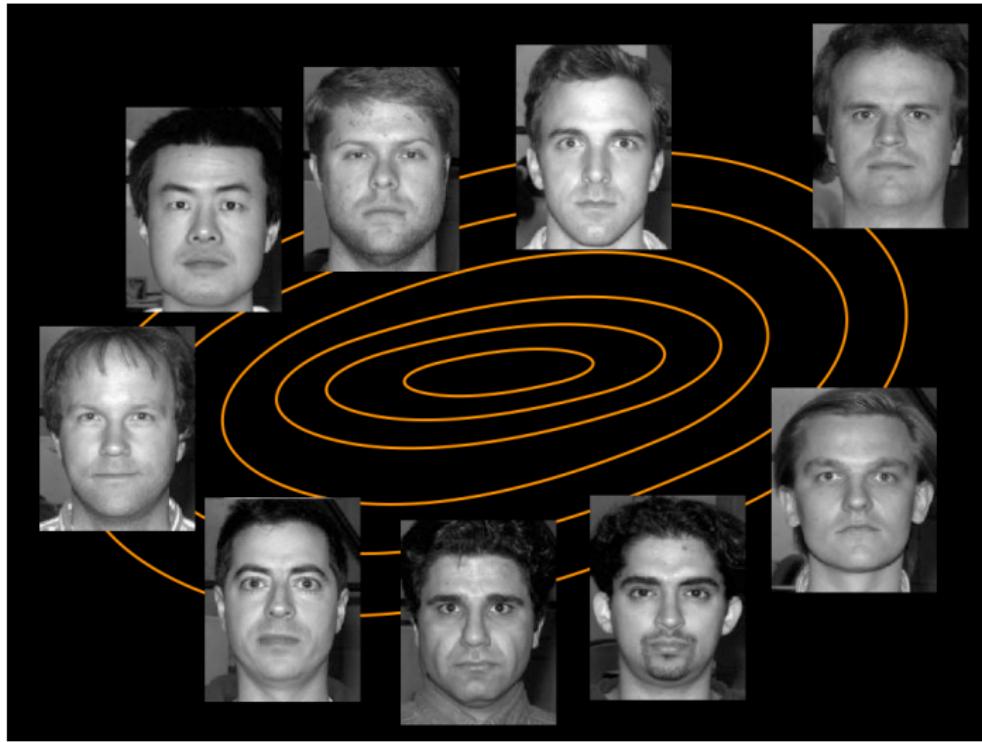
OPTIONS:

--version

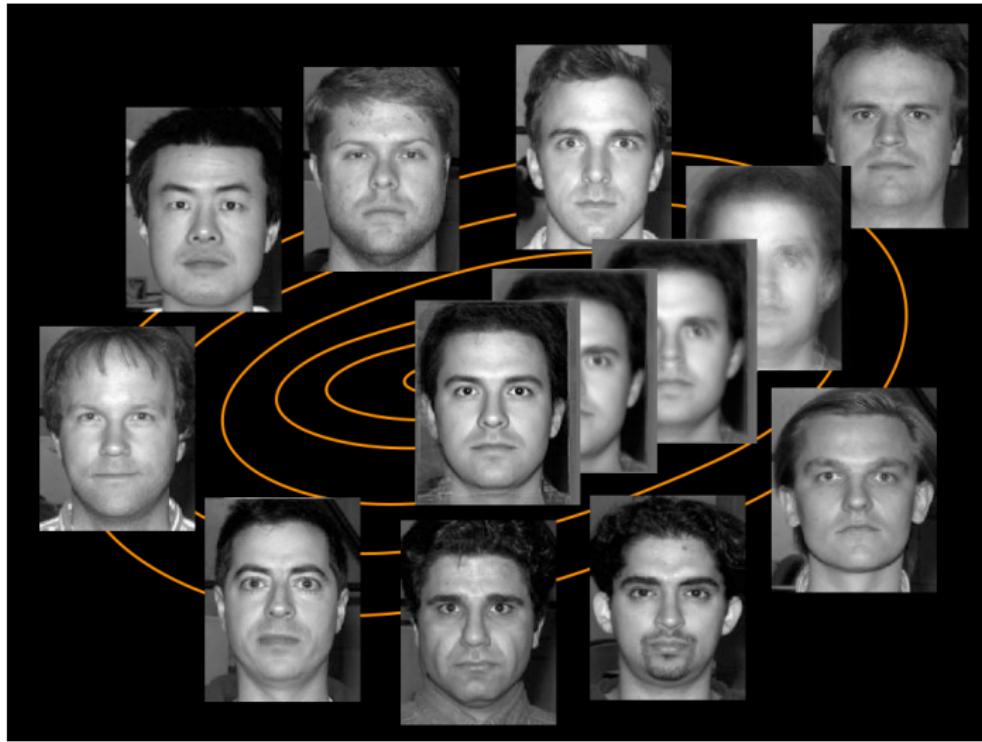
Get Version Information.

-d, --dimensionality 2/3

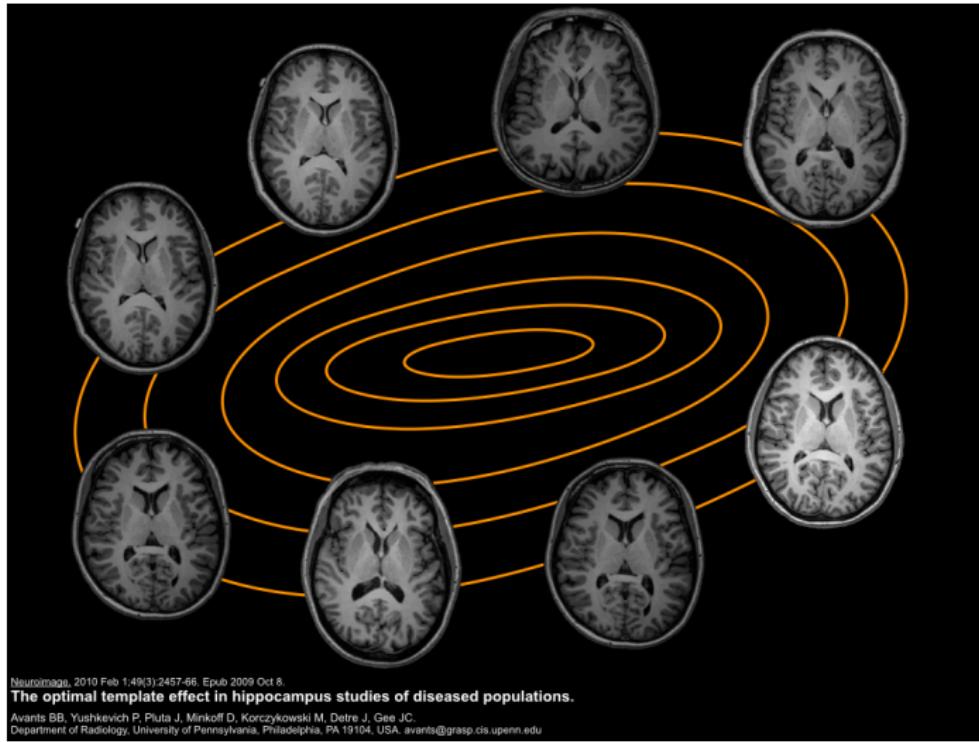
Template building: creating the average Joe



“Attractiveness” → mental processing?



What about brains?



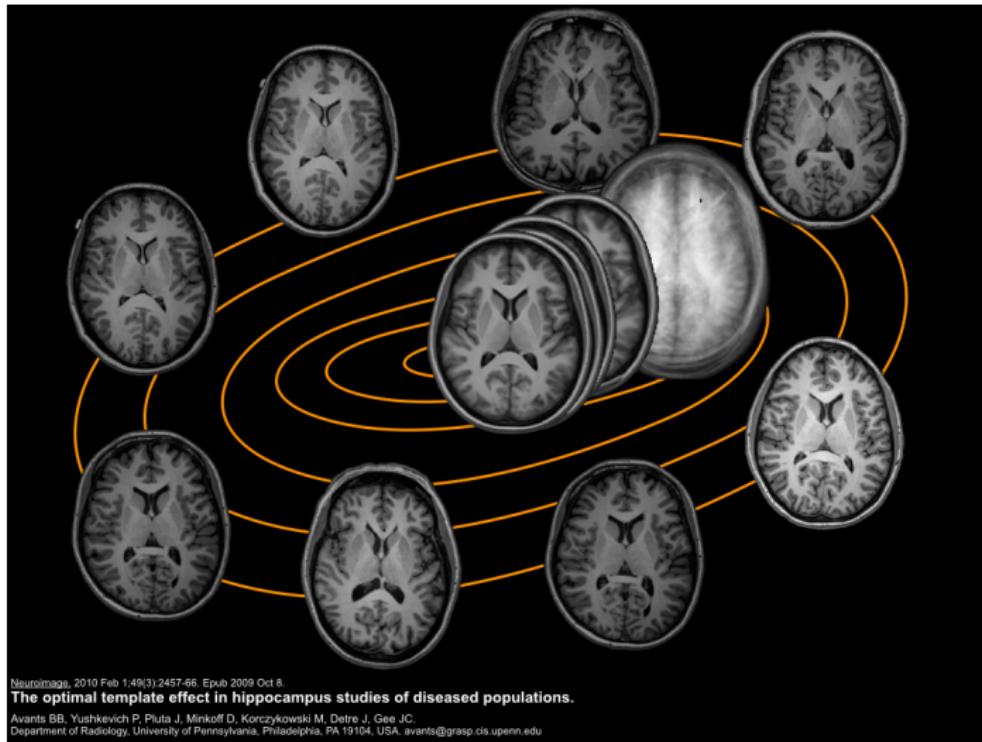
Neuroimage, 2010 Feb 1;49(3):2457-66. Epub 2009 Oct 8.

The optimal template effect in hippocampus studies of diseased populations.

Avants BB, Yushkevich P, Pluta J, Minkoff D, Korczykowski M, Detre J, Gee JC.

Department of Radiology, University of Pennsylvania, Philadelphia, PA 19104, USA. avants@grasp.cis.upenn.edu

Templates facilitate computation



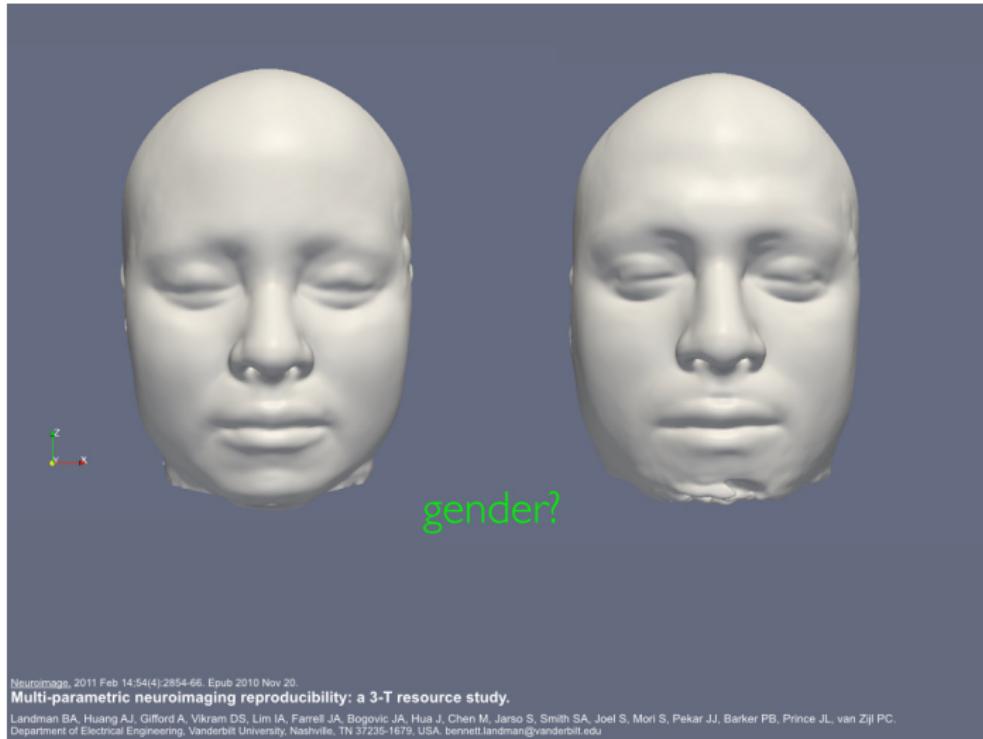
Neuroimage, 2010 Feb 1;49(3):2457-66. Epub 2009 Oct 8.

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Department of Radiology, University of Pennsylvania, Philadelphia, PA 19104, USA. avants@grasp.cis.upenn.edu

Gender discernibility?



Neuroimage, 2011 Feb 14;54(4):2854-66. Epub 2010 Nov 20.

Multi-parametric neuroimaging reproducibility: a 3-T resource study.

Landman BA, Huang AJ, Gifford A, Vikram DS, Lim IA, Farrell JA, Bogovic JA, Hua J, Chen M, Jarso S, Smith SA, Joel S, Mori S, Pekar JJ, Barker PB, Prince JL, van Zijl PC.

Department of Electrical Engineering, Vanderbilt University, Nashville, TN 37235-1679, USA. bennett.landman@vanderbilt.edu

antsMultivariateTemplateConstruction2.sh

```
$ antsMultivariateTemplateConstruction2.sh
```

Usage:

```
antsMultivariateTemplateConstruction2.sh -d ImageDimension -o
```

Compulsory arguments (minimal command line requires SGE/PBS cluster
-j options):

-d: ImageDimension: 2 or 3 (for 2 or 3 dimensional registration)

ImageDimension: 4 (for template generation of time-series data)

-o: OutputPrefix; A prefix that is prepended to all output files

<images> List of images in the current directory, eg *_t1.nii
of the command. Optionally, one can specify a .csv file

Nonparametric nonuniform intensity normalization (N3)

- Developed at the Montreal Neurological Institute (John Sled, 1998)

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 - *public availability*

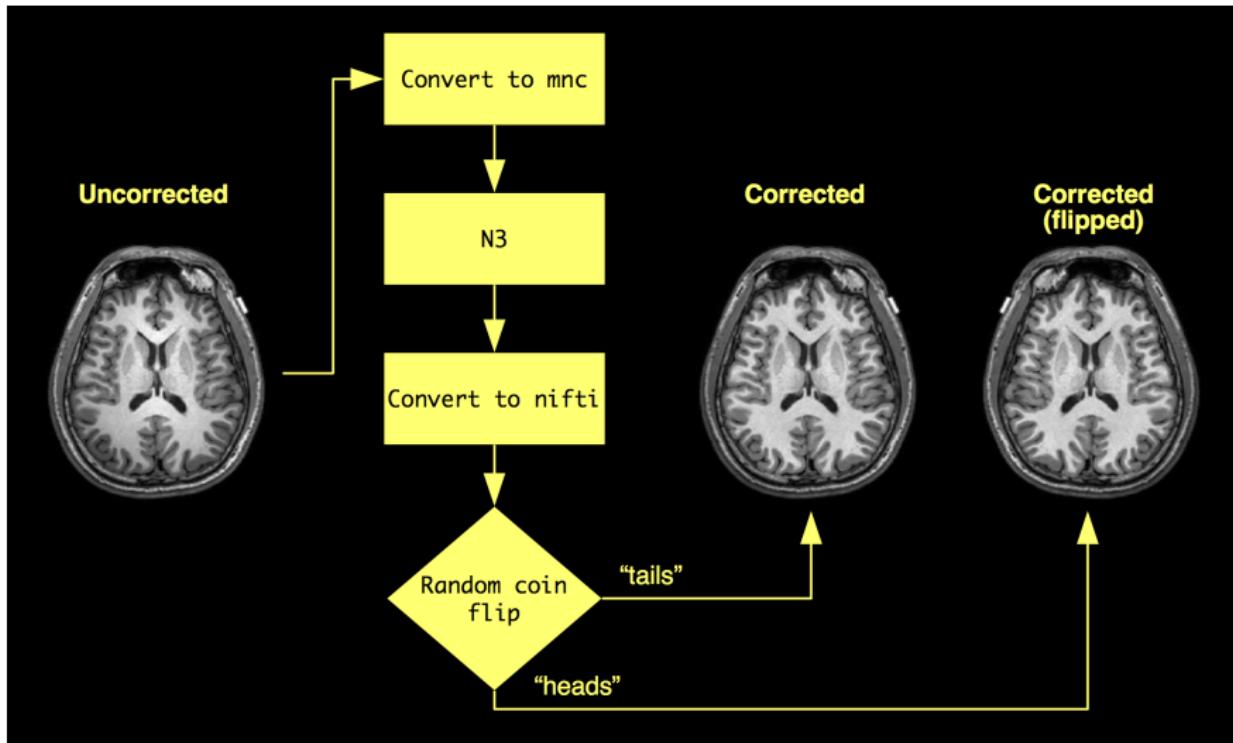
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 - *public availability*
- Public availability — set of perl scripts coordinating various C++ programs

Nonparametric nonuniform intensity normalization (N3)

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 - *public availability*
- Public availability — set of perl scripts coordinating various C++ programs
- “*Let's incorporate N3 into ANTs!*”

N3 adoption issues



N4

- comparative evaluation

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- small spline distances (useful for higher magnet strengths)

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N4

- comparative **evaluation**
- small spline distances (useful for higher magnet strengths)
- multiresolution
- weighted regional mask (used in `antsAtroposN4.sh`)
- fast execution times
- *publicly available*
- tested nightly within the ITK dashboard system

N4BiasFieldCorrection

```
$ N4BiasFieldCorrection --help
```

COMMAND:

N4BiasFieldCorrection

N4 is a variant of the popular N3 (nonparameteric nonrigid retrospective bias correction algorithm. Based on the corruption of the low frequency bias field can be modeled by a Gaussian, the basic algorithm iterates between deconvolving the intensity histogram of the intensities, and then spatially smoothing this model of the bias field itself. The modifications from and the original N3 algorithm are described in the following paper:
Wang, C., Lai, Y., and Yuille, A.L., N4ITK: Improved N3 Bias Correction, IEEE Transactions on Medical Imaging, 29(6):1310-1320, June 2010.

OPTIONS:

Atropos – cutting the threads of fate



“20+ years of development. *Show me the code!*”

Atropos: flexible code base

Initialization

- Gaussian
- Non-parametric
 - histogram Parzen windows
 - manifold Parzen windows

Likelihood models

- Gaussian
- Non-parametric
 - histogram Parzen windows
 - manifold Parzen windows

Atropos

Prior models

- Markov random field
- Prior label images
- Prior probability images

Miscellaneous

- Label geodesic/Euclidean propagation
- Outlier handling
- localized adaptive intensity handling

Atropos

```
$ Atropos --help
```

COMMAND:

Atropos

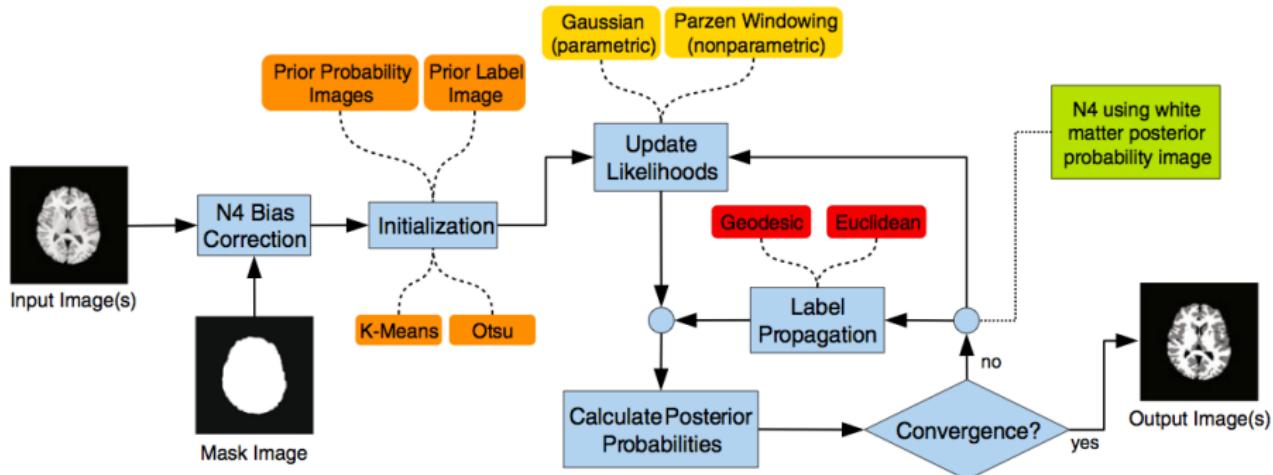
A finite mixture modeling (FMM) **segmentation** approach specifying prior constraints. These prior constraints of a prior label image, prior probability images (or MRF prior to enforce spatial smoothing of the labels) FAST and SPM. Reference: Avants BB, Tustison NJ, Wu source multivariate framework for n-tissue segmentation public data. Neuroinformatics. 2011 Dec;9(4):381-400.

OPTIONS:

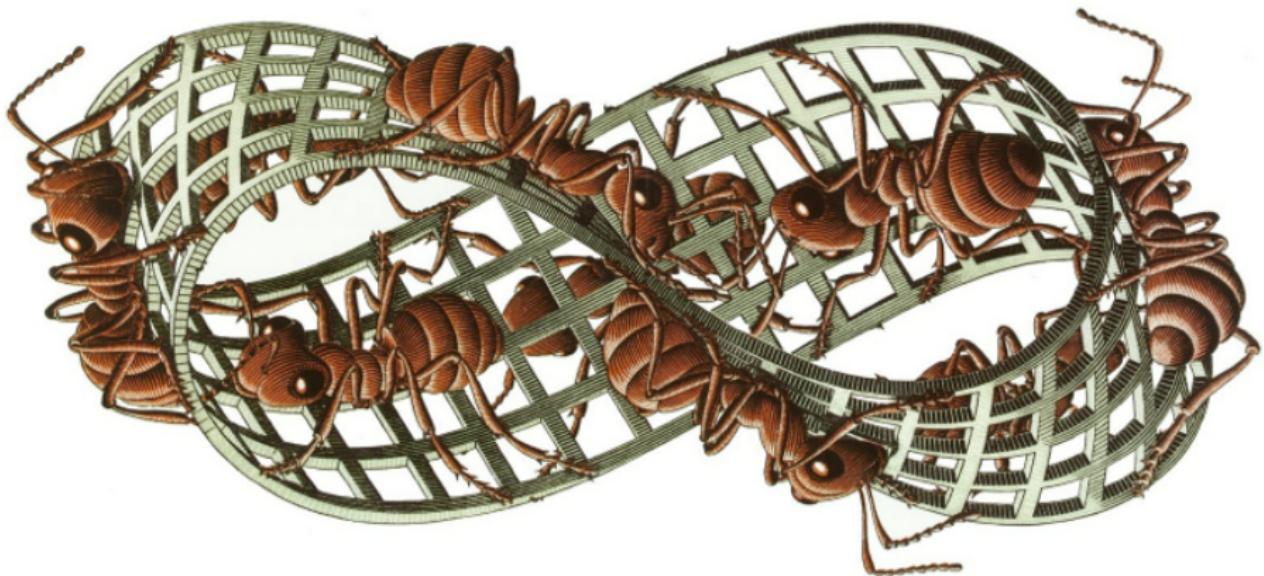
-d, --image-dimensionality 2/3/4

This option forces the image to be treated as a specific dimensionality if it is not specified. Atropos tries to infer the dimensionality from the image.

Atropos + N4 → antsAtroposN4.sh

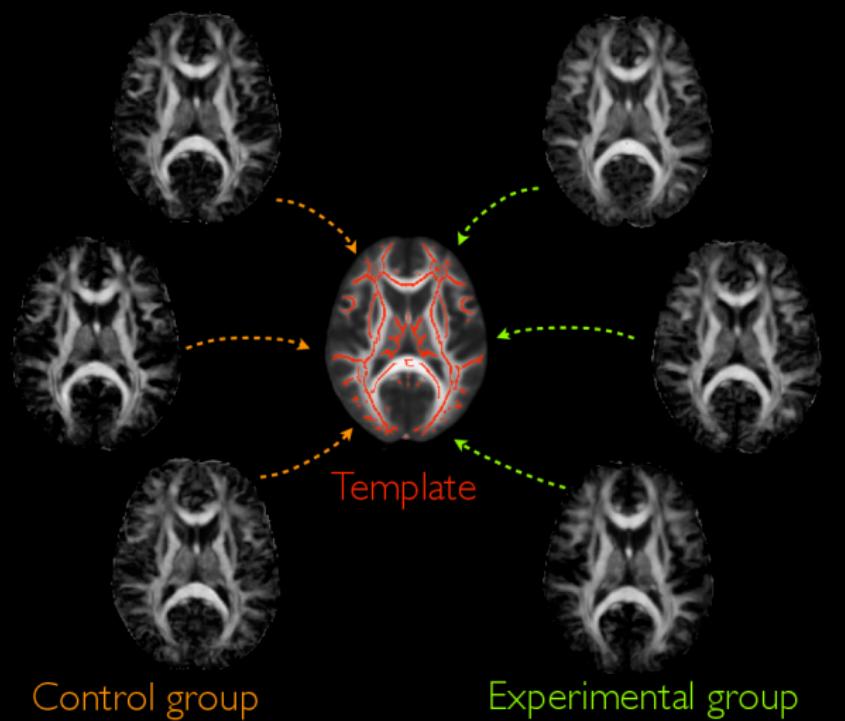


ANTs and the perils of circularity

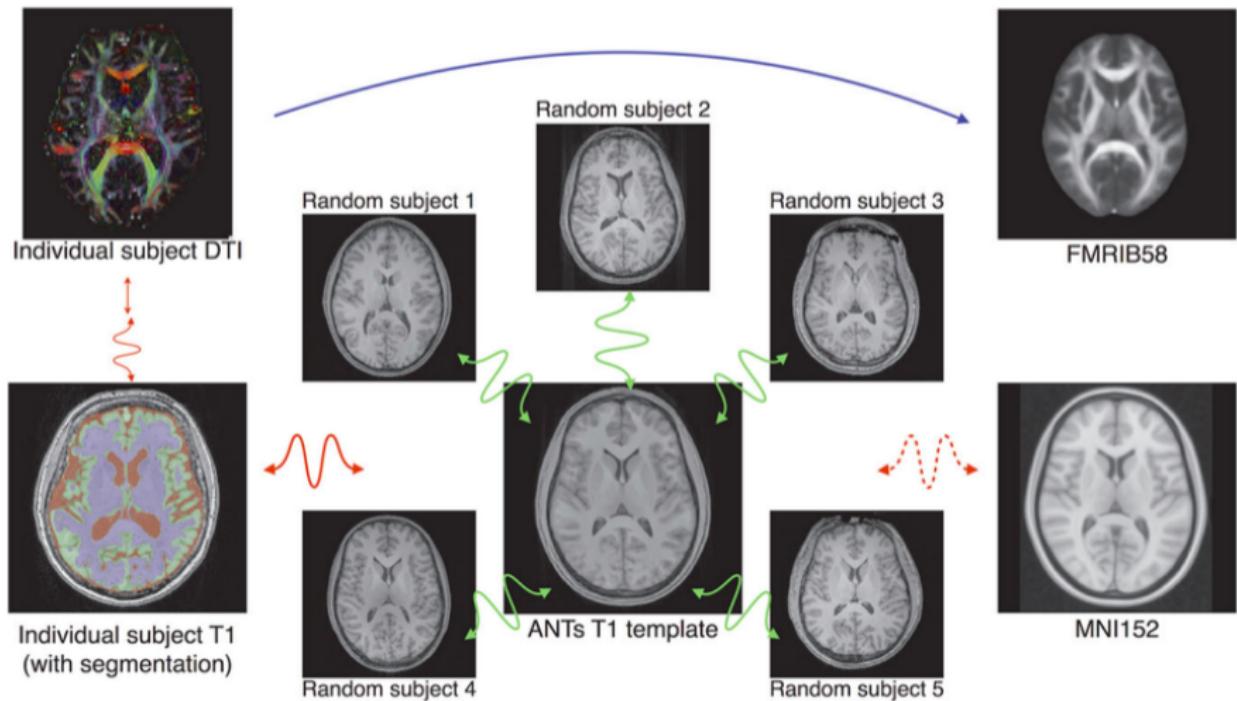


“Hey Brian, have you ever used TBSS?”

TBSS

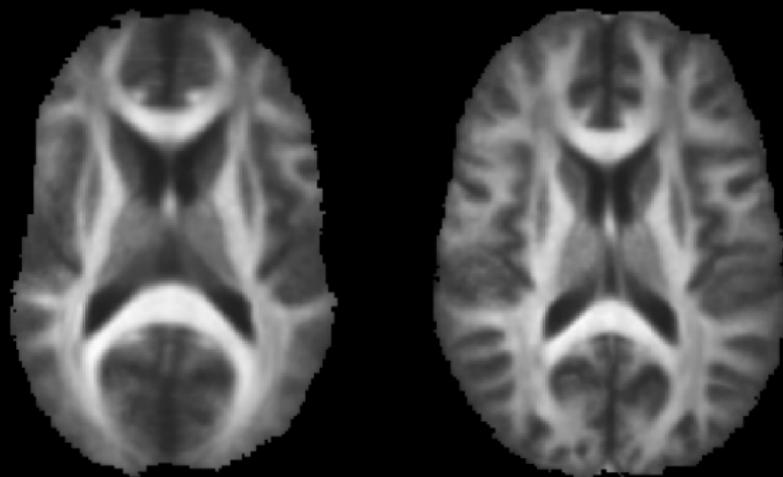


Use ANTs template building



Evaluation

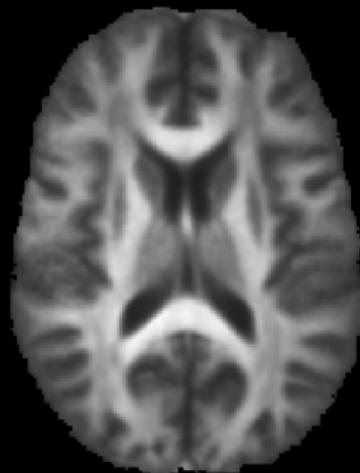
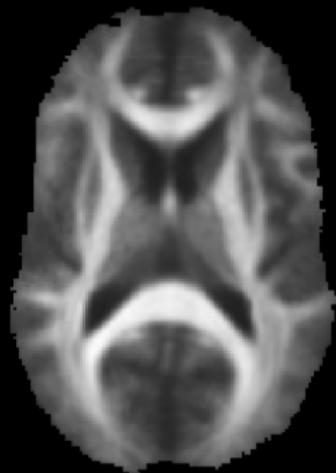
Let's write a paper!



We'll call the approach...

Let's write a paper!

ANTs-Flavored Tract-Based Spatial Statistics



Quantitative results

Let's write a paper!

ANTs-Flavored Tract-Based Spatial Statistics

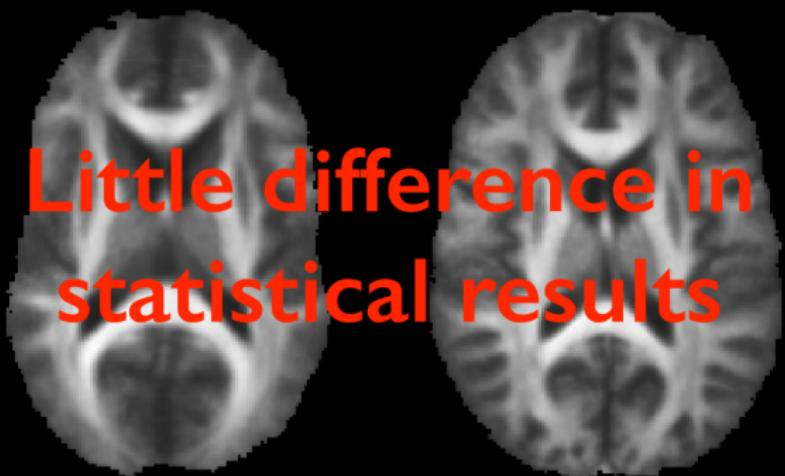


**Little difference in
statistical results**

So much for that idea. :(

~~Let's write a paper!~~

~~ANTs-Flavored Tract-Based Spatial Statistics~~

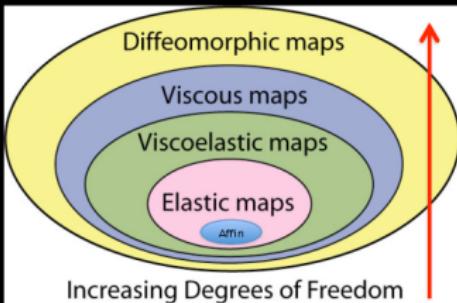


Little difference in
statistical results

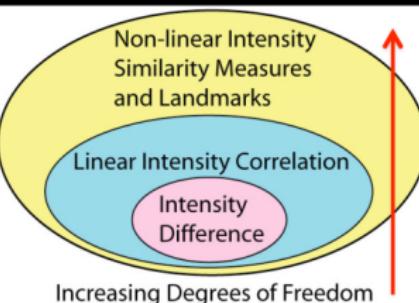
What happened?

Possible causes

Transformation model



Appearance model



Other possible causes

- smoothing
- statistical testing (parametric vs. non-parametric)
- skeletal projections (TBSS)

Insight to the major stumbling block

brian avants
to Nick ▾

May 8 ★ ↻ ⏴

nick

the only point i understand clearly is that the ssd metric + smoothing and standard fsl + smoothing have similar detection power and both are dissimilar to the other metrics (and t1 based mapping).

regarding this question

- > So, Brian, is all this smoothing simply spreading out the FA differences
- > between groups which is why the statistical power is higher?

i still dont know. a t-test is

$$(\text{mean_1} - \text{mean_2}) / \text{variance}$$

so either the difference in means (on the skeleton) is increased by the ssd+smoothing approaches or the variance is decreased. my guess is that it's the latter.

perhaps it's worth looking explicitly at each of these three values.

...

Academically “counting sheep”

$$\mathcal{T}^* = \operatorname{argmin}_{\mathcal{T}} \left\{ SSD(I, J, \mathcal{T}) = \frac{1}{N} \sum_{n=1}^N (I^n(\mathcal{T}(\mathbf{x})) - J)^2 \right\}$$



It sort of looks like the variance but the N

$$\mathcal{T}^* = \operatorname{argmin}_{\mathcal{T}} \left\{ SSD(I, J, \mathcal{T}) = \frac{1}{N} \sum_{n=1}^N (I^n(\mathcal{T}(\mathbf{x})) - J)^2 \right\}$$



Wait, that's not right.



There's a missing summation!

$$\mathcal{T}_1^*, \dots, \mathcal{T}_M^* = \operatorname{argmin}_{\mathcal{T}_1, \dots, \mathcal{T}_M} \left\{ \sum_{m=1}^M \sum_{n=1}^N (I_m^n(\mathcal{T}_m(x)) - J)^2 \right\}$$



We switch the summations,

$$\mathcal{T}_1^*, \dots, \mathcal{T}_M^* = \operatorname{argmin}_{\mathcal{T}_1, \dots, \mathcal{T}_M} \left\{ \sum_{n=1}^N \sum_{m=1}^M (I_m^n(\mathcal{T}_m(x)) - J)^2 \right\}$$



recast J as the mean image, and

$$\mathcal{T}_1^*, \dots, \mathcal{T}_M^* = \operatorname{argmin}_{\mathcal{T}_1, \dots, \mathcal{T}_M} \left\{ \sum_{n=1}^N \sum_{m=1}^M (I_m^n(\mathcal{T}_m(x)) - \overbrace{J}^{\mu_J})^2 \right\}$$



there it is!

$$\mathcal{T}_1^*, \dots, \mathcal{T}_M^* = \operatorname{argmin}_{\mathcal{T}_1, \dots, \mathcal{T}_M} \left\{ \sum_{n=1}^N \sum_{m=1}^M (I_m^n(\mathcal{T}_m(x)) - \underbrace{\mu_I}_{\text{voxelwise variance}})^2 \right\}$$



Okay, so now how do we show this?

Benefits of open science



Simulated Diffusion-Weighted Imaging for the ITK Masses
Published in The Insight Journal
Tusison N., Cook P., Avants B., Stone J.
A recent article by Van Hecke et al. [3] describes a framework for creating simulated diffusion-weighted images (DWI). The methodology allows for modeling intersubject variability, regional pathology, and noise and is quite useful for evaluation purposes. [...]
downloaded 163 times, viewed 963 times and 2 reviews.

	NKI/Rockland Sample Bharat Biswal, F. Xavier Castellanos, Barbara Coffey, Stan Colcombe, David Gulyfoyle, Matthew Hooper, Dan Javitt, Harold S. Koplowitz, Bennett Leventhal, Larry Maayan, Maarten Mennes, Michael Milham, Kate Noonan, Nunzio Pomara	Completed n=207	Psychiatrically- Evaluated Sample (ages 6-90)	 International Neuroimaging Data-sharing Initiative International Neuroimaging Data-sharing Initiative
--	---	---------------------------	--	---

Open science evaluation

```
$ CreateDTICohort -h
```

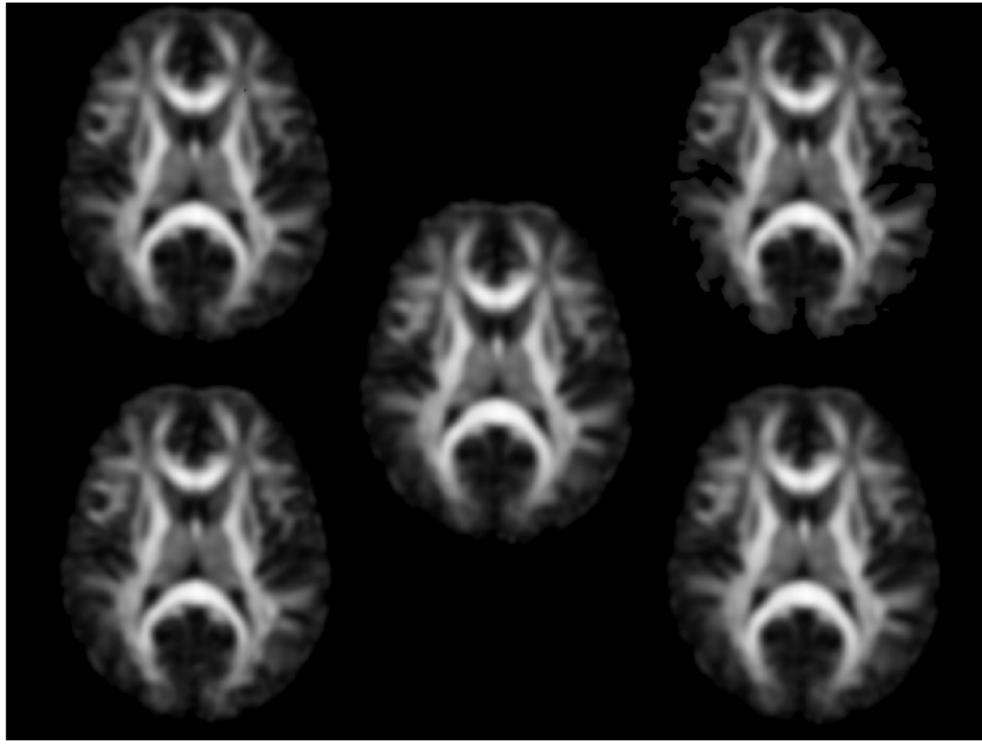
COMMAND:

CreateDTICohort

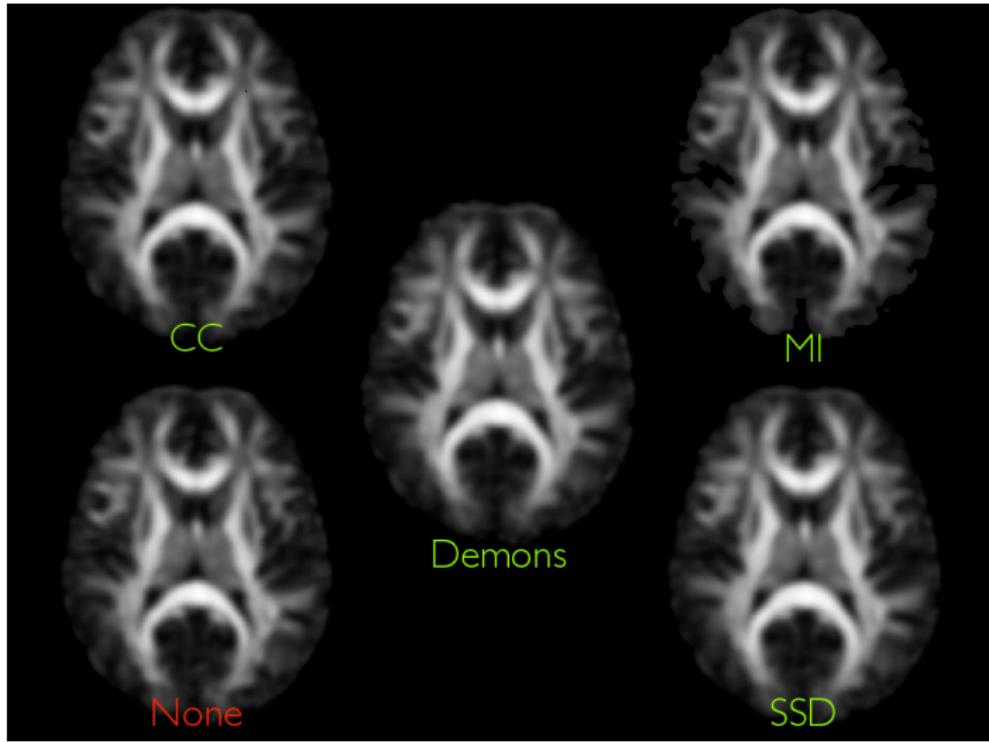
OPTIONS:

- d, --image-dimensionality 2/3
- a, --dti-atlas inputDTIAtlasFileName
- x, --label-mask-image maskImageFileName
 - lowerThresholdFunction
- n, --noise-sigma <noiseSigma=18>
- p, --pathology label [<percentageChangeEig1=-0.05>, <percentage>]
- w, --dwi-parameters [B0Image, directionFile, bvalue]
 - [B0Image, schemeFile]
- r, --registered-population textFileWithFileNames.txt
- o, --output [outputDirectory, fileNameSeriesRootName, <number>]

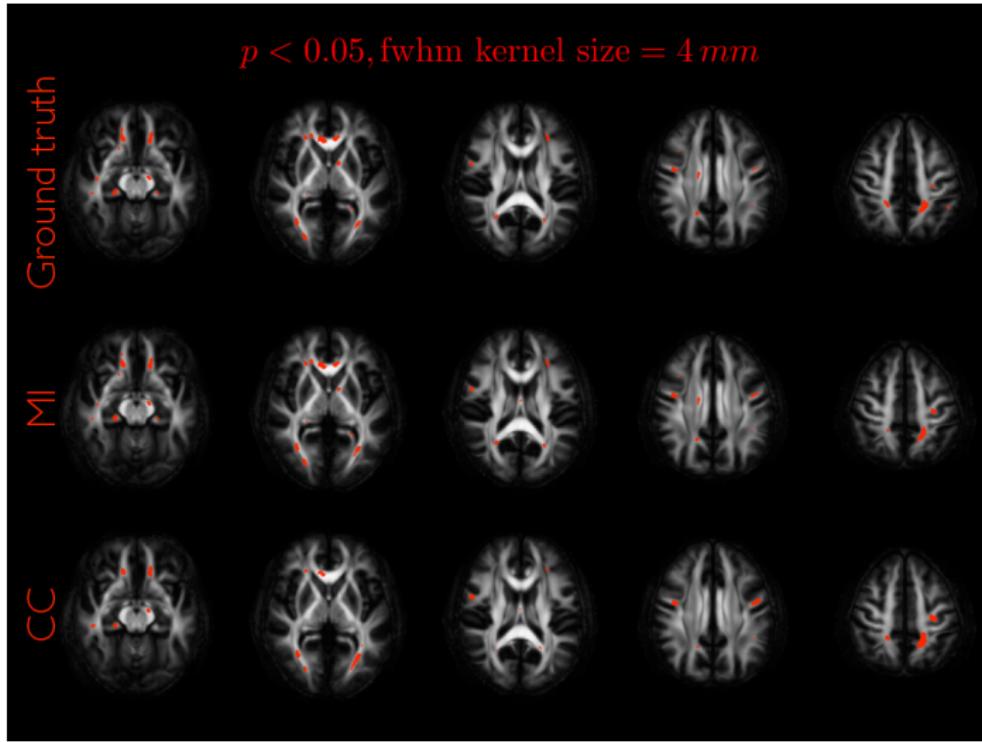
Which one is not warped?



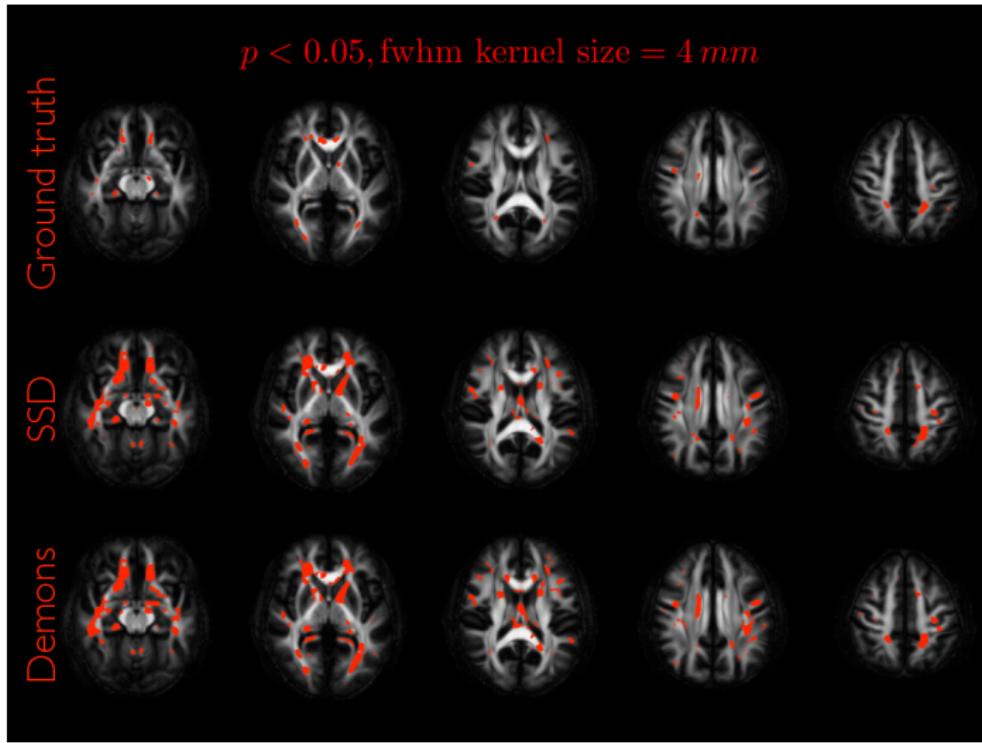
Answer



How does this vary with similarity metric?



How does this vary with similarity metric?



Bookstein review (blurb 1)

This is a signed review by Fred Bookstein.

This manuscript has an excellent point to make, and I would think so even if either

(1) I did not agree with its position, or (2) my own work were not cited so gently and appropriately within it, and even though (3) the title is truly terrible, since "circularity" has two ENTIRELY different meanings, one having to do with GEOMETRIC circularity and the other with LOGICAL circularity, and the meaning the authors intended is (I trust) the second one whereas the one that instantly leaps to the mind of the typical member of the medical imaging

community must necessarily be the first one, which is to say, the wrong one. The title should instead be something like

Circular reasoning about circles:
logical circularity in voxel-based analysis

or the like.

Anyway, assuming the title is repaired, it is impossible to disagree with the authors' position. My comment is only that this is old news, and that is not meant as a destructive criticism, but only as the suggestion that the literature review be made deeper and wiser than it is.

Bookstein review (blurb 2)

of any statistician's toolkit. In fact, my own article of 2001, which is appropriately cited by these authors, makes exactly the same point: the information in the registration is confounded with the information in the registered images; you can't say you are testing just one and not the other.

Bookstein review (blurb 3)

algebraically by a variant of the Akaike formula. I happen to think I said most of this already in 2001, but that was before the widespread availability of diffusion tensor data, which looks like it is susceptible to different paradoxes instead. But they are at root the same.

Fred L. Bookstein
University of Vienna,
University of Washington
March 23, 2012

Competitions

Algorithmic fight club



International competitions

- Klein 2009

International competitions

- Klein 2009
- EMPIRE 2010

International competitions

- Klein 2009
- EMPIRE 2010
- Multi-Atlas Label Challenge 2012

International competitions

- Klein 2009
- EMPIRE 2010
- Multi-Atlas Label Challenge 2012
- SATA Challenge 2013

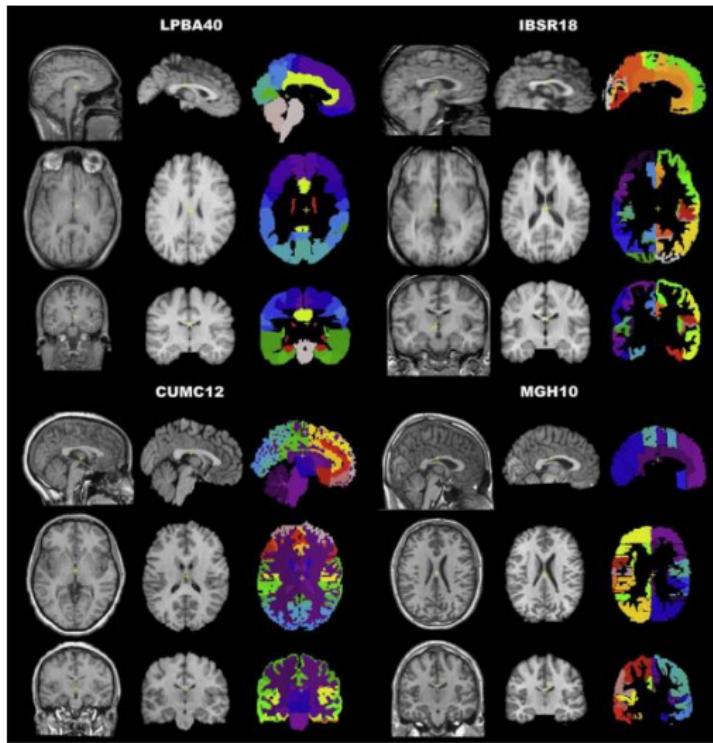
International competitions

- Klein 2009
- EMPIRE 2010
- Multi-Atlas Label Challenge 2012
- SATA Challenge 2013
- BRATS 2013

International competitions

- Klein 2009
- EMPIRE 2010
- Multi-Atlas Label Challenge 2012
- SATA Challenge 2013
- BRATS 2013
- STACOM 2014 MoCo Challenge

Klein, NeuroImage 2009



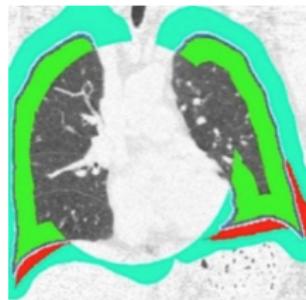
Klein results

	LPBA40	μ (SD)	IBSR18	μ (SD)	CUMC12	μ (SD)	MGH10	μ (SD)
rank 1	ART	.82 (.35)	SPM_D	.83 (.27)	SPM_D	.76 (.24)	SyN	.77 (.37)
	SyN	.60 (.38)	SyN	.72 (.51)	SyN	.74 (.51)	ART	.72 (.45)
	FNIRT	.49 (.66)	IRTK	.67 (.53)	IRTK	.74 (.50)	IRTK	.61 (.51)
	JRD-fluid	.49 (.66)	ART	.60 (.70)	ART	.60 (.70)		
2	IRTK	.43 (.63)	JRD-fluid	.30 (.82)			SPM_D	.27 (.23)
	D.Demons	.13 (.82)					D.Demons	.27 (.69)
	SPM_US	.11 (.83)					JRD-fluid	.24 (.66)
3	ROMEO	.08 (.73)	FNIRT	.16 (.82)	D.Demons	.20 (.84)	ROMEO	.06 (.63)
	SPM_D	.07 (.29)	D.Demons	.05 (.84)	FNIRT	.18 (.81)		
					JRD-fluid	.17 (.81)		

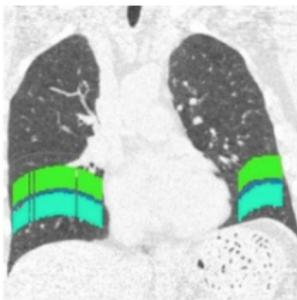
Take-away message

“One of the most significant findings of this study is that the relative performances of the registration methods under comparison appear to be little affected by the choice of subject population, labeling protocol, and type of overlap measure. . . . ART, SyN, IRTK, and SPM’s DARTEL Toolbox gave the best results according to overlap and distance measures, with ART and SyN delivering the most consistently high accuracy across subjects and label sets.”

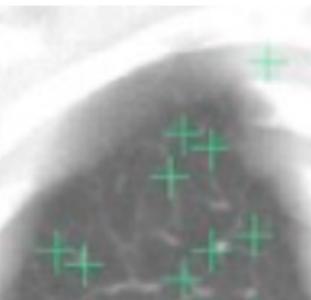
EMPIRE 2010



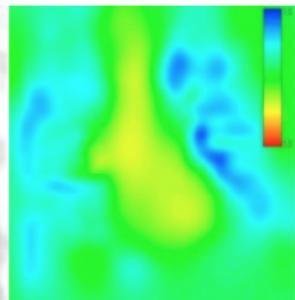
boundaries



fissures



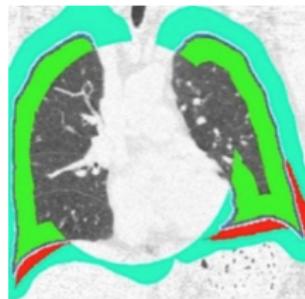
landmarks



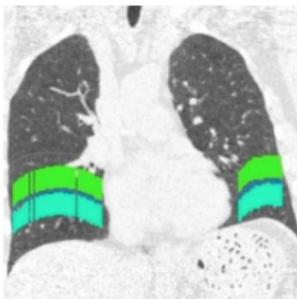
jacobian

- Alignment of lung boundaries,

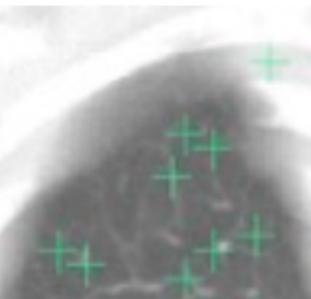
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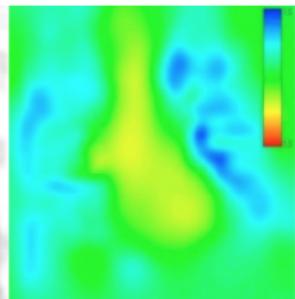
boundaries



fissures



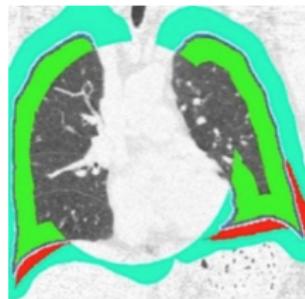
landmarks



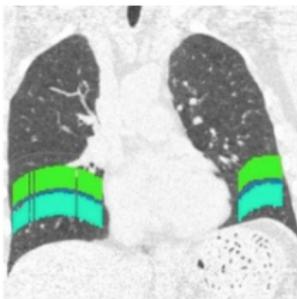
jacobian

- Alignment of lung boundaries,
- major fissures,

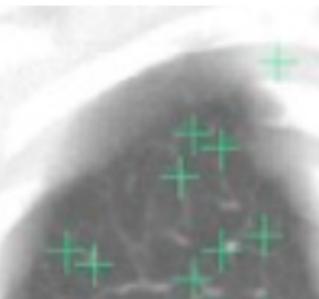
EMPIRE 2010



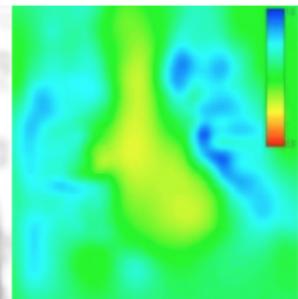
boundaries



fissures



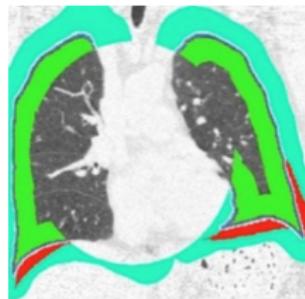
landmarks



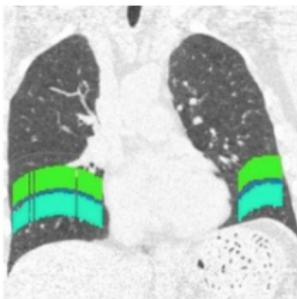
jacobian

- Alignment of lung boundaries,
- major fissures,
- annotated landmark pairs, and

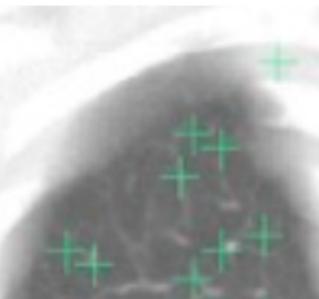
EMPIRE 2010



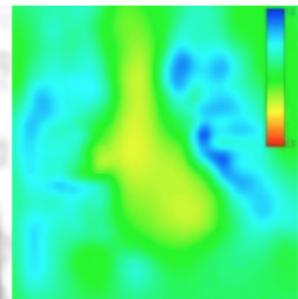
boundaries



fissures



landmarks



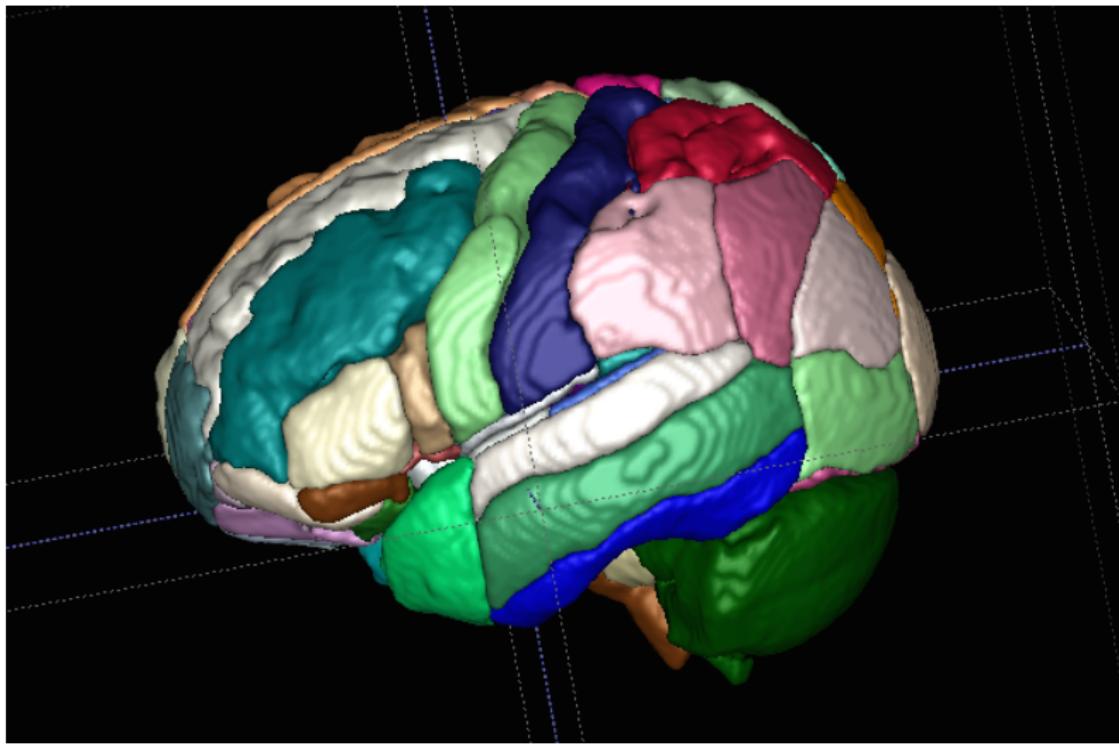
jacobian

- Alignment of lung boundaries,
- major fissures,
- annotated landmark pairs, and
- topology of displacement field.

EMPIRE 2010 results

	Lung Boundaries		Fissures		Landmarks		Folding		Overall			
Team Name	Avg Score	Avg Rank	Avg Score	Avg Rank	Avg Score	Avg Rank	Avg Score	Avg Rank	Avg Rank	Placed	Last Update	Method Type
picsl gsyn	0.12	8.00	0.03	9.52	0.75	3.65	0.00	13.77	8.73	1	25 Jun 2010	Fully Auto
Nifty Reggers	0.00	7.57	0.27	12.30	0.75	7.25	0.00	12.50	9.90	2	26 Jun 2010	Fully Auto
Iowa sstvd	0.00	10.00	0.00	10.07	0.70	6.05	0.00	10.00	10.75	3	26 Jun	Fully

Multi-atlas 2012



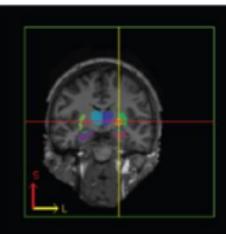
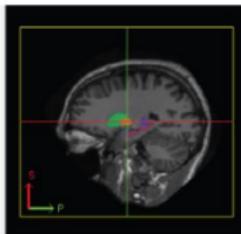
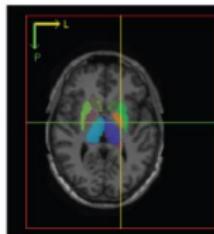
Multi-atlas 2012 results

Overall Rank †	Repro. Rank‡	Team Name	Mean DSC Overall	Mean DSC Cortical	Mean DSC Non-Cortical
1	1	PICSL_BC	0.7654	0.7388	0.8377
2	2	NonLocalSTAPLE	0.7581	0.7318	0.8296
3	3	MALP_EM	0.7576	0.7328	0.8252
4	4	PICSL_Joint	0.7499	0.7216	0.8271
5	6	MAPER	0.7413	0.7144	0.8144
6	7	STEPS	0.7372	0.7107	0.8095
7	5	SpatialSTAPLE	0.7372	0.7093	0.8130
8	9	CIS_JHU	0.7357	0.7131	0.7971
9	8	CRL_Weighted_STAPLE ANTS+Baloo	0.7344	0.7122	0.7950
10	10	CRL_Weighted_STAPLE ANTS	0.7308	0.7066	0.7966

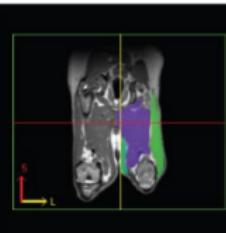
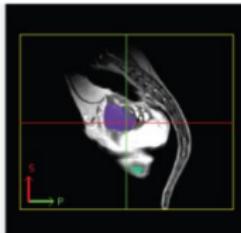
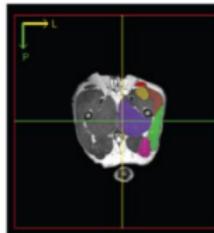
SATA 2013

Three very different problem domains

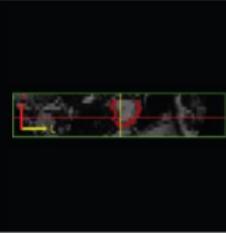
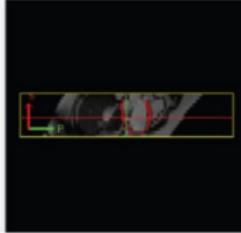
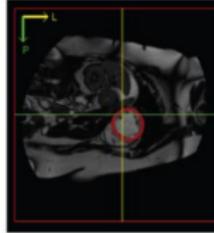
Diencephalon



Canine Leg



Cardiac Atlas Project

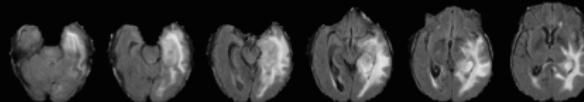


BRATS 2013

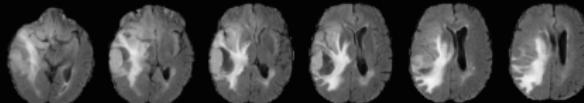
BRATS 2013 challenge results

FLAIR

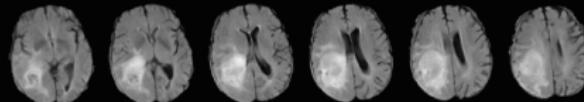
301



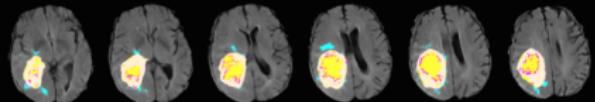
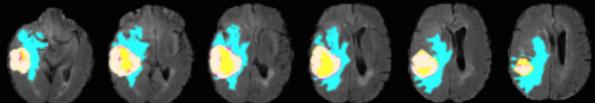
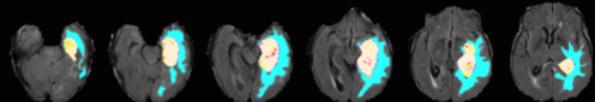
302



303



FLAIR with tumor labels



BRATS 2013 results

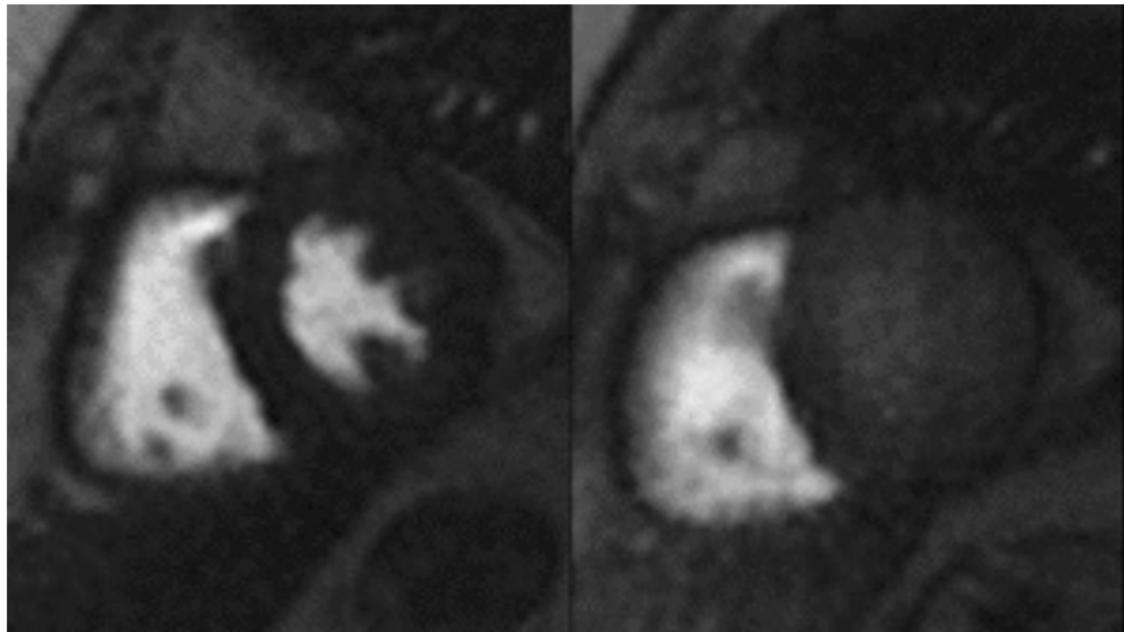
Results

Patient

Position	User	Dice			Positive Predictive Value			Sensitivity			Complete tumor		Tumor core Rank	Enhancing tumor Rank
		complete	core	enhancing	complete	core	enhancing	complete	core	enhancing	Kappa	Rank		
1	Nick Tustison	0.87 (1)	0.78 (1)	0.74 (1)	0.85 (2)	0.74 (4)	0.69 (4)	0.89 (2)	0.88 (1)	0.83 (1)	0.99 (1)	1.67	2.00	1.89
2	Raphael Meier	0.82 (5)	0.73 (2)	0.69 (3)	0.76 (6)	0.78 (2)	0.71 (1)	0.92 (1)	0.72 (4)	0.73 (3)	0.99 (4)	4.00	2.67	3.00
3	Syed Reza	0.83 (4)	0.72 (3)	0.72 (2)	0.82 (3)	0.81 (1)	0.70 (3)	0.86 (5)	0.69 (6)	0.76 (2)	0.99 (3)	4.00	3.33	3.22
4	Liang Zhao	0.84 (3)	0.70 (4)	0.65 (5)	0.80 (4)	0.67 (5)	0.65 (6)	0.89 (3)	0.79 (3)	0.70 (4)	0.99 (5)	3.33	4.00	4.11
5	Nicolas Cordier	0.84 (2)	0.68 (5)	0.65 (6)	0.88 (1)	0.63 (6)	0.68 (5)	0.81 (6)	0.82 (2)	0.66 (6)	0.99 (2)	3.00	4.33	4.33
6	Joana Festa	0.72 (6)	0.66 (6)	0.67 (4)	0.77 (5)	0.77 (3)	0.70 (2)	0.72 (7)	0.60 (7)	0.70 (5)	0.98 (6)	6.00	5.33	5.00
7	Senan Doyle	0.71 (7)	0.46 (7)	0.52 (7)	0.66 (7)	0.38 (7)	0.58 (7)	0.87 (4)	0.70 (5)	0.55 (7)	0.98 (7)	6.00	6.33	6.44

Optimal symmetric multimodal templates and concatenated random forests for supervised brain tumor segmentation (simplified) with ANTsR, *Neuroinformatics*.

STACOM 2014



ANTs: in summary

Show me the code!

**General purpose library for multivariate image registration,
segmentation & statistical analysis tools**

- 170,000+ lines of C++, 6+ years of work, 15+ collaborators.

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- 170,000+ lines of C++, 6+ years of work, 15+ collaborators.
- Generic mathematical methods that are tunable for application specific domains.
- no free lunch: *An algorithm must use prior knowledge about a problem to do well on that problem.*

Still quite a bit to do

On documentation



We are blind to deficiencies. Users blind to features.

