Image Registration

Is the process of finding the optimal transformation to maximize correspondence across images. Necessary components are:

- **Transformation model:** defines the type of geometric transform to be used (e.g., rigid, affine which are linear, deformable which are non-linear or elastic).
- **Similarity metric:** for registration basis measures the degree of alignment between images usually through measuring image intensity patterns (mutual information, cross-correlation, sum of squared intensity differences)
- **Optimization method:** tries to maximize the similarity measure
- **Validation protocol**

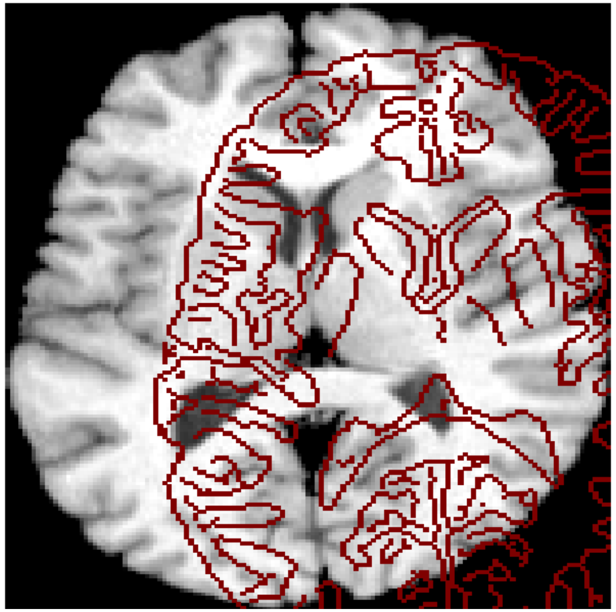
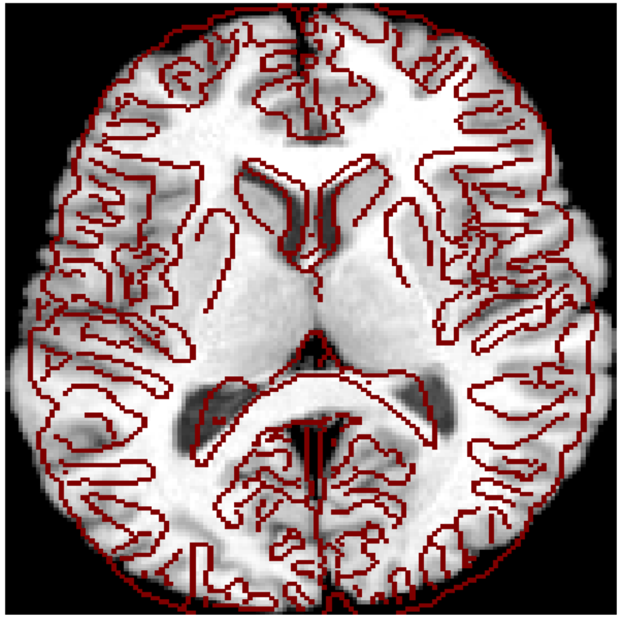
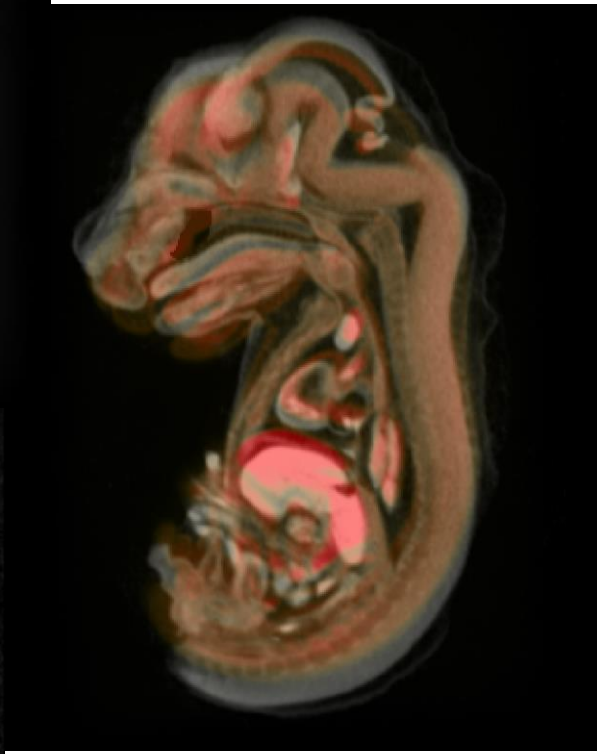



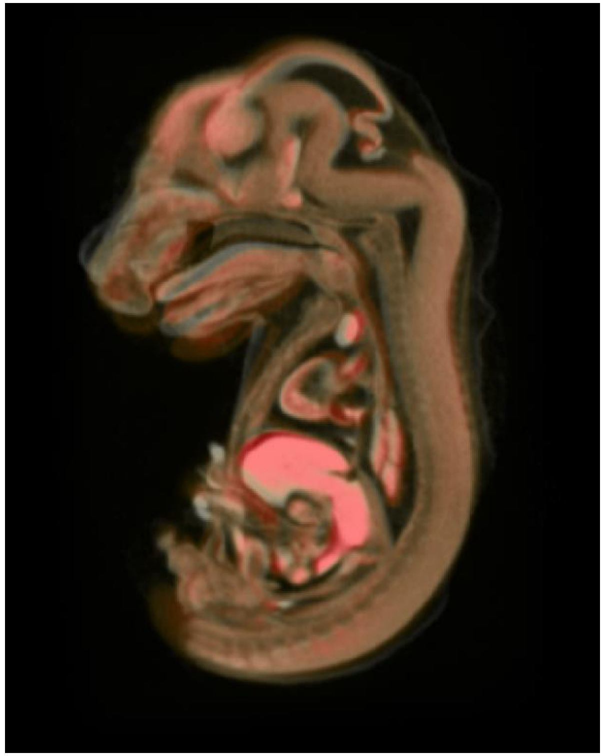

Image Registration: Transformation models

Rigid Transformation



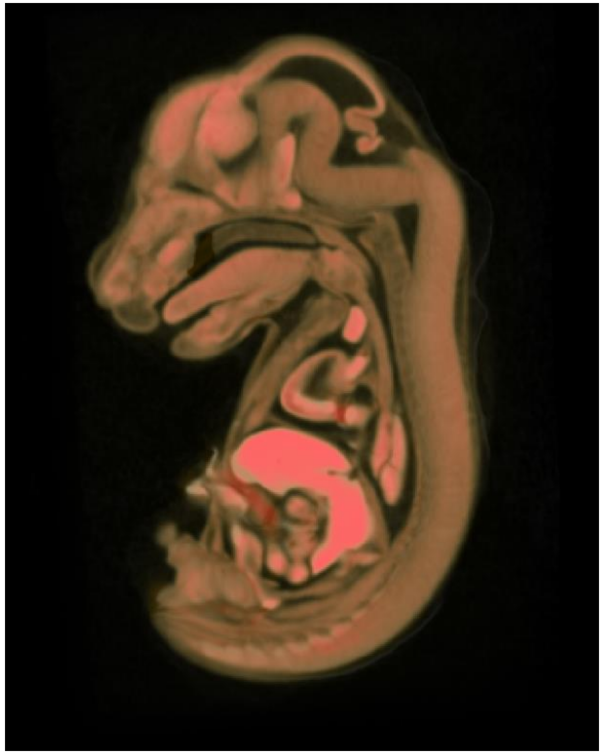
Rotation and translation only.
6 Degrees of Freedom (DOF) in movement

Affine Transformation



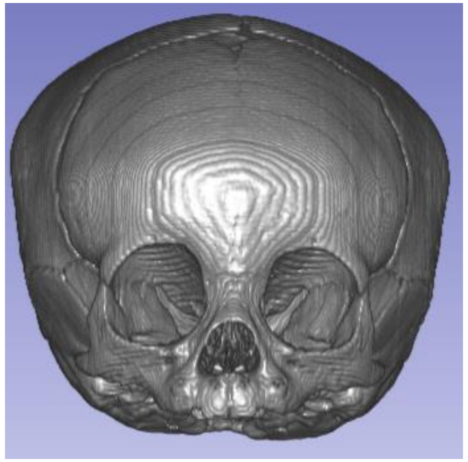
Rotation, translation, independent scaling and shearing on each axis
12 DOF

Deformable Registration

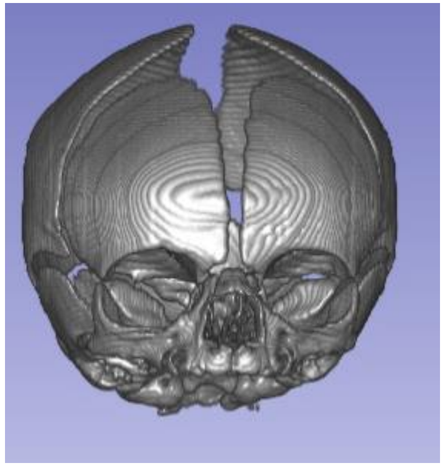


Every point can move (within constraints)

Image Registration: Similarity metric



Reference

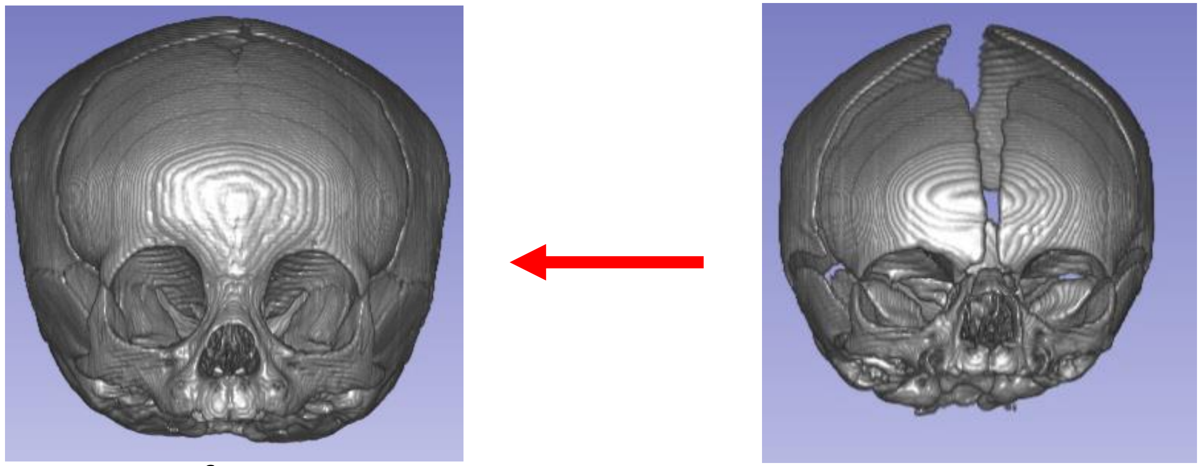


Target

A

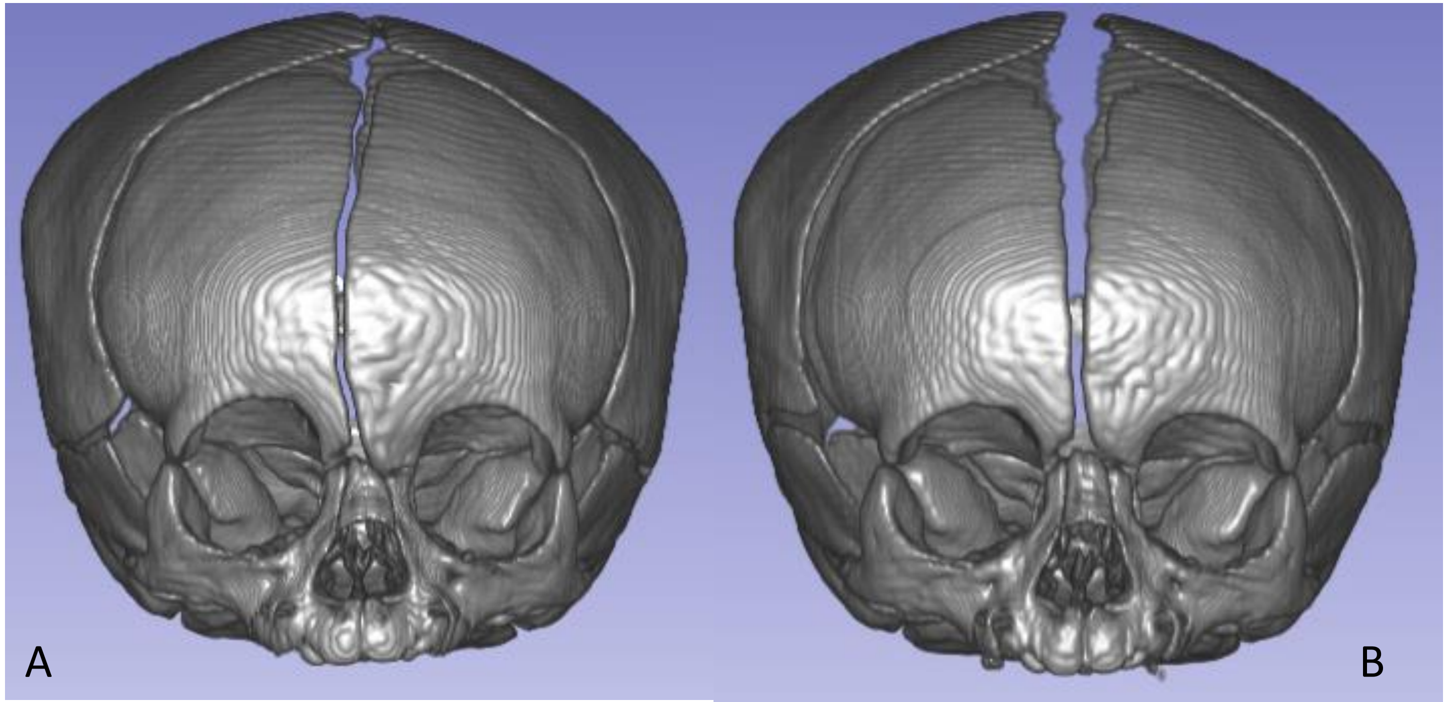
B

Image Registration: Similarity metric



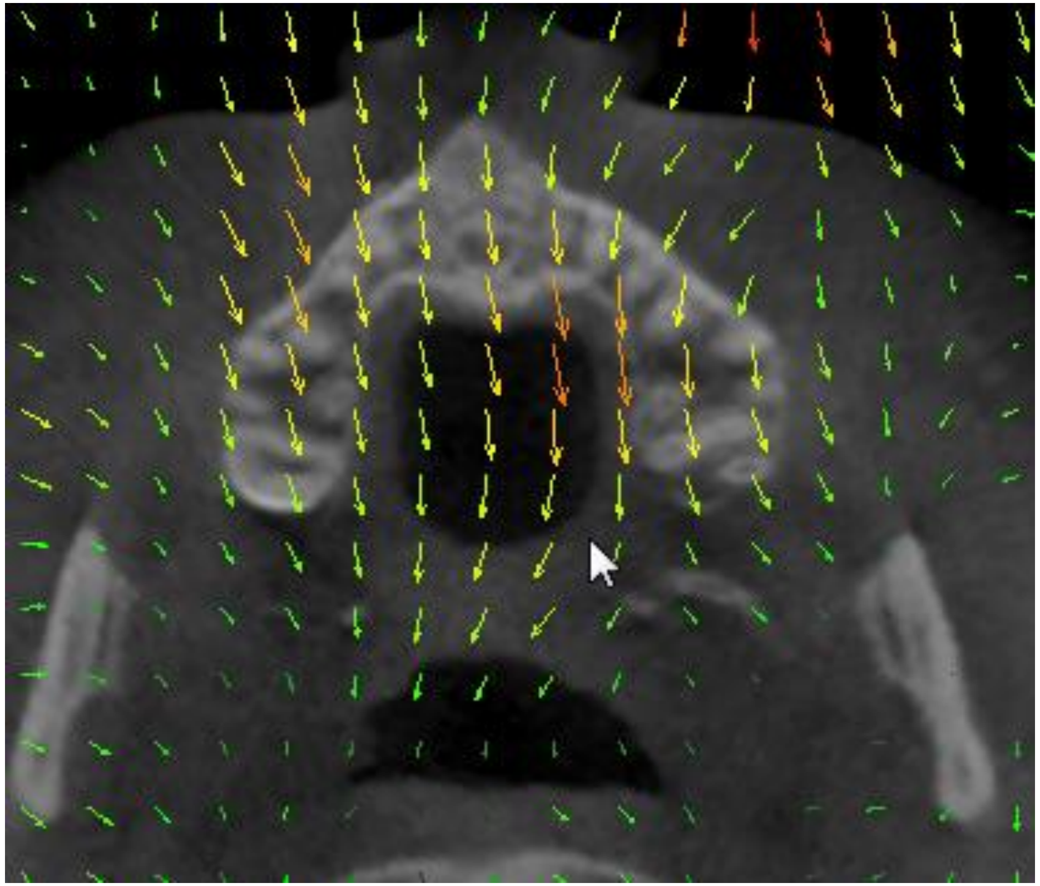
Reference Target

Similarity metric:
Demons

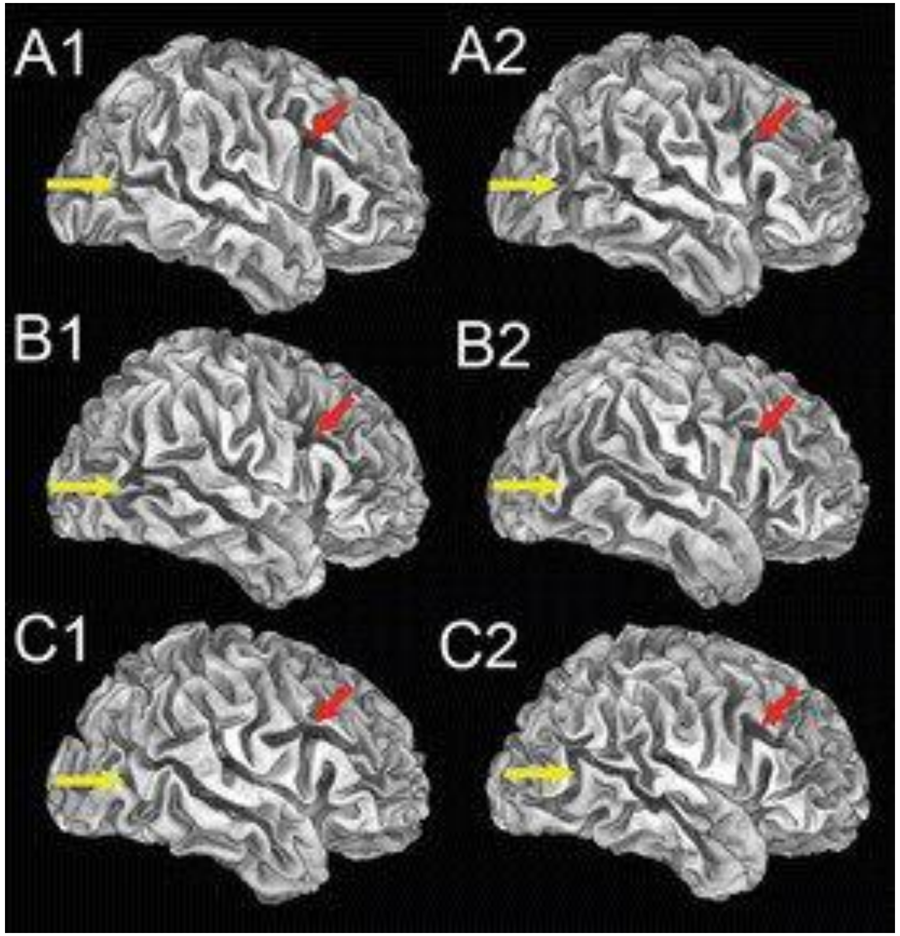


Similarity metric:
Cross-correlation

Deformable Image Registration



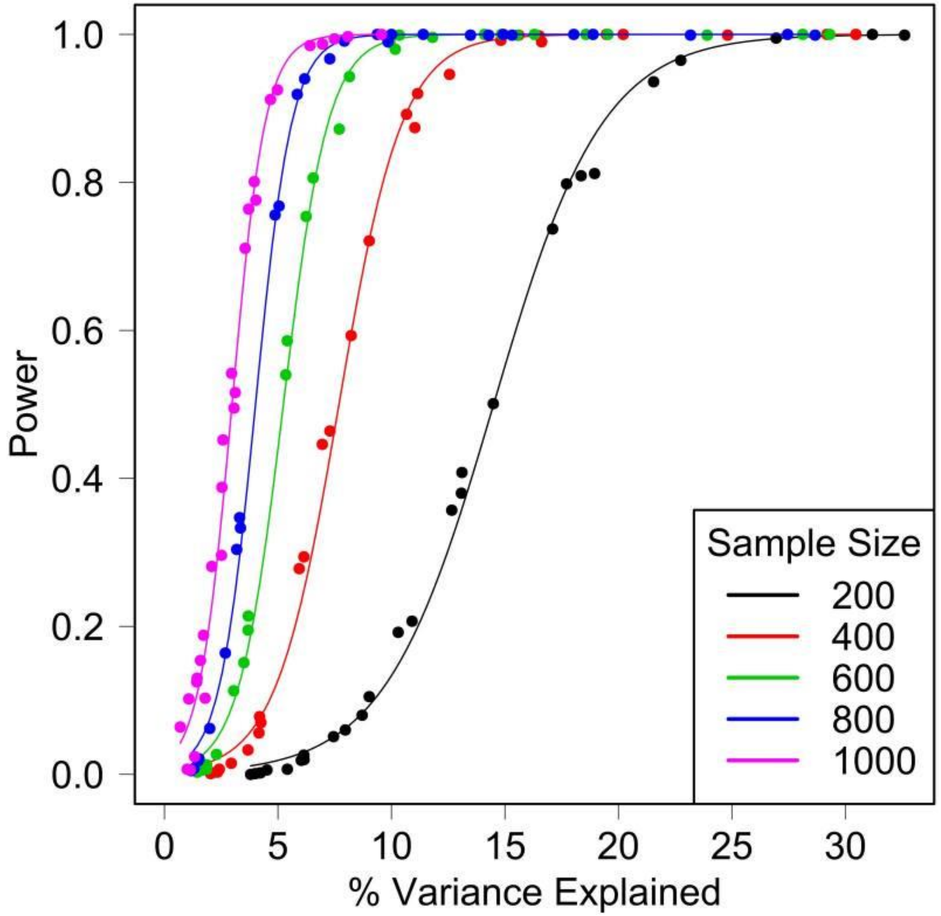
Folding variability in human cortex



Three pairs of identical twins
(A1–2, B1–2, C1–2),

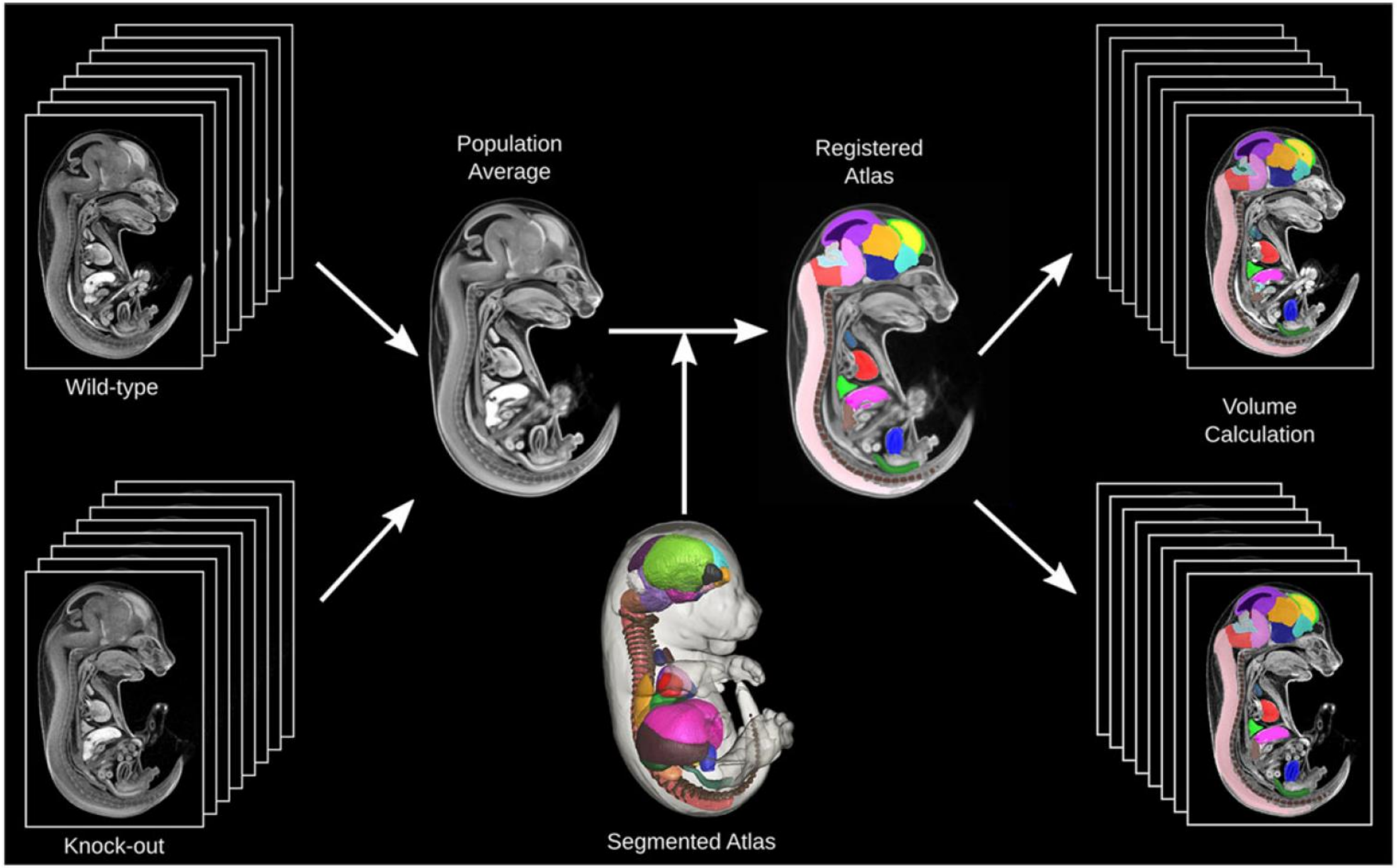
Van Essen DC, Donahue C, Dierker DL, et al. Parcellations and Connectivity Patterns in Human and Macaque Cerebral Cortex. 2016 Mar 11. In: Kennedy H, Van Essen DC, Christen Y, editors. *Micro-, Meso- and Macro-Connectomics of the Brain* [Internet]. Cham (CH): Springer; 2016. Available from: https://www.ncbi.nlm.nih.gov/books/NBK435771/ doi: 10.1007/978-3-319-27777-6_7

We might need large sample sizes



Gatti DM, Svenson KL, Shabalin A, Wu L-Y, Valdar W, Simecek P, Goodwin N, Cheng R, Pomp D, Palmer A, Chesler EJ, Broman KW, Churchill GA. 2014. Quantitative Trait Locus Mapping Methods for Diversity Outbred Mice. G3 4:1623–1633.

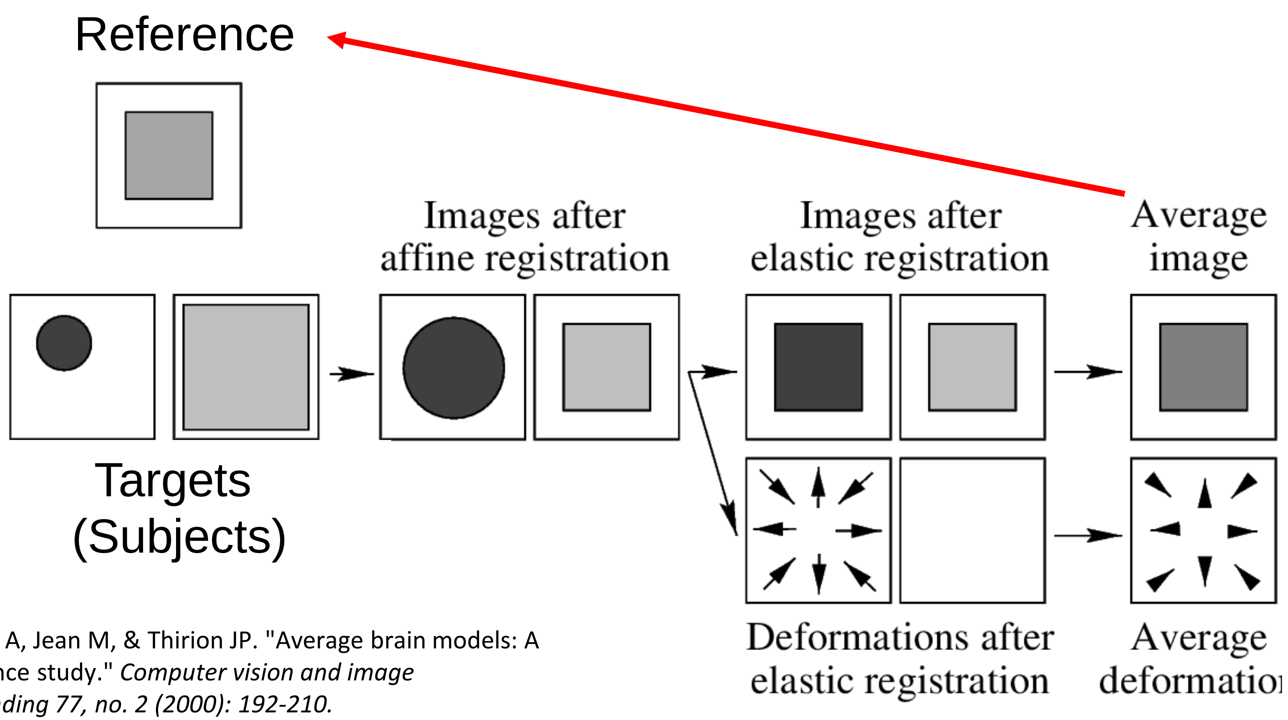
With standardization comes the throughput



Wong, M. D., Maezawa, Y., Lerch, J. P., and Henkelman, R. M. (2014). Automated pipeline for anatomical phenotyping of mouse embryos using micro-CT. *Development*.

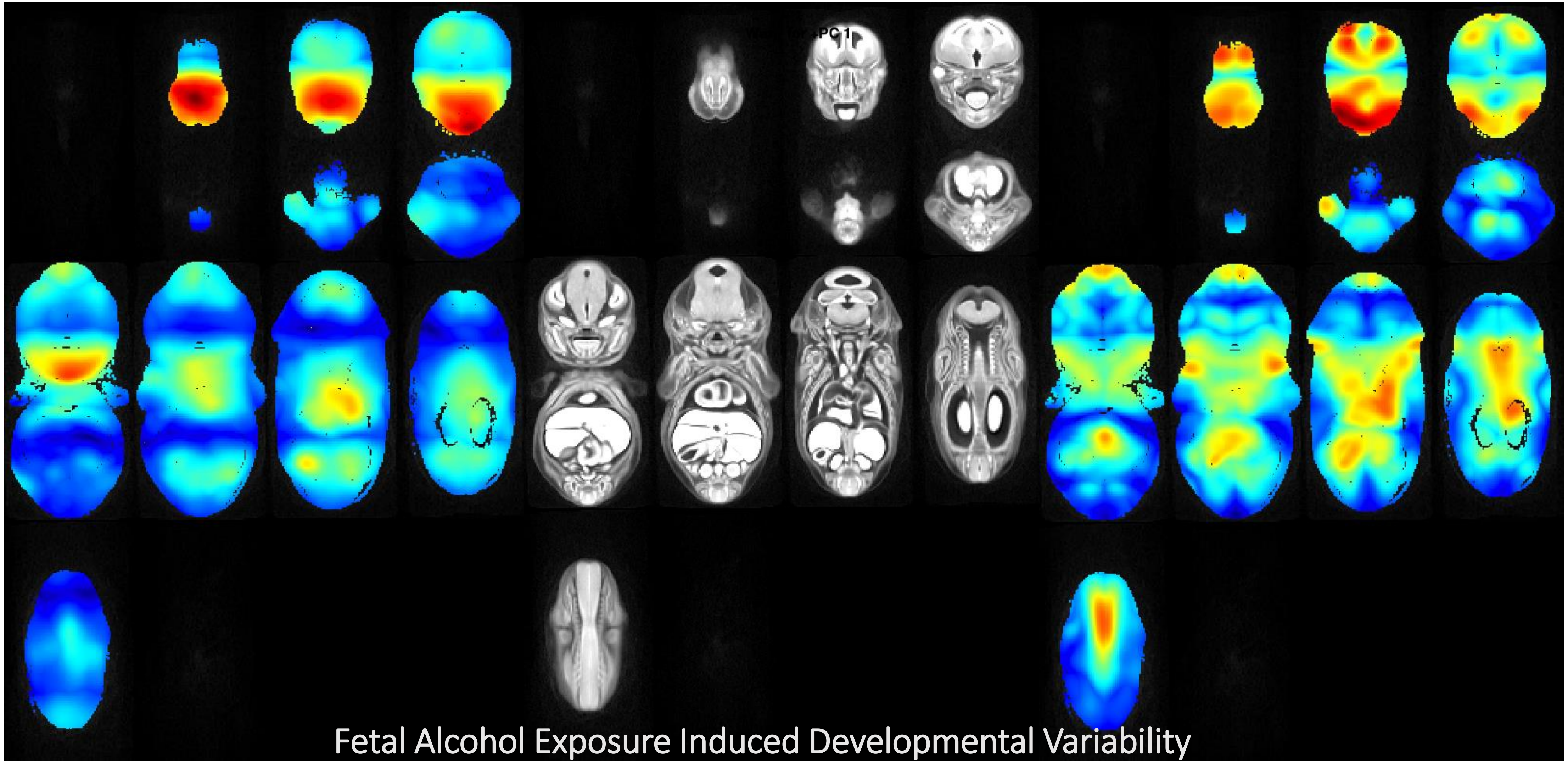
Atlas Building

The atlas construction framework iteratively finds a virtual space which resides in the centroid of the population (i.e. deformations needed to transform all subjects into this virtual space sum up to zero everywhere in this virtual space)



Guimond, A, Jean M, & Thirion JP. "Average brain models: A convergence study." *Computer vision and image understanding 77, no. 2 (2000): 192-210.*

PCA as a tool for exploratory analysis in mouse screens



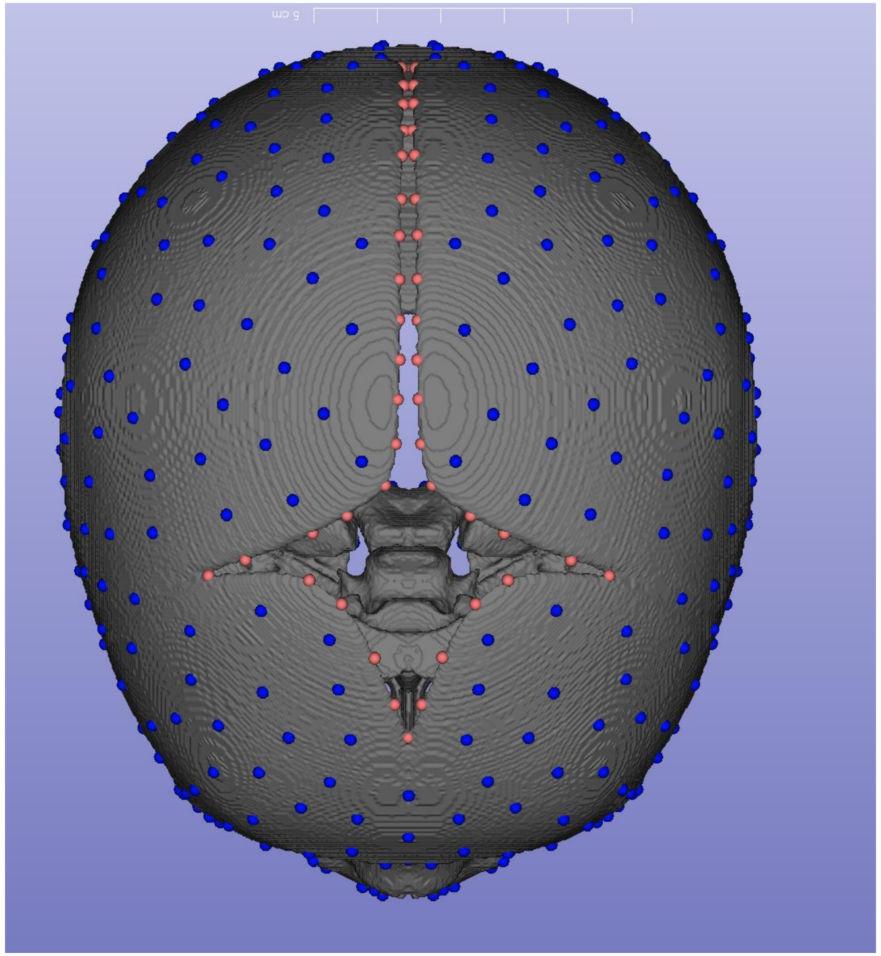
Control mice fetuses at E15

Maga lab unpublished data (undergrad project)

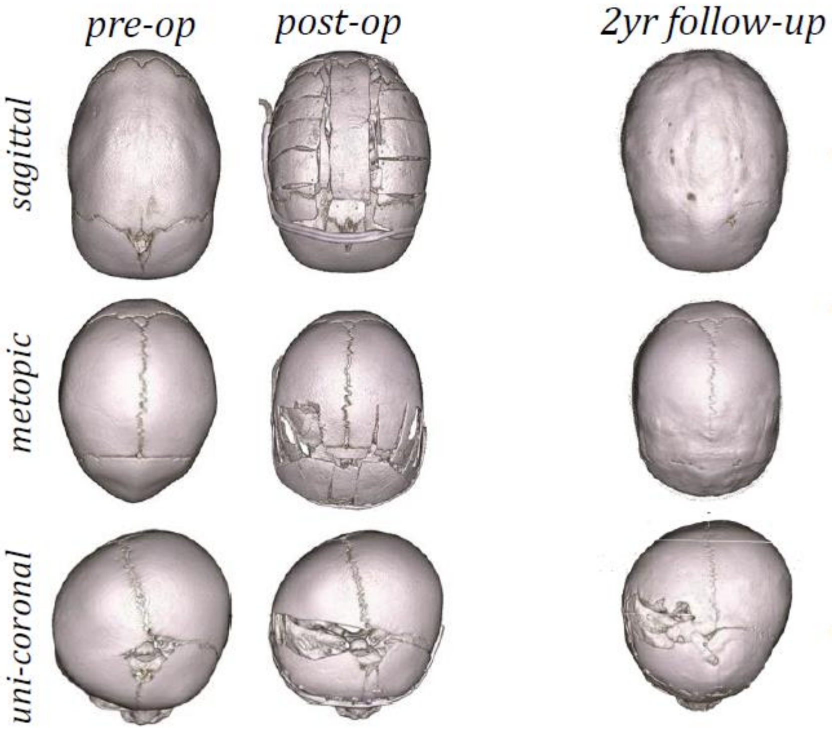
Study template
(Population average)

E15 fetuses from dams consumed 10% v/v EtOH *ad-libidum* during the first 8 days of pregnancy (E0-E8)

Clinical application: Skull growth in craniosynostosis



Cranial Reconstruction



Shape Maintenance

- What *changes* are due to growth ?
- What *factors* affect the long term outcome?
  - Timing of the repair
  - Initial severity
  - Individual characteristics
- How does the skull *grow* in different diagnoses?

Landmarks can be investigator specific!

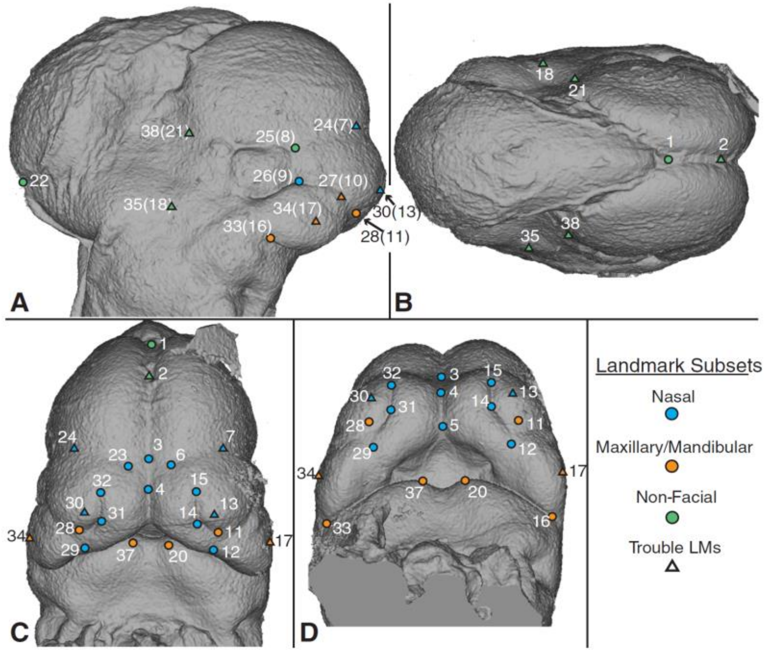
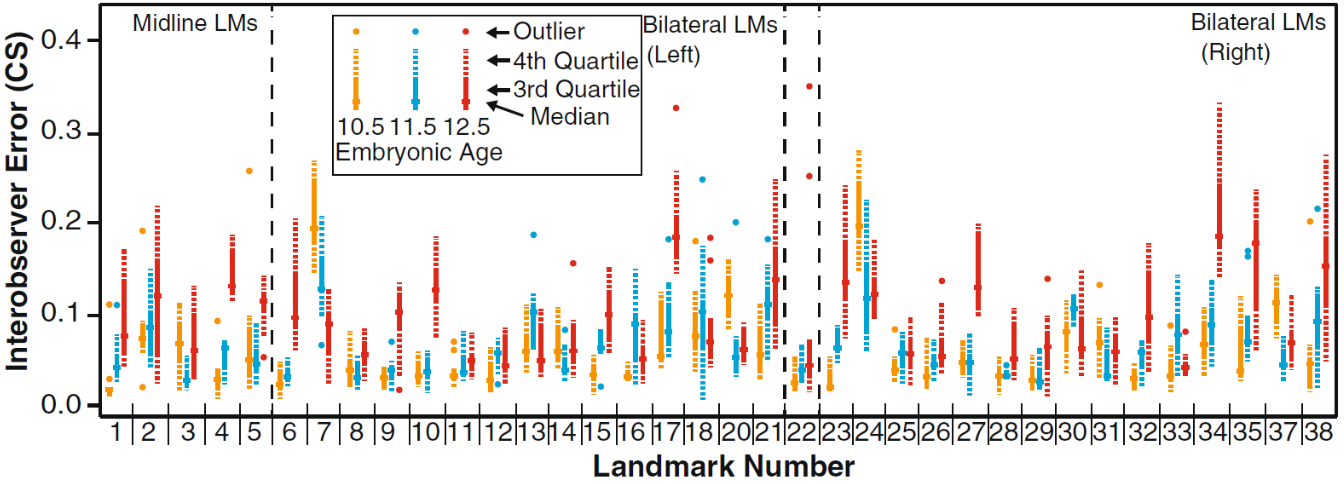
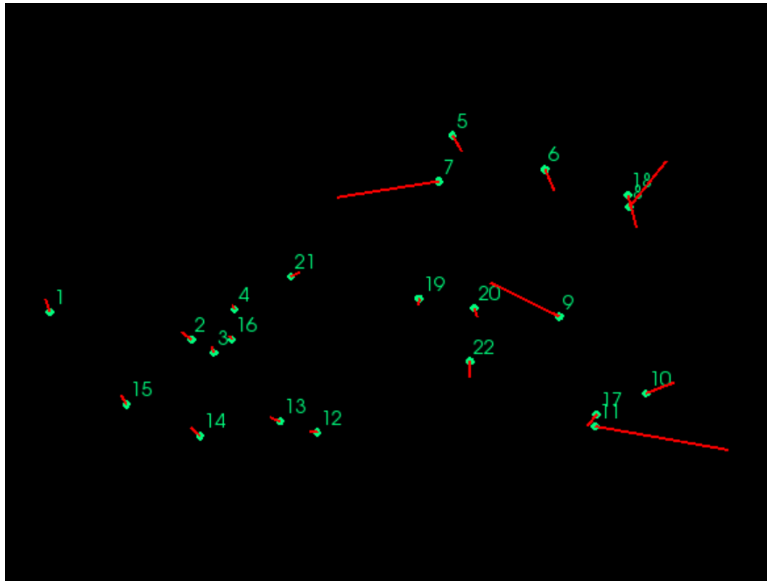


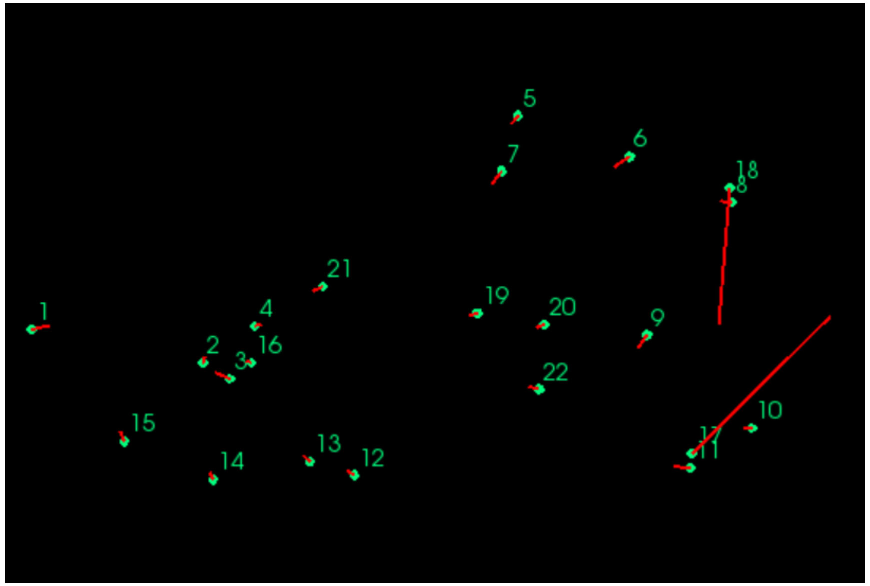
Figure 2 Landmarks defined on the craniofacial ectoderm. Landmark locations identified on the **A)** right lateral, **B)** dorsal, **C)** rostral, and **D)** rostro-ventral views of an E11.5 reference specimen, including the identification of the landmark subsets removed from ontogenetic regression analyses. Landmarks identified on 3D surfaces of all three ages are available in Additional file 5.

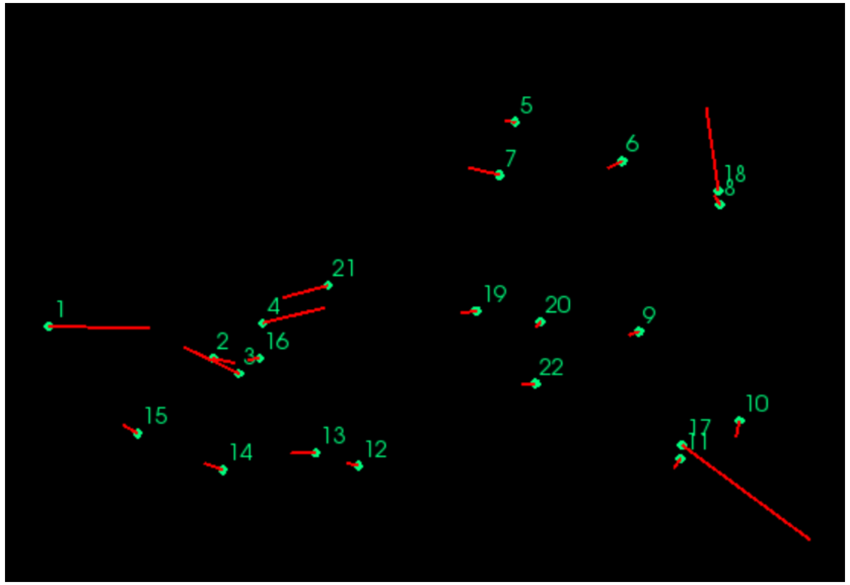


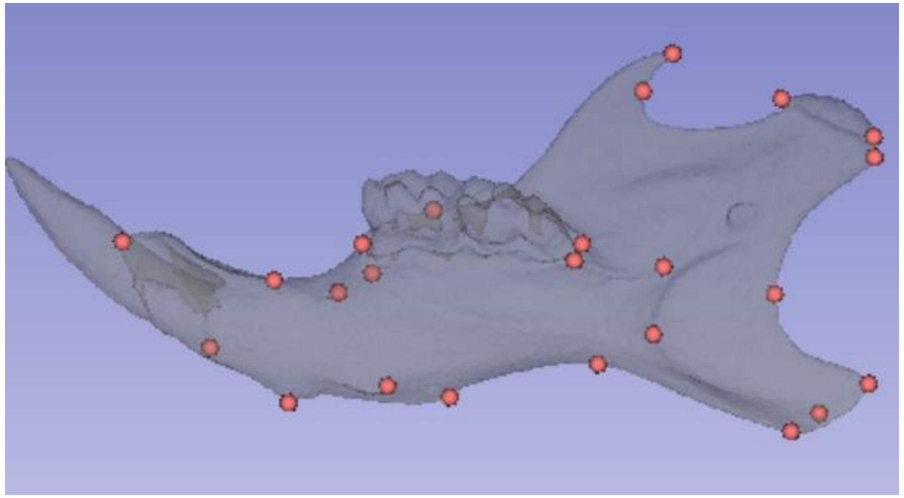
Percival CJ, Green R, Marcucio R, Hallgrímsson B. 2014. Surface landmark quantification of embryonic mouse craniofacial morphogenesis. BMC Developmental Biology 14:31.

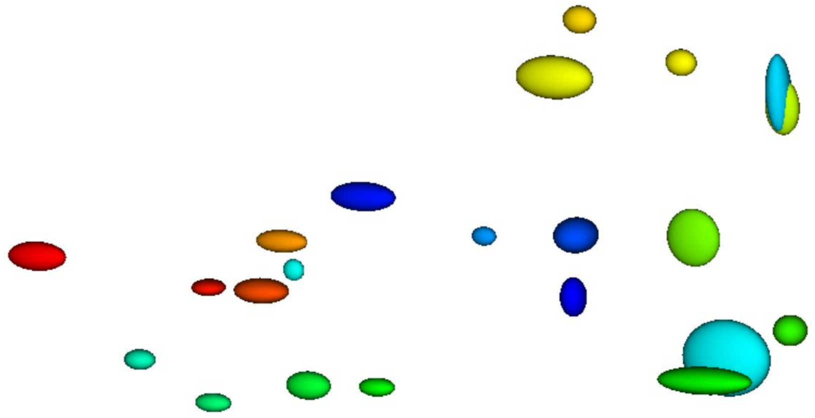
Or your student may not be paying attention!











Atlas-based Landmarking

Turn the question into a segmentation task:

0. Create a population average (atlas) from your sample (you can skip this step if you have an existing atlas –but more on this later).

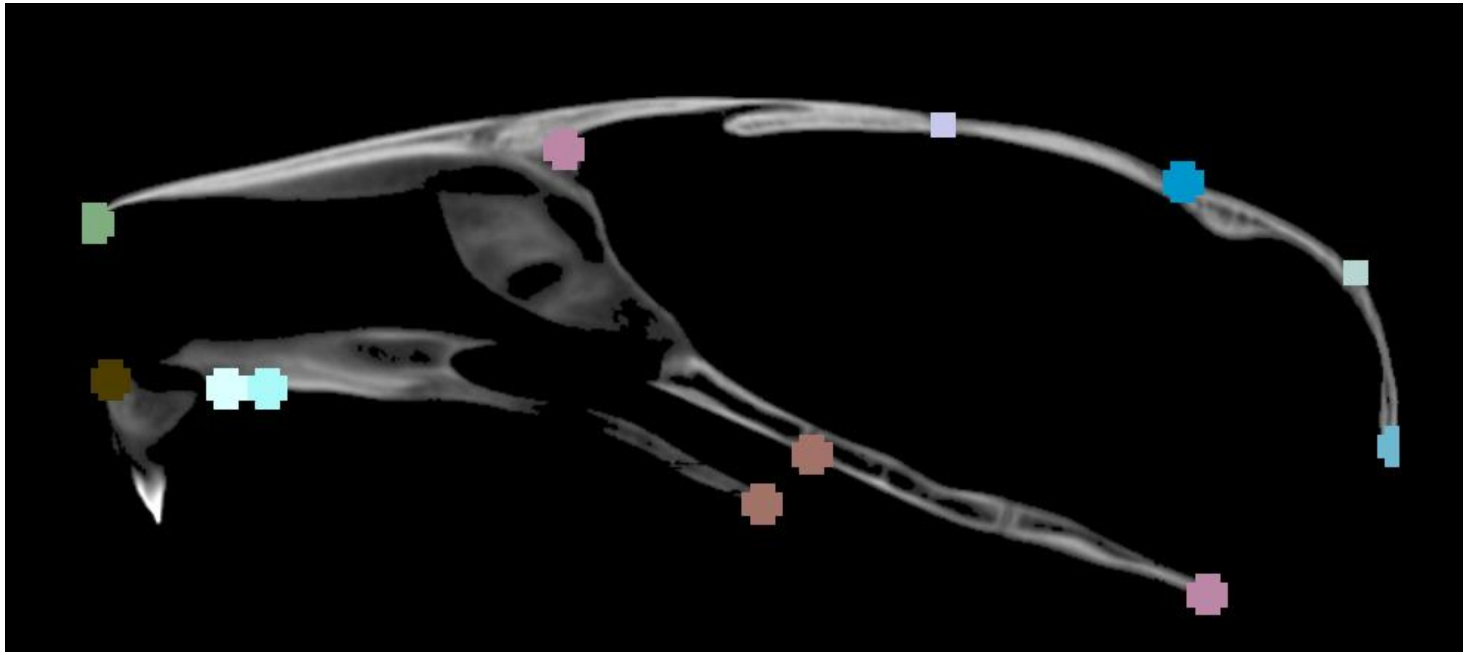
1. Landmark the atlas

2. Use deformable registration to warp atlas to every sample.

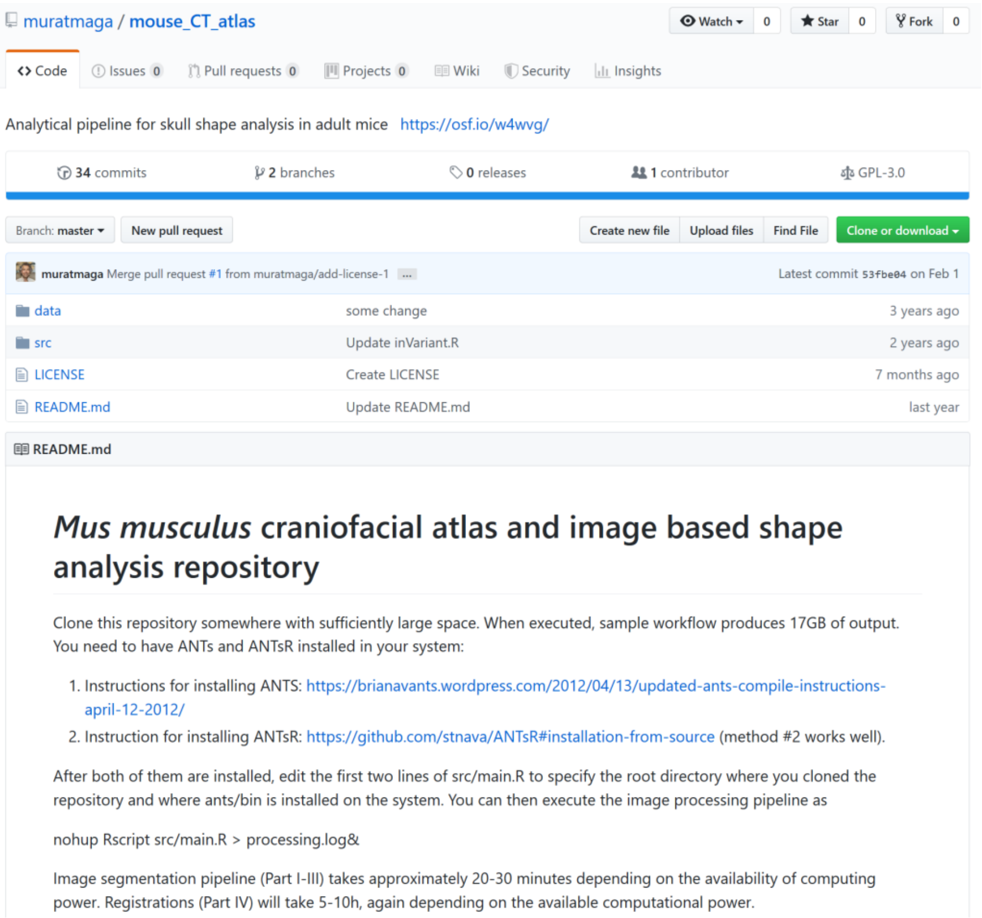
3. Use the resultant warp field to move atlas landmarks onto each sample

But how do you know it worked? (Validation step)

Using template-based segmentation to automate landmarking



Automated pipeline for mouse head microCTs


muratmaga / mouse_CT_atlas

Watch 0 | Star 0 | Fork 0

Code | Issues 0 | Pull requests 0 | Projects 0 | Wiki | Security | Insights

Analytical pipeline for skull shape analysis in adult mice https://osf.io/w4wvg/

34 commits | 2 branches | 0 releases | 1 contributor | GPL-3.0

Branch: master | New pull request | Create new file | Upload files | Find File | Clone or download

muratmaga Merge pull request #1 from muratmaga/add-license-1 … Latest commit 53fbe04 on Feb 1

data	some change	3 years ago
src	Update inVariant.R	2 years ago
LICENSE	Create LICENSE	7 months ago
README.md	Update README.md	last year

README.md

Mus musculus craniofacial atlas and image based shape analysis repository

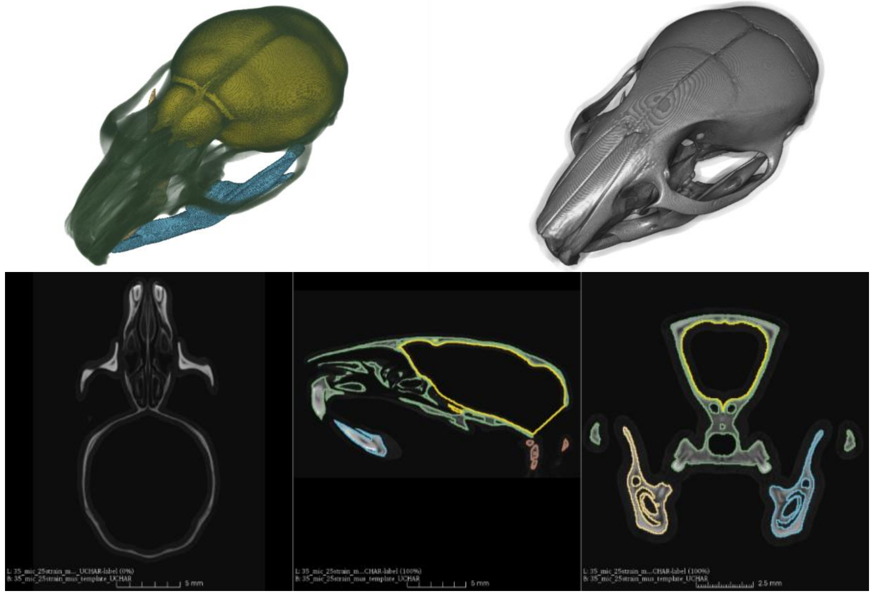
Clone this repository somewhere with sufficiently large space. When executed, sample workflow produces 17GB of output. You need to have ANTs and ANTsR installed in your system:

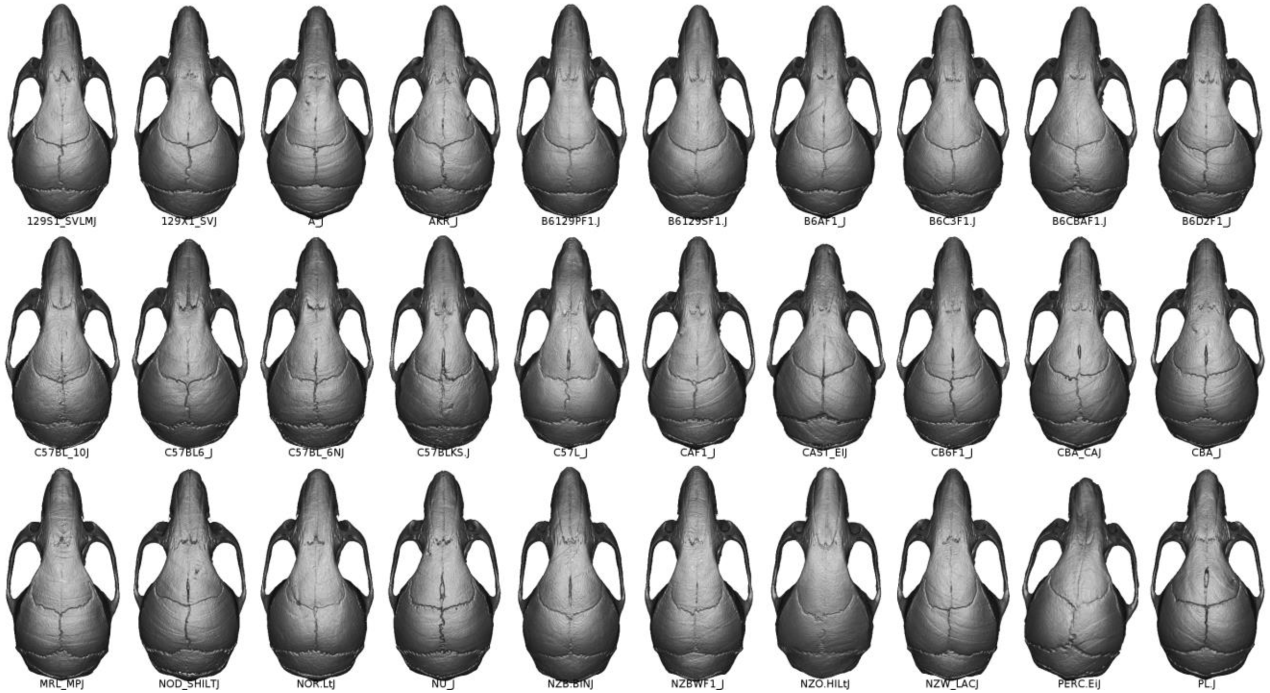
1. Instructions for installing ANTS: https://brianavants.wordpress.com/2012/04/13/updated-ants-compile-instructions-april-12-2012/
2. Instruction for installing ANTsR: https://github.com/stnava/ANTsR#installation-from-source (method #2 works well).

After both of them are installed, edit the first two lines of src/main.R to specify the root directory where you cloned the repository and where ants/bin is installed on the system. You can then execute the image processing pipeline as

nohup Rscript src/main.R > processing.log&

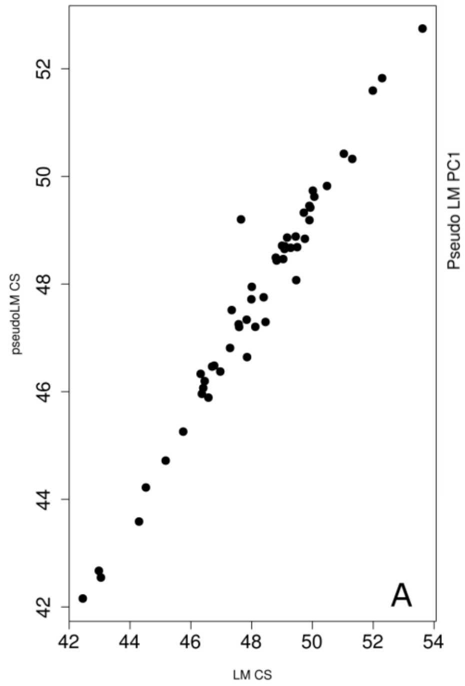
Image segmentation pipeline (Part I-III) takes approximately 20-30 minutes depending on the availability of computing power. Registrations (Part IV) will take 5-10h, again depending on the available computational power.

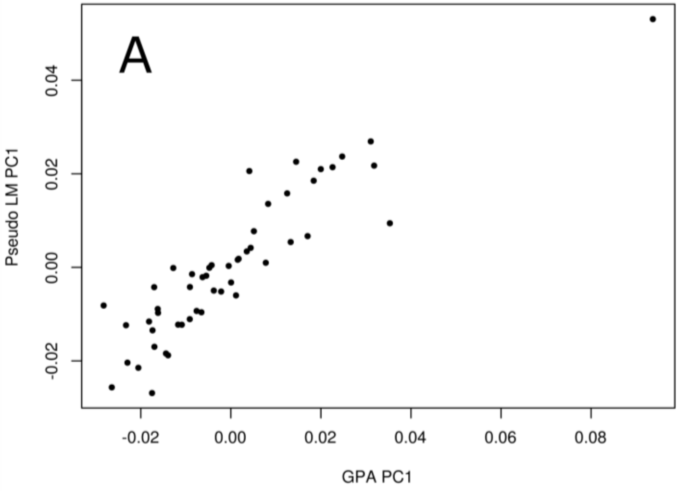


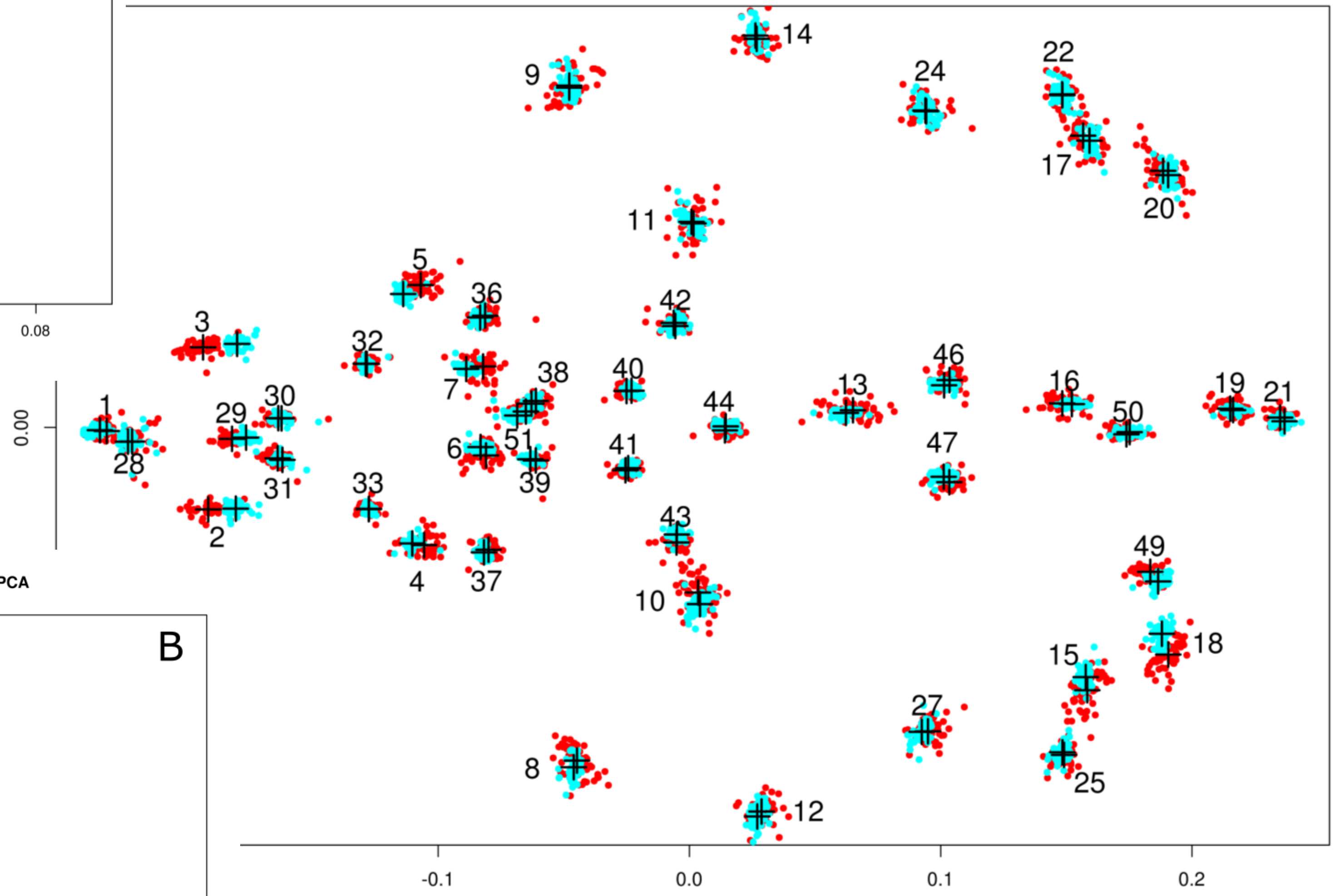


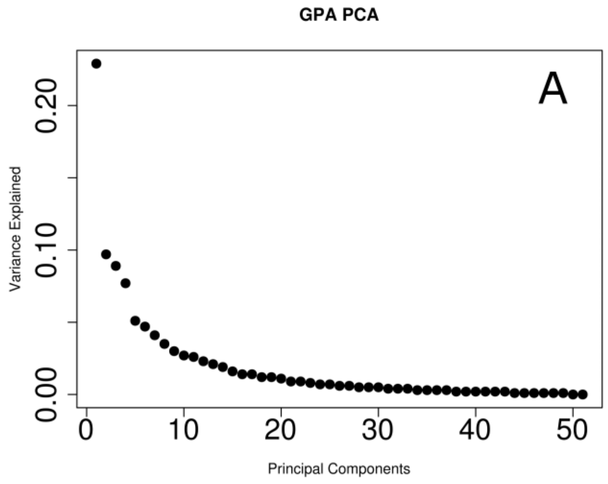
https://github.com/muratmaga/mouse_CT_atlas/

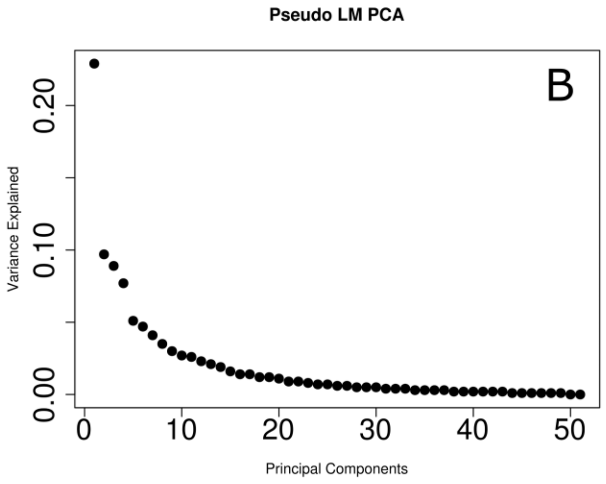
Atlas-based LM'ing of mouse skull





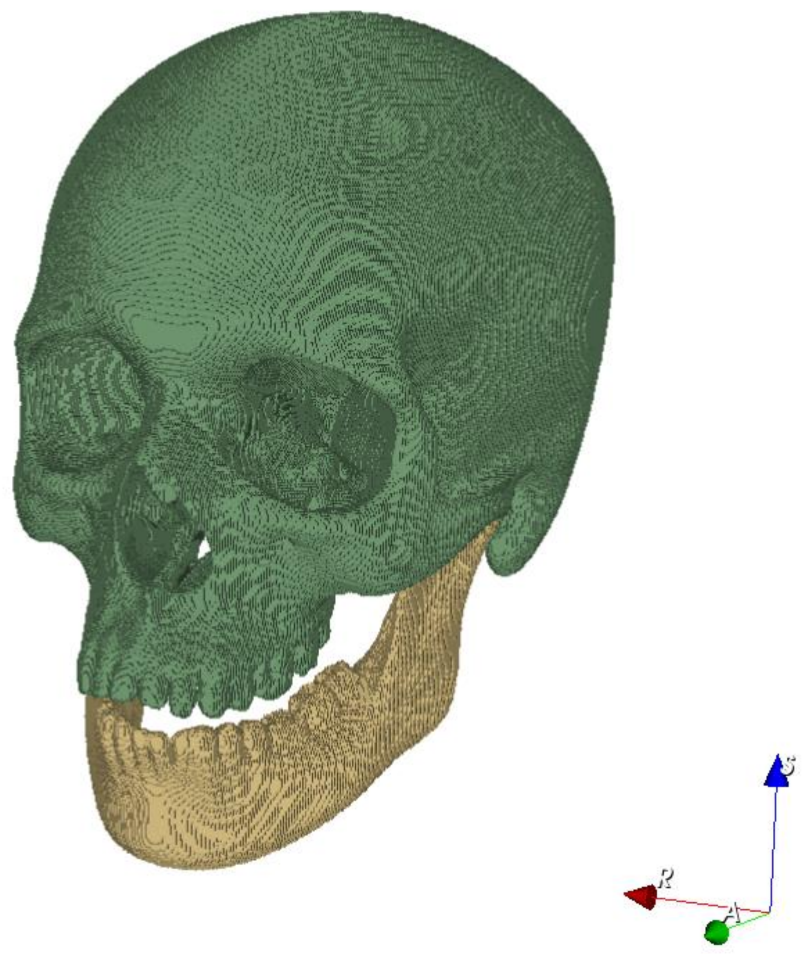


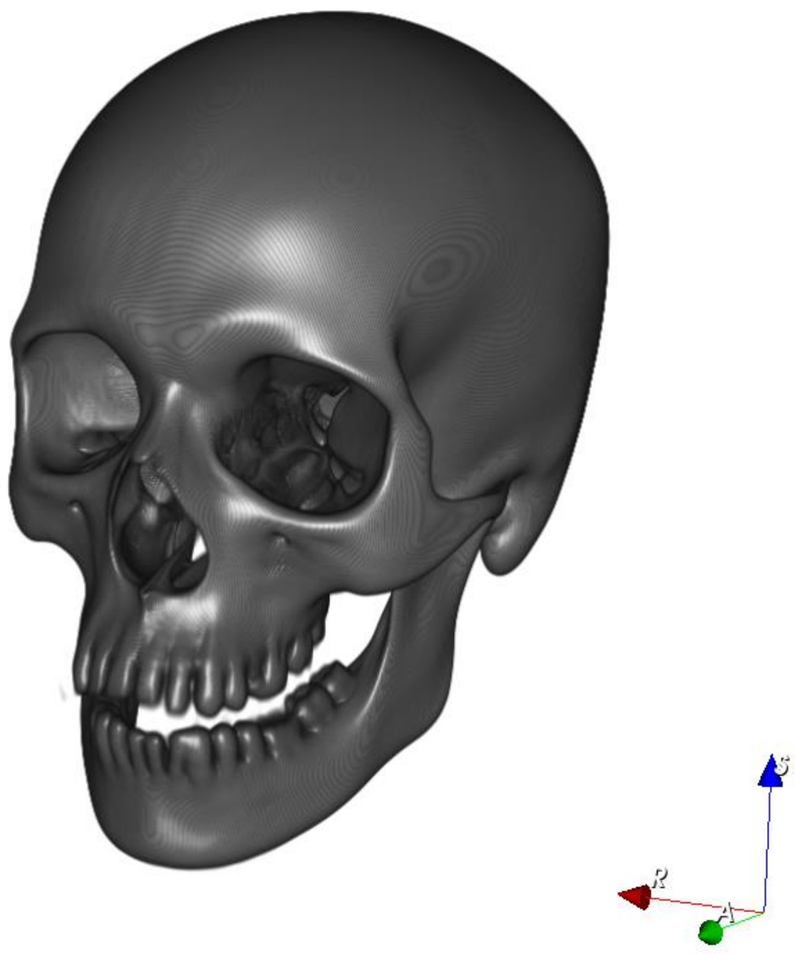




Maga, A. Murat, Nicholas J Tustison, and Brian B Avants. "A Population Level Atlas of Mus Musculus Craniofacial Skeleton and Automated Image-Based Shape Analysis." *Journal of Anatomy* 231, no. 3 (2017): 433–43. https://doi.org/10.1111/joa.12645.

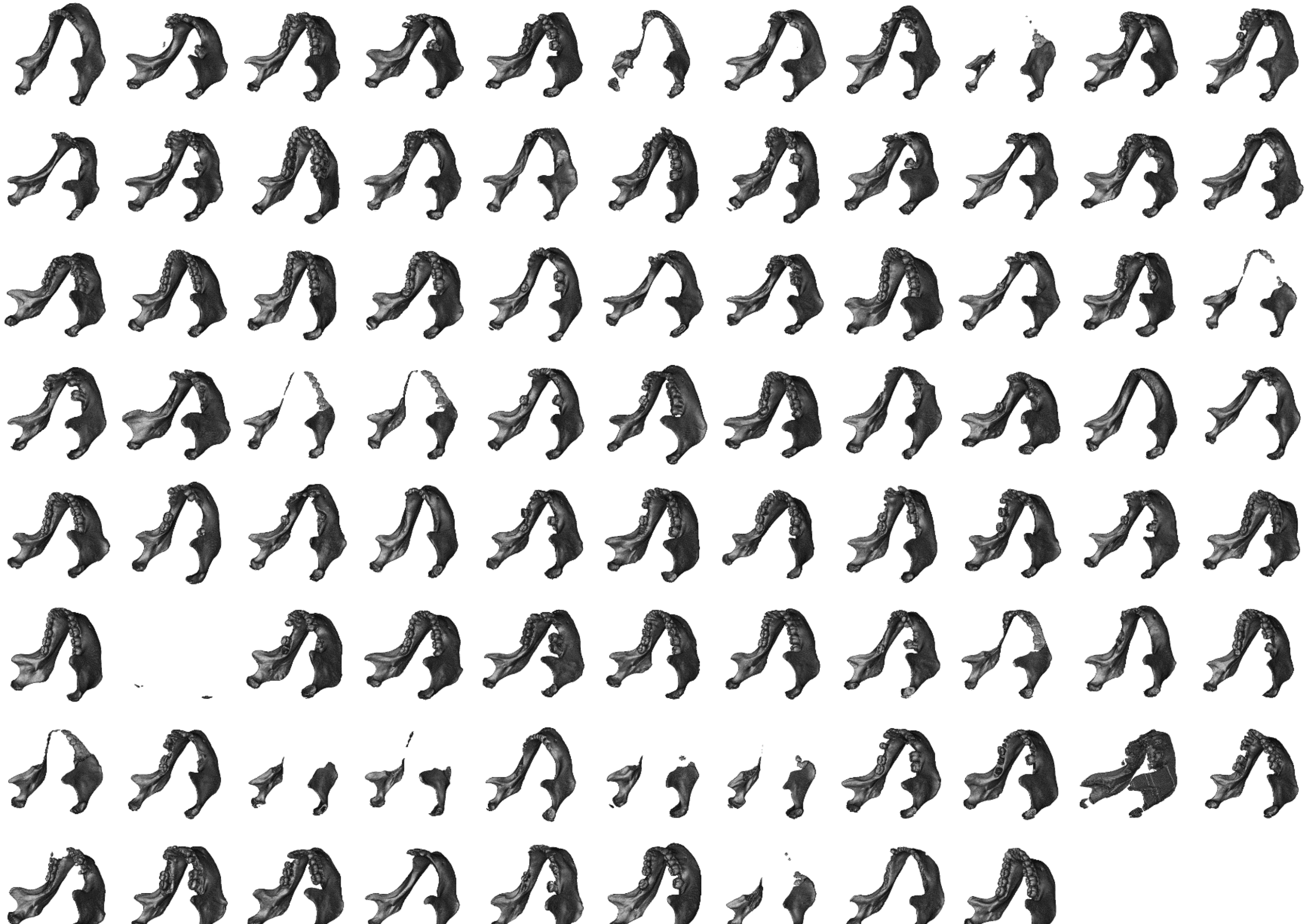
Skull templates for *Homo sapiens*



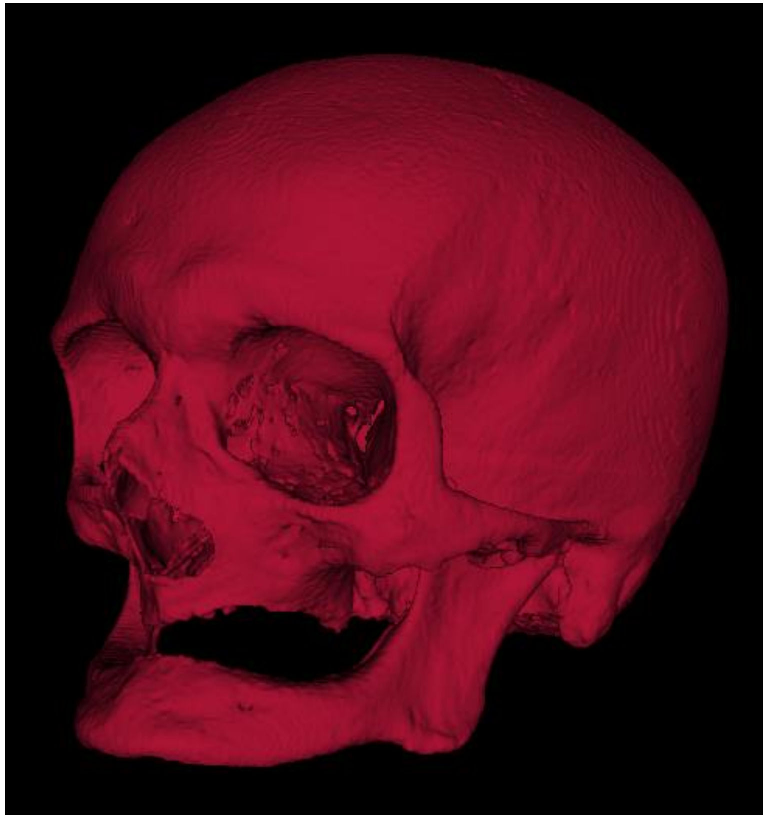


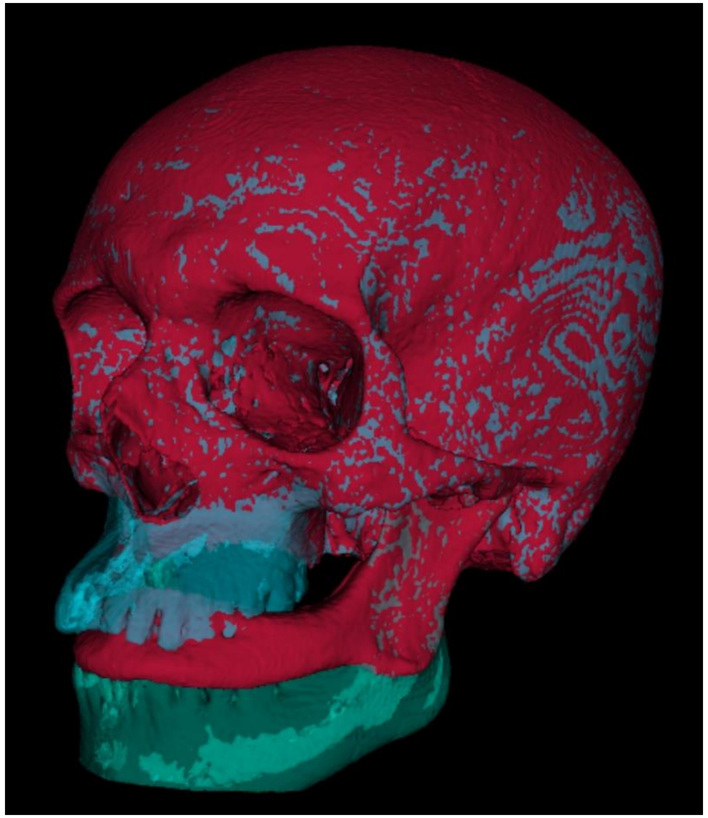
Data curtesy of Dr. Lynn Copes: Smithsonian Terry Collection. *https://www.lynncopes.com/human-ct-scans.html*

Segmenting Mandibles from Clinical CT



Single template captures limited amount of population variability

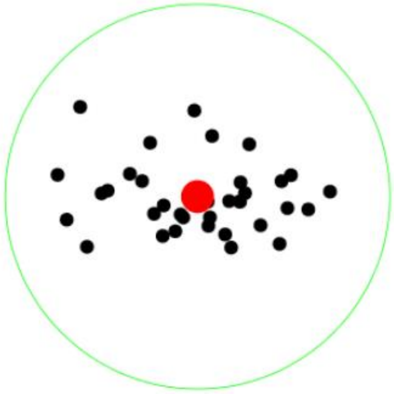




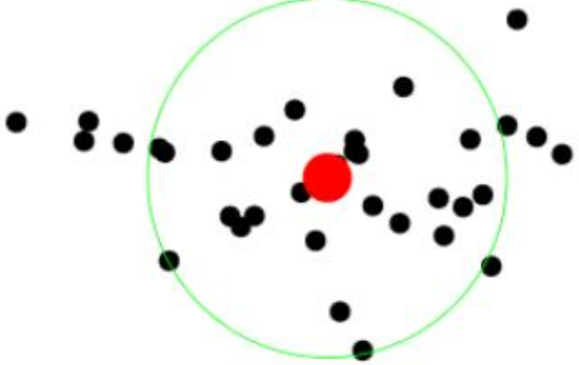
- Rohlfing et al. - 2005 - Quo Vadis, Atlas-Based Segmentation
- Rohlfing T, Brandt R, Maurer Jr CR, Menzel R. 2001. Bee brains, B-splines and computational democracy: generating an average shape atlas. In: IEEE Workshop on Mathematical Methods in Biomedical Image Analysis, 2001. MMBIA 2001. . p 187–194.

Problematic Landmark Detection

- Calculate the landmark location from each selected template
- If the distance between the final landmark location and any two template landmarks exceeds a threshold flag as problematic

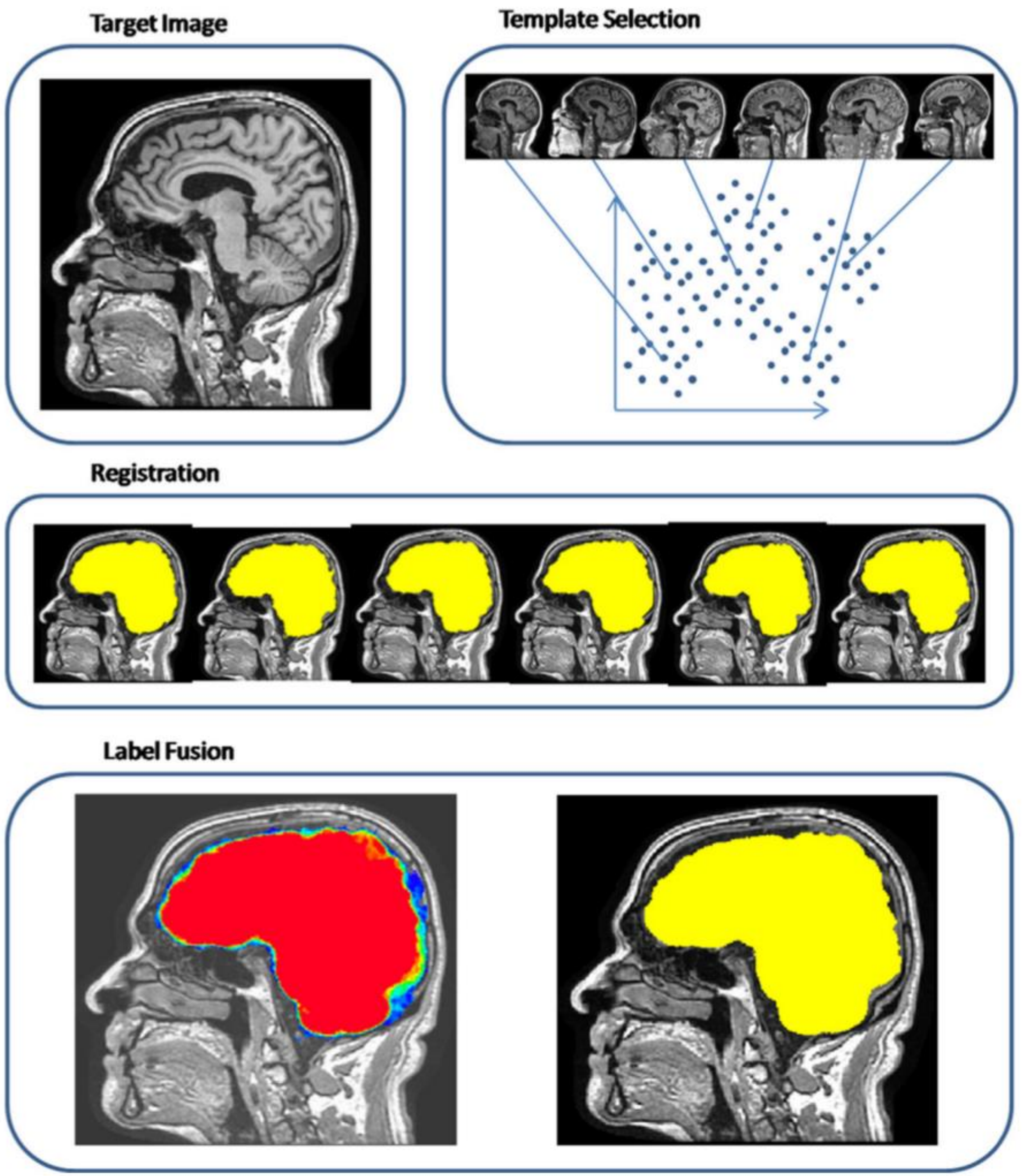


Reliable Landmark



Potentially problematic landmark

multi-atlas based methods



Label Fusion step gives us the probabilities

- Majority vote
- Warfield SK, Zou KH, Wells WM. 2004. Simultaneous truth and performance level estimation (**STAPLE**): an algorithm for the validation of image segmentation. Medical Imaging, IEEE Transactions on 23:903–921.
- Rohlfing T, Maurer Jr CR. 2007. **Shape-Based Averaging**. IEEE Transactions on Image Processing 16:153–161.

Template selection is a critical step. You have to somehow analyze your data first to pick your templates.

Mouse mandible auto-landmarking

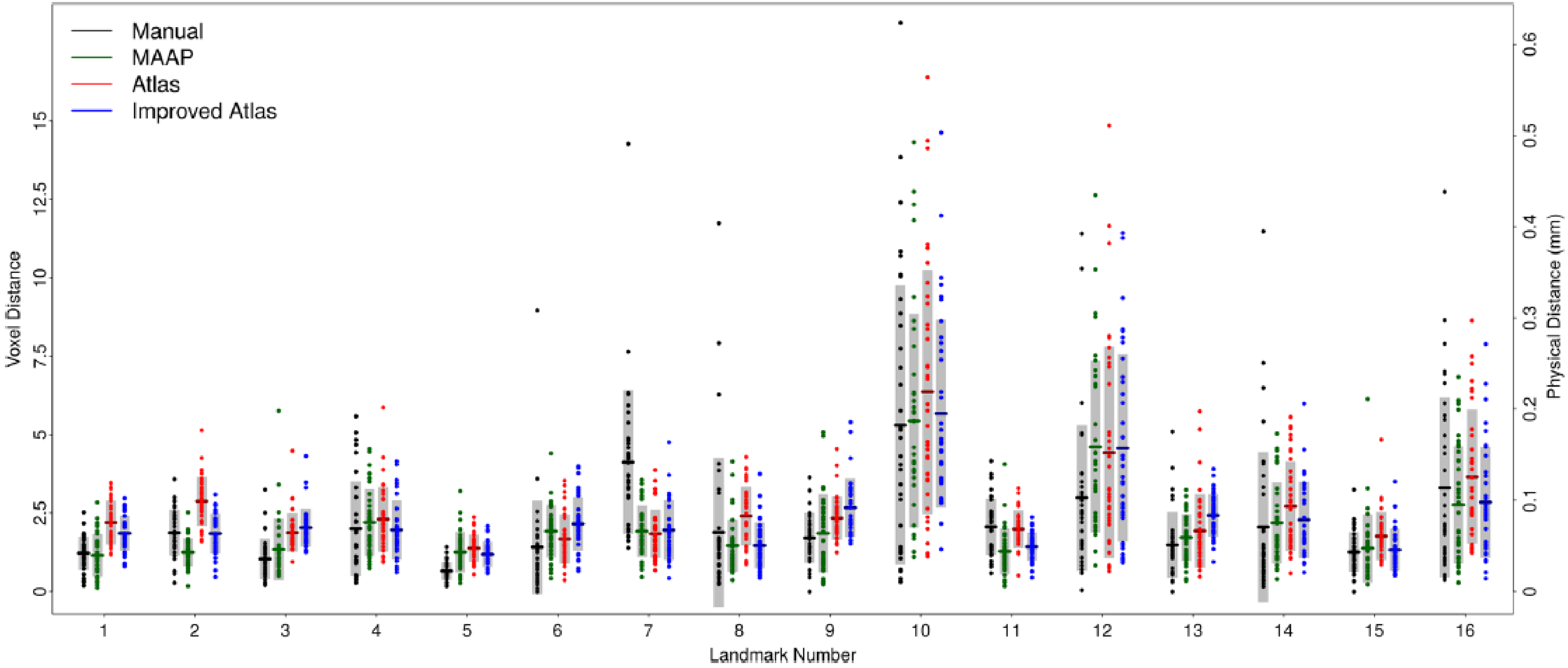
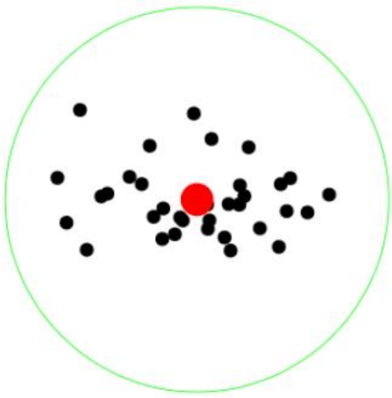


Fig. 2 Comparison of automated landmarking methods to the gold standard. Each point is the digitization error associated with that landmark in one sample in a given method. Horizontal tick marks are means for each landmark. Gray bars indicate +/−1 SD from the mean

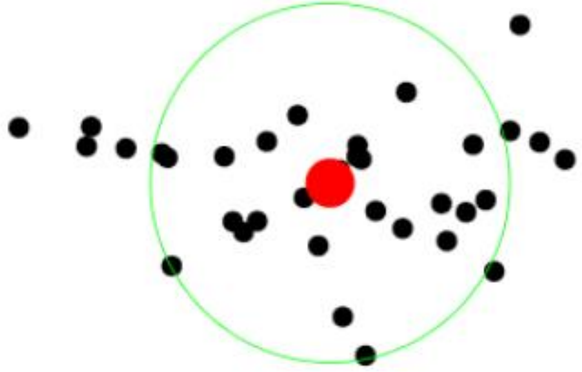
- Young R, Maga AM. 2015. Performance of single and multi-atlas based automated landmarking methods compared to expert annotations in volumetric microCT datasets of mouse mandibles. Frontiers in Zoology 12:33.

Problematic Landmark Detection

- Calculate the landmark location from each selected template
- If the distance between the final landmark location and any two template landmarks exceeds a threshold flag as problematic



Reliable Landmark



Potentially problematic landmark

Outlier detection is important

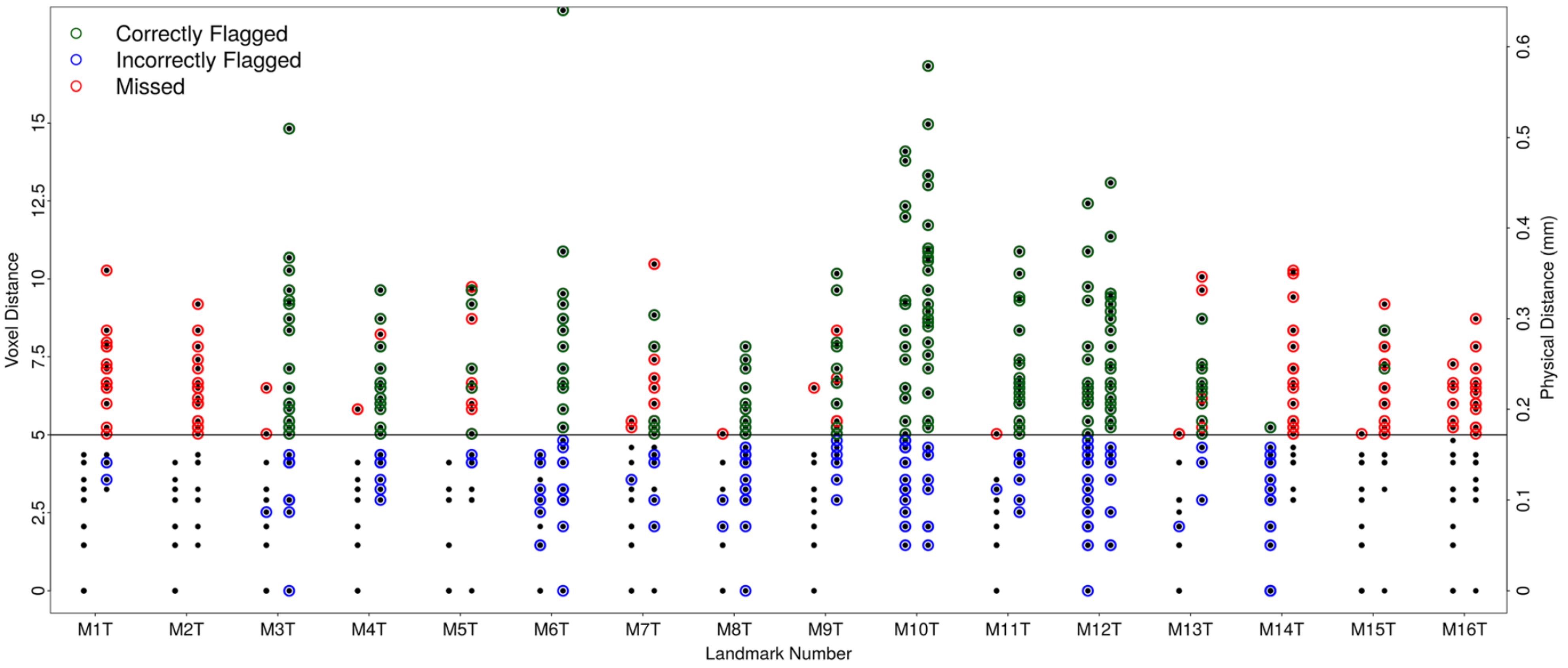
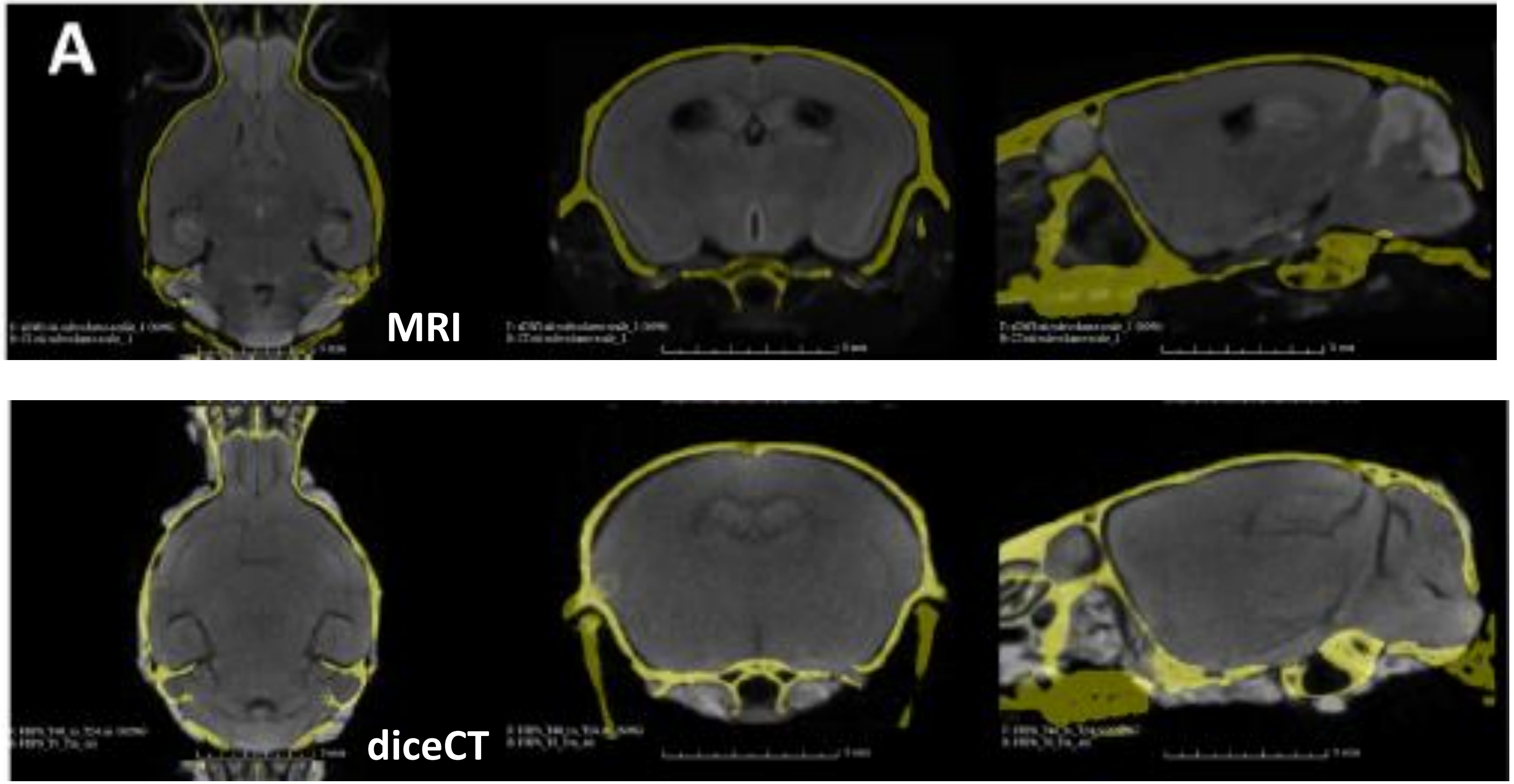


Fig. 4 Comparison of the outlier detection performance in MAAP and TINA. For each landmark left column (M) is the result for MAAP and right column (T) is the result for TINA. Each data point represents the difference of the estimated landmark to the corresponding GS one. Horizontal line at five voxel mark represent the threshold specified to assess the outliers in both methods. For MAAP, if two or more of the templates (out of 10) were outside of this threshold range, the software flagged the landmark for manual verification. Green circle indicates landmarks that are correctly flagged as outliers, red circle indicates landmarks that are in reality outliers but missed by detection software, and blue indicates landmarks that were incorrectly flagged since they were below threshold

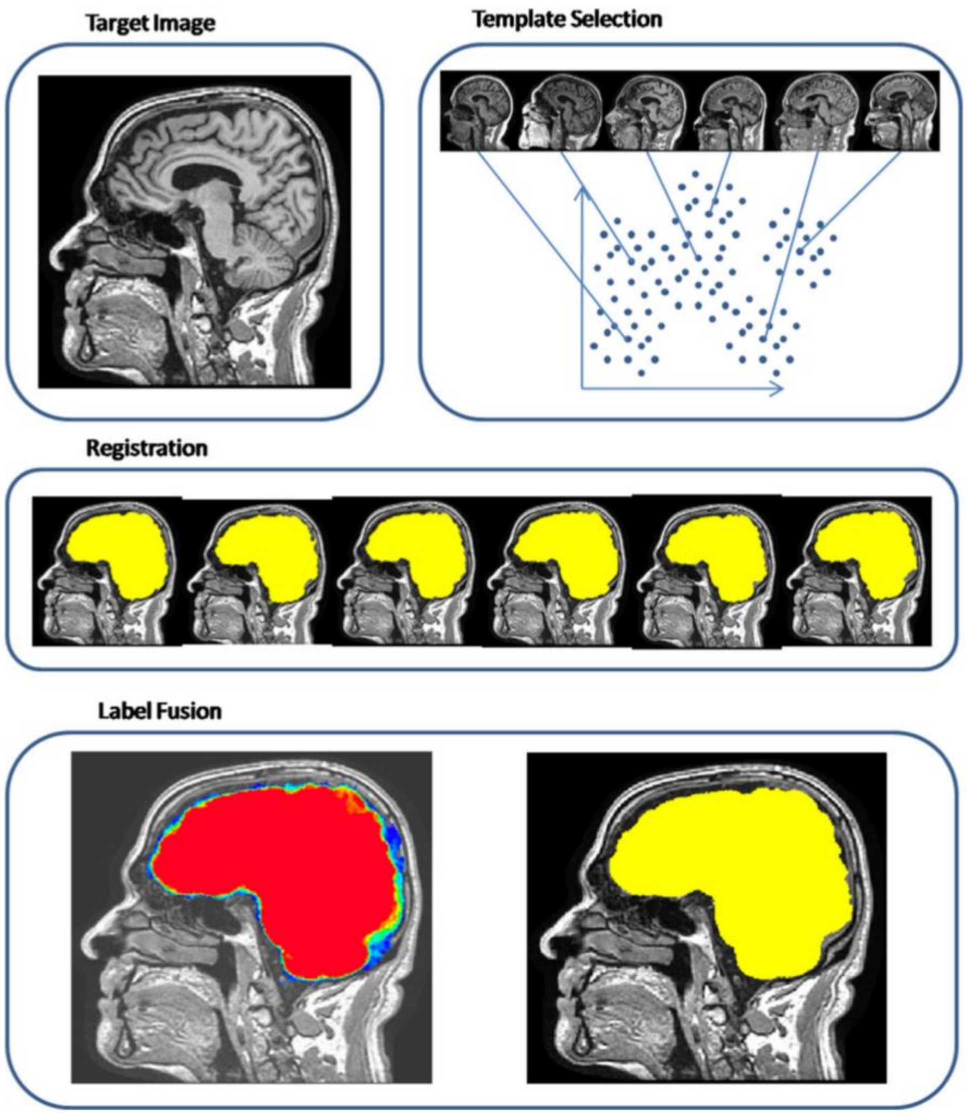
Young, Ryan, and A. M. Maga. "Performance of Single and Multi-Atlas Based Automated Landmarking Methods Compared to Expert Annotations in Volumetric MicroCT Datasets of Mouse Mandibles." *Frontiers in Zoology* 12, no. 1 (December 1, 2015): 33. https://doi.org/10.1186/s12983-015-0127-8.

Diffusible Iodine Contrast Enhanced (dice) CT



Anderson, R., and Maga, A. M. (2015). A Novel Procedure for Rapid Imaging of Adult Mouse Brains with MicroCT Using Iodine-Based Contrast. *PLoS ONE*

Multi Atlas Segmentation



Label Fusion step gives us the probabilities

- Majority vote
- Warfield SK, Zou KH, Wells WM. 2004. Simultaneous truth and performance level estimation (**STAPLE**): an algorithm for the validation of image segmentation. Medical Imaging, IEEE Transactions on 23:903–921.
- Rohlfing T, Maurer Jr CR. 2007. **Shape-Based Averaging**. IEEE Transactions on Image Processing 16:153–161.

Jimit Doshi, Guray Erus, Yangming Ou, Bilwaj Gaonkar, Christos Davatzikos. Multi-Atlas Skull-Stripping, MASS. Academic Radiology

Atlas-based automatic landmarking

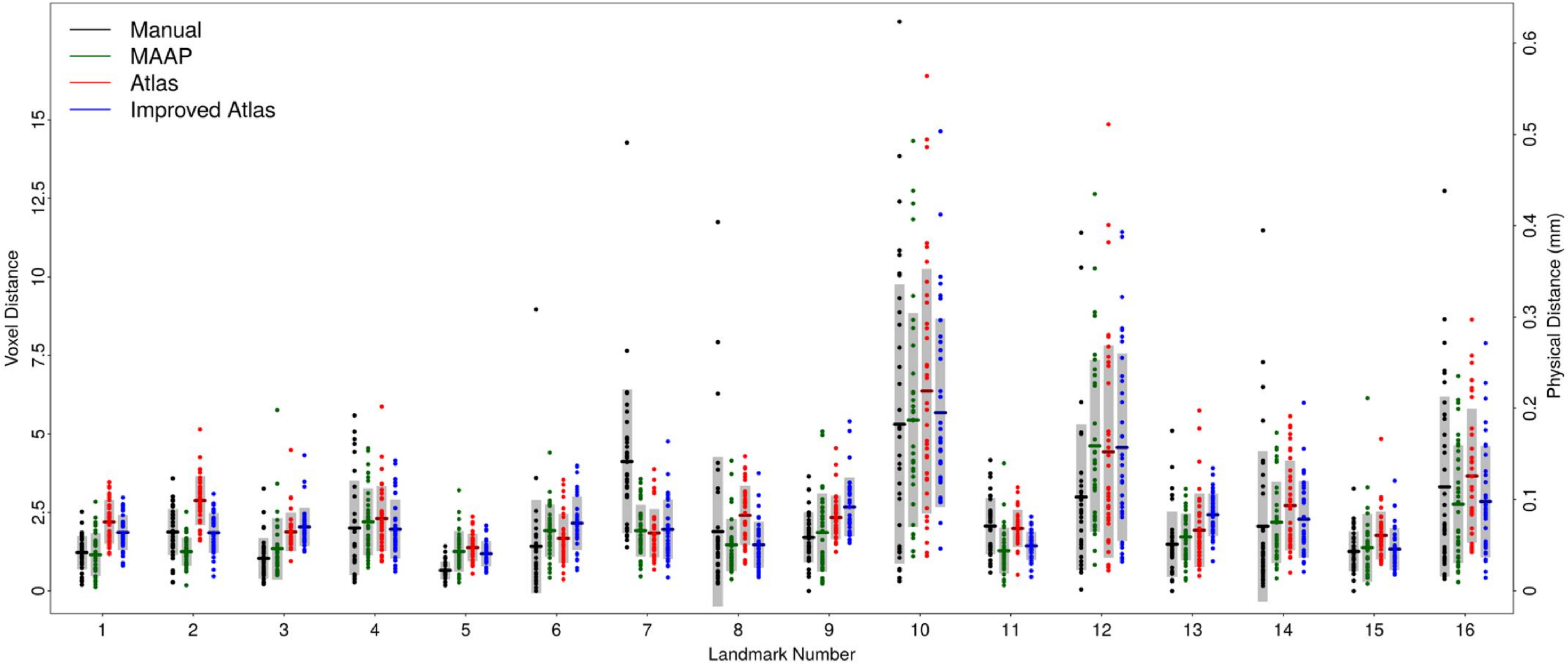


Fig. 2 Comparison of automated landmarking methods to the gold standard. Each point is the digitization error associated with that landmark in one sample in a given method. Horizontal tick marks are means for each landmark. Gray bars indicate +/−1 SD from the mean

Young, Ryan, and A. M. Maga. "Performance of Single and Multi-Atlas Based Automated Landmarking Methods Compared to Expert Annotations in Volumetric MicroCT Datasets of Mouse Mandibles." *Frontiers in Zoology* 12, no. 1 (December 1, 2015): 33. https://doi.org/10.1186/s12983-015-0127-8.