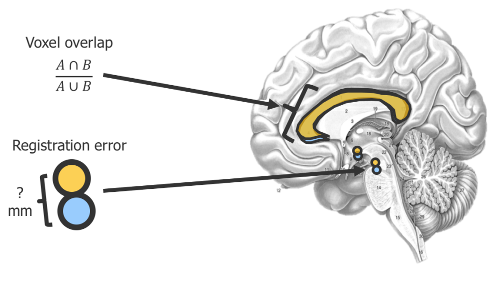
Development and Validation of a Simple Landmark Placement Protocol for Establishing Correspondence Between Brain Images

Jonathan C. Lau MD; Andrew G. Parrent MD; John Demarco; Ali R. Khan PhD; Terry M. Peters PhD
Western University, London, Ontario, Canada

Introduction

Template and atlas-guidance are fundamental aspects of stereotactic neurosurgery. Accurate spatial correspondence between the template and patient images is crucial so that we can use templates to assist with surgical implantation. We sought to propose and validate a set of point landmarks that could be quickly, accurately, and reliably placed on brain images.



Voxel overlap between regions-of-interest (ROIs) and landmark registration error.

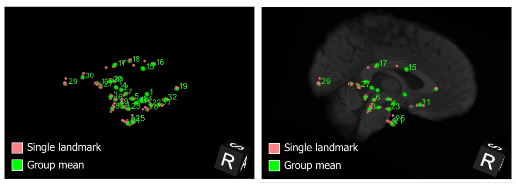
(1) Methods: Template evaluation

A series of neuroanatomical landmarks were identified in consultation with an experienced neurosurgeon. Consensus was achieved on a set of 32 landmarks. Over a series of neuroanatomy tutorials, novice participants (N=8) were trained to perform the protocol using 3D Slicer [1] on 3 publicly available brain templates: Colin27 [2], MNI2009b [3], and Agile12v1.0 [4]. For each template, our participants placed the landmarks four times (384 landmarks/participant). Fiducial localization error (FLE) was calculated to establish reliability (Euclidean distance derived from the group mean). We performed K-means clustering on the principal components of the landmark-specific point clouds.

(1) Results: Template evaluation

Intra- and inter-rater reliability were 1.24 +/- 0.17 mm and 1.24 +/- 1.94 mm respectively. Out of 3258 landmarks placed, there were 24 (0.74%) outliers more than 10 mm from the group mean, classified as mislabeled and thus discarded. Significant differences in FLE were identified between templates

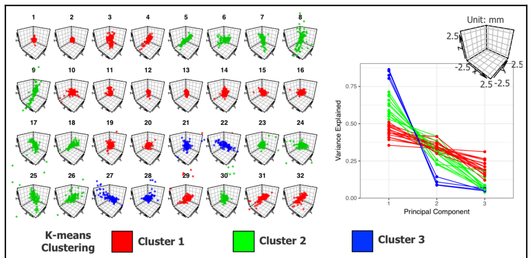
- Colin27: 1.11 +/- 1.05 mm
- MNI2009b: 0.95 +/- 0.82 mm
- Agile12v1.0: 1.02 +/- 0.94 mm



Three-dimensional visualization of landmark locations (left). A projection of a midsagittal slice relative to landmark points is provided for reference (right).

(1) Results: Clustering

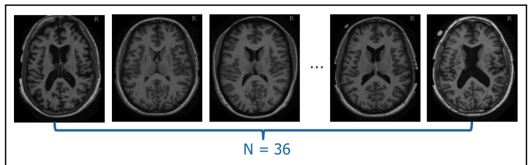
K-means clustering of the principal components identified three clusters (Figure 2). Landmark placement time was estimated at 30 minutes.



Differences in landmark placement error identified by K-means clustering (K=3) of the principal components of the point cloud distributions.

(2) Methods: OASIS1 dataset

After the training and validation phase (Phase 1), the same participants and the lead author (total N=9) performed additional landmark placement on a series of 36 brain images from the OASIS database (30 independent subjects; 6 additional images from the test-retest cohort) [4].



Subset of OASIS1 Dataset

(2) Results: OASIS1 dataset

9 participants placed 12 sets of points (=108 points sets) for a total of 3456 individual points. We identified 29 outliers out of 3456 independent points (0.84%), defined as individual point placements greater than 1 cm away from the group mean. 20/29 outliers (69.0%) were the result of mislabeled landmarks: three pairs of lateral (non-midline) landmarks and only one pair due to gross mislabeling of the target landmark structure (placement in bilateral frontal horns rather than occipital horns). Beyond left-right swapping, the landmarks most susceptible to outliers were the following landmark points: bilateral ventral occipital horns and bilateral indusium griseum origins. Inter-rater reliability across the 36 scans and landmark points was 1.23 +/- 2.81 mm. After filtering out the outliers, the reliability improved to 1.05 +/- 1.05 mm.

Conclusions

Our landmarks provide an intuitive and anatomically-driven framework for establishing quality of registration between brain images. While overall FLE was within an acceptable range, point cloud distributions were heterogeneous. The proposed protocol is reproducible, less manually intensive, and more sensitive to local errors than segmentation-based or qualitative evaluation of correspondence. This may hold value for a broad number of applications including template-to-patient registration and teaching neuroanatomy.

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