



Sandhitsu R. Das¹, Robyn T. Oliver², Brian B. Avants¹, Petya D. Radoeva³, David H. Brainard², Geoffrey K. Aguirre⁴, James C. Gee¹ Departments of Radiology¹, Psychology², Neuroscience³ and Neurology⁴, University of Pennsylvania Philadelphia, Pennsylvania, USA

Abstract

Increasing accuracy and reproducibility in determining visual area (VA) boundaries will improve vision studies based on retinotopy. Manual VA definitions are likely to be corrupted by a complex interaction between noisy data and variations in human perception. Semi-automated methods (Dougherty et al., 2003) have the potential to increase reliability of VA boundaries without sacrificing the validity contributed by a human rater.

We present a template-based method that deforms a canonical retinotopy to polar angle and eccentricity data from fMRI-based retinotopy experiments. Here, VA boundaries traced by human experts are used not only in initializing the canonical map, similar to Dougherty et al., but are also directly incorporated in template fitting by probabilistic curve matching. In contrast, Dougherty et al.'s method, after initialization, is driven only by the image data. Thus, our method is unique in that it strikes a balance between user-labeled VA boundaries and the statistically defined quality of the match between the smooth template and the noisy subject data.

This novel methodology improved overall reliability across three raters. Each rater labeled six visual area borders and the foveal confluence on an inflated 3D surface. Despite an effort to use similar segmentation criteria, considerable variability between tracings by different raters existed before template mapping. Template mapping significantly (p=0.002) decreased the variability of the traced borders across a dataset of 12 hemispheres, when variability was measured by the minimum distance sum across VA boundaries. Reliability was highest in dorsal V2 and lowest in ventral V3 both before and after template mapping. In conclusion, combining optimized template-based models with manual tracings of VA borders can improve the accuracy of retinotopic mapping. However, our work also indicates that fundamental issues of inter-rater reliability should be more carefully considered in retinotopy studies. More effort on defining optimization and evaluation criterion is also required.



Landmark guided registration to semiautomatically define visual areas. Top row shows the two canonical retinotopy templates and the canonical landmark image in atlas space. These are matched by deformable registration with corresponding data and trace images in the middle row. Bottom row shows the result of registration. In the rightmost column, VA labels in atlas space are deformed by the resulting warp to provide VA labels for the subject.

A semi-automated solution for increasing the reliability of manually defined visual area boundaries

2. InSANE: Surface tracing and flattening tool



Screenshot of InSANE flattening tool. The occipital lobe is traced on the inflated brain mesh on the left. The upper right panel shows the traced occipital lobe flattened to a disk. The functional data representing the polar angle map along with manually traced visual area boundaries are shown on both panels



Apply deformable transformation







Example of template fitting in 3d inflated space. Top row shows polar angle data with manual traces overlaid and the corresponding fit with fitted boundaries overlaid. Bottom row shows eccentricity data and the corresponding fit.



Red and blue traces are VA boundaries traced by two different raters. Depending on the quality of data, large variability may exist between manually traced VA boundaries, reducing reliability of VA labelings.

7. Variability in template fitting



Results of template fitting using traces by three different raters are shown for the same hemisphere in one subject. Top row: visual area labels obtained from template fitting. Middle row: fits to polar angle data. The average of measured polar angle values is plotted for a given template value (black line) in each visual area. Bottom row: fits to the eccentricity data for each visual area (data on the x-axis, template on the y-axis). The black line indicates perfect fit. Color represents visual area in all rows.





Eccentricity data

Eccentricity F-statistic map

Flat map representations of polar angle, eccentricity data, manually traced VA borders, and F-statistic map for the eccentricity data. These as well as the F-statistic map for the the polar angle data are available for atlas construction in the flat map space.

8. Discussion and Conclusions

Manual definition of visual areas in retinotopic mapping is subject to operator variability, particularly in noisy data. Fully automated approaches, however, lose the valuable priors provided by operator knowledge of visual area organization. We attempt to balance these constraints with a semiautomated method that uses landmark guided registration for both template initialization and optimization.

Our ongoing work aims at determining the appropriate weighting of the three image matching terms (panel 5). Initial work, reported in the abstract, used a simplified initial template that was constructed entirely from the rated boundaries. The use of that template combined with our fitting procedure produced an improvement in reliability across operators. Examples of fitting presented in this poster are obtained with a more flexible initial template whose generation incorporates eccentricity data. This works very well in some cases, but additional optimizations are required to increase the robustness of the template generation procedure. Ongoing work will continue to refine these techniques to improve reliability of retinotopic mapping.

9. References

Dougherty, RF et al. (2003), 'Visual field representations and locations of visual areas V1/2/3 in human visual cortex', Journal of Vision, vol. 3, no. 10, pp. 586-598. Avants, BB et al. (2006), 'Lagrangian frame diffeomorphic image registration: Morphometric comparison of human and chimpanzee cortex', Medical Image Analysis, vol. 10, no. 3, pp. 397-412.

10. Acknowledgements

This work was supported by NIH grants EB006266, NS045839 and EY10016, and the Burroughs-Wellcome Foundation. We also acknowledge support provided by the Neuroscience Neuroimaging Center grant number NS 045839 and the Center for Functional Neuroimaging at the University of Pennsylvania.