

New data visualization and analysis tools in AFNI-FATCAT





Paul Taylor, Gang Chen, Robert Cox, Daniel Glen, Richard Reynolds

Scientific and Statistical Computing Core, NIMH / NIH / DHHS, Bethesda, MD, USA **Contact:** paul.taylor@nih.gov http://afni.nimh.nih.gov





We describe new visualization and analysis tools for DTI and FMRI data in FATCAT¹, as part of AFNI² and interfacing with the 3D-viewer SUMA^{3,4}.

• In DTI analysis probabilistic tracking is more robust than deterministic⁵, but its outputs typically can't show information of directionality.



• New **@fat_tract_colorize** creates a smoothed surface of the tracked volume, converts V1 eigenvector to color representation, includes FA as optional brightness coloration, and opens AFNI+SUMA together with loaded volumes for viewing.



AFNI+SUMA: WM location, FA values and directionality. FATCAT Demo subject, visualized using **@fat_tract_colorize**.



Whole brain tracking of a macaque brain⁶ for standard tract viewing and colorized volumetric viewing, respectively. The high FA in the corpus callosum is highlighted, for example, in B using **@fat_tract_colorize**.

 In this imperfect world, DTI volumes often have to be removed (motion, distortion, etc.), which can bias tensor estimation at subject and group levels.

- fat_grad_plot.py allows user to: A) visualize gradients in a 'global map' to show missing data, B) highlight regions of many lost gradients (using spherical Voronoi tessellation polygons), C) quantify amount of bias due to lost gradients (as variation in polygonal area).
- fat_grad_plot.py provides useful QA, plots and quantitative output.

Individual QA: show remaining gradients after removal, and quantify effects on 'evenness' of gradient distribution.





<u>Group QA:</u> show overlap of remaining gradients across group; check subject motion, etc.; table of quantities also output

TEST1

sex(+F-M)

age

 Summarize network statistics for either functional (FMRI) or structural (DTI) connectivity using fat_mvm_review.py. • <u>One useful analysis pipeline:</u>

1) Calculate network connectivity matrices with 3dTrackID or 3dNetCorr, 2) Combine and model (using AFNI's 3dMVM⁷) with sample data using

fat mvm*py functions⁸,

3) Summarize and view results with fat_mvm_review.py, 4) Write paper and win Nobel prize*.

Example: statistical results from modeling DTI structural connectivity in terms of four variables (two categorical and two quantitative): Group(+HC-IL)

- Network level and all "within-network" post hoc model results are produced.
- Betas normalized for relative comparison; significance levels highlighted.



Not guaranteed; results may vary

+p<0.1, *p<0.05, **p<0.01, ***p<0.001

References

[1] Taylor PA, Saad ZS. 2013. Brain Connect 3:523-535. [2] Cox RW. 1996. Comput Biomed Res 29:162-173. [3] Saad ZS, Reynolds RC. 2012. Neuroimage 62:768-77. [4] Saad ZS, et al. 2004. IEEE ISBI, p. 1510.

[5] Moldrich RX, et al. 2010. Neuroimage 51:1027-1036. [6] Thomas C, et al. 2014. PNAS 111:16574-16579. [7] Chen G, et al. 2015. Front. Neurosci. 9:375. [8] Taylor PA, et al. 2016. Brain Connect 6(2):109-21.

Acknowledgements

The research was supported by the NIMH & NINDS Intramural Research Programs of the NIH, and by viewers like you.

Poster #3534 OHBM 2016 Stand By Time:

Wed, June 29

12:45 - 14:45

