

Harnessing cloud computing for high capacity analysis of neuroimaging data from NDAR



Daniel Clark¹, Christian Haselgrove², David Kennedy², Zhizhong Liu³,
Michael Milham¹, Petros Petrosyan⁴, Carinna Torgerson³, John Van Horn³, Cameron Craddock¹

¹Child Mind Institute, New York, NY, ² University of Massachussetts Medical School, Worcester, MA, ³University of Souther California, Los Angeles, CA, ⁴UCLA, Los Angeles, CA, ⁵Nathan S. Kline Institute for Psychiatric Research, Orangeburg, NY

Introduction

- ▶ The National Database for Autism Research (NDAR) hosts a vast collection of neuroimaging datasets that can be processed and utilized to yield significant scientific discoveries.
- ▶ This amount of resources necessitates a high-performance computing infrastructure

Methods

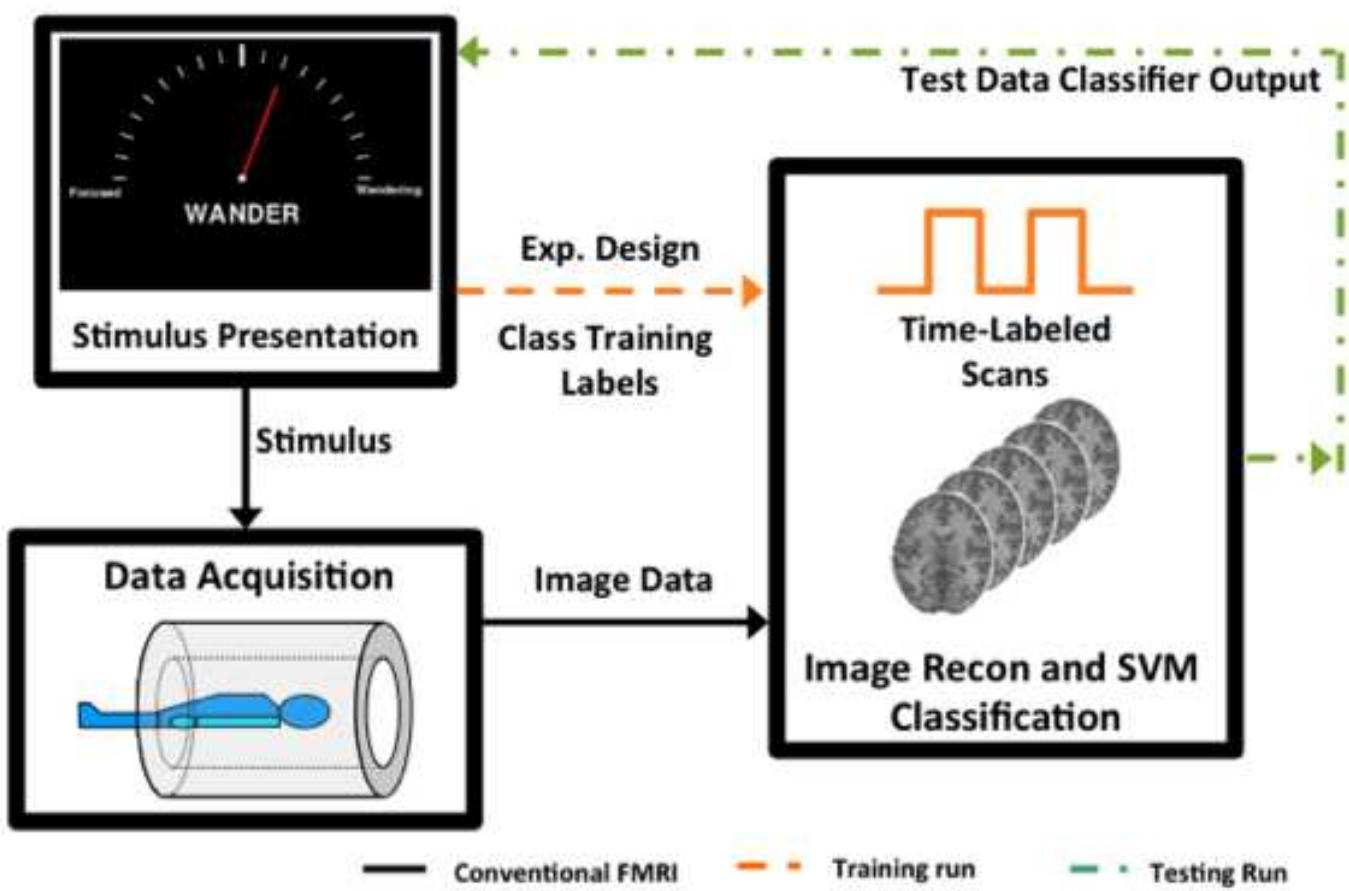


Figure 1 : Neurofeedback experiment, adapted from S. LaConte^{8,9}

Online Preprocessing

- ▶ RT denoising implemented in AFNI¹⁰ to remove contributions of confounds (intensity modulations induced by head motion, physiological noise, scanner drift, ...)
 - ▶ N^{th} order polynomial
 - ▶ Global mean
 - ▶ Mask average time series (i.e. WM, CSF)
 - ▶ Motion parameters (6 or 24 regressor models)
 - ▶ Spatial smoothing
- ▶ Adds < 5 ms of delay

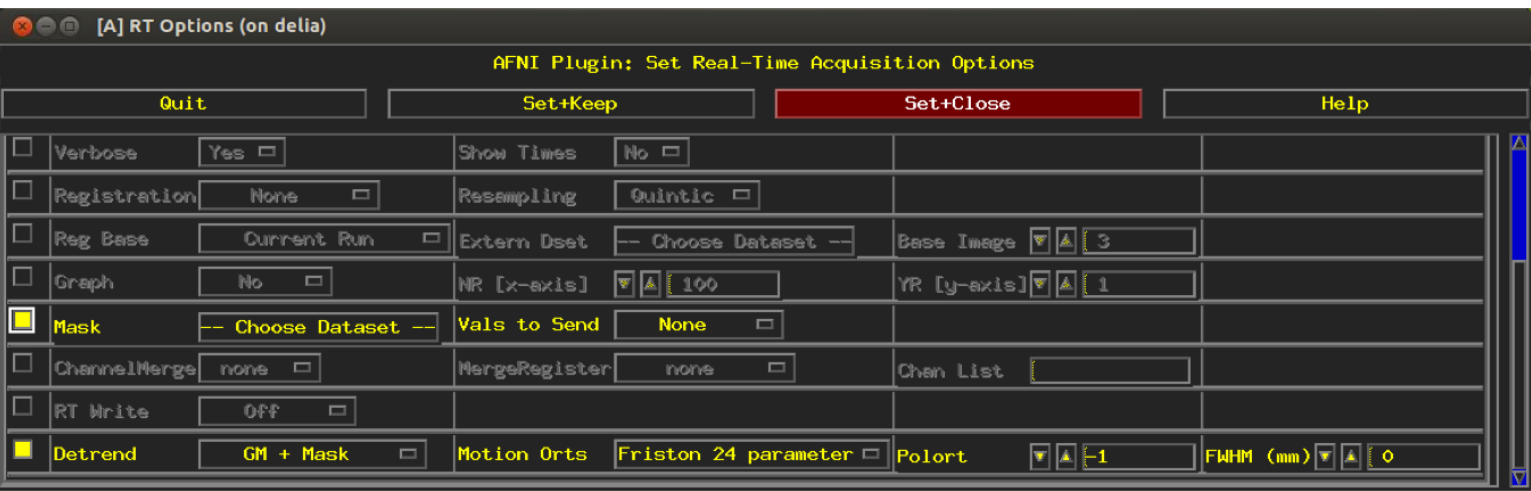


Figure 2 : AFNI interface for online denoising.

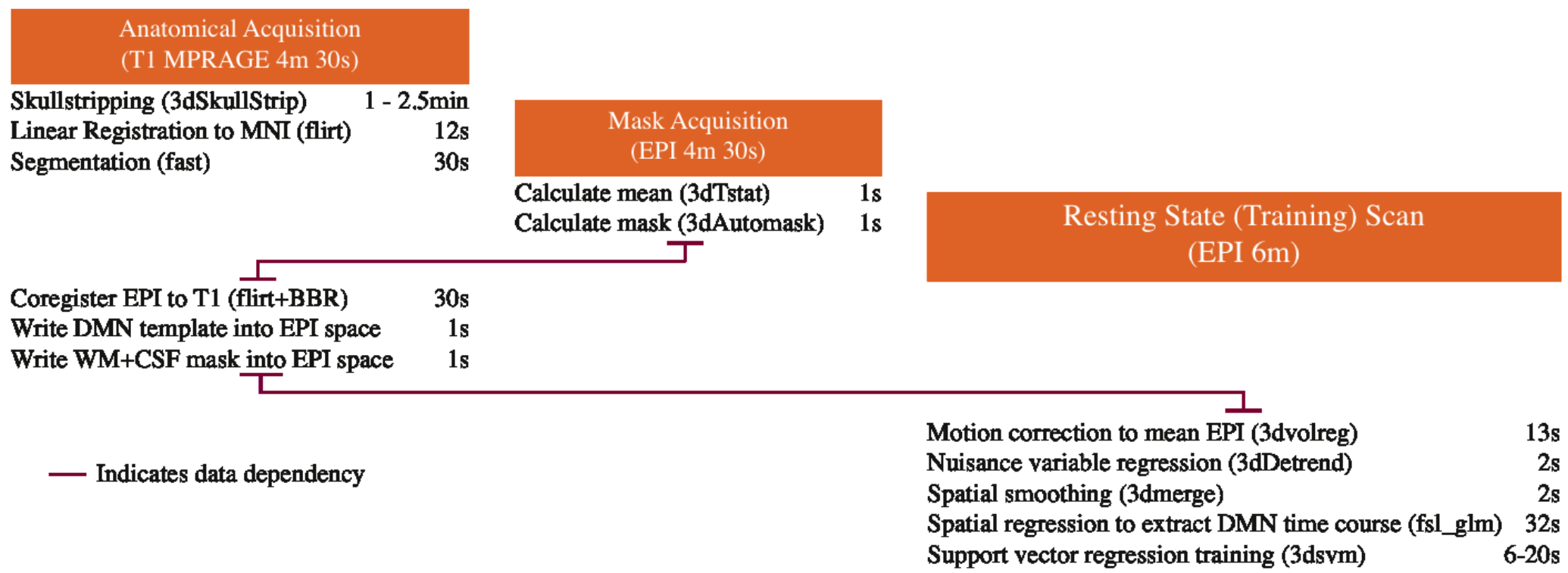


Figure 3 : Flow chart of neurofeedback experiment.

Results

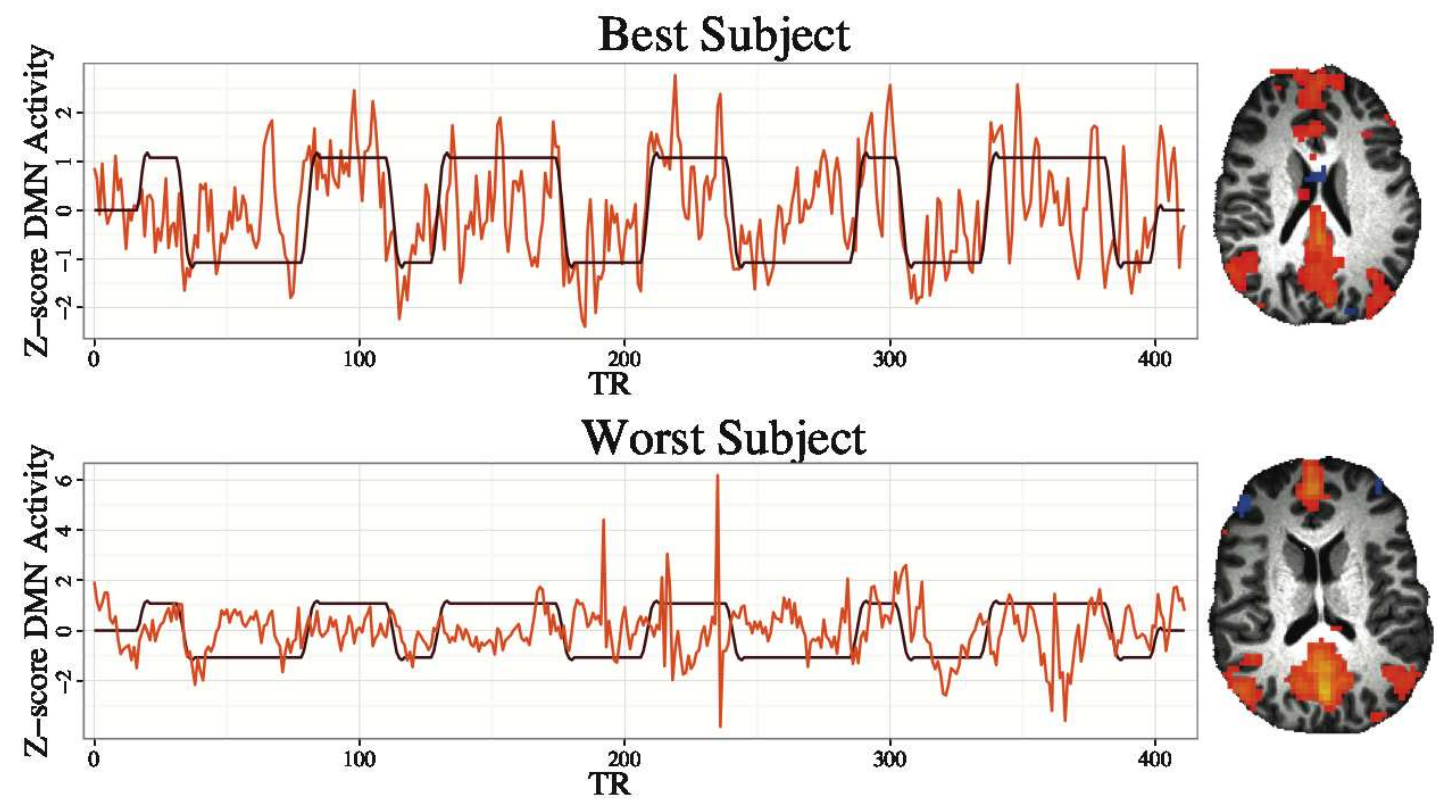


Figure 4 : Example of classifier and feedback timecourse for participants with the best and worst performance.

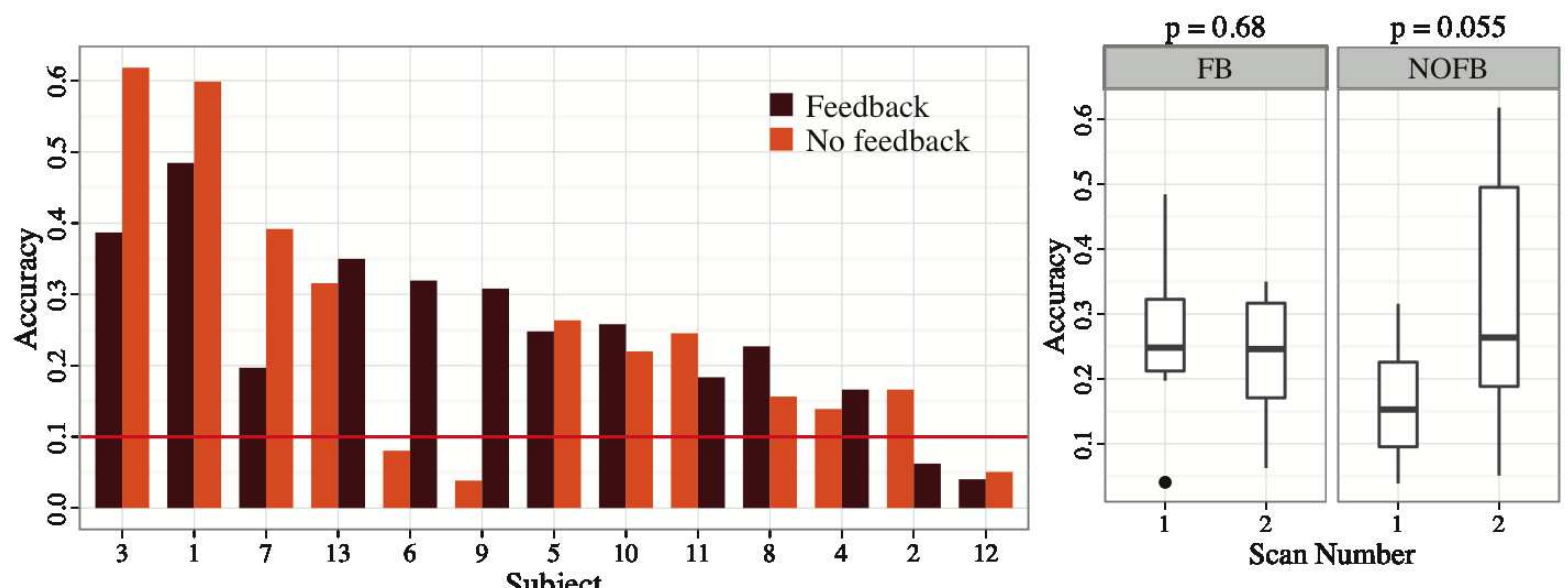


Figure 5 : Performance across participants (A) differs between feedback and neurofeedback scans as determined by their order (B).

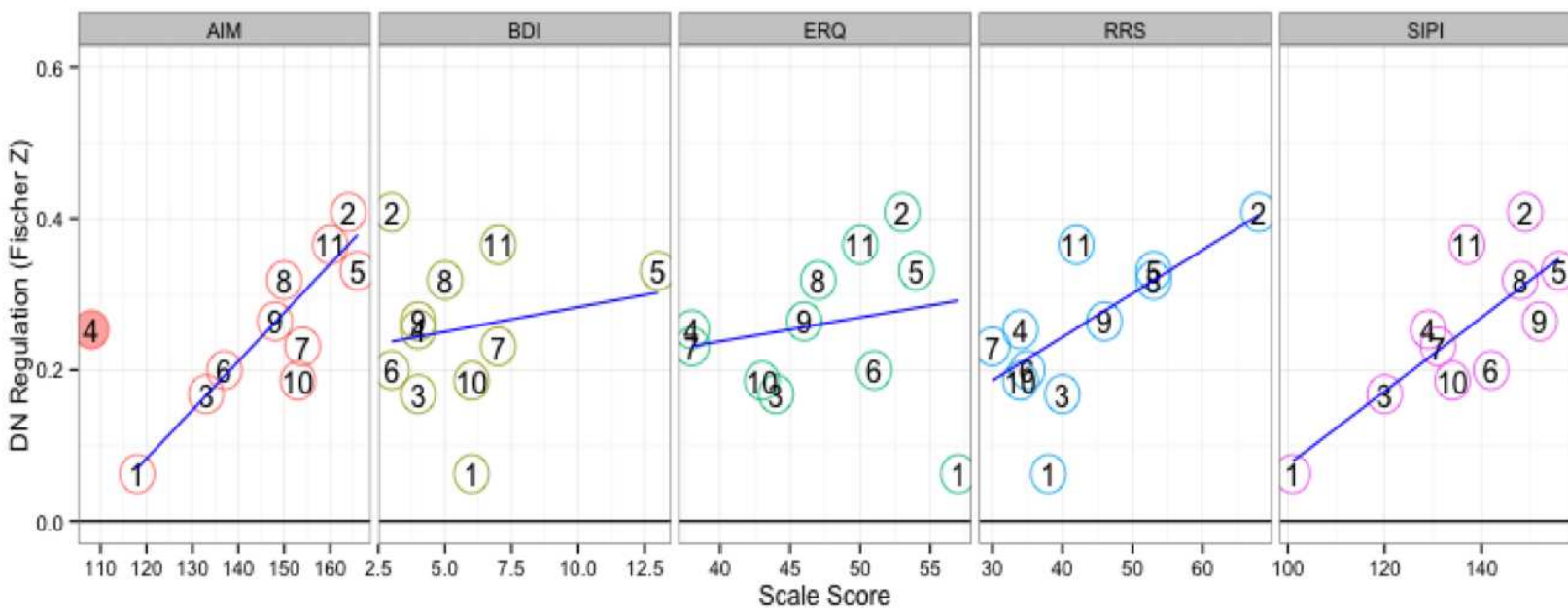


Figure 6 : Inter-individual variation in performance correlates with behavioral measures.

- ▶ As shown in figure 4 models learned for the best and worst performing participants match with the canonical pattern of the default network.
- ▶ The best participant was able to follow the instructions very well 4, the worst seems to have been corrupted by noise.
- ▶ Figure 5 shows 12 of the subjects were able to modulate the DN at above chance levels, performance on feedback runs is consistent independent of order, but performance on nonfeedback runs improves if they occur after feedback runs.
- ▶ Measures that were significantly associated with DN regulation include ($p < 0.05$, FDR corrected): the affect intensity measure (AIM), ruminative responses scale (RRS), and the imaginal processes inventory.

Conclusion

- ▶ We developed a system for measuring DN regulation using realtime neurofeedback.
- ▶ Participants were able to modulate their DN activity and their ability to do so was correlated with phenotype.
- ▶ This system provides a new experimental paradigm for understanding network dysregulation and how it maps to disease states and phenotype.

References and Acknowledgements

1. Sonuga-Barke, E. et al. (2007), Neuroscience and Biobehavioral Reviews 31:977-986.
2. Broyd, S. J. et al. (2009), Neuroscience and Biobehavioral Reviews 33: 279-296.
3. Sheline, Y.I. et al. (2009), PNAS 106: 1942-1947.
4. Whitfield-Gabrieli, S. et al. (2009), PNAS 106: 1279-1284.
5. Hamilton, J.P. et al. (2011), Biol. Psychiatry 70: 327-333.
6. Sylvester, C.M. et al. (2012), Trends Neurosci. 35, 527-535.
7. Castellanos, F.X. et al. (2012), Trends Cogn. Sci. 16, 17-26.
8. LaConte, S.M. et al. (2004). Human Brain Mapping, 11: 2551.
9. LaConte, S.M. et al. (2011). NeuroImage, 56(2), 440-454.
10. Cox, R.W. (1996) Comput. Biomed. Res. 29: 162-173.

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