
Extensions and Application of the Robust Shared Response Model to Electroencephalography Data for Enhancing Brain-Computer Interface Systems

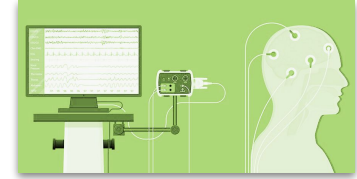
Authors: Andrew Graves, Cory Clayton, Gabe Yohe, Joon Yuhl Soh, Per B. Sederberg

Acknowledgements: Dr. Tim Clark, Dr. Mohammad Sadnan Al Manir

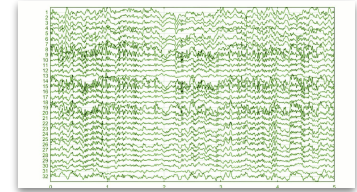
Predict Behavior Using Electrical Activity in Brain



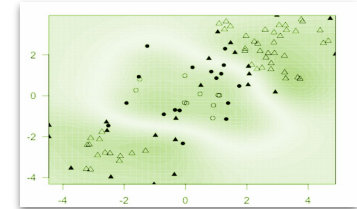
Record Trial



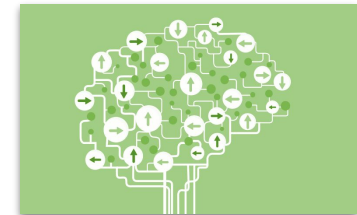
Process Data



Build Model



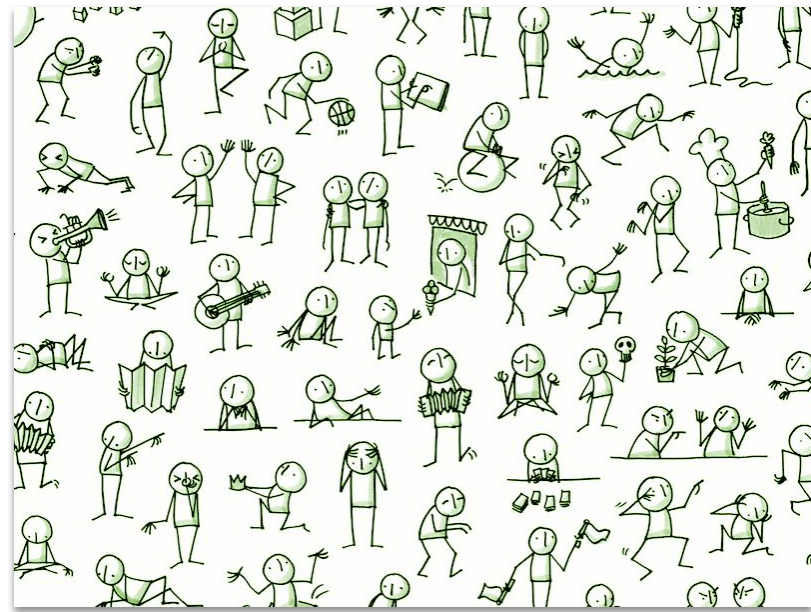
Predict



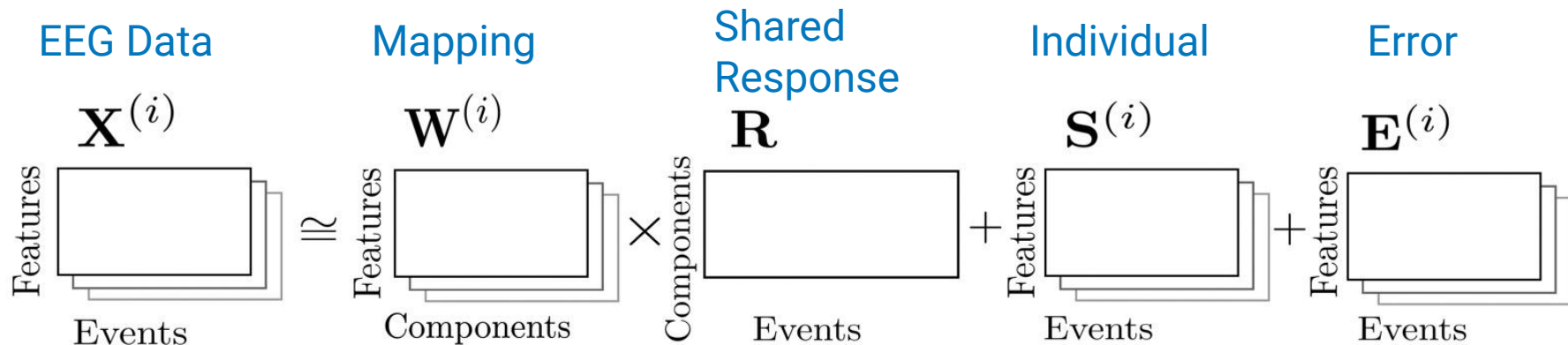
The Shared Response Model

Implementing:

A Robust Shared Response Model [2]



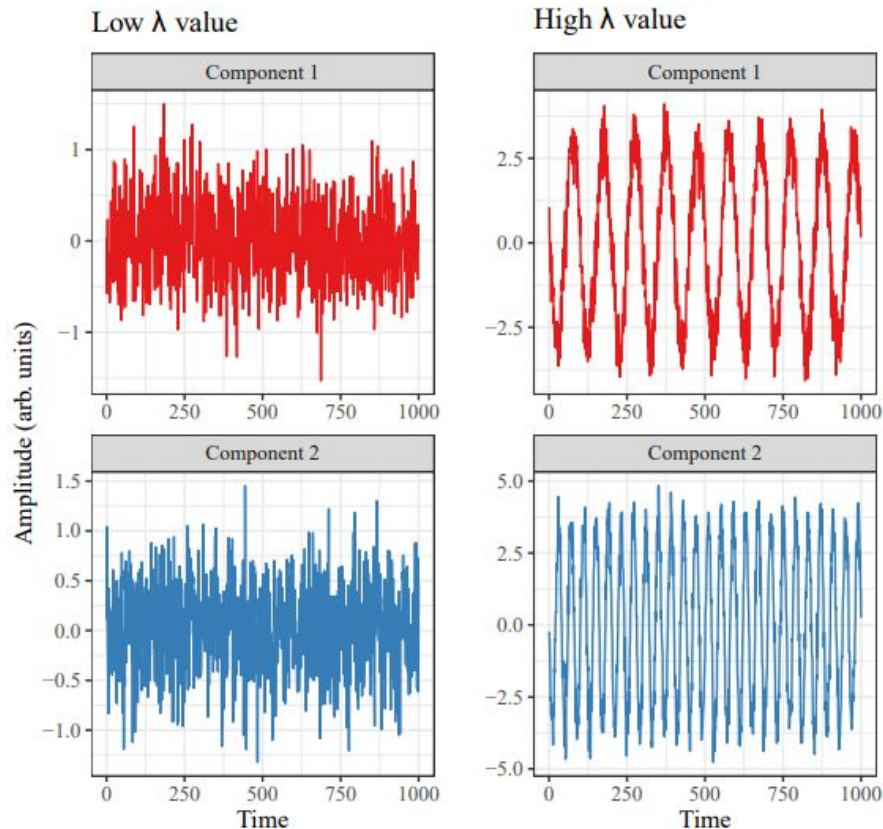
Robust Shared Response Model



Experiment 1: Results

- 100 individuals
- 32 electrodes
- 10 Hz, 25 Hz sine-waves
- Gaussian noise perturbation

RSRM simulation results visualizing the primary latent space vectors



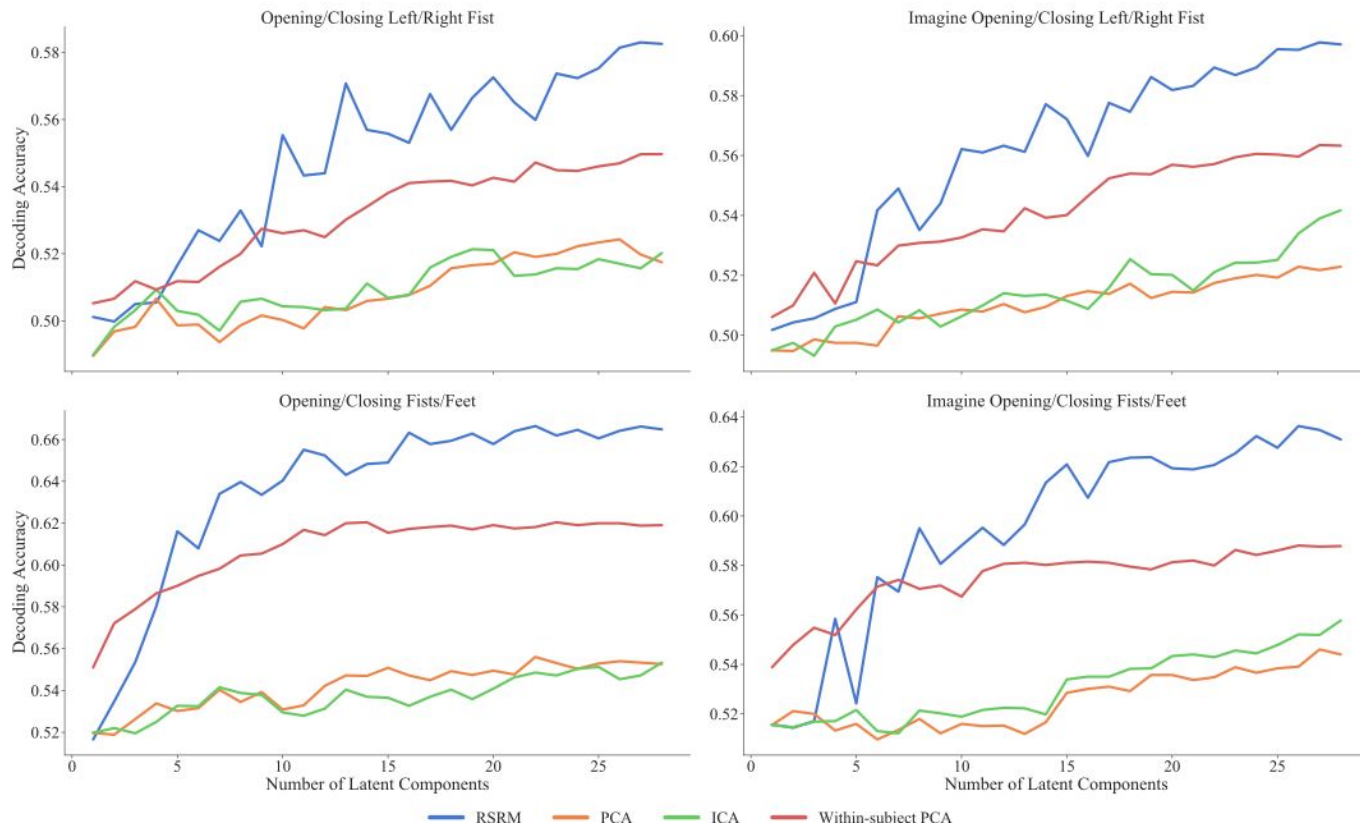
Experiment 2: EEG Dataset Description

Openly available Motor Movement/ Imagery dataset [5]

- Consists of 12 task-related two-minute recordings
- 4 tasks (all related to motor movement)
 - 109 subjects
 - 4110 classification labels for each task
- Test how RSRM functions as a dimension reduction step in feature engineering relative to other widely used methods.

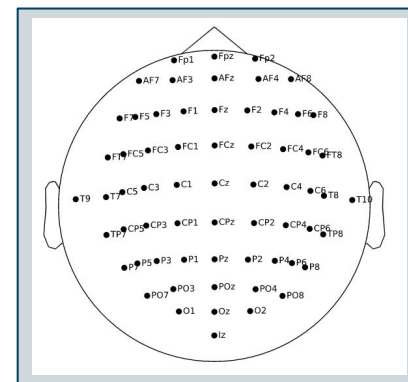
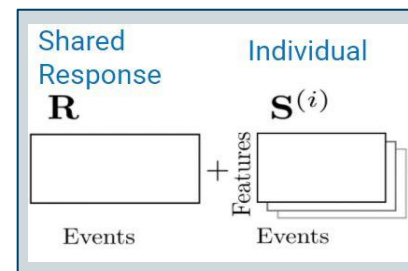
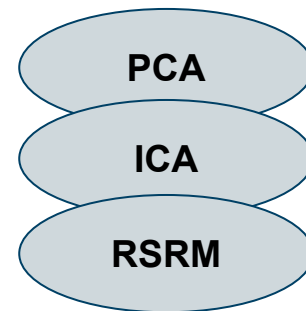
Experiment 2: Results

RSRM performs better on four distinct tasks relative to other dimension reduction methods



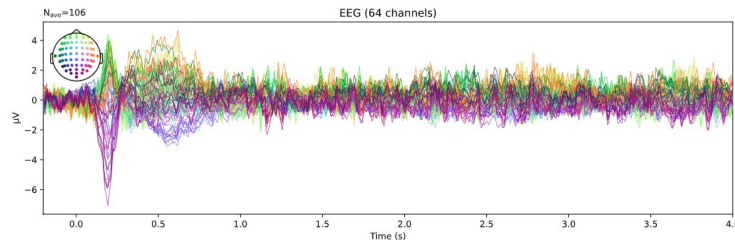
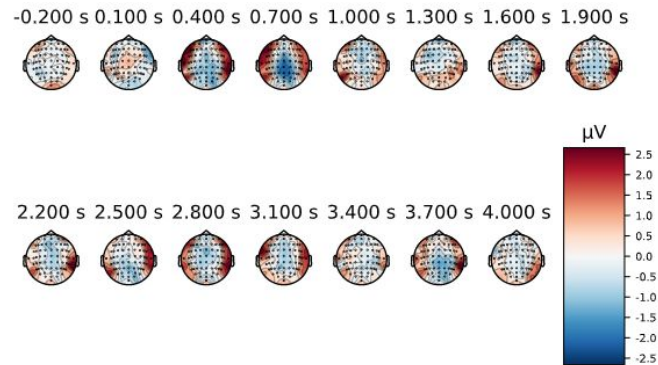
RSRM Summary

- A latent variable model for sequential data.
- Models common signals and individual differences.
- New evidence suggesting that it works well with EEG data.



Conclusion

- Superior performance to other dimension reduction techniques.
- Faster modeling than individual modeling
- Reduced model training time and data needed
- Wide-range of other applications



References

- [1] Chen, P.-H. (Cameron), Chen, J., Yeshurun, Y., Hasson, U., Haxby, J., & Ramadge, P. J. (2015). A Reduced-Dimension fMRI Shared Response Model. In C. Cortes, N. Lawrence, D. Lee, M. Sugiyama, & R. Garnett (Eds.), *Advances in Neural Information Processing Systems* (Vol. 28, pp. 460–468). Curran Associates, Inc.
- [2] Kumar, M., Ellis, C. T., Lu, Q., Zhang, H., Capotă, M., Willke, T. L., Ramadge, P. J., Turk-Browne, N. B., & Norman, K. A. (2020). BrainIAK tutorials: User-friendly learning materials for advanced fMRI analysis. In: *PLOS Computational Biology*, 16(1), e1007549. <https://doi.org/10.1371/journal.pcbi.1007549>
- [3] Turek, J. S., Ellis, C. T., Skalaban, L. J., Turk-Browne, N. B., & Willke, T. L. (2018). Capturing Shared and Individual Information in fMRI Data. In: *2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 826–830. <https://doi.org/10.1109/ICASSP.2018.8462175>
- [4] Gramfort, A., Luessi, M., Larson, E., Engemann, D., Strohmeier, D., Brodbeck, C., Goj, R., Jas, M., Brooks, T., Parkkonen, L., & Hämäläinen, M. (2013). MEG and EEG data analysis with MNE-Python. In: *Frontiers in Neuroscience*, 7, 267.
- [5] Schalk, G., McFarland, D. J., Hinterberger, T., Birbaumer, N., & Wolpaw J. R. (2004). BCI2000: a general-purpose brain-computer interface (BCI) system. In: *IEEE transactions on biomedical engineering* 51.6, 1034–1043. <https://doi.org/10.1109/TBME.2004.827072>.