

# Online classification of visual perception

Dr A.X. Stewart<sup>1\*</sup>

<sup>1</sup>Center for Mind & Brain, UC Davis, CA, USA

\*E-mail: [andrewXstewart@gmail.com](mailto:andrewXstewart@gmail.com)

**Introduction:** While motor output is a major focus for rehabilitative BCIs, examining the possibilities of other modalities may also be useful for basic neuroscience research. Here, we examine online classification of visual perception and attention, using Support Vector Machines (SVM) trained on EEG data from earlier visual presentation trials.

**Material, Methods and Results:** EEG data was recorded from 8 participants in a visual presentation environment, as in [1]. Lab Steaming Layer [2] – similar to BCILAB – was used to capture data from a Biosemi ActiveTwo with 32-70 active recording electrodes at low latency. Data was processed in real time, with minimal filtering, and very noisy channels identified and rejected.

### Stage III trial structure:

Independent Component Analysis was used to transform the EEG channel activity, to identify and focus on possible sources. We first trained a series of SVM classifier models using data from each EEG channel and IC in turn, with the classification task to distinguish data from one object presentation from another. Peak accuracy was found using a selected IC datasource, as in [1].

We find object-identifying accuracy of around 85% (0.9 AUC) in online object determination from EEG data. This was mostly from occipital alpha components.

In further tests, we attempted to classify not only currently-observed object identity, but also which of two on-screen objects the subject was focussing their attention on. While classification accuracy dropped greatly in response to this harder task, we could still identify attention targets at 0.73 AUC, whereas the attentional distractor was identified at 0.58 AUC. Through an extended online trial feedback experiment, as in [3], we could examine persistence and conscious control of this target-attention-specific classifier activity. With this, we find tentative evidence that subjects can consciously control the activity of a minority of ICs by choosing to attend to specific visual objects.

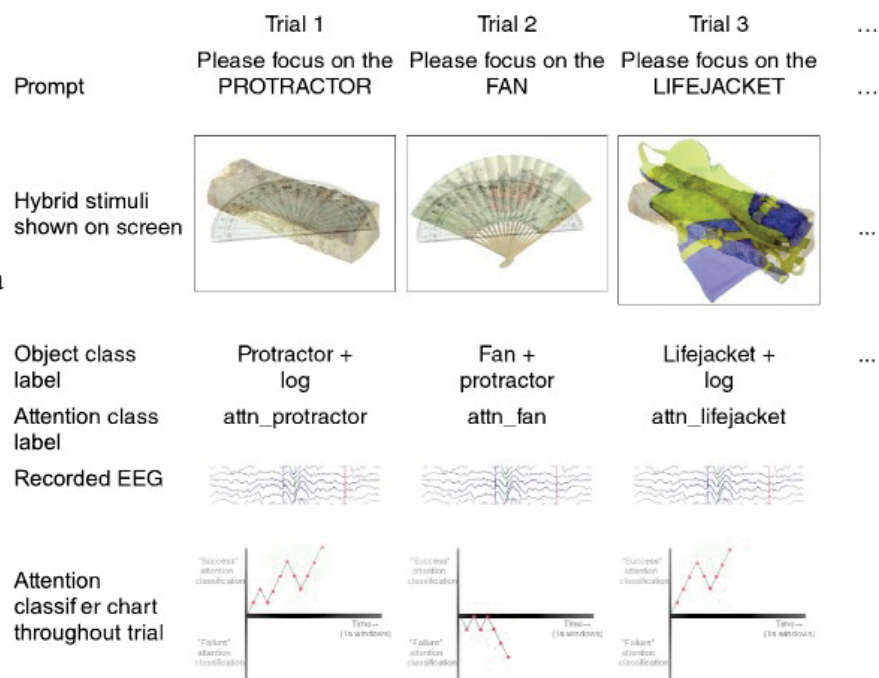


Fig 1 - trial structure and training label

### References

- [1] Stewart, A. X., Nuthmann, A., & Sanguinetti, G. (2014). Single-trial classification of EEG in a visual object task using ICA and machine learning. *Journal of Neuroscience Methods*, 228, 1–14. doi:10.1016/j.jneumeth.2014.02.014
- [2] Delorme, A., Mullen, T., Kothe, C., Akalin Acar, Z., Bigdely-Shamlo, N., Vankov, A., & Makeig, S. (2011). EEGLAB, SIFT, NFT, BCILAB, and ERICA: new tools for advanced EEG processing. *Computational Intelligence and Neuroscience*, 2011, 130714. doi:10.1155/2011/130714
- [3] Cerf, M., Thiruvengadam, N., Mormann, F., Kraskov, A., Quiroga, R. Q., Koch, C., & Fried, I. (2010). On-line, voluntary control of human temporal lobe neurons. *Nature*, 467(7319), 1104–8. doi:10.1038/nature09510