



A wireless, wearable Brain-Computer Interface for in-home neurorehabilitation.

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1. Introduction

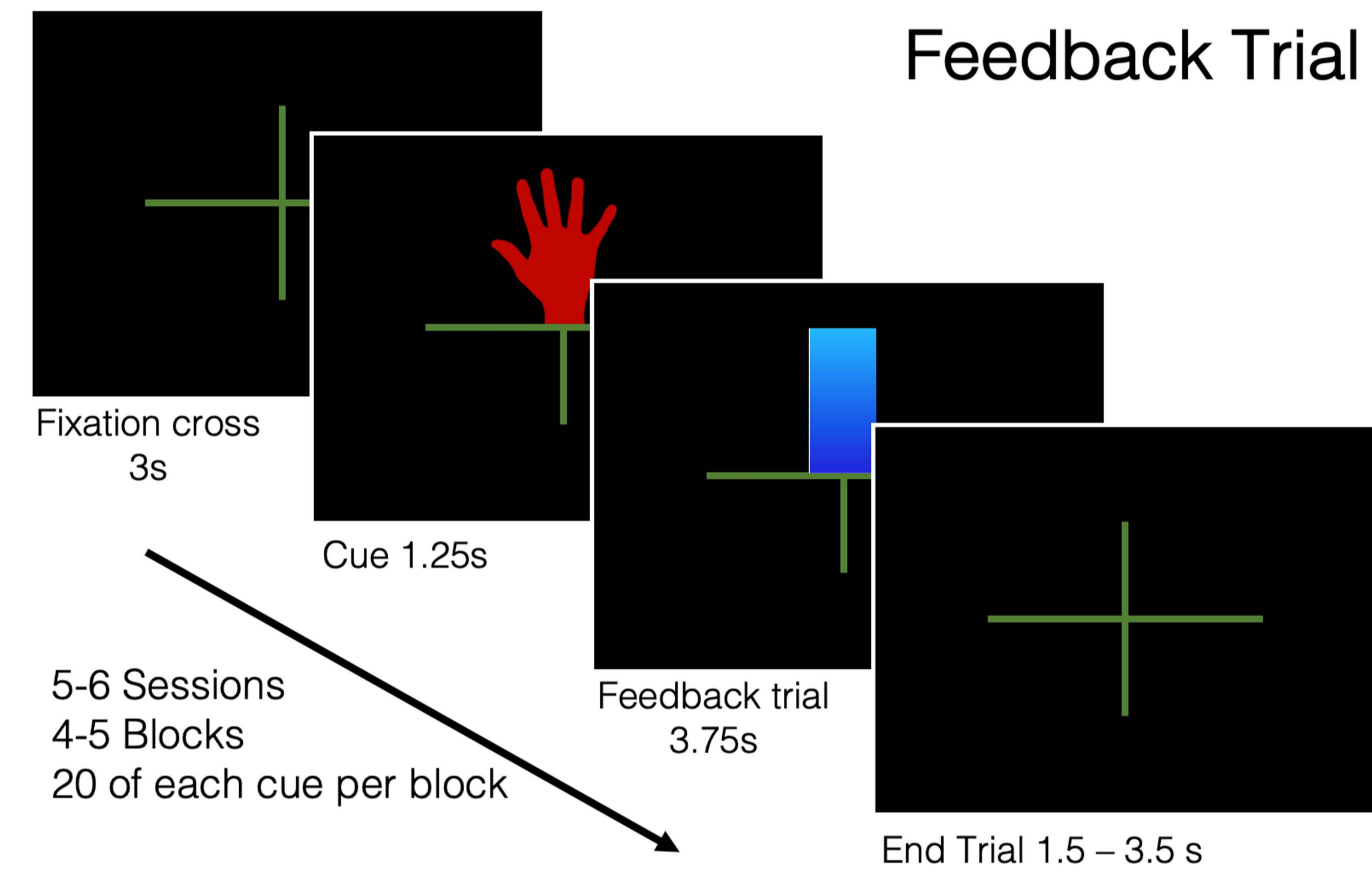
- Clinical trials using Brain-Computer Interface (BCI) for stroke rehabilitation have shown promising results, yet clinical adoption is lacking [1]. Unsupervised at-home BCIs may increase clinical use by reducing the burden on healthcare providers and increasing patient agency.
- We adapted a mainstream BCI protocol (Graz-BCI) [2] to fit a realistic stroke rehabilitation scenario [3] to test the feasibility of such a system.

Research Questions

- H1: Can participants control a BCI within six days, in their own homes with remote instruction?
- H2: Will successful BCI control be associated with electrophysiological changes in alpha (8-14 Hz) and beta rhythm (15-30 Hz) frequency bands?

2. Method

- The Graz-BCI [4] – which detects real time differences in brain activity between two mental tasks – was adapted in OpenVibE [2].
- Participants collected data without feedback, to train a Common Spatial Pattern and a Linear Discriminant Analysis. Then they proceeded to train with feedback for 4-5 blocks.
- Participants imagined right-handed finger movement (👉) and a cold, dead, detached right hand (☒); tasks that have been shown to modulate excitability of stroke-affected limbs [3]
- Under careful instruction and remote supervision, the participants collected data in their own homes.



Participants were mailed a dry electrode, 16 channel, wireless EEG cap. (Cumulus, Belfast, UK).

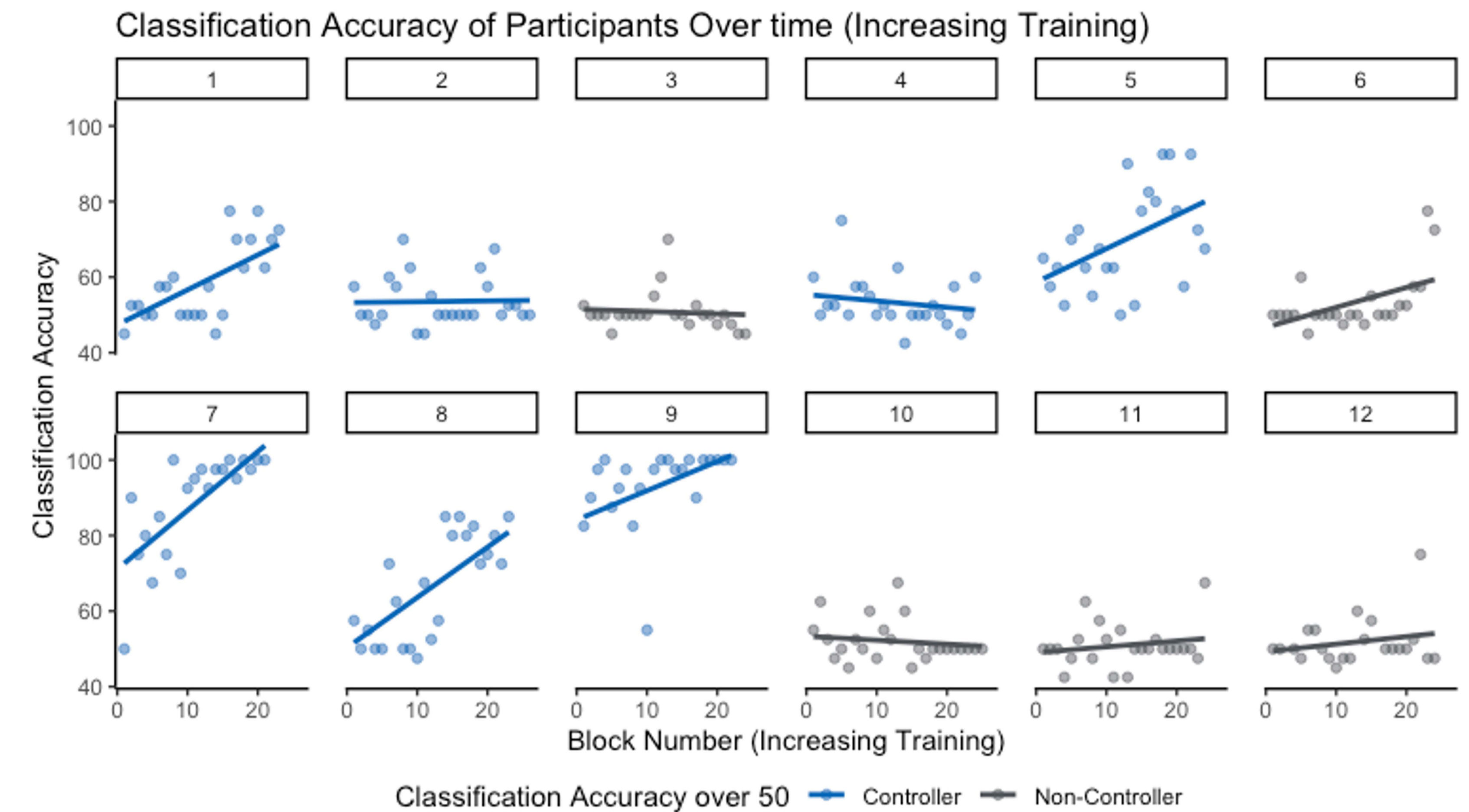
3. Analysis

- Lateralisation of brain activity was operationalised as the difference in power measured at FC3 and FC4.
- To investigate the influence of training on the EEG activity produced by participants, the averaged Riemannian distance – also called Distinctiveness [6] – of the EEG activity produced by the two tasks was analysed.
- A trained experimenter inspected the raw data and processed outputs to ensure the automatic processing was adequate.
- The EEG data was preprocessed using an automated pipeline:
 - 1 Lowpass Filter 45Hz
 - 2 Highpass Filter 1Hz
 - 3 Reference to Average
 - 4 Artifact Subspace Reconstruction (ASR)
 - 5 Interpolation of missing electrodes
 - 6 Reference to Average
 - 7 ICA, labelling and rejection
 - 8 Epoching

4. Results

Classification Accuracy (CA)

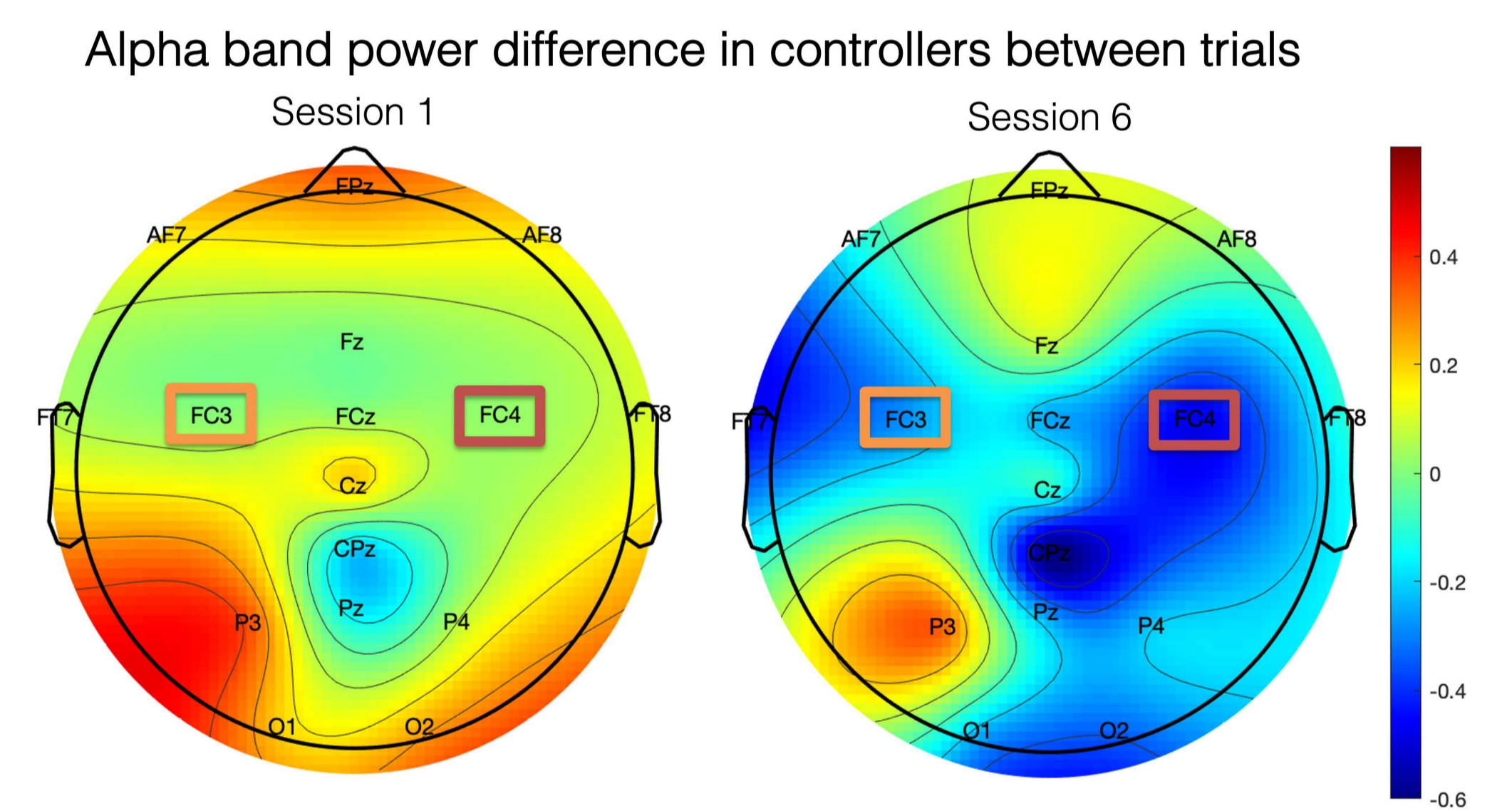
- 7 of 12 participants (1, 2, 4, 5, 7, 8, 9) achieved CAs above 50 and were classified as “controllers”.



A mixed effects linear model was used to predict CA, using block number (represents the effect of training) and a random intercept and slope per participant. The training effect was significant ($b = 0.42$, $t = 2.31$, $p = 0.044$). These data support H1.

Power differences between mental imagery conditions show changes in motor region activity for controllers

- Power changes of alpha and beta power band at the FC3 and FC4 electrode (orange/red square, nearest to motor cortex) were significant: between groups, and within controllers – but not within non-controllers. These data support H2.
- Controllers had significantly stronger lateralisation of brain activity in the alpha and beta power band compared to non-controllers.



Distinctiveness between the mental imagery conditions increases with training and predicts CA.

- The Distinctiveness of brain activity between the two mental imagery conditions increases with training.
- The Distinctiveness is a better predictor of CA than is training time alone.

Variable	Beta Coefficient	t-Value	p-Value
Increase of Distinctiveness predicted by training	0.0106	3.04	0.0131*
Increase of CA predicted by training†	0.354	1.76	0.112
Increase of CA predicted by Distinctiveness†	7.598	2.07	0.0402*

† Predicted using the same model.

Sources

[1] Simon, C., Bolton, D. A. E., Kennedy, N. C., Soekadar, S. R., & Ruddy, K. L. (2021). Challenges and Opportunities for the Future of Brain-Computer Interface in Neurorehabilitation. *Frontiers in Neuroscience*, 0. <https://doi.org/10.3389/fnins.2021.699428>

[2] Renard, Y., Lotte, F., Gibert, G., Congedo, M., Maby, E., Delannoy, V., Bertrand, O., & Lécuyer, A. (2010). OpenVIBE: An Open-Source Software Platform to Design, Test, and Use Brain-Computer Interfaces in Real and Virtual Environments. *Presence: Teleoperators and Virtual Environments*, 19(1), 35–53. <https://doi.org/10.1162/pres.19.1.35>

[3] Liang, W., Xu, Y., Schmidt, J., Zhang, L., & Ruddy, K. L. (2020). Upregulating excitability of corticospinal pathways in stroke patients using TMS neurofeedback: A pilot study. *NeuroImage : Clinical*, 28. <https://doi.org/10.1016/j.nicl.2020.102465>

[4] Pfurtscheller, G., & Neuper, C. (2018). Motor imagery based EEG features visualization for BCI applications. *Procedia Computer Science*, 126, 1936–1944. <https://doi.org/10.1016/j.procs.2018.08.057>

[5] Ruddy, K., Balsters, J., Mantini, D., Liu, Q., Kassraian-Fard, P., Enz, N., ... & Wenderoth, N. (2018). Neural activity related to volitional regulation of cortical excitability. *Elife*, 7, e40843. <https://doi.org/10.7554/eLife.40843>

[6] Lotte, F., & Jeunet, C. (2017, September). Online classification accuracy is a poor metric to study mental imagery-based bci user learning: An experimental demonstration and new metrics. 7th International BCI Conference. <https://hal.archives-ouvertes.fr/hal-01519478>



QR code or link lead to short video of the Setup and experiment. https://1drv.ms/v/s!Aoo1_Kelny2ke0RISYkZv76i2Jg7e-ljuyt

5. Conclusion

- It is possible to obtain control (improving CA) over an in-home BCI using a 16-electrode, wireless, EEG system
- Over time controllers produced more distinct and lateralized patterns of activity.
- Spectral analysis showed that the power of alpha and beta oscillations in the brain measured at FC3 and FC4 of power was significantly different between controllers and non-controllers, and within controllers, replicating similar results in literature [5].
- Future development of this work will aim to improve upon the extent and speed of learning to control the BCI and thus facilitates the development of new neurorehabilitation technologies.