User–Centric Performance Estimation in a Continuous Online BCI



Martin Billinger¹, Christa Neuper^{1,2}, Gernot Müller-Putz¹ and Clemens Brunner^{1,3} ¹Institute for Knowledge Discovery, BCI Lab, Graz University of Technology, Austria ²Department of Psychology, University of Graz, Austria ³SCCN, INC, University of Clafornia San Diego, CA, USA



Introduction

- How to meaure performance of continuous BCI control?
- \rightarrow User's control strategy, response time
- How does the user percieve BCI performance?
- \rightarrow Control response vs. goal completion
- Game–like continuous BCI application (2-class MI)



Data Processing:



Figure 1: (A) Training. (B) Transition between targets. (C) Positive feedback. (D) Negative feedback.

Methods

- Regression-based EOG removal
- Post-hoc exclusion of participants based on EMG
- Features: 1 session band power, 1 session autoregressive
- Naive Bayes classifier: class probabilities p_{Hand} , p_{Feet}
- Pitch: $(p_{\text{Hand}} p_{\text{Feet}}) \cdot 20^{\circ}$, Altitude: $0.5 \int (p_{\text{Hand}} p_{\text{Feet}}) dt$
- Performance estimation: fraction of time spent on the path.
 - Target hit rate: fraction of time spent on the path.
 - Accuracy: compares target and control signal.
 - Response time: maximum XCF of target and control.

Results



Study Design:

- Users steered a virtual airplane along a clear path.
 - Constant horizontal movement, 1-D MI control
 - Feedback: pitch, position, color
- 14 healthy volunteers (age 25.5 ± 4)
- 2 sessions: each 180 trials training, 3x5 minutes feedback
- Standard training procedure, but with game graphics



Figure 2: Target Signal. Optimal control choice, dependent on current altitude and visible path. Invalid combinations are grayed out.

Data Acquisition:

0 1 2 3 4 5 6 7 8 9 10 time lag [s]

Figure 4: Cross correlation function (XCF) of target and control signal for each individual run. Shading corresponds to classification accuracy. The weighted grand average XCF over all users and runs is plotted in bold blue.



Figure 5: Left: classification accuracy is higher when correcting for response time (red). Center: target hit rate is mostly unaffected by response time. Right: Without correcting for for response time (blue), classification accuracy appears below chance level (dashed line) for all runs.

Conclusion

- 1. Estimating continuous BCI performance requires knowledge about target, current state and control strategy.
- 2. Calculating classification accuracy alone is not enough. Also
- 3 Laplacian EEG derivations (C3, Cz, C4), fs = 300 Hz
- 3 monopolar EOG channels, $fs = 300 \,\mathrm{Hz}$
- 2 bipolar EMG channels (arm, leg), $fs = 2.4 \,\mathrm{kHz}$

• Participants rated the controllability of the BCI from -5 to 5.

the response time has to be considered.

3. User rating correlates better with target hit rate than with classification accuracy: Success at the task is more important to the user than control response.

References

Acknowledgements

[1] G. Pfurtscheller and C. Neuper. Motor imagery and direct brain-computer communication. *Proceedings of the IEEE*, 89:1123–1134, 2001.
[2] B. Laar, F. Nijboer, H. Gürkök, D. Plass-Oude and A. Nijholt. User experience evaluation in BCI: Bridge the gap. *International Journal of Biolectromagnetism*, 13(3): 157-158, 2000.

[3] G. R. Müller-Putz and R. Scherer and C. Brunner and R. Leeb and G. Pfurtscheller. Better than random? A closer look on BCI results. International Journal of Bioelectromagnetism, 10: 52-55, 2008. This work is supported by the FWF Project (P20848-N15) and the FP7 Framework EU Research Project ABC (No. 287774). This poster only reflects the authors' views and funding agencies are not liable for any use that may be made of the information contained herein.