Technical University of Munich

Improving user comfort in auditory-steady-state-response brain-computer interface by using a co-adaptive stimulus

Isabelle Hoxha[1], Fulvia Del Duca[1], Stefan K. Ehrlich[2], Florian Bergner[2], Nicolas Berberich[2], Gordon Cheng[2]

1. Elite Master of Science in Neuroengineering | Department of Electrical and Computer Engineering | Technical University of Munich
2. Institute for Cognitive Systems | Department of Electrical and Computer Engineering | Technical University of Munich

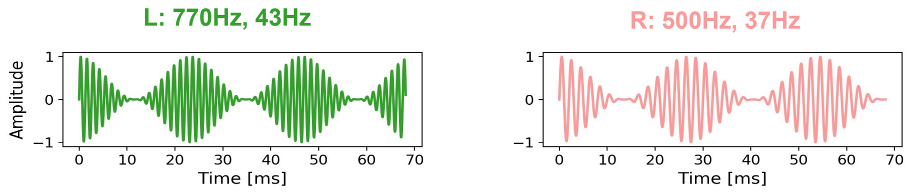
Motivation

- Auditory steady-state responses (ASSR) modulated through auditory selective attention (ASA) [1].
- ASSR generated without training: convenient for brain-computer interface use.
- Current paradigms: binary classification, but result in subject tiredness.
- Improvements of the bearability of the stimulus attempted [2], but level of attention required remains an issue if two beats are displayed continuously at the same level.
- Keeping focus on salient stimuli easier and requires less effort [3]: co-adaptive paradigm. We hereby prove the feasibility of such a paradigm.

Adaptive Auditory Stimulus

- Two amplitude-modulated tones (one per ear).
- Three intensity levels: *high* (no adaptation), *intermediate* (decrease of non-target sound to achieve enhanced comfort), *low* (lowest level to hold focus on a tone).

Stimuli



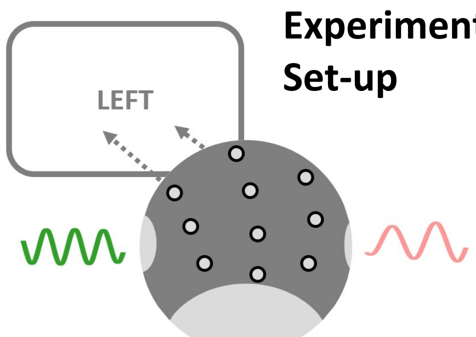
- Levels tuned to each subject by decreasing the intensity of the non-target tone to match the described perceptual conditions:
  1 high: 100% **2** intermediate: 81% **3** low: 64%

Experiment Design

- With 3 sound levels and the decision rules designed, we distinguish 5 combinations of accessible sound levels:

L1R1 L1R2 L2R1 L1R3 L3R1

- Subject listens to the two tones for 5 seconds while focusing on the instructed tone.
- Each of the 5 conditions is presented 50 times.
- Brain Product's actiCHamp.

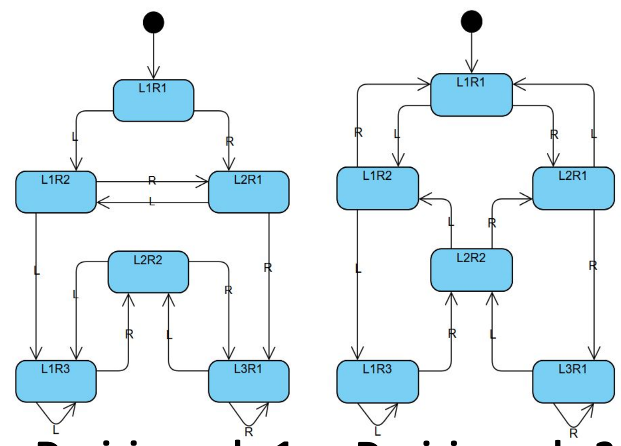


Experiment Set-up

Statistical simulation of online decoding

- Compare online performance to the non-adaptive paradigm on two probability tables and two decision rules.
- Choice of the decision rule for the best accuracy

Statistical simulation of online decoding



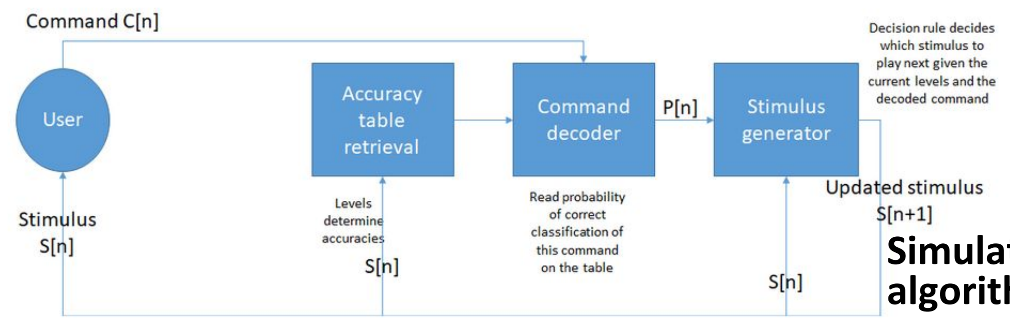
Decision rule 1 **Decision rule 2**

	R1	R2	R3
L1	80/80	80/65	80/50
L2	65/80	80/80	x
L3	50/80	x	x

Probability table 1 ("worst case scenario")

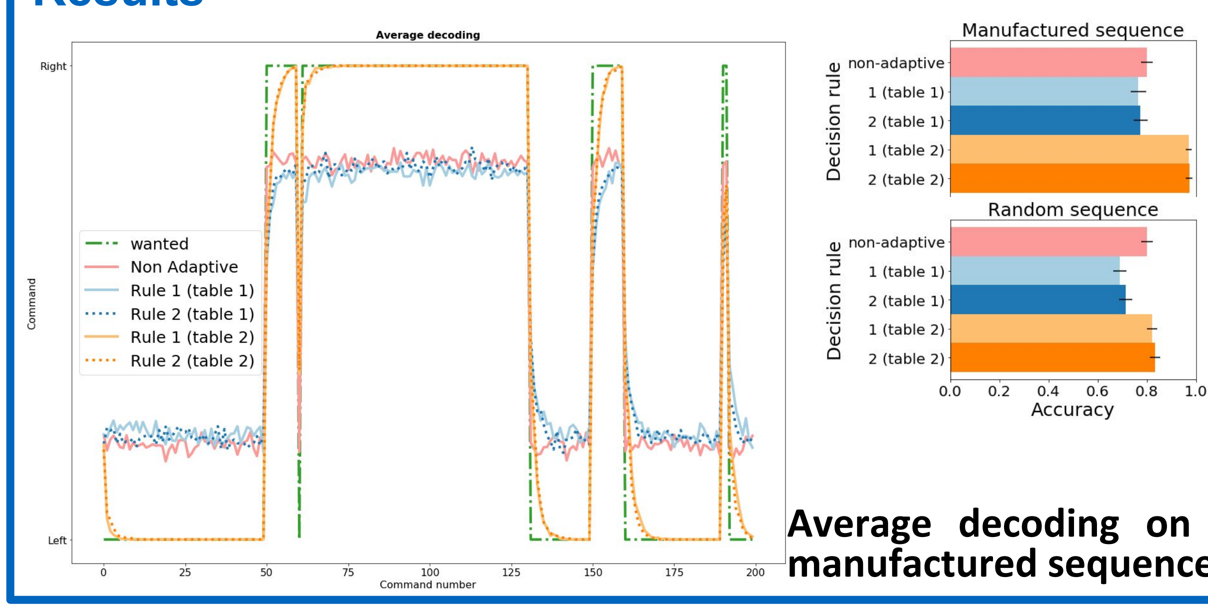
	R1	R2	R3
L1	80/80	100/75	100/65
L2	75/100	80/80	x
L3	65/100	x	x

Probability table 2 ("best case scenario")



Simulation algorithm

Results

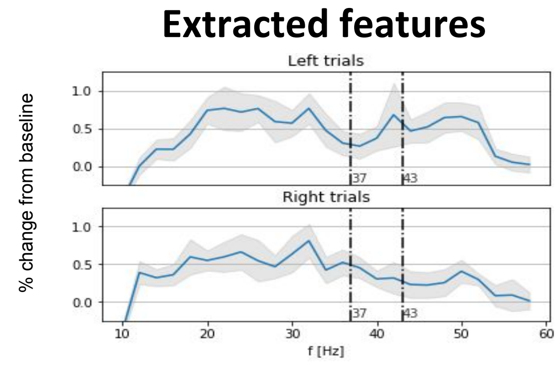


Average decoding on a manufactured sequence

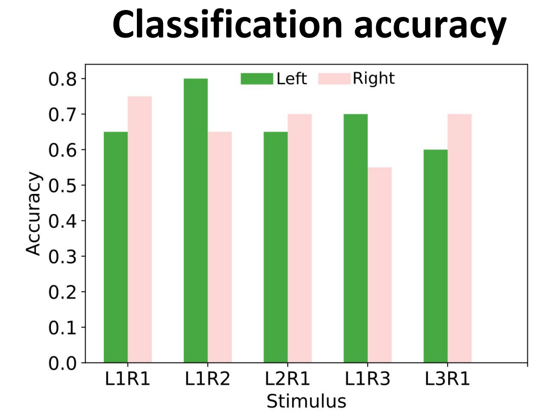
Offline results

- Classification: power in the bands $f_{L,R} \pm 2$Hz for LDA classifier
- Average decoding accuracy: 67%
- Accuracy increase when the target stimulus is the stimulus at highest volume

Extracted features



Classification accuracy



Conclusion

- Equally performant decoding of intent with unbalanced (adaptive) and balanced stimuli.
- Simulated co-adaptive online performance comparable to non-adaptive one, easier focus.

References:

[1]M.-A. Lopez, Hector Pomares, Francisco Pelayo, Jose Urquiza, and Javier Perez. Evidences of cognitive effects over auditory steady-state responses by means of artificial neural networks and its use in brain–computer interfaces.Neurocomputing, 72(16-18):3617–3623, 2009.

[2]Hyun Jae Baek, Min Hye Chang, Jeong Heo, and Kwang Suk Park. Enhancing the usability of brain-computer interface systems.Computational intelligence and neuroscience, 2019:5427154, 2019.

[3]Barbara Shinn-Cunningham and Antje Ihlefeld. Selective and divided attention: Extracting information from simultaneous sound sources. 06 2004.

DOI: 10.14459/2020md1544568