



Toward distinguishing the different types of attention using EEG signals

Léa Pillette, Andrzej Cichocki, Bernard N'Kaoua, Fabien Lotte

► To cite this version:

Léa Pillette, Andrzej Cichocki, Bernard N'Kaoua, Fabien Lotte. Toward distinguishing the different types of attention using EEG signals. Journée Jeunes Chercheurs en Interfaces Cerveau-Ordinateur et Neurofeedback (JJC-ICON'2018), Apr 2018, Toulouse, France. hal-01762978

HAL Id: hal-01762978

<https://inria.hal.science/hal-01762978>

Submitted on 10 Apr 2018

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

Toward distinguishing the different types of attention using EEG signals

Léa Pillette

Inria, LaBRI (Univ. Bordeaux,
CNRS, Bordeaux-INP), France /
RIKEN BSI, Wakoshi, Japan

Andrzej Cichocki

RIKEN BSI, Wakoshi, Japan /
SKOLTECH, Moscow, Russia

Bernard N'Kaoua

Handicap, Activity, Cognition, Health,
Univ. Bordeaux, France

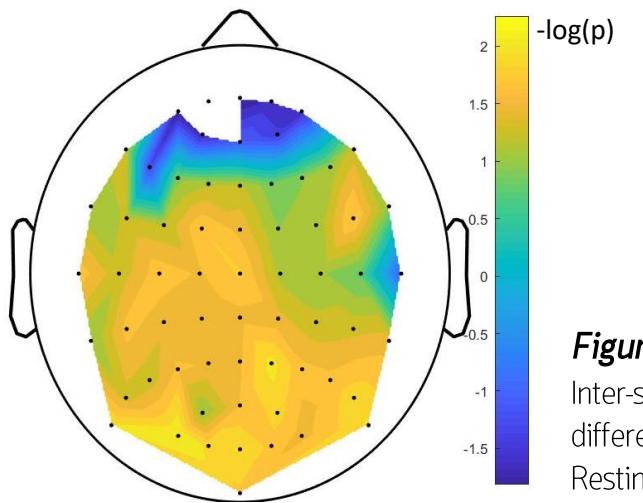
Fabien Lotte

Inria, LaBRI (Univ. Bordeaux,
CNRS, Bordeaux-INP), France /
RIKEN BSI, Wakoshi, Japan

"Attention" is a generic word encompassing *alertness* and *sustained attentions*, referring to the intensity of attention (i.e., strength), as well as *selective* and *divided attentions*, referring to its selectivity (i.e., amount of monitored information) [10]. BCI literature indicates an influence of both users' attention traits and states (i.e., respectively stable and unstable attentional characteristics) on the ability to control a BCI. Though the types of attention involved remain unclear [1,3,4,5]. Therefore, assessing which types of attention are involved during BCI use might provide information to improve BCI usability. Before testing this hypothesis, we first needed to assess if the different types of attention are recognizable using EEG.

Hence, we asked 16 participants to perform different tasks, each assessing one type of attention presented above, while we recorded their EEG. For each task, participants had to react as fast as possible -by pressing a keyboard spacebar- to the appearance of target stimuli. The tasks and types of attention were differentiated by the type of sensorial modality of the stimuli, number of distractors, presence of warnings before the stimuli and length of the task, in accordance with the literature [2,7,8,9].

Results from the preliminary analysis tend to indicate that EEG patterns of the different types of attention are distinguishable from both one another, and the resting state's (i.e., when participants are asked to relax and not to perform any specific task). For example, by using a Common Spatial Pattern filtering in the alpha range (8-12Hz) and a Linear Discriminant Analysis classifier, with 5-fold cross-validation we found that *sustained attention* is recognizable from the *resting state* with a classification accuracy of [55%, 92.5%] (above chance levels [62.5%, 65%] for 15 participants [6]). An inter-subject analysis of the differences of activation between these states suggested a key role of the frontal cortex (see figure).



Figure

Inter-subject mean significance in Power Spectral Density differences in alpha range for Sustained attention vs. Resting state (obtained using a t-test).

References

1. Daum, I., Rockstroh, B., Birbaumer, N., Elbert, T., Canavan, A., & Lutzenberger, W. (1993). Behavioural treatment of slow cortical potentials in intractable epilepsy: neuropsychological predictors of outcome. *Journal of Neurology, Neurosurgery & Psychiatry*, 56(1), 94-97.
2. Francis, A. L. (2010). Improved segregation of simultaneous talkers differentially affects perceptual and cognitive capacity demands for recognizing speech in competing speech. *Attention, Perception, & Psychophysics*, 72(2), 501-516. Grosse-Wentrup et al. J. Neural Eng., 2012.
3. Grosse-Wentrup, M., & Schölkopf, B. (2012). High gamma-power predicts performance in sensorimotor-rhythm brain-computer interfaces. *Journal of neural engineering*, 9(4), 046001.
4. Hammer, E. M., Halder, S., Blankertz, B., Sannelli, C., Dickhaus, T., Kleih, S., ... & Kübler, A. (2012). Psychological predictors of SMR-BCI performance. *Biological psychology*, 89(1), 80-86. Jeunet, Doct. disserr., Bdx Univ., 2016.
5. Jeunet, C. (2016). Understanding & Improving Mental-Imagery Based Brain-Computer Interface (Mi-Bci) User-Training: towards A New Generation Of Reliable, Efficient & Accessible Brain-Computer Interfaces (Doctoral dissertation, Université de Bordeaux).
6. Müller-Putz, G., Scherer, R., Brunner, C., Leeb, R., & Pfurtscheller, G. (2008). Better than random: a closer look on BCI results. *International Journal of Bioelectromagnetism*, 10(EPFL-ARTICLE-164768), 52-55.
7. Schmidt, R. A. (1968). Anticipation and timing in human motor performance. *Psychological Bulletin*, 70(6p1), 631.
8. Sturm, W., & Willmes, K. (2001). On the functional neuroanatomy of intrinsic and phasic alertness. *Neuroimage*, 14(1), S76-S84.
9. Van Leeuwen, C., & Lachmann, T. (2004). Negative and positive congruence effects in letters and shapes. *Perception & Psychophysics*, 66(6), 908-925.
10. Zomeren, A. H., & Brouwer, W. H. (1994). Clinical neuropsychology of attention. Oxford University Press, USA.