Auditory oddball classification with unobtrusive cEEGrid

Bertille Somon[1,2], Ludovic Darmet[2] and Frédéric Dehais[1,2,3]

[1]Artificial and Natural Intelligence Toulouse Institute (ANITI), Université de Toulouse, France

[2]ISAE-SUPAERO, Université de Toulouse, France

[3]School of Biomedical Engineering, Science Health Systems, Drexel University, Philadelphia, PA, United States

Neuroergonomics is a recent field of research that promotes the use of portable brain imaging to investigate complex cognitive processes that are difficult to observe and measure under laboratory settings (Dehais, Karwoswki & Ayaz, 2021). This is the case for inattentional deafness to auditory alarms that has been reported in accident analyses in many domains such as aviation (Dehais, Roy & Scannella, 2019b). To date, most of research that have addressed this phenomenon have used fMRI (Durantin et al., 2017), MEG (Molloy et al, 2015), cumbersome (Dehais, Roy, Scannella, 2019b) or painful dry EEG system (Dehais et al., 2019a). Fortunately, unobtrusive, easy-to-set-up systems have been developed: namely the cEEGrid (Hölle, Meekes, & Bleichner, 2021). It is a 10-flex-printed-electrode C-shaped EEG to be sticked behind the ears (Fig.1a and 1b). This system has been used recently in everyday life applications and tested against usual EEG caps for research (Bleichner, Mirkovic and Debener, 2016). In this study, we assess the feasibility to use cEEGrid recorded activity to classify event-related potentials in response to oddball sounds during flight simulation. Brain activity was continuously recorded via two cEEGrid (TMSi, Oldenzaal, The Netherlands) electrode sets (one behind each ear).
Eleven participants (French piloting license students) took part in this experiment (2 women, 10 right-handers, 23±2.05 y.o.) where they had to perform an approach and landing on Toulouse airport (fully described in Dehais et al., 2019) on the three-axis flight simulator with motion of ISAE-SUPAERO (designed by the French Flight Test Center). It simulates a twin-engine aircraft flight model with classical actuators and displays, broadcasts the simulated environment on eight screens in semi-circle outside the cockpit (Fig.1c), and the continuous engine sounds and oddball sounds through two stereophonic speakers inside the cabin. The auditory oddball task consisted in frequent (~75% of total sounds) and infrequent/odd (~25% of total sounds) chirp sounds (Fs= 44100Hz, 0.1s duration) with an increasing (up chirp) or a decreasing (down chirp) frequency (counterbalanced across participants; Artieda et al., 2004). The total number of sounds presented varied across participants according to the time it took them to perform the simulation but was on average 141.3±5.13 odd sounds and 423.4±14.48 standard sounds. Participants were asked to press the trigger on the sidestick whenever they heard an odd sound. During the whole experiment, participants were equipped with two cEEGrids based on recommendations of the manufacturer and literature (Mirkovic et al., 2016; Fig. 1a for montage). cEEGrid data were referenced, for both ears, at the L4a electrode during recording (Fig.1a) and amplified with a portable LiveAmp Bluetooth 24-bit DC-amplifier (Brain Products, GmbH, Gilching, Germany). EEG and flight simulator data (containing participants' responses) were continuously recorded at 500Hz and 100Hz respectively, streamed and synchronized via the Lab Streaming Layer (LSL; Kothe et al., 2019).
After recording, EEG data were preprocessed by downsampling at 250Hz, band-pass filtering (1-20Hz; Hamming-window FIR, order: 414) and ASR (Artifact Subspace Reconstruction) cleaning. Then, data from the left and right ears were re-referenced to the average of L6+L7 and R6+R7 respectively (recommended by Hölle, Meekes, & Bleichner; 2021). Next, ICA decomposition and

automated ICLabel removal (ICs>70% as eye, muscle, bad electrode or other were removed) were applied. ASR and ICA are two complementary techniques to remove inevitable artifacts in neuroergonomics studies. ASR algorithm corrects most of the noises caused by cap and cable movements, while ICA focuses on eye blinks and muscular activities (Blum et al., 2019). Then, data were epoched time-locked to the sounds ([-200;1000]ms), baseline-corrected ([-200;0]ms) and visually inspected leading to the removal of two participants due to very large portions of data interpolated. Finally, epoched data were fed into two different classifiers relying on Riemannian Geometry principles: Minimum Distance to the Mean (MDM) and classification in the Tangent Space using a Logistic Regression as classifier, referred to as Tangent Space Classifier (TSC), as recommended by Appriou et al. (2020). Riemannian classifiers rely on spatial covariance matrix estimation, thus as recommended in Lotte (2015) shrinkage is used (Schäfer-Strimmer shrinkage estimator). To counterbalance the imbalance between hits and misses, the majority class was downsampled using Tomek Links. Finally, a classic five-fold cross-validation performance estimation was applied to estimate the balanced accuracy of the classifiers.

Behavioral performances revealed a good sensitivity to sounds with a *d'* significantly above 0 (*d'*=2.8±0.19; $t(9) = 15.14$, $p<1.10^{-3}$), an average miss rate of 34.7±5.43% and average reaction times of 789.1±32.77ms (Fig.1d).

The MDM classifier disclosed an average accuracy of 63.52±3.05% whereas the TSC revealed an average accuracy of 71.45±3.45% to classify the cEEGrid ERPs (hits vs. misses - Fig. 1e). A pairwise t-test revealed that the TSC was significantly better at classifying hits vs. misses ($t(7) = -3.31$, $p<0.05$) than the MDM.

There is an increasing interest towards the transfer from lab tasks to everyday life settings, which has promoted the development of neuroergonomics studies with much more unobtrusive and lighter systems to record participants' activities in their everyday context without disturbing the ecological aspect of that environment. In this study, we tested a relatively new, electrical brain activity recording system: the cEEGrid (TMSi, Oldenzaal, The Netherlands). Using Riemannian Geometry-based classifiers, we managed to achieve a balanced accuracy of minimum 62% and up to 72% over 8 participants for the detection of auditory oddball-related ERPs. Also, these measures were performed in a very noisy environment both in terms of motion artifacts from participants who had to fly in a flight simulator with motion, and of electrical artifacts due to the many displays and electrical devices inside this flight simulator. These results are an improvement compared to many BCI studies where EEG recording systems tend to be cumbersome and/or uncomfortable, showing at the same time comparable classification results (Di Flumeri et al., 2019). Nevertheless, in contrast to other dry electrodes systems, cEEGrid localization is very specific (behind the ears) and its use to record brain activities other than auditory-related potentials should be tested. A more recent system, the fEEGrid located on the forehead, was also developed and could be a good alternative. Nevertheless, these results open very promising avenue for the use of such device in real-life.

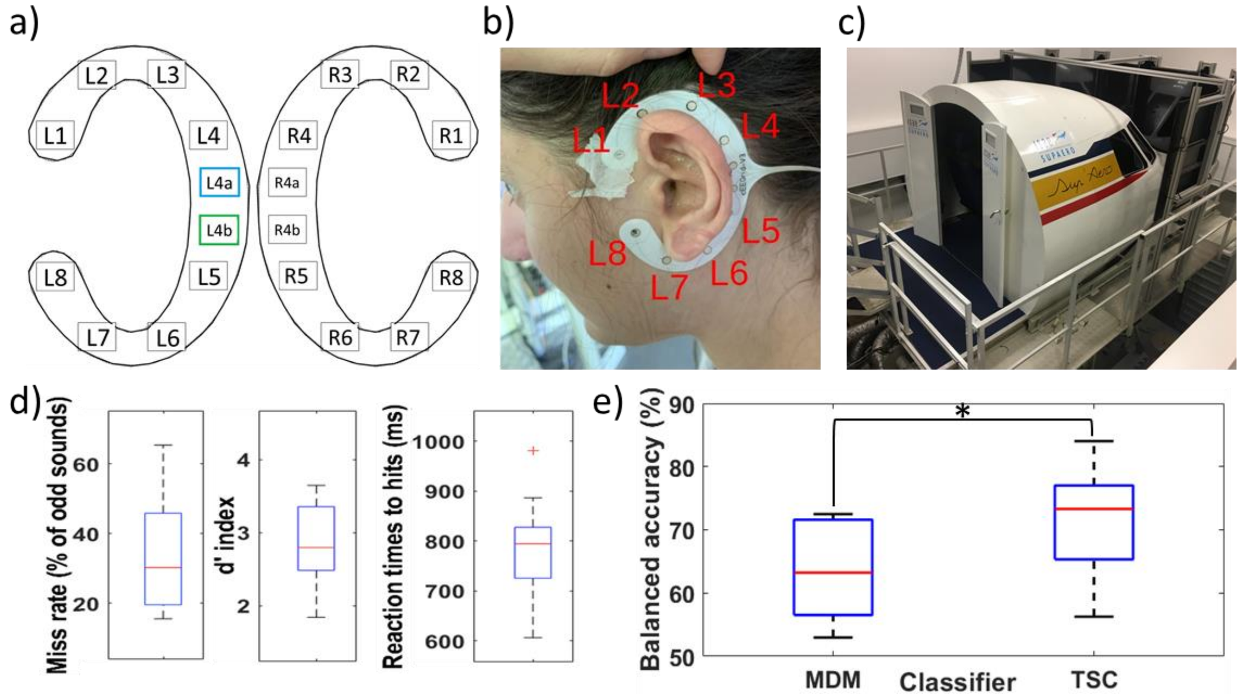

Figure 1. a) Disposition of the cEEGrid electrodes on the left (L1 to L8) and right (R1 to R8) grids with L4a (blue) as reference and L4b (green) as DRL for both grids during recording; b) Left cEEGrid (L1 to L8) sticked behind the left ear of a participant; c) ISAE-SUPAERO flight simulator with motion; d) Behavioral results to the auditory oddball task across participants; e) Classification results for the Minimum Distance to Mean (MDM, left) and Tangent Space Classifier (TSC, right) for the cEEGrid epoched data in response to the oddball paradigm.

References:

Appriou, A., Cichocki, A., and Lotte, F. (2020). Modern machine-learning algorithms: For classifying497cognitive and affective states from electroencephalography signals. IEEE Systems, Man, and Cybernetics498Magazine6, 29–38

Artieda, J., Valencia, M., Alegre, M., Olaziregi, O., Urrestarazu, E., & Iriarte, J. (2004). Potentials evoked by chirp-modulated tones: a new technique to evaluate oscillatory activity in the auditory pathway. *Clinical Neurophysiology*, *115*(3), 699-709.

Bleichner, M. G., Mirkovic, B., & Debener, S. (2016). Identifying auditory attention with ear-EEG: cEEGrid versus high-density cap-EEG comparison. Journal of neural engineering, 13(6), 066004.

Blum, S., Jacobsen, N. S., Bleichner, M. G., & Debener, S. (2019). A Riemannian modification of artifact subspace reconstruction for EEG artifact handling. Frontiers in human neuroscience, 13, 141.

Dehais, F., Karwowski, W., & Ayaz, H. (2020). Brain at work and in everyday life as the next frontier: grand field challenges for neuroergonomics. *Frontiers in Neuroergonomics*

Dehais, F., Rida, I., Roy, R. N., Iversen, J., Mullen, T., & Callan, D. (2019a). A pBCI to predict attentional error before it happens in real flight conditions. In *2019 IEEE International Conference on Systems, Man and Cybernetics (SMC)* (pp. 4155-4160). IEEE.

Dehais, F., Roy, R. N., & Scannella, S. (2019b). Inattentional deafness to auditory alarms: Inter-individual differences, electrophysiological signature and single trial classification. *Behavioural brain research*, *360*, 51-59.

Di Flumeri, G., Aricò, P., Borghini, G., Sciaraffa, N., Di Florio, A., & Babiloni, F. (2019). The Dry Revolution: Evaluation of Three Different EEG Dry Electrode Types in Terms of Signal Spectral Features, Mental States Classification and Usability. *Sensors*, *19*(6), 1365.

Durantin, G., Dehais, F., Gonthier, N., Terzibas, C., & Callan, D. E. (2017). Neural signature of inattentional deafness. Human brain mapping, 38(11), 5440-5455.

Hölle, D., Meekes, J., & Bleichner, M. G. (2021). Mobile ear-EEG to study auditory attention in everyday life. *Behavior Research Methods*, 1-12.

Kothe, C., Medine, D., Boulay, C., Grivich, M and Stenner, T., (2019) LabStreamingLayer's documentation. https://labstreaminglayer.readthedocs.io/info/intro.html [Accessed June 28, 2021]

Lotte, F. (2015). Signal processing approaches to minimize or suppress calibration time in oscillatory activity-based brain–computer interfaces. Proceedings of the IEEE103, 871–890

Mirkovic, B., Bleichner, M. G., De Vos, M., & Debener, S. (2016). Target speaker detection with concealed EEG around the ear. Frontiers in neuroscience, 10, 349.

Molloy, K., Griffiths, T. D., Chait, M., & Lavie, N. (2015). Inattentional deafness: visual load leads to time-specific suppression of auditory evoked responses. *Journal of Neuroscience, 35*(49), 16046-16054.