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DESIGN AND PRELIMINARY STUDY OF A NEUROFEEDBACK PROTOCOL TO SELF-REGULATE AN EEG MARKER OF DROWSINESS

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ABSTRACT : Neurofeedback (NF) consists in using electroencephalographic (EEG) measurements to guide users to perform a cognitive learning using information coming from their own brain activity, by means of a real-time sensory feedback (e.g., visual or auditory).

Many NF approaches have been studied to improve attentional abilities, notably for attention deficit hyper activity disorder. However, to our knowledge, no NF solution has been proposed to specifically reduce drowsiness. Thus, we propose an EEG-NF solution to train users to self-regulate an EEG marker of drowsiness, and evaluate it with a preliminary study.

Results with five healthy subjects showed that three of them could learn to self-regulate this EEG marker with a relatively short number of NF sessions (up to 8 sessions of 40 min). Clinical trials with sleep-deprived subjects should begin in 2019 to study possible cognitive and clinical benefits of this self-regulation. This NF solution implementation is available for free, with the OpenViBE platform, under the AGPL-3.0 license.

INTRODUCTION

Brain-computer interfaces (BCI) and Neurofeedback (NF) are two inter-related disciplines, that can and should learn from each other [12]. A substantial part of BCI research is dedicated to train computational models to classify patterns of brain activity and translate them into commands for a machine [16]. For instance, BCIs are often used to classify imagined movements of the left and right hand from brain signals [20]. NF, on the other hand, mostly focuses on teaching users to self-regulate their own brain activity to reach a desired state [23], which may possibly lead to clinical or cognitive benefits. For instance, the desired state could be an increased attention level, as measured by an electroencephalographic (EEG) marker of attention, to treat attention deficit hyperactivity disorder (ADHD) [18]. NF is thus a form of cognitive remediation guided by physiology.

One of the main clinical application of EEG-NF is ADHD rehabilitation [18, 19]. However, while several papers reported positive clinical benefits with NF, there is currently a debate in the community about the origin of these benefits [17, 26], and the level of evidence is still relatively weak [11, 12, 25]. This recently motivated the NF community to encourage further research into NF with higher research standards, e.g., by identifying open research challenges or by proposing consensus evaluation and reporting guidelines [1, 3, 9, 22]. Among the identified open challenges, exploring innovative psychiatric applications of NF, other than ADHD rehabilitation, has been encouraged [4].

To the best of our knowledge, there is no NF approach that has been studied to reduce excessive daytime sleepiness (EDS) and drowsiness so far. EDS is a common complaint among young people between 18 and 30 years of age [10]. EDS leads to increased accident risks. However, to date, there is no countermeasure to EDS based on the principles of cognitive remediation such as NF. Although EDS is linked to ADHD [2, 5], sleep disorders are rarely highlighted in ADHD research. Moreover, EDS may have a physiological target that can be more easily identified than attentional markers [7]. NF might thus be used to train subjects to regulate their EEG activity, and in particular an EEG marker of drowsiness, in order to reinforce their ability to stay awake. This could hopefully reduce their drowsiness and increasing their cognitive performance.

Therefore, in this paper, we present the design, implementation and preliminary evaluation of a complete NF protocol that is designed to train subjects to self regulate a neurophysiological target related to drowsiness. In this preliminary evaluation, we aim at validating our NF solution, i.e., at assessing whether subjects can self-regulate the identified marker of drowsiness using NF. The objective quantification of drowsiness, and how it varies with NF training, is not addressed in the present study. However, it will naturally be the primary outcome measure of the future clinical study based on our NF solution that is now validated.

This paper is organized as follows: first it details, in the materials and methods section, the different methodolog-

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ical, hardware and software elements used for our solution. Then, it describes the three main components of this protocol: the EEG signal processing methods, the training procedure and the learning evaluation. This section finishes by describing a preliminary evaluation of our NF solution with five healthy users. The results section then reports on the preliminary data obtained with such evaluation. The paper ends with a discussion on these results and the future clinical studies.

MATERIALS AND METHODS

Overview: Our NF system (see Figure 1) first consists in measuring and extracting a marker of drowsiness from EEG signals. Then, it consists in providing subjects with a visual feedback representing this EEG marker, in order to train them to self-regulate it. To do so, subjects are rewarded with an audio feedback if they manage to substantially reduce this EEG marker of drowsiness. To prevent artifacts from deteriorating this EEG self-regulation learning, we also need to detect them in order to adapt the feedback accordingly. In the following, we describe these various components.

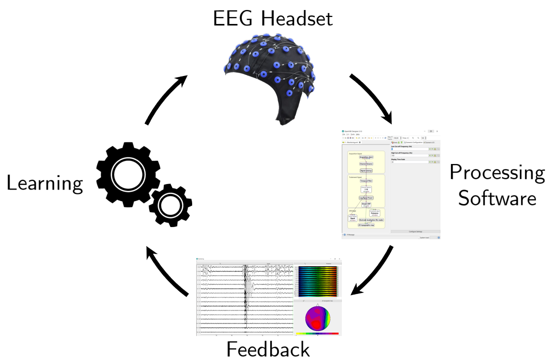

Figure 1: Our NF system: The EEG cap measures brain signals that the software analyzes to extract a marker of drowsiness. Then, a visual feedback representing this marker is provided to subjects. With feedback training, subjects should learn to self-regulate it and thus, hopefully, to reduce their drowsiness.

Hardware: We used a g.Nautilus (g.tec, Austria) wireless EEG acquisition device with 16 g.SAHARA active dry electrodes localized at Fp1, Fp3, F3, Fz, F4, T7, C3, Cz, C4, T8, P3, Pz, P4, PO7, PO8 and Oz.

Software: We used OpenViBE [21], a free and open source software platform for the acquisition, processing, classification and visualization of brain signals.

Signal Processing: As a neurophysiological target (EEG marker of drowsiness), we chose the homeostatic sleep pressure defined in [7] as the power of the spectral band θ-α (6.25-9Hz) in Cz. In that paper, it was shown that during sustained wakefulness, the θ-α spectral band in Cz was the one whose power increased the most over time.

However, this spectral band power may increase independently of the homeostatic sleep pressure, due to a general increase of EEG activity for example. In order to overcome this problem, we used a second spectral band, also related to drowsiness, to compute a ratio of spectral band power. This solution is quite common in NF [18]. Some noises and artifacts that may affect the whole signal will be attenuated (or suppressed) in a ratio of spectral band power, since we divide one band power by the other. Inspired by ADHD studies [18], we chose to divide our main target (i.e., θ-α power in Cz) by the power of the β (15-30Hz) spectral band, also in Cz. Indeed, this band is related to vigilance and its power should thus decrease with drowsiness [18].

Overall, we thus used as neurophysiological NF target $\frac{\theta\text{-}\alpha}{\beta}$, which should be related to the subject's level of drowsiness. The β band power should indeed decrease with increasing drowsiness whereas the θ-α band power should increase with increasing drowsiness. In order to give subjects a more positive impression of exercising, we defined their goal during NF training as to increase their wakefulness. Therefore, we reversed this ratio to use the $\frac{\beta}{\theta\text{-}\alpha}$ ratio as a target that subjects should learn to up-regulate, i.e., to increase.

To estimate the power of a spectral band, we first band-pass filtered the EEG signal, here in Cz, in the selected band (e.g., 15-30Hz) using a fourth order Butterworth filter [6]. Next, we used a sliding window analysis, with 1s long windows with an interval of 1/16s (0.0625s) between consecutive windows (with overlap). For each window, we squared the filtered EEG signals from that window, and then averaged them over the window duration to obtain the power of the selected spectral band. We then log-transformed the data ($x' = \log(1+x)$) to make these spectral band power values more normal-like.

In order to deal with artifacts, we eliminated the only easily identifiable ones, i.e., those leading to EEG signal amplitudes greater than 100 μV. These are typically considered as artifacts due to electrode movements or to muscular or ocular activities, resulting in larger EEG amplitudes. Epochs whose samples exceeded 100 μV were thus considered as artifacts and marked as such. These epochs were rejected and no feedback was provided to participants during them.

Training - sequencing: Regarding the duration and sequencing of the NF training, we arranged a NF session as follows (Figure 2):

- 1 calibration block of 2min.
- 6 work blocks of 5min.
- 1 transfer block of 5min.
- Each block is separated by a break of about 30s.
- Total Time $= 2+7\times(0.5+5) = 40.5$min

The calibration block (baseline) aims at measuring EEG activity "at rest", without any NF task. This was used as a reference, with measurements under similar conditions each time. During the work blocks, the subjects had to perform the various training tasks with feedback: the subject had to find a mental strategy to increase his

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wakefulness level by using the provided feedback. This feedback represents the value of the band power ratio described above. The last type of block is called a transfer block and consists in performing a work block without any feedback, in order to ease the transition between NF training and everyday life (where there is no feedback).

Training - rewards: Rewards were given to subjects via a sound (audio feedback) and a score system, when their wakefulness level, as measured using the EEG marker, became high enough during 0.25s. These audios rewards were thus provided when subjects managed to make their EEG band power ratio exceeds a given threshold. On the other hand, if subjects' wakefulness level was judged too low (i.e., lower than a given threshold), the experimenter was warned, as he could see the subject's count of "negative" points increasing on a visual display. Note that such negative points were not shown to subjects, who did not receive any negative feedback when their wakefulness level was too low. In order to deal with EEG signal non-stationarities, we regularly updated our threshold values. More precisely, we updated the thresholds every two work blocks (see Figure 2).

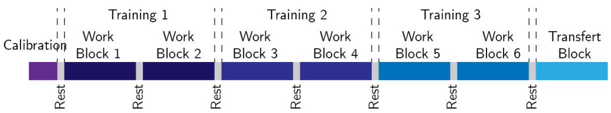

Figure 2: Session sequencing: 1 Calibration block, 3 pairs of work blocks (the dotted lines indicate the times when the threshold values were updated) and one last transfer block.

Current NF literature usually does not mention how the reward thresholds are defined, except when this is the paper central topic, see, e.g., [8]. This is however a crucial point in any NF protocol design. Indeed, such thresholds are used to define the EEG target values that subjects should reach or avoid. Here, we defined 4 thresholds:

- A theoretical minimum (S_m) and maximum (S_M), used to identify the interval in which the neurophysiological target value varies. They are used to create a standardized color range for the visual feedback.
- A threshold to be reached to receive a reward (S_R).
- A threshold to be avoided, not to receive negative points (S_C) (again, these negative points are only shown to the experimenter).

Visual inspections of our NF target empirical values showed that it was approximately normally distributed, or at least normal-like enough so we could define the thresholds according to its mean and variance. The NF target mean and variance are estimated before blocks 1, 3, 5 and 7 (Figure 2) on all the neurophysiological target values from the previous block pair (for block 3, 5 and 7), or from the calibration block (for the first work block).

By estimating the mean μ and variance σ of the NF target distribution (assuming a Gaussian distribution), we can then define our 4 thresholds as follows (see Figure 3):

$$S_\mathrm{m} = \mu - 3 \times \sigma \qquad S_\mathrm{M} = \mu + 3 \times \sigma$$
$$S_\mathrm{C} = \mu - 1.5 \times \sigma \qquad S_\mathrm{R} = \mu + 1.5 \times \sigma$$

Assuming normally distributed data, we can estimate the probability of a value to belong to a specific interval (Figure 3) :

$$\mathbb{P}(S_\mathrm{m} \leq x \leq S_\mathrm{M}) \approx 99.73\%$$
$$\mathbb{P}(S_\mathrm{C} \leq x \leq S_\mathrm{R}) \approx 86.64\%$$

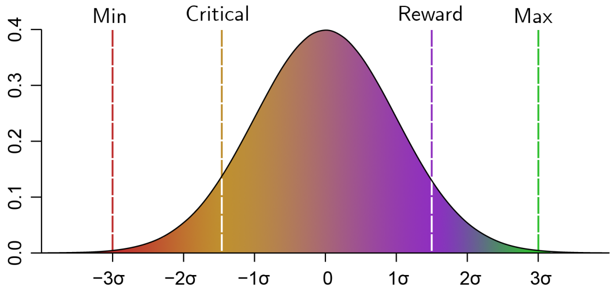

Figure 3: Distribution of thresholds (with σ the standard deviation and an average of 0 for this example).

Training - feedback: The last key element of NF training is the neurophysiological target visualization, i.e., the feedback. As a metaphor of the notion of wakefulness, we displayed as feedback a gray level that goes from black (low wakefulness) to white (high wakefulness), as can be seen in Figure 4. The gray color range was delimited by our thresholds S_m and S_M. Subjects could also see, at the bottom of the screen, the elapsed time since the beginning of the block, the time points at which they received rewards and the time points when artifacts were detected.

Learning: NF training aims at favoring learning over sessions, which requires to define the number and frequency of the training sessions. This project is a proof of concept of NF training in a small number of sessions. We thus chose to train subjects for a maximum of eight sessions. In order to help subjects to assimilate their training sessions, to reflect on their strategies and to test them in a real situation, the training frequency was defined as from 1 to 2 sessions per week. Finally, the 8 sessions had to be completed in a maximum of 6 weeks.

In addition, to facilitate EEG self-regulation learning, which is not something humans are used to do consciously, we offered subjects discussion times at the beginning of the protocol, between the work blocks and at the end of each session. The first discussion explained subjects the principle of the protocol, to demystify the NF process. Note that subjects were already provided with information on NF beforehand, but this allowed them to ask questions if necessary. This step aimed at preventing any apprehension with the EEG machine or any suspicion with the overall NF method. The discussions between work blocks were used to guide subjects to gain

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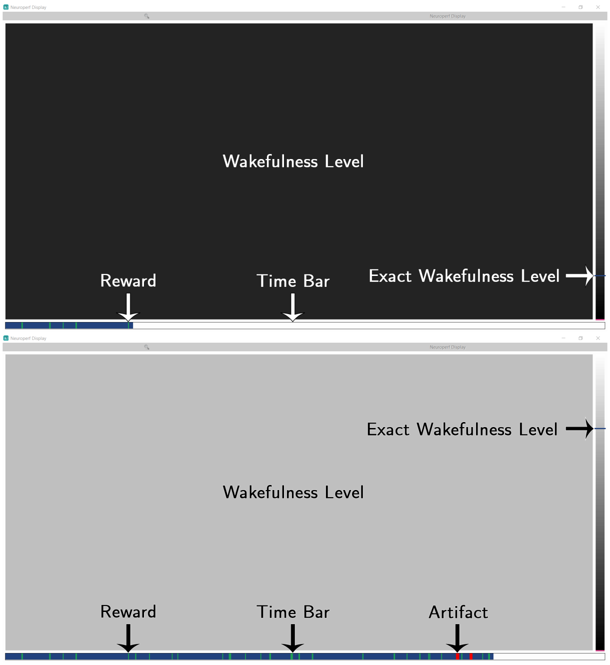

Figure 4: Work block Feedback for low (top figure) and high (bottom figure) wakefulness level estimates.

insights about the strategies they used and their effectiveness. Thus, oriented questions were used to help subjects becoming aware of what they thought and felt during the NF training. In addition, when thresholds were changed, the practitioner indicated to the subjects whether it increased or decreased. At the end of each session, subjects were shown the different curves representing the EEG signal, the $\frac{\beta}{\theta\text{-}\alpha}$ ratio, the number of rewards received and the threshold changes over time and blocks.

Preliminary Experimental Validation: As a proof of concept, in order to assess whether our NF training protocol could enable subjects to self-regulate the selected EEG marker of drowsiness, we tested it with five healthy medical students (two women and three men). They were able to perform between 4 and 8 NF sessions each, depending on their availability. Each session was held at a fixed time for each subject (at 10am for S1 and S2 and 2pm for the others) with a minimum of 2 days between two sessions.

RESULTS

Figure 5 shows the evolution of the average value of the $\frac{\beta}{\theta\text{-}\alpha}$ ratio over sessions, for each subject, while Figure 6 shows the same information averaged across all subjects. Such results suggest a positive evolution of the neurophysiological target of interest for 3 subjects (S1, S3, S4). For one subject (S2), there does not seem to be any subtantial change over time. Moreover, for this subject, the experimenter could observe that the subject was bored during the sessions, due to a lack of success with self-regulating the EEG marker. The last subject (S5) obtained inconclusive results because he obtained rewards during two sessions by playing with the artifacts detection system, using micro movements of his jaw.

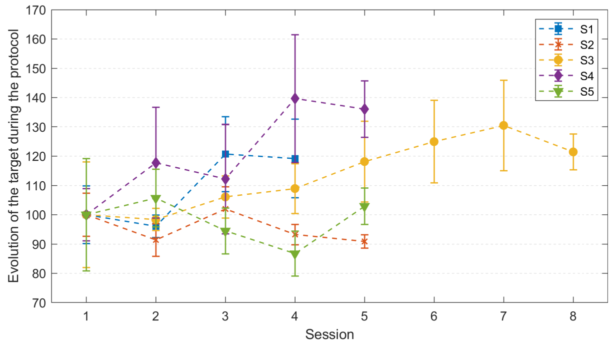

Figure 5: Evolution of the physiological target ($\frac{\beta}{\theta\text{-}\alpha}$ ratio) during the sessions. For each subject, we averaged the value of the physiological target on each session. We then normalized these values so that the first session normalized value was 100. Thus, this gave us a percentage of evolution over the sessions. The displayed standard deviations represent the variation of the ratio average value across work blocks.

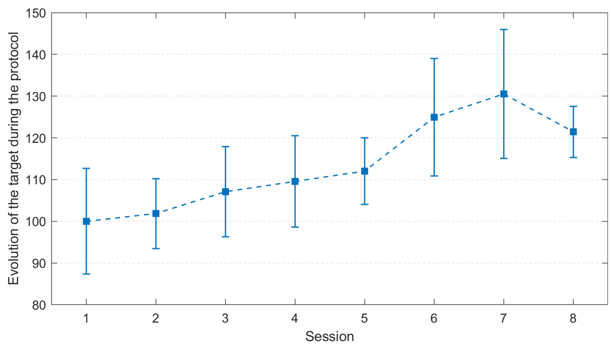

Figure 6: From Figure 5. Average across subjects, for the sessions in which they participated.

We also analyzed the change of the average target value during NF blocks as compared to its average value during the baseline of each session (see Figure 7), i.e., the relative increase of EEG marker value with respect to the baseline. To do so, we estimated the difference of the average target value during work blocks with its value during the baseline, expressed as relative percentage of the baseline value. Positive values thus indicates that the target value was higher during the work blocks than during the baseline of the same session.
Here as well, we observed that the same 3 subjects who showed a substantial increase in EEG marker absolute value across sessions, also showed a subtantial increase of EEG marker relative increase with respect to the baseline, across sessions. Interestingly enough, the other 2 subjects, who did not reveal any subtantial change of absolute target value across sessions, are the ones with the weakest intra-session relative target changes. This further confirmed that these 2 subjects did not succeed to learn to self-regulate our EEG marker of drowsiness.

Finally, we statistically analyzed these relative EEG

 DOI: 10.3217/978-3-85125-682-6-37

marker increases, to assess whether learning did occur across sessions, or whether this was due to chance. To do so, for each subject, we computed the pearson correlation between the time index of each work block and the relative EEG marker increase of that block. We obtained correlation of $\rho = 0.67$ ($p < 0.00005$), $\rho = -0.36$ ($p = 0.02$), $\rho = 0.7$ ($p < 0.000000001$), $\rho = 0.66$ ($p < 0.000005$) and $\rho = -0.13$ ($p = 0.43$), for subjects S1, S2, S3, S4 and S5 respectively. This confirmed that subjects S1, S3 and S4 significantly improved across blocks and sessions, and thus successfully learned to self-regulate the EEG marker, whereas subjects S2 and S5 did not.

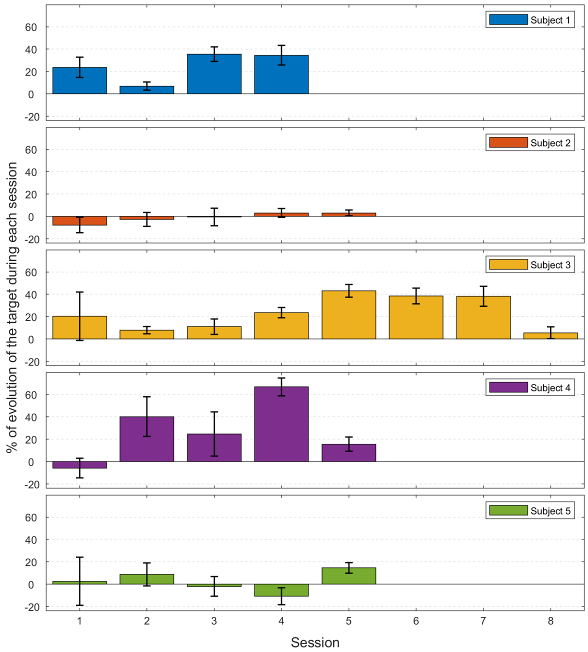

Figure 7: Average value of the physiological target ($\frac{\beta}{\theta\text{-}\alpha}$ ratio) for each session, evaluated as a relative percentage difference with the baseline average target value.

DISCUSSION

The results of the preliminary study described above on five subjects are encouraging, as they show that three of them could learn to increase the neurophysiological target across sessions. However, it is still unknown whether this successful self-regulation could lead to improved vigilance in day-to-day tasks, or whether this could reduce drowsiness for people affected by EDS. Thus, further studies are necessary. Accordingly, a clinical trial with a panel of 20 sleep-deprived subjects should start in the coming months. Such clinical trial will include clinical and objective measures of drowsiness and cognitive performances. It will aim at complementing, confirming or invalidating our results, as well as at assessing this NF training influence on subjects drowsiness and cognitive performances.

There are many open questions about the effectiveness of NF [25], as well as about how to best design relevant NF protocols. Some of these questions are actually common with BCI research. Is there a better neurophysiological target? Here, we used results from neurophysiology research to define the main target of interest according to a spectral band that was found related to drowsiness. However, it is likely that the optimal spectral band and EEG channel may be slightly different depending on the subjects. Another open question is whether we could further improve learning by exploring different feedback. For example, could the use of screen brightness in our experiment have a similar influence on performance as tactile feedback had for motor imagery BCI experiments [14]?

Next, we should evaluate whether learning is effective in the long term and therefore induces neuroplasticity. Moreover, as often in NF and BCI experiments, the results between subjects vary greatly. Thus, research on identifying predictive variables of learning [13, 15] could help us to understand the cause of these variations, and thus possibly help us to reduce them.

CONCLUSION

In this article, we presented a complete NF protocol to train subjects to self-regulate an EEG marker of drowsiness, with a longer-term objective to reduce drowsiness. Starting from the neurophysiological target to be analyzed and the signal processing methods, we have defined a training program for NF that aims at guiding subjects to learn to develop strategies to self-regulate their wakefulness level. We conducted a preliminary study on five healthy subjects, that showed that three of them managed to learn to increase the selected neurophysiological target across sessions.

The work done during this study allowed us to develop a set of signal processing algorithms, features, feedback and scripts for the OpenViBE software. All sources are available[1] under AGPL-3.0 license for later use with or without modification. In addition, we did our best to report all the parameters of our experiment to favor reproducibility.

A clinical trial is planned in 2019 to validate these preliminary results, and assess possible clinical benefits.

Many of the previously mentioned NF training parameters could be optimized to further improve learning. For instance, we believe that interviews could be used to reinforce the insights that subjects have about their strategies. Pre NF training procedures, as meditation training did to improve some BCI protocols [24], could also be considered to improve this NF protocol. Finally, it would also be interesting to identify the optimal frequency, duration, and form of training and feedback that would maximize the subjects' performance, learning and clinical benefits.

REFERENCES

[1] `https://github.com/tmonseigne/NEUROPERF`

 DOI: 10.3217/978-3-85125-682-6-37

[1] Arns M., Heinrich H., Strehl U. Evaluation of neurofeedback in ADHD: The long and winding road. Biological Psychology. 2014;95:108–115.
[2] Arns M., Kenemans J. L. Neurofeedback in ADHD and insomnia: Vigilance stabilization through sleep spindles and circadian networks. Neuroscience & Biobehavioral Reviews. 2014;44:183–194.
[3] Arns M. et al. Neurofeedback: One of today's techniques in psychiatry? L'Encéphale. 2017;43(2):135–145.
[4] Batail J-M et al. EEG neurofeedback research: A fertile ground for psychiatry? L'Encéphale. 2019.
[5] Bioulac S. et al. Excessive daytime sleepiness in adult patients with ADHD as measured by the Maintenance of Wakefulness Test, an electrophysiologic measure. The Journal of clinical psychiatry. 2015;76(7):943–948.
[6] Butterworth S. On the theory of filter amplifiers. 1930.
[7] Cajochen C., Brunner D., Krauchi K., Graw P., Wirz-Justice A. Power density in theta/alpha frequencies of the waking EEG progressively increases during sustained wakefulness. Sleep. 1995;18(10):890–894.
[8] Dhindsa K., Gauder K. D, Marszalek K. A, Terpou B., Becker S. Progressive Thresholding: Shaping and Specificity in Automated Neurofeedback Training. IEEE Transactions on Neural Systems and Rehabilitation Engineering. 2018;26(12):2297–2305.
[9] Fovet T.s et al. On assessing neurofeedback effects: should double-blind replace neurophysiological mechanisms? Brain. 2017;140(10).
[10] Jaussent I., Morin C. M., Ivers H., Dauvilliers Y. Incidence, worsening and risk factors of daytime sleepiness in a population-based 5-year longitudinal study. Scientific Reports. 2017;7(1).
[11] Jeunet C., Glize B., McGonigal A., Batail J.-M., Micoulaud-Franchi J.-A. Using EEG-based brain computer interface and neurofeedback targeting sensorimotor rhythms to improve motor skills: Theoretical background, applications and prospects. Neurophysiologie Clinique. 2018.
[12] Jeunet C., Lotte F., Batail J.-M., Philip P., Micoulaud-Franchi J.-A. Using Recent BCI Literature to Deepen our Understanding of Clinical Neurofeedback: A Short Review. Neuroscience. 2018;378:225–233.
[13] Jeunet C., N'Kaoua B., Subramanian S., Hachet M., Lotte F. Predicting Mental Imagery-Based BCI Performance from Personality, Cognitive Profile and Neurophysiological Patterns. PLOS ONE. 2015;10(12).
[14] Jeunet C., Vi C., Spelmezan D., N'Kaoua B., Lotte F., Subramanian S. Continuous Tactile Feedback for Motor-Imagery Based Brain-Computer Interaction in a Multitasking Context. In: Human-Computer Interaction – INTERACT 2015, 2015, vol. 9296, 488–505.
[15] Jeunet Camille, N'Kaoua Bernard, Lotte Fabien. Advances in user-training for mental-imagery-based BCI control: Psychological and cognitive factors and their neural correlates. In: Progress in brain research, 2016, vol. 228, 3–35.
[16] Lotte F. et al. A review of classification algorithms for EEG-based brain–computer interfaces: a 10 year update. Journal of neural engineering. 2018;15(3):031005.
[17] Micoulaud-Franchi J.-A., Fovet T. A framework for disentangling the hyperbolic truth of neurofeedback: Comment on Thibault and Raz (2017). The American psychologist. 2018;73(7):933–935.
[18] Micoulaud-Franchi J.-A., Geoffroy P. A., Fond G., Lopez R., Bioulac S., Philip P. EEG neurofeedback treatments in children with ADHD: an updated meta-analysis of randomized controlled trials. Frontiers in Human Neuroscience. 2014;8.
[19] Micoulaud-Franchi J.-A., McGonigal A., Lopez R., Daudet C., Kotwas I., Bartolomei F. Electroencephalographic neurofeedback: Level of evidence in mental and brain disorders and suggestions for good clinical practice. Neurophysiologie Clinique/Clinical Neurophysiology. 2015;45(6):423–433.
[20] Pfurtscheller G., Neuper C. Motor imagery and direct brain-computer communication. Proceedings of the IEEE. 2001;89(7):1123–1134.
[21] Renard Y. et al. OpenViBE: An Open-Source Software Platform to Design, Test and Use Brain-Computer Interfaces in Real and Virtual Environments. Presence: Teleoperators and Virtual Environments. 2010;19(1):35–53.
[22] Ros T. et al. Consensus on the reporting and experimental design of clinical and cognitive-behavioural neurofeedback studies (CRED-nf checklist). 2019.
[23] Sitaram R. et al. Closed-loop brain training: the science of neurofeedback. Vol. 18. Nature Reviews Neuroscience. Nature Publishing Group, 2016.
[24] Tan L.-F., Dienes Z., Jansari A., Goh S.-Y. Effect of mindfulness meditation on brain–computer interface performance. Consciousness and Cognition. 2014;23:12–21.
[25] Thibault R. T., Lifshitz M., Raz A. Neurofeedback or neuroplacebo? Brain. 2017;140(4):862–864.
[26] Thibault R. T., Raz A. The psychology of neurofeedback: Clinical intervention even if applied placebo. The American psychologist. 2017;72(7):679–688.