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Using Recent BCI Literature to Deepen our Understanding of Clinical Neurofeedback: A Short Review

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Abstract—In their recent paper, Alkoby et al. (2017) provide the readership with an extensive and very insightful review of the factors influencing NeuroFeedback (NF) performance. These factors are drawn from both the NF literature and the Brain–Computer Interface (BCI) literature. Our short review aims to complement Alkoby et al.'s review by reporting recent additions to the BCI literature. The object of this paper is to highlight this literature and discuss its potential relevance and usefulness to better understand the processes underlying NF and further improve the design of clinical trials assessing NF efficacy. Indeed, we are convinced that while NF and BCI are fundamentally different in many ways, both the BCI and NF communities could reach compelling achievements by building upon one another. By reviewing the recent BCI literature, we identified three types of factors that influence BCI performance: task-specific, cognitive/motivational and technology-acceptance-related factors. Since BCIs and NF share a common goal (i.e., learning to modulate specific neurophysiological patterns), similar cognitive and neurophysiological processes are likely to be involved during the training process. Thus, the literature on BCI training may help (1) to deepen our understanding of neurofeedback training processes and (2) to understand the variables that influence the clinical efficacy of NF. This may help to properly assess and/or control the influence of these variables during randomized controlled trials.

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Key words: neurofeedback, brain–computer interfaces, training, adaptation, cognitive profile, personality.

INTRODUCTION

Through their recent paper, Alkoby et al. (2017) provide the readership with an extensive and very insightful review of the factors influencing NeuroFeedback (NF) performance. These factors are drawn from both the NF literature and the Brain–computer interface (BCI) literature. Our short review aims to complement the review of Alkoby et al. by depicting some additional recent BCI literature. The object is to highlight this literature and discuss its potential relevance and usefulness to better understand the processes underlying NF and further improve the design of clinical trials assessing NF efficacy. Indeed, we are convinced that while they have fundamental differences, by building upon one another both the BCI and NF communities could reach compelling achievements.

As extensively described by Alkoby et al. (2017), the efficacy of clinical NeuroFeedback (NF) is subject to significant between-patient and between-study variability. The clinical efficacy of NF is heavily debated, particularly regarding psychiatric disorders. For this reason, this paper is devoted specifically to clinical NF. Some researchers indeed suggest that the clinical efficacy of NF is underlain by a placebo effect (Thibault et al., 2017). We agree that the level of evidence is still weak concerning the clinical efficacy of NF, and that a placebo

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Abbreviations: ADHD, Attention Deficit Hyperactivity Disorder; BCI, brain–computer interface; MI-BCIs, Mental-Imagery-based BCIs; PMC, Pre-Motor Cortex; RCT, randomized controlled trials; SMR, SensoriMotor Rhythm; SNR, signal-to-noise ratio; SoA, sense of agency.

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effect may be involved to some extent. However, it is unlikely that this lack of evidence is due to the fact that NF is fully underlain by a placebo effect. Rather, we hypothesize that it may be due to the lack of randomized controlled trials (RCT) assessing NF learning effects. Yet, in order to rigorously estimate these learning effects, and provide a higher level of evidence for the clinical efficacy of NF, the variables influencing these effects should first be identified. In this paper, we argue that recent BCI results could be relevant and useful to identify such variables and help us deepen our understanding of the clinical efficacy of NF.

As stated by Sitaram et al. (2016) "much remains to be investigated, including the integration of the vast knowledge of training and learning psychology into NF protocols". Thus, a human-factor-centered standpoint, considering the influence of the technology and the way it was designed on patients' achievements (Sanders and McCormick, 1993) is required. A human-factor-centered standpoint would take into account the interaction between the patient and the system during the NF procedure. Such an approach could help us understand how various factors affect the ability of patients to learn to modulate the target neurophysiological pattern – i.e., the EEG feature(s) that the patient is learning to self-regulate (e.g., alpha rhythm power, the theta/beta power ratio, etc.) – during NF training (Micoulaud-Franchi et al., 2015; Arns et al., 2017). These include factors such as the design of the NF training protocol (e.g., type of feedback), the neurophysiological features, and the states (e.g., motivation) and traits (e.g., self-reliance) of the users (Jeunet et al., 2015b). This human-factor-centered standpoint was adopted in the review by Alkoby et al. (2017), in which the authors depict many factors that affect NF efficacy. Their goal in doing so was to promote the use of these factors to adapt NF training protocols to the user's personality, and to their cognitive and neurophysiological profiles. In order to adapt these training protocols, the authors propose to focus on three aspects: neurophysiological features, feedback and mental strategies.

Although their review is already extensive and very instructive, further insight can be gained by studying the recent literature on training and learning in the field of BCIs, and more specifically in the field of Mental-Imagery-based BCIs (MI-BCIs) (Wolpaw and Wolpaw, 2012; Jeunet et al., 2016; Jeunet, 2016). MI-BCIs differ from NF in that the goal of MI-BCIs is to control an application without moving, by modulating specific brain rhythms through the completion of Mental-Imagery (MI) tasks. These tasks can be motor-imagery tasks, such as imagining moving one's hands (Pfurtscheller and Neuper, 2001), or non-motor-imagery tasks, such as mental calculation or mental rotation (Friedrich et al., 2012; Jeunet et al., 2015b), all these mental tasks being detectable in EEG signals. The rationale for this approach is that performing each of these mental-imagery tasks will induce modulations of different brain rhythms, which are theoretically specific to each task. Each task is associated with a specific control command, such as "imagine left-hand movements to turn the wheelchair towards the left" and "imagine right-hand movements to turn the wheelchair towards the right" (Clerc et al., 2016). Thus, the system is able to detect modulations of the user's brain activity and determine which command the BCI user intended to send. For instance, a decrease in mu amplitude over the left sensorimotor cortex should occur when users imagine a right-hand movement, i.e., when they want to turn right (Pfurtscheller and Neuper, 2001).

Both NF and MI-BCI users need to learn to regulate their neurophysiological EEG activity, using the feedback they are provided with, in order to produce specific EEG patterns (Neuper and Pfurtscheller, 2009; Sherlin et al., 2011; Lotte et al., 2013; Strehl, 2014). The objective is either to reach a target EEG pattern in NF (Sherlin et al., 2011; Strehl, 2014; Gruzelier, 2014a) or to produce a given EEG pattern that can be translated into a given command for an application in BCI (Neuper and Pfurtscheller, 2009; Lotte et al., 2013; Clerc et al., 2016). Consequently, similar cognitive and neurophysiological processes are likely to be triggered during both BCI and NF training procedures. Thus, we advocate considering the literature on BCI training to deepen our understanding of NF efficacy – in the same way that the BCI community should avail themselves of the NF literature.

First, we attempt to give a brief review of the relevant BCI literature, in order to complement the review by Alkoby et al. (2017). Indeed, the BCI community is also currently investigating the factors that influence user performance, training and learning. Notably, three main categories of factors were identified based on a review of the literature (Jeunet et al., 2016): task-specific factors, cognitive and motivational factors and technology-acceptance[†]-related factors. We suggest that these factors could be relevant for clinical NF training as well. Next, we elaborate on the potential implications of this research for improving the design of NF sessions and clinical NF efficacy, i.e., to reduce the clinical symptoms to which the target neurophysiological patterns are associated. We conclude with a summary and a diagram that outlines a framework (in Fig. 1), which takes into account the different factors identified in the review, in order to deepen our understanding of EEG signal self-regulation during NF, thereby potentially improving the clinical efficacy of NF.[‡]

ADAPTING THE NEUROFEEDBACK TRAINING PROTOCOL USING A HUMAN-FACTOR-CENTERED STANDPOINT

In the coming section, we provide information from the BCI training literature that could be relevant to adapt NF procedures to each patient, following the structure used by Alkoby et al. (2017), namely: (1) adapted neurophysiological

[†] The name of this category of factors was inspired by the "technology-acceptance model" (Venkatesh and Davis, 2000). This model depicts the factors that affect the use and acceptance of technologies by their users.

[‡] As stated earlier, this short review is intended to complement Alkoby et al.'s (2017) review in the same special issue. Thus, we advise reading both papers together.