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TOWARDS A COGNITIVE MODEL OF MI-BCI USER TRAINING

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ABSTRACT: Mental-Imagery based Brain-Computer Interfaces (MI-BCIs) enable users to control applications using their brain activity alone, by realising mental-imagery tasks. Although promising, MI-BCIs remain barely used outside laboratories, notably due to the difficulties users encounter when attempting to control them. We claim that understanding and improving the user-training process could greatly improve users' MI-BCI control abilities. Yet, to better understand the training process, we need a model of the factors impacting MI-BCI performance. In other words, we need to understand which traits and states impact MI-BCI performance, how these factors interact and how to influence them to improve this performance. Such a model would enable us to design adapted and adaptive training protocols, to guide neurophysiological analyses or design informed classifiers, among others. In this paper we propose a theoretical model of MI-BCI tasks, which is the first step towards the design of this full cognitive and computational model.

INTRODUCTION

Mental-Imagery based Brain-Computer Interfaces (MI-BCIs) enable users to control an application using their brain activity alone, through the realisation of mental imagery tasks. For instance, using MI-BCIs, paralysed patients can control a wheelchair by imagining left/right hand movements to make the wheelchair turn left/right, respectively [33]. Although very promising for a wide range of applications, MI-BCIs remain barely used outside laboratories, in particular due to the difficulties users encounter when attempting to control them. Indeed, 10 to 30% of users are unable to control MI-BCIs [3].

Two main factors have been identified to explain the low reliability of MI-BCIs. The first, which has been extensively investigated, concerns brain signal processing, current classification algorithms being still imperfect [3]. On the other hand, the potential role of user-training in MI-BCI performance requires much further investigation. Controlling an MI-BCI requires the acquisition of specific skills, and particularly the ability to generate stable and distinct MI brain activity patterns [21]. An appropriate training procedure is required in order to acquire these skills and an inefficient training protocol could consequently be partly responsible for users' modest performances. Yet, although current training protocols are theoretically inappropriate for skill-acquisition, rather little research is done towards their improvement [10]. We claim that understanding and improving the user-training process could greatly improve MI-BCI performance.

In [11], we reviewed the available literature on MI-BCI training protocols, which gave rise to several guidelines for the design of MI-BCI training protocols. For instance, regarding the *instructions*, it appears promising to explicitly specify the object of the training process. Furthermore, we should provide *training tasks* that are specific to each user. Then, visual *feedback* with emotional connotations seems to increase user motivation levels and, consequently, performance, although formal comparisons with non-emotional feedback are missing. Finally, it has been shown that gamifying the *training environment* increases motivation, and consequently performance.

These guidelines show that several promising avenues regarding the training protocols have been explored. Unfortunately, such studies remain scarce and, critically, their results are rarely taken into account by the BCI community. By building on theories in disciplines such as psychology and instructional design, it is possible to suggest new approaches for further improving user performance. However, being able to do so requires to understand the MI-BCI training process, and how it is impacted by users' specificities, in order to adapt the training protocols to their individual profiles. In order to reach a better understanding of the training process, we need a model of the factors impacting MI-BCI skill acquisition. In other words, we need to understand which users' traits and states impact MI-BCI performance, how these factors do interact and how to influence them through the experimental design or specific cognitive training procedures in order to improve MI-BCI performance. Such a model is called a *Cognitive Model*. Busemeyer and Diederich describe cognitive models as models which aim to scientifically explain one or more cognitive processes or how these processes interact [7]. Three main features characterise cognitive models: (1) their goal: they aim to explain cognitive processes scientifically, (2) their format: they are described in a formal language, (3) their background: they are derived from basic principles of cognition [7]. Cognitive models guarantee the production of logically valid predictions, they allow precise quantitative predictions to be made and they enable generalisation [7].

In the context of BCIs, developing a cognitive model is a huge challenge due to the complexity and imperfection of BCI systems. Indeed, BCIs suffer from many limitations, independent from human learning aspects, that could explain users' modest performance. For instance, the sensors are often very sensitive to noise and do not enable the recording of high quality brain signals while the signal processing algorithms sometimes fail to recognise the correct mental command. But it is also a huge challenge due to the lack of literature on the topic and to the complexity and cost associated with BCI experiments that are necessary to increase the quantity of experimental data. Nonetheless, as stated earlier, a cognitive model would enable to reach a better understanding of the MI-BCI user-training process, and consequently to design adapted and adaptive training protocols. Additionally, it would enable us to guide neurophysiological analyses by targeting the cognitive and neurophysiological processes involved in the task. Finally, it would make it possible to design classifiers robust to variabilities, i.e., able to adapt to the model factors. To summarise, building such a model, by gathering the work done by the whole BCI community, could potentially lead to substantial improvements in MI-BCI reliability and acceptability.

Different steps are required to build a cognitive model [7]. First, building a cognitive model requires a formal description of the cognitive process(es) to be described based on conceptual theories. Next, since the conceptual theories are most likely incomplete, *ad hoc* assumptions should be made to complete the formal description of the targeted cognitive process(es). Third, the parameters of the model, e.g., the probabilities associated with each element of the model, should be determined. Then, the predictions made by the model should be compared to empirical data. Finally, this process should be iterated to constrain and improve the relevance of the model.

In this paper, we propose to do the first step of this process: the formal description of the cognitive processes involved. Therefore, in a first section, we will introduce briefly the different factors depicted in the literature as influencing MI-BCI performance. Then, we will describe the first step of the cognitive model. Finally, we will propose future work that will aim at completing the model.

FACTORS IMPACTING MI-BCI PERFORMANCE

In [12] we proposed a literature survey dedicated to the description of the factors impacting MI-BCI performance, also called predictors. It has to be noted that we used the classification accuracy as a measure of performance, as most current MI-BCI studies do. This survey enabled us to classify most of the predictors into three categories representing higher-level cognitive concepts:

Category 1 - The user-technology relationship & the notion of control: indeed, it appears that people who apprehend the use of technologies (and more specifically the use of BCIs) and who do not feel in control, experience more trouble controlling BCIs. This category gathers different concepts such as self-efficacy, mastery confidence, sense of agency, computer anxiety or self-reliance.

Category 2 - Attention: this category includes both attentional abilities (trait) and attention level (state). The latter can fluctuate with respect to different parameters such as mood or motivation. Both these aspects of attention have been repeatedly suggested to be predictors of BCI performance, and more generally of learning performance.

Category 3 - Spatial Abilities: many predictors depicted in the literature are related to motor abilities (e.g., 2-hand coordination) or to the ability to produce mental images (e.g., kinaesthetic imagination). These predictors can be gathered under the label of "spatial abilities", which are described as the ability to produce, manipulate and transform mental images [28].

As explained in [12], the involvement of *Category 1* predictors can be explained by the fact BCI users were naïve [1], while the involvement of *Category 2* and *Category 3* predictors is relevant with the Ackerman model [2]. Indeed, this model states that inter-individual differences of performance in early stages of training are due to differences in attentional (*Category 2* predictors) and task-specific (*Category 3*) abilities. Interestingly enough, this model was already used by Neumann and Birbaumer to interpret BCI performances in 2003 [20].

COGNITIVE MODEL - STEP #1: DESCRIPTION OF THE COGNITIVE PROCESSES

While our survey in [12] enabled us to gather the BCI performance predictors into 3 categories, it lacks a global view of the relationships between these factors, of how they interact to impact MI-BCI performance and of how they can be influenced by external factors. We propose to fill this lack in this section. It should be noted that we only considered the factors that are supposed to impact performance based on the MI-BCI literature: thus, several relevant factors, that have not yet been studied by the BCI community, are likely to be missing. They will be investigated in the second phase of the construction of this model. Also, since we are dealing with a model, it is of course only a simplified representation of the complex cognitive processes underlying MI-BCI tasks that will require formal validation, testing and updating in the future.

To provide a formal description of the cognitive processes leading to good BCI performances, two steps had to be completed. First, we described both the intrinsic factors (i.e., users' states and traits) which impact performance as well as the connections between these factors. Then, the extrinsic elements impacting the users' states/traits, and consequently their performance, as well as the nature of this impact was formalised. These extrinsic elements include design artefacts and different cognitive activities or exercises. The next paragraphs are dedicated to the description of both these stages.

Stage 1 - Building a Model of the Intrinsic Factors Influencing MI-BCI Performance

The intrinsic factors included in this model correspond

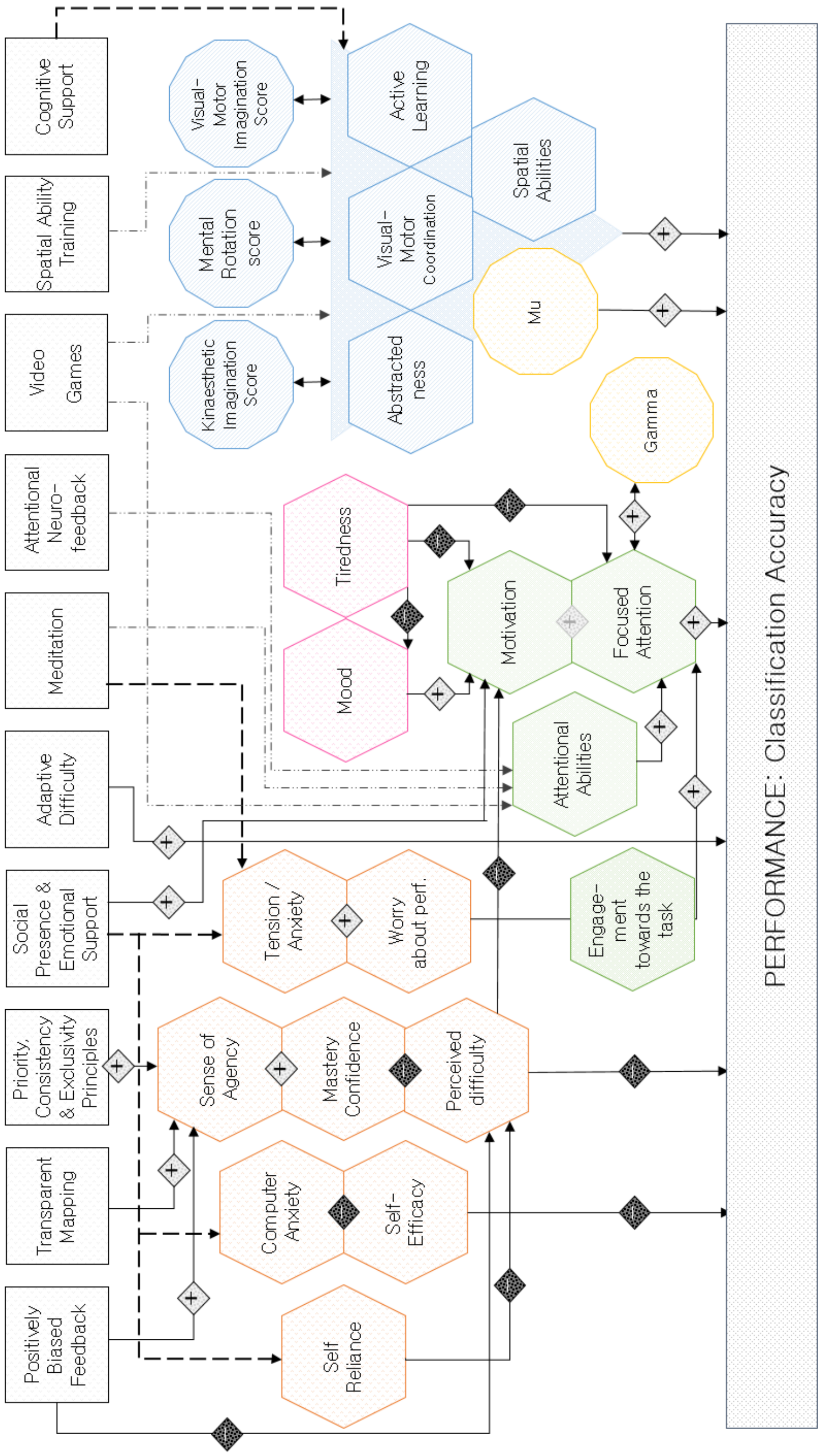

Figure 1: This network gathers the factors impacting MI-BCI performance, according to the literature and the extrinsic elements that can influence these factors. The factors are represented by hexagons. The circles represent ways to measure these factors: they are either neurophysiological markers or psychometric test scores. Moreover, vertically juxtaposed hexagons as well as unidirectional arrows represent causal relationships (if factor A is above factor B, then factor A influences factor B). The plus and minus signs indicate if the causal relationship between 2 factors is positive or negative. Concerning the links with extrinsic factors, solid lines represent a “direct influence on user state”, dashed lines correspond to a “Help for users with a specific profile” while dash-dot lines represent extrinsic factors that can “Improve abilities”.

on the one hand to users' cognitive and motivational states and on the other hand to users' traits, i.e., personality traits and malleable cognitive abilities that can be trained. All these factors are represented as hexagons in the model, see Figure 1. The circles represent ways to measure these factors: they are either neurophysiological markers or psychometric test scores. Moreover, the plus and minus signs indicate if the causal relationship between 2 factors is positive or negative. Subsequently, we briefly describe all the factors included in the model. For more information about these factors or the studies that revealed their relationship with MI-BCI performance, please refer to our review of performance predictors in [12]. This first model can be divided into 3 main parts, corresponding to the 3 categories of predictors mentioned earlier. On the left of the model we can find the factors related to the user-technology relationship (in orange), in the middle, those related to attention (in green) and to mood (in pink) and on the right, the factors related to the ability to perform an MI-task (in blue). All these factors can modulate the user's ability, at a given moment in time, to perform a MI task and to reach good performance. Each of these blocks is described more precisely in the following paragraphs.

Factors pertaining to the user-technology relationship are gathered on the left of Figure 1. Users showing low self-reliance traits, according to the 16-PF5 test [8], tend to perceive the task as more difficult [19]. Moreover, the phenomenon of computer anxiety, that is to say the apprehension of the user towards BCI use, has been shown to reduce users' self-efficacy [29], which in turn will induce a higher perceived difficulty [6] and a decrease in performance. On the other hand, by reducing computer anxiety, and consequently improving self-efficacy, it is possible to improve users' engagement towards the task and thus their motivation and performance [1]. This can be explained by the fact that self-efficient users do not consider difficulty as a threat but as a challenge which encourages them to persevere to reach good performance [1]. In order to reduce computer anxiety, the sense of agency should be improved. Besides, a high sense of agency will also increase the feeling of mastery of the system and consequently reduce perceived difficulty, increase motivation and performance [31]. Finally, tense(anxious) users tend to have lower performances which is notably due to the fact they devote a lot of resources to off-task considerations (such as worrying about their performance) and thus have fewer resources to allocate to focusing attention on the task [6]. To summarise, in order to enable users to reach good performance, training protocols should enable them to experience a high sense of agency and a low level of computer anxiety. Also, protocols should be adapted to non self-reliant and highly tense users so that their personality does not hinder their progress.

Tiredness has a negative impact on motivation, focused attention and mood. However, a good mood positively affects motivation and performance [25]. Then, the block in the middle comprises factors related to attention. We have previously shown that engagement towards the task as well as motivation are modulated by the user-technology relationship and by users' state (mood and tiredness). Motivation as well as general attentional abilities will determine how much focused attention is dedicated to the MI-BCI task. The more resources are allocated to the task, the better the performance. One neurophysiological predictor has been shown to correlate with attention state: the central gamma power (in attentional networks related to executive control - [9]).

Finally, on the right of the model the elements represent the various factors that have been suggested to be related to the ability to perform MI tasks. Indeed, abstractedness abilities correspond to the ability to produce mental images [8]. Also, visual-motor coordination is one aspect of spatial abilities. Finally, active learners prefer "learning by doing" [16] and might thus be more prone to producing kinaesthetic mental images, which have been shown to be more efficient than visual ones [22]. These abilities can be measured by different scores such as the Kinaesthetic Imagination score, the Visual-Motor Imagination Score [32] or the Mental Rotation Score [30] (the latter correlating with BCI performance [13, 10]). Moreover, the mu rhythm could enable, to a certain extent, to measure the ability to perform motor-imagery. Indeed, [4] have shown that a high mu amplitude at rest correlates with motor-imagery based BCI performance.

Stage 2 - A First Attempt at a Cognitive Model of the Task

Once all the intrinsic factors had been integrated into a network, we added the extrinsic elements that can be seen as levers to optimise users' performance, see Figure 1. These extrinsic elements are mainly based on theoretical hypotheses. Their impact on the users' states, traits and performance are yet to be quantified. Thus, although these links make sense from a theoretical point of view, they should still be considered with caution. These extrinsic elements are of two kinds: design artefacts and cognitive activities. We determined three types of links between the extrinsic elements and the intrinsic factors: *"Direct influence on user state"* (solid lines): this link connects extrinsic elements in the "design artefacts" category to intrinsic states (mainly). These extrinsic factors are suggested to influence the user's state and, consequently, are likely to have a direct impact on performance. For instance, proposing a positively biased feedback has been suggested to improve (novice) users' sense of agency [17]. *"Help for users with a specific profile"* (dashed lines): this link connects extrinsic elements to traits; they indicate that these extrinsic elements could help users who have a specific profile to improve their performance. For instance, proposing an emotional support has been suggested to benefit highly tense users [26]. *"Improved abilities"* (dash-dot lines): finally, this link connects extrinsic elements in the "cognitive activities" category to abilities that could be improved thanks to these activities. For instance, attentional neurofeedback has been suggested to improve attentional abilities [34].

The extrinsic elements related to the experimental design that theoretically impact users' state are listed hereafter. First, providing novice users with a positively biased feedback [17] is thought to improve their sense of agency and consequently decrease perceived difficulty and increase their motivation. Then a transparent mapping as well as the priority, consistency and exclusivity principles [31] all aim to improve users' sense of agency. Moreover, providing users with emotional support and social presence could improve their motivation [26]. Emotional support can be provided as smileys or avatars, but not only. It is also important not to forget the role of the therapist/researcher/experimenter, notably concerning: (1) the demystification of the BCI technology to reduce a priori computer anxiety, through scientific mediation and communication with the media, (2) the writing of informed-consent forms and explanations, that should be clear and informative, and provide an objective estimation of the benefit on risk balance and enable to regulate any form of hope that may be generated [24], and (3) the social presence and trust relationship with the user, which are essential in facilitating the learning process [15]. Finally, adapting the difficulty and proposing progressive difficulty has also been suggested to improve performance [33]. On the other hand, meditation, emotional support and social presence have been suggested to help highly tense and non-autonomous users [27]; while cognitive support (i.e., guidance to find a good strategy) could help users to produce mental-images that the system can recognise efficiently. Finally, the last type of links (dash-dot links) connects cognitive activities/exercises to the specific abilities they could benefit. Indeed, video-games, meditation and attentional neurofeedback have been suggested to improve attentional abilities [5]; while video-games and spatial-ability exercises may improve the ability to create mental-images.

FUTURE WORK

The model proposed comprises intrinsic factors impacting BCI performance, their relationships, as well as extrinsic factors that can be manipulated to modulate BCI performance. This model has been built based on the BCI and skill acquisition literature. As such, it represents the first phase in the development of a cognitive model [7], here for MI-BCI tasks. The next phases will consist first in making assumptions about the missing factors that should be included. For instance, our model includes factors also present in the ARCS (Attention Relevance Confidence and Satisfaction) model [14], notably attention and confidence, but relevance and satisfaction are missing. Yet, they may prove meaningful as well for MI-BCI. Then, with all the factors and their relationships identified, we will have to computationally implement this model, e.g., using a Bayesian network, and thus to determine its parameters (i.e., the probabilities for each factor and the weights -impact- of each factor on the BCI performance). Ideally, this could be estimated from data. Finally, we will have to assess this computational model based on unseen BCI experiments data. It will also be worth considering alternative performance metrics, beyond classification accuracy [18]. This could indeed bring additional insights about MI processes.

CONCLUSION

In order to bring BCIs out of the lab, both their reliability and usability should be enhanced. To this end, all their components should be considered: EEG caps should be both reliable and aesthetic [23]; algorithms should enable the improvement of BCI robustness and reduction of the calibration time [35]; the user training should be improved [12]. In this paper, we focused on this last axis. Indeed, we have provided the first theoretical cognitive model of MI-BCI performance. This is the first step towards a full model of MI-BCI tasks, which appears necessary to fully understand and then improve MI-BCI user training approaches, as well as to inform MI-BCI signal processing tools. In the future, we are going to try to complement this model with additional relevant factors, start first computational implementations of it and collect additional data to make that implementation possible. We hope other BCI researchers could join us in that endeavour to contribute to make the full model a reality.

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REFERENCES

[1] N. Achim and A. Al Kassim. Computer usage: The impact of computer anxiety and computer self-efficacy. *Procedia-Social and Behavioral Sciences*, 172:701–708, 2015.

[2] P. L. Ackerman. Determinants of individual differences during skill acquisition: cognitive abilities and information processing. *Journal of experimental psychology: General*, 117(3):288, 1988.

[3] B. Allison and C. Neuper. Could anyone use a BCI? In D. Tan and A. Nijholt, editors, *Brain-Computer Interfaces*, pages 35–54. Springer London, 2010.

[4] B. Blankertz, C. Sannelli, S. Halder, E. Hammer, A. Kübler, K.-R. Müller, G. Curio, and T. Dickhaus. Neurophysiological predictor of SMR-based BCI performance. *Neuroimage*, 51(4):1303–09, 2010.

[5] T. Brandmeyer and A. Delorme. Meditation and neurofeedback. *Frontiers in psychology*, 4, 2013.

[6] M. J. Brosnan. The impact of computer anxiety and self-efficacy upon performance. *Journal of computer assisted learning*, 14(3):223–234, 1998.

[7] J. R. Busemeyer and A. Diederich. *Cognitive modeling*. Sage, 2010.

[8] R. B. Cattell and H. E. Cattell. Personality structure and the new fifth edition of the 16pf. *Educational and Psychological Measurement*, 55:926–37, 1995.

[9] M. Grosse-Wentrup. What are the causes of performance variation in brain-computer interfacing? *International Journal of Bioelectromagnetism*, 2011.

[10] C. Jeunet, E. Jahanpour, and F. Lotte. Why standard brain-computer interface (BCI) training protocols should be changed: an experimental study. *Journal of neural engineering*, 13(3):036024, 2016.

[11] C. Jeunet, F. Lotte, and B. N'Kaoua. *Brain-Computer Interfaces 1: Foundations and Methods*, chapter Human Learning for Brain–Computer Interfaces, pages 233–250. Wiley Online Library, 2016.

[12] C. Jeunet, B. N'Kaoua, and F. Lotte. Advances in user-training for mental-imagery-based BCI control: Psychological and cognitive factors and their neural correlates. *Progress in brain research*, 2016.

[13] C. Jeunet, B. N'Kaoua, S. Subramanian, M. Hachet, and F. Lotte. Predicting mental imagery-based BCI performance from personality, cognitive profile and neurophysiological patterns. *PLOS ONE*, 10(12):e0143962, 2015.

[14] J. M. Keller. *Motivational design for learning and performance: The ARCS model approach*. Springer, 2010.

[15] S. Kleih, T. Kaufmann, E. Hammer, I. Pisotta, F. Pichiorri, A. Riccio, D. Mattia, and A. Kübler. Motivation and SMR-BCI: fear of failure affects BCI performance. In *Proc. Int. BCI Meeting*, 2013.

[16] D. A. Kolb. *Learning style inventory*. McBer and Company, 1999.

[17] A. Kübler, N. Neumann, J. Kaiser, B. Kotchoubey, T. Hinterberger, and N. Birbaumer. Brain-computer communication: self-regulation of slow cortical potentials for verbal communication. *Arch Phys Med Rehabil*, 82:1533–39, 2001.

[18] F. Lotte and C. Jeunet. Online classification accuracy is a poor metric to strudy mental imagery based BCI user learning: an experimental demonstration and new metrics. *accepted - Int. BCI Conf.*, 2017.

[19] M. Miserandino. Children who do well in school: Individual differences in perceived competence and autonomy in above-average children. *Journal of Educational Psychology*, 88(2):203, 1996.

[20] N. Neumann and N. Birbaumer. Predictors of successful self control during brain-computer communication. *Journal of Neurology, Neurosurgery & Psychiatry*, 74(8):1117–1121, 2003.

[21] C. Neuper and G. Pfurtscheller. *Brain-Computer Interfaces*, chapter Neurofeedback Training for BCI Control, pages 65–78. 2010.

[22] C. Neuper, R. Scherer, M. Reiner, and G. Pfurtscheller. Imagery of motor actions: differential effects of kinesthetic and visual-motor mode of imagery in single-trial EEG. *Brain Res Cogn Brain Res.*, 25(3):668–677, 2005.

[23] F. Nijboer. Technology transfer of brain-computer interfaces as assistive technology: Barriers and opportunities. *Annals of physical and rehabilitation medicine*, 58(1):35–38, 2015.

[24] F. Nijboer, J. Clausen, B. Z. Allison, and P. Haselager. The asilomar survey: Stakeholders' opinions on ethical issues related to brain-computer interfacing. *Neuroethics*, 6(3):541–578, 2013.

[25] F. Nijboer, A. Furdea, I. Gunst, J. Mellinger, D. MacFarland, N. Birbaumer, and A. Kübler. An auditory brain-computer interface. *Journal of Neuroscience Methods*, 167(1):43–50, 2007.

[26] R. Nkambou, J. Bourdeau, and R. Mizoguchi. *Advances in intelligent tutoring systems*, volume 308. Springer, 2010.

[27] L. Pillette, C. Jeunet, B. Mansencal, B. N'Kaoua, R. N'Kambou, and F. Lotte. PEANUT: Personalised emotional agent for neurotechnology user-training. In *submitted*, 2017.

[28] S. E. Poltrock and P. Brown. Individual differences in visual imagery and spatial ability. *Intelligence*, 8(2):93–138, 1984.

[29] A. Simsek. The relationship between computer anxiety and computer self-efficacy. *Contemporary Educational Technology*, 2(3):177–187, 2011.

[30] S. G. Vandenberg and A. R. Kuse. Mental rotations, a group test of three-dimensional spatial visualization. *Percept Mot Skills*, 47:599–604, 1978.

[31] R. Vlek, J.-P. van Acken, E. Beursken, L. Roijendijk, and P. Haselager. BCI and a user's judgment of agency. In *Brain-Computer-Interfaces in their ethical, social and cultural contexts*, pages 193–202. Springer, 2014.

[32] A. Vuckovic and B. A. Osuagwu. Using a motor imagery questionnaire to estimate the performance of a brain–computer interface based on object oriented motor imagery. *Clinical Neurophysiology*, 124(8):1586–1595, 2013.

[33] J. Wolpaw and E. Wolpaw. *Brain-computer interfaces: principles and practice*. Oxford Press, 2012.

[34] T. Zander, B. Battes, B. Schoelkopf, and M. Grosse-Wentrup. Towards neurofeedback for improving visual attention. In *Proc Int BCI Meeting*, 2013.

[35] T. O. Zander, K. Ihme, M. Gärtner, and M. Rötting. A public data hub for benchmarking common brain–computer interface algorithms. *Journal of neural engineering*, 8(2):025021, 2011.