Predicting Mental-Imagery Based Brain-Computer Interface Performance from Psychometric Questionnaires

Camille Jeunet, Bernard N'Kaoua, Martin Hachet, Fabien Lotte

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Camille Jeunet
University of Bordeaux / Inria
200 Avenue de la Vieille Tour
Talence, France
camille.jeunet@inria.fr

Bernard N'Kaoua
University of Bordeaux
3ter Place de la Victoire
Bordeaux, France
bernard.nkaoua@u-bordeaux.fr

Martin Hachet
Inria Bordeaux/LaBRI/CNRS
200 Avenue de la Vieille Tour
Talence, France
martin.hachet@inria.fr

Fabien Lotte
Inria Bordeaux/LaBRI/CNRS
200 Avenue de la Vieille Tour
Talence, France
fabien.lotte@inria.fr

ABSTRACT
Mental-Imagery based Brain-Computer Interfaces (MI-BCIs) allow their users to send commands to a computer via their brain activity, measured while they are performing specific mental tasks. While very promising (e.g., assistive technologies for motor-disabled patients) MI-BCI remain barely used outside laboratories because of the difficulty encountered by users to control such systems. Indeed, although some users obtain very good control performance after training, a substantial proportion remains unable to reliably control an MI-BCI. This huge variability led the community to look for predictors of MI-BCI control ability. In this paper, we introduce two predictive models of MI-BCI performance, based on a dataset of 17 participants who had to learn to control an MI-BCI by performing 3 MI-tasks: mental rotation, left-hand motor imagery and mental subtraction, across 6 sessions. These models include aspects of participants' personality and cognitive profiles, assessed by questionnaires. Both models, which explain more than 96% and 80% of MI-BCI performance variance, allowed us to define user profiles that could be associated with good BCI performances.

Keywords
Brain-Computer Interfaces, Mental Imagery, Performance Predictors, Personality, Cognitive Profile

1. INTRODUCTION
A brain computer interface (BCI) is a hardware and software communication system that enables its user to interact with the surroundings without the involvement of peripheral nerves and muscles, i.e., by using control signals generated from electroencephalographic (EEG) activity [16]. More specifically, this paper focuses on BCIs for which these control signals are sent via the execution of *mental tasks*: so-called Mental-Imagery based BCIs (MI-BCIs). MI-BCIs represent a new, non-muscular channel for relaying users' intentions to external devices such as computers, speech synthesizers, or neural prostheses [10]. Unfortunately, most of these promising BCI-based technologies cannot yet be offered on the public market since a notable portion of users (estimated to be between 15 and 30%) does not seem to be able to learn to control such a system [1]: this phenomenon is often called "BCI illiteracy" or "BCI deficiency". This high "BCI illiteracy" rate could be due to several BCI-related flaws like EEG non-stationarity, poor signal/noise ratio or imperfect classification algorithms [1]. Standard training protocols [13] have also been questioned [8] as they do not follow recommendations from instructional design. However, although there is a large proportion of "illiterates", some users perform excellently [5] and the previous elements do not explain the important variability in users' ability to control an MI-BCI. From this observation emerged the idea of a relation between users' characteristics and their ability to control an MI-BCI. It led the community to look for predictors of MI-BCI control performance. Indeed, the training process to learn to control an MI-BCI being time- and resource-consuming, being able to predict users' success (or failure) could avoid important loss of time and energy for both users and experimenters. From another perspective, knowing these predictors can guide the design of new training protocols that would be adapted to users' characteristics. The main contribution of this paper is to propose, for the first time, a predictive model of MI-BCI performance generated from the data of 17 participants who were trained to perform 3 mental tasks (mental rotation, mental subtraction and left-hand motor imagery) for 6 sessions.

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2. RELATED WORK
Mood, motivation [12] and the locus of control score related to dealing with technology [2], have been shown to be correlated with motor-imagery based BCI performance. Fear of the BCI system has also been shown to affect performance [2][11]. In [4], attention span, personality and motivation play a moderate role for one-session motor-imagery based

BCI performance, but a significant predictive model of performance, including the visuo-motor coordination and the degree of concentration, is depicted. In a recent study [5], this model has been tested in a 4 session experiment within a neurofeedback paradigm. Results show that these parameters explain almost 20% of the BCI performance within a linear regression, even if visuo-motor coordination failed significance. While offering interesting perspectives, none of these studies proposes a highly reliable model. Also, most of these studies determine predictors based on one session. Yet, no evidence shows that this performance is representative of longer-term MI-BCI control performance. Finally, these studies only considered motor-imagery, while it has been shown that the best combination of tasks for users was composed of both motor and non-motor MI-tasks [3]. In this paper, we propose to overcome these limitations by (1) considering users' mean performances across 6 sessions to get a better idea of their longer-term MI-BCI control ability, and (2) asking users to learn to perform three MI-tasks: one motor (left-hand motor imagery) and two non-motor (mental rotation and mental subtraction tasks).

3. MATERIAL & METHODS

3.1 Participants

18 BCI-naive participants (*9 females; aged 21.5 ± 1.2*) took part in this study, which was conducted in accordance with the relevant guidelines for ethical research according to the Declaration of Helsinki. All the participants signed an informed consent form at the beginning of the experiment and recieved a compensation of 100 euros at the end. All the participants were healthy and right handed.

3.2 General Procedure

Each participant took part in 6 sessions, spread out over several weeks. Each session lasted around 2 hours and was organised as follows: (1) completion of psychometric questionnaires (see Section 3.4), (2) installation of the EEG cap, (3) completion of 5 sequences of 7min each during which participants had to learn to perform three MI-tasks and (4) uninstallation and debriefing. The 3 MI-tasks were chosen for being the ones associated with the best performances on average across subjects in [3]. During each sequence, participants had to perform 45 trials (15 trials x 3 MI-tasks, presented in a random order). Each trial lasted 8s. At t=0s, a cross was displayed with a left hand pictogram on its left (representing the left-hand task), a subtraction on top (to be done in the case of a subtraction task) and a 3D shape on its right (representing the rotation task). At t=2s, a "beep" announced the coming instruction and one second later, at t=3s, a red arrow (overlapping the cross) was displayed for 1.25s. The direction of the latter informed the participant which task to perform, and the corresponding pictogram was framed. Finally, at t=4.25s, a visual feedback was provided in the shape of a blue bar (overlapping the cross). The bar was extending in the direction of the recognised task and its length was proportional to the classifier output (see Section 3.3). This feedback was only positive, i.e., it was displayed only if the instruction and the recognised task matched. The feedback lasted 4s and was updated at 16Hz (using a 1s sliding window). During the first sequence of the first session (i.e., the calibration sequence) as the system was not yet trained to recognise the mental tasks being performed, the user was provided with an equivalent sham feedback, i.e., a bar randomly varying in length [3]. A gap lasting between 1.50s and 3.50s separated each trial.

3.3 EEG Recordings & Signal Processing

The EEG signals were recorded from a g.USBamp amplifier (g.tec, Graz, Austria), using 30 scalp electrodes (F3, Fz, F4, FT7,FC5, FC3, FCz, FC4, FC6, FT8, C5, C3, C1, Cz, C2, C4, C6, CP3, CPz, CP4, P5, P3, P1, Pz, P2, P4, P6, PO7, PO8, 10-20 system) [3], referenced to the left ear and grounded to AFz. EEG data were sampled at 256 Hz. In order to classify the 3 MI tasks, EEG signals were first band-pass filtered in 8-30Hz, using a Butterworth filter of order 4. Then they were spatially filtered using 3 sets of Common Spatial Pattern (CSP) filters. Each set of CSP filters was optimized on the calibration sequence of each user (i.e., the first sequence of the first session) to discriminate EEG signals for a given class from those for the other two classes. We optimised 2 pairs of spatial filters for each class, thus leading to 12 CSP filters. The band power of the spatially filtered EEG signals was then computed by squaring the signals, averaging them over the last 1 second time window (with 15/16s overlap between consecutive time windows) and log-transformed. It resulted in 12 band-power features that were fed to a multi-class shrinkage Linear Discriminant Analysis (sLDA) , built by combining three sLDA in a one-versus-the-rest scheme. The resulting classifier was then used online to differentiate between the 3 MI-tasks. The sLDA classifier output for the mental imagery task to be performed was used as feedback provided to the user. To reduce between session variability, the LDA classifiers' bias were re-calculated after the first sequence of the sessions 2 to 6, based on the data from this first sequence, as in [3]. EEG signals were recorded, processed and visually inspected with Open ViBE (openvibe.inria.fr).

3.4 Psychometric Questionnaires

Participants were asked to complete the following validated psychometric questionnaires, distributed over the 6 sessions in a counterbalanced order, to assess different aspects of their personality and cognitive profiles: (1) 6 subscales of the *Wechsler Adult Intelligence Scale* (WAIS-IV), assessing the four IQ dimensions: similarities & vocabulary (verbal comprehension abilities), digit span (verbal working memory abilities), matrix reasoning (perceptive reasoning abilities), coding & symbol search (speed of treatment abilities); (2) the *Corsi Block task* focuses on visuo-spatial short term and working memory abilities; (3) the *Revised Visual Retention test* quantifies visual retention abilities as well as perceptive organisation; (4) the *Learning Style Inventory* (LSI) allows to identify the students' preferred learning styles according to four dimensions: visual/verbal, active/reflective, sensitive/intuitive and sequential/global; (5) the *16 Personality Factors - 5* (16 PF-5) measures sixteen primary factors of personality (warmth, reasoning, emotional stability, dominance, liveliness, rule-consciousness, social boldness, sensitivity, vigilance, abstractedness, privateness, apprehension, openness to change, self-reliance, perfectionism and tension) as well as five global factors of personality (extraversion, anxiety, tough mindedness, indepedence and self control); (6) the *Internal, Powerful others and Chance scale* (IPC) is a multi-dimensional locus of control assessment; (7) the *State Trait Anxiety Inventory* (STAI) is composed of two subscales, STAI Y-A and STAI Y-B, assessing respectively the state anxiety and the trait anxiety; (8) the *Bruininks-Oseretsky Test of Motor Proficiency* (BOT-2) evaluates motor abilities (e.g, fine motor skills and upper limb coordination [4]); (9) the *Mental Rotation test* measures spatial abilities; (10) the *Arithmetic test* is one of the WAIS-IV subscales, quantifying working memory abilities and more specifically the ability to concentrate while manipulating mental mathematical problems.

4. RESULTS

4.1 MI-BCI Performances

Performance was measured as the percentage of MI-tasks correctly recognised by the classifier over the feedback periods. The data of one outlier participant were rejected as he outperformed (67.21%) the group performance over the six sessions ($\bar{X}_{group}$ = 52.50%; SD = 5.62). Thus, the following analyses were performed considering 17 subjects. Over the six sessions, participants acheived a mean performance of $\bar{X}$ = 51.63% (SD = 4.39; *range*: [43.04, 60.14]).

4.2 Correlations Between MI-BCI Performance & Questionnaires' Scores

Bivariate Pearson correlation analyses revealed correlations between mean performances and (1) Mental Rotation scores [r = 0.696, $p \leq$ 0.005], (2) Tension [r = -0.569, $p \leq$ 0.05], (3) Abstractness ability [r = 0.526, $p \leq$ 0.05] and (4) Self-Reliance [r = 0.514, $p \leq$ 0.05] (see Figure1). Tension, Abstractness and Self-Reliance were assessed by the 16PF-5.

4.3 Predictive Models of MI-BCI Performance

A Step-Wise Linear Regression was used to determine a predictive model of users' MI-BCI performance. This regression resulted in a model including six parameters [R^2_{adj} = 0.962, p = 0.000] (see Figure2): Mental Rotation score, Self-Reliance, Memory Span, Tension, Apprehension and the"Visual/Verbal" subscale of Learning Style. It explained more than 96% of performance variance. In this model, mental rotation was selected first and highly correlated with performance (r=0.696). Consequently, a second regression analysis was performed without the mental rotation variable, as it was likely that it hid the effects of other variables. It resulted in a model [R^2_{adj}=0.809, p=0.000], described in Figure 3, including 4 parameters: Tension, Abstractedness, Learning Style "Active/Reflective" subscale and Self-Reliance.

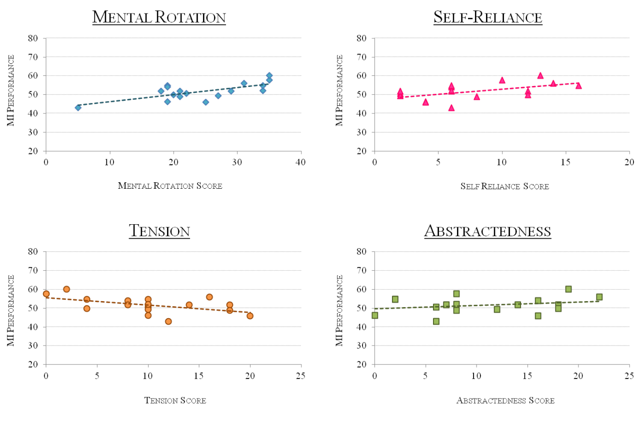

Figure 1: Graphs representing MI-BCI performance as a function of (1) mental rotation scores (top left), (2) self reliance (top right), (3) tension (bottom left) and (4) abstractness (bottom right)

R	R²	R² adjusted	Standard Error
0.988	0.976	0.962	0.859

	Non Stand. coefficients A	Non Stand. coefficients Standard Error	Stand. coefficients B	T	Sign.
(Constant)	34.089	3.772		9.037	.000
Mental Rotation	.468	.036	.858	13.064	.000
Self-Reliance	1.749	.171	.677	10.202	.000
Memory Span	-1.042	.232	-.272	-4.487	.001
Tension	-.430	.111	-.239	-3.889	.003
Apprehension	.836	.155	.452	5.411	.000
LSI visual/verbal	.260	.086	.206	3.040	.012

Figure 2: *Model ♯1* explains 96.2% of MI-BCI performance variance of our dataset.

R	R²	R² adjusted	Standard Error
0.925	0.857	0.809	1.919

	Non Stand. coefficients A	Non Stand. coefficients Standard Error	Stand. coefficients B	T	Sign.
(Constant)	46.783	2.472		18.928	.000
Tension	-1.320	.227	-.733	-5.816	.000
Abstractedness	.863	.227	.458	3.806	.003
ILS active/reflective	.723	.175	.527	4.172	.001
Self-Reliance	.853	.340	.330	2.250	.027

Figure 3: *Model ♯2* explains 80.9% of MI-BCI performance variance of our dataset.

5. DISCUSSION

In this paper, we propose 2 predictive models of MI-BCI performance based on the data of 17 participants. The originality of this work has been two fold. First, we proposed a 6-session experiment in order to attenuate the between-session variability and thus to estimate more precisely the participants' longer-term MI-BCI control ability, which is relevant when looking for performance predictors. Second, we determined these predictors in a context shown to be associated with the best MI-BCI performances [3] since in our study, participants were asked to perform one motor imagery task (left-hand movement imagination) and two non-motor MI-tasks (mental rotation and mental subtraction).

Three major results were obtained. The first one is the correlation of four factors with MI-BCI performance: mental rotation scores, tension, abstractness abilities and self-reliance. The second result is a model explaining more than 96% of the variance of participants' MI-BCI performance. This model is composed of six factors: mental rotation, self-reliance, visuo-spatial memory span, tension, apprenhension and the "visual/verbal" dimension of the learning style. The third result is also a model, from which the mental rotation factor has been excluded. This second model explains more than 80% of the variance and is composed of four factors:

tension, abstractness, self-reliance and the "active/reflective" dimension of the learning style.

The most relevant result is the prominent role of mental rotation scores: this factor is highly correlated with MI-BCI performances and the first one to be selected in the regression model. Mental rotation scores reflect spatial abilities [14], i.e., the capacity to understand and remember spatial relations between objects. The mental rotation test is actually used to evaluate mental imagery abilities, for instance in healthy subjects and patients with brain injuries [15]. The fact that the mental rotation test assesses imagery abilities could explain its strong implication in participants' capacity to perform the MI tasks proposed to control a BCI system.

Two other personality factors are strongly correlated with MI-BCI performance and are included in both models: *tension* and *self-reliance*. These factors seem to be more related to the nature of MI-BCI training which is a *distance learning*. Indeed, in [6] the authors show that learners feel confusion, frustration and anxiety when confronted to distance education due to the lack of feedback from an instructor, compared to classic classroom education. As high scores at the *tension* dimension reflect highly tense, impatient and frustrated personalities, it seems relevant that such learners encounter more difficulties learning tasks based on distance education such as the one presented in this study. On the other hand, the *self-reliance* dimension, also called self-sufficiency, reflects the learners' ability to learn by themselves, i.e., in an autonomous way. Yet, in [9], autonomy is presented as being a dimension of utmost importance of independent learning, and thus of distance learning. During an MI-BCI training, users are alone with the system. Consequently, they have to lead important metacognitive reflexions in order to build their knowledge about the system and about what they have to do to improve their performance. It explains why users with low *self-reliance* scores are in difficulty when confronted to MI-BCI training protocols. These users may need more guidance about what strategies to employ at each specific step of the training.

Furthermore, the *abstractness* dimension is also correlated with MI-BCI performance and included in the second model. Abstractness refers to creativity and imagination abilities. Yet, it has been reported that creative people frequently use mental imagery for scientific and artistic productions [7]. Thus, it makes sense that users with higher scores at this dimension also have better MI-BCI performances.

The other factors included in the models are more anecdotal, while consistent. First, visuo-spatial memory span and the "visual/verbal" dimension of the learning style are both related to visuo-spatial abilities, the influence of which on MI-BCI performance has been discussed here above. Concerning the "active/reflective" dimension of the LSI, active learners who prefer learning by doing often perform better, whatever the learning field.

6. CONCLUSION

This paper is part of an important research that could result in understanding the huge between-subject variability in terms of MI-BCI performance. Once understood, this difficulty could be overcome by designing MI-BCI training protocols adapted to the users' personality and cognitive profile, thus helping them to improve their performance. Consequently, it could promote the accessibility of MI-BCI based applications and improve patients' living standards.

7. REFERENCES

[1] B. Allison and C. Neuper. *Could Anyone Use a BCI?* Springer London, 2010.

[2] W. Burde and B. Blankertz. Is the locus of control of reinforcement a predictor of brain-computer interface performance? *Proceedings of the 3rd International Brain-Computer Interface Workshop and Training Course*, 2006:108–09, 2006.

[3] E. V. Friedrich, C. Neuper, and R. Scherer. Whatever works: A systematic user-centered training protocol to optimize brain-computer interfacing individually. *PloS one*, 8(9):e76214, 2013.

[4] E. M. Hammer, S. Halder, B. Blankertz, C. Sannelli, T. Dickhaus, S. Kleih, K.-R. Müller, and A. Kübler. Psychological predictors of smr-bci performance. *Biological psychology*, 89:80–86, 2012.

[5] E. M. Hammer, T. Kaufmann, S. C. Kleih, B. Blankertz, and A. Kübler. Visuo-motor coordination ability predicts performance with brain-computer interfaces controlled by modulation of sensorimotor rhythms (smr). *Frontiers in Human Neuroscience*, 8, 2014.

[6] N. Hara. Student distress in a web-based distance education course. *Information, Communication & Society*, 3:557–79, 2001.

[7] N. LeBoutillier and D. F. Marks. Mental imagery and creativity: A meta-analytic review study. *British Journal of Psychology*, 94:29–44, 2003.

[8] F. Lotte, F. Larrue, and C. Mühl. Flaws in current human training protocols for spontaneous BCI: lessons learned from instructional design. *Frontiers in Human Neurosciences*, 7:568, 2013.

[9] M. G. Moore. Learner autonomy: The second dimension of independant lerning. *Convergence*, 5:76–88, 1972.

[10] L. F. Nicolas-Alonso and J. Gomez-Gil. Brain computer interfaces, a review. *Sensors*, 12:1211–79, 2012.

[11] F. Nijboer, N. Birbaumer, and A. Kübler. The influence of psychological state and motivation on brain–computer interface performance in patients with amyotrophic lateral sclerosis–a longitudinal study. *Frontiers in neuroscience*, 4, 2010.

[12] F. Nijboer, A. Furdea, I. Gunst, J. Mellinger, D. J. McFarland, N. Birbaumer, and A. Kübler. An auditory brain-computer interface (bci). *Journal of Neuroscience Methods*, 167:43–50, 2008.

[13] G. Pfurtscheller and C. Neuper. Motor imagery and direct brain-computer communication. *proceedings of the IEEE*, 89(7):1123–1134, 2001.

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

[15] A. Vromen, J. A. Verbunt, S. Rasquin, and D. T. Wade. Motor imagery in patients with a right hemisphere stroke and unilateral neglect. *Brain Injury*, 25:387–93, 2011.

[16] J. R. Wolpaw and E. W. Wolpaw. *BCI: Principles and Practice*. Oxford University Press, 2012.