Proceedings of the
8th Graz Brain-Computer Interface Conference 2019 DOI: 10.3217/978-3-85125-682-6-39

ARE USERS' TRAITS INFORMATIVE ENOUGH TO PREDICT/EXPLAIN THEIR MENTAL-IMAGERY BASED BCI PERFORMANCES?

C. Benaroch[1], C. Jeunet[2], F. Lotte[1]

[1]Inria, LaBRI (Univ. Bordeaux, CNRS, Bordeaux INP), France
[2]CLLE (Univ. Toulouse Jean Jaurès, CNRS), France

E-mail: camille.benaroch@inria.fr

ABSTRACT: Mental-Imagery based Brain-Computer Interfaces (MI-BCIs) make use of brain signals produced during mental imagery tasks to control a computerised system. The current unreliability of MI-BCIs could be due, at least in part, to the use of inappropriate user-training procedures. In order to improve these procedures, it is necessary first to understand the mechanisms underlying MI-BCI user-training, notably through the identification of the factors influencing it. Thus, this paper aims at creating a statistical model that could explain/predict the performances of MI-BCI users using their traits (e.g., personality). We used the data of 42 participants (i.e., 180 MI-BCI sessions in total) collected from three different studies that were based on the same MI-BCI paradigm. We used machine learning regressions with a leave-one-subject-out cross validation to build different models. Our first results showed that using the users' traits only may enable the prediction of performances within one multiple-session experiment, but might not be sufficient to reliably predict MI-BCI performances across experiments.

INTRODUCTION

Brain computer interfaces (BCIs) enable users to interact with the environment using their brain activity alone (which is measured, most of the time, using electroencephalography - EEG) [1]. In this work we particularly focus on Mental-Imagery based BCIs (MI-BCIs), that require users to perform specific mental-imagery tasks, e.g., imagining movements of a hand or performing mental calculations, to control systems such as assistive technologies [2] or video games [3]. While promising, those new technologies remain barely used outside laboratories notably because of their low reliability [4]: the average performance of MI-BCI users is most of the time rather low, i.e., around 75% of classification accuracy for 2 class MI-BCIs [5]. In addition, a large proportion of MI-BCI users, between 15% to 30% [6], seems to be unable, while they are performing MI tasks, to produce brain activity patterns that can be discriminated by the system. To make MI-BCIs more reliable, researchers have mainly focused on hardware (e.g., electrodes) and software (e.g., signal processing algorithms) improvements, but less on the improvement of user-training procedures. Yet, this aspect is also essential. Indeed, if MI-BCI users cannot generate "understandable" signals (i.e. stable and distinct brain signals for each task), they will not be able to control the system, even if provided with the best hardware and software solutions. Producing such brain signals is a skill to be acquired by the MI-BCI user [7]. Each user having different skills, states and traits, the training procedure should be specifically adapted to each of them, which is not currently the case [8]. In order to better understand the mechanisms underlying MI-BCI control, and consequently design training strategies adapted to each user, several studies have investigated MI-BCI performance predictors [9]. These predictors could explain between-subject differences and thus variability in terms of MI-BCI control abilities. They can be related to demographic characteristics. For instance, in [10] a positive interaction was found between the participants' age and amount of daily hand-and-arm movements (e.g., practice of video games, musical instruments or sports) and their mu-power at rest, which itself has been shown to correlate with MI-BCI performances [11]. Moreover, Randolph et al. [12] have suggested that playing at least one instrument, not being on effective drugs, being a woman, and being over the age of 25 increased the likeliness of obtaining high MI-BCI performances. Beyond demographic variables, psychological traits like self-reliance and apprehension have been shown to linearly correlate with MI-BCI performances [13], just as mental rotation scores do, which suggests that spatial abilities influence MI-BCI performances. This last correlation was replicated in two further studies [14, 15]. Finally, [16] revealed a positive significant correlation between BCI performances and visuo-motor coordination abilities, which was replicated in [17], strengthening the fact that spatial abilities might strongly influence MI-BCI users' performances. Once the factors influencing MI-BCI performance have been identified, this influence can be quantified using modeling. For instance, [13] experimentally revealed a model including 4 factors (mental rotation scores, self-reliance, apprehension and the visual/verbal sub-scale of the Learning Style), using a step-wise linear regression. The average prediction error of this model was below 3%. Hammer et al. [16] proposed a model including the visuo-motor coordination factor and tested it across studies [18]. The average prediction error of this model

 DOI: 10.3217/978-3-85125-682-6-39

was below 10% for more than 50% of the participants. While they are potentially insightful, these results have been revealed in individual experiments, each including a small number of subjects and sessions or univariate models. Moreover, most of the highlighted factors have not been replicated since. Yet, to be useful, these correlations/models should be stable, accurate, should consider multiple variables and should generalize across experiments and datasets. Thus, in this paper, by combining data from three different experiments based on the same BCI paradigm, we explored the feasibility of determining stable, accurate and generalizable multivariate models that would explain/predict MI-BCI performance variability. The participants of the included datasets took part in 3 (for two of the datasets) or six (for one dataset) MI-BCI sessions, each session being structured into 5 runs. We gathered data from 42 subjects, for 180 BCI sessions in total. In these 3 experiments, the participants had to complete psychometric tests and were asked to learn to perform three MI tasks, namely, left-hand movement imagination, mental rotation and mental subtraction. We created six groups from the 3 datasets in order to pair the participants of the different experiments according to their specific experimental paradigms. We used a LASSO (Least Absolute Shrinkage and Selection Operator) regression to determine explanatory and predictive models of MI-BCI performance for each group.

MATERIALS AND METHODS

In order to build predictive and explanatory models of performance, we used a LASSO regression that only selected relevant features. We ensured the stability of the selected features by using a leave-one-subject cross validation. Then, to evaluate the reliability of the models and guarantee that the prediction was not due to chance, we empirically estimated the chance level in mean absolute error, based our data, using permutation tests. This approach is detailed in the following paragraphs.

Data sets: To maximize the number of subjects, we used data from three different experiments [13, 19, 20]. They were all based on the same BCI paradigm, as indicated before. The participants' personality and cognitive profiles were computed using different questionnaires (detailed in the *Variables and factors* section). Nonetheless, they were designed with some differences (see Fig. 1). The purpose of the first experiment (XP1 [13]), was to determine how users' cognitive and personality profiles influenced their MI-BCI performances. For this experiment, 18 BCI-naïve participants (9 women, 9 men; aged 21.5±1.2 year-old) took part in 6 MI-BCI sessions, on 6 different days. The second experiment (XP2 [19]) was designed to assess the influence of a Spatial Ability (SA) training procedure on MI-BCI performances. Fourteen participants (8 women, 6 men; aged 22.6±4.6 year-old) took part in this XP2. Each of them did 3 MI-BCI training sessions and 3 other cognitive training sessions (without BCIs), which consisted either

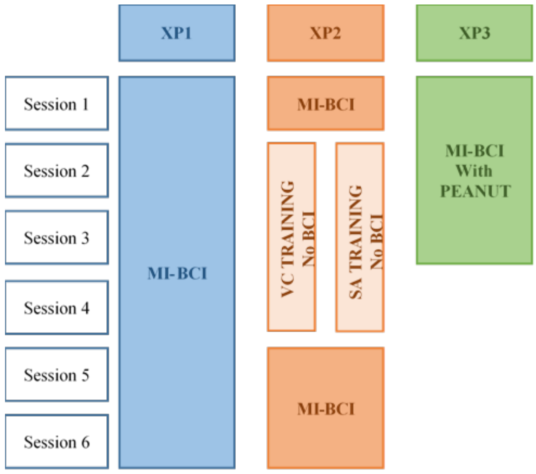

Figure 1: Details of the three different studies:XP1, XP2, XP3

in a SA training (7 participants) or in a verbal comprehension training (7 participants) procedure. In the third experiment (XP3 [20]), 10 subjects (5 women, 5 men; aged 20.7±2.1 year-old) were accompanied by a Learning companion called PEANUT (Personalized Emotional Agent for Neurotechnology User-Training) providing social presence and emotional support during 3 MI-BCI training sessions. The goal of this XP3 was to evaluate the influence that PEANUT had on MI-BCI performances. The 3 studies were conducted in accordance with the relevant guidelines for ethical research according to the Declaration of Helsinki and approved by the ethical committee of Inria. In total, we included the data of 42 participants (22 women, 20 men; aged 21.6 ±2.9 year-old) among which 18 took part in 6 MI-BCI sessions (with 5 runs per session, i.e. 30 runs) and 24 took part in 3 MI-BCI sessions (with 5 runs per session, i.e. 15 runs).

Experimental paradigm: Each BCI session was divided into 5 runs of 45 trials each. The paradigm was the same for all studies (see FIG. 2). For each trial, a cross was first displayed with on its left, a left hand pictogram (representing a L-HAND MI task); on top, a subtraction to perform (mental SUBTRACTION task) and on its right a 3D shape (mental ROTATION task). The MI task to be performed was then announced by a "beep" and a red arrow pointing towards the corresponding pictogram. Then, a blue bar was displayed as continuous visual feedback. The direction of this bar indicated the MI task recognized by the classifier and its length the classifier confidence in this recognition. The bar was displayed only when there was a match between the instruction and the recognized task. The first run of the first session was used as the calibration run to train the BCI classifier and a sham feedback (i.e. a blue bar) was provided to the user. For more details about the experimental paradigm, please refer to the related papers [13, 19, 20].

EEG recordings and pre-processing: For all studies, EEG signals were recorded using 30 active scalp electrodes. The EEG signal-processing pipeline used to classify the three mental imagery tasks online was the same one for all studies. EEG signals were spatially filtered

 DOI: 10.3217/978-3-85125-682-6-39

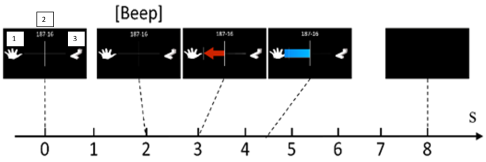

Figure 2: Timing of a trial. The first black screen shows each task, i.e., (1) L-HAND, (2) SUBTRACTION & (3) ROTATION.

using 3 sets of Common Spatial Pattern (CSP) filters [21] and classifier using a shrinkage Linear Discriminant Analysis (sLDA) classifier [22]. For more details about the preprocessing, please refer to [13, 19, 20].

Variables and factors: In the 3 studies, the participants were asked to complete psychometric and personality questionnaires, which aimed to assess different aspects of their personality and cognitive profile. The learning style inventory [23] was used to identify the participants' preferred learning styles according to four dimensions: visual/verbal, active/reflective, sensitive/intuitive and sequential/global. The 16 Personality Factors 5 (16 PF5 – 5) [24] provided a score for sixteen primary factors (warmth, reasoning, emotional stability, dominance, liveliness, rule consciousness, social boldness, sensitivity, vigilance, abstractness, privateness, apprehension, openness to change, self-reliance, perfectionism and tension) as well as for five global factors (extraversion, anxiety, tough mindedness, independence and self-control) of personality that are computed as linear combinations of the primary factors. The Mental Rotation test [25] assessed the participants' spatial abilities. In total, we used 21 parameters (only the 16 primary factors of 16PF5 were used in our study to avoid colinearities between primary and global factors) to represent the personality and cognitive profile of each participant. We thus had 21 features available to find a predictive/explanatory model.

Grouping the experiments: As not all the three studies had the same number of sessions, we made 6 groups out of the 3 datasets. The first three ones correspond to the BCI sessions of the three datasets taken separately (i.e. XP1, XP2 and XP3). The fourth group corresponds to the sessions 1, 5 and 6 of both XP1 and XP2 (the sessions 2, 3 and 4 of XP2 not being BCI sessions but SA or VC sessions, see Fig. 3). The fifth group gathers the sessions 1, 2 and 3 of XP1 and the three sessions of XP3. Finally, in order to have all the 42 subjects together, the last group includes the first session of XP1, XP2 and XP3 (Fig. 3) as it is the only session where all participants were trained to BCI control at the same time in the protocol (see Fig. 3).

Performances: MI-BCI performance was assessed in terms of mean classification accuracy $\overline{X}$ (mean performance measured over all the windows of the feedback periods of the runs 2 to 5 i.e., all 1s long sliding windows -separated by 0.0625s- between t=4.250s and t=8.250s of each trial). We used the mean performance $Perf_{real}$ over the different sessions as the target variable to be explained/predicted by our models. All participants man-

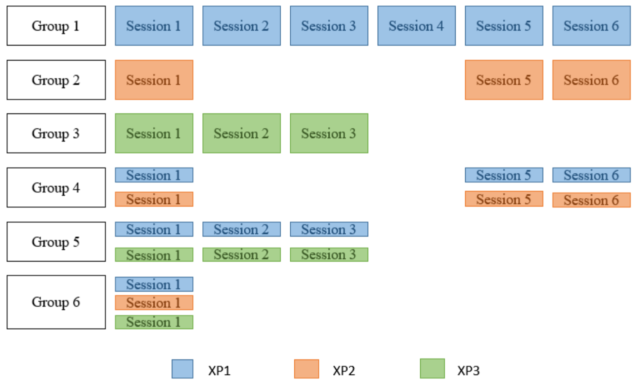

Figure 3: Details of BCI sessions for each group. In Blue sessions concerning XP1, in orange XP2 and in green XP3

aged to control the BCI interface. The outcome models provided us with a predicted performance $Perf_{pred}$. Our objective consisted in minimizing the mean absolute error ($|Perf_{real} - Perf_{pred}|$).

LASSO regression: In order to have a stable and reliable model, we used a LASSO [26] regression to obtain models that could predict the performances of MI-BCI users from their profile. The LASSO regression uses a L1 regularization (see Eq. 1) that promotes sparse solutions, i.e., that selects only a small number of variables (many coefficients will be zero using this regularization). It is particularly adapted to reduce the number of relevant features (21 in this study) when the number of those features tend to be higher than the number of subjects [27]. In addition, the LASSO regression is more robust than a simple linear regression [28] and is easily interpretable as only few features are selected for the model. For a usual linear regression set up, we have a continuous output vector $Y \in \mathbb{R}^n$ (MI-BCI performance to be explained/predicted), a matrix $X \in \mathbb{R}^{n \times p}$ of p features (users' traits) for n examples (the users) and a coefficient vector $\beta \in \mathbb{R}^n$. The LASSO estimator is defined as:

$$\beta_{lasso} = \underset{\beta \in R^P}{\operatorname{argmin}} ||Y - X\beta||_2^2 + \lambda ||\beta||_1 \tag{1}$$

where, $||u||_2^2 = \sum_{i=1}^{n} u^i$ for $u \in \mathbb{R}^n$ and $||\beta||_1 = \sum_{j=1}^{p} |\beta_j|$. For some values of the penalty parameter λ, some components of β_{lasso} will be set exactly to 0. Once β_{lasso} obtained, the MI-BCI performances of the i^{th} user $Perf_{pred}^i$ can be predicted from this user's traits x_i as $Perf_{pred} = \beta_{lasso} \times x_i$. In order to evaluate the stability and reliability of the different models, we use a leave-one-subject-out cross validation process. We also use an inner cross-validation (total number of subjects N - 2) to find the optimal λ (200 $\lambda \in [0.1; 0.5]$), i.e. the one that minimizes the mean absolute error and provides us with a small number of features. We use this optimal λ to build a model and then, the outer cross-validation (N-1 subjects for training, 1 for testing) is used to evaluate this model.

Random model: In order to determine the reliability of the models we estimated the empirical chance level in terms of mean absolute error, given our data. First, we

 DOI: 10.3217/978-3-85125-682-6-39

Table 1: Group details. Mean performance ($\overline{X_{Group}}$) and Standard Deviation (SD) for the 3-class MI-BCI over the sessions, for each group (chance level is estimated to be 37.7% [29])

Group	$\overline{X_{Group}}$	SD	Outlier (Mean Performance)
1	52.50%	5.62	Subject 1 (67.21%)
2	50.64%	9.47	-
3	50.74%	7.77	-
4	51.48%	7.87	-
5	52.04%	6.40	Subject 1 (67.21%) Subject 37 (38.97%) Subject 38 (38.49%)
6	53.27%	9.54	Subject 7 (32.80%)

randomly permuted the mean MI-BCI performances of the training sets, while keeping the profile variables identical, thus breaking the relationship between profile and performance. Then, we used the LASSO as explained above to predict the MI-BCI performance of the left-out subject. We repeated this process 10000 times and stored each mean absolute error to obtain the distribution of the prediction performance. Then, we sorted those values in descending order and the 99^{th}, 95^{th} and 90^{th} percentiles were used to identify the chance level for the mean absolute error for p=.01, p=.05 and p=.1, respectively.

RESULTS

Outliers' detection: We excluded from the analyses all the participants whose mean classification accuracy was above or below two standard deviations (SD) of the group's performance (see Table. 1).

Predictive models of MI-BCI Performances for each group: A LASSO regression and a leave-one-subject-out cross-validation (CV) were used to reduce the number of features and determine a reliable predictive model of each user's average MI-BCI performance obtained across the different training sessions. For each cross-validation of each group, different features were selected (see Fig. 4). We only showed three groups (1, 5 and 6) on Fig. 4: Group 1 because it was better than chance level ($p \leq .05$), *Group 5* as it failed to reach significance but still had a tendency towards significance and *Group 6* as the selected features are quite stable but the average prediction error is high. This first step allowed us to assess the stability of the results. For the *Group 1*, 16 models among the 17 generated included the same three factors: Mental Rotation scores, Self-reliance and Tension. Regarding the *Group 5*, 24 models among 25 included Warmth, Reasoning and Mental Rotation scores. Finally, for the *Group 6*, 36 models among 42 included Reasoning, Rule Consciousness, Social Boldness and Self-Reliance. The results or these 3 groups are depicted in Fig. 4. For the *Groups 2, 3* and *4*, the results were not conclusive (we decided not to show them due to space restrictions). Indeed, for the *Group 2*, an average of 9 features were selected for each generated model and 14 features (among 21) were chosen in total. For the *Group 3*, a different model was generated for each CV

Table 2: Comparison of the Mean absolute error with the mean absolute error of the random model (after 10000 permutations)

Group	Mean absolute error (%) (pValue)	Mean absolute error (%) of random model ($p < .01$)	Mean absolute error (%) of random model ($p < .05$)	Mean absolute error (%) of random model ($p < .10$)
1	3.03 ($p = 0.047$)	2.60	3.05	3.21
2	7.98 ($p = 0.19$)	6.26	7.02	7.16
3	11.09 ($p = 0.86$)	3.28	4.51	5.24
4	6.69 ($p = 0.37$)	5.62	6.03	6.22
5	3.87 ($p = 0.11$)	3.35	3.68	3.84
6	7.85 ($p = 0.20$)	6.98	7.43	7.62

and 17 different features were selected in total and finally for the *Group 4*, rule-consciousness, Apprehension, Self-Reliance, the "Active/Reflective" subscale of the Learning Style were all selected in half of the models. In a second step, we determined the reliability of the models by testing each of them on the participant not included in the training set during the cross-validation process. We then computed the mean absolute error of all the models, i.e, $\sum_{i=1}^{n} \frac{|Perf_{pred(i)} - Perf_{real(i)}|}{n}$, n being the total number of models generated for the group. In order to ensure that the prediction of MI-BCI performances was not due to chance, we performed a permutation test (see Section *Random model* and Table. 2). The results indicated that only the *Group 1* was better than chance (p<.05), with a mean absolute error of 3.03%. The chance levels for each group are displayed on Table. 2. We also computed the correlation between the real and predicted MI-BCI performances for each subject. We only obtained a significant correlation for *Group 1* [r = 0.6, p<.01].

DISCUSSION

In this study, we gathered the data of 3 experiments in order to maximize the number of subjects, and investigated the feasibility of predicting/explaining MI-BCI performances, independently of the experiment, using a statistical model based on the participants' traits only. We were able to find a model reaching significance for the *Group 1* (p<.05) with an average prediction error of 3.03%. This model included three main factors: Self-reliance, Tension and the Mental Rotation scores. Those factors were only slightly different from the ones revealed, on the same dataset, by Jeunet et al. [13] using a step-wise-linear-regression. Indeed, the Self-Reliance, Apprehension, visual/verbal subscale of the Learning Style and the Mental Rotation scores were included in their model. It should be noted that both the Apprehension and Tension factors are related to the same global factor, Anxiety. Besides, the Apprehension and Self-Reliance factors were also selected in 80% of the CV models of the *Group 4* (even though the reliability for this group was not better than chance –p=0.37–). However, these factors were not automatically included in all the models for the other groups. For instance, in the *Group 5* (XP1 and XP3), no factor representing the anxiety of a subject was selected in the CV models (Fig. 4). Regarding the Mental Rotation scores, they were selected in both our models and in [13]. This result stresses that this parameter has a strong influence on MI-BCI performances. Further-

 DOI: 10.3217/978-3-85125-682-6-39

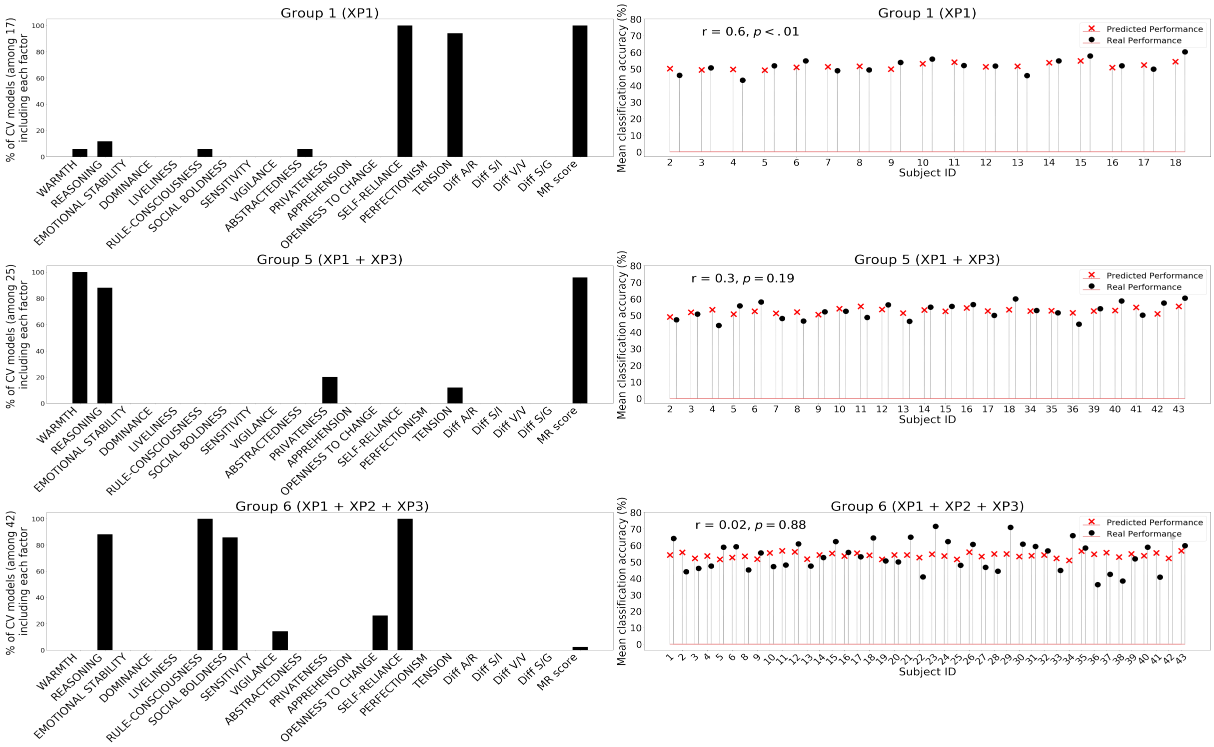

Figure 4: Results of the different models generated for Groups 1, 5 and 6. On the left, the percentage of Cross-Validation models including each factor. On the right, in black (circle), the real performance of each subject and in red (cross), the predicted performance of each subject generated using the model generated from the training dataset (All subjects except the target one). Finally, in the right plots, the correlation between the real and predicted performances. Only the models for group 1 had better than chance predictions.

more, even though the other models failed to reach significance, in five out of the six groups, the Mental Rotation scores were included in a large majority of the CV models. Interestingly enough, both XP2 and XP3 had been designed to influence the factors that had been identified in XP1 [13]: with a spatial ability training in XP2 dedicated to the improvement of the participants' Mental Rotation scores, and a learning companion in XP3 aiming to help the anxious and non self-reliant participants. Therefore, it is consistent to observe a reduced influence of the Mental Rotation scores and Apprehension/Self-Reliance factors in the groups including the data of XP2 and XP3, respectively. Still it is interesting to notice the tendency towards a stable and reliable model when grouping XP1 and XP3. In fact, the Mental Rotation scores were selected for all the CV models except one. It strengthens the fact that having good spatial abilities might have a positive influence on MI-BCI performances [14, 15].

Furthermore, only the average error of *Group 1* models reached significance, which could be due to the many differences existing between the 3 studies. Indeed, they did not include the same number of participants, nor the same number of MI-BCI sessions. The number of sessions over which performances are averaged is likely to influence the average performance variability (because of between-session variability due to, e.g., fatigue or motivation changes). Those variations can be significant and become an issue when computing the mean performance over all the MI-BCI sessions. Averaging performances over 6 sessions enabled us to reduce the between-session variability, and make the mean MI-BCI performance estimation more accurate. This might be one possible explanation of the fact that we only found stable and reliable models for the *Group 1* (XP1). As Traits are supposed to remain stable in time, having a more stable measure of performance (here with more sessions) could help us to find a more reliable model. Alternative metrics of performance, reflecting users performances rather than classifier performances, such as the ones proposed in [30], could also be used in the future to predict or explain BCI performances better.

Regarding the LASSO regression, it appears to be more stable than a regular linear regression as only a few factors were chosen for most of the groups. However, by using the LASSO we hypothesized that there was a linear correlation between those factors and MI-BCI performances, while it could be non-linear. In the future, combining users' traits with their states (e.g., inferred from neurophysiological data or questionnaires) could help us explain the between- and within-subject variability and better explain/predict MI-BCI performances over several sessions, but also better predict performances per session, per run and per trial.

CONCLUSION

In this study, we used a LASSO regression to determine experiment-independant predictive and explanatory

 DOI: 10.3217/978-3-85125-682-6-39

model of MI-BCI users' performances using their traits alone. Our results suggest that using only traits might not be sufficient to build such a model. Indeed, the between-session variability is high and seems to be multi-factorial. Further studies considering, for instance, an estimation of the users' states, the timing of the experiment and new metrics to assess performances are necessary to reveal more reliable models.

Acknowledgments This work was supported by the European Research Council with project BrainConquest (grant ERC-2016-STG-714567).

REFERENCES

[1] Wolpaw JR, Birbaumer N, McFarland DJ, Pfurtscheller G, Vaughan TM. Brain–computer interfaces for communication and control. Clin Neurophysiol. 2002;113(6):767–791.

[2] Pfurtscheller G, Neuper C, Flotzinger D, Pregenzer M. EEG-based discrimination between imagination of right and left hand movement. Electroencephalogr Clin Neurophysiol. 1997;103(6):642–651.

[3] Lécuyer A, Lotte F, Reilly RB, Leeb R, Hirose M, Slater M. Brain-computer interfaces, virtual reality, and videogames. Computer. 2008;41(10).

[4] Clerc M., Bougrain L., Lotte F. Brain-Computer Interfaces 1: Foundations and Methods. ISTE-Wiley, 2016.

[5] Guger C, Edlinger G, Harkam W, Niedermayer I, Pfurtscheller G. How many people are able to operate an EEG-based brain-computer interface (BCI)? IEEE Trans Neural Syst Rehabil Eng. 2003;11(2):145–147.

[6] Allison BZ, Neuper C. Could anyone use a BCI? In: Brain-computer interfaces, 2010, 35–54.

[7] Neuper C, Pfurtscheller G. Neurofeedback training for BCI control. In: Brain-computer interfaces.

[8] Lotte F, Larrue F, Mühl C. Flaws in current human training protocols for spontaneous brain-computer interfaces: lessons learned from instructional design. Front Hum Neurosci. 2013;7:568.

[9] Jeunet C., N'Kaoua B., Lotte F. Advances in user-training for mental-imagery-based BCI control: Psychological and cognitive factors and their neural correlates. Prog. Brain Res. 2016;228:3–35.

[10] Randolph AB, Jackson MM, Karmakar S. Individual characteristics and their effect on predicting mu rhythm modulation. Int J Hum Comp Int. 27(1).

[11] Blankertz Benjamin et al. Neurophysiological predictor of SMR-based BCI performance. Neuroimage. 2010;51(4):1303–1309.

[12] Randolph AB. Not all created equal: individual-technology fit of brain-computer interfaces. In: Proc. HICSS. 2012, 572–578.

[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):e0143962.

[14] Jeunet C, Jahanpour E, Lotte F. Why standard brain-computer interface (BCI) training protocols should be changed: an experimental study. J Neural Eng. 2016;13(3):036024.

[15] Pacheco K, Acuña K, Carranza E, Achanccaray D, Andreu-Perez J. Performance predictors of motor imagery brain-computer interface based on spatial abilities for upper limb rehabilitation. In: Proc. IEEE EMBC. IEEE. 2017, 1014–1017.

[16] Hammer EM et al. Psychological predictors of SMR-BCI performance. Biol. Psychol. 89(1).

[17] Botrel L, Kübler A. Reliable predictors of SMR BCI performance—Do they exist? In: Brain-Computer Interface (BCI), 2018 6th Int. Conf. on. IEEE. 2018, 1–3.

[18] Hammer EM, Kaufmann T, Kleih SC, Blankertz B, Kübler A. Visuo-motor coordination ability predicts performance with brain-computer interfaces controlled by modulation of sensorimotor rhythms (SMR). Front Hum Neurosci. 2014;8:574.

[19] Teillet S, Lotte F, N'Kaoua B, Jeunet C. Towards a spatial ability training to improve Mental Imagery based Brain-Computer Interface (MI-BCI) performance: A Pilot study. In: Proc. IEEE SMC. 2016, 003664–003669.

[20] Pillette L, Jeunet C, Mansencal B, N'Kambou R, N'Kaoua B, Lotte F. Peanut: Personalised emotional agent for neurotechnology user-training. In: 7th International BCI Conference. 2017.

[21] Ramoser H., Muller-Gerking J., Pfurtscheller G. Optimal spatial filtering of single trial EEG during imagined hand movement. IEEE Trans Neural Syst Rehabil Eng. 2000;8(4):441–446.

[22] Lotte F. Signal Processing Approaches to Minimize or Suppress Calibration Time in Oscillatory Activity-Based Brain–Computer Interfaces. Proc. IEEE. 2015 (;103):871–890.

[23] Kolb DA. Learning style inventory: Version 3. Hay/McBer Training Resources Group, 1999.

[24] Cattell RB, P. Cattell HE. Personality structure and the new fifth edition of the 16PF. Educ Psychol Meas. 1995;55(6):926–937.

[25] Vandenberg SG, Kuse AR. Mental rotations, a group test of three-dimensional spatial visualization. Percept Mot Skills. 1978;47(2):599–604.

[26] Tibshirani R. Regression shrinkage and selection via the lasso. J R Stat Soc Series B Stat Methodol. 1996;267–288.

[27] Fonti V, Belitser E. Feature selection using lasso. VU Amsterdam Research Paper in Business Analytics. 2017.

[28] Xu H, Caramanis C, Mannor S. Robust regression and lasso. In: Proc NIPS.

[29] Müller-Putz G, Scherer R, Brunner C, Leeb R, Pfurtscheller G. Better than random: a closer look on BCI results. Int J Bioelectromagn. 2008;10:52–55.

[30] Lotte F., Jeunet C. Defining and quantifying users' mental imagery-based BCI skills: a first step. J Neural Eng. 2018;15(4):046030.