Investigating the Effect of User Profile during Training for BCI-based Games

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Abstract— **Since brain-computer interface (BCI) systems have moved outside the laboratory settings, their use in virtual reality and games promised to offer a more compelling experience to the user. BCI for entertainment yields interesting applications with the main purpose to create positive experiences that enrich our lives. However, the main challenge in the use of BCIs lies in the lack of reliability and satisfactory performance that inexperienced users have. To evaluate such systems, not only user experience but also user profile (e.g., gender, role etc.) needs to be considered, helping us understand how a BCI system can better enhance the brain-to-game interaction. This paper illustrates the importance of gender, individual role (i.e., user profession), and time of use when interacting with a BCI game, with a total of 34 participants. Furthermore, we present the effect of reported workload and loss of self-consciousness during the game play on performance. Finally, we highlight the need for considering user profile in BCI research, and we show how this information could benefit BCI by improving the selection of suitable mental tasks.**

Keywords—brain-computer interfaces; motor-imagery; games; interaction

I. Introduction

Brain–Computer Interfaces (BCIs) are communication systems which bypass the central nervous system for providing an alternative pathway between the user and a computer system [1]. With the growing computing power of the information technologies, new findings about the underlying mechanisms of the human brain are uncovered. BCIs offer an important role on prosthetic devices [2] that could assist or rehabilitate physically disabled people and stroke survivors [3]. More recently, games and Virtual Reality (VR) have also been used in BCI, offering a more compelling experience to the user through 3D virtual environments [4]. In turn, VR experience characteristics have been found to affect exhibited biophysical responses such as heart rate [5]. The fusion of BCI and games encompasses a wide range of experiences where participants can control various aspects of their virtual environment, by using mental imagery alone [6]. This unique direct brain-to-game communication can provide increased immersion by inducing the sense of movement illusion, mostly relying on the sensorimotor contingencies between perception and action [7].

In the last few years, there is an effort to commercialize BCI with the launch of low-cost physiological signal devices used outside laboratory environments. Unfortunately, current BCI systems used for gaming[1,2,3] still fail to offer a compelling user experience due to low performance. While the best BCIs in terms of performance are often too expensive or not mobile enough, there is a common misconception that cheaper mobile systems are not as accurate as their more expensive counterparts are. Recent findings have showed that BCI performance/throughput of users, is not technology related and it can be accomplished without requiring high-end and high-cost devices [8], [9].

In BCI for games research, despite previous findings have shown that prior game experience has an effect on faster learning during a motor-imagery BCI paradigm [10], information concerning the user profile and user experience has so far been ignored. Information about user profile can be vital for understanding how a BCI system can be personalized and used for gaming and other purposes. The aim of this paper is to examine the effect of user profile during BCI calibration session, and BCI control. Additionally, based on previous research concerning realistic BCI feedback [11], we aim to assess whether motor-observation through video stimulation during training improves users performance compared to traditional training. To achieve this, a minimalistic BCI-game has been developed, together with two training modalities: motor-observation and motor imagery. A study with total of 34 participants, undergoing two different BCI training paradigms was performed, followed by an online BCI-game session. Results showed that gender, role (student or staff) and time of the day, have a significant effect not only on EEG modulation but also on reported workload and loss of self-consciousness during the game play.

The rest of the paper is structured as follows. Chapter II provides background information for BCIs, motor imagery and BCI games. Chapter III describes the goals of the study and our research questions. Chapter IV, presents the methodology, describes the game development, the BCI training modalities and the data analysis. Chapter V illustrates the results. Finally, in Chapter VI, the conclusions and future work are discussed.

II. Background

A. Brain-Computer interfaces

BCIs are an emerging multidisciplinary field, which includes the utilization of machine learning, neuroscience, cognitive psychology and signal processing. It is a hardware

[1] Neurosky Mindwave (NeuroSky. San Jose, California, USA)
[2] Emotiv EPOC (Emotiv, San Francisco, California, USA)
[3] Muse Headband (Toronto, Ontario, Canada).

978-1-5090-5812-9/17/$31.00 ©2017 IEEE

and software communication system that enables humans to interact with their surroundings, without the involvement of peripheral nerves and muscles, by using control signals generated from electroencephalographic activity alone [12]. As such, BCIs are particularly useful for people suffering with severe motor disabilities since they can significantly improve their quality of life (e.g., help control artificial limbs). A BCI system can identify a set of patterns in brain signals following five consecutive stages: i. signal acquisition, ii. pre-processing or signal enhancement, iii. feature extraction, iv. classification, and v. the control interface [13]. The signal acquisition stage records the brain signals, often with the use of electroencephalography (EEG). The preprocessing stage is responsible for enhancing the signals by removing noise and artifacts, extracting the different EEG bands before passing the signals in a form that can be processed in the next stage. The feature extraction stage identifies discriminative features that have been recorded and maps them onto a vector. The classification stage separates the feature vectors into different classes. Finally, the control interface stage translates the classified signals into meaningful commands for any connected device, such as a wheelchair or a game, which provides feedback to the user.

B. Motor-Imagery

Motor imagery is a mental process by which an individual rehearses or simulates a given action only by thought and not actual movement. It is widely used in sport training as a mental practice of action, neurological rehabilitation [3], and has also been employed as a research paradigm in cognitive neuroscience and cognitive psychology to investigate the content and the structure of covert processes (i.e., unconscious) that precede the execution of action [15]. The effectiveness of motor imagery has been also demonstrated in musicians [16]. In recent years, motor imagery has been used in the BCI research as well [17], and in fact, according to a study in 2013, motor imagery is the most popular brain–computer game control mechanism [18].

C. BCIs and Games

Playing is an essential part of human life. Playing games can help people obtain new knowledge through exploring the unknown. During playing, our minds and bodies are challenged, thus games help us improve ourselves by acquiring skills, knowledge and experiences. Given that playing involves certain cognitive processes (e.g., learning, remembering, problem solving etc.), it should be no surprise that games have found their way into the BCI technology as well. Ever since the BCI development began, basic computer games have been a tool that researchers used to keep people interested and focused on the experiments due to the entertaining and challenging nature of gaming.

A number of different BCI paradigms have been employed in various BCI games. These include motor imagery, Steady State Visually Evoked Potential (SSVEP), P300 (delay between stimulus and response of roughly 300 ms) and combinations of different paradigms. Motor imagery however, requires multiple training sessions for participants to achieve acceptable precision. Another drawback of motor imagery is the fact that some people seem to be unable to master it regardless of the amount of training sessions [19]. Motor imagery works best when a person is calm and focused. Poor performance can cause frustration and distraction, so the ability to relax is very beneficial. In addition, motor imagery's ability to provide continuous control of an object in a game environment makes it different from the other BCI paradigms. Most importantly, motor imagery BCI games are utilized also in neurorehabilitation, where patients with low level of physical motor control, such as those suffering of flaccidity or increased levels of spasticity, could not benefit due to low range of motion, pain, fatigue, etc.[20].

Concerning game genres, action games challenge people's skills and their quick thinking. It is also the most commonly used genre in BCI games. The BCI paradigm used the most with action games, is motor imagery because of its continuous input. BCI for gaming, vaguely promises a unique way for interacting with a virtual environment. Current limitations have not yet allowed BCI to show its full potential as an alternative input device. To evaluate such systems, not only have we to approach the problem from a system perspective, but also from the user point of view. This paper illustrates the importance of gender, role and time in BCI games but also the effect of reported workload and immersion during the game play. In this study, we hypothesize that users with different roles (i.e., profession) will display significantly different engagement in the tasks they had to perform. Also, hour of day may have a plausible effect on participants' ability to perform well during a task within a BCI game.

III. Research Questions

In this study, we investigated the following research questions when using BCI for gaming:

i. **Will participants' role affect their achieved scores and the way they perceived the tasks at hand (RQ 1)?** Experiments and studies that are carried out in the workplace are known to positively influence employees' measured performance, as a result of them feeling observed. We thus expect that this "observer effect" will manifest in our study too, between employees and students in a University setting.

ii. **Will participants' gender influence how well they performed in the tasks and how they perceived them (RQ 2)?** Research has shown that gender has an effect on visuospatial navigation in maze exploration tasks, such as the one employed in this study [21]. Thus, we assume plausible differences will emerge between the two genders.

iii. **Does hour of day influence how well participants performed (RQ 3)?** Cognitive performance is known to fluctuate throughout the day as an effect of the daily circadian rhythm [22]. Hence, we expect some fluctuations in participants' scores as an effect of the hour of the day the task was performed.

IV. Methodology

A. Participants

The experiment was carried out at the Human-Computer Interaction Laboratory of Faculty of Informatics of Masaryk University. Thirty-four (N = 34) participants between 18 - 33 years of age took part in the experiment, in a balanced sample of 17 males and 17 females. The BCI training process varied between 50 and 90 minutes per participant, with all participants providing their signed informed consent together with demographics data before participating in the study.

B. BCI Setup

For EEG acquisition, the Enobio 32 system (Neuroelectrics, Barcelona, Spain) was used. Enobio, is a wearable, wireless EEG sensor with 32 EEG channels and a triaxial accelerometer, for the recording and visualization of 24-bit EEG data at 500 Hz. The spatial distribution of the electrodes followed the 10 - 20 system configuration [23] and were placed on frontal (F3, F4, F7, F8), temporal (T7, T8), central (C1, C2, C3, C4), parietal (P7, P3, P4, P8, P03, P04), central–parietal (CP1, CP2, CP5, CP6), frontal–central (FC1, FC2, FC5, FC6), intermediate (AF3, AF4) mid-line (Oz, Pz, Cz, Fz) and occipital (O1, O2) placements. During the experiment, the BCI system was connected via Bluetooth to the dedicated computer for the EEG signal acquisition. The EEG data processing was performed through the OpenVibe platform [24] via the VRPN protocol [25] that supported the communication with the game. (Fig. 1). For all conditions, a Common Spatial Patterns (CSP) filter was used for feature extraction, for separating a multivariate signal into additive subcomponents which have maximum differences in variance between two windows [26]. CSP has been shown to deliver better performance in motor-imagery experiments [27]. In addition, Linear Discriminant Analysis (LDA) was used for the classification of the two classes (left | right hand imagery) from the feature vector.

C. BCI Training Feedback

- Motor-observation. Two 5-seconds long videos were filmed. In them, a participant (turned with his back to the camera) slowly raises his right or left hand respectively, from waist to a shoulder level (sideways, not in front of the body) and then slowly back down again. Videos are identical, only the hand that is being raised changes. One

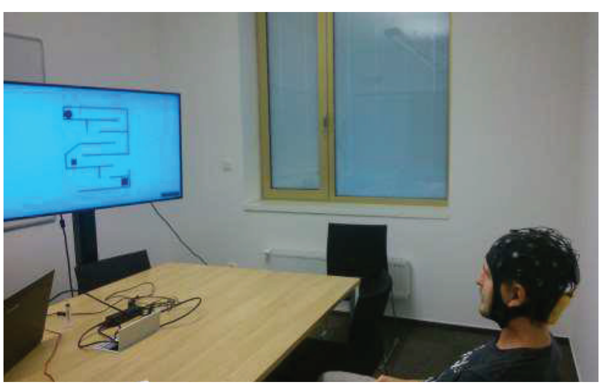

Fig. 1. Experimental setup. Left: the game feedback. Right: participant during game control through the BCI.

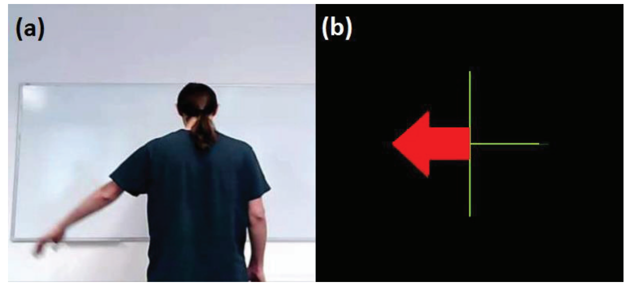

Fig. 2. (a) Filmed video, displaying left or right-hand movement for the motor-observation task during training. (b) Motor-Imagery feedback of Graz-BCI with unidirectional arrow for each class (left/right).

video is for the right hand, the other video is for left hand (see Fig. 2(a)).
- Motor-imagery. The visual stimulation was based on the Graz-BCI paradigm [28] with a standard bars-and-arrows feedback (see Fig. 2(b)). When an arrow appears on the screen, the user should perform a mental imagery of the corresponding hand (based on arrow direction) performing a task.

D. Game Design

The game was developed in Unity3D game engine with C# scripts in Visual Studio. The game mechanics have been implemented based on the following criteria to be used by the BCI system as a primary input:

1. **Task**. The game was designed to be a simple 2D maze-like game, where a player controls the ball by moving the game to right or left side with the use of right-hand and left-hand motor-imagery, respectively. The ball was placed at the top platform and the goal was to move the ball to a side that has a hole in it, so that the ball could fall into a lower platform. This process would repeat until the ball reaches the lowest platform, where the maze exit would be located. The maze exit was in this case represented by a square (see Fig. 3). The first level was designed for familiarization of both the task and the BCI system, using motor-imagery for control. The second level provided the player with 2 choices in 2 separate areas, resulting in a total of 4 possible routes, with one of them being the fastest. With the

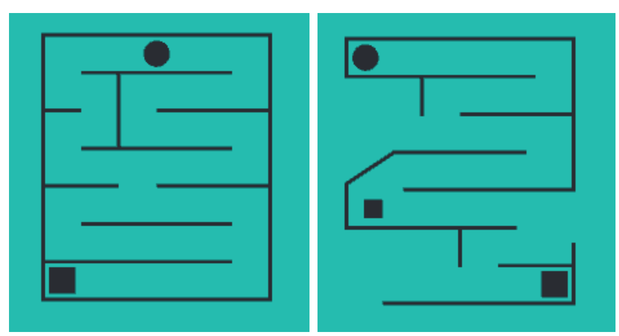

Fig. 3. Basic concept for the game, minimalistic design to achieve non-distractive environment

experience from the first level, the player should be able to choose the shortest route to finish. The third level introduced a new challenge in the form of punishment on unsuccessful ball control. The ball could be pushed outside of the maze, as a result of a bad user movement, and fall outside of the screen. In the event of ball falling outside the screen, it would re-spawn at the start (or checkpoint) location. The player had 5 attempts to complete the maze, without the ball falling off.

2. **Control.** The game was designed to receive the classifier output through a VRPN client for self-paced control. The received input was the classifier's result for left or right motor-imagery (a value of the distance to a hyperplane).
3. **Non-distracting environment.** The game environment was designed in 2D, excluding as many visual distractions as possible, providing only the target (black square) and current position of the player (black circle) (see Fig. 3).
4. **Simplicity.** The game's goal should be easy for people to grasp immediately so they could focus on the control instead of figuring out objectives.
5. **Enhancing the feeling of progress.** The target was to reward success without punishing failure. Users should have positive motivation while performing a highly cognitively demanding task, while being concentrated on the BCI control.
6. **Continuous control.** The game required continuous control in order to facilitate with the constant input of the BCI classifier.
7. **Multiple levels with increasing degree of difficulty.** The game was progressing through new levels of increased difficulty, depending on users' performance in order to avoid a plateau of performance that would result in low engagement.
8. **Data logging.** The game was logging the level name and index, the score achieved in respective levels, and their immediate goal. In addition, current time and date and player name were also recorded.

E. Questionnaires

Before each BCI training session, demographics and user data were gathered. After the BCI task, the following questionnaires were administered:

1. **Presence Questionnaire**. For assessing users sense of presence, the Presence questionnaire (PQ) was used to collect feedback on the experience [29]. The presence questionnaire was adapted for the BCI-game interaction, consisted of 10 questions rated on a 7-point scale.
2. **NASA-TLX.** For assessing workload, the NASA Task Load Index (NASA-TLX) was used. TLX is a widely used, subjective, multidimensional assessment tool that rates perceived workload [30]. There are 6 aspects of workload that subjects are asked to rate on a 21-point scale. TLX was used twice, once for the training part of the experiment, and the second time for the game playing part.
3. **Flow Scales Questionnaire.** As an additional metric, we used the Game Experience Questionnaire (GEQ) [31]. The flow scales are self-report instruments designed to assess the construct of flow, or optimal experience. The scales were designed and validated primarily in physical activity settings. The questionnaire consists of 9 dimensions with 4 statements per dimension (36 questions in total), where a test subject rates the agreement with a statement on a 5-point scale.

F. EEG Data

Based on the acquired EEG signals, we computed the following metrics:

1. **Power Spectral Density.** EEG signals were processed in MATLAB (MathWorks Inc., Massachusetts, USA) with the EEGLAB toolbox [32] for extracting the Power Spectral Density (PSD). The power spectrum was extracted for the following frequency rhythms: Delta (1 Hz - 3 Hz), Alpha (8 Hz - 12 Hz), Beta (12 Hz - 30 Hz), Theta (4 Hz - 7 Hz), and Gamma (25 Hz - 90 Hz). Independent Component Analysis (ICA) was used for removing major artefacts related with power-line noise, eye blinking, ECG and EMG activity and a Notch filter at 50Hz for filtering out power-line noise.
2. **Engagement Index.** The Engagement Index (EI) is a metric proposed by Pope et al, at NASA Langley for evaluating operator engagement in automated tasks [33], and has been validated through a bio-cybernetic system for Adaptive Automation [34]. We therefore computed engagement index from the sums of powers at Cz, Pz, P3, and P4 locations [33], according to the EI formula (eq.1), where α = Alpha band, β = Beta band and θ = Theta band:

$$EI = \beta/(\alpha+\theta) \qquad (1)$$

G. Statistical Analysis

Normality of the distribution of all data was assessed using the Shapiro-Wilk (S-W) normality test. For unveiling any significant differences in continuous variables between the two levels of our grouping variables, we performed independent samples *t*-tests. All independent *t*-tests reported significance is set to 2-tailed with equal variances assumed. For discrete variables (e.g., scales), non-parametric tests were performed. For independent variables with more than 2 levels and for an analysis with covariates and random effects, ANOVA and ANCOVA was performed respectively. Finally, non-parametric, Spearman correlations were performed between electrophysiological (EEG) and questionnaire data. For all statistical tests the significance level was set to 5 % ($p < .05$). All statistical analyses were performed with IBM SPSS 21 (SPSS Inc., Chicago, IL, USA). Our variables are described as follows:

- **Independent Variables.** Condition (Video, Arrows - 2 levels), Gender (Male, Female - 2 levels), Hour of Day (12:00, 14:00, 15:00, 16:00, 17:00, and 18:00 - 6 levels) and Role (Student, Technical - 2 levels).
- **Dependent Variables.** For dependent variables, we included two types, discrete and continuous. The discrete variables included Workload: TLX (2 sets of 6 items in 1 - 21 scale), Presence: PQ (10 items in 1 - 7 scale) and Flow: GEQ (9 items in 1 - 5 scale). For continuous variables, we

used LDA (classification accuracy in %), EEG bands (Delta, Theta, Alpha, Beta, Gamma in dBs), Engagement Index (EI), Workload in Training (overall) and Workload in Game (overall).

V. Results

In the following section, we describe our findings about the user profile and the time the task was executed, and how these influenced our training during a BCI-based game.

A. Effect of Role

Despite that the participants were recruited from the University premises, not all of them were students. In fact, some of them (N = 6) were university employees (e.g., technicians). We expect that those employed by the university will display higher engagement to the tasks they had to perform, simply because the experiment was conducted at their work place and thus this may have induced a feeling of responsibility or obligation to perform better (RQ 1).

A series of independent samples *t*-test revealed significant differences in reported Workload during gameplay ($t(31) = 2.295$, $p < .05$), exhibited Theta brain band power ($t(31) = 1.386$, $p < .05$), Alpha brain band power ($t(31) = 1.779$, $p < .01$), and EI ($t(31) = - 2.241$, $p < .05$), between university students and employees. However, no significant differences were found in LDA classification performance between students and employees ($t(31) = - .038$, $p = .97$). Particularly, university employees, displayed significantly lower Theta ($M_E = 11.065839$, $SD_E = 7.052343$) and Alpha ($M_E = 4.587$, $SD_E = 2.929$) band power than students did (Theta: $M_S = 22.517$, $SD_S = 19.735$ | Alpha: $M_S = 11.267$, $SD_S = 8.99$). As a result, university employees were found with a significantly higher EI ($M_E = 0.403$, $SD_E = 0.711$) than students were ($M_S = .114$, $SD_S = .012$). Surprisingly, despite employees were significantly more engaged in the experiment than students were, they (i.e., employees) reported a significantly lower overall TLX workload ($M_E = 33.862$ %, $SD_E = 15.122$ %) for the game stage, than students did ($M_S = 46.061$, $SD_S = 11.011$).

A series of Mann-Whitney U tests confirmed the previous findings, revealing significant differences in TLX scores (for gaming stage) Mental Demand ($U = 37.5$, $p < .05$), Temporal Demand ($U = 43.5$, $p < .05$), from PQ: "*How much did you feel in control of the ball in the game?*" ($U = 45$, $p < .05$), PQ: "*How often do you perform a sport or an activity including active movement?"* ($U = 37.5$, $p < .05$), and PQ: "*How proficient in moving and interacting with the application did you feel at the end of the experience?*" ($U = 25.5$, $p < .01$) between university students and employees. In particular, students found the Game to require significantly higher Mental Demand ($Mdn_S = 17$) and higher Temporal Demand ($Mdn_S = 10$) than employees did (Mental Demand: $Mdn_E = 12.5$ | Temporal Demand: $Mdn_E = 4$). Moreover, students reported that at the end of the study they were significantly less in control of the ball in the game (PQ2: $Mdn_S = 5$), that they perform sports significantly more frequently (PQ: "*How often do you perform a sport or an activity including active movement?*": $Mdn_S = 5$), and that they were significantly less proficient in the ball game at the end of the experiment (PQ: "*How proficient in moving and interacting with the application did you feel at the end of the experience?*": $Mdn_S = 5$) than the university employees did (PQ: "*How much did you feel in control of the ball in the game. Do you think your thoughts correlated with the actions performed by the game?*": $Mdn_E = 5.5$ | PQ: "*How often do you perform a sport or an activity including active movement?*": $Mdn_E = 3$ | PQ: "*How proficient in moving and interacting with the application did you feel at the end of the experience?*": $Mdn_E = 6$).

B. Effect of Gender

A series of independent *t*-tests revealed significant differences in Delta ($t(32) = - 2.075$, $p < .05$, $M_F = 132.785$, $SD_F = 126.042$ | $M_M = 69.404$, $SD_M = 29.165$), in Theta ($t(32) = - 2.258$, $p < .05$, $M_F = 27.281$, $SD_F = 24.246$ | $M_M = 13.863$, $SD_M = 6.645$), in Alpha ($t(32) = - 2.164$, $p < .05$, $M_F = 13.079$, $SD_F = 10.968$ | $M_M = 7.08$, $SD_M = 4.047$), and in Beta ($t(32) = - 2.309$, $p < .05$, $M_F = 4.645$, $SD_F = 3.695$, $M_M = 2.524$, $SD_M = 1.186$) band power between Female and Male conditions. No significant differences were found in the remaining LDA, total workload during training, workload during game, Gamma and EI variables between Female and Male conditions. Similarly, a series of Mann-Whitney U tests revealed a significant difference in GEQ: "*Concentration on the Task at Hand*" ($U = 73.5$, $p < .05$), with the females ($Mdn_F = 3$) reporting significantly less concentration at hand than the Males ($Mdn_M = 4$) did. No significant differences were found in the remaining TLX, PQ, and GEQ variables between Female and Male conditions. Hence, gender was found to have an effect on most participants' exhibited band powers and perceived task concentration (RQ 2).

1) Condition Effect for Females

Since male and female participants displayed significant differences in most band power spectra, we performed two separate analyses for females and males. For females, a series of independent samples *t*-tests revealed no significant differences in LDA, total workload during training, total workload during game, Delta, Theta, Alpha, Beta, Gamma and EI, between Arrows and Video condition. A series of Mann-Whitney U tests for females revealed a significant difference in PQ: "*How natural was the mechanism which controlled movement?*" ($U = 13.5$, $p < .05$) and GEQ: "*Loss of Self-Consciousness*" ($U = 14$, $p < .05$) between Arrows and Video conditions. In Arrows condition, females reported significantly more natural control of movement PQ: ($Mdn_A = 6$) and a significantly higher loss of self-consciousness GEQ: "*Loss of Self-Consciousness*" ($Mdn_A = 4$) than they did in Video condition PQ: "*Unambiguous Feedback*" ($Mdn_V = 4$), GEQ: "*Loss of Self-Consciousness*" ($Mdn_V = 3$).

2) Condition Effect for Males

For males, similarly to females, a series of independent samples *t*-tests found no significant differences in LDA, total workload during training, total workload during game, Delta, Theta, Alpha, Beta, Gamma and EI, between Arrows and Video condition. A series of Mann-Whitney U tests for males revealed a significant difference only in GEQ: "*Loss of Self-Consciousness*" ($U = 91$, $p < .05$) between Arrows and Video conditions. Similarly, to females, in Arrows condition males reported significantly higher loss of self-consciousness ($Mdn_A = 5$) than they did in Video condition ($Mdn_V = 4$). However, no significant differences were found in PQ: "*How natural was the mechanism which controlled movement?*" (U = 133.5, p = .35) between Arrows and Video conditions for male participants.

C. Effect of Hour of Day

A Multivariate Analysis of Variance (MANOVA) was ran with the LDA, LDA, Delta, Theta, Alpha, Beta, Gamma, EI, total workload during training, total workload during game as dependent variables and the hour of day (in 24h format) as an independent variable. Before proceeding to the analysis, we removed observations that occurred only once (i.e., a trial at 21:00). The analysis displayed a significant main effect of hour of day on exhibited Gamma band power ($F(6,25) = 3.388$, $p < .05$, $\eta_p^2 = .448$) and on Engagement Index (EI) ($F(6,25) = 4.075$, $p < .05$, $\eta_p^2 = .494$). Post hoc tests using the Bonferroni correction revealed that participants' exhibited Gamma band power at 15:00 (M = 6.423, SD = 6.966, $p < .05$) was significantly higher than at 12:00 (M = 0.885, SD = 0.455), 17:00 (M = 0.903, SD = 0.315), 18:00 (M = 1.423, SD = 0.541), and at 19:00 (M = 0.724, SD = 0.195). Similarly, post hoc tests using the Bonferroni correction revealed that participants exhibited EI was significantly higher at 15:00 (M = 0.993, SD = 1.217, $p < .05$) than at all other hours when trials were performed (12:00: M = 0.109, SD = 0.013 | 14:00: M = 0.119, SD = 0.002 | 16:00: M = 0.123, SD = 0.020 | 17:00: M = 0.115, SD = 0.011 |18:00: M = 0.106, SD = 0.011 | 19:00: M = 0.109, SD = 0.017). Multiple Kruskal Wallis H tests displayed no significant differences in TLX, PQ and GEQ scores among different hours of day trials took place. This indicates that hour of day did not influence significantly participants' self-reported measures. Hence, hour of the day had a significant effect on participants' exhibited engagement index (EI) but not on participants' perceived measures (RQ 3).

D. Condition and Role Effect

In the recruitment of our participants "snowball sampling" was applied, that is we strived for maximizing our sample size while keeping a rather balanced distribution for gender. However, the recruitment was not limited to a special "target" group (e.g., only students) but instead included additional participant groups such as university employees (e.g., technicians). While participants' role was recorded in a dedicated variable (i.e., role), we can think of additional levels we did not observe in our participants' group to be samples of a larger population. For example, the human resources of a university do not only include students or technicians but people with highly different expertise, such as professors, secretaries, cleaning personnel etc. We therefore assume that the participants' role has a random effect as an independent variable in our analysis. Furthermore, we were able to unveil plausible effect of gender and hour of day that we suspect influenced participants exhibited cognitive activity and thus may have a combined effect on our classification performance. For these reasons, we decided to run a Random Effects Analysis of Covariance (i.e., Random effects ANCOVA) for determining the effect of condition (independent variable) on our classification performance (dependent variable), while taking into account any plausible random role effects, and controlling for participants' gender as well as the hour of day when trials were conducted. However, the analysis did not display a combined significant main effect of condition and role (condition*role) on LDA classification performance score ($F(1,26) = 2.99$, $p = .096$, $\eta_p^2 = .103$). This indicates that condition and role did not have a synergistic influence on the accuracy of our classification while controlling for gender and hour of day, as we had previously hypothesized.

E. Relationship of EEG data with Reported Experience

Non-parametric Spearman correlations, revealed significant relationships in EEG bands (see Table 1). In particular, for Alpha with TLX: Effort ($r_s = .348$, $p < .05$, N = 34), and GEQ: Unambiguous Feedback ($r_s = -.355$, $p < .05$, N = 34). Theta is related with TLX: Effort ($r_s = .365$, $p < .05$, N = 34), GEQ: Unambiguous Feedback ($r_s = -.348$, $p < .05$, N = 34), GEQ: Transformation of Time ($r_s = .344$, $p < .05$, N = 34), and GEQ: Autotelic Experience ($r_s = -.348$, $p < .05$, N = 34). Finally, EI as extracted from EEG, is correlated only with PQ: 7. "*How quickly did you adjust to the experience?*" ($r_s = .466$, $p < .05$, N = 34).

F. Effect of Condition

A series of independent *t*-tests revealed no significant differences in LDA, Delta, Theta, Alpha, Beta, Gamma, EI, total workload during training, total workload during game variables between Video and Arrows conditions. Similarly, a series of Mann-Whitney U tests revealed no significant differences in all TLX item ratings for both training and game stages, all Presence (PQ) item ratings and all Flow (GEQ) item ratings between Video and Arrows conditions.

VI. CONCUSSIONS AND FUTURE WORK

Current results shown that demographic data like gender has an effect on EEG patterns, being consistent with previous research [10], [35], [36]. For this, the sample was divided between the two genders, and two conditions were assessed separately. For the two different training conditions, females reported less concentration in the task compared to male participants in overall. In the first condition (i.e., Arrows), females reported significantly more natural control of movement during the game and a significantly higher loss of self-consciousness than they did in the second condition with the Video training. Males, similarly to females, in Arrows condition, reported significantly higher loss of self-consciousness than they did in Video condition, but not a

Table 1. EEG-band Power Correlations (p<0.05)

	TLX: Effort	GEQ: Unambiguous Feedback	GEQ: Transformation of Time	GEQ: Autotelic Experience	PQ: 7. How quickly did you adjust to the experience?
Alpha	.348	.355	-	-	-
Theta	.365	- .348	.344	.348	-
Gamma	-	-	-	-	
EI	-	-	-	-	.466

difference in the natural control of movement during the game between Video and Arrows conditions.

Although prior research has illustrated the superiority of the realistic feedback over a more abstract feedback in motor-imagery training [17], [37], this study does not validate whether video stimulation during motor-imagery training improves a user's performance over the abstract feedback. Current findings show that the reported loss of self-consciousness was experienced during the game session following the abstract feedback session (i.e., Arrows) instead of the video feedback. A possible explanation –and the difference with other studies in motor-imagery based BCIs– is that the game task feedback was unrelated to the training feedback (arrow and hand movement versus moving a sphere in a maze). This rendered the abstract feedback (i.e., Arrows) capable of producing more personalized imagined movements, whereas on the video condition, a specified task through motor-observation, forced their motor-imagery practice to relate with a specific feedback but not the preferred.

Concerning the difference between user roles, students vs. employees, current findings show that employees produced increased EEG activity during training (for Alpha, Theta bands), as well as increased EI. On the other hand, the reported workload during the game play was lower than that of students. We hypothesize that an increased engagement during training could result in better game play –due to better performance– reflected in decreased workload. In addition, it was found that students reported significantly higher mental effort and higher temporal demand during the game play than employees did. This is reflected also in the students reporting that at the end of the study they were significantly less in control of the game, and less proficient in the game than the university employees reported. These findings showcase a clear effect of the user role, indicating that a more committed user will be able to perform better in a BCI game.

Another important finding is the difference in hour of the day the task was performed in terms of the extracted engagement index and the Gamma band at 15:00. Since time influences engagement, this feature can be useful in the field of neuro-ergonomics (application of neuroscience to ergonomics), by providing insights on human factors issues such as: performance, stress, workload etc. during a BCI session. This might also offer additional insights on understanding the day-to-day variability of the EEG signals due to their non-stationarity. This is known to inhibit learning algorithms to generalize to new data, hence resulting in deficient performance.

Overall, this study showcased that *gender*, *role* and *time* have a significant effect not only on EEG modulation but also on reported workload and loss of self-consciousness during the game play. This demonstrates how sensitive BCI interaction can be, easily affected by insufficient attention due to user distraction or frustration.

For future work, we will include the analysis of specific electrode locations, over the somatosensory area, during motor-imagery training, and create models of user profiles that could be included in a personalized training together with the EEG data. Moreover, we will investigate if a plausible association is present between participants' gender and gender of people in videos used for motor-imagery stimulation. Finally, we will explore BCI games with additional training paradigms, including P-300 and SSVEP in a comparative study, assessing user experience to identify the best BCI modality for games used for either explicit or implicit input.

ACKNOWLEDGMENTS

Part of this work was supported by the Horizon 2020 i-MareCulture project (Advanced VR, iMmersive Serious Games and Augmented REality as Tools to Raise Awareness and Access to European Underwater CULTURal heritagE, Digital Heritage) with grant agreement No 727153 and by the Fundação para a Ciência e Tecnologia (Portuguese Foundation for Science and Technology) through SFRH/BD/97117/2013.

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