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Effect of Continuous and Discrete Feedback on Agency and Frustration in a Brain-Computer Interface Virtual Reality Interaction

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Abstract—**Brain-computer interfaces (BCIs) provide users with a means to control external devices or applications using only voluntarily produced brain activity. Controlling a BCI through motor imagery is a skill that must be acquired, however, little evidence is available on how the user's agency and frustration are affected by different types of feedback during an interaction with a BCI. This was investigated during a virtual reality interaction where 14 naïve participants controlled an avatar with a BCI while receiving either continuous or discrete feedback on their performance. The agency, frustration, ownership and BCI performance were assessed after each of the two conditions (continuous and discrete feedback). There was no statistical difference between the conditions although the participants generally rated agency higher for the continuous feedback which was also uncorrelated to the BCI performance. This suggests that continuous feedback can be useful for increasing agency for users with poor BCI performance by providing them with some knowledge of performance.**

Keywords—brain-computer interface, motor imagery, feedback, agency, frustration, virtual reality

I. INTRODUCTION

A brain-computer interface (BCI) is a technology that can be used to control an external device using only voluntarily controlled brain activity [1]. Often the electrical brain activity is recorded from the surface of the scalp (electroencephalography – EEG) after which it is being pre-processed to enhance the signal-to-noise ratio. Features are extracted from the pre-processed signals and can be classified into a number of classes that are translated to specific actions of the external device. Generally, BCIs have been used as a communication tool for people with severe motor impairments or for controlling e.g. wheel chairs and robotic arms [2]. Another major BCI application is for neurorehabilitation of stroke patients by inducing neural plasticity [3]. Lastly, BCIs have been investigated in other domains such as brain monitoring (passive BCIs) and for game control [4]. Brain control generally has a low information transfer rate compared to other control modalities such as keyboards, joysticks and muscle control. A large amount of research has been dedicated to optimize the signal processing aspects of the BCI to improve the BCI performance, and improvements in the EEG electrodes and amplifiers have been made to improve the EEG signal quality. However, BCI control is a skill, especially for BCIs operated using motor imagery (MI), which is an important control signal within neurorehabilitation and for asynchronous BCI control. Thus, it could be a possibility to improve the BCI performance by focusing on the MI training as well. However, this has been less explored compared to the optimization of the signal processing aspects. Some studies have investigated how training protocols should be structured to improve the skill acquisition of BCI control [5], [6]. Feedback is an integral part of skill acquisition in general and for BCI control, especially for MI from which no feedback can be obtained through proprioception, and it is difficult to know whether it has been performed correctly/optimally. BCI input can be mapped to feedback in many ways. The dominant two in research are discrete and continuous [7]. The former will provide a single instance of feedback if the BCI signal from MI surpasses a given threshold [8] while the latter provides users with continuous feedback about their progress during their MI attempts [9]. Continuous feedback has been reported to improve BCI interactions [9]-[12], however, none compared how continuous feedback affects agency, embodiment, and frustration compared with discrete feedback. Most studies have investigated methods of implementing and mapping signals to continuous feedback but have not investigated its effects on the interaction. As a result, there is a gap in the literature about how BCI users react to continuous feedback compared to what is known of the interaction with discrete feedback [7]. Discrete feedback does not occur at the same time as the users' input nor does it vary during MI, which weakens the natural coupling to its input.

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Weak natural coupling discourages users during input, which reduces their performance with BCIs [13], [14]. The BCI literature has referred to natural coupling as feedback congruency, i.e. how much the feedback matches the users' expectations of what they intended to achieve with their input [15]. Congruency can be broken down into temporal and spatial congruency. Temporally congruent feedback occurs close in time (<1s) to the users' MI attempts [16]. Spatially congruent feedback mimics the direction and movement of the users' input [17] (e.g. a 3D model of a human closing its hand as the user attempts to close it using MI) [18]. Embodying users with a first-person perspective of an avatar that mimics their MI strengthens their sense of ownership (how much the avatar feels like their own body) increasing feedback's spatial congruency [15], [18]. BCI studies have hypothesized temporally congruent feedback may still be more important for skill acquisition than spatially congruent feedback and achieve the congruency that discrete feedback is missing [8]-[10], [14]. The hypothesis states that continuous feedback induces "motor resonance" in the user that strengthens congruency and the users' sense of agency [13]. Despite having an active role performing MI in BCI interaction, users feel like they have little control of the outcomes in the system [19]. The amount of control users feel during interaction has been defined as their sense of agency [19]. Congruent feedback strengthens users' sense of agency during interaction [15], [16], [19], and is beneficial for their motivation to use and becoming proficient with using a BCI [18], [19]. Conversely, weakened agency frustrates users, which lowers their ability to control their brain signals [20]. In summary, neither the effect of continuous feedback on congruency and agency has been directly investigated in BCI interactions nor performing a direct comparison between continuous and discrete feedback. The aim of this study was to investigate how continuous and discrete feedback affect the sense of agency and frustration during a BCI controlled virtual reality (VR) interaction.

II. METHODS

A. Participants

Fourteen able-bodied participants took part in a counterbalanced single factor within-participant study. Four females and 10 males between the ages 21-55 years (mean: 26 years, median: 24 years). All of the participants were naïve BCI users and had no experience with MI. Nine participants had prior experience with virtual reality.

B. BCI System

The BCI in this study was implemented using the "Motor Imagery BCI" from OpenViBE [21]. Continuous EEG (Cyton Biosensing Board and EEG Electrode Cap Kit, OpenBCI, USA) was recorded from F3, F4, C3, Cz, C4, P3, and P4 according to the International 10-20 System. The EEG was sampled with 250 Hz, and the signals were grounded at AFz and referenced to CPz. The signals were bandpass filtered between 8-30 Hz with a 5th order Butterworth filter, and they were filtered with a common spatial pattern filter to maximize the difference in spectral power between MI and idle activity. The common spatial pattern coefficients were determined from the calibration data, which consisted of 30 imaginary movements of the right hand closing. The calibration data were divided into windows with a length of one second, which were shifted with 1/16 second. The logarithmic band powers were extracted from each window and used as features in a linear discriminant analysis classifier, which was calibrated using 5-fold cross-validation. The common spatial pattern coefficients and linear discriminant analysis classifier were used in the online BCI. The output of the classifier (ranging between 0-1) was streamed to a VR scene, which decided if the output was below or above two different types of thresholds (depending on the condition). The thresholds were: 1) MI activation threshold (the participant has started to perform MI), and 2) MI terminal threshold (the MI exceeded a threshold indicating that the imaginary hand closing was completed). The activation threshold was fixed at 0.3 for all participants as the idle activity generally was below this threshold. The second threshold was individualized for each participant. Before the actual experiment started, the participant performed MI two times, and the output associated with these attempts were rounded down to the nearest single decimal place (e.g. an output of 0.74 would be translated to a threshold of 0.7) and used as the terminal threshold.

C. Interaction Design

The participants experienced a virtual 3D room from a first person perspective of a male avatar sitting at a table with his hands on the surface (see Fig. 1). The participants had to try two different conditions, one with discrete feedback and one with continuous feedback. In both conditions, the participants were seated in the same position as the avatar to strengthen their sense of ownership over the avatar. A previous study reported that there was no impact from the avatar's gender, ethnicity, clothes, and visuals on ownership [22]. The avatar's right hand held a balloon, which the participants could close to pop it by performing MI. The balloon changed color depending on which phase the participants was in (see Fig. 1). In both conditions, the participants needed to cross a terminal threshold by performing MI during the task phase. This resulted in the avatar popping the balloon accompanied by a popping sound. When the participants failed to pop the balloon before the end of the task phase a buzzer sounded signifying a failed attempt. The task phase lasted up to five seconds and the participants were instructed to pop the balloon within this period. The participants were allowed to attempt to pop the balloon as many times as needed using MI. In the discrete feedback condition, the avatar's hand that the participants controlled remained stationary, unless the participants crossed a terminal threshold, which triggered an animation.

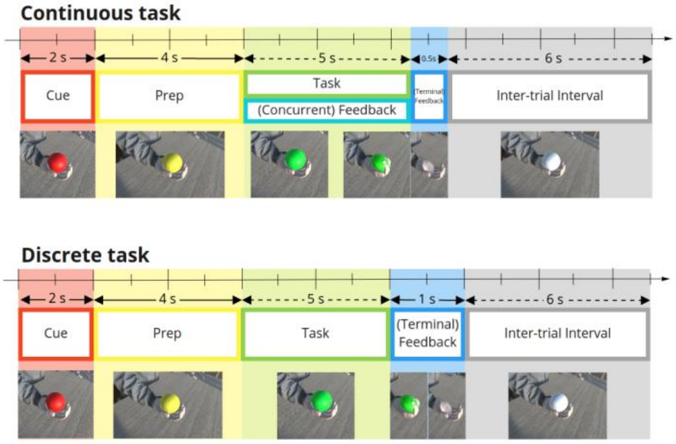

Fig. 1. Timeline of the interaction paradigm in the continuous and discrete condition. The dotted arrows represent that the duration of the phase varies depending on the performance of the participants.

The avatar’s hand closed, squeezed the balloon, popped it, and reopened again. The animation took one second and ended the task phase. The continuous feedback condition mapped the interval between the activation and terminal threshold into the animation of the hand closing. Crossing the activation threshold marked frame 0 of the animation with the hand completely open, the terminal threshold marked the last frame with the hand completely closed; the halfway point marked the middle of the animation, and so on. After crossing the activation threshold, the avatar’s hand began to close as the participants got closer to the terminal threshold and opened as they went further away. Going below the activation threshold re-opened the hand completely again. When the participants crossed the terminal threshold and the hand was completely closed, the balloon popped and the task phases ended. If they failed, the hand opened back up completely and moved to the inter-trial period.

D. *Experimental Procedure*

Initially, the participant received oral information about the experiment. The participants had received a written description of the experimental procedure prior to the experiment. The participants filled in a questionnaire about their mood and motivation followed by verbal instructions on how to perform kinesthetic MI. Afterwards, the EEG cap was mounted and data for calibrating the BCI were recorded. During the recordings of the EEG for the calibration and interaction, the participants were asked to sit as still as possible and minimize the blinking and activation of facial muscles. After the BCI was calibrated, a VR headset (Oculus Quest 2) was mounted over the EEG cap, and the participants were placed in the VR scene, they had to position themselves with both hands on the table with their left hand palm down and right hand palm up to match the avatar. The order of the two conditions (discrete and continuous feedback) was randomized. When the participants were comfortably seated, the first condition consisting of 30 trials of popping the balloon started. Both conditions consisted of 30 trials. After each condition, while not wearing the VR headset, the participants answered a questionnaire with seven 7-point Likert scale items. The items were agency (’I felt like I was in control of closing the virtual hand’), ownership (’I felt like the virtual hand was part of my body’), proprioception (’I felt the movement of the virtual hand in my real hand’), frustration (’It was frustrating when I was trying to close the hand’), mental effort, physical effort, and comfort. In addition, the participants were asked about their perceived BCI performance (how many balloons did they think they popped). After answering the questionnaire for the second condition, there was a debrief session during which the participants provided further context about their answers in the questionnaires in a semi-structured interview. Participants estimated for each condition the number (out of 30) of balloons they think they popped and the number of times they attempted performing MI in each trial. The participants went through each question to compare their answers across conditions, and the interviewer probed into why they rated conditions differently or similarly.

E. *Statistics*

A Wilcoxon test between the discrete and continuous feedback was performed for the rating of each item on the post-experiment questionnaire. Moreover, Spearman’s rank correlation was calculated between the variables: agency, objective BCI performance, perceived BCI performance and frustration. Tests were considered significant when $P<0.05$.

III. RESULTS

One participant (no. 14) was according to the mood pre-questionnaire and post-experiment interview very anxious about the BCI and concerned about his/her performance. He/she was concerned about being embarrassed. In the first condition (discrete), he/she popped all balloons but reported feeling like the BCI gave false positives hence rating the agency low, but still rated frustration low because he/she was excited that all balloons were popped. This participant was removed from the analysis.

A. *Post-Experiment Questionnaire*

The results of the post-experiment questionnaire are presented in Table 1 and Fig. 2. The participants rated higher agency when provided with continuous feedback ([4, 5, 5]) compared to discrete feedback ([3, 4, 5]), however, this difference was not significant (P=0.09). The frustration was similar across the two conditions, and the statistical analysis revealed no statistical difference for frustration or the other items on the questionnaire. The participant popped on average 21±5 (recognition rate: 70±16%) and 22±6 (recognition rate: 73±18%) balloons in the discrete and continuous feedback session, respectively.

TABLE I. RESULT SUMMARY OF THE POST-EXPERIMENT QUESTIONNAIRE. THE RESULTS IN COLUMN 3 AND 4 ARE PRESENTED AS PERCENTILES [25, MEDIAN AND 75]. WILCOXON TESTS COMPARED ITEMS ACROSS THE TWO CONDITIONS (DISCRETE AND CONTINUOUS FEEDBACK).

Item	**P-value**	**Discrete**	**Continuous**
Agency	0.09	[3, 4, 5]	[4, 5, 5]
Ownership	0.32	[3, 4, 5]	[3, 5, 6]
Proprioception	0.72	[2, 3, 5]	[3, 3, 4]
Frustration	0.92	[3, 5, 6]	[3, 4, 5]
Mental effort	0.86	[5, 5, 5]	[4, 5, 6]
Physical effort	0.57	[2, 3, 4]	[2, 2, 4]
Comfort	0.07	[4, 4, 6]	[5, 6, 6]

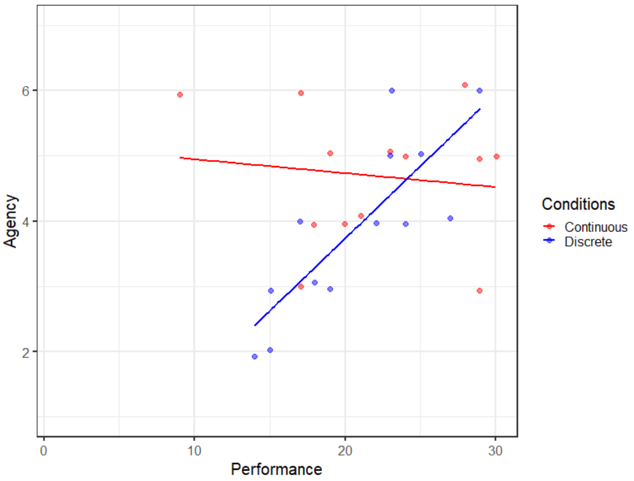

Fig. 2. Agency ratings as a function of BCI performance. The agency was rated from 1-7, and the x-axis represent the number of popped balloons between 0-30.

The correlation analyses revealed that the participants rated agency higher with better objective performance for the discrete (Rho: 0.81, P<0.001) but not for the continuous feedback (Rho: -0.08, P=0.79). The participants' frustration decreased when the agency increased, however, this was not significant for either discrete (Rho: -0.53, P=0.06) or continuous feedback (Rho: -0.15, P=0.63). They were less frustrated the more balloons they popped (Rho: -0.76, P<0.001) or remembered popping (Rho: -0.65, P<0.001). Lastly, there was a high correlation between the participants' objective and perceived performance (Rho: 0.87, P<0.001).

B. Post-Experiment Interview

While our data on performance showed no difference between feedback types, participants preferred continuous feedback (n = 4), supported by seven participants who found the discrete feedback not useful. Others stated that because the hand did not move at all in failed discrete attempts, they gave up after their first failed MI attempt, and thereby did not utilize the full task phase. In the continuous condition few (n = 2) mentioned that the fluctuations in the hand movements disrupted the congruency of movement. A participant reported: "*It's like, if I was in control, I wouldn't be twitching. Because I wasn't thinking of twitching. I was thinking of moving. And it somehow felt different.*" Another six found the fluctuations frustrating, compared to the participants (n = 6) who stated that they disliked only receiving feedback at the end of an attempt in the discrete condition. But the majority (n = 8) found it easier to see their progress in closing the hand, which according to them made the task easier. They also said that when they missed a bit more to pop the balloon, it enhanced their sense of agency. Some participants (n = 2) found the fluctuations motivating. Failing attempts led to frustration (n = 7), which resulted in blaming themselves (n = 5) for not doing well enough. This could result in consecutive failed attempts before regaining their focus and popping the balloon. The proprioception assisted in embodying the participants (n = 11). Furthermore, ownership gave some participants more agency (n = 2), where six participants stated that proprioception made MI easier. When the participants felt stronger agency, they focused more on the hand (n = 5), which also assisted the participants in learning more, especially in the continuous condition (n = 9).

IV. DISCUSSION

This paper investigated how discrete and continuous feedback affected agency and frustration in a BCI controlled VR interaction. Contrary to hypotheses in previous studies [20], [23], our continuous feedback design did neither decrease frustration, nor strengthen ownership or proprioception compared to discrete feedback, but did render agency uncorrelated from recognition rates. The continuous feedback provided the users with the additional knowledge of performance and not just knowledge of result as in the discrete feedback. This could explain why when experiencing poor BCI performance those participants experiencing continuous feedback generally rated agency higher compared to the ones with discrete feedback (see Fig. 2). While some participants claimed learning more about performing MI when presented with continuous feedback, the recognition rate was only slightly higher for the BCI with continuous compared to the discrete feedback. Receiving continuous feedback while trying different techniques for performing MI allowed for optimizing their performance and their agency ratings may be linked to the movement congruency with the avatar. Regarding the design of feedback, future studies should be wary of presenting negative feedback during MI input as this can weaken users' agency and frustrate them [23]. But having users exclusively experience positive feedback would not provide them with the same quality of knowledge of result and performance. However, by adding fabricated input the users' frustration can decrease and perceived control increase [24]. Another design consideration relates to how small fluctuations due to noise and signal variability can be avoided as the fluctuations/twitching in the hand movements disrupted movement congruency. This could be addressed by smoothing the feedback in intervals, but at the expense of weakened temporal congruency as the users may expect to see continuous changes as they perform MI [10]. However, providing users with more knowledge of result and performance may relieve their anxiety about performance and ease their introduction to MI. Future studies should validate the finding in the current work with more participants and over several experimental sessions as learning to control a BCI using MI may take several training sessions [25], [26]. In addition, it should be investigated if the findings are applicable for experienced BCI users and for potential end-users such as stroke patients performing motor rehabilitation with a BCI. Overall, for BCI designers faced with low BCI performance seeking to improve agency our results suggest using continuous feedback, where the agency was 50-100% higher for the worst performing users.

V. CONCLUSION

In this study it was shown that in a BCI-controlled virtual reality interaction there was no statistical difference between continuous and discrete feedback when rating ownership, frustration and agency. However, the participant generally rated agency higher for continuous feedback despite being uncorrelated from BCI performance. Thus poor BCI users may benefit from continuous feedback for improving agency.

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