Enhancing Motor-Imagery Brain-Computer Interface Training With Embodied Virtual Reality: A Pilot Study With Older Adults

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***Abstract*—Electroencephalography-based Brain-Computer Interfaces (BCI's) can provide an alternative non-muscular channel of control to stroke survivors, especially to those who lack volitional movement. This is achieved through motor-imagery (MI) practice, involving the activation of motor-related brain regions. MI is reinforced in a closed-loop BCI through rewarding feedback, and it has been shown to be able to strengthen key motor pathways. Recently, growing evidence of the positive impact of virtual reality (VR) has accumulated. When combined with BCI, VR can provide patients with a safe simulated environment for rehabilitation training, which could be adapted to real-world scenarios. However, not all users have the ability to sufficiently modulate their brain activity for control of a MI-BCI, a problem known as BCI illiteracy. In this study, we investigate the role of embodied feedback and how we can help elderly adults increase their BCI performance during MI-BCI training in VR. The elderly population was selected to age-match with the typical stroke age-range demographic, accounting for age-related confounds. Participants have received MI-BCI training in two conditions: *Abstract* feedback (Graz BCI), and embodied feedback (NeuRow VR-BCI). Current results show differences between the two conditions in terms of Event-Related Desynchronization (ERD), lateralization of ERD and classifier performance in terms of arm discriminability.**

***Index Terms*—Brain-Computer Interfaces, Motor-Imagery, Virtual Reality, Embodiment**

I. Introduction

In restorative Brain-Computer Interfaces (BCI's), the use of Motor-Imagery (MI) training is commonly exploited. Concretely, MI is the mental rehearsal of a movement, and it can activate the primary sensorimotor area [1]. Moreover, MI practice leads into the modulation of the sensorimotor (SMR) rhythms within the range of Alpha (8-12 Hz) and Beta (13-28 Hz) frequency bands, over the contralateral hemisphere. This band modulation, due to motor behavior, can be captured through Electroencephalography (EEG), and it is known as event-related desynchronization (ERD) [2]. In a closed-loop MI-BCI paradigm, these signals can be reinforced by BCI feedback, so they can be used to strengthen key motor pathways that are thought to support motor recovery after stroke [3], [4].

A number of recent clinical studies indicate that repeated use of such BCI's might trigger neurological recovery that could lead to improvement in motor function [5]. Moreover, there is increasing evidence that BCI's could promote long-lasting improvements in motor function in chronic stroke patients, although more evidence is necessary for providing further proof of clinical impact [6].

Recently, growing evidence of the positive impact of virtual reality (VR) in BCI training is accumulating [7]. Specifically, VR can provide a safe simulated environment, under controlled conditions, where patients can train in real-world scenarios [8]. Moreover, VR can deliver embodied feedback to the user through a virtual avatar. With the use of a virtual body, VR can induce illusions of movement and corporal awareness [9], shown to be able to enhance motor learning [10]. This is important in rehabilitation, since patients with no volitional movement, could benefit from embodied VR training.

Nonetheless, a commonly reported limitation in MI-BCI's is the inability of a set of participants to modulate sufficiently their sensorimotor rhythms, commonly referred to as BCI illiteracy [11]. This was also reinforced by recent studies showing that the vividness of motor imagery of the users can have a significant impact on MI-BCI performance [12]. Therefore, it is more difficult for users to interface with MI-BCI training due to the low usability levels, caused by the low accuracy of the BCI.

Latest findings in improving performance in MI-BCI control, highlight the importance of visual and tactile feedback [13], task gamification [14], [15], VR modality and electrode number [16], motor-priming prior to the MI-BCI training session [17], but also, further evidence for the benefits of embodied feedback during BCI training has been accumulated [18]. Specifically, prior research has shown that MI skills can be augmented by using humanlike hands [19], and that the sense of embodiment in VR can be enhanced by multisensory feedback related to body movements [20].

Moreover, besides the impact that the sensorimotor stimulation of the user has during MI, prior research has highlighted

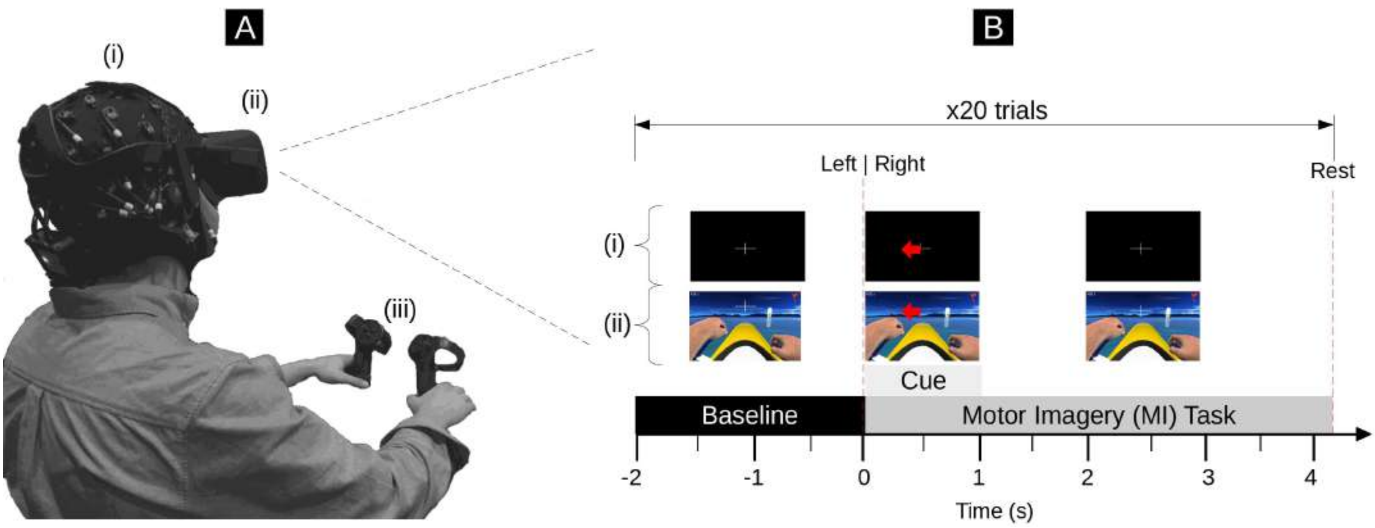

Fig. 1. A. Experimental setup: (i) 32 active electrodes EEG system; (ii) HMD VR; (iii) VR controllers, including custom support, B. MI trial of the cue-based training protocol: 2-seconds of baseline, followed by 1-second cue (directional arrow) for left or right-hand, and 4 seconds of MI. (i) *Abstract* feedback condition with directional arrow and (ii) the *NeuRow* condition, with movement of the virtual arm after the cue.

the importance of additional predictors related to MI-BCI performance. Specifically, user-technology relationship, user attention, user spatial abilities, and gender [21], [22].

Finally, given the age-related differences, the current body of literature does not report the impact of MI-BCI training in the elderly population. Further, reports of ERD measures during embodied VR training is scarce. Thus, we argue that in restorative MI-BCI it is crucial to account for the aforementioned limitations, since most of the target demographic is composed of elderly adults, with no prior experience in most of the technological aspects of a BCI system. Hence, the aim of this study is to identify and validate ways to increase performance in MI-BCI training through embodied feedback in VR in older adults.

II. Methods

In this study, we have implemented an MI-BCI protocol used currently in clinical interventions with chronic stroke patients [7]. All participants received a single session of MI-BCI training followed by functional Magnetic Resonance Imaging (fMRI).

A. Participants

We recruited 5 elderly participants (4 female), right-handed, with an average age of 51 years ($SD = 5.5$). All participants had no prior known neurological disorders, and no prior experience with BCI's or VR. Finally, from every participant, a written informed consent was obtained upon recruitment in accordance with the 1964 Declaration of Helsinki.

B. Experimental Setup

1) EEG amplifier: For EEG data acquisition, the g.Nautilus (g.tec, Graz, Austria) system was used (Figure 1A(i)). g.Nautilus has 32 EEG channels, at 24-bit of resolution and a sampling rate of 500 Hz. The spatial distribution of the electrodes followed the 10–20 EEG system. The EEG amplifier was interfaced wirelessly to a dedicated desktop computer.

2) Head-Mounted Display: For delivering the visual feedback to the users, the Oculus Rift CV1 head-mounted display (HMD) was used (Reality Labs – formerly Oculus from Facebook, Inc., United States). The HMD consists of a 2 x AMOLED binocular display, with a 1080x1200 resolution per-eye, 87° horizontal Field of View (FoV), and 6 degrees-of-freedom (DoF) tracking (Figure 1A(ii)).

C. BCI-VR Training Protocol

The MI-BCI training session involved two conditions in a randomized order: Abstract feedback and embodied feedback. The *Abstract* feedback was based on the Graz-BCI training paradigm [23], with participants visually instructed through directional arrows for when to perform left or right MI (Figure 1B(i)). The embodied feedback was based on *NeuRow* VR-BCI paradigm [15], with the same protocol as the *Abstract* feedback, but with virtual hands rendered from a first-person perspective, and moving according to the arrow direction after the cue (Figure 1B(ii)). The training protocol for acquiring the BCI calibration data was cue-based and involved 40 trials (20 per hand) in a randomized order, with an initial baseline of 2-seconds, followed by 1-second cue and 4-seconds of the MI task (Figure 1B).

D. Assessment Scales

Besides demographic data (age, sex, schooling years), a set of clinical and non-clinical scales were used, matching the same scales used in current clinical interventions. Specifically, for assessing cognitive disabilities, the Montreal Cognitive Assessment (MoCA) was used [24], and the Beck inventory [25] for assessing depression. Moreover, MI ability was assessed through the kinesthetic and visual-motor imagery

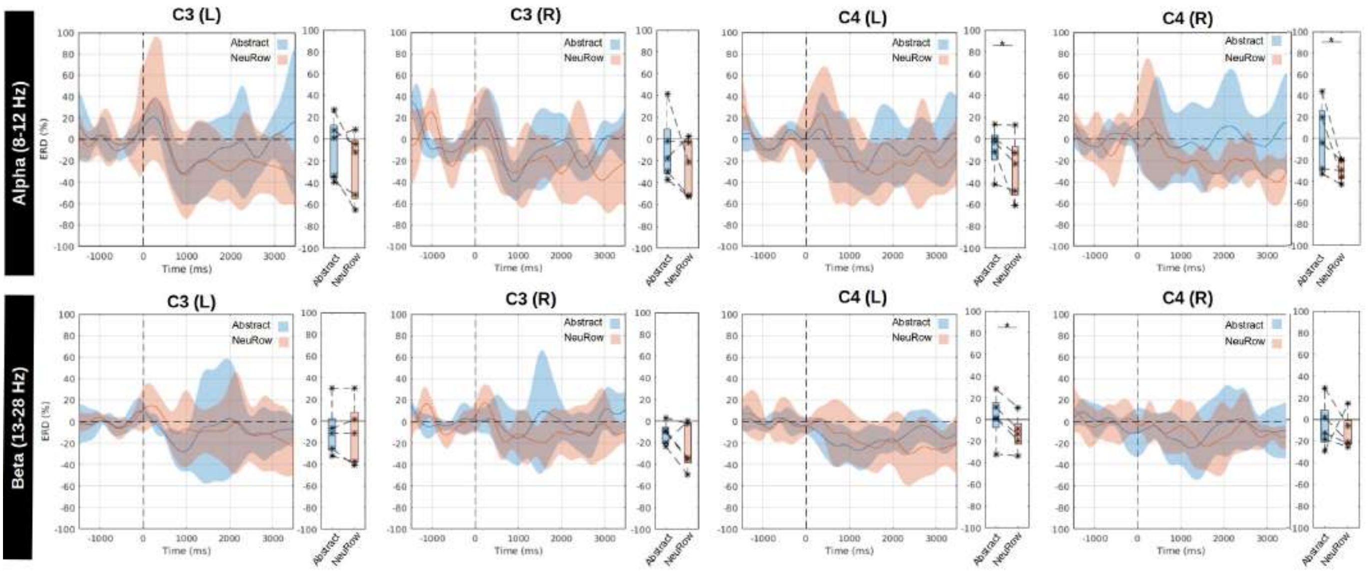

Fig. 2. Group results of the ERD over C3,C4 electrodes, (L)eft and (R)ight MI trials, from Alpha (top) and Beta (bottom) bands. Left sub-figure: ERD over time and standard deviation for *Abstract* (blue shade), and *NeuRow* (red shade) conditions. Right sub-figure: the average ERD of each subject. *indicates significant differences ($p<0.05$).

questionnaire (KVMIQ) [26]. Finally, although the sample was consisted by healthy participants, the clinical scales were used to serve as a baseline when compared to patients.

E. EEG Analysis

For the post-hoc analysis, EEG signals were processed using MATLAB R2016b (The MathWorks, MA, United States) and the EEGLAB toolbox v2020.0 [27].

1) Pre-processing: All signals were initially down-sampled to 128Hz to reduce the data size and remove unnecessary information above the Nyquist frequency, followed by band-pass filtering between 1-40 Hz. For rejecting artifacts and bad channels, we applied the offline version of the Artifact Subspace Reconstruction (ASR) method [28]. Further, after interpolating any missing channels, we re-referenced the data to common average and epoched the data between left and right MI trials. Moreover, we performed an Independent Component Analysis (ICA) [29] for removing all unwanted components from the signal. For this, we employed also IClabel [30], an automated method that is using a trained classifier for EEG independent components. In our pipeline, we followed a conservative approach, by removing only "Muscle" and "Eye" components with a confidence level of greater or equal to 90% probability.

2) ERD power: The event-related spectral perturbation (ERSP) was calculated over the epoched data as a time/frequency representation of the event-related synchronization/desynchronization (ERS/ERD) across the Alpha (8–12Hz) and Beta ($13-28Hz$) bands. ERSP acts as a generalization of the ERS/ERD [31], hence, we computed also the ERD as a percentage of the drop of power relative to baseline according to Pfurtscheller et al. [32]. Here, we focus on the analysis of the C3 and C4 electrodes, since they are located over the sensorimotor cortices and are the ones who show characteristic patterns of Alpha and Beta ERD during MI [33]. Finally, we extracted the Median ERD value between 1000ms (after the cue) and 4000ms (end of trial) for building an ERD distribution per condition for further statistical analysis (Figure 1).

3) Lateralization Index: Lateralization between hemispheres is generally assessed by a lateralization index (LI), and it is commonly used to quantify the asymmetry of neural activation intensity in brain imaging studies. In this study, LI was computed with ERD from the C3 and C4 electrodes. Specifically, contralateral electrode to the MI side (C3 for right and C4 for left MI), was subtracted from that at ipsilateral electrodes [34]. Finally, the LI was computed as the average of the right and left side differences. If the LI value is positive, it indicates a more contralateral desynchronization during MI.

F. Offline BCI Performance

For assessing the discriminability of the features per condition, we used the pre-processed data. Since we wanted to exclude any other confounds that could affect the evoked ERD in a feedback loop (e.g. miss classification rate), we only used the training session data. Specifically, we computed 6 Common Spatial Patterns (CSP) filters between the Alpha and Beta bands (8-28 Hz). CSP is a feature extraction method that can create spatial filters able to maximize the discriminability of two classes [35], and it is considered one of the most popular and efficient algorithm for BCI design [36]. Next, we designed a classification pipeline with a monte-carlo cross-validation method using 10 re-shuffling and random splitting iterations for training an LDA classifier. The final classification accuracy (%) was calculated as the average score of the cross-validation.

G. Statistical Tests

Initially, for assessing the normality of the data, we performed a Kolmogorov-Smirnov test. Since data distributions were not normal, but also due to the small sample size, non-parametric tests were used. Specifically, for assessing the ERD differences between the two conditions, the Wilcoxon signed-rank test was employed. Next, we performed Pearson correlations between the questionnaires, the ERD power of C3,C4 electrodes, and LI. For all statistical comparisons, the significance level was set to 5% ($p < 0.05$) and were computed using MATLAB R2016b.

III. Results

Here, we report the EEG results during MI-BCI training between both conditions, and specifically the median ERD power of Alpha ($8 - 12Hz$) and Beta ($13 - 28Hz$) bands, from both left and right MI trials, from the ipsilateral and contralateral electrodes $C3, C4$. Moreover, we report the lateralization of the ERD and the classifier discriminability in terms of LDA performance. Finally, we performed a correlation analysis between the extracted ERD measures and the questionnaire data.

A. Event-Related Desynchronization (ERD)

In terms of Alpha band, we observe differences in ERD during the *NeuRow* condition compared to *Abstract* MI for both left and right trials. Specifically, for contralateral electrodes during right MI, C3 ($Abstract : Mdn = -17.5\%, SD = 31\%; NeuRow : Mdn = -20.9\%, SD = 26\%$) ERD has small changes, but with no statistically significant differences ($Z = 1.2136, p = 0.22$), while for left MI, C4 ($Abstract : Mdn = -2.7\%, SD = 20.3\%; NeuRow : Mdn = -22.4\%, SD = 28.9\%$), NeuRow has significantly lower ERD ($Z = 2.0226, p = 0.04$). Similarly, for ipsilateral electrodes, during left MI, C3 ($Abstract : Mdn = 1.3824\%, SD = 28.1\%; NeuRow : Mdn = -12\%, SD = 31.5\%$), has lower ERD during *NeuRow* but not statistically significant, ($Z = 1.7529, p = 0.0796$). Nonetheless, for right MI over C4 ($Abstract : Mdn = -4.1\%, SD = 32.4\%; NeuRow : Mdn = -29.8\%, SD = 9.9\%$), ERD during *NeuRow* is significantly lower than *Abstract* MI ($Z = 2.0223, p = 0.04$) (Figure 2).

In Beta band, we observe also differences between conditions. For contralateral electrodes during right MI over C3 ($Abstract : Mdn = -10.3\%, SD = 10\%; NeuRow : Mdn = -34.4\%, SD = 22\%$), ERD is lower during *NeuRow* but not significantly different ($Z = 1.4832, p = 0.13$). Moreover, and during left MI over C4 ($Abstract : Mdn = 1.07\%, SD = 22\%; NeuRow : Mdn = -13.7\%, SD = 16.1\%$), ERD is statistically significant lower ERD during *NeuRow* ($Z = 2.0226, p = 0.04$). Further, for ipsilateral electrodes, during right MI over C4 ($Abstract : Mdn = -12.4\%, SD = 22.4\%; NeuRow : Mdn = -20.5\%, SD = 16.4\%$), ERD is lower during the *NeuRow* condition but not significantly ($Z = 0.6742, p = 0.5$). Nonetheless, C3 during left MI is the only case where *Abstract* MI has lower ERD compared to *NeuRow* ($Abstract : Mdn = -11.4\%, SD = 24.2\%; NeuRow : Mdn = -11.2\%, SD = 29.3\%$) although not significant ($Z = 0.4045, p = 0.68$) (Figure 2).

B. ERD Lateralization

In terms of lateralization of ERD, in the Alpha band we observe small differences with almost similar median LI between conditions ($Abstract : Mdn = 1.21, SD = 16.7; NeuRow : Mdn = 1.68, SD = 15.2$), although, we observe a higher lateralization in the *NeuRow* condition in the Beta ERD lateralization ($Abstract : -5.18, SD = 10.6; NeuRow : Mdn = 8.3, SD = 13$) (Figure 3). Nonetheless, the Wilcoxon Signed-Rank test yielded no statistically significant differences for both Alpha ($Z = 1.2136, p = 0.22$), and Beta ($Z = -1.7529, p = 0.08$).

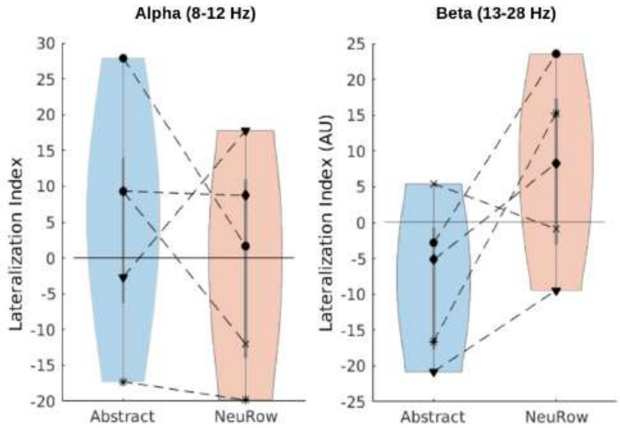

Fig. 3. Distributions across participants of Lateralization Indices for Alpha and Beta ERD, between *Abstract* and *NeuRow* conditions. Positive values indicate increased contralateral ERD.

C. BCI Performance

In terms of BCI performance, we observe an increased LDA classification score in favor of the *NeuRow* condition, meaning that the classifier was able to discriminate better the features from *NeuRow* than the *Abstract* MI ($Abstract : Mdn = 52.5\%, SD = 10.3\%; NeuRow : Mdn = 65\%, SD = 13.6\%$) (Figure 4). Nonetheless, no statistically significant differences were found ($Z = -1.2136, p = 0.22$).

D. Relationship with Questionnaires

The correlation analysis did not yield any significant relationships between the extracted ERD and LI with the demographics or assessment scales. Nonetheless, we can observe from the coefficients in Table I, that *NeuRow* has stronger r than *Abstract* feedback in Age, MoCA and KVMIQ. Moreover, from the r sign, we can observe some interesting trends between ERD and Age but due to the absence of statistical significance and small sample size, we cannot claim an effect.

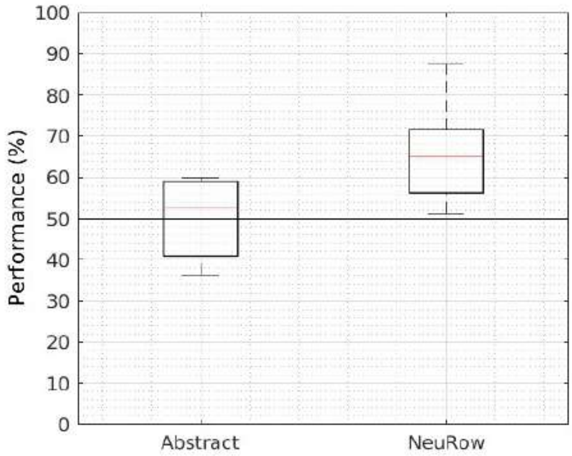

Fig. 4. LDA classifier performance distributions of the mean classification accuracy of all 5 participants in both conditions.

TABLE I
PEARSON CORRELATION COEFFICIENTS (R) OF ERD POWER AND LI WITH PARTICIPANT DEMOGRAPHICS AND CLINICAL SCALES.

		Age	Schooling	Depression	MoCA	KVMIQ
Abstract	**C3 L**	0.67	-0.63	0.09	-0.49	-0.55
	C4 L	0.42	0.13	0.44	-0.81	-0.55
	C3 R	0.15	-0.54	-0.38	-0.11	0.02
	C4 R	-0.02	0.10	-0.17	-0.18	0.18
	LI	0.37	-0.46	-0.16	0.19	-0.01
NeuRow	**C3 L**	0.54	-0.13	0.33	-0.76	-0.57
	C4 L	0.52	-0.55	0.12	-0.52	-0.57
	C3 R	0.73	-0.47	0.33	-0.69	-0.74
	C4 R	0.64	-0.47	0.09	-0.47	-0.43
	LI	-0.24	0.64	0.03	-0.06	0.35

IV. DISCUSSION

Current findings from this pilot study help gather additional information concerning the impact of embodied VR in MI-BCI training, not only in terms of BCI performance, but also through the evoked ERD. Specifically, we illustrate the ability of older adults to modulate their sensorimotor rhythms during MI-BCI training in both *Abstract* and *NeuRow* conditions.

Concretely, we can observe increased ERD in amplitude as well as duration to be sustained during *NeuRow* in relation to *Abstract* feedback. This is suggesting that by rendering the movement of a virtual avatar across the MI trial, we can help the user to produce stronger ERD through MI and action observation, that could lead also to a faster learning for better BCI control. This is of high importance in restorative-BCI's since prior research has shown that sensorimotor desynchronization in response to action observation can activate also areas of the Mirror Neuron System (MNS) [37], [38]. This has led to the notion of an "extended MNS" including, among others, the sensorimotor areas [39], thus, providing an alternative or additional source of motor training that may be useful to promote recovery after stroke. [40].

In terms of the lateralization of Beta activity, we observe an increased effect from the embodied feedback condition with increased LI. Specifically, prior research has shown that Beta lateralization is less strong for imagination compared to motor execution [41], while there is lateralized modulation of Beta power in sensorimotor areas during action observation [42]. This is an interesting finding, showing the importance of observation during MI, and that embodied feedback could provide a more ecologically valid training, given that it can provide similar sensorimotor activation as in motor execution.

Overall, our results illustrate the potential of embodied VR feedback in MI-BCI training as a way to evoke similar brain activation patterns as in actual movement [17], involving potentially overlapping sensorimotor areas. This is of high importance in the rehabilitation domain, given that the primary goal is the activation of sensorimotor areas, including the MNS, for inducing neuroplastic changes.

V. CONCLUSIONS

Overall, in this pilot we found that MI training through *NeuRow* can provide lower ERD compared to *Abstract* feedback, and more lateralized in terms of Beta power. Ultimately, *NeuRow* provided more discriminative features, yielding better classification outcome in terms of the LDA score. Finally, no significant correlations were found, although they need to be interpreted with caution since the current test can lead to false positive errors. In the future, we are planning to increase the sample size and perform a multiple regression analysis for avoiding Type I errors.

Current results, although with limited sample size, contribute to gather further evidence concerning the impact of embodied feedback in the desynchronization of sensorimotor rhythms during MI-BCI in VR. Specifically, given the age-related differences of electrophysiological responses, this paper extends prior research by including elderly adults, and provides more ecologically-valid data, closer to the demographics of stroke survivors. This is quite relevant for the future development of restorative BCI systems, given the impact that embodied VR could have in re-training the lost functions in chronic stroke patients.

VI. ACKNOWLEDGEMENTS

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