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Feasibility of Immersive Virtual Reality Feedback for Enhancing Learning in Brain-Computer Interface Control of Ambulation

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***Abstract*—After prolonged paralysis, paraplegic spinal cord injury (SCI) patients typically lose the ability to generate the expected electroencephalogram (EEG) α/β modulation associated with leg movements. Brain computer interface (BCI)-controlled ambulation devices have emerged as a way to restore brain-controlled walking, but this loss of EEG signal modulation may impede the ability to operate such systems and prolonged training may be necessary to restore this physiologic phenomenon. To address this issue, this study explores the use of immersive virtual reality (VR) in providing more convincing feedback to enhance learning within a BCI training paradigm. Here, an EEG-based BCI-controlled walking simulator with an environment composed of 10 designated stop zones along a linear course was used to test this concept. Able-bodied subjects were tasked with using idling or kinesthetic motor imagery (KMI) of gait to control an avatar to either dwell at each designated stop for 5 s or advance along the course respectively. Subject performance was measured using a composite score per run and learning rate across runs. Composite scores were calculated as the geometric mean of two subscores: a stop score (reflecting the number of successful stops), and a time score (reflecting how fast the course was completed). The learning rate was calculated as the slope of the composite scores across all runs. A random walk procedure was performed to determine the statistical likelihood that each BCI run was purposeful ($p \leq 0.001$). Three able-bodied subjects were recruited (2 in immersive VR group and 1 in non-immersive VR group), and operated the simulator for up to 4 separate visits. The immersive VR group achieved an average composite score of 60.4% ± 12.9, while the non-VR group had an average composite score of 79.0% ± 12.2. The learning rate was 1.07%/run and 0.42%/run for the immersive and non-immersive VR groups, respectively. Purposeful control was attained in a higher proportion of runs for the immersive VR group than in the non-immersive VR group. Although limited by small sample size, this study demonstrates a conceptual framework of implementing immersive VR feedback using more convincing sensory feedback to aid training with BCI devices. Future work will test this protocol in SCI patients and with larger sample size.**

***Index Terms*—Brain Computer Interface, Virtual Reality, Ambulation, Rehabilitation, Spinal Cord Injury**

I. Introduction

Paraplegic or severely paraparetic individuals with spinal cord injury (SCI) are unable to walk due to disruption of communication between the brain and the lower extremities. With no current biomedical solution, technologies such as robotic exoskeletons have been used to restore ambulation in these individuals. However, these devices do not enable the brain-control of walking required in simulating able-bodied function. Brain computer interface (BCI)-controlled lower extremity prostheses are one such emerging method of enabling brain-control of walking after SCI [1], [2]. However, after long periods of lower extremity disuse in SCI patients, the brain no longer readily generates the electroencephalogram (EEG) α/β band modulations typically seen during leg movements [3], which are necessary for BCI control. Extended periods of motor imagery or attempted movement practice are needed to restore the expected EEG signal modulation [3]. It has been shown that BCI training in non-immersive virtual reality (VR) can be used to aid individuals with SCI in this process, but without aid this process may take up to several weeks [4]. This is especially problematic in cases where patients have limited time to work with BCI systems, such as the case of implanted electrodes. It is hypothesized that headset-driven immersive VR systems (e.g., Oculus Rift, Meta Quest, HTC VIVE, Valve Index, etc.) could facilitate faster learning due to their more convincing feedback mechanisms. This study sought to provide a conceptual framework for exploring whether enhanced feedback via a headset driven immersive VR system could facilitate faster acquisition of BCI control.

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II. Methods

This study aimed to propose a training paradigm using immersive VR feedback (i.e., VR headset) to improve the rate of learning in BCI operation compared to non-immersive VR feedback (i.e., standard monitor display). Subjects were randomly assigned to operate an EEG based BCI controlled walking simulator with either a VR headset or a standard monitor. Their performance scores were measured and used to compare differences in learning rates in these two conditions.

A. BCI System Description

The BCI hardware used an architecture similar to [5]. Briefly, the system consisted of 2 microcontrollers connected to supporting circuits and an amplifier array integrated circuit (IC) (Intan Technologies, Santa Monica, CA) to acquire, digitize, and decode EEG signals. This system was implemented as an embedded system on a custom printed circuit board. During operation, the BCI system was connected to an extended 10-20 64 channel EEG cap. To facilitate BCI operation, training EEG data was first acquired. Able-bodied subjects (age $\geq$18 years) without prior neurological injury, VR, or BCI experience were recruited. Subjects underwent EEG cap placement and electrode gel was placed into the following electrodes: CZ, C1, C2, C3, C4, and AFz. Impedances between each electrode and the AFz reference electrode were reduced to $\leq$10kΩ. Subjects followed alternating 10-s cues of idling and kinesthetic motor imagery (KMI) of walking over a total of 480 s while EEG was acquired (common average reference, 200 Hz).

Training data was analyzed offline to generate an EEG decoding model by using of classwise principal component analysis [6] and linear discriminant analysis for dimensionality reduction and feature extraction, as described in [5]. Bayes rule was used to calculate the posterior probability of "walk" state, $P(M|f)$, given feature f. The offline accuracy of the decoding model was estimated using 10-fold cross validation.

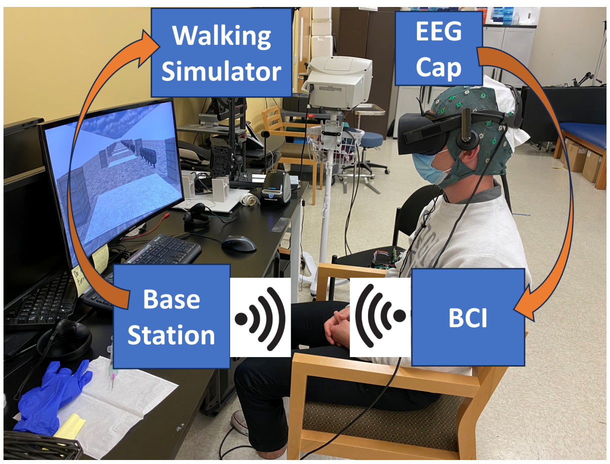

Fig. 1. Schematic of the VR-BCI system.

In the online mode, novel EEG signals were acquired in 250-ms windows. The spectral powers in three consecutive windows were averaged and fed to the decoding model to obtain the posterior probability of the "walk" state, $\bar{P}(M|f)$, from the 750-ms sliding window. A state machine governed the BCI transitions between the idle and walk states, as dictated by transition thresholds T_I and T_W. More specifically, when $\bar{P}(M|f) \leq T_I$, the BCI was in the idle state; $\bar{P}(M|f) \geq T_W$, the BCI was in the walk mode; $T_I < \bar{P}(M|f) < T_W$, the BCI defaulted to the previous state.

To set T_I, T_W, the subject was asked to alternate between idling and walking KMI for $\sim$30 s each while recording the $\bar{P}(M|f)$ values. Thresholds T_I and T_W were empirically set to maximize the separation between the walk and idle states.

In the online operation of the system, subjects were asked to utilize idling and walking KMI to control an avatar in the walking simulator. The walking simulator was developed within the virtual reality game Half-Life: Alyx (Valve Corporation, Bellevue, WA) using the Valve Hammer Editor, and executed on a desktop base station computer. When the BCI decoded the walk state, the system transmited a command over WiFi to the base station. The base station software in turn passed a command to the walking simulator to advance the avatar forward ($\sim$ 75 in-game units [IGU]/s). During the idle state,

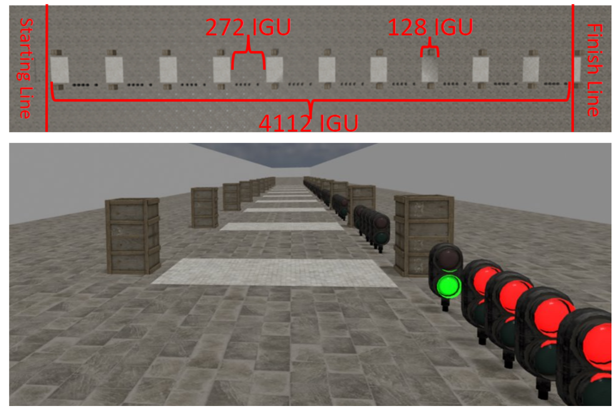

Fig. 2. Top: Overhead view of VR course. Bottom: Walking simulator as seen by subjects. Light colored patches: designated stops. IGU: In-game unit.

the signal held the avatar still. Communication between the base station software and the walking simulator was facilitated by OpenVR-InputEmulator Mod [7] which converted virtual keyboard commands to VR controller commands.

The objective of the walking simulator was to progress forward along a linear path and stop in each of 10 designated stop zones for 5 seconds before proceeding to the next stop zone. The total length of the linear course was 4112 IGU with 272 IGU between each zone. Each stopping zone was 128 IGU long, as shown in Fig. 2. If the walking task is performed without error, the entire course can be traversed in 104.8s. 5 traffic lights were placed in each stop zone to visually cue when to switch to "walk" state again. Subjects were given a maximum of 900s to complete the course before the trial was stopped. The walking simulator environment was displayed to the subject either with immersive VR via an Oculus Rift VR headset or a non-immersive standard 29-inch monitor display.

B. Comparison of immersive vs non-immersive BCI feedback

Each subject was invited to train and operate the BCI for up to 4 separate visits. Each visit involved the subject undergoing EEG placement, training data acquisition, and operation of the BCI-controlled walking simulator. At each visit, up to 3 offline training sessions were attempted to reach an offline decoder accuracy $\geq$ 70%. If the subject could not achieve this decoder accuracy within 3 attempts, the decoding model with the highest accuracy was used. Subjects then operated the BCI-controlled walking simulator for at least 5 runs while their performances were recorded and assessed as below.

The avatar's positional data within the walking simulator throughout each run was exported and analyzed to generate a composite performance score, similar to that in prior work [8], [4]. Briefly, the composite score comprises of two subscores, a stop score, c_s, and a time score, c_t:

$$c = \sqrt{c_s c_t}$$
$$c_s = \frac{\sum_{i=1}^{10} s_i}{10 \cdot s_{max}}$$
$$c_t = \frac{t_{max} - t}{t_{max} - t_{ideal}}$$

where s_i is the dwell time in the i^{th} stop zone (s_i is capped at 5 s), s_{max} is 5 s, t_{max} is the maximum allowed trial time of 900 s, t is the subject's time to completion, and t_{ideal} is

TABLE I
SUBJECT DEMOGRAPHICS AND BCI PERFORMANCE. SJ: SUBJECT; CS: COMPOSITE SCORE; RW: RANDOM WALK; NIM/IM: (NON)-IMMERSIVE VR

Sj. #	*Age/Sex*	*Group*	*Visit (Runs/visit)*	*Decoding Accuracy*	*T_I Range*	*T_W Range*	*Avg. CS (%)*	*RW Avg. CS (%)*	*% Purposeful*
1	25/M	IM	1 (6)	59.8%	0.15-0.5	0.3-0.65	41.1 $\pm$ 14.3	43.7 $\pm$ 15.5	0.33
			2 (6)	66.9%	0.001	0.0025-0.003	61.8 $\pm$ 6.8	30.1 $\pm$ 0.0	1
			3 (3)	74.4%	0.0015-0.002	0.002-0.003	56.9 $\pm$ 1.3	30.1 $\pm$ 0.0	1
			4 (8)	64.8%	0.009 - 0.01	0.012-0.013	65.3 $\pm$ 9.2	30.1 $\pm$ 0.0	1
2	20/M	NIM	1 (5)	62.7%	0.4	0.5	71.6 $\pm$ 8.2	50.2 $\pm$ 9.2	0.2
			2 (5)	63.4%	0.4	0.45	79.5 $\pm$ 11.5	47.9 $\pm$ 8.6	0.6
			3 (5)	67.5%	0.32	0.35	83.9 $\pm$ 7.6	38.9 $\pm$ 6.4	1
			4 (5)	69.8%	0.45	0.55	79.0 $\pm$ 12.2	56.5 $\pm$ 9.4	0.4
3	25/M	IM	1 (3)	49.4%	0.08	0.12	49.9 $\pm$ 21.9	30.3 $\pm$ 0.7	0.8
			2 (5)	57.9%	0.70	0.83	47.6 $\pm$ 22.9	0.3 $\pm$ 1.2	0.8
			3 (5)	58.0%	0.55	0.57	52.5 $\pm$ 14.9	65.7 $\pm$ 8.5	0

the theoretically ideal minimum time required to achieve the maximum stop score. Here, t_{ideal} is 104.8 s, which is the time taken to complete the course without error.

A linear regression was performed on the composite score across all runs, and the slope was used to estimate the learning rate. A random walk procedure was performed as in [4] to determine the statistical likelihood that each BCI run was purposeful. Briefly, for each run performed by a subject, 10,000 random walks were simulated within the walking simulator using the same T_I and T_W as the subject. The resultant composite scores were compared to that of the subject's for that run to determine the empirical *p*-value. A purposeful run was defined as one with an empirical $p \leq 0.001$.

III. RESULTS

The study was approved by the University of California, Irvine Institutional Review Board. Three able-bodied subjects provided their informed consent to participate in this study.

The BCI hardware and walking simulator were both successfully implemented as described above. Three able-bodied subjects provided their informed consent to participate in the study. Subjects 1 and 3 were randomized to immersive VR feedback, and subject 2 was randomized to the non-immersive standard monitor feedback. Subjects operated the BCI-walking simulator over three to four separate visits. Their demographics and performances are summarized in Table 1. Each subject successfully completed the walking simulator course at least 5 times during each visit with the exception of the subject 1's third visit which only had 3 runs.

The composite score across all runs was calculated for both groups and summarized in Fig. 3. The immersive VR feedback group demonstrated a composite score improvement rate of 1.07%/run, compared to 0.42%/run for the non-immersive feedback group. Average performance on first visit for the immersive VR feedback group was 44.020% $\pm$ 16.350, and 71.571% $\pm$ 8.195 for the non-immersive feedback group. Average performance on final visit was 60.372% $\pm$ 12.867, and 79.009% $\pm$ 12.158 for the non-immersive feedback group. The proportion of purposeful runs during each day is reported in Table I. Note that the composite scores achieved by the random walk is predominantly driven by the T_I and T_W.

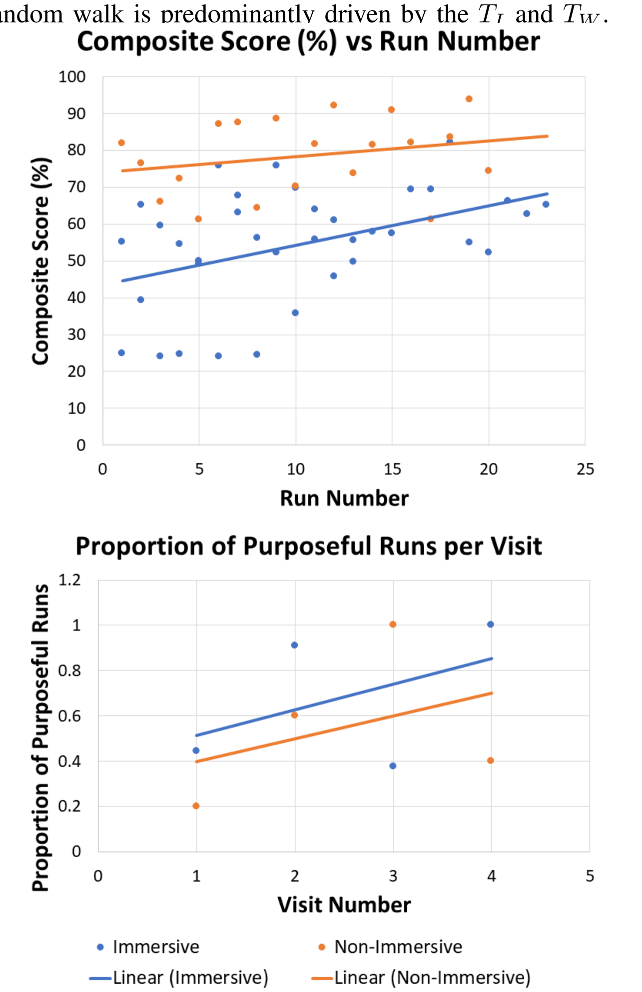

Fig. 3. Top: Composite score across run number. Bottom: Proportion of purposeful runs across visits.

IV. DISCUSSION

In this study, we successfully designed and implemented a BCI-controlled walking simulator with both immersive and non-immersive VR feedback. Able bodied subjects were able to operate the BCI-controlled walking simulator and demonstrate improvement in performance over time. For the immersive VR system, the subjects' overall composite score improvement rate (1.04%/run) was approximately double that of the non-immersive VR group (0.42%/run). Purposeful control was immediately established at a higher rate at the first visit for the immersive VR group, and remained consistently higher (Fig. 3). This provides preliminary proof-of-concept that immersive VR feedback may facilitate more rapid acquisition of purposeful BCI control through enhanced learning.

Despite the initial findings, it is important to note that subjects in the immersive VR group started at a lower composite score than the non-immersive VR group, which may indicate some potential pitfalls with immersive VR feedback. For example, users with little to no prior exposure to immersive VR may find it initially overstimulating and distracting. Additionally, the VR headset straps often run directly over the EEG cap electrodes, potentially causing motion artifact. These issues may have contributed to a lower initial composite score. Additionally, subjects who are more readily able to generate KMI may also start with higher composite scores leaving less capacity for improvement as seen with subject 2 in the NIM group. However, given that learning rate and purposeful control remained higher, immersive VR feedback may still ultimately lead to faster and more robust acquisition of BCI control. The first issue may be rectified in the future by exposing subjects to immersive VR in an alternative context prior to BCI training. The second issue may require VR headset straps to be redesigned to minimize interference with electrodes, or electrodes to be integrated into the headset itself, such as recently shown in [9].

The major limitation of this study was the use of able-bodied subjects and a small sample size. Since it is unclear if similar results can be generalized to the target population, this study will need to be repeated in a cohort of paraplegic SCI patients and with a larger sample size. It is hypothesized that SCI subjects would use different mental strategies for controlling BCI systems, in particular they could perform attempted ambulation rather than walking KMI.

If similar findings hold in an SCI cohort with a larger sample size and if BCI-based gait therapies prove effective in the future, then an improved rate of learning from immersive VR feedback may have significant implications. Immersive VR feedback could allow SCI patients to achieve control of BCI-driven systems for ambulation or gait therapy faster and more robustly. Faster acquisition of BCI control would translate to more time engaging in BCI-mediated gait rehabilitation, potentially leading to improved patient outcomes. This may improve their experience and lead to more significant and/or faster gains of function. Alternatively, this may lead to more rapid achievement in proficiency in operating BCI-controlled lower extremity prostheses for individuals whose severity of injury limit rehabilitative potential. Lastly, faster acquisition of BCI control would also reduce the financial cost associated with future BCI-mediated therapies for SCI gait rehabilitation.

To the best of our knowledge, other studies have not examined whether the use of immersive VR affects the rate of learning for the purposes of controlling a BCI-based prosthesis. Other studies have examined similar themes, such as the efficacy of immersive VR as a rehabilitation aid (without BCI) [10]. Studies such as [11] used immersive VR-BCI systems directly as tools for upper extremity rehabilitation, rather than as a training modality for BCI controlled prostheses. Other studies, such as [12] developed immersive VR-BCI systems for gaming purposes rather than simulation efforts. Finally, some investigations such as [13] compared subjects' ability to control BCI systems while using immersive VR and non-immersive VR, but did not examine the longitudinal learning rate for BCI operation over the course of days.

In conclusion, this feasibility study provides a conceptual framework for exploring whether immersive VR feedback improves the rate at which subjects learn to control a BCI system for gait rehabilitation. If BCI-mediated gait therapies prove effective for SCI rehabilitation in the future, immersive VR feedback may enhance learning, leading to better outcomes and more economical implementation of BCI-based therapies.

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