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

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***Abstract*—After prolonged paralysis and disuse of the lower extremities, patients with paraplegia due to spinal cord injury (SCI) typically lose the ability to generate the proper electroencephalogram (EEG) α and β modulation associated with leg movements. With the emergence of brain computer interface (BCI)-controlled ambulation devices to restore brain-controlled walking in this population, the loss of these EEG signal modulation may impeded the ability to operate such systems, and evidence suggests that a prolonged period of training may be necessary to restore this physiological phenomenon. To address this issue, this study explored whether immersive Virtual Reality (VR)-feedback can facilitate faster acquisition of the EEG signal modulation necessary to control BCI systems for walking, due to the more convincing sensory feedback. Here, we designed an EEG-based BCI-controlled walking simulator to test this concept. The walking simulator is composed of 10 designated stop zones along a linear course. Able-bodied subjects were tasked with using idling or kinesthetic motor imagery (KMI) of gait to control an avatar to advance along the course, dwell at each designated stop for 5 s. The subjects performance was measured by a composite score was generated by two subscores. A stop score is generated according to the number of correct stop within designated zones. A time score was calculated to account for any extra time taken by the user. The geometric mean of these two scores was used to calculate the composite score. Three able-bodied subjects were recruited to operate the BCI-walking simulator. Two were assigned to the immersive VR group and one to the non-immersive VR group. Subjects operated the BCI-walking simulator for up to 4 separate sessions. The immersive VR group achieved an average of 60.4% $\pm$ 12.9 composite score by their last session, while the non-VR group had an average composite score of 79.0% $\pm$ 12.2. Overall, the immersive VR feedback group achieved a learning rate of 1.07% per run whereas the non-immersive VR feedback group achieved an improvement of 0.42% per run. This provides early evidence that immersive VR feedback may hasten the rate at which subjects can achieve BCI-control. However, this study was conducted with only three able-bodied subjects and therefore future work will focus on determining of similar outcomes are seen in a larger cohort of SCI subjects with paraplegia.**

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

I. Introduction

Paraplegic or severely paraparetic individuals due to 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, technology such as robotic exoskeletons have been used to restore ambulation in these individuals. However, these devices do not enable brain-control of walking and hence do not mimic the much sought after able-bodied function. Brain computer interface (BCI) controlled lower extremity prostheses is one emerging method to enable 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 and β band modulations typically seen during leg movements [3], [4], which are necessary for BCI control. This requires extended periods of of motor imagery or attempted movement practice to restore the EEG signal modulation associated with attempted movements [5]. It has been shown that BCI training in non-immersive virtual reality (VR) can be used to aid subjects with SCI in this process, but without aid this process may take up to weeks [6]. This is especially problematic in cases where patients have limited time to work with BCI systems, such as when they have implanted electrodes. It is hypothesized that headset-driven immersive VR systems (e.g., Oculus Rift, Meta Quest, HTC VIVE, Valve Index, etc.) can facilitate faster learning due to their more convincing feedback mechanisms. This study seeks to provide an early assessment whether BCI feedback via a headset driven immersive VR system can facilitate faster acquisition of BCI control compared to feedback from existing non-immersive monitor displays.

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II. Methods

A. Overview

This study aims to investigate whether immersive VR feedback (i.e., VR headset) improves the rate of learning in BCI operation compared to that of non-immersive VR feedback (i.e., standard monitor display). Subjects were asked to play a EEG based BCI controlled walking simulator with either a VR Headset or a standard monitor. Their performance scores were measured and used to establish if there were any differences in the learning rates in these two conditions.

B. BCI System Description

The BCI hardware utilizes an architecture similar to that which was described in [4]. Briefly, the system consists of

2 microcontroller cores 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 is connected to an extended 10-20 64 channel EEG cap. To facilitate BCI operation, training EEG data is first acquired prior to operation. Able-bodied subjects (age $\geq$18 years) with no prior neurological injuries and no prior BCI experience were recruited for this study. 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 were asked to follow alternating 10-s cues of idling and kinesthetic motor imagery (KMI) of walking over a total of 480 s while their EEG was acquired (common average reference) at 200 Hz.

The training data was analyzed offline to generate an EEG decoding model using a combination of classwise principal component analysis [7] and linear discriminant analysis (LDA) as described in [4]. The offline accuracy of the decoding model was estimated using 10-fold cross validation.

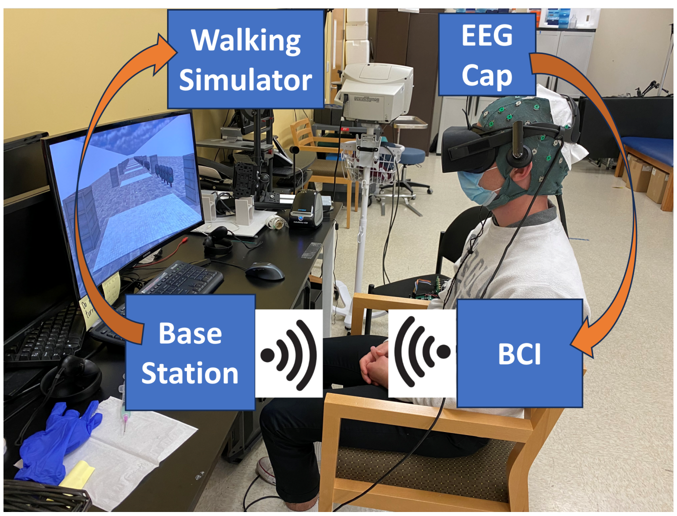


Fig. 1. Schematic of the VR-BCI system.

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 is in the idle state; $\bar{P}(M|f) \geq T_W$, the BCI is in the walk mode; $T_I < \bar{P}(M|f) < T_W$, the BCI defaults to the previous state.

To set (T_I, T_W) the subject was asked to alternate between idling and walking KMI for $\sim$30 seconds each while recording their $\bar{P}(M|f)$ value. Thresholds (T_I, T_W) were set empirically by the operator 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 using the Valve Hammer Editor within the virtual reality game Half-Life: Alyx (Valve Corporation, Bellevue, WA), and executed on a desktop base station computer designated as the base station. When the BCI decodes the walk state, the BCI system transmit a command over WiFi to the base station. The base station software in turn passes a command to the walking simulator to advance the avatar forward ($\sim$ 75 in-game units [IGU]/s). During the idle state, it will hold the avatar still. Communication between the base station software and the walking simulator was facilitated by OpenVR-InputEmulator Mod [8] which converts virtual keyboard commands to VR controller commands.

The objective of the walking simulator is 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 is 4112 IGU with 272 IGU between each zone. Each stopping zone is 128 IGU long, as shown in Fig. 2. If the walking task was performed without any error, the entire course can be traversed in 104.8s. Five lights were placed in each stop zone to visually cue a subject on when to switch to "walk" state again. Subjects are given a maximum of 900 s to complete the course before the trial is ended by the experimenter. The walking simulator environment was displayed to the subject with either immersive VR mode via an Oculus Rift VR headset or non-immersively via a standard 29-inch curved monitor display.

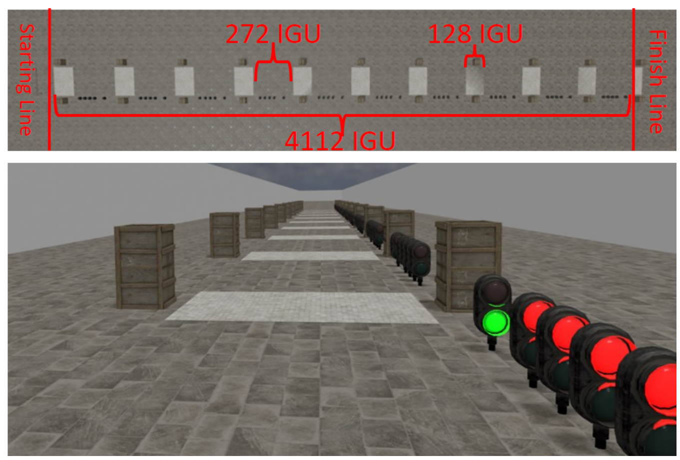


Fig. 2. Top: Overhead view of VR course. Bottom: image of walking simulator as seen by participant. Light colored patches represent designated stops. IGU: In-game unit.

C. Performance assessment of immersive VR vs non-immersive VR

Each subject was invited to train and operate the BCI for up to four separate visits. At each visit the subject would undergo EEG placement, training data acquisition, and operate the BCI-controlled walking simulator. At each visit, up to 3 offline training attempts 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 would be used. Subsequently, subject 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 [9], [6]. Briefly, the composite score comprises 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 900 s, t is the subject's time to completion, and t_{ideal} is 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 any errors.

A linear regression was performed on the composite score across all runs, and the slope was used to estimate the learning rate.

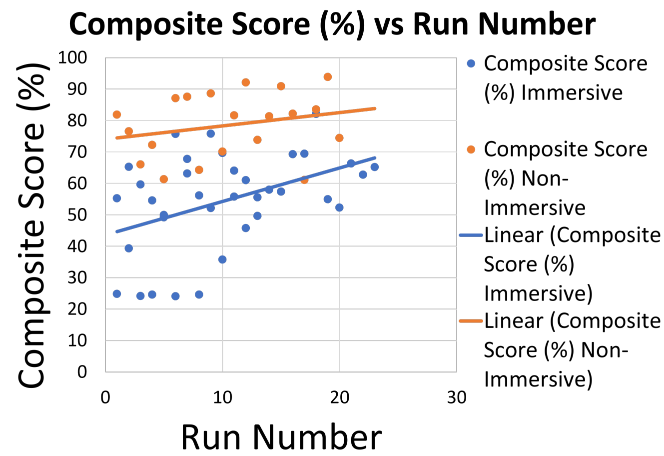
A random walk procedure was performed as in [6] to determine the statistical likelihood that each BCI run was purposeful. Briefly, for each run performed by a subject, 10,000 random walks were simulated within the walking simulator using the same T_I and T_W as the subject did. The resultant composite 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 designed and implemented as described above. Three able-bodied subjects provided their informed consent to participate in the study. Subject 1 and 3 were randomized to immersive VR feedback, and subject 2 was randomized to the non-immersive standard monitor display feedback. Both subjects operated the BCI-walking simulator over four separate visits. Their demographics and performances are summarized in Table 1. Each subject successfully completed the walking simulator course at least five times during each visit with the exception of the VR subject's third visit which only had 3 successful completions of the course.

The composite score across all runs was calculated for both groups and is summarized in Fig. 3. The Immersive VR feedback group demonstrated an composite score improvement rate of 1.07%/run, whereas this was 0.42%/run for the non-immersive feedback group. The 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. The 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 acheived by the random walk is predominantly driven by the T_I and T_W.



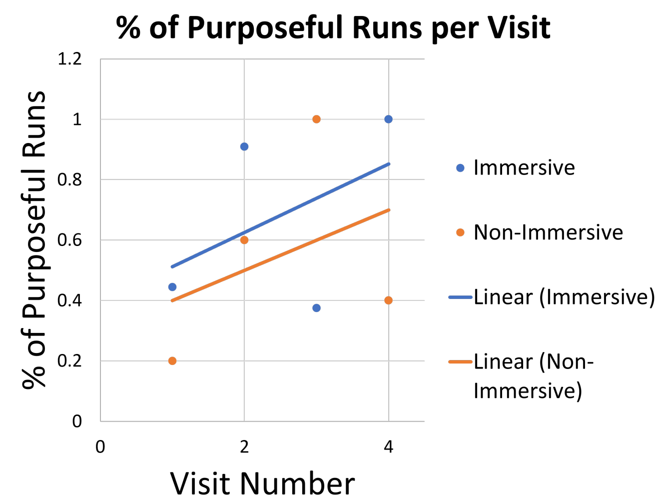


Fig. 3. Composite score all subjects divided by group distributed across run number.

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 demonstrated improvement in their composite score over time. For the immersive VR system, the subjects' overall composite score improvement rate (1.04%/run) was much higher than 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 and higher BCI learning rates.

Despite the initial findings, it is important to note that subjects in the immersive VR group started at a lower composite rate than the non-immersive VR group, and this may indicate some potential pitfalls with immersive VR feedback. For example, users with little to no prior exposure to immersive VR may find it is initially overstimulating and distracting.

TABLE I

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

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

Additionally, the VR headset straps often run directly over the electrodes of the EEG cap, potentially causing a motion artifact. These issues may have contributed to a lower initial composite score. However, the higher leaning rate, immersive VR feedback may ultimately still lead to faster and more robust acquisition of BCI control. The above problems may be rectified in the future by exposing subjects to immersive VR in an alternative context before beginning BCI training. Also, the VR headset straps may need to be redesigned to minimize interference with electrodes, or electrodes can be integrated into the headest itself, such as recently shown in [10].

The major limitation of this early study was carried out with able-bodied subjects and a small sample size. This study will need to be repeated in a cohort of SCI patients with paraplegia, as it unclear if similar results will be observed. In particular, it is expected that the SCI subjects with paraplegia will use a different mental strategy to control the BCI. Namely, we expect that they can perform attempted ambulation rather than walking KMI (as with able-bodied subjects).

If similar findings hold in an SCI cohort and if BCI-based gait therapies prove effective in the future, then the increased learning speed from immersive VR feedback may have significant implications. For example, it could allow SCI patients to initiate use of BCI-controlled systems for ambulation or gait therapy faster and more robustly. Specifically, faster acquisition of BCI control will translate to more time engaging in BCI-mediated gait rehabilitation, potentially leading to improved patient outcomes. This in turn may improve their experience and lead to more significant and/or faster gains of function. Alternatively, this may lead to more rapid ability to initiate use of a BCI-controlled lower extremity prostheses for individuals whose injuries are so severe that there is no rehabilitative potential. Finally, faster acquisition of BCI control will 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 immersive VR-BCI systems affect the rate of BCI 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) [11]. Studies such as [12] used immersive VR-BCI systems directly as tools for rehabilitation of upper extremities, rather than as a training mechanism for BCI control of prostheses. Other studies, such as [13] developed immersive VR-BCI systems, but only for gaming purposes. Finally, some investigations such as [14] have 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.

In conclusion, this study provides early evidence that immersive VR feedback can greatly increase the rate at which patients can learn to control a BCI system for SCI rehabilitation purposes. If BCI-mediated gait therapies prove effective for SCI in the future, immersive-VR feedback may help facilitate faster initiation. This may in turn lead to better outcomes and more economical implementation of BCI-based therapies for gait after SCI.

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