Title
A comparison study of motor-imagery-based brain-computer interfaces with allocentric and egocentric visual feedback in virtual reality

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A comparison study of motor-imagery-based brain-computer interfaces with allocentric and egocentric visual feedback in virtual reality

A thesis submitted in partial satisfaction of the requirements for the degree Master of Science

in

Bioengineering

by

Dylan Lee Davis

Committee in charge:

Professor Tzyy-Ping Jung, Chair
Professor Gert Cauwenberghs, Co-Chair
Professor Chung-Kuan Cheng

2022

The thesis of Dylan Lee Davis is approved, and it is acceptable in quality and form for publication on microfilm and electronically.

University of California San Diego

2022

DEDICATION

In recognition for the guidance given by Masaki Nakanishi while formulating and conducting this study, throughout the trying time of gathering subjects in the current environment.

EPIGRAPH

"*I think, and my thoughts cross the barrier into the synapses of the machine — just as the good doctor intended. But what I cannot shake, and what hints at things to come, is that thoughts cross back. In my dreams the sensibility of the machine invades the periphery of my consciousness. Dark. Rigid. Cold. Alien. Evolution is at work here, but just what is evolving remains to be seen*"

— **Commissioner Pravin Lal**, "Man and Machine", *Sid Meier's Alpha Centauri*

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ABSTRACT OF THE THESIS

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by

Dylan Lee Davis

Master of Science in Bioengineering

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Professor Tzyy-Ping Jung, Chair
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Motor Imagery based Brain Computer Interfaces (MI BCI) have been studied as applications for the improving rehabilitation and recovery, as well as augmenting existing function. The feedback in these MI BCI systems is traditionally presented in an egocentric reference frame, with allocentric reference frame stimuli restricted to supplementary stimuli or Mirror Therapy. This study proposes to assess whether the use of an allocentric reference frame for stimulus presentation is comparable to egocentric stimuli, by evaluating both allocentric and egocentric stimuli presented in a dynamic Virtual Reality (VR) environment during the execution of left-handed and right-handed grasping motor imagery. When assessed in terms of inter-rater agreeability and precision, there were comparable results between the allocentric and egocentric reference frame tasks. The Cohen's kappa score of the classified

activity was not significantly different between the two reference frames. Additionally, when the data was trained on the first VR Dynamic trial and evaluated cross-reference frame and session, the precision and Cohen Kappa score increased compared to the 2D calibration derived classifier. The results suggest that Allocentric reference frames can serve as a viable MI BCI framework, outside of mirror therapy, and should be explored further in environments that invoke VR Body Ownership Transference (BOT).

Chapter 1. Introduction

Brain computer interfaces (BCIs) serve as a system of communication between the mind and a target device, for rehabilitation, augmentation, compensation of lost functions, and additionally for new methods of interaction [1], [2]. In clinical conditions, BCIs are used largely to address conditions such as amyotrophic lateral sclerosis (ALS), strokes [3] [4] and Glaucoma [5], but they have also been used to aid patients recovering from stroke and motor impairment [6]. BCI has been used for performance enhancement and as an alternative control device outside of clinical settings

Electroencephalography (EEG) serves as a low cost, non-invasive method of capturing brain activity, with high temporal resolution that can use both evoked and spontaneous designs in indirect and direct applications [7], [8]. Within the multiple control paradigms employed in EEG-based BCIs, motor imagery (MI), in which the imagined movements of a subject are translated to direct commands, has provoked the most interest due to both its science-fiction origins and the potential uses it has across the spectrum of BCI applications [6], [9]–[11]. MI itself relies upon the mirror neuron systems (MNS), which are a distinct class of neurons that discharge during intent centric action and observation of comparable actions, involve in recognizing action intent via generalized components as well as imitation [3], [4], [12]. Subjects using MI paradigms have reported difficulty executing visualization needed to perform MI tasks, which necessitates trial and error via feedback congruent to that of the presented stimuli [13], [14].

Dynamic and object-directed visual feedback within a Virtual Reality (VR) environment has been used to improve the performance of Motor Imagery-based BCI (MI-BCI), as shown in [15]–[18]. As mentioned, the core of MI is the MNS which is also directly connected to the advent of VR and its link to body ownership transference (BOT). VR allows a subject to immerse themselves within a new or modified perspective, embodying a new frame of reference [12], [19]–[23]. These designs use an egocentric reference frame for visual feedback, relaying the visual stimuli within a first person object-self reference system [4], [21], [24]. Allocentric reference frames, which use an object to object referencing system , have been traditionally restricted to mirror-therapy based applications, however the impact of allocentric reference frames within VR environments plays a large role when it comes to navigation and dynamic movement, with recent research focusing on its impact within cognitive and spatially grounded tasks [25]–[29].

While studies have shown that BOT, agency and localization, components associated with the somatosensory illusions such as the rubber hand illusion (RHI) and virtual rubber hand illusion (VRHI) are more effectively elicited in egocentric reference frames [12], [20], [30], the usage of allocentric reference frames and the impact of coupled stimuli have been successfully employed [31]–[33]. These results were improved when considerations for the environmental consistency, avatar embodiment-adaptation, and components of how the illusions were displayed regarding the VR-BCI hardware [27], [34]–[38] .

The strength and dimensionality of the illusion (and its transferred sensations) have a direct impact on the importance of the Allocentric and Egocentric processing regions of the brain [38] , with the latency of the experiences fed to the MNS inversely correlated to the complexity of the signal for goal and intent interpretation [24]. Additionally, existing signals weaken the strength of the illusion, with aspects of proprioception and sensory input definitively reducing the signal responses observed in motion control paradigms versus MI-BCIs. Because of this, any proposed method of teleoperation or avatar embodiment as reliant upon a system that has the greatest complexity of sensory inputs from the illusion, with reduced input from the existing body [23].

These control schema and general investigative aims into the impact of VR in MNS also explore the concept of error monitoring systems within MNS, which affects the recruitment and construction of MNs for intent detection and recognition [12]. The next steps in determining whether allocentric VR embodiment can be equivalent to that of first-person VR embodiment is to determine the levels of immersion required for BOT and the learning rate/capacity for MNS development when these new systems can. In the same manner that both one experiences a dissociation of ownership during changes in temporal delay and in the more explored artificial processes for spatial encoding that occur from immersive VR.

As such, this study proposes that a third-person perspective-controlled avatar in a VR environment could create an artificial sense, in which the state of BOT could be fully expressed. In order to investigate this, and the efficiency of allocentric versus egocentric reference frames as visually dynamic MI-based VR-BCI feedback, an environment in which both a third person and first-person perspective can be viewed across the same task was designed. Subjects performed object-oriented motor imagery while situated in a seated VR environment and observed visual feedback from egocentric and allocentric reference frames.

The results of this study show that there was comparable performance between the implementation of allocentric and egocentric reference frames and justify further investigation of VR MI BCI with supernumeral stimuli..

Chapter 2. Background

2.1 BCI

The general process for a BCI application is outlined in Figure 1, consisting of five components: signal acquisition, preprocessing, feature extraction, classification, and translation. Brain activity is captured via sensor data, which can be obtained via EEG, positron emission tomography, functional magnetic resonance imaging, magnetoencephalography, electrocorticography, or functional near-infrared spectroscopy, which then have preprocessing applied to remove motion artifacts and noise, such as blinking. The signals are then described by features dependent upon the paradigm used for the BCI and classified via machine learning to ultimately be translated to a command within the application [8]. Of the signal acquisition methods, the most widely used modality is EEG, which can employ paradigms for evoked potential and spontaneous paradigms.

A variety of paradigms are used within BCI devices, depending on the nature of the signals, the desired controls and the application, ranging from direct and indirect to evoked and spontaneous potentials. Subjects employing the spontaneous motor imagery paradigms have reported difficulty in execution of the visualization needed to perform MI tasks, and requires trial and error via feedback congruent to that of the stimuli given.

Within BCI specific frequency bands are associated with activity, ranging from awareness to active thinking specifical in delta (.5 to 4 Hz) which is associated with deep sleep,

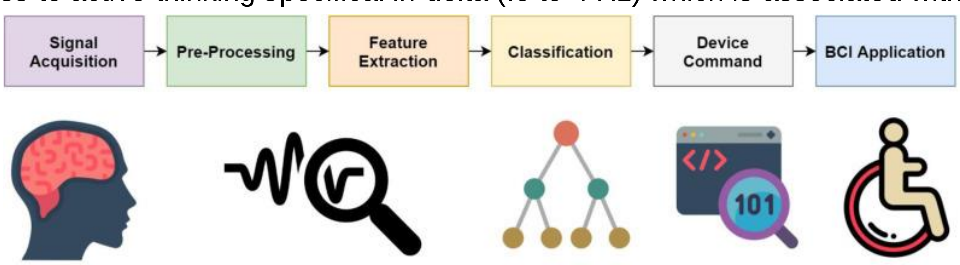

Figure 1 taken from [8], shows the general framework of a BCI

theta (4-8 Hz) for awareness, alpha/mu (8-13 Hz) for relaxation, beta (13-30 Hz for active thinking, and gamma (>30 Hz) for hyperactivity and somatosensory activity [8]

2.2 Mirror Neuron System

The mirror neuron systems (MNS) are composed of a distinct class of neurons that discharge during intent centric action and observation of comparable actions. The MNS is involved in recognizing action intent via generalized components that can semantically form intent forgoing respect of the executing agents or direct imitation [39]. The agent, intent and consequence form a context with which intent can be relayed, via a flexible symbolic model based upon parietal mirror neuron activities and the fate of the action as it relates to motivation.

The MNS primarily activates within the 15-30 Hz beta band of activity during action observation, originating from the M1 region in the primary motor cortex, with beta band power modulations during action observation, with attenuation of the ipsilateral sensorimotor cortex corresponding to allocentric vs egocentric perspective, modulated by egocentric processing not allocentric processing [21], [24].

2.2.1 MNS and VR

Within VR BOT, the mental representation is synchronized to the optical stimulation of the virtual environment in the form of a virtual hand illusion (VHI), where intensity of the illusion depends upon the dimensionality of the sensory simulacra [19]–[23]. Multisensory integration provided the strongest illusion. When presenting MNS visual stimuli, limb presence does not affect the activity of the MNS, and MNS based feedback serves to access the motor system in a manner dependent majorly upon the visual presentation of the stimuli, though integrated multisensory stimuli increase the efficiency of the feedback provided [22], [35], [36]. Social interaction and perceptual motor coupling across group dynamics is also supported by the MNS, reflecting adaptation and interaction and translation, which is possibly degraded by disruptions from media and virtual interaction [36].

Chapter 3. Methods

3.1 Experimental Procedure

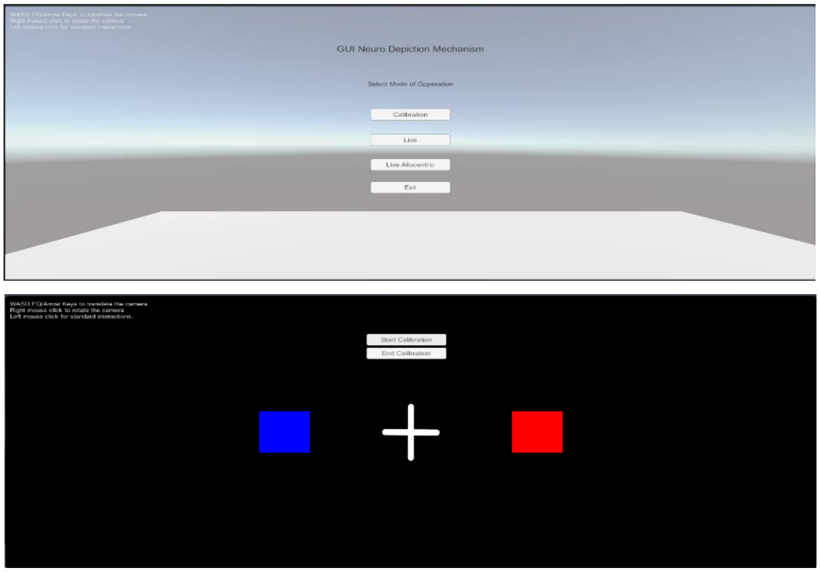

Figure 2. Unity component main menu and calibration screen. (2A) From the main menu, the subject can enter both live modes of testing and the calibration mode. Below (2B) is the calibration menu, showing the 2 stimuli and the fixation cross prior to

The experimental procedure consists of two components, a 2D calibration procedure and with visually dynamic feedback. At the beginning of each session the subject was asked to acknowledge that they understand the calibration protocol, the stimuli designation, and the execution of motor imagery. The headset was fitted and the Unity component, which contains the VR environment developed for the MI tasks in C#, was launched showing the Main menu screen (Figure 2A), after again confirming their understanding of the procedure, the subject is then directed to 2D calibration screen (2B). With the calibration after a 5-second delay, the first stimulus was presented in a cue-based BCI paradigm, consisting of the imagination of movement of grasping an object with the left hand (class 1) and right hand (class 2) and a resting state (class 3) over 1 session of 3 runs. The subject was shown either a blue square on the left hand side (Figure 3 C), or a red (Figure 3 B) square on the right hand side of their view. When the stimulus is shown, the subject was instructed to perform a motor imagery task of grasping an object in front of them with either the left hand (blue stimulus) or right hand (red stimulus). After 4 seconds a fixation cross (Figure 3 A) was shown with a rest period of 2 seconds. One run consists of 60 pseudo-randomized trials with 2 seconds of breaks in between each stimulus (20 for each class), yielding a total of 360 trials per session per subject. The timings of the trial are recorded within unity and streamed over the labstreaminglayer (LSL) to LabRecorder (figure 3D), where it is combined with the signal from the headset is and sent to

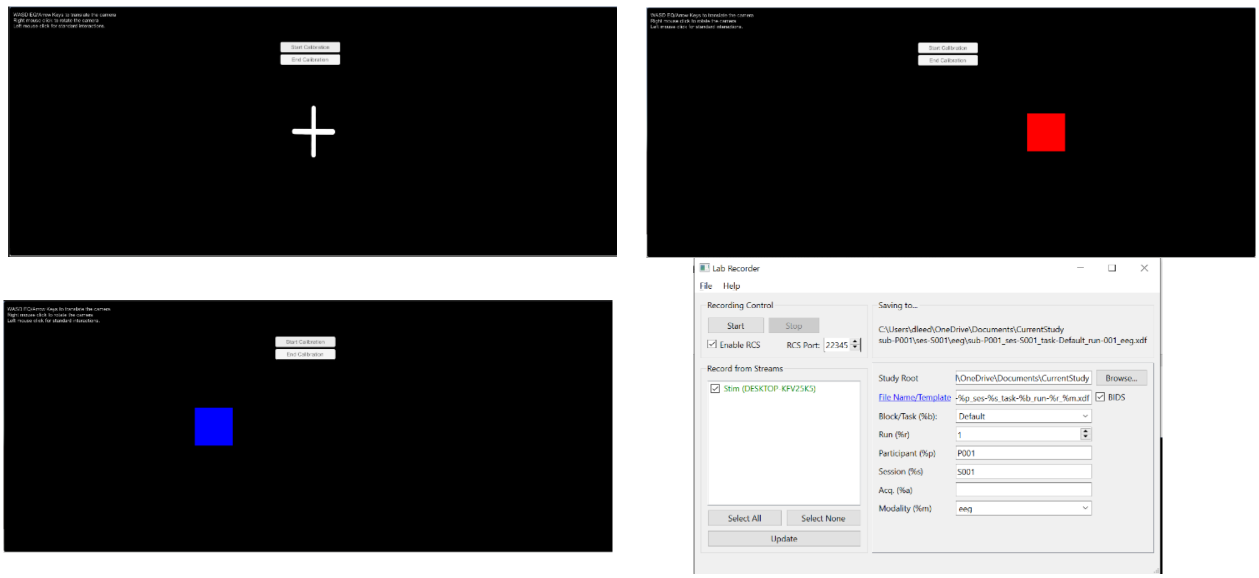

Figure 3. Calibration stimuli and LabRecorder. (A-C) The stimuli shown in the calibration are depicted. (D) Within LabRecorder, the experimenter will need to select the stream and start the recording.

Python as a stream data object. Once calibration data was recorded, a filter bank common spatial pattern filter (FBCSP) and support vector machine (SVM) classifier was generated and saved.

For the visually dynamic component of the experiment, each subject was randomly assigned 4 sessions over a single 1-hour experiment period, in either the allocentric or egocentric reference frames, each consisting of three runs of 30 trials (10 trials per class) for 360 trials over the 4 sessions. Consistent with the calibration procedure, the stimuli were shown for 4 seconds each with 2 seconds in between. Within this component, the Robot Kyle Unity asset was used as an avatar of the user and provided visual feedback of the grasping motor imagery. The egocentric view of the VR visual feedback and a left handed feedback stimuli is shown in Figure 4A and 4C respectively, while the allocentric VR visual feedback of the same stimuli is shown in Figure 4B and 4D.

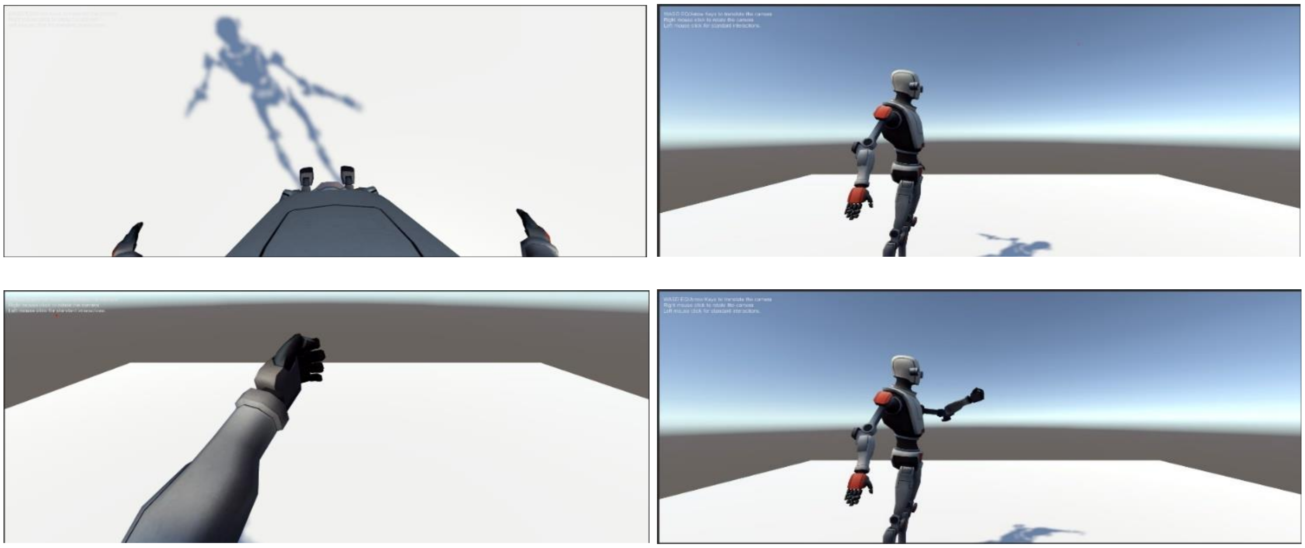

Figure 4. Live egocentric and allocentric testing. (A) The live egocentric testing view before and during (C) classification of a class 1 left hand motor imagery task. The same task is shown for the allocentric task (B & D).

3.2 Environment and BCI design

A MI-based VR-BCI was designed as shown in figure 5. The 3D environment was designed within Unity that communicated to an external Python BCI and processed the incoming EEG signals from the EEG headset. In the experimental setup, a Samsung Odyssey headset was used, employing a Windows Mixed Reality platform, while a BioSemi ActiveTwo system was used for the EEG recording. For the 3D environment, Unity was used to design both the calibration and experimental environments. Python 3.8.6 was used for the classification and processing of the EEG data and was modeled after components of the mother of all BCI module (MOABB) [40], the neurophysiological toolkit MNE-Python and ScikitLearn, as well as the UCSD designed PyLSL, which was used to communicate between the EEG

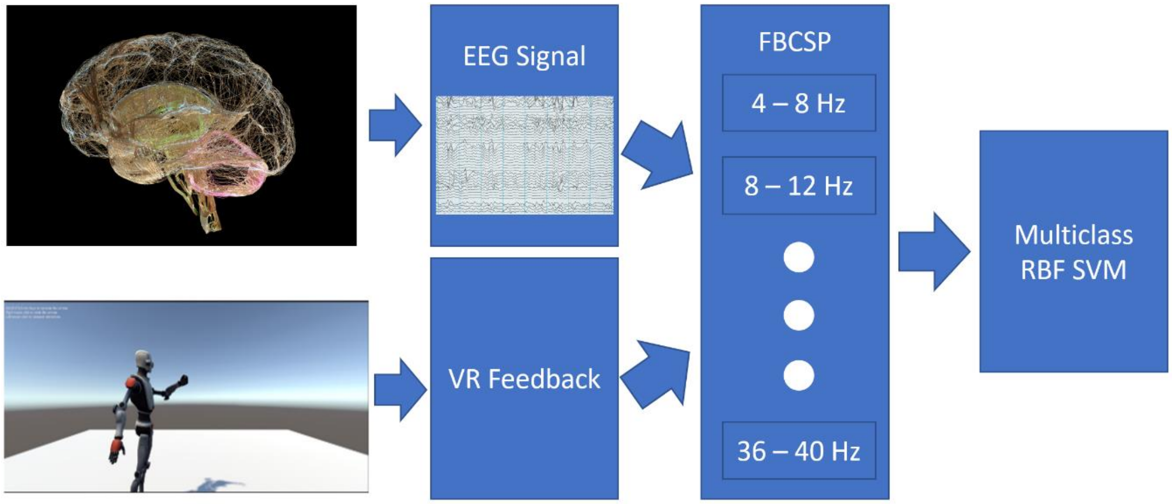

Figure 5 Architecture of the proposed VR MI-BCI. The 64 channel EEG signals and event markers are combined into a stream object and separated into filter banks with a width of 4 hz then a CSP is applied across each and classified with an SVM

headset, Python, and the 3D unity environment. The additional software of LabRecorder and BioSemi Actiview were used to connect the headset to LSL in addition to PyLSL. Within the Unity component, the environment contains the 2D calibration screen, the menu for mode selection, and the 3D environment, scripted in C#. Unity allowed for direct interfacing with the Steam VR platform and WMR headset, with the behavioral scripts for task swapping and display of stimuli executed alongside streaming of the signals between Unity, Python and the LabRecorder software.

3.3 EEG acquisition and analysis

3.3.1 EEG Signal Processing

The EEG data was across 64, with references at the common mode sense (CMS) and driven right leg (DRL) recorded at 2048 Hz and subsampled at 512 Hz. In this study, the recorded data was epoched via MNE dependent upon the event marker stream, into 4 second windows of data, with each epoch containing the data from a single event 0.1 seconds after initiation and 0.1 seconds after the conclusion of the stimuli. Each epoch is regarded as a sample used to extract features for classification. All remaining preprocessing occurs within the bandpass filters of the FBCSP.

3.3.2 Feature extraction and Classification Algorithm

The common spatial pattern (CSP) algorithm was implemented based upon the existing MNE CSP commonly used to extract features from EEG signals, across nine 4 Hz width bandpass filters from 4 to 40 Hz in accordance with [41]–[43]. The FBCSP maximizes dissimilarity between classes with CSP features specific towards each bandpass, detecting event-related desynchronization and event related synchronization [42]. All features from the nine bands were used to train the classifier, a multiclass SVM. Multiclass SVM has been shown to perform the best out of classical non-Bayesian machine learning classifiers across MI tasks[44], and was implemented via ScikitLearn[45]. For the model, the radial basis function (RBF) was used as the kernel function with a cost function parameter of C=10 and a γ of .07 for the RBF as determined by grid optimization method.

3.3.3 Data Analysis Methods

The calculation of the Cohen's Kappa and precision of the data are as follows from [45]:

$$\kappa = (p_o - p_e)/(1 - p_e)$$

$$p_e = \frac{1}{N^2} \sum_k n_{k1} n_{k2},$$

where p_o is the probability of agreement and p_e is the expected agreement across two raters over the class labels, with $\kappa = 1$ representing complete agreement and $\kappa = 0$ representing chance level.

4.1 Against the Calibration Classifier

Table 1. Results from the calibration based classification of the MI-BCI tasks. The Cohen kappa score and precision are shown for each task. Allocentric tasks are shown in blue, and egocentric in grey.

Calibration Scores		1				2				3				4			
Subject	Calibration Kappa	Kappa	Precision			Kappa	Precision			Kappa	Precision			Kappa	Precision		
1	0.6834	0.6106	0.4	0.54	0.7222	0.3220	0.3315	1.0000	0.3246	0.6569	0.9268	0.8302	0.6543	-	-	-	-
2	0.7063	0.7166	1	1	0.6421	0.6984	0.8846	1.0000	1.0000	0.6265	0.9236	1	0.8236	-	-	-	-
3	0.3457	0.1527	0.3333	0.5	0.4483	0.1986	0.6667	0.5714	0.4138	0.0211	0.4	0.2727	0.3529	-0.0122	0.2632	0.4444	0.3333
4	0.4780	-0.0145	0.4048	0	0	0	0	0	0	-0.0055	0.2336	0.3035	0.2984	-0.0859	0.3415	0.2273	0
5	0.1588	0.0457	0.4545	0.3333	0.3390	-0.1072	0.3529	0.1250	0.2459	0.0110	0.4074	1.0000	0.3000	-0.08	0.3400	0.1250	0.0321
6	0.4419	0.1146	0.4468	0.3750	0.4286	0.0258	0.4024	0.0000	0.6667	0.0164	0.3857	0.5	0.2	0.0331	0.3922	0.3750	0.3684
7	0.4744	0.1543	0.7059	0.4667	0.3333	0.0085	0	0.3448	0.3019	0.0187	0	0.3824	0.3182	-0.0245	0.2500	0.2813	0.3235
8	0.6565	0.6124	0.7234	0.7436	0.7609	0.1172	0.5263	0.3488	0.3846	0.0225	0.4151	0.3333	0.3077	0.0382	0.3704	0.3500	0.5385
Average	0.4931	0.2991	0.5586	0.4948	0.4593	0.1579	0.3956	0.4238	0.4172	0.1710	0.4615	0.5778	0.4069	-0.0219	0.3262	0.3005	0.2660
Std	0.1871	0.2948	0.2288	0.2940	0.2495	0.2556	0.3044	0.4046	0.2996	0.2908	0.3184	0.3145	0.2143	0.0533	0.0575	0.1142	0.2088

The classification accuracy results of study as compared are shown in table 1, with the color coding for the trial type. When evaluating the visually dynamic feedback against the 2D calibration, the egocentric reference framed data had an average Cohen kappa of 0.1876 0.0567 greater that of the allocentric reference frame. Table 2 groups the task categorization into allocentric and egocentric reference frames across all subjects, with the precision for each classifier per trial, represented as the ratio of true to total positive classifications. Across the calibration classification, the average precision

Table 2. Calibration classified results divided into egocentric and allocentric tasks

	Kappa	Precision			Kappa	Precision		
	0.6106	0.4	0.54	0.7222	-0.0145	0.4048	0	0
	0.7166	1	1	0.6421	0.0457	0.4545	0.3333	0.3390
	0.1527	0.3333	0.5	0.4483	0.1146	0.4468	0.3750	0.4286
	0.1543	0.7059	0.4667	0.3333	0.6984	0.8846	1.0000	1.0000
	0.6124	0.7234	0.7436	0.7609	0.1986	0.6667	0.5714	0.4138
	0.3220	0.3315	1.0000	0.3246	0.1172	0.5263	0.3488	0.3846
	0	0	0	0	0.6265	0.9236	1	0.8236
	-0.1072	0.3529	0.1250	0.2459	-0.0055	0.2336	0.3035	0.2984
	0.0258	0.4024	0.0000	0.6667	0.0110	0.4074	1.0000	0.3000
	0.0085	0	0.3448	0.3019	-0.0122	0.2632	0.4444	0.3333
	0.6569	0.9268	0.8302	0.6543	-0.0859	0.3415	0.2273	0
	0.0211	0.4	0.2727	0.3529	0.0331	0.3922	0.3750	0.3684
	0.0164	0.3857	0.5	0.2	-0.0245	0.2500	0.2813	0.3235
	0.0187	0	0.3824	0.3182				
	0.0225	0.4151	0.3333	0.3077				
	-0.0800	0.3400	0.1250	0.0321				
	0.0382	0.3704	0.3500	0.5385				
Average	0.1876	0.4	0.44	0.4029	0.1310	0.4765	0.4726	0.3820
std	0.2814	0.2880	0.3097	0.2300	0.2475	0.2232	0.3223	0.2728
Ttest	0.5698	0.5420	0.7359	0.8520				

of the left hand and null classifier was greater in the allocentric reference frame than that of the egocentric reference frame, by 0.0596 and 0.0396 respectively while the right-hand classifier was 0.0291 greater in the egocentric reference frame. These differences however were non-significant, due to the high variance in the individual subjects' capabilities to reproduce MI, the low subject count, and the possible considerations for embodiment.

4.2 Inter-session and cross frame

Table 3. Results from the cross session and reference frame classification of the MI-BCI tasks. The Cohen kappa score and precision are shown for each task. Allocentric tasks are shown in blue, and egocentric in grey.

	1v2				1v3				1v4			
Subject	Kappa	Precision			Kappa	Precision			Kappa	Precision		
1	0.6544	0.3390	1	0.5438	0.9814	0.9390	1	1	-	-	-	-
2	0.7102	1	0.8636	1	0.6846	0.5857	0.55	0.6857	-	-	-	-
3	0.2332	0.2350	0.3590	0.3333	0.3293	0.1	0.35	0.5	0.0345	1	0.3333	0.1536
4	0.1256	0.5	0.2000	0.4242	0.0191	0.4167	0.2	0.3125	0.1327	0.4516	0.2136	0.5789
5	0.1851	0.4545	0.5682	0.3390	0.1307	0.4535	0.325	0.4322	0.2459	0.3654	0.7516	0.3333
6	0.1578	0.4082	0.3333	0.2941	0.1170	0.4762	0.50	0.3704	0.1076	0.3548	0.3965	0.2174
7	0.2620	0.6364	0.2973	0.5000	0.0719	0.3636	0.2963	0.8000	0.0359	0.2	0.3014	0.3406
8	0.6549	1	0.4	1	0.1560	0.5102	0.3846	0.3143	0.0851	0.4688	0.2500	0.5263
Average	0.3729	0.5716	0.5027	0.5543	0.3112	0.4806	0.4507	0.5519	0.1070	0.4734	0.3744	0.3584
Std	0.2527	0.2889	0.2867	0.2879	0.3435	0.2346	0.2481	0.2519	0.0784	0.2751	0.1955	0.1671

In the intersession classification, the Cohen kappa value of the egocentric reference frame was .0066 greater than the allocentric reference frame. The average precision of the left- and right-hand classifiers within the allocentric reference frame was 0.1063 and 9.97 E-3 greater than that of the egocentric, with the null classification 0.10003 greater in the egocentric frame of reference. Generating a classifier from the VR feedback motor imagery resulted in an increase in the average Cohen kappa score across both reference frames, as shown in table 3 and increased precision across all but the null classifier in the allocentric task. As with the calibration classified performance, the efficiency of the egocentric and allocentric reference frames across the subject population were comparable between the tasks.

Table 4. Cross session and reference frame classified results divided into egocentric and allocentric tasks

Cross Session	Kappa	Precision			Kappa	Precision		
	0.6544	0.3390	1	0.5438	0.7102	1	0.8636	1
	0.1256	0.5	0.2000	0.4242	0.2332	0.2350	0.3590	0.3333
	0.1851	0.4545	0.5682	0.3390	0.6549	1	0.4	1
	0.1578	0.4082	0.3333	0.2941	0.6846	0.5857	0.55	0.6857
	0.2620	0.6364	0.2973	0.5000	0.0191	0.4167	0.2	0.3125
	0.9814	0.9390	1	1	0.1307	0.4535	0.325	0.4322
	0.3293	0.1	0.35	0.5	0.0345	1	0.3333	0.1536
	0.1170	0.4762	0.50	0.3704	0.1327	0.4516	0.2136	0.5789
	0.0719	0.3636	0.2963	0.8000	0.1076	0.3548	0.3965	0.2174
	0.1560	0.5102	0.3846	0.3143	0.0359	0.2	0.3014	0.3406
	0.2459	0.3654	0.7516	0.3333				
	0.0851	0.4688	0.2500	0.5263				
Average	0.2810	0.4634	0.4943	0.4955	0.2743	0.5697	0.3942	0.505
Std	0.2709	0.1977	0.2806	0.2122	0.2892	0.3165	0.1925	0.3043
Ttest	0.9564	0.3475	0.3515	0.9289				

Chapter 5. Discussion

Allocentric stimuli for BCI has been viewed as less effective in eliciting motor imagery, both due to mirror effect and the presentation of the stimuli [33], [38], and did not evaluate VR and direct comparisons with appropriate stimuli that fully encapsulated the visual feedback required. Ono et al. 2018 [33] demonstrated the usage of stimuli for altered perspectives, however the stimuli were not appropriate for the purpose of eliciting VR BOT including embodiment, agency, and translocation [20], [22]. This study applied appropriate reference frames for the visual stimuli, showing no significant difference between the reference frames, however the results are highly skewed by the low subject number, single day session, variability within the subject's capacity to produce MI, and their comfort within the experimental procedure. Subjects reported slight discomfort from the egocentric reference frame due to having to look down for the 6 minutes of each run. As MI is directly impacted by posture and comfort that may have contributed to increased variability, alongside their initial ability to produce MI [46]. Additionally, the electrodes used during the initial 5 subjects were replaced after partial damage was discovered after the data from the subjects was recorded, which may have impacted the results of subjects 4 and 5.

As the usage of allocentric stimuli and the effectiveness of allocentric vs egocentric referenced VR-BCI is tied to the environment and the display of the stimuli, both regarding accuracy of the representation to natural movement and the choice of avatar for the subject, the paradigms required needed to be constructed in the same environment with stimuli that are directly comparable to those the subjects have experienced [37], [46]–[48]. [34] shows that manipulation of characteristics of VR *"including screen size, duration of exposure, the realism of the presentation, and the use of animated avatar, i.e., a third-person view of the user that appears as a player in the VR*" while [12], [17] demonstrated increased mu suppression in synchronized and congruent conditions, which was increased for subjects who responded better to the spatial illusion and had an increased tendency for empathy. As such, a questionnaire to evaluate both the empathy and familiarity of the subjects with VR and BCI, a training period where the subject adjusted to the avatar, and an avatar that was provoked a higher sense of embodiment to the subject by being a closer approximation of a human figure with pre-defined bounds for the animation constraints would have elicited higher responses of BOT [21], [22]. The questionnaire would have allowed for weighting of the BOT experienced within the VR experience across both frameworks and reduced variability.

Regardless of the high variability, within the 3 classes, the mean precision of the classifiers was greater than that of random chance, with all but the precision of the null and right classifications in the allocentric reference frame greater than 0.4. Generating the classifier from the visually dynamic stimuli in the VR environment also increased the precision across both cross-reference frame and inter session, and as such recording the initial calibration data with visually dynamic stimuli instead of the 2D Cue and fixation cross may have increased the accuracy of the initial classification. Using the FBCSP allowed us to analyze the contributions of the signal across the spectrum of 8 frequency banks, however without reducing the dimensionality the contributions of the individual filter banks, and differentiating between the mu, beta and gamma bands associated with MI, MNS and VR spatial components[49].

In this study, though there is much to improve in the methodology, the results of the VR enhanced MI-BCI suggest that there was no significant difference between the reference frames both across multiple sessions and no significant impact from training bias, though that is potentially due to the impact of fatigue and posture. Future improvements upon the study as noted prior, would involve increasing the experience of embodiment and improving the presentation of the stimuli, as well as having consistent presentation of the stimuli in the VR environment. Additionally, incorporation of an online BCI in which the subject would receive an ERD feedback that modified the speed and strength of the stimuli was planned, however due to constraints of time this component was removed. Lastly the usage of multiple frames of reference within a single BCI, to evaluate multiple stimuli in a singular sense or multi-sensory stimuli has been shown to improve the classification accuracy of MI BCI.

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