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A Comparison Study of Egocentric and Allocentric Visual Feedback for Motor-Imagery Brain-Computer Interfaces

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***Abstract*—Motor imagery (MI) based brain-computer interfaces (BCIs) have been studied as applications for the improving rehabilitation and recovery, as well as augmenting existing function. MI BCI systems typically provide feedback in an egocentric rather than an allocentric reference frame. This study aims to see if presenting stimuli in an allocentric reference frame is comparable to presenting egocentric stimuli. We used dynamic visual stimuli in egocentric and allocentric reference frames to induce motor imagery in a virtual reality (VR) environment. Eight participants imagined grasping actions with their left and right hands while observing egocentric or allocentric stimuli. The allocentric and egocentric reference frame tasks had comparable inter-rater agreement and precision, indicating that allocentric visual feedback is as effective as egocentric one for MI BCI.**

***Index Terms*—Brain Computer Interface, Mirror Neuron System, Motor Imagery, Virtual Reality**

I. Introduction

Brain-computer interfaces (BCIs) serve as a means of communication between the mind and a target device for rehabilitation, augmenting functionality, compensating for lost functionality, as well as enabling a new form of interaction [1], [2]. Electroencephalography (EEG) is a low-cost non-invasive method to capture brain activity with high temporal resolution, and it can be used to measure both evoked and spontaneous brain activities [3], [4]. Because of its potential applications in a variety of BCI applications, motor imagery (MI), in which imagined movements are translated to direct commands, has received a lot of attention among the various control paradigms used in EEG-based BCIs. [5]–[8]. Mirror neuron systems (MNS) are a distinct class of neurons that discharge during intent-centric action and observation of comparable actions, and are involved in recognizing action intent via generalized components as well as imitation. [9]–[11]. Subjects using MI paradigms have reported difficulty visualizing the motor activity required while performing MI tasks, which is related to aspects of coordination and working memory, necessitating trial and error via feedback congruent to the chosen motor imagery task within the presented stimuli [12], [13].

Dynamic and object-directed visual feedback in a virtual reality (VR) environment has been used to improve the performance of MI-based BCI (MI-BCI) [14]–[17]. 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) and the sense of ownership to the virtual avatar. BOT, and the larger sense of agency, are factors in the participants' immersion in their environment and body, whether virtual or physical. A VR environment allows a subject to immerse themselves in a new or modified perspective, embodying a new frame of reference [11], [18]–[22]. These designs use an egocentric reference frame for visual feedback, relaying the stimuli of the selected task within a first person object-self reference system as the motor imagery is executed [10], [20], [23]. Allocentric reference frames, which use an object to object referencing system, have traditionally been used only in mirror-therapy applications. Recent research has focused on the impact of allocentric reference frames within VR environments, and its role in navigation and dynamic movement within cognitive and spatially grounded tasks [24]–[28]. Navigation is one of the tasks heavily studied in the application of BCI and cognition that is impacted by allocentric processing. As aspects of real-world tasks require non-standard environments with reference frames that vary with the environment, such as space, the accuracy of navigation within the environments will depend upon the strength and presentation of allocentric stimuli as well as the application of allocentric control schemes. Outside of the task itself, allocentric processing relies heavily on the bottom up components of dual cognition, including working memory. As such, this gives rise to applications of BCI as an evaluative tool of working memory and spatial cognition, by applying allocentric designs that incorporate both environmental stimuli and varied layouts.

Traditionally, studies have shown that components of ownership and agency associated with somatosensory illusions such as the rubber hand illusion (RHI) and virtual rubber hand illusion (VRHI) are biased toward egocentric reference frames [11], [19], [29]. However, allocentric reference frames and perceptually-coupled stimuli, such as showing a grasping arm while asking participants to imagine grabbing an object, have been successfully employed in previous studies [30]–[32]. Results from therapy and illusory studies within allocentric reference frames were comparable to egocentric reference frames when environmental consistency, avatar embodiment-adaptation, and components of how the illu-

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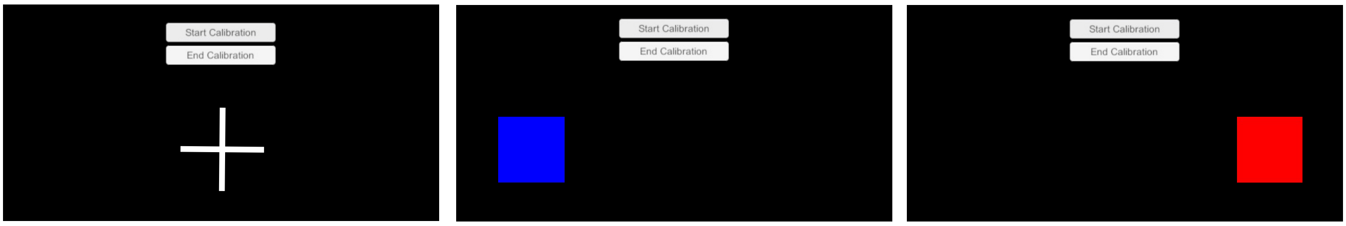

(a) (b) (c)

Fig. 1. The visual stimuli used in the calibration procedure. (a) The fixation cross, the stimuli that indicated the imagined grasping actions with (b) left and (c) right hands.

sions were displayed regarding the VR-BCI hardware were considered [26], [33]–[37]. In this nature, the strength and dimensionality of the illusion (and its transferred sensations) are coordinated with the presentation itself. Varying the environment to increase embodiment with perceptual feedback results in better performance within perceptually linked processes. Ultimately, the aspects of translocation brought upon by this sense of ownership directly impacts the functionality within the allocentric and egocentric processing regions of the brain [37], with the latency of the experiences fed to the MNS being inversely correlated to the complexity of the signal for goal and intent interpretation [23]. Additionally, existing perceptual signals (posture, environmental sounds and visuals) 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. As a result, any proposed method of teleoperation or avatar embodiment must rely on a system with the greatest complexity of sensory inputs from the illusion, with less input from the existing body [22]. 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 [11]. The next steps in determining whether allocentric VR embodiment can be equivalent to that of first-person VR embodiment are to determine the levels of immersion required for BOT and the learning rate/capacity for MNS development when these new systems can. And, in that same manner, to address the dissociation of ownership during changes in temporal delay and spatial encoding that occur from immersive VR.

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 perspectives could be viewed across the same task, was designed. Subjects performed object-oriented motor imagery in a VR environment while seated and received visual feedback from egocentric and allocentric reference frames.

II. Methods

A. Participants

Eight healthy adults (1 female; mean age 27 $\pm$ 4 years) participated in this study. Each participant was asked to read and sign an informed consent form approved by the Human Research Protections Program of University of California San Diego.

B. Experimental Procedure

The experimental procedure consists of two parts: calibration in a 2D space and imagery in VR with dynamic visual feedback. The experimental tasks included imagining a grasping movement with the left hand (class 1), right hand (class 2) and resting state (class 3). At the beginning of each part, the subject was asked to acknowledge that they understood the calibration protocol, the stimuli designation, and the execution of motor imagery. After putting on the headset, the Unity component, which contains the VR environment developed for the MI tasks in C#, was launched, showing the Main menu screen.

The subjects were first asked to complete the calibration. The calibration is based on a cue-guided BCI paradigm, in which the participants were asked to perform a task indicated by a cue generated by the stimulation program. The subject saw either a blue square on the left-hand side (Fig. 1B) or a red (Fig. 1C) square on the right-hand side of their view for four seconds. When the stimulus was 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 each imagery task, a fixation cross (Fig. 1A) was shown for two seconds as a short break. The subjects were asked to complete four runs, each consisting of 60 pseudo-randomized trials (20 for each class).

In the procedure with dynamic visual feedback, either the allocentric or egocentric reference frames were randomly assigned at each of four sessions over a single 1-hour experiment period for each participant. For the allocentric frame, the avatar was presented sideways from an observer's perspective. Each session consisted of four runs of 45 trials (15 trials per class), for a total of 180 trials. Consistent with the calibration procedure, the stimuli were shown for 4 seconds with 2-second intervals. Within this procedure, the Robot Kyle Unity asset was used as an avatar of the user and provided visual feedback of the grasping motor imagery, shown in Fig. 2. Fig. 2A and B show the egocentric view of the visual feedback in VR and a left-handed feedback stimuli in the egocentric view, respectively, while Fig. 2C and D show the allocentric view of the same scenes.

C. Experimental Environment

A MI-based BCI was implemented in VR as shown in Fig. 3. A 3D environment was designed using Unity and

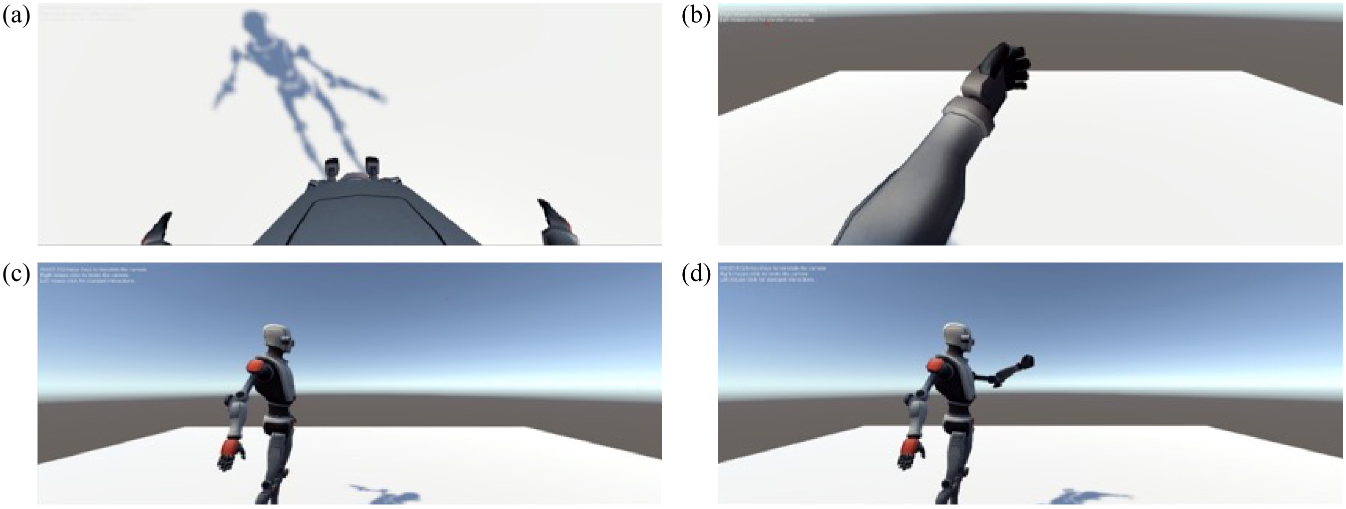

Fig. 2. The visual stimuli used as dynamic visual feedback. The egocentric view (a) before and (b) during imagining grasping movements with the left hand. The same task is shown for the allocentric task (c & d).

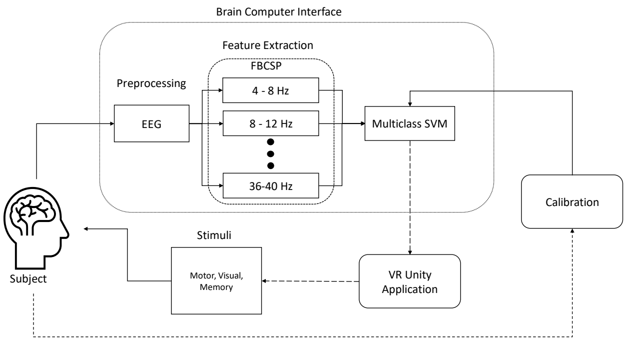

Fig. 3. Architecture of the proposed MI-BCI in an VR environment. The 64-channel EEG signals were recorded with event markers, separated into filter banks with a width of 4 Hz, a CSP is applied to each sub-band and then classified with an SVM.

C# and communicated with an external Python script that processed incoming EEG data from an EEG device. A Samsung Odyssey head-mounted display (Samsung Electronics Co., Ltd.) was used to present the virtual environment. EEG data were recorded with 64 Ag/AgCL electrodes using a BioSemi ActiveTwo EEG system (Biosemi, Inc.) with a sampling rate of 512 Hz. Each electrode was referenced to the common mode sense (CMS) and driven right leg (DRL). The communication between the EEG device and the python script was done by the PyLSL interface via the Lab Streaming Layer (LSL) [38]. The timings of the trial are recorded within Unity and streamed over the LSL to LabRecorder, where they are combined with the signal from the headset as a Python data object.

D. EEG Analysis

1) Preprocessing: The recorded data were epoched into 4-second segments via MNE based on the event marker stream. Each epoch contained the data from 0.1 seconds after initiation and 0.1 seconds after the conclusion of the stimuli. Each epoch is regarded as a sample from which features for classification are extracted. All remaining pre-processing occurs within the band-pass filters of the filter bank common spatial pattern (FBCSP) filter.

2) Feature Extraction: The common spatial pattern (CSP) algorithm was implemented using the existing MNE CSP, which is commonly used to extract features from EEG signals, across nine 4-Hz width band-pass filters from 4 to 40 Hz in accordance with [39]–[41]. The FBCSP maximizes dissimilarity between classes at each band-pass, detecting event-related desynchronization and synchronization (ERD/ERS) [40].

3) Classification: All features from the nine bands were used to train a multi-class support vector machine (SVM). Multi-class SVM has been shown to outperform classical non-Bayesian machine-learning classifiers for MI tasks [42], and was implemented using scikit-learn [43]. The radial basis function (RBF) was used as the kernel function in the model, with a cost function parameter C of 10 and a γ of 0.07 as determined by grid optimization method.

4) Evaluation: To evaluate the classification performance, the SVM was trained with the data acquired during the calibration procedure and then used to classify data in the imagery tasks with the dynamic visual feedback. In addition, we assessed the performance of cross reference frames, in which the SVM was trained using the data with egocentric feedback and classified the data with allocentric feedback, and vice versa. The classification performance was quantified as the Cohen's kappa and precision. The Cohen's kappa measures inter-rater reliability and chance-independent agreement within the classification, whereas precision measures the rate of positive predictions and overall relevancy of the classifier.

III. Results

Table I shows the classification accuracy of the MI data with egocentric and allocentric feedback using the SVM trained with calibration data. Averaged Cohen's kappa across subjects on the egocentric reference framed data was 0.195, which was 0.009 greater than that on the allocentric reference framed data of 0.186. On the other hand, averaged precision across subjects on the egocentric reference framed data

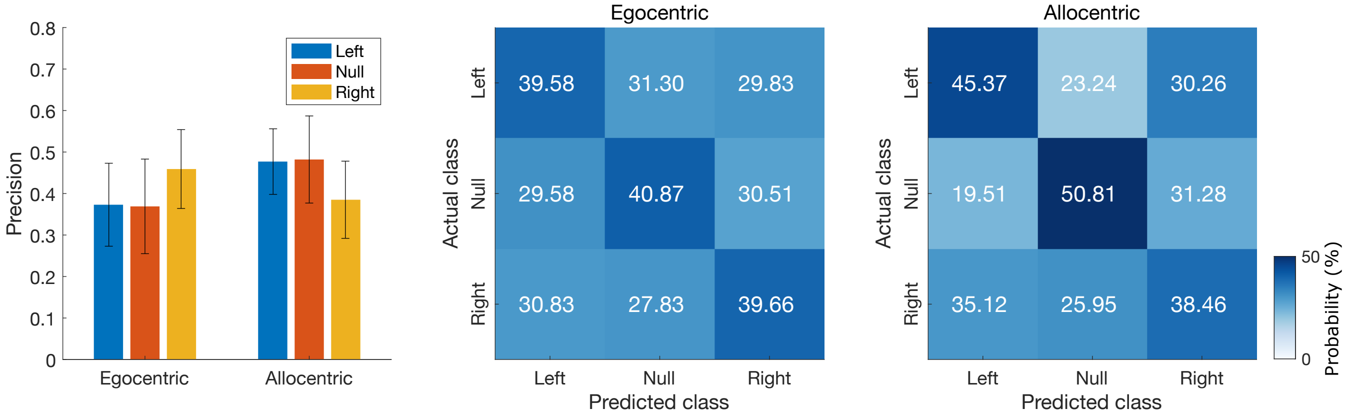

Fig. 4. Confusion matrices in classifying motor imagery data with classifiers trained by the calibration data for all subjects and precision for each of the three classes. The error bars indicate standard errors.

TABLE I
CLASSIFICATION PERFORMANCE OF THE MOTOR IMAGERY DATA WITH CLASSIFIERS TRAINED BY THE CALIBRATION DATA FOR EACH SUBJECTS

	Egocentric		Allocentric	
Subject	Kappa	Precision	Kappa	Precision
1	0.530	0.637	-	-
2	0.717	0.881	0.662	0.939
3	0.087	0.385	0.093	0.449
4	0.000	0.000	0.129	0.201
5	-0.094	0.203	0.085	0.472
6	0.021	0.359	0.238	0.398
7	0.061	0.251	-0.025	0.285
8	0.239	0.457	0.117	0.420
Average	0.195	0.397	0.186	0.452
Std	0.285	0.253	0.224	0.235

TABLE II
CLASSIFICATION PERFORMANCE OF THE MOTOR IMAGERY DATA WITH CLASSIFIERS TRAINED BY THE CROSS-REFERENCE-FRAME DATA FOR EACH SUBJECTS

	Egocentric		Allocentric	
Subject	Kappa	Precision	Kappa	Precision
1	0.818	0.804	-	-
2	-	-	0.697	0.781
3	0.281	0.313	0.035	0.496
4	0.126	0.375	0.076	0.362
5	0.216	0.469	0.131	0.404
6	0.137	0.397	0.108	0.323
7	0.167	0.482	0.036	0.281
8	0.121	0.409	0.655	0.800
Average	0.266	0.464	0.248	0.492
Std	0.250	0.139	0.295	0.186

was lower than that on the allocentric reference framed data (Egocentric: 0.397 vs. Allocentric: 0.452). Unpaired t-tests showed no significant difference between the reference frames in the Cohen's kappa (p = 0.944) and the precision (p = 0.682). Figure 4 shows the confusion matrices and precision for each class. The precision of all classes on both egocentric and allocentric reference framed data was greater than its chance level (i.e., 0.333). Interestingly, the confusion matrix of the egocentric data shows a bias towards the imagined right-hand movements (Precision, left: 0.373, null: 0.369, right: 0.459). The allocentric data shows the inverted relationship (Precision, left: 0.477, null: 0.482, right: 0.385).

Table II shows the classification performance of the MI data with egocentric and allocentric feedback using the SVM trained by data with the other reference frames. Averaged Cohen's kappa across subjects on the egocentric reference framed data was 0.018 greater than that of allocentric reference framed data (egocentric: 0.266 vs. allocentric: 0.248). Averaged precision across subjects on the allocentric reference framed data was 0.492, which was 0.028 greater than that of egocentric reference framed data of 0.464. Unpaired t-tests showed no significant difference between the reference frames in the Cohen's kappa (p = 0.902) and the precision (p = 0.785). Figure 5 shows the confusion matrices and precision for each class. In general, the classifier trained by the cross-reference-framed data showed better precision than that trained by the calibration data on both egocentric (left: 0.446, null: 0.482, right: 0.482) and allocentric (left: 0.507, null: 0.400, right: 0.526) data.

IV. DISCUSSION

Allocentric visual feedback for BCI has been viewed as less effective in eliciting motor imagery because of mirror effect and the presentation of the stimuli [32], [37]. Direct comparisons with appropriate stimuli in a VR environment that fully encapsulated the visual feedback have yet to be performed. Although Ono *et al.* 2018 demonstrated the use of stimuli for altered perspectives [32], the stimuli were not designed for eliciting VR BOT including embodiment, agency, and translocation [19], [21]. This study applied allocentric and egocentric reference frames for the visual stimuli in a VR environment. The results showed no significant difference between the two reference frames.

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 regarding accuracy of the representation to natural movement and the choice of avatar, the paradigms required needed to be constructed in the same environment with stimuli that are directly comparable to those the subjects have experienced [36], [44]–[46]. Calabrò *et al.* [33] showed that manipulating VR characteristics such as 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 other studies demonstrated increased mu suppression in synchronized and congruent

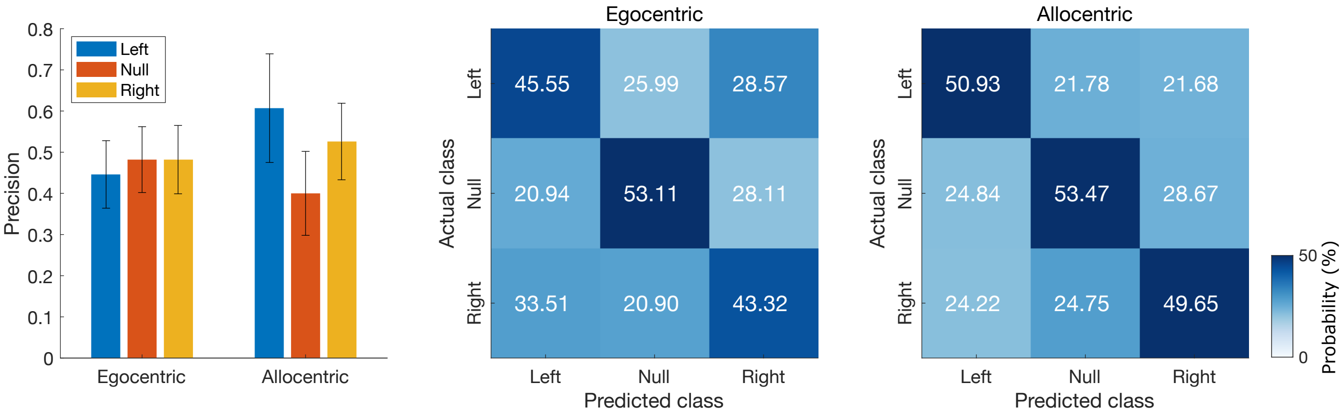

Fig. 5. Confusion matrices in classifying motor imagery data with classifiers trained by the cross-reference-frame data for all subjects and precision for each of the three classes. The error bars indicate standard errors.

conditions, which was increased for subjects who responded better to the spatial illusion and had an increased tendency for empathy [11], [16]. As such, a questionnaire to assess 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 elicited a higher sense of embodiment in the subject being a closer approximation of a human figure with pre-defined bounds for the animation constraints would have elicited higher BOT [20], [21]. The questionnaire would have allowed for the weighting of the BOT experienced during the VR experience across both frameworks and reduced variability. In this study, regardless of the high variability, within the three imaged movements, the mean precision of the classifiers was greater than its chance level. Training the classifier using the data with dynamic visual feedback in the VR environment increased precision. Therefore, recording the initial calibration data with dynamic visual feedback instead of the 2D cue and fixation cross may have resulted in increased precision of the initial classification. Using the FBCSP, we were able to analyze the contributions of the signal across the spectrum of eight frequency banks without reducing the dimensionality of the contributions of the individual filter banks, and differentiating between the mu, beta and gamma bands associated with MI, MNS and VR spatial components [47].

The results of the VR enhanced MI-BCI in this study indicate that there was no significant difference between the reference frames and no impact from training bias. However, some subjects reported minor discomfort from the egocentric reference frame because they had to look down for six minutes in each run. Because posture and comfort have a direct impact on MI, the results with no significant difference could be due to the impact of fatigue and posture. Future improvements would necessitate testing the impact of immersion via avatar selection bias, and having consistent presentation of the stimuli in the VR environment. In addition, an online experiment should be conducted in which the subject will receive feedback that aids in imagining the movements in real-time to evaluate the reference frames in practical situations and their long-term effects.

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