Computers & Graphics 94 (2021) 62–75

Contents lists available at ScienceDirect

Computers & Graphics

journal homepage: www.elsevier.com/locate/cag

Special Section on VRCAI

A comparative study on inter-brain synchrony in real and virtual environments using hyperscanning

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ARTICLE INFO

Article history:
Received 12 July 2020
Revised 4 October 2020
Accepted 11 October 2020
Available online 16 October 2020

Keywords:
Hyperscanning
Virtual Reality
Brain synchronization
Social neuroscience
Remote collaboration
Computer Supported Collaborative Work (CSCW)

ABSTRACT

Researchers have employed hyperscanning, a technique used to simultaneously record neural activity from multiple participants, in real-world collaborations. However, to the best of our knowledge, there is no study that has used hyperscanning in Virtual Reality (VR). The aims of this study were; firstly, to replicate results of inter-brain synchrony reported in existing literature for a real world task and secondly, to explore whether the inter-brain synchrony could be elicited in a Virtual Environment (VE). This paper reports on three pilot-studies in two different settings (real-world and VR). Paired participants performed two sessions of a finger-pointing exercise separated by a finger-tracking exercise during which their neural activity was simultaneously recorded by electroencephalography (EEG) hardware. By using Phase Locking Value (PLV) analysis, VR was found to induce similar inter-brain synchrony as seen in the real-world. Further, it was observed that the finger-pointing exercise shared the same neurally activated area in both the real-world and VR. Based on these results, we infer that VR can be used to enhance inter-brain synchrony in collaborative tasks carried out in a VE. In particular, we have been able to demonstrate that changing visual perspective in VR is capable of eliciting inter-brain synchrony. This demonstrates that VR could be an exciting platform to explore the phenomena of inter-brain synchrony further and provide a deeper understanding of the neuroscience of human communication.

1. Introduction

Social interaction is an innate need of humans, and collaboration forms an integral part of this interaction. People cannot complete many essential tasks in life, such as work and learning, without collaboration and communicating with each other. The mechanisms of communication have been studied for a long time, and researchers have begun to explore the neuroscience of collaboration. For example, recent studies have observed synchrony between the brain activity of people undertaking real world collaborative tasks [1,2]. These are some of the first studies to shed light on the neural underpinnings of collaboration by providing empirical results of inter-brain synchrony among collaborators.

In our research we are interested in measuring the brain activity of people collaborating in Virtual Reality (VR). We believe this study will help us understand inter-personal communication, and as a result collaboration in VR, from a neuroscience perspective. Remote collaboration in a virtual environment (VE) has been the subject of research for close to three decades [3]. Research has demonstrated that VEs are capable of facilitating remote collaboration by immersing users in a life-like environment. VEs can be designed to mimic nearly every possible collaborative scenario that exists in the real-world. Additionally, the ability to alter visual perspectives in VEs makes them an ideal platform that can facilitate effective remote collaboration [4]. Researchers have studied several aspects of collaboration in remote environments and how they benefit the users. An exhaustive list of interaction techniques have been investigated in order to understand how interactions in VEs, with other participants and the environment, work. The focus of this paper is to delve into the inter-personal interactions that characterise collaboration in VEs. This has been dealt with, to some

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https://doi.org/10.1016/j.cag.2020.10.003
0097-8493/

degree, by researchers who have studied the effects of gaze [5–7], avatars [5,6,8] and other manifestations of bodily interactions both implicit and explicit in VEs [9]. Despite this, there is a lack of clear understanding regarding the underlying neural mechanisms that underpin these interactions and/or behaviours. While this has been addressed to some extent in the real-world, there appear to be no corollaries in VEs. Therefore, there is a need to explore the neural correlates of inter-personal interaction in VEs in order to better understand how brains behave in such an environment. This will help develop methods that can be used to engage two or more brains and potentially induce synchrony between them as a means to enhance the experience of collaboration by inducing a state of 'flow'.

To the best of our knowledge, this is the first paper to investigate inter-brain synchrony between people undertaking collaborative tasks in a VE. We conduct our research using hyperscanning, which is a technique that is used to simultaneously record brain activity from two or more participants [1] and is being increasingly used to study social interaction among people. Previous hyperscanning studies have shown that brain activities can be synchronized among people engaged in real world cooperative tasks such as card playing [10], computer games [2], movement imitation [11,12], and simulator based training exercises [13,14]. Higher levels of inter-brain synchrony can increase collaborative performance and provide a greater sense of connection between collaborators [11]. These types of studies are important in being able to understand how inter-personal interactions work. It must be noted that these inter-personal interactions can be of an implicit or explicit nature. Either way, they play an important role in communication between two individuals, and are able to provide us with a significant amount of information on how they are used and affect inter-personal interactions. What the studies cited earlier bring into focus are the neural mechanisms that underpin these interactions. Knowing how and what the brain reacts to in collaborative scenarios is important in being able to design a virtual collaborative system capable of exploiting its perceptual capabilities to create an immersive and engaging collaborative VE. To that end, this paper explores inter-brain synchrony between two participants in a collaborative VE using the hyperscanning technique.

As a result, this paper makes three important contributions. Firstly, it is the first research that reports on inter-brain synchrony between two people for a collaborative task in VR. Secondly, it compares synchrony between two brains when undertaking the same task in the real-world and VR environments. Thirdly, it explores how different viewing perspectives in VR affect inter-brain synchrony. Finally, the research results obtained by us can be used to begin the process of collating data that can inform the design of collaborative VEs to enable better experiences of collaboration.

2. Background – state of the art

2.1. Brain Computer Interfaces

Monitoring neural activity is used primarily for Brain Computer Interfaces (BCI). BCIs mediate interactions between a user and a computing system by monitoring and 'decoding' neural activity [15]. While BCIs are not the focus of this paper, it is important to note their role in an increasingly multi-disciplinary research area of Human-Computer Interaction (HCI). In VEs, BCIs have been used as control devices. For example, Scherer et al. have demonstrated the use of BCI to control a robot in a VE [16]. EEG hardware is also used to monitor neural activity in response to VR. Some researchers have demonstrated how EEG hardware can be used to measure cognitive load in a VR application [17,18]. The study by Dey et al. demonstrated how measuring cognitive load using EEG can be used to dynamically adjust the complexity of a VR training task [17]. This clearly indicates that it is possible to use EEG hardware to measure neural activity in VR.

2.2. Hyperscanning

Beginning with functional Magnetic Resonance Imaging (fMRI) [1,19–22], hyperscanning studies cover the entire spectrum of equipment used for recording neural activity from EEG [10–12,23,24] to fNIRS (functional-Near Infrared Spectroscopy) [25,26]. An important factor that has played a part in EEG being widely adopted for such hyperscanning studies is its high temporal resolution [27].

The number of hyperscanning studies have increased owing to the growing availability of low cost, high quality EEG hardware and software tools. In recent years, EEG hardware has evolved from an unwieldy, wired and hard-to-setup piece of equipment to a wireless and easy-to-use tool. Modern day EEG headsets enable researchers to carry out studies in more real-world environments and even allow for ambulatory studies to be carried out.

A common thread that links all hyperscanning studies is that they were mostly carried out in a traditional lab setting [11,19] or were set-up to mimic a real world scenario [10,13]. Some studies attempted to investigate the effect of face-to-face interactions between participants using a variety of different tasks, including finger pointing and/or tracking exercises [11], music performance [24] and economic exchange [26]. The finger tracking task is especially popular among researchers because gesture is thought to represent the most basic form of social interaction, besides eye gaze [11]. Finger tracking allows us to look at synchrony from a neural as well as physical perspective, i.e. physical manifestation of inter-brain synchrony by means of identical or mirrored body movements among participant pairs.

Hyperscanning has been used to explore collaborations in the real world, but there has been little or no work that looks at hyperscanning in VR. Given the lack of research in this area, we attempt to bridge this gap by studying how VR and neural activity measurements can be combined to enhance collaboration in VR. Our study attempts to gather information on how monitoring neural activity in VR can also help promote inter-brain synchrony in VEs.

2.3. EEG and VR

EEG and VR have been used in tandem for the last two decades. The EEG hardware and its associated software components have primarily been used as BCIs to mediate interactions in the VE for a range of applications. VR has also served as a medium for displaying real-world like visual stimuli in order to measure humanistic traits such as attention [28,29], emotion [30,31], and imagination [32,33] from a neuroscience perspective.

The use of BCIs and VEs has also played a significant role in physical and mental healthcare. For example, research has demonstrated that children with Attention Deficit Hyperactivity Disorder (ADHD) responded better to treatment using a BCI in a VE versus the real-world [28]. The BCI and a VE have also been used as training aids to help those with lower limb paralysis navigate a wheelchair using motor imagery (MI) [34]. Patients were taught to engage certain areas of their brain in order to enable movement of the wheelchair. This was done in a gradual and safe manner using a VE.

However, in addition to the use EEG devices as BCIs in VEs, they have also been used study the neural correlates of perception in VE. For example, Kober et al. [35] have demonstrated the relationship between the different cortical regions in the perception of spatial presence. They have also demonstrated the activation of the different bands based on the quality of spatial presence afforded by

the systems that were used in their study. Other researchers have used similar environments to assess the neural correlates of spatial presence in arousing and non-interactive VEs [36] and spatial navigation abilities in VR [37]. Other interesting uses of VR and EEG include the study of the effects of olfactory interfaces in combination with VR to promote relaxation [38], neural correlates of error detection in human beings [39] and the study language processing in naturalistic environments [40].

In addition to the applications described above, VEs and EEG have also been used to provide the sense of embodiment and ownership of virtual limbs [41], avatars [42] and robots [43,44]. Another interesting aspect of VEs is the ability to change the user's visual perspective, i.e. providing the user(s) with a visual perspective that differs from their own [45]. This altered visual perspective could be a first-person perspective of another user in the VE or a 'God-view' like third-person perspective, among others [45]. Research has demonstrated that the ownership of the body and embodiment are significantly affected by the visual perspective [46]. A part of the studies detailed in this paper aims to investigate whether this phenomenon can be exploited to elicit inter-brain synchrony between two participants in a VE.

2.4. Objectives of research

The aim of this research is to explore if the phenomenon of inter-brain synchrony can also be observed in VR. In this context, this research attempts to investigate the following questions:

1. Can existing results from a real-world hyperscanning study be replicated in a reliable manner?
2. Can those same activities in VR induce similar inter-brain synchrony as observed in the real-world?
3. Does a change in visual perspective affect inter-brain synchrony?

We hypothesize that we may observe inter-brain synchrony in VR that is similar to that observed in the real-world for the same collaborative tasks, e.g., finger pointing and tracking tasks that have been shown to elicit inter-brain synchrony in the real-world [11].

3. Method

3.1. Participants

Twenty-four participants (19 Male, 5 Female) who did not know each other were recruited for this study. Participants were divided into pairs for all three conditions of the study. The participant pairing was changed for each condition to ensure that none of the participants developed familiarity with each other. The study was approved by the Human Participants Ethics Committee of the host institute. All participants signed a consent form after having been briefed about the experiment and given time to clarify any doubts. All participants were given a $20 gift voucher as compensation for taking part in the study.

3.2. Equipment

3.2.1. Electroencephalography (EEG)

Two g.GAMMAsys[1] active electrode systems along with EEG caps were used. Sixteen electrodes were put on each subject in accordance with the international 10–20 system electrode placement [47]. The electrode locations used were FP1, FP2, F7, F8, F3, F4, FZ, T7, T8, C3, C4, CZ, P3, P4, O1 and O2 as shown in Fig. 1.

[1] https://www.gtec.at/product/ggammasys/.

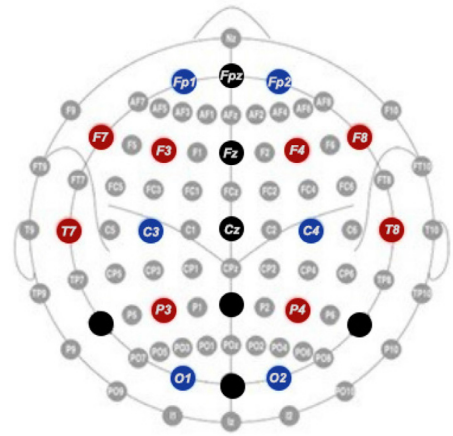

Fig. 1. Electrode locations (10–20 international system) [48]. The electrode locations highlighted in red and blue were used for the study. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

For each set of electrodes, a corresponding g.GAMMAbox was used as a power source. A g.USBamp was used to amplify the signal and a g.RECORDER was used to record data. Markers were placed in correspondence with the vocal commands using the National Instruments (NI) Labview software[2]. The channel data was cleaned with a band-pass filter between 0.5 and 60 Hz, and a notch filter at 50 Hz to reduce electrical interference. A 512 Hz sampling rate was used to record the data. Each set of electrodes were connected to a dedicated computer system for data capture.

3.2.2. Virtual Reality (VR)

The VR study was conducted in a shared VE where two subjects could see each other represented as virtual avatars that mimicked their hand motion (see Fig. 3). The VE for the study was built using the Unity Game Engine[3] (Version 2019.1.1) and the C# language was used to implement Inverse Kinematics (IK) for animating virtual avatars, VR control (SteamVR[4]) and to network the VE for use with two VR headsets in a host-client setup.

The VE was networked using the Mirror library[5]. This enabled a host-server setup where one of the machines could host the VR environment and simultaneously act as a client for the experiment. To minimize the applications bandwidth, and delay between the clients, only data about the IK targets and head orientation was sent between clients instead of every joint in the player model. This allowed player movement to be updated on the client-side using the local IK solver. The position update interval was set to 1/10,000 of a second to minimize network latency.

The two machines running the VR environment were networked over an Ethernet connection. Network latency between machines revealed by a ping test was less than 1ms. Both machines were able to run the VE at the maximum refresh rate of 90 Hz. An HTC Vive and a Samsung Odyssey were used as HMDs for the VR portion of the study. The HTC Vive has a combined resolution of 2160 × 1200 (1080 × 1200 per eye) while the Samsung Odyssey has a combined resolution of 2880 × 1600 (1440 × 1600 per eye). These headsets were chosen to maintain positional accuracy and the visual quality of the VE.

[2] https://www.ni.com/en-nz/shop/labview.html.
[3] https://unity.com/.
[4] https://www.steamvr.com/en/.
[5] https://github.com/vis2k/Mirror.

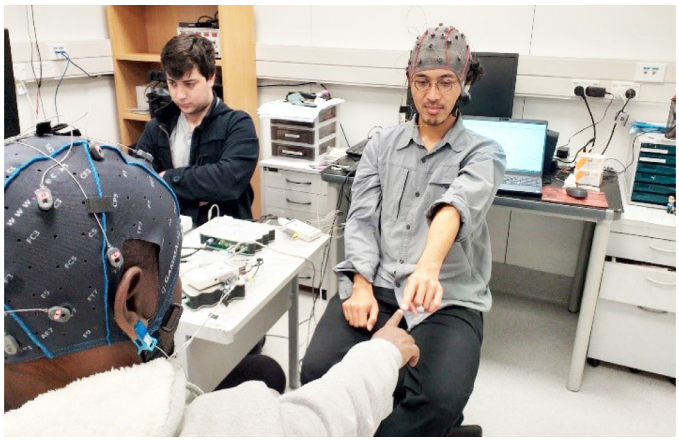

Fig. 2. Experimental setup: real world condition.

3.3. Procedure

We conducted a series of studies under three different scenarios to test our hypotheses. This involved asking the participants to perform the same finger pointing and finger tracking tasks in both real-world and VR environments. The tasks in the real-world and VR were divided as follows:

1. Real-world (RW): Face-to-face finger pointing and tracking task (scenario 1).
2. VR: Face-to-face (FtF) finger pointing and finger tracking task (scenario 2).
3. VR: First person perspective (FPP) finger pointing and finger tracking task (scenario 3).

These scenarios were not counterbalanced during the experiment. All participants performed the tasks in the sequence listed above. Given the short duration of the task we felt participants would not exhibit any learning effects between the two environments. Exposure to the environments was spaced at least one week apart, further ensuring that any residual effects of inter-brain synchrony or learning were minimal. Additionally, changing pairs as described earlier for the real-world and VR portions of the study would, in our opinion, help counter any potential ill-effects of not counterbalancing the scenarios. Neural activity for all three scenarios of the experiment was recorded using the EEG system described in Section 3.2.1. Each of these experimental scenarios was conducted approximately a week apart from each other with different pairs of participants. This was done to negate any effect of inter-brain synchrony that may have been induced by the studies and retained for a short period [49]. It also helped to preserve the legitimacy of the experiment by helping negate the effect of different study scenarios on each other [50].

The experimental setup of the real-world (RW) scenario is shown in Fig. 2. Participants sat opposite to each other, facing one another. They sat far enough so that their extended index fingers nearly touched each other when their hands were outstretched.

For the VR portion of the experiment, we created a virtual environment that was modeled on the room in which the real-world part of the study was conducted (Fig. 3). Participants were represented by generic, gender-neutral avatars designed using MakeHuman [51] and edited using Blender [52]. The avatars created the illusion of sitting across from one another in the virtual environment even though participants did not necessarily adopt the same seating positions as they did for the real-world part of the study (Fig. 4). In the face-to-face (FtF) condition within the virtual environment, participants saw each other as they would in the real-world (RW) condition (Fig. 3).

Fig. 3. The face-to-face condition in VR.

Fig. 4. The experimental setup: VR conditions (VR-FtF and VR-FPP).

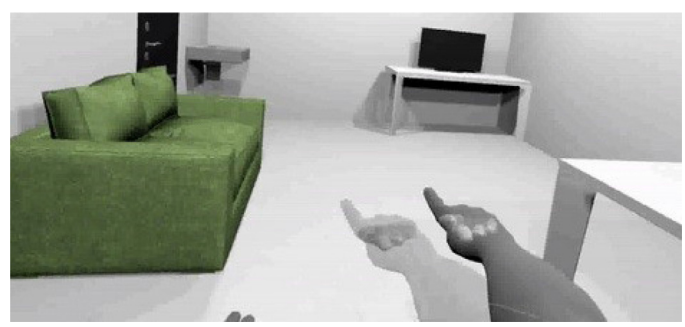

Fig. 5. FPP of the two participants hands during a finger tracking exercise. The translucent hand belongs to the person from whose perspective the scene is being viewed.

In the case of First person perspective (FPP) scenario in VR, participants saw their own hand as they did in the FtF scenario with the exception that the other participants hand appeared as a translucent overlay (Fig. 5). In this case, both participants used the same hand for the finger pointing and finger tracking task of the study.

Finger pointing and tracking was achieved in VR using the controllers of the respective HMDs. The head of the avatar followed the orientation of the VR headset. Unitys IK solver was implemented on the arms to emulate arm motion. A model of a hand was used to provide participants with a sense of embodiment in VR (Fig. 5).

Each of the scenario followed a simple three step process which involved (1) a pre-training finger pointing exercise, (2) a training or finger tracking exercise and (3) a post-training finger pointing exercise. All of these sessions of each scenario were initiated by verbal commands given by the experimenter. Each of the verbal commands was also logged using a marker in the

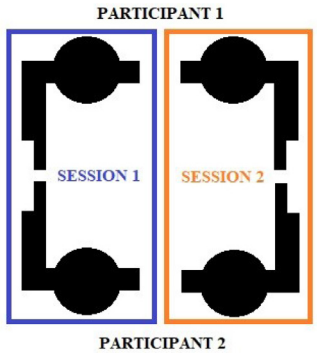

Fig. 6. Pre-training finger pointing task divided into two sessions [11].

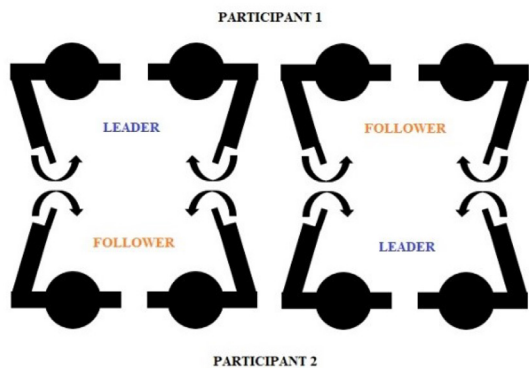

Fig. 7. Training session – finger tracking task. Both participants play the role of a leader and a follower [11].

recording software. Each of these sessions is explained in detail in the following section. All of the sessions mentioned here were run once each for every hand per participant.

3.3.1. Session 1 pre-training

For this session, participants were required to perform a simple finger pointing exercise. This session was split into two parts one for each arm of the two participants. Prior to starting this session, participants were asked to sit facing each other and stretch one of their arms out with the index finger pointing out. Each participant raised the opposite arm so as to form a mirror image (Fig. 6). In other words, if participant 1 raised the right arm, then participant 2 raised the left arm.

When the session started, participants were asked to look at the finger tip of the person sitting opposite to them. They were asked to keep the tips of their fingers as steady as possible and level with each other while continuing to look at each others finger tips. After a minute, the participants changed their hands and repeated the same process with the opposite hand for another minute.

3.3.2. Session 2 training

In the training session, participants were asked to perform a simple finger tracking exercise. This involved following the finger tip of the person designated as the leader, as closely as possible (Fig. 7). The training was repeated, similar to session one, with both arms in addition to switching the leader–follower roles between the participants. The roles and the arms to be used for each part of this session were verbally communicated to the participants by the researcher. A random order of leader–follower and arms assignments was followed. Finger tracking lasted one minute for each hand. The rationale behind carrying out this exercise was to promote some form of social interaction based on the premise that social interaction promotes the onset of inter-brain synchrony as mentioned by Yun et al. [11].

3.3.3. Session 3 post-training

The post-training task was the same task performed in pre-training session of the study. Participants were required to keep their finger as steady as possible while continuing to look at the other participants finger tip for one minute, then repeating the process with the other hand for another minute.

The entire study, excluding an approximate setup period of 10 min, took close to 10 min. Another 10 min was set aside to provide a detailed explanation of the tasks and to obtain informed consent from the participants. Each of the sessions described before were designed to replicate social interaction at a very low level, as described in [11].

4. Analysis and results

4.1. Pre-processing of EEG data

The study used EEGLAB (version 14) [53] and MATLAB software (R2018b) for analysis of the EEG data. Prior to carrying out the two analysis methods detailed later in this section, the raw EEG data was pre-processed and filtered using two separate methods. The first method used an automated pre-processing pipeline proposed by Makoto [54] (Pipeline 1), while the second method used the approach proposed in [55] (Pipeline 2) and openly available at [56]. The automated pipeline proposed by Sareen et al. [55] filtered the raw EEG data using a 0.5-60 Hz band-pass filter. The electrical line noise of 50 Hz that contaminated the EEG signals was also eliminated using a notch filter. The pipeline further rejected the artefacts linked to aberrant muscle activity, eye activity and channel noise via independent component analysis (ICA). For this, it computed the spatial and temporal features linked to each artefact, for all the components. The components, for which the features' values exceeded the permissible threshold, were identified as the artifact components. To prevent data loss, only the worst two of the identified components were rejected, and the remaining components were used to reconstruct the cleaned EEG signals that were noise and artefact-free. This pre-processing pipeline has been earlier used by Sareen et al. [57].

Two types of analyses were carried out on the EEG data to understand the neural activity recorded within the signals. These consisted of: a) using EEG source localization techniques to identify neural activation for the activities of interest (finger pointing) and b) network connectivity measures to identify the number of connections and the areas of brain that displayed synchrony. The first analysis method used data obtained from Pipeline 1, while the second utilised data from Pipeline 2.

The following sub-sections present the details of the analysis techniques, followed by the results and a brief discussion.

4.2. Phase Locking Value (PLV) analysis

The Phase Locking Value (PLV) [58] is used to measure inter-brain synchrony by detecting the rhythmicity between the recorded EEG signals of two brains. This is a standard technique for analyzing the instantaneous phase of two signals in EEG hyper-scanning studies.

The instantaneous phase value of the signal was extracted from the filtered and pre-processed EEG data using the Hilbert transform. This phase information was used as a measure of neural synchrony to compute the time varying phase locking values, PLV, as originally proposed by Lachaux et al. [58] and was estimated as

$$PLV_{ij} = \left| \frac{1}{N} \sum e^{(\phi_i - \phi_j)} \right|, \quad (1)$$

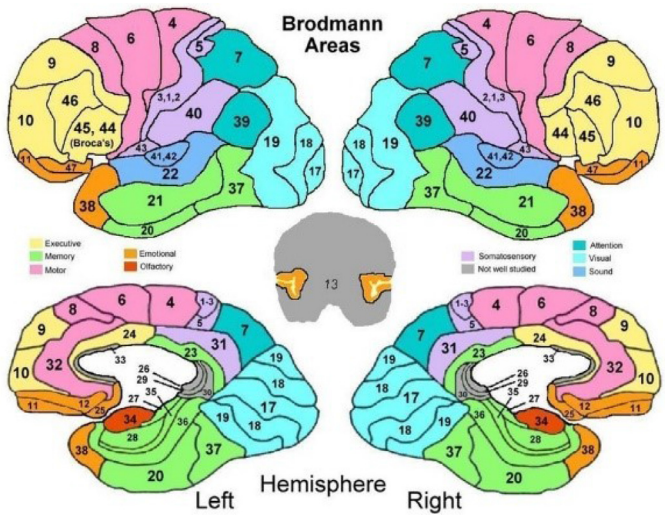

Fig. 8. Broadmann Areas (BAs) and their associated cognitive functions; source of image: [61].

where N represents the total number of epochs, ϕ_i and ϕ_j represent the phase of a signal for electrodes i and j, respectively. The phase difference between the electrodes is given by $\phi_i - \phi_j$. For the inter-brain analysis, the PLV value for each pair of electrodes i and j, with i belonging to one subject and j belonging to the other, was computed. The value of the PLV measure varies from 0 to 1, with 1 indicating perfect synchronization or phase locking and 0 indicating no synchronization or phase locking between the signals.

We adopted two methods of analysis in order to understand functional connectivity between the two interacting brains: (1) via the number of active connections between the two brains and (2) via inter-hemispheric inter-brain synchrony analysis. The first method investigates the change in all possible inter-brain connections between the pre- and post-training states. The second method investigates inter-brain synchrony by grouping only the inter-hemispheric connections between the two interacting brains. Additionally, this method maps the sensors to the nearest Brodmann area to explore the neurophysiological implications as well. Both these methods used PLV to assess connectivity. Details of these two methods are explained in the Sections 4.4 and 4.5.

4.3. Brain activation analysis using EEG source localization

Source localization of the EEG data was achieved using eLORETA (exact Low Resolution Electromagnetic Tomography), implemented within the LORETA-key software[6] package [59]. LORETA converts the electrode-level potential distribution into three-dimensional intra-cortical localized brain activity. The solution space of eLORETA spans the cortical gray matter, sampled over a spatial resolution of 5 mm, resulting in a total of 6239 voxels for which the current density is calculated. The electrode coordinates and head model for eLORETA are based on the MNI152 brain map [60]. These voxels conform to specific Broadmann Areas (BA) (Fig. 8) according to the MNI152 brain map.

An extended 10/10 electrode system template was employed to select 16 channels used in the study to estimate the 3D MNI coordinates (Table 1), although data was collected using the 10/20 electrode system. Same positions were selected from the extended 10/10 system which also covers the 10/20 electrodes. These coordinates were used to compute the eLORETA transformation matrix that provides an authentic inverse solution with exact zero-error localization. For each subject, 5 s epoch averaged, cross-spectral matrices were computed for the delta (0.5 3.5 Hz), theta (4 7.5 Hz), alpha (8 11.5 Hz), beta (12 29.5 Hz), and gamma (30 60 Hz) bands. Next, the cross-spectral subject data was transformed into eLORETA files using the eLORETA transformation matrix. These computed eLORETA images depict the intra-cortical activity generators over the 6239 voxels with a spatial resolution of 5 mm. The notation BA-x/y was followed in this work which collectively represents adjacent Broadmann areas that majorly share similar cortical functions.

[6] http://www.uzh.ch/keyinst/loreta.htm.

Table 1
16 cortical ROIs.

Scalp electrodes	ROI MNI coordinates			Broadmann areas
	X	*Y*	*Z*	
FP1	−25	65	−5	10, 11
FP2	25	65	−5	10, 11
F7	−50	40	−10	45, 47
F8	50	40	−10	45, 47
F3	−45	40	30	9, 46
F4	45	40	30	9, 46
Fz	5	45	50	6, 8
T8	70	−20	−10	21, 22
T7	−65	−15	−15	21, 22
C4	55	−20	55	3, 4
C3	−50	−20	60	3, 4
Cz	5	−10	70	6
P3	40	−70	45	7, 40
P4	45	−70	45	7, 40
O1	−20	−100	10	18, 19
O2	20	−100	5	18, 19

4.3.1. Results of EEG source localization

For comparing the difference in activation i.e. the current density distribution between pre- and post-training states, a non-parametric statistical analysis was performed for each of the five frequency bands. This analysis was implemented using the statistical non-parametric mapping (SnPM) of LORETA software. SnPM was performed over the previously obtained eLORETA images for each voxel, epoch, and frequency band.

This method uses a voxel-wise permutation test with 5000 permutations for this study and employs the logarithm of F-ratio as the test statistic. The permutation testing incorporated in SnPM has fewer and weaker assumptions compared to other parametric tests, corrects itself for multiple comparisons and has the highest possible statistical power [62]. Results of source localization in RW scenario indicate theta band activity in BA-31 and gamma band activity in BA-31/7 to be significantly higher (non-parametric permutation testing, $p = 0.074$) in pre-training compared to post-training. During the VR-FtF condition, we observed delta band activity in BA-18/19 to be significantly higher ($p = 0.074$) in pre-training compared to post-training. However, in the case of the VR-FPP scenario, we observed significantly higher delta band activity in BA-8/9 ($p = 0.036$) in the post-training session compared to pre-training. The cortical locations of the BA's are depicted in Fig. 8. The maximal current density is depicted in Fig. 9. Note that results obtained with slightly higher threshold of significance ($0.05 < p < 0.08$) have also been reported because these results are almost at the margin.

These results indicate significantly greater neural engagement in the pre-training session compared to the post-training session. This could be because a human brain would try to draw larger amount of neural resources in the pre-training session in order to learn and adapt to a task that is relatively new to it. In the RW scenario, higher activation was observed in (1) BA-31 region that is linked to joint attention and top-down control of visual attention

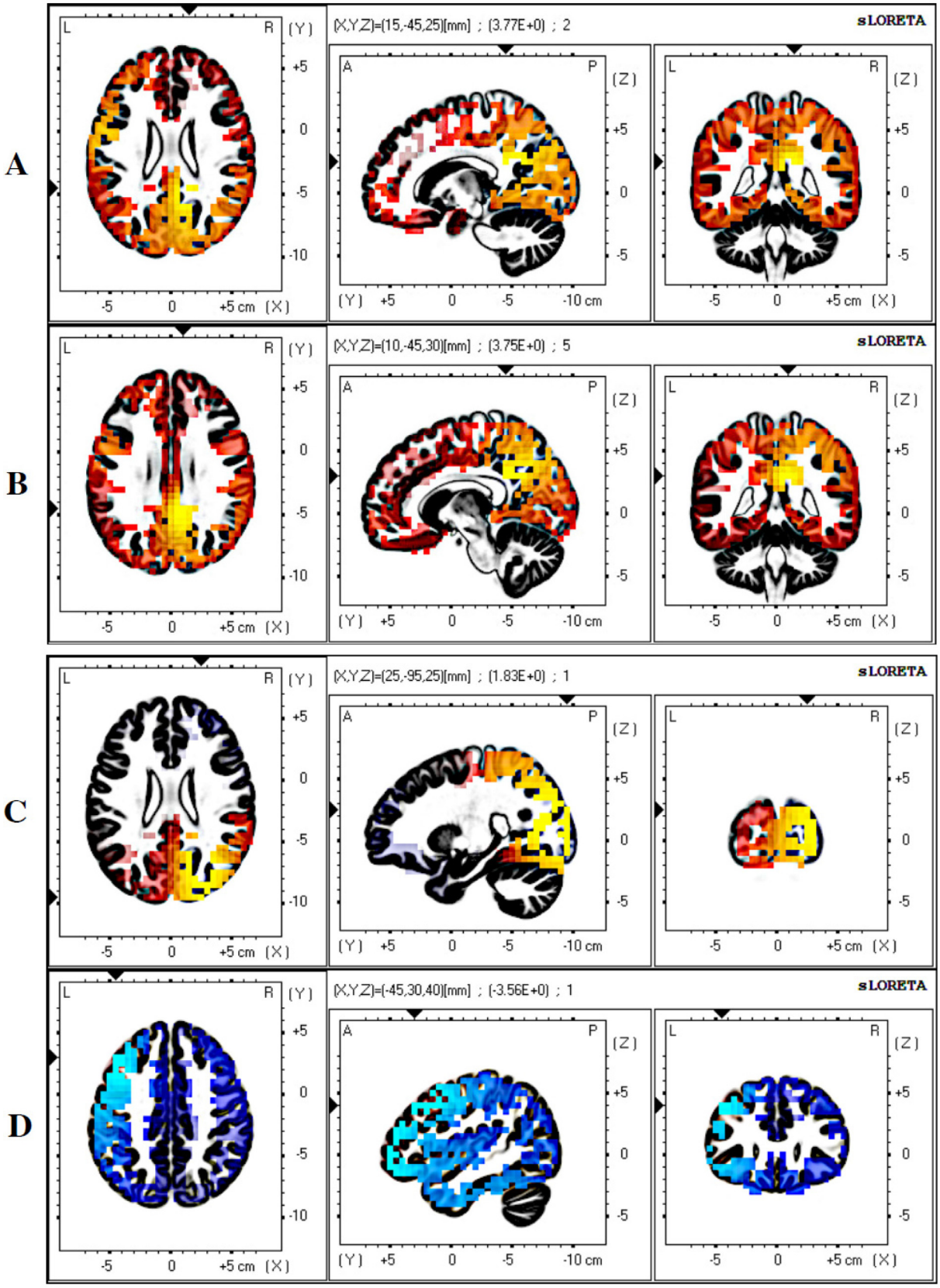

Fig. 9. eLORETA source localization. Images of horizontal (left), sagittal (middle), and coronal (right) sections obtained using eLORETA are displayed. These images depict the difference in current source density between the pre-training and post-training sessions. Only the statistically significant results are shown: (a) RW scenario theta band (b) RW scenario gamma band (c) VR-FtF delta band (d) VR-FPP delta band. The spatial extent of the voxels with significant difference in current density are represented by colored areas. The color in these images denotes the log F-ratio values, which is used as the test statistic. Yellow color indicates higher pre-training activation and blue color indicates higher post-training activation. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

and (2) BA-7 region that is linked to neuron function and visuomotor attention. This increase in neural activity in the pre-training sessions and the task-related BAs supports the argument that a greater amount of neural resource is required when a new activity is being learned. Similarly, higher activation during the pre-training session in BAs 18/19 (tracking visual motor patterns) for the VR-FtF condition corroborate the hypothesis of a greater amount of neural resources being devoted to learning a new activity. This suggests that the VR simulation of a task performed in the real-world is able to elicit similar cognitive responses in the brain.

In VR-FPP scenario, higher activation was observed (1) in the pre-frontal cortex BA9 that is thought to be the seat of emotion, empathy etc. and executive functions like focus, effort, action etc. and (2) in the BA8 region that is responsible for frontal eye field. It appears that the brain takes a longer time to accustom to the lack of a person in front during the pre-training session. A significant amount of resources appear to be deployed in the pre-post training sessions towards focusing and imitating the action(s) that are visible to the participants. Further exploration is required to be carried out in VR-FPP scenario to understand the functioning of human brain. It must be noted here that we have only studied activation of brain regions in this section. How these activated regions are related to inter-brain synchrony is explained in the following sub-sections.

4.4. Analyzing inter-brain synchrony via the number of active connections in pre- versus post-training sessions

In this subsection, we investigate the number of inter-brain connections active in the pre- versus post-training Sessions. Each electrode was paired for comparison with every electrode between the two brains providing a total of 3072 connections (256 connections/pair (=(16 electrodes/participant)^2) $\times$ 12 participant pairs). Firstly, for each pair of connection (256 connections/pair), we calculated the PLV score (designated as the 'real' PLV for the purpose of the analysis) using Eq. (1). A second set of PLV scores, designated as the 'random PLV', was also calculated for which the epoch of the recorded data was randomised prior to calculating the PLV. The shuffling was performed 200 times that provided 200 randomized PLV scores for each pair of electrode connections.

The real PLV score was then compared against the PLV score obtained from the 200 randomized iterations. This calculation was similar to the one detailed by Yun et al. in their study [11]. For example, say, PLV between FP1 of participant 1 and FP1 of participant 2 is 0.2. In order to determine whether this PLV score is statistically significant (and hence, there is a connection between these regions), the epoch of EEG data of the pair was randomized and PLV score was again calculated. Such randomization was conducted 200 times, providing 200 PLV scores. The real PLV score of 0.2 was then compared with the distribution of 200 random PLV scores via the p-value threshold of 0.05. If $p < 0.05$, the real PLV was considered significant and it was counted as one connection. Otherwise, the connection was disregarded. This method of statistical testing was carried out for all possible electrode connections in both pre- and post-training sessions. To test the statistical difference in the number of electrode connections obtained between the pre- and post-training sessions, chi-squared analysis was carried out as was done by Yun et al. [11].

4.4.1. RW scenario

In the RW scenario, our analysis demonstrated results similar to those of the previous study [11] that showed an increase in the number of brain connections in the beta and theta bands. For the beta band, the number of inter-brain connections significantly increased in the post-training session (210) in comparison to the pre-training (169) session, ($X^2(1, N = 3072)$=4.7, p= 0.02). In the case of theta band, the number of connections rose significantly from 160 connections (pre-training) to 209 connections (post-training), ($X^2(1, N = 3072)$=6.9, $p = 0.008$).

A further look at the connections revealed that the statistical difference observed in the number of connections between the two brains occurs primarily at certain PLV scores. In case of the beta band, the score was 0.2, while in the theta band, statistically significant difference between the number of pre and post-training connections was observed at the PLV score of 0.4. For a PLV score of 0.2 in the beta band, the connections in post-training session (196) were higher than the ones in the pre-training (156), $X^2(1, N = 3072) = 4.82$, p=0.02). The rest of the connections were observed for a PLV score of 0.1. The number of connections for this PLV score of 0.1 in the post-training sessions (14) did not differ significantly in comparison to the number of connections in the pre-training session (13), ($X^2(1, N = 3072) = 0.81$, $p > 0.05$). For a PLV score of 0.4 in the theta band, the post-training connections (57) were significantly higher than the pre-training (23) connections ($X^2(1, N = 3072) = 14.64$, $p < 0.001$). The rest of the connections were observed at the PLV score of 0.3, where the post-training session had 152 connections, while the pre-training session had 137 connections. However, this difference was not statistically significant, ($X^2(1, N = 3072) = 0.81$, $p > 0.05$).

In addition to the band-wise analysis performed on the data to obtain the statistical significance between the number of connections in the pre- and post-training sessions, we have also obtained head plots which represent more frequent significant inter-brain synchrony between similar areas of the brain in different pairs of participants. So, more connections in these figures mean more pairs had the same connectivity in those areas of the brain. These head plots demonstrate that the frontal and parietal areas display higher levels of activation during the real-world experimental session (Fig. 10).

4.4.2. VR-FtF scenario

Analysis of the EEG signals in the VR-FtF scenario demonstrates that the alpha band showed a significantly higher number of connections in the post (197) versus pre-training(154) sessions, ($X^2(1, N = 3072) = 5.58$, $p = 0.01$). The largest number of connections were observed at a PLV score of 0.3. A statically significant difference between the number of connections during the pre-training session (150) versus the post-training session (190) was observed ($X^2(1, N = 3072) = 4.98$, $p = 0.02$) at this PLV score. Rest of the connections were present at a PLV score of 0.4. No statistically significant difference between the connections in the post-training session (7) versus the pre-training session (4) was observed at 0.4 ($X^2(1, N = 3072) = 0.81$, $p > 0.05$) (Fig. 11).

4.4.3. VR-FPP scenario

Analysis of beta frequency band of EEG signals in the VR-FPP scenario demonstrated a significantly higher number of connections in the post- (196) versus pre-training sessions (141) ($X^2(1, N = 3072) = 9.49$, $p = 0.002$). Furthermore, a majority of those connections were observed at a PLV score of 0.2. The number of post-training session connections (177) at 0.2 were significantly higher than those in the pre-training session (127) ($X^2(1, N = 3072) = 8.65$, $p = 0.003$). The rest of the connections were concentrated at a PLV score of 0.1. Although the number of connections in post-training session (19) was higher than in pre-training session (14), no statistically significant difference was observed at 0.1 ($X^2(1, N = 3072) = 0.76$, $p > 0.05$) (Fig. 12). Table 2 shows the frequency bands across all conditions with their respective pre and post training connections. Connections that do not display a statistically significant difference between pre and post training conditions have been listed as well.

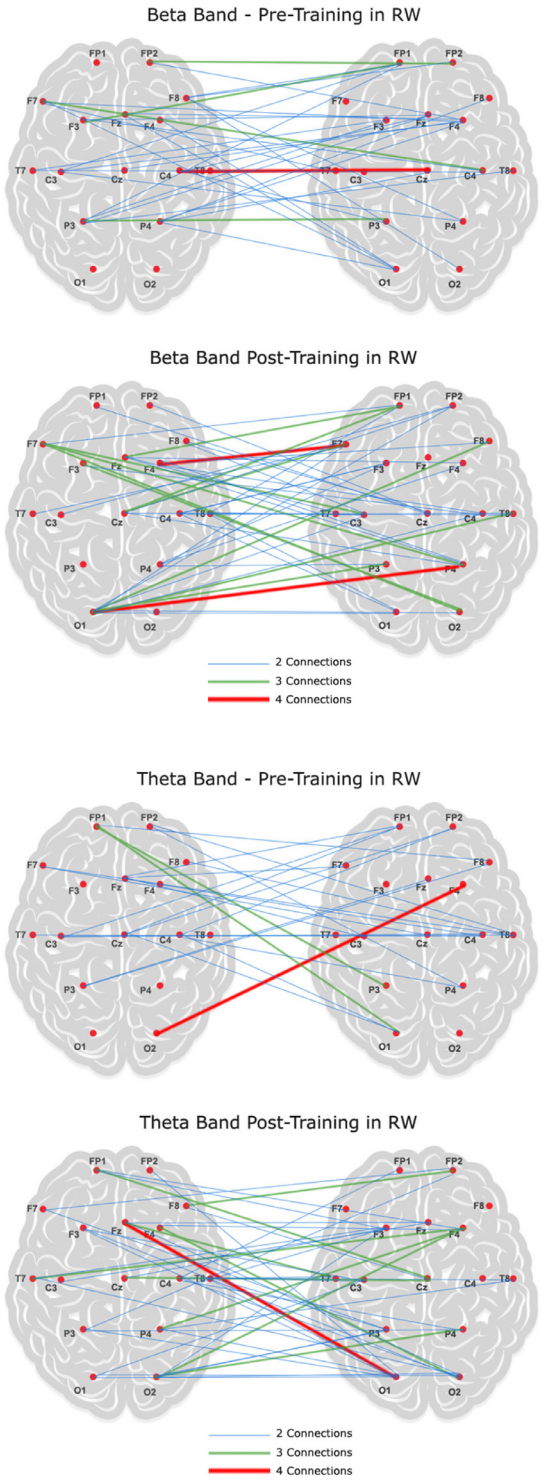

Fig. 10. Inter-brain synchronization based on the number of electrode connections in RW scenario, before and after training.

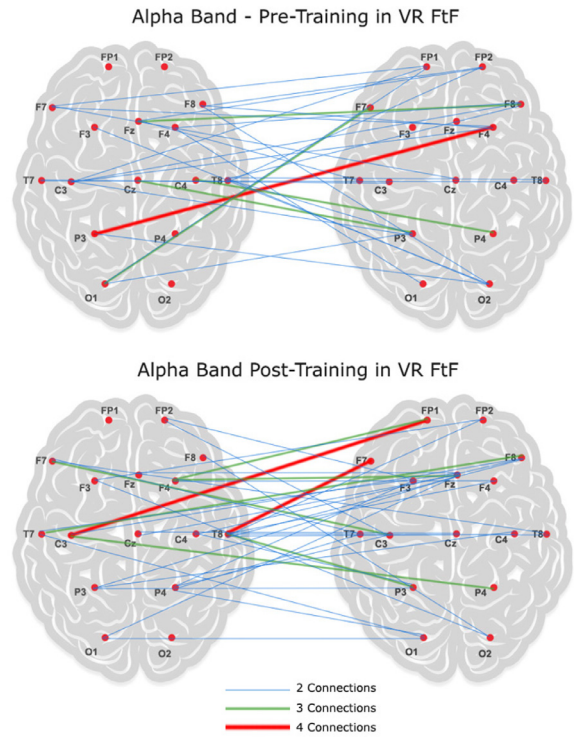

Fig. 11. Inter-brain synchronization based on the number of electrode connections in VR-FtF scenario, before and after training.

Table 2
The number of inter-brain connections observed in the pre-training and post-training phase. Connections shown here only cover the frequency bands for which statistically significant differences were observed between the pre and post-training phases across all three experimental conditions.

RW				
Frequency	Pre-training	Post-training	Chi-square	*p*-value
Alpha	173	191	0.9	0.3
Beta	169	210	4.7	0.02
Delta	133	160	2.6	0.1
Theta	160	209	6.9	0.008
VR-FtF				
Frequency	Pre-training	Post-training	Chi-square	*p*-value
Alpha	154	197	5.58	0.01
Beta	179	165	0.6	0.43
Delta	151	155	0.05	0.81
VR-FPP				
Frequency	Pre-training	Post-training	Chi-square	*p*-value
Alpha	154	186	3.1	0.07
Beta	141	196	9.49	0.002
Delta	137	160	1.8	0.17

4.5. Inter-hemispheric inter-brain synchrony analysis

In this subsection, we present the analysis of inter-hemispheric inter-brain synchrony. The analysis was carried out for seven pairs of electrodes (one electrode from each subject of the paired participants), namely FP1-FP2, F7-F8, F3-F4, T8-T7, C4-C3, P3-P4, and O1-O2. The Fz and Cz electrodes were not considered for this analysis because the study focused on left and right inter-hemispheric PLV pairs, to analyze the inter-brain synchronization between the two subjects in a pair during the experiment. Further, to understand the role of cortical regions in inter-brain synchronization, we determined the nearest BAs associated with the scalp electrodes. For this, we mapped the electrodes to the single nearest voxel at 0 mm spatial resolution (i.e., area just below the scalp electrodes) in eLORETA. This resulted in each Region of Interest (ROI) consisting of a single voxel (with a corresponding BA), which was closest to the seed (scalp electrodes). Table 1 depicts the 16 cortical ROIs determined by eLORETA.

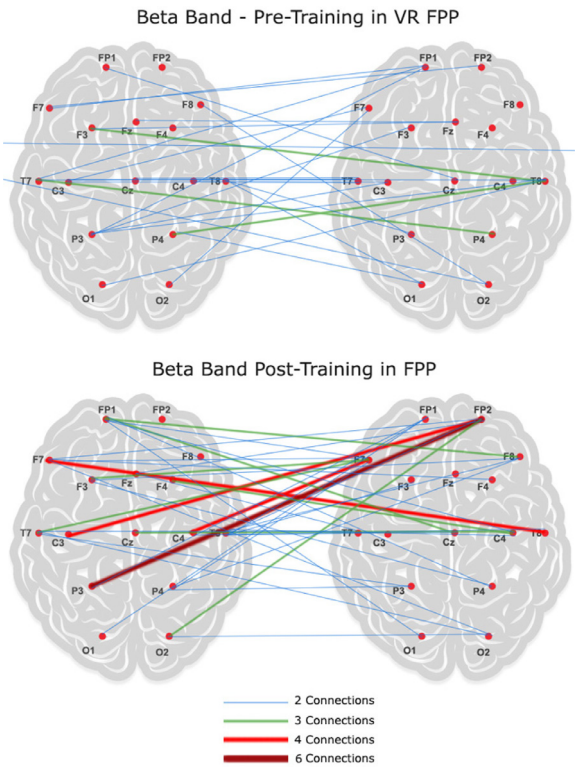

Fig. 12. Inter-brain synchronization based on the number of electrode connections in VR-FPP scenario, before and after training.

Table 3
Band-wise inter-brain functional connectivity analysis for the RW scenario.

Real-world condition ($p < 0.05$)							
Theta		Alpha		Beta		Gamma	
BAs	p-value	BAs	p-value	BAs	p-value	BAs	p-value
45, 47	0.032	45, 47	0.032	10, 11	0.032	21, 22	0.0113
9, 46	0.0113	9, 46	0.0033	9, 46	0.0033	18, 19	0.0113
3, 4	0.0113	21, 22	0.032	21, 22	0.032	–	–
–	–	3, 4	0.0113	3, 4	0.0113	–	–
–	–	7, 40	0.032	7, 40	0.032	–	–

4.5.1. RW scenario

In the RW scenario, the functional connectivity analysis suggested an overall significant inter-brain synchrony in post-training session as compared to pre-training session in theta band with three significantly activated BAs (45/47, 9/46, 3/4), alpha band with five significantly activated BAs (45/47, 9/46, 21/22, 3/4, 7/40), beta band with five significantly activated BAs (10/11, 9/46, 21/22, 3/4, 7/40) and gamma band with two (21/22, 18/19) significantly activated BAs. These findings suggest an observation, labeled as O_1, that the cooperative training exercise between the participants in a pair, increased the inter-brain synchrony between the participants. The significantly activated BAs in the post-training session and their corresponding p-values for the RW condition are shown in Table 3.

In the RW scenario, increased inter-brain synchrony was mainly observed in BA-9/46 i.e. dorsolateral prefrontal cortex (DLPFC), BA3/4 i.e. postcentral gyrus (PoCG) and primary motor cortex (PMC) and BA 21/22 i.e. middle temporal gyrus (MTG). BA-45/47 i.e. inferior frontal gyrus (IFG) and BA-7/40 i.e. somatosensory association cortex (SAC) also depicted some increased inter-brain synchrony. Increased synchrony in IFG, PoCG, and MTG after the training session is consistent with other hyperscanning literature [11]. However, our findings also demonstrate that increased synchrony is evident in the DLPFC and PMC regions as well. According to functional neuroimaging studies, DLPFC (linked to BA9/46) is majorly responsible for motor planning, organization, and regulation [63], while PMC (linked to BA-4) is responsible for finger proprioception and hand/finger movement [64]. Thus, increased synchrony in these cortical regions remains consistent with the earlier stated observation O_1. Additionally, in frequency band-level analysis, we specifically observed higher inter-brain synchrony in alpha and beta bands, with approximately 70% of the ROIs having significantly higher synchronization in post-training sessions.

Many research studies have suggested that strong inter-brain alpha band and beta band session synchronization is known to play a central role in human brain activity coordination while executing coherent action, cognition and perception [65–68]. Interestingly in the alpha band specifically, we observed significant synchronized inter-brain activation of BA-45 (inferior frontal gyrus), BA-21 (middle temporal gyrus) and BA-3/4 (postcentral gyrus/premotor cortex). Research studies have suggested that BA-3/4/21 participate in finger proprioception and learning motor sequences, while BA-45 is known to be the hub for mirror neuron system of the brain. From this, we develop an insight that synchronized activation of these cortical regions is an indication of mirror neuron system activation between the two participants while performing the task. Owing to the activation of such cooperative systems of social cognition and empathy [67] after the training task, the inter-brain cortical regions became synchronized. These findings suggest that the cooperative training exercise between the participants in a pair increased the inter-brain synchrony between the participants (O_1).

4.5.2. VR-FtF and VR-FPP scenarios

In VR-FtF and VR-FPP scenarios, we did not observe any statistically significant difference between the inter-brain synchrony during pre-training and post-training sessions at $p < 0.05$ significance level. However, we observed some significant differences in the pre- and post-training sessions in the VR-FtF condition at a slightly higher p-value or lower significance level ($p = 0.076$). We observed that the inter-brain synchrony was significantly higher in the post-training as compared to pre-training sessions in the delta, alpha and beta bands with one significantly activated BA as well as in gamma band with three significantly activated BAs. The significantly activated BAs in the post-training session are depicted in Table 4.

In the VR-FtF scenario ($p = 0.076$) we observed increased inter-brain synchrony in the post-training session primarily in the DLPFC (BA 10/11) and IFG (BA 45/47) cortical regions. Based on the cognitive functions associated with these areas, increased synchrony in these areas corroborate the observation O_1, made in the RW scenario. It is important to note that we observe a significant increase in inter-brain connectivity in only about a 30% ROIs in the post-training session collectively in all the bands. Some reasons and possible explanations for this drop in the two environments are discussed in the following section.

5. Discussion

A comparative study between the same activities and their effects on inter-personal neural coupling in two different environments, real and virtual, was conducted. The results from this study have demonstrated that inter-brain synchrony is observed for the same activity in both the real and virtual environments. It must be re-emphasised that the inter-brain synchrony reported in this study in both these environments was between pairs that did not know each other i.e. every participant was paired with a different person for the real-world and VR portions of the study. While these results are encouraging, they must be evaluated in the context of the research questions stated in Section 2.4.

Table 4
Band-wise inter-brain functional connectivity analysis for the VR-FtF scenario.

VR-FtF condition ($p < 0.10$)							
Delta		Alpha		Beta		Gamma	
BAs	*p*-value	BAs	*p*-value	BAs	*p*-value	BAs	*p*-value
10, 11	0.0758	45, 47	0.0758	10, 11	0.0758	10, 11	0.0758
–	–	–	–	–	–	45, 47	0.0758
–	–	–	–	–	–	9, 46	0.032

Our first research question has broached the most basic aspect of the relatively nascent research area of hyperscanning: can the results from an existing hyperscanning study be replicated using the methodology and equipment that approximate the ones used in the reference study. As we have mentioned in Section 3, we chose to replicate the study detailed by Yun et al. [11]. Overall, our results demonstrated that inter-brain synchrony was observed in the replication of Yun et al.'s study. A closer analysis of the results demonstrated that the results of our study closely aligned with those reported by Yun et al. This is evidenced by the fact that we observed a significant difference in the inter-brain connections between the pre and post-training sessions in the beta and theta bands; something that was also reported by Yun et al. These results have helped established that it is possible to obtain similar results and thereby validate the methodology utilised by previous studies. This is of course premised on the fact that similar experimental conditions, and to a lesser extent equipment, are employed for a given study. It is also important to note that the analysis detailed in the previous section ensures that we have not detected any spurious connections, or that the inter-brain synchrony is not simply a function of the task and its effect on the the brains.

Keeping with our incremental approach to this topic, our next research question dealt with the subject of task replication in the VR environment. Given that we were able to demonstrate real-world replication was possible successfully, we shifted our focus to VR. The aim of this part of the study was to explore the the possibility of replicating the results from the face-to-face real-world study in VR. The same finger pointing and tracking tasks were performed in VR with the avatars of the participants facing each other. The VR environment that loosely resembled the one in which they carried out the real-world portion of the experiment. Functional connectivity analysis demonstrated that there was significantly higher inter-brain synchrony in the post-training sessions compared to the pre-training sessions in the delta, alpha, beta and gamma bands. However, a band level analysis determined that this activity was mainly confined to the alpha and beta bands. While the roles of these bands is not yet fully understood, there is some evidence that points to the role of the alpha band in attention suppression [69] i.e. an increase in alpha activity in the areas of the brain required to attend a specific task while simultaneously suppressing inputs from other modalities. Similarly, a plausible explanation of the activity seen in the other bands can be attributed to evidence that demonstrates their role to accurate upper limb movement [70]. It is also interesting to note that some of the activity reported in this study was centered around BA47; an area that deals with emotion regulation. This in our opinion could potentially be an indication that the two participants were in some manner "emotionally coupled" or at least empathetic towards each other. Indeed, the hand tracking results from Yun et al.'s study [11] support this as a plausible explanation; given that they demonstrated that the leader in their experiment attempted to regulate hand movement in a manner which would allow the follower to easily keep up. While these results are encouraging, it must be remembered that the differences seen in the inter-brain synchrony between the pre and post-training sessions were observed only in 30% of the ROIs. One of the reasons for this could be the novelty of using VR. Most participants who took part in the study did not have any experience using a VR headset. This may have resulted in some amount of disorientation, and a lack of body ownership in the VE.

Our final research question sought to study the effects of providing a first person perspective to the two participants in VR. VR is unique in that it is possible to easily change visual perspective. This part of the study sought to explore how inter-brain synchrony would be affected when each participant viewed the environment from their partner's visual perspective. It is interesting to note that the most active ROIs in this part of the study were seen in the BAs associated with executive functions and emotion regulation. From these initial results it appears that there is value in providing someone with a first person visual perspective. However, the surprising element during a band level analysis is the presence of delta band activity in addition to the alpha and beta bands. The increased activity in the alpha and beta bands is likely due the reasons listed earlier i.e. attention suppression and upper limb co-ordination. It is possible that delta band activity indicates the presence of an adaptive neural process that allows the monitoring and processing errors [71]. This in turn helps update the state of sensorimotor networks that help drive limb movement.

Overall, the results from the two environmental conditions clearly demonstrate that inter-brain synchrony can be achieved in the real-world and VR. It is particularly exciting that we have been able to demonstrate that inter-brain synchrony in VR is quite similar to the real-world. These results provide preliminary evidence, via neurological data, that collaborative VR environments have the same effect on human-human collaboration as seen in the real-world. Another important result has been the demonstration of inter-brain synchrony in the VR-FPP scenario. While this was seen at relatively lower levels, it demonstrates that there is significant value in exploring this aspect of remote collaboration using the hyperscanning technique. However, it must be mentioned that there could be some effects of not counterbalancing the experiment. Since all participants performed the real-world task first, it is expected that they had already acquired a certain level of familiarity by the time they were asked to repeat the task in VR. Despite this, we believe that the novelty of using VR along with a change in the participant pairs between the real-world and VR conditions may have been sufficient to negate any order effects that may have arisen from failing to counterbalancing the conditions during the study. In the remainder of this section we will discuss how the methods of analysis chosen for this study have helped us arrive at the results and list a alternate methods that future studies can employ. We also look at the implications of some of the findings regarding the activation of specific cortical regions, and list future directions in which research in the area can be steered.

Our methods of brain region activation analysis via source localization (with eLORETA) and inter-brain synchrony analysis using PLV scores have demonstrated that it is possible for VR to elicit similar inter-brain synchrony as seen in the real world. This has also allowed us to validate our hypothesis that VR is

able to effectively elicit similar inter-brain synchrony using a common metric i.e. PLV scores. An interesting result has also been the demonstration of increased number of inter-brain synchrony connections in the VR-FPP condition in post versus pre-training sessions using the PLV analysis shown in Section 4.4.3. However, the inter-hemispheric inter-brain connections depicted a significant difference in the level of synchrony in a statistical sense using the second PLV analysis detailed in Section 4.5.2 only at a relaxed significance level. We see this as an opportunity to further investigate and develop new approaches to user study design and analysis techniques that can be used to evaluate inter-brain synchrony in the real-world and VEs. Future studies can use other methods such as Partial Directed Coherence (PDC) [72] and Circular Correlation Coefficient (CCorr) [73] to evaluate inter-brain synchrony. An overview of the other analysis techniques applied to hyperscanning studies can be found in the work of Burgess [74].

PLV analysis revealed a larger number of inter-brain connections in the post-training session compared to the pre-training one in RW scenario. Further, inter-hemispheric inter-brain PLV analysis demonstrated significant differences between the pre and post-training sessions for the VR-FtF scenario, although only when the significance level was dropped ($p < 0.10$). This indicates that participants in our study found it marginally harder to assimilate and execute the task required to demonstrate inter-brain synchrony. One of the main reasons for this finding could be the design of the virtual environment (VE). The study used a simplistic approximation of a room that was populated by the most basic elements that exist in the real-world environment such as couches, PCs, etc. Further, generic, gender-neutral models sourced from freely available online content were used as avatars to represent participants in a VE. The combination of a familiar, yet simplistic environment, coupled with an ill-defined representation of the participants is likely to have resulted in the lesser number of connections and lower level of synchrony observed with the PLV analysis techniques for the VR conditions (VR-FtF and VR-FPP).

From the perspective of the activated regions of the brain and the cognitive processes associated with these regions, our results suggest that IFG, PoCG, MTG, PMC, SAC, and DLPFC cortical regions show increased inter-brain synchrony and thus, can be considered as the neurophysiological substrates of inter-brain synchronization. These results are not only consistent with the work of Yun et al. [11], but also augment their findings in identifying other cortical regions that play a part in inter-brain synchronization especially in the context of finger pointing and tracking tasks. The interaction between DLPFC (frontal) and SAC (parietal) as a frontoparietal network and PoCG (central) and SAC (parietal) as centroparietal networks, has been attributed in many neuroimaging studies for engaging in social cognitive processes [75], cognitive control [76] and inter-personal action synchronization [77]. These findings from neuroimaging studies accentuate the participation of frontoparietal and centroparietal networks in social synchronization tasks, and stand consistent with related hyperscanning studies as well [11,49].

A holistic view of the activated cortical regions and inter-hemispheric inter-brain synchrony demonstrate an inverse relationship while learning a new task, i.e., the greater the level of activation, the lower the inter-brain synchrony recorded. This is evident in the pre and post-training data analysis presented in Sections 4.3 and 4.5. While pre-training sessions demonstrated higher activation, post-training sessions demonstrated greater inter-brain synchrony. These results lead us to postulate that a significant investment of cognitive resources is required during the training session in learning a new task. Once both participants have learned the task and were able to perform in near unison, we observed an increased level of synchrony between the two brains while demonstrating a significant reduction in activation. This trend was observed in both RW and VR scenarios (except VR-FPP).

This consistency in neural activation in different environment types is an encouraging sign. It points to the usefulness of VR as a medium to elicit inter-brain synchrony between two participants. From an application standpoint, this can be deployed as a means to monitor and enhance remote collaboration interactions, particularly, in the field of remote training. For example, an individual delivering a training session remotely will have the ability to monitor the neural activity of a trainee or a group of trainees using the hyperscanning technique. In such a scenario, the trainer will be shown a real-time 'classified' output of the synchrony between his/her own brain and that of the trainee(s). This will allow the trainer to dynamically alter content to engage attention based on the brain synchrony measure. The main purpose of displaying the brain synchrony measure will be to provide the trainer with a 'target', ideally perfect inter-brain synchrony, to aim at to ensure optimum 'flow'. Achieving a high level of inter-brain synchrony, and as a result, flow has been shown to increase the level of task performance [78].

While we have discussed the implications of the results from the perspective of neuroscience, it is important to assess them in the context of HCI as well. Unlike a BCI, the use of the EEG here is not to provide explicit instructions to a machine as is the case with traditional EEG-VR based applications seen in HCI. In this study, we have made use of EEG devices as means to monitor collaboration between two participants in a VE by monitoring neural activity. We believe monitoring neural activity in collaborative environments has the ability to significantly improve the quality of these collaborations by:

1. Assessing the similarity in neural activity between participants in a collaborative VE, and actively modifying the environment to promote 'neural coherence' between them.
2. Conveying cognitive and/or emotional states of participants to each other to promote behavioural changes that induce or boost neural synchrony.

It must be noted that these outcomes form the overarching goal of using hyperscanning to monitor neural activity in collaborative environments. It is also evident that for such a system to be implemented in the HCI domain, a two pronged approach must be applied. The first one entails the use of the EEG as a monitoring device; while the second one involves using the EEG device as a BCI to monitor, classify and act on the neural activity of participants in the collaborative VE. This study has presented the some of the first steps that we have taken in the direction of integrating the ability to monitor and classify inter-brain synchrony between participants in a VE.

Future studies should explore the use of avatars that closely resemble real participants, and also model VE to closely resemble the real-world setting. The use of different HMDs, while not a conscious choice, may have also affected the results. Particularly, the manner in which tracking of the controllers is implemented in both HMDs may have caused some discrepancies in the hand movement and positioning within the VE. The controllers themselves might have also played a role in the results. The use of hand models with minimal articulation might have affected the participants' sense of ownership and embodiment of the hands. Additionally, controllers did not allow for a fine motor control, generally afforded by fingers. Future studies will explore the use of full hand tracking that is afforded by devices such as LeapMotion[7]. With respect to the analysis method, future investigation should attempt various types of analysis such as PDC [72] and CCorr

[7] https://www.leapmotion.com/.

[73] to evaluate inter-brain synchrony. Other limitations that could have influenced the outcome of the study are:

1. Virtual Environment (VE): The VE used for this study was relatively simplistic. As we have detailed in the Section 3 (Method), the VE was designed to look similar to the space that the participants entered, but lacked the detail present in the space. This could have influenced the way they perceived the environment and as a results their interactions within it.
2. Finger pointing/tracking tasks: The finger pointing/tracking tasks that were used for this study themselves have likely influenced the inter-brain synchrony results to a great extent. Future studies will look at designing tasks that represent scenarios closer to plausible uses for remote collaboration technology that utilises immersive VEs.

6. Conclusion

A hyperscanning study was conducted in real-world and VR environments. We have successfully been able to replicate the findings of an earlier real-world study in our experiment for the real-world and VR environments. The results of this study raise some interesting questions and possibilities regarding the use of VR to elicit inter-brain synchrony. Equally interesting is the possibility to be able to empirically measure this synchrony using neurophysiological measurement tools. The results of our study support the hypothesis that VR can be used to elicit synchrony between two brains. While we have shown this to be true in the VR-FtF case, more work needs to be undertaken to ascertain if inter-brain synchrony can be achieved in a VR-FPP like scenario in the future. The cortical regions identified in the study in addition to the cognitive inferences drawn, specifically from the VR scenario should be read with caution as a relaxed significance level was considered for this scenario.

However, we believe the studies detailed in this paper have far reaching implications for the social neuroscience and Human–Computer Interaction (HCI) communities. We have been, to the best of our knowledge, able to demonstrate for the first time that the phenomena of inter-brain synchrony can be replicated in a VE. This opens up the possibility of studying how multiple brains interact in a VE in real-time, and whether inter-brain synchrony on a larger scale can be achieved in a VE. In addition to a greater number of participants, in the immediate future, we would like to explore how inter-brain synchrony is affected by implicit cues such as eye gaze and facial expressions. These are integral facets of human-human communication and have been shown to have a significant effect on the quality of communication and other factors like presence and attention. Besides these avenues, future studies can also investigate how VEs can be tailored in order to speed up inter-brain synchrony. Additional methods for exploring novel ways to analyze the data and present an accurate picture of the neural activity of two or more interacting individuals must also be researched.

Declaration of Competing Interest

Mark Billinghurst, one of the authors listed on this paper, also serves as a guest editor for the Computer & Graphics journal.

CRediT authorship contribution statement

Ihshan Gumilar: Investigation, Formal analysis, Data curation, Writing - original draft. **Ekansh Sareen:** Supervision, Writing - review & editing. **Reed Bell:** Investigation, Formal analysis, Software. **Augustus Stone:** Investigation, Formal analysis, Software. **Ashkan Hayati:** Formal analysis, Writing - review & editing. **Jingwen Mao:** Formal analysis. **Amit Barde:** Supervision, Writing - original draft. **Anubha Gupta:** Formal analysis, Visualization, Writing - review & editing. **Arindam Dey:** Formal analysis, Visualization, Writing - review & editing. **Gun Lee:** Supervision, Writing - review & editing. **Mark Billinghurst:** Conceptualization, Supervision, Funding acquisition, Resources, Project administration, Methodology.

Acknowledgment

We would like to thank the Tertiary Education Commission/Te Amorangi Mtauranga Matua, New Zealand for funding this research and TCS Centre for Design and New Media, IIIT-Delhi, India for their support in this work.

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