High stimuli virtual reality training for a brain controlled robotic wheelchair

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***Abstract*— Smart robotic wheelchairs, as well as other assistive robotic devices, can provide an effective form of independent mobility for those who suffer with motor disabilities. Although many control interfaces exist to operate these devices, brain computer interfaces (BCI) offer a control modality for those who have little to no motor function, as well as being able to re-associate movement with brain functionality. Although BCIs have been designed for robotic wheelchairs, more research and development is required before they can be adopted for use in the 'real world'. One key challenge on that journey is the user training required to achieve an acceptable accuracy of the control. In this paper, we aim to identify the best training method by comparing users trained on a simple task, in a simulated environment on a 2D display (VR-2DD) and in a virtual environment using a virtual reality headset (VR-HMD). We trained 16 participants in mix of high and low noise virtual environments or on a simple training task, and found a significant improvement in the classification accuracies of the participants who trained using the VR-2DD task compared with those who were trained with the simple task. We also carried out active (online) tests across all participants in the same virtual training environment, with a varying level of external stimuli, and found a significant improvement in the performance of participants in both VR groups compared to participants in the simple task group.**

I. INTRODUCTION

Brain computer interfaces (BCI) can provide an innovative way for users with severe motor disabilities to control assistive robotic devices that help them with their everyday lives. These assistive devices can take many forms such as wheelchairs, prostheses and tele-presence robots [1]–[4]. Although similar systems have been designed and implemented previously, the challenge of deploying them in real-world active environments while maintaining a level of accuracy that allows for consistent effective control of the device persists. Typically, BCI users are trained on the system in a quiet environment with few external stimuli. However, the goal is to translate their use into the real world, which is full of dynamic stimuli. Therefore, one of the key challenges is to recognise 'noise' introduced into the recorded brain signals due to stimuli that might be encountered in real world environments. By training users of a BCI system in a simulated real world environment, we aim to create a BCI that can recognise an instruction despite this added 'noise' so it can better translate to real-world situations.

We hypothesise that users trained in a virtual environment will perform better over time, as well as perform better in high stimuli environments.

In line with the theme of ICRA'24, *'Connect +'*, we believe that BCI combined with Robotics can provide many benefits to the healthcare, medical and other communities, and that effective training of BCI users is one of the key challenges to overcome before robotic BCI systems can be more widely deployed in the real world.

II. RELATED WORK

For those who have motor disabilities, are of old age or have suffered accidents permanently affecting their core motor function, assistive technologies can provide life-changing equipment to help them regain their ability to navigate the world and perform everyday tasks that would otherwise be impossible. Robotic powered wheelchairs are an innovative way to give people who have lost all motor function below the neck the possibility to regain (some of) their independent mobility [5], [6]. Many robotic powered wheelchairs rely on the remaining physical movement of their users as a control interface such as eye trackers and sip–and–puff switches, which requires removing or re-purposing one of the few remaining functionalities the user has to interact with the world. Brain computer interfaces offer an alternative way to control a robotic wheelchair without using any physical features, and in some cases, access parts of the brain that would otherwise remain unused, such as the motor cortex [1].

Robotic wheelchairs differ from regular commercial powered wheelchairs through the addition of features to help the user navigate a space effectively and safely, normally through the process of shared control, or by providing different forms of feedback. They are essential for wheelchair users who are unable to effectively navigate using a conventional powered wheelchair. These features can include different forms of human-machine interfaces, such as touchscreens, voice recognition, and haptic feedback devices, as well as automatic collision avoidance, navigational assistance and using sensors to map a space and plan a safe route between its current position and destination, including difficult-to-navigate spaces such as doorways and crowds [5], [7], [8].

Shared control functions on the principle of giving the robotic device some influence on the final action taken. Use and autonomy of shared controlled device varies greatly depending on their application, but all share the common goal of improving the accuracy or efficiency of a task being completed with a robotic tool or device while reducing the effort of the user [9]. Accurate non-invasive brain computer interfaces usually only allow for a limited number of instructions, so shared control can be designed to overcome

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this limitation, such as predetermining the available paths for the user to select, as well as avoiding and navigating around obstacles and groups of people [1], [2].

Many forms of electroencephalography- (EEG) based BCIs have been designed and implemented to date [10]. Most BCI paradigms can be split into two main categories: synchronous and asynchronous. Synchronous BCIs rely on the measuring the user's neuronal response to a stimulus presented at a specific time or frequency to the user. Common examples of theses systems are the P300 detector [11] and steady state visually invoked potentials (SSVEP) [6], which both require the user to focus on the corresponding images or lights to perform actions. The P300 system will look for activity around 300ms after the stimuli is presented, whereas SSVEP looks for a change in spectral power in the frequency band corresponding to the frequency of the stimuli over the section of the brain associated with sensory system being affected (e.g. the Visual Cortex).

Asynchronous BCIs do not rely on an external stimuli and instead rely on the user voluntarily performing a mental task to modulate their own neuronal activity. One of the most common and easiest mental tasks to perform is motor imagery (MI) [12], which relies on the user imagining moving a limb [13] and consequently causing a change in spectral power across the part of the motor cortex associated with that limb.

Many BCI EEG papers train 'offline' classifiers on data from participants who have been through a training process; they then use the tested classifier accuracy to evaluate their approach [14]. Conversely, we have focused on the very early user training and adaptation process that is required, before the participant becomes proficient in BCI control, in an attempt to improve this often tedious process.

Virtual reality has the potential to improve education and learning. Whether it be foundational knowledge, such as the laws of physics, or the advanced concepts such as medical imagery [15]. The immersive virtual environments that can be created for both 2D displays (VR-2DD), or head mounted displays (VR-HMD) allow the user to interact with and feel as if they are a part of a virtual world, yielding a better learning experience. It has been shown in previous studies, that virtual reality and virtual reality head mounted displays can increase BCI performance during the training process and during online classification [16]–[18]. Virtual environments create a more interesting and engaging task for the users, providing them with more motivation to complete the required task [17], [19]. However, these studies have used virtual reality to display simple environments only containing dynamic objects or stimuli that provide feedback to the user about the BCI classification. We intend to build upon this concept to improve the learning stage and introduce new, unrelated stimuli, both to improve the learning process and to expose participants to a range of simulated stimuli that would typically be encountered in a real world setting.

III. BCI SYSTEM

We designed a BCI control system with 3 instructions to be used on a robotic wheelchair. In order to create a voluntary control system similar to our natural movement ability, we decided to implement an asynchronous control system that does not rely on external stimuli to decipher the users intentions. Control through motor imagery (MI) is a control system based on the user performing the mental task of imagining the movement of a limb or specific body part. While the user is at rest, the neurons in the motor cortex fire in a synchronised rhythm, producing a relatively high spectral power within the 8-13 Hz band and these are known as Mu rhythms [13]. When the user imagines moving a limb, a decrease in spectral power can be seen within the 8-13 Hz band over the part of the brain associated with the limb being imagined. This effect is known as Event-Related Desynchronisation (ERD) and is described by Pfurtscheller as "the short lasting (phasic) and regional localized amplitude attenuation or blocking of oscillations in the alpha and beta bands that occurs in direct relation to an event" [20]. In our protocol, each user imagined the movement of 3 specific limbs to perform 3 distinct instructions: the left hand to turn left; the right hand to turn right; and both feet to move forward [1]–[3]. In response to a forward instruction, the wheelchair would move a small set distance forward, whereas left and right hand instructions cause the wheelchair to rotate 15° in the corresponding direction.

A. EEG System and Montage

Using the g.Tec g.USBamp with g.GAMMAsys [21], brain activity was recorded over the pre-motor, primary motor and somatosensory cortex. 16 active electrodes were placed in accordance to the 10-20 layout at positions shown in Fig. 1. The ground electrode was placed at position AFz and a reference electrode was placed on the right ear lobe.

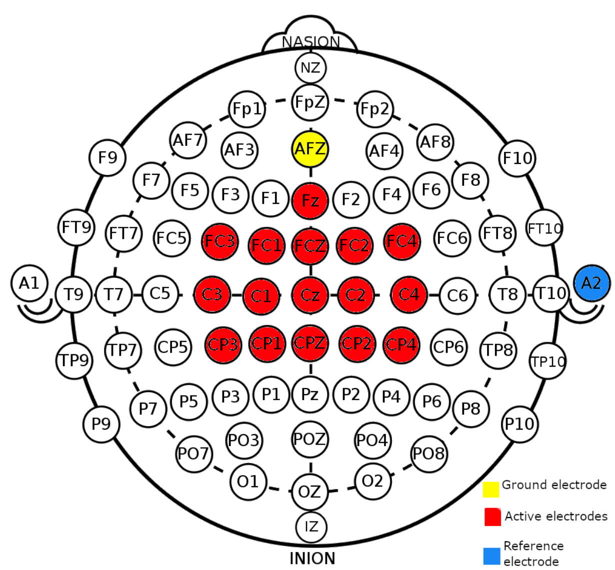

Fig. 1: Montage of our electrodes for Motor Imagery, in the 10-20 system.

B. Signal Processing and Feature Extraction

The user's brain activity is processed in 1-second windows (0.5 s overlapping). The recorded signal is then spacial filtered using a Small Laplacian filter to reduce effects of artefacts [22]. A 6-40 Hz 3rd order Butterworth bandpass filter was then applied to the signal [23] and the power spectral density (PSD) was calculated by squaring the single sided fast fourier transform of the epoch with a frequency resolution of 1Hz [12].

C. Signal classification

Due to the large range of different signals that can be produced by the brain, almost all BCIs use a machine learning algorithm to classify the signal acquired from the user. One of the most popular machine learning algorithms and one that is often used in EEG BCIs, is the support vector machine (SVM) [24]. SVMs function by creating *hyper-planes* between areas of maximum difference between each class of labeled data in n-dimensional space. How these hyper-planes are created is decided by the kernel provided to the classifier. In our system, the SVM classifiers implemented using the Sci-Kit-learn python library, use the exponential *RBF* kernel [25].

D. Feature Selection

Mu rhythms across the motor cortex oscillate within the alpha band (8-13Hz) of neurological activity [13]. For this reason we selected the power between 8-13Hz for each of the PSDs of each electrode.

IV. Shared control and signal classification

In order to train each participant effectively, a balance of challenge and reward is required during the mutual learning process. The sense of reward helps secrete dopamine, which in turn helps the brain adapt through synaptic plasticity [26]. As new users must be trained to use a motor imagery BCI, the task can often feel too difficult and will present no reward to the user while they struggle to complete the task. Through the process of shared control, where the assistive device has an influence on the final movement made by the user [9], we can create a form of mental '*haptic*' feedback to make the desired motor imagery task *feel* easier to complete while the user is adjusting to and learning to use the system [27]. By calculating the classification probability of a single recorded instruction and adding a *bias* value to the probabilities, we can vary the difficulty and ease of achieving an instruction. The bias value decreases incrementally throughout the training period, progressively removing the assistance and consequently increasing the difficulty of the task as the user improves, which allows us to maintain the reward cycle.

A. Evidence accumulation and training

Evidence accumulation is the process of collecting and classifying multiple samples of time series data before making a decision or performing an action [28] and this has previously been applied in a BCI context [29]. This is beneficial for data that has a high chance of containing noise introduced by other elements, which could affect the classification and then subsequent action of the system. We have implemented an evidence accumulation window of the 10 previous classification outputs. During the training processing, 70% of the user's classifications within the evidence accumulation window must be of the same instruction in order to move the wheelchair. This allows the user to have improved control of the system, albeit at a slight cost in terms of increased latency. Either singular or a small number of anomalous miss-classifications by the BCI system will not move the user in an unwanted direction. Therefore, with our system decoding a new instruction every 0.5 seconds, the user can successfully stop the wheelchair in 1.5 seconds and issue a different control command to the wheelchair every 4 second while also being able to maintain constant movement by successively performing similar mental inputs.

V. Virtual reality and Simulated environments

The main aim of the VR environment is to provide a simulation of a space in which the user might commonly find themselves. The objective of this approach is to elicit brain activity that is similar to the neural response corresponding to the real-world stimuli. While training, our users are placed withing a simulation of a large park within a urban city area. The park contains a few static obstacles, such as trees and flowers (Fig. 2). The VR simulation was designed the Unity 3D 2021 game engine [30] and runs on the Meta/Oculus Quest 2 VR headset [31].

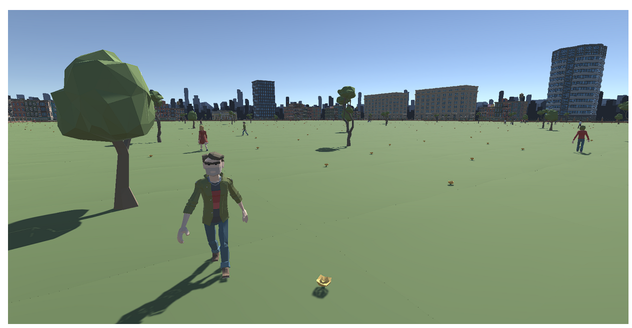

Fig. 2: Screenshot of the simulated environment

During the training sessions, the environment can be changed depending on the stage of training and the hypothesis being tested. We can also vary the amount of auditory and visual stimuli being presented to the user. The simulation can play either classical music, or a recording of common sounds heard in a city environment at an appropriate volume through out the training session. The environment can also accommodate multiple 3D dynamic characters in the form of diverse individuals encountered in everyday life. These characters will take random paths inside the park area, avoiding any obstacles and the user (should the user come close to colliding with any of them). This allows the characters to appear or act as constant distractions, while not actually impeding the user's intended movement. High stimuli sessions had both music and common sounds playing throughout the experiment and 50 dynamic characters present in the park area. Alternatively the low stimuli sessions contained no auditory stimuli or dynamic characters.

VI. Experiment Methods

Our experiments were approved by the UCL Research Ethics Committee (ref: 6860.017). Sixteen healthy, able-bodied participants who were novice BCI users (without experience), were randomly split into different groups (Table I), taking into account the exclusion criteria for each experiment: e.g. users who commonly experience motion sickness were excluded from the VR-HMD experiment.

Training Group	Simple	VR-2DD	VR-HMD
Num participants	4	5	6

TABLE I: Number of participants in each training group

One group is used as a control group, performing the same MI tasks on a simple BCI task (Fig. 3), where the participant is instructed to move a dot into the corresponding segment. Every participant attended one or more 1-1.5 hour sessions, where they attempted the Motor Imagery task in conjunction with their allocated simulation condition (i.e. VR-2DD or VR-HMD).

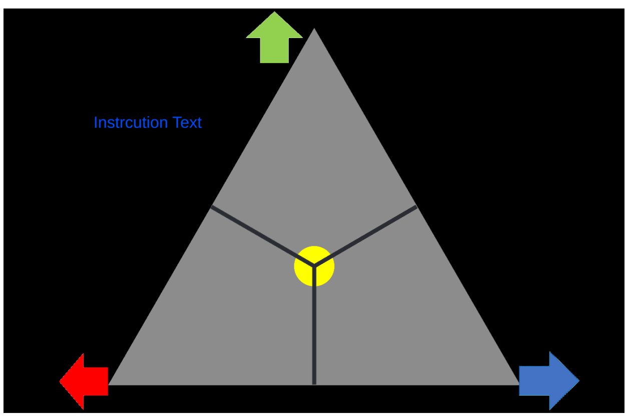

Fig. 3: Simple BCI task feedback: the yellow dot moves to represent the output of evidence accumulation framework, gravitating towards the most likely decoded class.

Each participant was first given a stress ball to squeeze, and asked to imagine the feeling and the movement to familiarise them with the task [32]. The EEG cap was placed on their head and the BCI system was set up by applying electro-conductive gel between the electrodes and the scalp. The user was then asked to complete a randomly ordered set of the three MI actions linked with the movement of the wheelchair over a 5 minute time period while the simulation is running. The user was then given a 5-10 minute rest between each session. For the first two, 5-minute training simulations in the first session, the bias was set so the BCI always gave the correct classification (fake feedback), while the user performs the MI task. This initial data set was then used to retrain the classifier system to calibrate it to the participant. The bias was decreased on the subsequent tasks, as both the user and the BCI system adapt to each other during the mutual learning process.

Test condition	**Low Stimuli**	**High Stimuli**
Virtual Task	VR-2DD	VR-2DD
Static obstacles	Yes	Yes
Number of dynamic obstacles (visual distractors)	0	50
Audio distractors	None	Classical music & Common street sounds

TABLE II: Conditions present during each online test session

Our dataset was focused on the training process of new participants, rather than the acquisition of clean EEG to improve classification accuracy. Therefore, after two *training* sessions, each user undertook a high noise and low noise *test* session (online) on the VR-2DD simulated environment (Table II), where the training bias was removed and the user had full control authority. The test session produced a record of the instruction that was given to the participant, the classification of each epoch and the current evidence accumulation window classification probability. To ensure the level of external stimuli is kept consistent across the test sessions, participants were tested in the virtual environment rather than the real world.

VII. Results

A. 2-class accuracy (offline)

We first calculated the 2-class accuracy to ensure that this was inline with current literature. We achieved a mean accuracy across all training groups and training sessions of 79.8% and a mean best accuracy across all participants of 89.2%, which is comparable to previous 2-class classifiers, commonly found in the literature [33].

B. 3-class accuracy (offline)

Fig. 4: Box plot of all accuracies achieved within each training class (offline)

We then analysed the full 3-class performance. The differences between each of our classifier accuracies (Fig.4) were found to be statistically significant (ANOVA *p=0.009*, *f=4.763*). The VR-2DD condition achieved the highest performance, with the simple condition yielding the lowest performance.

Repeated t-tests were then performed which enabled us to accept the hypothesis that the VR-2DD tasks yielded higher performance than the simple tasks ($p < 0.05$). However, we could not accept the hypothesis that the VR-HMD task achieved higher training performance than the simple tasks ($p > 0.05$) .

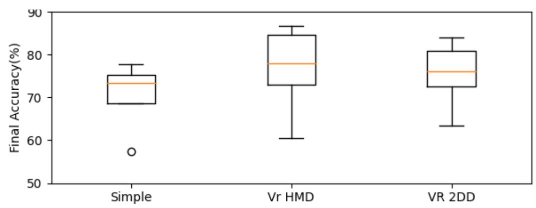

Fig. 5: Box plot of best accuracies for each participant within each training class (offline)

	Median (%)	IQR (%)	Best (%)
Simple task	54.4	11.9	77.7
VR-2DD	60.3	23.9	84.0
VR-HMD	59.1	20.0	86.6

TABLE III: Median, IQR and best accuracies achieved across participants in each class

C. *Active testing (online)*

Our dataset also contained the labeled EEG recordings from the 'online' high- and low-noise experiments. We used this data as a test set on the final classifier trained for each participant during the training process, to measure their ability to use the system online, without any bias added to the classification (Fig.6).

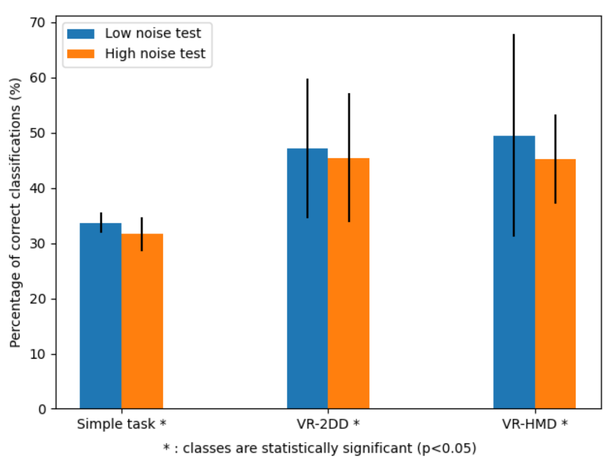

Fig. 6: Mean accuracy for each group for each test carried out at the end of the training cycle (online)

Multiple between-group Welch t-tests were carried out on the scores of the test session that took place at the end of each training session.

Repeated t-tests allowed us to accept the hypothesis that both VR-2DD and VR-HMD increases user proficiency in using a BCI when no bias is provided and the user has free control ($p < 0.05$). T-tests carried out between each user's high-noise and low-noise test performance (Fig. 6) did not provide enough evidence to accept the hypothesis that users trained in high noise environments maintain a higher performance in high noise environments relative to the performance of users trained in low noise environments ($p > 0.05$).

VIII. Discussion

We conducted an experiment with sixteen participants to test our hypothesis that EEG-based wheelchair users trained in virtual environments (VR-HDM and VR-2DD) are able to achieve a higher level of accuracy compared to participants trained using a simple task(Table III, Fig: 6). We trained our participants in either a high- or low-noise variation of the virtual environment containing multiple active stimuli to test our hypothesis that users trained in high stimuli environments would maintain a higher level of performance in high stimuli environments compared to users who trained in low stimuli calm environments.

A. *Offline Classifier Results*

Our results (Fig. 6) support the hypothesis that training within a virtual environment is more beneficial to the user than training using only a simple feedback, which is inline with and builds upon findings in the literature [16], [19]. This suggests that training in virtual environment will be more effective for BCI systems designed for robotic devices.

We calculated the mean accuracy across all groups throughout the training process to be 57.9% and a mean best accuracy of 82.8% (Table III). Our mean best accuracy (Fig: 5) is comparable with accuracies recorded in recent literature [14], whereas our mean accuracy across all classes and points in the training process (Fig: 4) is below this level, indicating that learning is indeed taking place. Our mean accuracy was calculated using data throughout the training processes, whereas some performances in the literature are calculated only on datasets comprised of proficient participants completing a task, and neglecting the training process e.g. in BCI competition data sets [14]. Since our dataset was comprised of novice users learning to use a BCI for the first time, some epochs in the recording may include the user changing their mental task slightly in response to the classifier feedback, as well as different neurological signals occurring due to neuronal adaption to the system. The epochs containing these variations may not display the same trends that the SVM classifier uses to determine the class of the recorded epoch.

B. *Active testing (online)*

Compared with our offline classification results, our active testing (online) results were lower. This is aligned with previous literature, which has shown that in the few papers that do actively test their system in an online setting, a decrease in accuracy or effectiveness is observed compared to the offline BCI classifier accuracy [12]. In both high and low noise evaluation tasks, the participants who trained on the simple feedback, only achieved a classification rate of around random chance for a three class classifier (33%) (Fig. 6), despite having achieved an offline classifier accuracy similar to the participants who trained in the other two VR conditions. The statistically significant difference between the correct classifications achieved by the simple task participants compared to the VR-2DD and VR-HMD (Table 6) suggest that training using a virtual reality environments will provide a user with a higher level of control of a robotic wheelchair in an environment containing multiple active stimuli, further demonstrating that virtual training environments are better for training users to use a BCI that they may use in real life. Across all training groups, the mean accuracies of the low noise test was slightly higher compared to the high noise test, although we did not find any significant difference in this performance.

C. Future work and robotic applications

As well as implementing a form of mental 'haptic' feedback to bias the classification to avoid obstacles, as has been demonstrated with tele-presence robots [27], we may be able to combine the system with a wheelchair that maps out the environment, and provides the user with a range of 3 or fewer choices [1]. In future experiments, we intend to design a task where participants will drive our simulated or real robotic wheelchair [34] with the goal of reaching a specific location, rather than focusing purely on the classification accuracy.

Training time could have a significant effect on the classifier performance achieved, as each participant had less time to adapt to the system, compared to the participants of other studies [1], [35]. With a longer training time, we expect to see an increase in the ability of the users to actively control the system, making future robotic applications developed in other literature viable [5], [7], [8]. However, it remains an overall goal to reduce BCI training time, whilst simultaneously making the process more engaging to improve user acceptance of BCI systems [36].

Our findings suggest that training with a virtual reality head-mounted display does provide some benefit over the simple task. Both the VR-HMD and the simple task participants completed both of their tasks on the 2D digital display, changing the form of training. This was done to allow all participants, including those who may suffer from motion sickness, to complete the same test task and allowing for complete control and replication of the level of stimuli throughout all tests. Although both groups changed task, the VR-HMD group achieved a significantly (Table 6) higher mean classification accuracy in the test phase, suggesting that VR participants may perform better when changing environments, as well as in varying levels of stimuli, but this will require further investigation.

Previous literature has used EEG BCIs to control other robotic devices including robotic arms, telepresence robots and unmanned aerial vehicles [37], [38]. By combining commands it is possible to create a larger set of instructions allowing for movement of a robotic system in all three dimensions [39]. However, by requiring multiple consecutive commands for a single action of the device, the difficulty of the task increases due to the compounding uncertainty of each classification. In these systems, accurate and effective training will be required to reduce this compounding uncertainty, allowing further research into the creation of these devices.

IX. Conclusion

The purpose of this study was to determine which training method achieved the best performance for an EEG-based BCI controlled robotic wheelchair. We collected training data from 16 participants, which included two sets of 1.5-hour training (offline) sessions and one active (online) testing session. After screening for exclusion criteria, the participants were randomly split into separate groups and were training on a simulated robotic wheelchair in either a high-noise virtual environment, displayed either through a 2D display (VR-2DD) or virtual reality headset (VR-HMD) or a simple BCI task. Each user had the same number of training sessions, which increased in difficulty over time by reducing the bias towards the correct instruction. Users then performed two tests in the 2D simulated task, each test having either a high or low amount of dynamic stimuli. In these final tests, the participants had complete control of the simulated robotic wheelchair.

We found that there was a statistically significant improvement for both groups of participants trained in the virtual environments compared to the those trained in the simple environment ($p < 0.05$), suggesting that users who train in simulated environments are better prepared for using a BCI in an environment with multiple active stimuli. The participants who completed the VR-2DD training showed a significant improvement in their performance during the training process compared to the simple task participants ($p < 0.05$), but no significant improvement was found between the VR-HMD and VR-2DD participants ($p > 0.05$). Additionally our findings did not provide enough evidence to support our hypothesis that users who trained in high noise environments maintaining a high level of control in high stimuli environments compared to those who trained in low noise environment ($p > 0.05$). However, in future work will will investigate this further and in particular whether the results carry over from the simulated environment to controlling our physical robotic wheelchair in the real world.

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