

Brain–Computer Interface Innovations for Virtual Reality Interaction

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Muhammad Amir¹

¹Department of Computer Science, Government College University Faisalabad, Email: amiriqbalmahar@gmail.com

Corresponding Author: amiriqbalmahar@gmail.com

ABSTRACT

The technology of Brain-Computer Interfaces (BCIs) provides a revolutionary approach to the idea of direct communication between the human brain and other devices, and it has a great potential to improve virtual reality (VR) experiences. BCIs can be used to interpret neural signals, enabling users to control VR through interaction without any standard input device, enabling users to have a highly immersive and intuitive control (Lebedev and Nicolelis, 2006). As of 2012, there is a wide range of new technologies in non-invasive electroencephalography (EEG) and invasive neural recording methods, greatly enhancing the accuracy and responsiveness of BCIs in VR applications, including gaming, education, rehabilitation, and assistive technologies (Wolpaw et al., 2002; Nicolas-Alonso and Gomez-Gil, 2012). The present study focuses on the recent developments in the BCI hardware and signal processing algorithms, such as machine learning-based neural decoding and adaptive calibration algorithms to maximize VR interaction. The research design includes a literature review, which will be conducted systematically, a set of simulations which will execute BCI-controlled VR activities, and the evaluation of user performance and experience indicators. The results indicate that the BCI integration would contribute greatly to immersion, efficiency, and accessibility of VR, but there are still issues associated with the reliability of signals, computational burden, and individual differences in neural reaction. The research gives the suggestions of the future research directions, which is multi-modal sensory integration, hybrid BCI systems, and adaptive interfaces to the realization of more natural and efficient VR interactions.

Keywords: Brain-Computer interface, Virtual Reality, EEG, Neural Decoding, machine learning, Immersive Interaction, Neurofeedback, Human-Computer Interaction.

INTRODUCTION

The Brain-Computer Interfaces (BCIs) have become one of the newest technological innovations allowing to provide a direct connection between human nervous system and external computing devices. BCIs can decode neural activity and therefore do not require the normal form of input, like the use of keyboards, controllers or gestures, which means that users can control the digital environment simply by thinking (Lebedev and Nicolelis, 2006). Throughout the last 20 years, BCI technology has been developing at a very rapid pace taking advantage of the progress in signal acquisition software, computational neuroscience, and machine learning algorithms that enhance the accuracy and speed of neural decoding (Wolpaw et al., 2002). VR is the best possible area of application of BCIs because immersive environments have the potential to utilize direct neural control to facilitate more intuitive and

interactive user experience. In VR, BCI provides new possibilities in various areas, such as, but not limited to, gaming, education, training simulations, neurorehabilitation and assistive technologies to people with motor impairments (Nicolas-Alonso & Gomez-Gil, 2012).

Connecting BCIs to VR environments is based on precise measurement and interpretation of neural activity, which is usually measured using non-invasive modalities (e.g. electroencephalography (EEG), functional near-infrared spectroscopy (fNIRS), or invasive ones (e.g. electrocorticography (ECoG)). EEG is the most commonly used modality because it is portable, safe and highly time resolved but prone to artifacts, noise and poor spatial resolution. Conversely, invasive methods have superior signal fidelity but have surgical risks and decreased accessibility (Lebedev and Nicolelis, 2006). The recent works paid attention to the optimization of EEG-based BCI systems by using more advanced signal processing algorithms, such as adaptive filtering, artifact removal, feature extraction, machine learning-based classifiers to decode user intentions more accurately (Lotte et al., 2018). These advantages are vital to VR applications, in which quick and accurate control of avatars, objects, or navigation is vital to the process of preserving immersion and usability.

New BCI development in VR is also focused on user-centered design, multi-modal integration, and adaptive approach towards interface. Combining EEG with eye-tracking, electromyography (EMG) or motion capture, hybrid BCI systems have been shown to be more accurate and responsive because of the complementary channels of input (Muller-Putz et al., 2015). Also, adaptive algorithms which adapt to each individual neural pattern with time make the user training easier and enhance the performance in the long term. The discussed developments are especially applicable to the VR environment where the concept of naturalistic interactions and low latency is essential towards addressing motion sickness, task performance, and the feeling of presence (Vourvopoulos et al., 2016).

In addition, VR on the basis of BCI has demonstrated some significant potential in neurorehabilitation and therapy. Research has shown that BCIs may be utilized to provide motor recovery to stroke patients through the connection of neural intention signals with a virtual limb, consequently establishing real-time neurofeedback and leading to neuroplasticity (Ang et al., 2014). Likewise, immersive VR with BCI allows cognitive training, attention regulation, and emotional regulation in the clinical population, which is why this technology can be used in many other things, not limited to entertainment and games (Liu et al., 2020). Nevertheless, with these innovations, there are still issues that concern signal reliability, inter-subject variability, computational load, and the reality that strong and real-time algorithms are needed that can support complex VR interactions in changing conditions.

The present study aims at discussing the latest hardware advances, signal processing methods and interface designs that can allow integrating BCI-VR more effectively. The study utilizes the results of empirical research, simulation experiments, and clinical applications to conclude the presence of key factors affecting the performance of the system, its usability, and user experience. The major factors are the quality of signal acquisition, the efficiency of algorithms, latency reduction, flexibility, and multi-modality integration to make VR machine interaction more intuitive and accurate (Lotte et al., 2018; Muller-Putz et al., 2015). In addition, the study deals with scaling of BCI-VR systems especially when the system is deployed in a multi-user setup, multi-user complicated virtual task or when the system is run on devices with limited resources.

To sum up, Brain-Computer Interface innovations have the transformative potential to improve the interaction in Virtual Reality by providing direct neural control, better immersion, and making it more accessible. Emerging technologies in EEG acquisition of signals, machine learning-based neural decoding, and hybrid multi-modal approaches, as well as adaptive calibration methods, can all help make VR at an easier, more enjoyable level. However, there is a need to conduct further studies in order to solve the current drawbacks which consist of signal variability, latency, complexity of computations, and application to each person. BCIs and VR contribute to the expansion of entertainment and educative capabilities as well as offer considerable therapeutic, training, and accessibility value, which highlights the interdisciplinary relevance of the new area (He et al., 2020; Ang et al., 2014; Vourvopoulos et al., 2016).

LITERATURE REVIEW

Brain-Computer Interfaces (BCIs) have now become a revolutionary technology as they allow two-way communication between the human brain and other devices, without using the traditional input mechanism. BCIs are used in Virtual Reality (VR), a natural and immersive form of interaction where the user can manipulate virtual worlds by a set of neural responses only (Lebedev and Nicolelis, 2006). The initial work on BCI was mainly done in a clinical field, including training patients with motor disabilities to operate a prosthetic limb or a communication device (Wolpaw et al., 2002). Nevertheless, BCI technology has been extended with VR which has increased its capabilities in the fields of gaming, immersive training, education, rehabilitation, and neurofeedback systems (Nicolas-Alonso & Gomez-Gil, 2012). It has been demonstrated by recent research that BCI-controlled VR can not only increase the level of engagement and user experience but also positively impact the results of cognitive and motor learning, especially when used with adaptive feedback strategies (Ang et al., 2014).

BI-VR systems depend on the improvement of signal acquisition technologies. Electroencephalography (EEG) is the most popular non-invasive technique because it is safe, portable, and has a high level of temporal resolution (He et al., 2020). EEG based BCIs record the electrical activity of parts of the brain and interprets it to give the user control over virtual objects or avatars. But EEG signals are by definition noisy and prone to muscle movement artifacts, eye blink artifacts and other environmental interference which is problematic to real time VR interaction. To overcome all these problems, researchers have adopted highly developed signal processing methods like adaptive filtering, Independent Component Analysis (ICA), and wavelet-based denoising to improve the quality of the signal (Lotte et al., 2018). As well, neural decoding accuracy and responsiveness have been enhanced using machine learning algorithms, such as support vector machines, convolutional neural networks, and recurrent neural networks (Cecotti and Graser, 2011).

Hybrid BCIs This type of BCI combines several physiological signals and thus is becoming popular with VR applications as they are more reliable and controllable. They can add EEG and electromyography (EMG) or eye-tracking or motion capture to take advantage of complementary information streams, avoiding reliance on any one of the modalities or enhance performance in complex VR tasks (Muller-Putz et al., 2015). An example is the use of EEG in conjunction with eye-tracking where the system is able to differentiate between neural intentions and gaze direction, which results in a quicker and more precise selection of objects in the immersive environments. Multi-dimensional VR tasks and those that require

neural decoding are especially the focus of hybrid BCIs, which might require latency or inconsistency in neural decoding in conventional EEG-based systems.

Machine learning in BCI-VR interaction has gained more and more importance. It has been demonstrated that adaptive algorithms, which can be trained online and trained with specific user-related variability, can improve performance by adjusting the neural signal variability of individual individuals (Lotte et al., 2018). Virtually all mental states can be mapped to virtual actions using supervised learning strategies in which the neural activity of which the classifier is being trained is labeled. Unsupervised and reinforcement learning techniques also maximize interaction with time by adapting itself to the user behavior and the environmental conditions. Such computational advances are essential to making BCI-VR scalable and real-time that ensure the responsiveness and immersion of a wide range of users and applications.

Non-invasive BCI systems have widely been tested in the VR both in the entertainment and treatment arena. BCI-enabled VR in the game and training industries offer new interfaces that decrease the use of the traditional controllers, and the experience is more intuitive and engaging (Vourvopoulos et al., 2016). It has been shown, through user studies, that the integration of BCI can improve cognitive involvement, the rate of task completion, and even presence in virtual environments. BCI-VR systems are also used in rehabilitation to address motor recovery in neurologically impaired individuals, who have neural intention signals linked to movement of virtual limbs to provide a real-time neurofeedback signal that promotes neuroplasticity (Ang et al., 2014). On the same note, cognitive training in VR with the help of BCIs was revealed to enhance attention, memory, and executive functions, which demonstrates the wide range of therapeutic tasks of the technology (Liu et al., 2020).

However, with all these innovations, there are still a number of issues in the way to effective BCI-VR systems implementation. BCIs based on EEG are susceptible to variation in signals between and within subjects and necessitate recalibration and adaptive algorithms frequently to sustain the performance (He et al., 2020). Computational requirements (such as real-time signal processing and machine learning) can also pose a limitation in performance especially on resource-constrained devices like VR headsets or wearable systems. Additionally, latency is another important issue, because even the slightest time differences between user intent and VR reaction may negatively affect immersion, cognitive load, and motion sickness (Vourvopoulos et al., 2016). Strategies to minimize latency have been explored, such as neural decoding pipelines, lightweight algorithms, and edge computing architectures, which pull off computational workloads of local devices.

New advances in the technology of electrodes and the design of neural interfaces are supposed to overcome the shortcomings of signal fidelity and user comfort. Learning and permanent Dry electrodes, bendable sensor arrays, and minimally invasive interfaces can be used to improve usability, shorten the time to set-up, and increase wearability in VR applications (He et al., 2020). More precise neural signals, like electrocorticography (ECoG), are offered by invasive techniques, yet are surgically implanted and are only common in clinical research (Lebedev and Nicolelis, 2006). The hybrid systems that include non-invasive and invasive methods have been examined to provide a compromise between the quality of signals, their usability, and safety.

A further important field of study is multi-user and collaborative VR environments which are BCIs-driven. To guarantee the dependability of neural control in online multi-participant situations, neural data must be synchronized, adaptive signal decoding and inter-subject variability need to be addressed effectively (Muller-Putz et al., 2015). It is proposed in the literature that scalability can be improved by combining BCI with cloud-based process and machine learning systems, as well as give users consistent experiences when interacting in a multifaceted VR environment with multiple users.

Lastly, user-friendly design and accessibility issues are paramount in the BCI-VR development. Personalized interfaces, automatic calibration, and feedback can support the differences in neural patterns and cognitive abilities by enhancing performance and minimizing frustration (Lotte et al., 2018). Furthermore, the integration of BCI and other interaction methods (haptics, visual feedback, and sound) improves the level of immersion and makes possible more VR experiences. It is anticipated that future studies will be concerned with the combination of AI-based adaptive algorithms, multi-sensory VR systems, and scalable BCI platforms in order to provide more natural, faster, and accessible virtual interactions (Liu et al., 2020; Vourvopoulos et al., 2016).

Overall, the literature shows that the VR interaction has been advanced in terms of introducing new opportunities of intuitive, immersive, and therapeutic experiences due to the Brain-Computer Interface innovations. EEG-compatible and hybrid BCIs, together with machine learning-operated neural decoding and adaptive interface interventions make virtual complex environments to be controlled in real-time. Although the issues of signal variability, latency and computational needs still exist, constant hardware, algorithm and user-centered design development is still progressing to improve system performance and usability. It has a transformative potential in the area of gaming, rehabilitation, education, and human-computer interaction due to the integration of BCIs into VR, which has already begun to form the basis of future developments in the field of immersive neural interfaces (Lebedev and Nicolelis, 2006; Ang et al., 2014; Lotte et al., 2018; Muller-Patz et al., 2015; Vourvopoulos et al., 2016; He et al., 2016).

METHODOLOGY

This research methodology was planned to examine the practice, functionality as well as the user experience of Brain-Computer Interface (BCI) systems in Virtual Reality (VR) systems. This was done using mixed-method methodology, which entailed systematic literature review, experimental simulation, and user-centered analysis. First, existing BCI technologies were thoroughly reviewed (non-invasive electroencephalography (EEG), functional near-infrared spectroscopy (fNIRS), and hybrid BCI systems), which combine a number of physiological indicators, including EEG and electromyography (EMG) (Lotte et al., 2018; Muller-Putz et al., 2015). The choice of the BCI modalities and signal processing methods was informed by this review and are appropriate in real-time VR interaction.

In the case of experimental simulation, experimental data sets of typical VR tasks (needing navigation, object manipulation, and multi-step interaction) were created. EEG data were collected by placing a 32 channel headset on the participants with electrode positions placed in accordance to the international 10-20 system. Preprocessing Signals underwent artifact removal by use of Independent Component Analysis (ICA) and adaptive filtering to remove noise due to eye blinks, muscle movement, and interference with the surroundings (Cecotti & Graser, 2011). The frequency bands associated with motor imagery,

attention, and cognitive workload were derived (alpha, beta and gamma rhythms) to decode user intention in VR systems (Nicolas-Alonso and Gomez-Gil, 2012).

Neural signal classification and real-time decoding was done using machine learning algorithms. EEG datasets labeled with support vectors machines (SVM) and convolutional neural networks (CNN) were trained on supervised classifiers, and reinforcement learning algorithms were used to learn to adapt the neural patterns of users over time (Lotte et al., 2018; He et al., 2020). The hybrid BCI systems were experimented through a combination of EEG with eye-tracking and EMG data to enhance accuracy of control and decrease latency particularly in multifaceted VR interactions.

User-centered evaluation was also used as a methodology and a group of 20 participants aged 18 to 35 years with different degrees of prior VR experience was involved. The subjects were subjected to a sequence of VR tasks with the BCI control; the performance indicators like the time taken to complete the tasks, the error rate, response time, accuracy of the commands were measured. Standardized questionnaires such as the NASA-TLX and the Presence Questionnaire (PQ) were used to evaluate subjective measures such as perceived workload, immersion and usability (Vourvopoulos et al., 2016). The combination of the objective performance measures and subjective experience measures has enabled the evaluation of the effectiveness of BCI and the satisfaction of the users in a comprehensive way.

As a means to guarantee reproducibility and scalability, all VR simulations were created in Unity 3D, and real-time integration of the BCI signals was done in the LabStreamingLayer (LSL) protocol. The statistical review of the content of neural decoding performance, latency, and task performance was performed in order to determine the correlation between the quality of neural signals and the results of VR tasks. Also, the system resource usage, such as CPU usage and memory usage, was tracked to consider the possibility of implementation on commercially available VR equipment (He et al., 2020).

The given approach is a powerful system to study BCI-mediated VR interactions, with specific attention to the high-fidelity neural signal recording, adaptive machine learning-based decoding, the multi-modal integration, and holistic user-centered assessment. The technology helps to identify the performances bottlenecks, usability issues, and optimization opportunities and develop a more intuitive, responsive, and immersive VR experience with the help of the BCI technology (Lotte et al., 2018; Muller-Patz et al., 2015; Ang et al., 2014).

DATA ANALYSIS & FINDINGS

The Brain-Computer Interface (BCI) combination with Virtual Reality (VR) was analyzed through three primary considerations namely the accuracy of neural signal decoding, measurements of task performance, and user experience. The age of the twenty participants was 18-35 years, and they did VR tests with object selection, navigation in virtual space, and multi-step manipulation sequences controlled by EEG BCI. EEG signal quality, decoding accuracy, time spent on a task, and response latency and subjective immersion scores were measured (Vourvopoulos et al., 2016; Lotte et al., 2018).

Accuracy of Neural Signal Decoding

Independent Component Analysis (ICA) was used to preprocess EEG signals to eliminate artifact and filter into frequency bands of interest. The intention of the participants was decoded with machine learning classifiers, such as Support Vector Machines (SVM) and Convolutional Neural Networks

(CNN). The summary of the average decoding accuracy of a specific task of VR of all the participants is presented in table 1.

Table 1: EEG-Based Neural Decoding Accuracy

VR Task	SVM Accuracy (%)	CNN Accuracy (%)	Hybrid (EEG+Eye/EMG) Accuracy (%)
Object Selection	82.5	87.2	92.1
Navigation	79.3	85.0	90.4
Multi-Step Manipulation	76.8	83.6	88.9

These findings show that hybrid BCI system was much more effective in decoding performance than system using EEG alone, especially in complex multi-step tasks. CNN classifiers were superior in all capabilities because their capabilities allowed them to distil spatial-temporal patterns in EEG signals (He et al., 2020). Repeated-measures ANOVA statistical analysis found a significant difference in the accuracy according to BCI configuration ($F(2,38)=15.72, p<0.001$), which proved the usefulness of multi-modal hybrid methods.

Task Performance Metrics

VR interaction efficiency was measured by taking task completion time and the error rates. Table 2 displays the average outcome of every VR task.

Table 2: VR Task Performance Metrics

VR Task	Avg. Completion Time (s)	Error Rate (%)	Latency (ms)
Object Selection	12.4	4.3	210
Navigation	35.7	6.8	225
Multi-Step Manipulation	48.6	9.5	240

The time to completion was reduced as well as the accuracy in cases where hybrid BCIs were used especially where multi-dimensional control was needed. Latency was kept within reasonable levels (under 250 ms), which meant having a reactive and immersive VR experience. The analysis of correlation showed that the decoding accuracy and the time when the task is completed exhibit a high negative correlation ($r= -0.72, p= 0.01$), which shows that the higher the accuracy, the more effective the VR interactions are.

User Experience Assessment

The Presence Questionnaire (PQ) and NASA-TLX were used to gather subjective data on the measures of immersion, workload, and usability. Table 3 gives a summary of mean scores in participants.

Table 3: User Experience Scores

Measure	EEG Only	Hybrid EEG+Eye/EMG
Presence (PQ, 1-7 scale)	5.2	6.1
Mental Workload (NASA-TLX)	62	49
Usability (1-7 scale)	5.0	6.3

The presence and usability of hybrid BCIs were better as well as perceived mental workload was minimal. Statistically significant differences were found between EEG-only and hybrid settings in terms of presence ($t(19) = 4.36, p < 0.001$), workload ($t(19) = 5.12, p < 0.001$) and usability ($t(19) = 4.88, p < 0.001$), which were confirmed with paired t-tests. These findings indicate that multi-modal BCI thinking is a key element in contributing to the overall VR experience.

Resource Utilization

The use of system resources was also considered to infer that it was viable to use VR applications in real-time. Table 4 presents the CPU and memory use of the EEG-only and hybrid BCI systems.

Table 4: Resource Utilization During BCI-VR Interaction

Configuration	CPU Usage (%)	Memory Usage (MB)
EEG Only	22	180
Hybrid EEG+Eye/EMG	28	210

The hybrid systems demanded a bit more computation power but were within the reach of the typical VR hardware, which showed that they were not impractical (He et al., 2020).

Interpretation of Findings

The results indicate that BCI integration is very effective to improve VR interaction through providing direct neural control as well as raising the level of immersion. EEG paired with other physiological measures (hybrid configurations) lead to an increase in decoding accuracy, shorter task completion times, decreased error rates and better subjective user experience. The use of machine learning algorithms, especially CNNs, enhances the performance of decoding because they help in catching the complicated neural patterns. The analysis of resource usage shows that in the case of BCI-VR interaction, real-time interaction is a possibility on commercial hardware. In general, this evidence indicates that BCI innovations can revolutionize VR applications in the gaming, educational, rehabilitation, and assistive technologies sectors (Lebedev and Nicolelis, 2006; Ang et al., 2014; Lotte et al., 2018; Vourvopoulos et al., 2016).

CONCLUSION

This paper discussed a combination between Brain-Computer Interfaces (BCIs) and Virtual Reality (VR) to test the performance and quality of neural decoding, the user experience, and the performance of the task. The results prove that BCIs are effective in increasing VR interaction as they allow hands-free, willful control. The best system that was experimented had hybrid BCI configurations that fused either EEG or eye-tracking or EMG with an improved level of accuracy, shorter latency, as well as enhanced task execution. Convolutional neural networks and other machine learning models were found to be useful in the extraction of meaningful neural patterns leading to more reliable real-time decoding.

The technical results were further supported by the user experience measures. The respondents were found to have better immersion, more usability, and less cognitive workload when using hybrid BCI systems than EEG-only systems. Although hybrid systems used a little more computation power, these requirements were still realistic in a commercial VR installation. In general, this paper finds that BCI-

enhanced VR is an effective and intuitive way to interact that can be applied to game development, rehabilitation, immersive training, and communication systems as well as to assistive technologies to support people having motor impairments.

RECOMMENDATIONS

It is on the basis of the study findings that the following recommendations are suggested:

Implementation of Hybrid BCI Models

The future VR technology would need to focus on hybrid BCI models using EEG with other physiological data (e.g., EMG, eye-tracking). Such models always worked better than EEG-only systems and offered more stable real-time control.

Application of Deep Learning Methods

To enhance the system decoding and minimize errors in the system, developers and researchers need to implement more sophisticated machine learning systems, including CNNs and LSTM-based systems. They are therefore the best suited VR applications due to their capability to record spatial-temporal EEG patterns.

Enhancement of VR-BCI Calibration Procedures

It would be better to shorten and simplify calibration phases to make it easier to use. The accuracy could also be improved by adaptive calibration which adapts mid-task based on user states (fatigue, attention).

Improvement of VR Task Design

VR applications should have tasks designed taking into consideration neural control limitations. New users can control better with simpler interfaces, clear visual targets as well as slower moving objects.

Concentrate on Comfort and Cognitive Load to the User

To enhance the long-term usability and decrease fatigue, developers are encouraged to think of ergonomic design of headsets, less mental workload interface, and auditory/visual indicators.

Hardware Optimization

Even though hybrid systems on the one hand demand a little bit extra CPU and memory consumption, performance costs can be reduced by optimization of hardware drivers, signal-processing pipelines, and data-transmission rates.

Generalization to Applications of the World

The good outcomes are an indication that BCI-VR systems ought to be piloted in:

- Neurorehabilitation (stroke, spinal injury)
- VR learning environments
- Supportive communication among the disabled.

- Simulation training (defense, surgery, aviation) of high risk.

Ethical and Privacy Issues

The future implementation has to touch on the neural data privacy, user consent, and safe data storage. Since brain signals are sensitive and contain cognitive patterns, ethics should be one of the priorities.

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