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Review

Combining VR with electroencephalography as a frontier of brain-computer interfaces

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THE BIGGER PICTURE Electroencephalography (EEG) is a non-invasive method that records the electrical activity of the brain from the surface of the scalp. The integration of EEG with virtual reality (VR) offers a unique opportunity for monitoring real-time brain activity in an immersive and interactive environment. VR-EEG has an exciting potential to advance brain-computer interfaces (BCIs) because it opens new possibilities for how we interact with digital environments, control avatars or virtual devices using brain signals, and even understand how to enhance brain function. Emerging VR-EEG systems have already demonstrated applications in gaming, cognitive training and enhancement, and neurorehabilitation. However, there are still several challenges to maximizing the signal quality, long-term comfort, and ease of use. This review offers a brief overview of the progress in EEG-integrated VR headsets, delves into the challenges of EEG posed by both hair and the VR headset, and explores the prospects of VR-EEG systems.

SUMMARY

This review presents an overview of the integration of virtual reality (VR) and electroencephalography (EEG), known as VR-EEG systems, and their promising applications as brain-computer interfaces (BCIs), including motor and cognitive rehabilitation, entertainment, and education. We outline the progress thus far and highlight the challenges still faced, such as hair compatibility, seamless integration of EEG sensors and VR headsets, and limited EEG recording sites and signal quality. This review also points out areas requiring advancements, such as the development of electrodes, multimodal systems, and closed-loop systems, for providing a more tailored, immersive BCI experience.

INTRODUCTION

Electroencephalography (EEG) is a non-invasive technique that records cumulative postsynaptic potentials in the superficial cortex from the scalp. Owing to its high temporal resolution, affordability, and versatility,[1,2] EEG has been widely used in a variety of applications, including sleep monitoring,[3,4] cognitive and brain function evaluation,[5,6] probing of effective states of the brain,[7,8] and clinical diagnosis and treatment of neurological disorders, such as epilepsy,[9–11] stroke,[12,13] and attention disorders.[14,15] In addition, EEG also works as a modality for both clinical and non-clinical brain-computer interfaces (BCIs), which allow users to manipulate physical or virtual environments by modulating their brain activity.[16–18] As such, various EEG decoding methods have been developed, linking EEG measurements to human brain activities of interest such as error perception,[19,20] movement intention,[21–23] mental workload,[24,25] emotional arousal,[26,27] fatigue,[28–30] and attention.[31–33] Meanwhile, virtual reality (VR), while not new, has advanced from being a niche tool to popular use in recent years due to increased accessibility to hardware, standardization of VR application development interfaces, and increasing interest in virtual environments for entertainment,[34] education and training,[35–38] and neurorehabilitation.[12,39–44]

The integration of EEG and VR allows for real-time monitoring of the brain activity of a user interacting with the virtual environment. For researchers, this represents a powerful paradigm for studying human cognition under enhanced reality, immersion, and interactivity provided by the virtual environment, which has

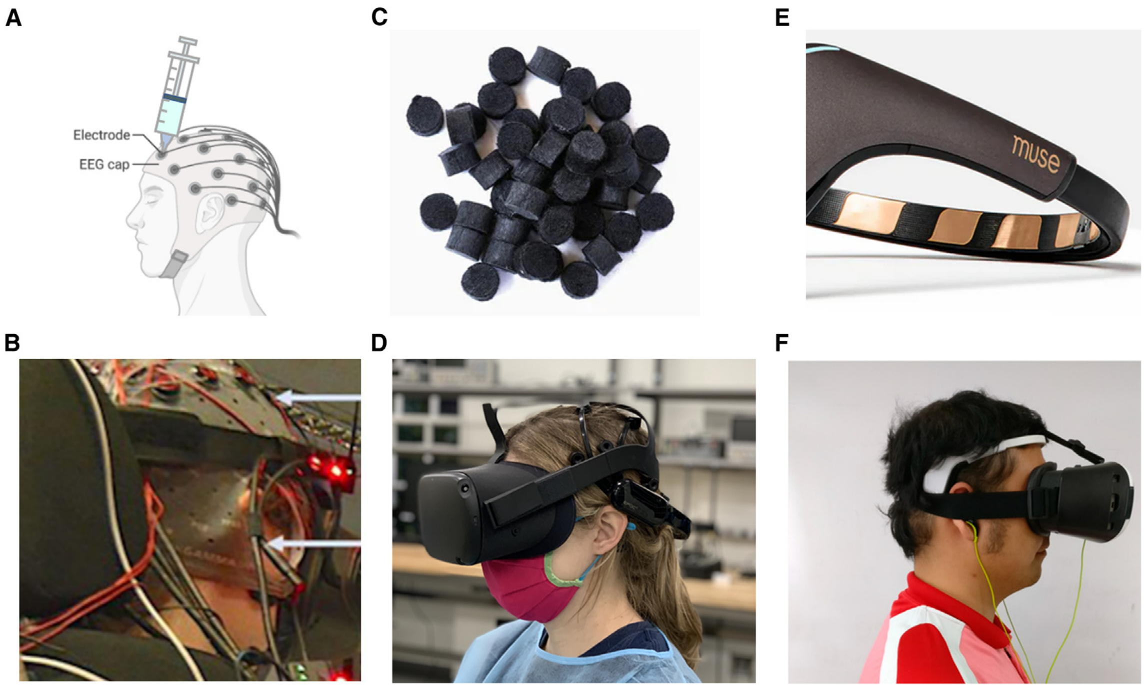

Figure 1. Examples of independent VR headset and EEG sensors worn together

(A) A schematic of the wet gel electrode application. Created with BioRender.com.

(B) An HTC Vive VR head-mounted display (HMD) combined with an EEG cap filled with wet gel electrodes. Reproduced with permission.[59] Copyright 2023, Elsevier.

(C) An image of the EMOTIV EPOC semidry electrodes. Reproduced from https://www.emotiv.com.

(D) An Oculus Quest VR headset combined with the EMOTIV's EPOC X 14-channel wireless EEG headset with semidry sponge electrodes. Reproduced with permission.[81] Copyright 2021, IEEE.

(E) The 4-channel gold-plated dry electrodes on Muse 2 EEG headband. Reproduced from https://choosemuse.com.

(F) A VR headset worn together with the Muse 2 EEG headband with 4-channel dry electrodes. Reproduced with permission.[83] Copyright 2022, MDPI.

been shown to evoke stronger event-related potential and event-related synchronization/desynchronization responses than using desktop monitors.[45–47] For BCI research, VR can serve as an experimental middle ground between the highly controlled but simplified nature of traditional neuroscientific tasks and the relatively uncontrollable and inaccessible nature of real-world experimentation. For instance, mental workload, drowsiness, attention, and error perception decoders can be validated by pilots in VR flight simulators[48–51] and drivers in VR driving simulators.[52–54] For designers of VR applications, VR-EEG unlocks brain activity as a source of direct, real-time, and quantitative information about the user status, adding the mental domain to the suite of multimodal sensors already available on modern VR systems. Proposed uses include the estimation of perceived difficulty for real-time modification of game content[55,56] and the detection of VR-induced motion sickness[57,58] or breaks in embodiment from the VR avatar[59–61] for potential intervention.[62] Moreover, motor imagery (MI) BCIs can be implemented in VR to enable users to control avatars or objects, respectively.[63–67] Therefore, the prospect of seamless integration between EEG and VR technology is of interest to researchers,[68,69] clinicians,[42,70] VR developers, and users alike. Although this review focuses on BCI-related applications of the VR-EEG technology, the development of VR-EEG devices will have a far-reaching impact on immersive entertainment, such as EEG-adaptive VR content,[55] EEG for avatar control,[63] and body ownership[71]; education and training, including immersive education support,[72] EEG adaptive training/education,[56] and BCI training[73]; and healthcare, such as mental state evaluation[74] and cognitive impair and stroke rehabilitation.[42,70]

SYSTEMS WITH SEPARATE VR HEADSET AND EEG MONITOR

Most existing VR-EEG studies are implemented using separate VR and EEG hardware, i.e., the EEG cap is first secured in place, and then the VR headset is overlaid on top of the EEG sensors. Conductive wet gel electrodes, regarded as the standard for EEG recordings, are commonly employed due to their hair compatibility, reliable signal integrity, and relative tolerance to motion artifacts (Figures 1A and 1B).[59,60,75,76] However, wet gel electrodes, despite their advantages, have drawbacks such as lengthy setup times, potential for leakage during the injection process, risk of skin irritation, and dehydration over time. In contrast, semidry electrodes, which utilize saline-solution-soaked sponges, offer a quicker setup and are easier to remove.[77,78] Semidry sponge electrode systems have been combined with VR headsets, such as that from the EMOTIV EPOC

EEG headset (Figures 1C and 1D).[79–81] This integration has been explored for various applications, including monitoring human emotional responses to different visuals in VR rooms,[81] measuring the mental workload of pilots in simulated suborbital flights,[80] and enabling mind-controlled VR games through BCIs.[82] A wireless configuration like the EMOTIV EPOC EEG headset offers users the greater freedom of movement expected for a full VR experience and practicality compared to VR-EEG systems that use wired EEG caps. However, the headset's plastic slots that hold the electrodes are relatively rigid, which can impede the precise montage of the EEG electrodes, especially in areas covered by the facial padding of the VR headset. Like wet gel electrodes, semidry electrodes also face the issue of liquid-spreading-induced short circuits.[77] Additionally, to maintain electrode impedance, it is necessary to periodically replenish the saline solution in the sponge electrode, which limits their useability in VR-EEG.[77]

Dry electrodes offer the advantages of an easy and quick setup and no issues of dehydration, making them suitable for extended use and outside-of-laboratory applications. EEG headbands, with the Muse headband as an example, have been worn together with VR headsets to classify emotional states induced by VR stimuli (Figures 1E and 1F).[83] However, the Muse headband, which features planar gold electrodes for the forehead and the region behind the ears, is tailored for hairless regions of the head, which significantly limits the sensing locations. In a recent work, Goh et al. developed a hair-compatible 4-channel EEG headset named WalkingWizard.[84] This headset employs gold-plated, spring-loaded pin electrodes designed to be able to capture EEG from hairy regions, particularly the occipital and parietal regions. The springs in the pins help maintain consistent electrode-scalp impedance, thereby increasing signal quality and minimizing motion-induced artifacts. As a result, this electrode design enabled the stable recording of steady-state evoked potentials (SSVEPs) under VR stimuli, even while walking on a treadmill at 3 km/h. However, the rigidity of the pin electrodes can cause discomfort during prolonged use. Despite these advancements, separate VR and EEG systems suffer from inherent issues such as time-consuming setup, user discomfort, and isolated VR and EEG computations, which may limit their applicability and practicality.

COMMERCIALLY INTEGRATED VR-EEG SYSTEMS

Compared with separate VR and EEG setups, EEG-integrated VR headsets offer a few advantages, such as quick setup, improved comfort, and enhanced immersive and interactive experience for users.[65] Although nascent, several commercial products featuring integrated VR-EEG are already showcasing their effectiveness in areas such as gaming and healthcare. For instance, Looxid Labs has introduced a mobile-powered VR headset named LooxidVR, which has six gold-plated EEG electrodes embedded into its facial padding, enabling EEG recording from the forehead (Figure 2A).[85] This setup can be effective for analyzing emotional and cognitive responses in virtual environments, provided that care is taken to remove muscular and ocular artifacts that easily contaminate EEG from the forehead. However, it is unable to record brain activities from hair-covered regions, which is essential for most BCI applications. Wearable Sensing has pioneered the creation of the first active dry EEG electrode headset designed for integration with VR headsets, known as the DSI-VR300 (Figures 2B and 2C).[86] This device features soft pillar electrodes strategically positioned at the parietal and occipital regions of the head, making this headset highly suitable for BCI applications requiring visually evoked potentials, such as P300-based spellers.

In 2018, OpenBCI launched their EEG-integrated VR headset, known as Galea (Figure 2D).[87] This device is equipped with 8 channels of active EEG electrodes in the form factor of soft pillars and 2 channels of passive EEG electrodes. Additionally, Galea incorporates a variety of other sensing modalities, such as electromyography (EMG) sensors for monitoring facial expressions, electrooculography (EOG) sensors for eye movement detection, electrodermal activity sensors for stress measurement, and photoplethysmography sensors for heart rate monitoring. Galea has differentiated itself from earlier VR-EEG systems by allowing for a multimodal, real-time analysis of the user's physical and mental states. MindMaze is another company that has integrated other biometric sensors into its VR-EEG system. Their system includes a head mesh featuring rigid pin electrodes for EEG recording from multiple brain regions (Figure 2E).[88] Additionally, they have incorporated gold electrodes into the facial padding to capture facial expressions, allowing for a more comprehensive understanding of a user's reactions and emotions while they interact with virtual environments. A similar design was employed by Cognixion One, which integrated 6 occipital-placed pillar electrodes with the VR headset (Figure 2F).[89] However, the pillar electrodes in Cognixion One generally require additional wet gel to assist the EEG recording.

Distinct from the aforementioned EEG electrodes that are integrated with specific VR headsets, Next Mind has developed the Next Mind Dev Kit, which features 9 comb-shaped dry electrodes (Figure 2G).[90] This versatile Dev Kit can be clipped onto any VR headset, effectively recording EEG signals from the occipital regions, even through dense hairs.[91] The SSVEP patterns captured by this device enabled the control of VR games.

From these examples, it is evident that most current commercially integrated VR-EEG systems adopt dry electrodes for their ease of setup. Conductive polymer-based pillar electrodes are particularly favored for recording EEG signals from hair-covered regions, owing to their ability to penetrate through the hair and their compatibility with the scalp. However, these dry electrodes often exhibited high contact impedance, reducing the signal-to-noise ratio and often requiring on-site amplifiers connected to the electrodes to reduce the noise to acceptable levels for EEG analysis. This active amplification requirement, while is also used in many standard EEG recording equipment, works against VR-EEG system design priorities by increasing the weight, power, and number of wires (at least two additional wires for power and ground for each active electrode). Additionally, the interfaces formed between these dry electrodes and the skin are not consistently stable, making them susceptible to motion artifacts, which is a concern because moderate motions are expected during most VR applications, with quick head movements being especially common, as the user needs to looks around the virtual environment.

Figure 2. Commercially integrated VR-EEG systems

(A) Looxid VR headset with 6 gold-plated EEG electrodes facing the forehead. Reproduced from https://looxidlabs.com. Copyright Looxid Labs.

(B and C) DSI-VR300 EEG headset with 7 pillar electrodes integrated with the HTC VR HMD and the EEG headset in the DSI-VR300. Reproduced from https://wearablesensing.com/dsi-vr300. Copyright Wearable Sensing.

(D) Galea VR-EEG system with 8-channel pillar electrodes integrated with the Varjo VR HMD. Reproduced from https://galea.co/. Copyright Open BCI.

(E) MindMaze with the head mesh. The inset shows the installed pin electrodes. Reproduced from https://fortune.com/2016/02/22/mindmaze-treats-amputee-veterans-with-vr. Copyright MindMaze.

(F) The Cognixion One headset with 6 pillar electrodes contacting the occipital. The inset shows the installed pillar electrodes. Reproduced from https://one.cognixion.com/Copyright Cognixion.

(G) Next Mind Dev Kit attachable to the rear of a VR headset. Reproduced from https://www.roadtovr.com/ces-2020-nextmind-400-brain-computer-interface-developer-kit. Copyright Next Mind.

INTEGRATED VR-EEG SYSTEMS IN DEVELOPMENT

Research VR-EEG systems can lay the groundwork for future commercial VR-EEG products, particularly through electrode material innovations. Unlike gold, conductive textiles offer the advantages of greater flexibility, cost effectiveness, and enhanced compatibility with the foam padding used in VR headsets.[92] As such, Zhang et al. developed an EEG-integrated VR headset with 3 conductive textile electrodes embedded into the facial foam padding (Figure 3A).[74] These electrodes consist of Ni/Cu nanoparticle-coated polyester fibers wrapped around a Ni nanoparticle-coated polyurethane foam.[93] This textile EEG-integrated VR headset was applied in emotion classification[94,95] and mental relaxation evaluation across different VR environments.[74,96] However, these textile electrodes cannot access the scalp through hair, restricting their capability to target hair-covered scalp regions.

Cassani et al. developed an 11-channel EEG-integrated VR-EEG system.[97] The system features Ag/AgCl-coated conductive polymer electrodes in a pillar shape for targeting hairy scalp areas, along with planar metal electrodes on the facial padding for hairless regions (Figure 3B). Additionally, their system incorporates four EOG electrodes to track eye movements, offering comprehensive physiological data collection within a VR environment. Li et al. (and other authors of this review) developed a type of soft and conductive sponge electrode composed of poly(3,4-ethylenedioxythiophene):polystyrene sulfonate (PEDOT:PSS) coated on melamine sponges (Figure 3C and the inset image).[98] The softness of the sponge allows them to deform to partially contact with the scalp skin covered by relatively thin hairs for reliable EEG recording. These sponges were integrated onto a Meta Quest 2 VR headset using a flexible connector array, ensuring a non-destructive integration of the EEG electrodes with the commercial VR headset. This setup enabled contingent negative variation recording during a custom-designed VR driving game, with a classification accuracy of 66%.

In addition to VR-integrated EEG electrodes, VR-compatible electrodes were developed. For instance, Mahmood et al. developed a portable, wireless, soft scalp electronics (SSE) platform that can be combined with a VR headset to capture MI signals. The SSE comprises 6 microneedle array EEG electrodes, stretchable and flexible interconnects, and flexible circuits (Figure 3D).[73] The microneedle array can penetrate the stratum corneum layer and offer reduced and more stable contact impedance for reliable EEG recordings. However, microneedle arrays are limited in practical applications due to infection risks. On-skin-formed hydrogels provide another promising candidate for hair-compatible VR-EEG systems due to the fluidity of their liquid precursors before they solidify into a gel. Additionally, these hydrogels have matched softness with the skin, making them almost imperceptible to wear. Gelatin is a highly biocompatible material, which is widely used in both wearable and implantable electronics.[99] Wang et al. therefore developed a

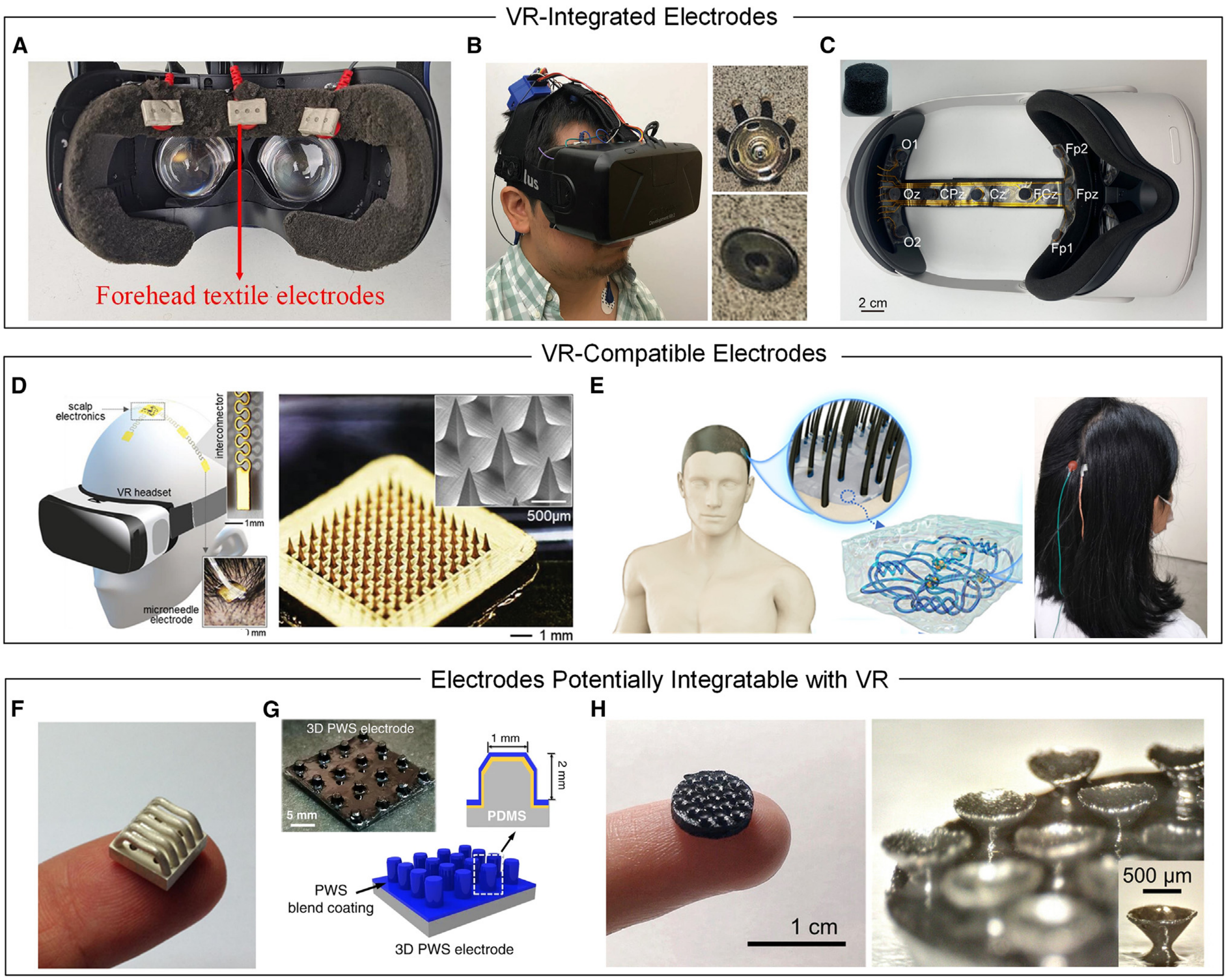

Figure 3. VR-EEG systems reported in literature

(A) 3-channel conductive textile EEG electrode-integrated VR headset for recording from the forehead. Reproduced with permission.[74] Copyright 2021, Frontiers Media.

(B) 11-channel flat and pillar EEG electrode-integrated VR headset for recording from both the forehead and hairy regions. Reproduced with permission.[97] Copyright 2020, IEEE.

(C) Conductive PEDOT:PSS-melamine sponge electrode-integrated VR headset for recording from both hairless and hairy sites. Reproduced with permission.[98] Copyright 2023, OAE Publishing.

(D) Soft scalp electronics with 6 microneedle EEG electrodes for recording from hairy sites. Reproduced with permission.[73] Copyright 2021, Wiley-VCH.

(E) Hair-compatible hydrogel electrodes capable of recording EEG signals for long periods of time. Reproduced with permission.[100] Copyright 2022, AAAS.

(F–H) Reverse-curve-arch-shaped silver electrodes (F), PEDOT:PSS-coated PDMS micropillars (G), and carbon nanotube (CNT)/PDMS conical microstructure array (H) for EEG recording on hairy sites. Reproduced with permission.[101–103] Copyright 2015, Institution of Engineering and Technology, 2020, Springer Nature, 2023, Wiley-VCH.

gelatin-based biogel electrode, which forms *in situ* on the skin after cooling (Figure 3E, left).[100] The biogel is adhesive and can be directly connected to an external recording system using flexible Ag/AgCl wires (Figure 3E, right). Moreover, the biogel doped with glycerol has excellent water retention properties, demonstrating stable SSVEP recording in a VR environment even after 48 hours.

Besides EEG electrodes that have been directly applied to VR headsets, several innovative hair-compatible electrodes have shown promising material properties and EEG recording performance, making them potential candidates for VR-EEG systems. For instance, a 3D-printed sterling silver electrode with a reverse-curve-arch shape offers an increased contact area and enhanced comfort compared to those of traditional pillar-shaped electrodes (Figure 3F).[101] Additionally, electrodes made from adhesive PEDOT:PSS-coated polydimethylsiloxane (PDMS) pillars are more flexible than their metal-based counterparts (Figure 3G).[102] Furthermore, this adhesive coating has led to a more stable electrode-skin interface and, consequently, more consistent EEG recordings. Another innovative design involves a conical microstructure array made from carbon nanotube-doped PDMS, which excels in both adhesion and contact area (Figure 3H), representing another promising option for integrated VR-EEG systems.[103]

The above discussions demonstrate that research-focused EEG electrodes are diverse in their structure designs and have enhanced electrode-skin interfaces. They have been successfully implemented as primarily passive electrodes, eliminating the need for amplification due to their superior electrode-skin interface contact impedance and stability. A notable limitation of these electrodes is their reliance on either complex fabrication processes or costly materials. Additionally, the discomfort caused by the skin-penetrating microneedle or non-invasive but stiff protruding pillars also hinders the wide adoption of these electrodes. Therefore, when developing these electrodes, it is crucial to strike a balance between performance, ease of manufacturing, and overall cost effectiveness of the materials.

VR-EEG SYSTEMS FOR BCIs

Following an analysis of the VR-EEG hardware, we delve into the key components and aspects of their applications in BCIs. VR-EEG-based BCIs control the VR system by decoding either endogenous EEG patterns like sensorimotor rhythms, which can be volitionally modulated by subjects imaging movements,[62,73] or exogenous EEG responding to external stimuli that give rise to evoked potentials like P300[65,104] or SSVEPs.[67,84,100] In addition, the BCI can modify some parameters of the VR experience after detecting some brain states of the user like workload, task difficulty,[55] or error awareness.[60]

Early examples of EEG-based BCIs in VR navigation relying on MI,[105–108] SSVEPs,[109] and P300.[104] MI studies have included tetraplegic[106] and paraplegic subjects.[108] BCIs also have allowed subjects to interact with smart homes in VR using P300.[110,111] In the case of MI BCIs, VR can enable the avatar to execute more complex or a larger number of motor commands than those the user can reliably deliver via MI. Once the BCI decodes a basic MI command (e.g., right hand movement), the avatar performs a functional movement appropriate to the current task (e.g., reaching and grasping an object with the right arm or opening a door by turning the handle with the right hand). This possibility is relevant for not only gaming and entertainment but also motor rehabilitation interventions that exploit the principles of mirror therapy.[112]

Although VR is increasingly deployed in entertainment[34] as well as in education and training,[35,36] it is expected that VR-EEG-based BCI systems will also have an impact on these areas. Nevertheless, this is not yet the case, and only a limited number of studies have been conducted. In the case of entertainment, the potential of VR-EEG-based BCI applications has been partially shown in the popular multiuser game World of Warcraft, where the BCI decoded the user's affective state that made the avatar adopt either a "positive" or a "negative" animal form in the fantasy world.[113] BCI proof of concept has also been reported in education and training,[37,38] where the BCI detects a user's attention and provides feedback to help them remain focused. Another distinctive feature of learning and consolidation of skills is a decrease in the involvement of the cerebral attention system since those skills are transferred from cortical to subcortical areas and executed automatically. A BCI, then, could assess real-time users' cognitive efforts to determine learning progress. This information will be critical in disentangling whether behavioral improvement (performance and speed increases) is truly due to the acquisition of the skill, and so the user has freed cortical resources that could be eventually engaged in tackling other concurrent tasks. In this respect, initial evidence shows EEG markers correlated with skill learning progression.[114] As a final example, the theory of challenge point[115] states that the optimal performance resides at a task difficulty level that is neither too high nor too low. This is also the point that promotes learning. Thus, a BCI that assesses the user's workload/task difficulty[55] can automatically adapt the level of difficulty of the task to enhance the user's experience and facilitate the acquisition of the necessary skills.

Apart from entertainment and education, VR-EEG and MI BCIs have demonstrated their benefits in neurorehabilitation.[42,43] Such work includes clinical trials, where subacute stroke patients controlled the opening and closing of a virtual hand by imagining the movements of their paretic hand.[116] At the more basic level, different studies have provided support for the potential benefits of the combination of VR-EEG and MI BCIs. In one of those studies, the authors reported that BCI training in an immersive VR setup allowed healthy subjects to better modulate sensorimotor rhythms, which were more similar to actual motor execution, than without the VR component.[117] Another study found that an MI BCI coupled with an immersive VR setup and functional electrical stimulation significantly improves MI classification accuracy.[118] Both components, stronger electrophysiological patterns and higher accuracy, are directly related to functional motor recovery after stroke.[43,119] VR-EEG and BCIs have also been combined beyond motor rehabilitation. For instance, a study has reported that a BCI that detects a subject's attention and controls a VR cognitive training program increased attention levels in children suffering from attention-deficit hyperactivity disorder.[120] Finally, VR-EEG and MI BCIs have been combined to investigate cognitive neuroscience questions such as body ownership and agency over a virtual hand, which subjects control by imagining opening and closing their own hand.[121,122] VR-EEG and BCIs have also been used to embody virtual humanoid robots.[71] A case study with a VR-EEG and MI BCI was shown to reduce pain in a patient with chronic dystonia who imagined movements of his own hand to control that of an avatar.[123]

REMAINING CHALLENGES

Despite emerging efforts and advancements in integrating EEG with VR technologies and imaginative uses of VR-EEG systems, there are several remaining challenges obstructing their practical adoption.

Hair compatibility

EEG signals from hair-covered regions are vital for numerous BCI applications. Presently, hair-compatible EEG electrodes include wet gel, semidry, and dry pillar electrodes, each with their own particular benefits and disadvantages. Wet gel electrodes allow optimum skin contact on hairy areas and mitigate

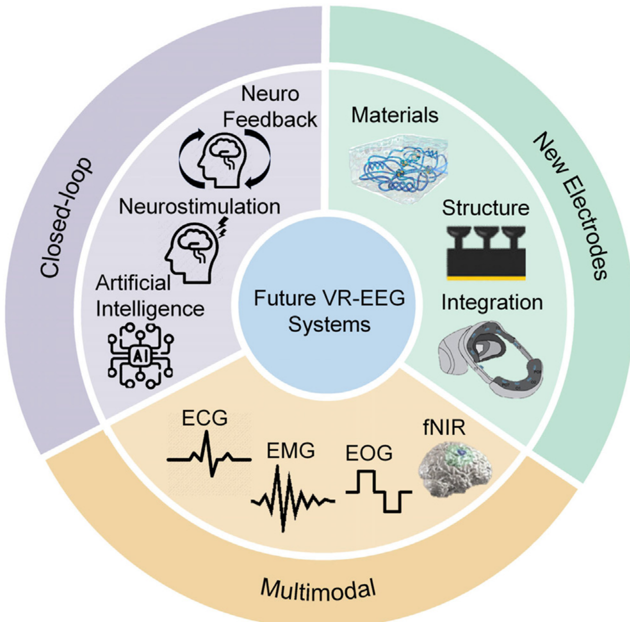

Figure 4. Future opportunities of VR-EEG devices
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motion-induced anomalies, but they pose problems such as time-consuming application, drying, and undesirable leftover gel in the hair after use. Semidry electrodes provide better skin contact than dry electrodes due to saline solution bridging and are simpler to remove than gel electrodes, but they also dry with time. Additionally, semidry electrodes may mold or leave saltwater on the skin after use. Dry pillar electrodes are preferred for their user-friendly aspects, hence their popularity in commercial VR-EEG systems. However, they cause discomfort for the users, especially if worn for a long time. Additionally, dry electrodes exhibit high contact impedance with the skin, necessitating on-site amplification, and fall prey to motion-induced artifacts, necessitating more intrusive signal processing including heavier removal or modification of original data, which directly impacts downstream BCI performance or neural data analyses.[124] There is currently no electrode type that encapsulates all the ideal characteristics for stable, long-term EEG recording on hairy regions with easy installation and removal.

Seamless integration between EEG sensors and VR headsets

Hair-compatible VR-EEG systems require EEG sensors built into VR headsets. Although some EEG electrodes are soft, their supporting layers often lack adequate flexibility. Therefore, the VR headset causes extra scalp pressure and decreased user comfort. However, if the pressure is eliminated, then the electrodes may not establish a steady interface with the scalp. EEG electrodes designed for hairless areas can be integrated into the VR headset's facial padding but often include rigid connectors or are rigid themselves. Consequently, the original functions of the facial padding—to conform to the head shape, isolate external light, and provide comfort—may be compromised.

Wireless VR-EEG systems

Most VR-EEG systems are wired due to better recording stability and compatibility with existing EEG amplifiers and provide precise time triggers for VR events to evoke different types of EEG potentials. However, considering that VR interactions often involve user mobility without being aware of cables, these cables can pose safety hazards and degrade immersion. Wireless VR-EEG systems are desired for this reason. In principle, a successful VR-EEG integration should reach a compromise between the design priorities of VR and those of EEG systems. As such, although simply adding a wired EEG system to a VR setup may be ideal for eliminating issues with power, signal integrity, and trigger recording, doing so goes against the priorities of VR users. Therefore, we believe that a successful VR-EEG device would be completely wireless. To achieve this, wireless VR-EEG system developers should contemplate a low-power circuit design to match the increasing battery lives of VR systems; include reference and ground electrodes to match the usability and common mode rejection capabilities expected from a high-fidelity EEG system; reduce EEG packet loss by optimizing data buffering, transmission power and frequency, and antenna placement to match the robustness of wired systems; and enhance the precision of wirelessly recordable triggers to match EEG samples with events in the VR environment, which may be managed on a separate computer.

Limited EEG recording sites

Most VR-EEG systems feature a restricted set of channel locations, commonly positioned in the parietal, prefrontal, and occipital regions. This limitation primarily arises from differing priorities in designing a conventional VR headset and a full-head EEG system. As a consequence, all current VR-EEG system designs have limited capabilities to comprehensively measure whole-head brain activity, which is necessary for complex neurofeedback applications that are based on the analysis and modification of EEG patterns in several brain regions.[125,126] Low and uneven channel coverage also restricts the use of traditional EEG spatial filtering or channel interpolation techniques and source imaging methods fundamental for advanced decoders or neuroscientific studies.

FUTURE DIRECTIONS AND OUTLOOK

Here, we discuss the future directions and outlook for VR-EEG systems (see Figure 4).

New type of electrodes

Presently, VR-EEG systems' challenges revolve around EEG electrodes, especially how to effectively target hair-covered regions. To counter this, it is crucial to devise new electrodes that blend the close contact and steady performance of wet gel electrodes with the skin with the convenient setup of dry electrodes. Innovative conductive and adhesive materials for coating on relatively soft dry electrodes could be the solution. Alternatively, design or structure enhancements to improve the skin-electrode interface are useful. For example, micropillar and microcrater structures have shown promising results in increasing the contact area and skin adhesion.[102,103] They also maneuver well through hairs, making them suitable candidates for hair-compatible dry electrodes. Additionally, integrating these electrodes seamlessly into the VR headset is paramount for creating a comfortable and effective EEG and VR interface. This integration can enhance user comfort and may improve the signal recording quality in VR-EEG systems. Also, recently reported EEG electrodes around[127,128] or in the ear[4,129] have attracted particular attention with their advantages of non-gel EEG recording, wearability, and successful use in some applications that do not always require high channel density or neural activity from hairy regions including sleep monitoring,[4,130] seizure detection,[131] and visually evoked potentials.[132,133] In-ear EEG sensors do not overlap physically with conventional VR headsets, making them easy to use simultaneously with VR systems based on separate hardware. But it is difficult to seamlessly integrate them into one VR-EEG device. In contrast, around-the-ear EEG electrodes could potentially be integrated into the head straps of VR headsets. Thus, they have the potential to be integrated as a VR-EEG device capable of EEG recordings from the temporal and/or mastoid process regions.

Multimodal VR-EEG systems

Current VR-EEG systems are primarily focused on monitoring brain activity. However, user interaction with VR is multifaceted and includes factors like eye movement, heartbeat, stress levels, and facial expressions. Incorporating the recording of these factors along with EEG data can provide a comprehensive understanding of human mental and physical states.[87,97] This multimodal approach can complement the many types of non-physiological human activity sensing that VR headsets typically provide such as gyroscopes, accelerometers, cameras, depth sensors, and microphones. Companies like OpenBCI and MindMaze have advocated for this approach by integrating multiple modalities, such as EOG and EMG, alongside EEG in VR-EEG systems. For brain activity alone, it is beneficial to consider incorporating other modalities. While EEG offers high temporal resolution, it has limited spatial resolution, making it difficult to precisely pinpoint brain activity regions. EEG's limitation in assessing prefrontal cortex function (critical for cognition) due to contamination by facial and ocular movements can be overcome using functional near-infrared spectroscopy (fNIR).[134] When incorporating multimodality in VR-EEG systems, designers should take particular care to ensure temporal synchronization between the multimodal sensors and the VR elements. Delays between sensors can be acceptable if known, but jitters are unacceptable, as they make any multimodal analysis significantly less meaningful. The integrated hardware should use a crystal with sufficient frequency stability for the intended operating conditions and a timed signal to control and minimize intersensor delays. As for synchronization with VR, a wireless method based on software is preferable considering interoperability with VR development application programming interfaces such as Unity or OpenVR and also the fact that VR applications commonly run on external computers. In this case, a careful review of the hardware sampling configuration is still required to supply accurate local sampling times to the software layer.

Closed-loop VR-EEG systems

The field of BCI represents a significant application area for VR-EEG systems, where closed-loop decoding of brain activity dictates VR feedback. BCIs and VR can profoundly enhance interactive experiences in neurorehabilitation and entertainment scenarios. Here, VR amplifies BCI feedback by immersing subjects in ecological, challenging, and rewarding environments. In neurorehabilitation, VR neurofeedback can be complemented with closed-loop neurostimulation,[135] enhancing brain plasticity and recovery.[43,119] VR-EEG systems' success rate in BCIs will also depend on the control level that subjects have over VR elements. The clinical application of using VR-EEG systems could be farfetched. Such systems can help clinicians to better understand the underlying mechanism of motor recovery after stroke[43] and develop patient-centered neurorehabilitation programs. They could also advance remote rehabilitation programs through telehealth[44] by monitoring the real-time change in brain function remotely and subsequently refine the interventions. Future artificial intelligence advancements are poised to enhance BCI performance,[136] with potential customization of BCI results driving the VR experience.[137] Developers of closed-loop VR-EEG systems should focus on making the online EEG decoder outputs user friendly and timely for the VR application through dedicated programming interfaces.

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AUTHOR CONTRIBUTIONS

H.L., J.d.R.M., and N.L. conceived the idea; H.L., H.S., and J.d.R.M. made the literature survey and wrote the manuscript; and L.S., K.-C.S., J.d.R.M., and N.L. revised the manuscript.

DECLARATION OF INTERESTS

The authors declare no competing interests.

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