Microprocessors and Microsystems 88 (2022) 104392

Contents lists available at ScienceDirect

Microprocessors and Microsystems

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

A review on Virtual Reality and Augmented Reality use-cases of Brain Computer Interface based applications for smart cities

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ARTICLE INFO

Keywords:
Brain Computer Interfaces
Extended Reality
Virtual Reality
Augmented Reality
Smart cities

ABSTRACT

Brain Computer Interfaces (BCIs) and Extended Reality (XR) have seen significant advances as independent disciplines over the past 50 years. XR has been developed as an umbrella domain, covering Virtual Reality (VR), Augmented Reality (AR) and Mixed Reality (MR), giving rise to human–machine interactions. This intersection sees diverse applications ranging from rehabilitation, navigation, entertainment, robotics and home control for smart cities. This review takes an in-depth look at BCI and XR technologies, and gives examples of how their combination produces promising results pertaining to the above stated applications. It presents a detailed discussion on the background of BCI, VR and AR technologies and further their individual applications. The review then discusses the works that use the conjunction of these technologies for various real life applications in smart cities. In addition, we also present the future scope of applications that use a combination of BCI and XR technologies.

1. Introduction

The domain of healthcare applications has seen an unprecedented growth in the last decade in terms of incorporation of technologies like image processing [1], blockchain [2], Internet of Things (IoT) [3], Deep Learning [4], VR [5] and BCI [6]. A BCI acquires and analyses bio-signals obtained from sensors, and translates them into commands that are forwarded to devices that give feedback to the users or complete desired actions. Over the years of development, the term BCI applies to not only computers but other machines as well and thus can be used interchangeable with Brain Machine Interface (BMI). Though the initial intent of BCI was to restore or replace function for people with neuromuscular disorders, its applications have not been limited to the medical field. The Third International BCI Meeting in 2005 established the value of BCI technology on discussing its useful applications [7]. BCI has the potential to improve the quality of life and finds applications in various areas such rehabilitation [8,9], entertainment [10], navigation [11], and home control [12] to name a few. Since the initial development of Electroencephalography (EEG) [13] based spellers and simple BCIs for device control, researchers have developed BCIs for neuro-rehabilitation [14], cursor control [15], robotics [16,17] and prostheses [18], wheelchairs [11], gaming [19] and to make many other complex devices [20]. Based on the application the bio-signals processed may be the electrical activity of the brain, the corneo-retinal standing potentials existing between the front and back of the eye, or the electrical signals from muscle tissues. Brain signals are collected through non-invasive sensor monitoring with EEG [21] or through invasive methods such as intercranial EEG (iEEG) also known as Electrocorticography (ECoG) [22]. Signals from the eyes and muscles can be recorded using Electrooculography and Electromyography respectively [23]. Such non-brain signals can often be a source of valuable information. Functional Magnetic Resonance Imaging (fMRI) and Near-Infrared Spectroscopy (NIRS) are gaining popularity as well [24].

BCI poses multiple challenges [30]. The signals gathered from EEG sensors generally have low signal to noise ratio (SNR) [31] because of environmental disturbances such as channel noise, motion artifacts and electrode-contact noise. SNR is not consistent across sessions, making it more difficult for researchers to perform multiple human experiments with the same profile without frequent calibrations. The useful signal is a small portion of raw output EEG. Multiple filters and processing algorithms are employed to obtain the required refined signal. An electrode measures superposition of several brain activities, making the isolation of the required signal difficult [32]. The algorithms developed for a specific person might not work for another because of the difference in

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https://doi.org/10.1016/j.micpro.2021.104392
Received 19 June 2021; Received in revised form 28 September 2021; Accepted 30 October 2021
Available online 17 December 2021
0141-9331/

Table 1
Technologies in conjunction with BCI.

Technology	Feedback	Details	Main Uses	References
Haptics	Haptic	Tactile sensations may be created in mid-air without the need to touch a physical object or through vibrations of a device in contact.	Entertainment Electronic Devices Exoskeletons Navigation	[25] [26] [27]
FES	Electrical	Electrical Impulses are sent to paralyzed muscles to restore function. The technology is used to assist with walking, standing, breathing grasping and to improve bowel function.	Neurorehabilitation	[28] [29]
VR	Visual	Subjects can visually see whether their actions bring desired results and correct themselves accordingly.	Entertainment Navigation Neurorehabilitation	[25] [28]

cortex folding and functional mappings. The brain folding is different even in the case of identical/monozygotic twins [33]. EEG signals resulting from a summation of multiple neural firing processes can be leveraged to perform desired actions. Only certain kinds of neural activities can be captured by surface electrodes, primarily, the event of pyramidal neuron firing. Since these neurons lie perpendicular to the surface of the cortex, their potentials undergo interference, giving a value detectable by external surface electrodes [34]. Generally, events such as the flash of a light or sound [35], produce a cascaded effect. All these are examples of oscillatory processes that create EEG-observable changes. This technology has successfully been deployed in multiple use-cases. As an example, this may be used by a differently-abled person to trigger certain actions. Authors in [36] used this for navigating in a virtual environment (VE). Neuro-mapping is also a critical pre-requisite for brainwave analysis. But mapping a staggering 100 billion neurons in the brain is not feasible. Therefore, certain parts of the brain are mapped to functions they are expected to perform. This is also known as 'localization of function'. Neurosurgeons use neuro-mapping to scheme out strategies for intricate surgeries. As an example, fMRI is extensively used to pinpoint the location of the epileptic center, thereby acting as a guide for the doctors for further progress [37]. The user security and privacy challenges [38] of BCI are beyond the scope of this paper.

VR technology [39] utilizes computer graphic systems to create VEs. It places users into a simulated 3D environment which they can interact with. This is achieved with head-mounted displays (HMD) [40,41], differentiating VR systems from traditional user interfaces. Some of the commercially available VR headsets include Occulus (Facebook) [42], HTC-Vive series [43] and Valve Index (Steam) [44]. Senses such as vision, hearing, touch and smell are also simulated, thus providing an immersive experience. VR is used in military training [45], education [46], rehabilitation [6], business [47] and several other fields. AR on the other hand utilizes smartphones and hence are closer to the physical world. It provides users with a real-time interactive experience wherein the real-world objects are enhanced and superimposed with computer-generated information across various sensory modalities such as auditory, visual, haptic, olfactory and somatosensory. AR finds applications in navigation, architecture, archaeology, STEM education, manufacturing, entertainment, commerce and visual arts. Merging AR and VR technologies gives rise to MR environments and visualizations, in which virtual objects interact with real objects in real-time. MR does not take place exclusively in either the real or virtual world, but rather in a hybrid of the two. Its applications range from interactive product content management, simulation-based learning, military training, remote working, medicine and the creative arts. XR is the umbrella term that covers the different reality technologies and human machine interactions.

VR is currently one of the best available technology that provides testing grounds for applications involving physical limitations such as training, education, rehabilitation and even to improve user experience and quality of life [48]. As also discussed later in the paper, BCI research involves the use of tools for visual, haptic, electrical and auditory feedback. Table 1 shows a few examples of haptics, functional electrical stimulation (FES) and VR used in conjunction with BCIs. VR provides the most rich visual experience and its applications with BCI include rehabilitation, entertainment, navigation and robotics. Applications of AR and MR with BCI include X-ray vision, auditing, home and device control among several others. These technologies pose various challenges.

There are challenges posed by VR devices as well [49]. First, high-grade VR headsets require high graphics processing power to show high-resolution imagery. Second, tracking head rotations in VR is one of the key metrics to increase immersion. Current technology uses gyroscopes and accelerometers to track direction, but BCI may provide a potential solution to this [50]. By predicting required field of view, highly optimized VR headsets can be used for high graphic requirements by utilizing occlusion culling algorithms. Therefore, simpler GPUs will be able to handle intense imagery tasks. It can further be used with holography to decrease the load on the CPU.

The main contributions of this review are as follows

i. We present an overview of BCI and XR technologies, their classifications and their use cases.
ii. We review existing works which use a fusion of BCI and VR/AR/MR technologies for applications ranging from navigation, entertainment, rehabilitation, robotics and home control.
iii. We present the future scope of XR and BCI-based applications.

Having discussed the individual nuances of BCI and XR, their combination comes with several challenges of its own. Further in this paper, the background concepts and tools of BCI and XR technologies are explained in Section 2, followed by an in-depth discussion on previous research and their feasibility on the applications of their combination in navigation, entertainment, rehabilitation, robotics and home control in Sections 3 and 4. In addition, insights on future use cases are also presented in Section 5.

2. Background information

This section gives an overview of systems and frameworks employed to create BCI and XR. Specifically details on BCI-classification, EEG positioning system, details on extended reality, motor imagery, event related potentials and other information are discussed, which would assist the reader to further understand the core concepts. BCI can be divided into various categories on different rationals as shown in Fig. 1.

2.1. BCI and use-cases

Methods used to capture the signals can vary depending on the application. On the basis of medical approach used, BCIs can be classified as non-invasive and invasive [51]. Non-invasive BCI makes use of either dry or wet electrodes placed directly on the scalp or on the skin on other parts of the body. They measure surface potentials. Invasive systems are implanted directly into the brain during a neurosurgery. These can be single-unit BCIs [52], used for acquiring signals from a specific area of

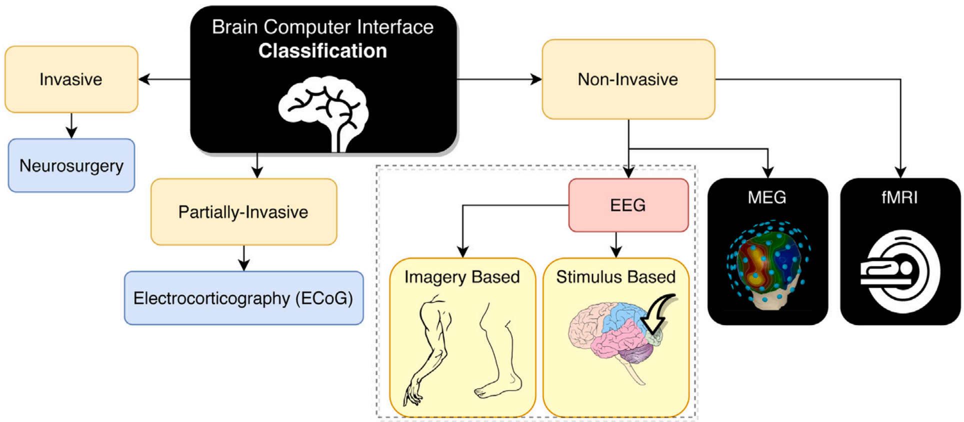


Fig. 1. BCI classification.

brain, or multi-unit BCIs [53], which are used to capture signals from multiple areas.

There are three common sub-types of BCIs based on the flow of information: Passive, Active and Reactive. Passive BCIs are predominantly used to gauge the mental and emotional states of the subject [54]. This is done by monitoring brain signals, Galvanic Skin Response (GSR) and eye tracking. On the contrary only brain activity is monitored in an active BCI. Active BCIs are commonly used for stroke rehabilitation [6]. In case of Reactive BCI, the brain's response to an external stimulus or event is analyzed, thus making it a perfect fit for gaming and entertainment applications [55].

BCIs can also be classified as endogenous or exogenous [56]. An endogenous BCI [57] relies solely on brain patterns that are spontaneously generated, an example of which is motor imagery (MI). Exogenous BCI on the other hand is based on the brain's response to external stimulus, for example, P300 and Steady State Visually Evoked Potentials (SSVEP). [58].

BCIs can also be classified as independent and dependent [59]. Independent BCIs rely solely on brain activity, whereas dependent BCIs access signals from peripheral nerves and muscles as well. Endogenous BCIs, as discussed above, are a part of the independent BCI paradigm.There are several techniques used for brain imaging including functional Near Infrared Spectroscopy (fNIR), fMRI, Magnetoencephalography (MEG), Positron Emission Tomography (PET) etc. fNIRS makes use of blood oxygen levels by shining infrared light and analyzing response. Most of these are not practical enough to be used by general public. EEG based BCIs are inexpensive depending on application.

Electrode location for EEG systems needs to be consistent for all head shapes and sizes. A standard electrode positioning system used for this is the international 10–20 system [60]. The electrodes are marked as per their locations to achieve positive mapping results. The basis of this system is the relationship between the electrodes and the underlying cerebral cortex area. Fig. 2(a) shows the different important regions of the brain and electrodes pertaining to them. The electrodes are identified by a letter followed by a number. F, T, C, P and O stand for the Frontal, Temporal, Central, Parietal and Occipital regions of the cortex. Among the numbering from 1–8, all odd numbered electrodes (1,3,5,7) lie on the left hemisphere while the even numbered electrodes (2,4,6,8) lie on the right hemisphere. The numbers in the 10–20 rule refer to the 10% and 20% electrode distance as shown in Fig. 2(b).

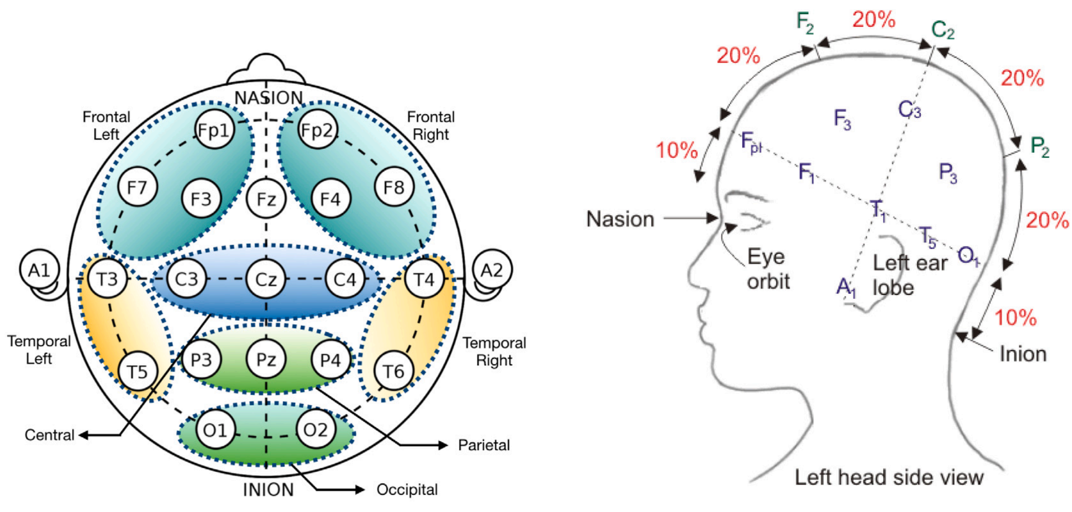
BCI systems can employ big data based cloud analytics as done in past works for healthcare systems [41,61]. A major target use-case of BCIs is to restore, or replace useful neuro-muscular function for people with neuro-muscular disorders such amyotrophic lateral sclerosis (ALS), tetraplegia, cerebral palsy, stroke and spinal cord injury. ALS is a condition wherein the patient loses his/her motor capability, also known as locked-in syndrome. BCI systems have the potential to provide people with motor disabilities with a means to control artificial limbs i.e. neuro-prosthetics [62]. Speller programs that utilize reactive BCI are used for treatments of tetraplegia. EEG, ECoG, intracortical and other brain signals have also been used for complex control of cursors [15], robotics and prosthesis [18], and wheelchairs [20], and also to secure the IoT [63]. Passive BCI is steadily entering the general public domain as companies like EMOTIV [64], NeuroSky [65], Natus-Medical [66] and MindMaze [67] introduce BCI-powered applications. BCI has also been used along with FES for the treatment of Spinal cord injuries [68]. Neuro-rehabilitation is an emerging research field where researchers are using this technology, which is also discussed in its dedicated section as well in this paper. In the area of forensics BCI is used for brain fingerprinting [69] and lie detection [70].

Brain-wave sensors are used for reading EEG signals from the brain. The sensor data can be analyzed using various programming languages including Python, MATLAB etc. The aim is to classify the signals into certain useful tasks. Hardware headsets available in the consumer market include headsets such as MindWave Mobile [71], Epoc Neuro-headset [72], Muse [73] and Enobio [74]. These are affordable and can help start BCI development. Software such as BCI2000 [75], Open-vibe [76] and Asterics [77] are open source platforms for acquiring and analyzing data. These may also include synchronization with other interfaces such as joysticks and keyboards. They are python-based platforms developed for users who are willing to address various applications of BCI. Advances in machine learning techniques [78] are paving the way to extract information from more entangled signals with greater ease. Pattern recognition in EEG data can be done using linear classifiers such as Linear Discriminant Analysis (LDA), non-linear classifiers like Support Vector Machines (SVM) and k-Nearest Neighbots (kNN) and neural network-based methods such as MLPs. An overview of these Machine Learning based classification techniques in BCI-VR systems is presented in [79].

Among the sub-classes of BCIs, Event Related Potential (ERP) and Motor Imagery (MI) are the two most commonly used ones. The sub-sections below give a background on these sub-classes:

Event Related Potentials: Event Related Potentials (ERPs) occur when sensory or cognitive processes are used to trigger brain responses. The most commonly used Sensory Evoked Potentials (SEPs) are either Visual Evoked Potentials (VEPs) [80] or Auditory Evoked Potentials (AEPs) [81]. ERP waveforms are usually described by their amplitudes and latencies. P300 is a commonly seen ERP, predominantly known through the P300 speller [82], as shown in Fig. 3. SSVEPs are another type of VEP, that are evoked by using a repetitive optical stimulus.

Motor Imagery: The act of thinking or observing an action activated the motor cortex. Even if the person is unable to perform motor movement, they can still produces the same signals, by imagining the action.



(a) Brain regions for electrode placement

(b) 10-20 Rule

Fig. 2. Electrode placement and brain regions.

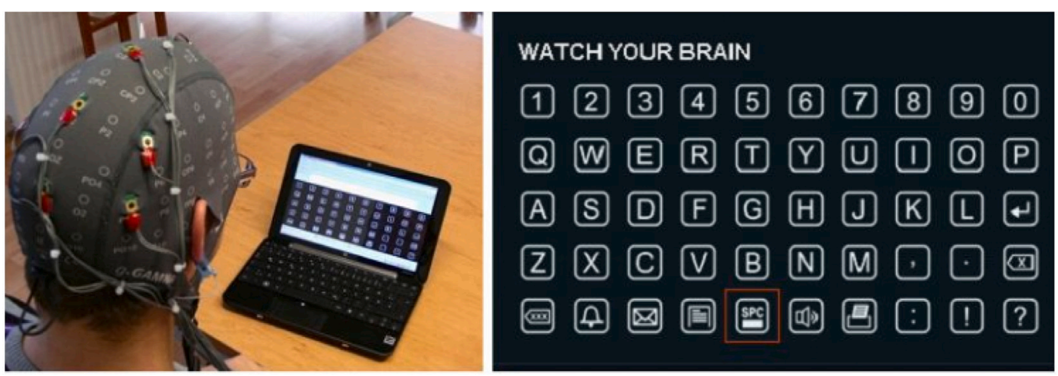


Fig. 3. P300 typing.

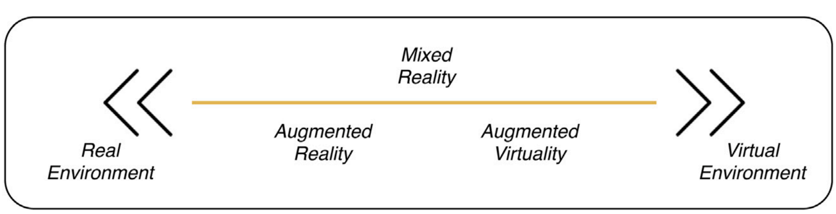


Fig. 4. Reality–Virtuality continuum.

Motor imagery requires mental practice of movements without actual physical movement. It can be implicit (person imagining an activity that indirectly requires motor use) or explicit (example, imagining the movement of the left hand).

2.2. XR and use cases

Extended Reality (XR) is an advanced form of immersive technology which covers virtual, augmented and mixed reality along with human machine interactions. XR has innumerable applications which include (but not limited to) entertainment, education, professional or military training. VR is useful when a high extent of immersion is necessary and the real environment cannot meet the requirements.

The Reality-Virtuality continuum scale [83] incorporates all XR variations, as shown in Fig. 4. For VR, specialized head-mounted displays (HMDs) from Oculus (Facebook), HTC-Vive, Valve Index etc are available in the market. These use high fidelity optics and well developed motion sensing. They have dedicated controllers for interaction with the projected reality. VR is used in multiple areas and the democratization of this technology has brought the technology in the hands of common people. Using Google's cardboard viewer, even a mobile phone with gyroscope and accelerometer can be used as a VR device. These devices are being used as a part of exposure therapy to create immersive environments. VR is extensively used in the industry for recruitment [84], training [45], treatment of PTSD [5], work collaboration and for many other applications [85]. 3D modeling software [86] like 3DSMax, Maya, Rhino, Fusion360 can be used to create

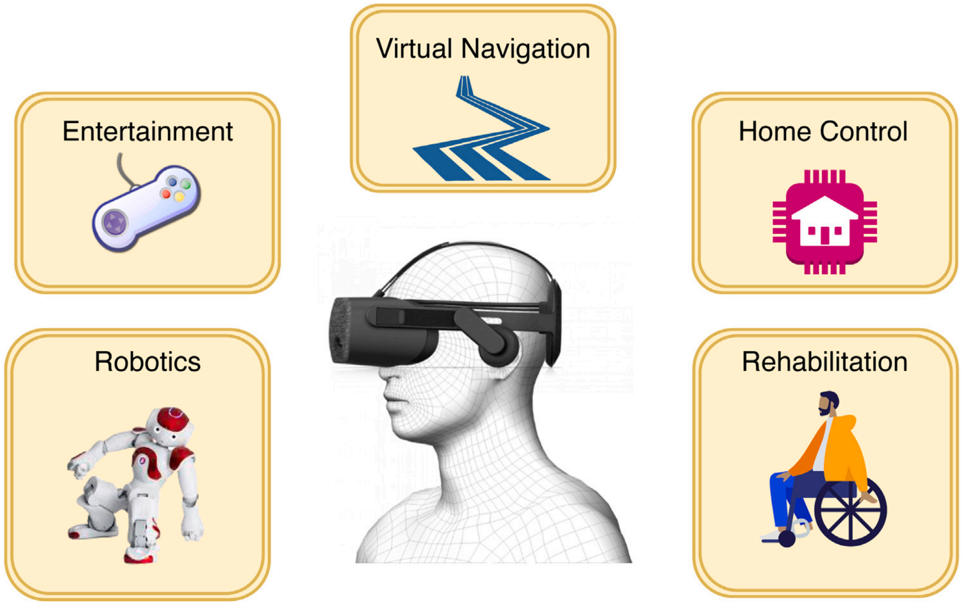


Fig. 5. BCI-XR applications.

3D models and environments alongside tools like substance painter for textures. Further, these 3D models are used inside development engines like Unity3D [87] and Unreal Engine [88], in which programming languages along with blueprints are used to control object behavior.

In the case of AR [89,90], most current smartphones make use of ARkit (iOS) or ARcore (Android) for augmented reality based applications. Specialized AR headsets like Tesseract are also available in the Asian market for a smartphone independent experience. AR finds several applications in smart home control, auditing, healthcare and surgery [91]. On the other hand, the first hardware for Mixed Reality (MR), HoloLens, was launched by Micosoft in 2016. Other companies include Google, Samsung, Nintendo and Huawei. The Virtual Fixtures platform, developed by Armstrong Laboratories in 1992, was the first MR system providing enveloping sound, touch and sight. It demonstrated improved human performance by overlaying virtual objects on the real physical environment.

The following sections will now focus on the past research on the applications of BCI and XR in navigation, entertainment, rehabilitation, home control and robotics.

3. BCI-VR applications

BCIs increases the communication bandwidth of interactions between humans and VR systems. Illusions of an artificially perceived reality can be induced to offer various immersive scenarios [92]. The multiple areas of application for BCI-XR can be seen in Fig. 5. This section discusses the existing BCI-VR research in depth, following the previous work in the fields of navigation, entertainment, rehabilitation and robotics.

3.1. Navigation

This sub-section discusses motor imagery-based VR navigation. Using brain signals to navigate in a virtual world has been worked upon by multiple research groups extensively. BCI-VR navigation systems are used in areas including gaming, rehabilitation and neuro-feedback training. The ease of navigation is an important supporter of VR environments because of physical space and action constraints. But environment designers always need to ensure that motion sickness is avoided which can also hamper the process. Fig. 6 shows a typical BCI-VR navigation system. In the late 1990s, researchers from Lancaster University developed one of the first systems with which subjects could navigate through and interact with a virtual world [93]. Subject training was based on a reward system depending on a threshold of maintaining the EEG component signal. The environment for training was constructed from sets of VR Modeling Language (VRML) components. VR in general has proved to be more engaging for similar use-cases. Although both motor imagery and evoked potentials have been used for VR based navigation, our focus is mainly on MI-based navigation as discussed in the following subsection.

3.1.1. Navigation using motor imagery

Visual feedback is useful for reinforcing behaviors and neuroplasticity plays an important role in this process. Rigorous training may be required to enforce such intended thoughts and imagined situations. A typical protocol for training a subject in an MI-BCI is the execution of an MI task with a bar of variable length or a moving object as feedback. The bar or an object gives a visual feedback on how the person is performing. This induces a sense of embodiment which significantly increases the rate of learning in MI tasks [94]. The training process can hinder the progress if the feedback is not positive. But the current machine learning techniques can decipher the signal even if the SNR ratio is not appropriate. MI techniques are generally preceded by capturing the signals in offline mode, because the range of signals captured can vary.

Motor imagery provides a step away from cue-based and synchronized BCIs, making the use of BCI closer to the real world. A study conducted on MI based navigation in a VE showcased that the graphical capabilities of VR opens possibilities to create new BCI paradigms with improved feedback [95,96]. Another study discussed the feasibility of using MI-BCI for navigating through a virtual city [97]. The tasks included moving forward, backward or staying stationary to navigate from one place to the other in the city. The motion control in the VE was based on 2-class MI classification, left hand for turning left and right hand for turning right. A 3-channel EEG and Motor Imagery were employed with naive subjects trained over three sessions to comfortably navigate a VE for viewing apartments [98]. Goal-oriented tasks, varied decision periods and high mental workload was kept in mind while designing the virtual apartment. Subjects could maintain stable MI over a minimum of two seconds. In addition to the use case, it was also observed that the dedicated and motivated subjects performed better

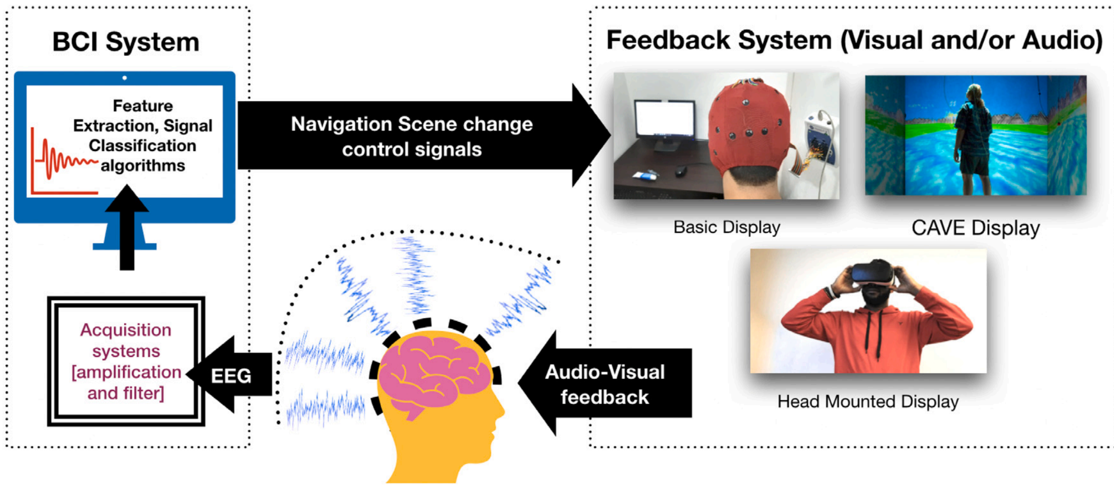


Fig. 6. BCI-VR navigation.

than their unmotivated counterparts. Leeb et al. in 2006 [99] proposed a Graz-BCI system, wherein subjects were made to navigate a CAVE with an HMD. In [100], an experimenter-cued asynchronous BCI was designed to navigate through the Australian National Library.

Navigation is also closely linked to controlling the virtual object being moved through the VE. Luu et al. explored the possibility of closed-loop non-invasive BCI-based avatar walking, using delta band (0.1–3 Hz) as a feature [101]. Subjects' r values increased significantly over the course of 8 training days for hip, knee and ankle control. The study also reveals that cortical involvement is different with and without closed-loop BCI control. While such a system is useful in navigation of human like avatars in VEs, it may also prove to be useful for post-stroke rehabilitation patients, which are reviewed in a later section. Scherer et al. presented a 3-class Graz-BCI-based on the detection of sensorimotor rhythms (SMRs, 13–15 Hz) [102]. EOG and EMG artifacts were removed and 3 bipolar EEG channels were used. The paper presents two applications, freeSpace VE and Brainloop. freeSpace is a computer game where subjects can navigate collect coins as rewards [103]. Brainloop provides an interface between Google Earth and Graz-BCI. A multi projection based stereo VE called DAVE was used by Lotte et al. in 2012 [48].

An MI based navigation system designed for people with special needs was presented in [36]. The system comprises of an MI-BCI, communication module, EEG analyser and a VE linked to the real world apartment. The study showed reasonable classification of MI to be used in a VR setting. Fujisawa et al. demonstrated training-less BCI-VE navigation employing a common spatial pattern (CSP) for 2 class MI, left and right hands [104]. Friedman et al. used a CAVE system in a virtual bar to navigate through using left hand and right hand (2 class) MI [105]. The subjects were also made to navigate along a street in 1D by imagining either hands or feet motion. In [106], a 3-class BCI was presented to navigate through a single path maze. The 3 classes are left and right hands, and feet. The study showed an increase in user engagement while using BCI-VR. Table 2 summarizes the MI based BCI research conducted so far by categorizing the navigation as self-paced (at the pace of the subject) or synchronous (subjects are given progress cues). The MI commands used in the studies may either be low-level or high-level based on the complexity of the action.

3.1.2. Navigation using event related potentials

Research groups are also consistently working on creating P300-based virtual navigation environments. Navigation in the MazeSuite virtual environment was achieved by using a 3 × 3 P300 matrix containing navigation icons. The ERP generated are processed and online classification commands are generated to achieve the desired result [107]. Curtin et al. used this for spatial navigation control in MindMaze virtual environment shown on one computer screen, and the 3 × 3 matrix on another. 82%–89% accuracy was found depending on the complexity of environment. Cattan et al. showed that using a P300-VR and a P300-PC has little difference in BCI accuracy [108]: only P300 is wider in the virtual case.

3.2. Entertainment

The creative industry, and researchers have come up with ways to connect VR and BCI for entertainment. EEG signals can also be used to interact with the VEs in leisure VR. As discussed before, EEG signal acquisition takes time and is not easy to use. But with strong algorithms, BCI and VR have seen a shift and have come up as a promising mode of human computer interaction. Andujar et al. [115] recently published their work on P300-based painting in VR which can be used by patients with ALS as a channel to communicate more creatively, by painting objects usiing a 6 × 6 grid. BCI games are also used in rehabilitation applications, for example, to give biofeedback therapies to ADHD and trauma patients. Real-time games use synchronous BCI for online classifications. As noticed above, the processes differ in terms of feature extraction, classification, ease of use and accuracy. Games can be classified into categories based on Mental state/Attention level of user, SSVEP and P300.

Mental state detection (attention: focused/relaxed or an emotional state) can be used to trigger actions in VEs. Other than noise, these signals also contain eye artifacts which are produced by eye movements and blinks. A good overview of these signals and related concepts can be found in [116]. Some gaming systems even make use of these artifacts as a part of control signal. For understanding the subjects' mental state, the band power of signals give the amounts of θ (4–8 Hz), α (8–15 Hz), δ (15–30 Hz) and γ (30–70 Hz) waves. θ waves are connected to the meditative concentration and deep relaxation. δ waves are only observed in adults when they are in deep sleep. α rhythms are related to visual processing and memory brain functions. Also, a suppression in α waves can be seen during an increase in mental efforts. The alpha activity indicates that the brain is in a state of relaxation. Beta rhythms are connected to excitement of the brain and also they are de-synchronized during real movements/motor imagery and its symmetrical distribution changes. The relaxation, attention and focus levels are calculated based on the band-power values calculated by taking required α, β, θ ratios [117]. Power Spectral Density (PSD) points can also be selected as feature vectors (FV) to train machine learning classifiers with labeled examples. Different emotional states

Table 2
BCI-VR navigation.

Reference	VE/Object	Number of MI tasks	Type	Commands	Target area
[102]	Google Earth	3	Self-Paced	Low-level	Games
[103]	Free Space	3	Self-paced	Low-level	Games
[106]	Maze	3	Self-paced	Low-level	Games
[109]	Museum	3	Self-paced	High-level	General
[99]	Street	2	Synchronous	Low-level	General
[110]	Street	2	Synchronous	Low-level	General
[97]	City	2	Self-paced	Low-level	General
[98]	Apartment	2	Semi-Synchronous	Low-level	General
[98]	Pub	2	Synchronous	Low-level	General
[95]	Conference Room	2	Self-paced	Low-level	General
[105]	Bar and Street	2	Synchronous	Low-level	General
[36]	Apartment	2	Self-paced	Low-level	Medical
[111]	Maze or Park	1–2	Self-paced	Low-level	Medical
[112]	Park	1–2	Self-paced	Low-level	Medical
[100]	Library	1	Self-paced	Low-level	Medical
[113]	Wheelchair	1	Synchronous	High-level	Medical
[114]	Space Ship	1	Self-paced	Low-level	General
[100]	Street	1	Self-paced	Low-level	Medical

can be analyzed by using the band power values at different frequencies. Required frequencies are selected uniformly from alpha, beta and theta ranges irrespective of the frequency band length. A number of games that make use of these states are discussed in this section (computer games, followed by immersive virtual games in conjunction with BCI).

Several research articles have been published that utilize attention-based BCI for gaming. Jiang et al. created a BCI controlled 3D hand that took hold of fruits on a plate [118]. Authors use concentration measure as a parameter to change the position of the hand and grasping force. Joselli et al. created a game similar to fruit ninja, where the aim was to slice maximum number of fruits in one minute [119]. Retaining the attention during the game-play helps keep the value above the limit set initially to progress ahead in the game. Neuro-feedback games have far-reaching potential other than entertainment as well: these can be used to check students' attention levels and help boost the learning process in case of attention deficit. A drawing game was presented by Moon et al. which also utilizes gaze tracking to know the coordinates of players' focus points in addition to attention state analysis [120]. High player attention leads to the creation of patterns whereas low attention creates a negative feedback. Lalor et al. in 2005 developed game that uses attention along with SSVEP and the aim is to secure 1D character balance over a rope [121]. Two checkerboards were placed beside the character, phase reversed (17, 20 Hz). The player has to focus on the right checkerboard to ensure the stability of the character. Koo et al. designed a VR maze game with the goal to guide a ball into a given space in the 3D VE using a 4 option SSVEP [122]. The experiments show an increase of 10% information transfer rate using an HMD rather than a monitor screen. The research thus demonstrates that SSVEP stimulus through an HMD is more engaging for BCI.

3.3. Rehabilitation and robotics

One of the common causes of paralysis are strokes, which cause cognitive and motor impairment due to the damage to a large number of brain cells. Low-cost, effective BCI-VR solutions capable of presenting neuro-feedback and analyzing the BCI performance of subjects can increase the functional capabilities of stroke rehabilitation systems [123]. Table 3 compiles various studies conducted on BCI-VR-based rehabilitation. Several companies are now using BCI-VR to help stroke survivors. The REINVENT platform [6] lets stroke patients use VR for body immersion and BCI for limb movements, which helps provide better observation and rehabilitation ground to patients as well as doctors in figuring out the brain signals and observing them. This makes it possible for researchers to predict the brain damage by observing the gamified signals of the brain, without using any sensors or invasive methods. It can be used for physiotherapy for paralyzed patients who need to exercise everyday. Further extension can also include rehabilitation for astronauts who have spent enough time in the space that they have forgotten to perform earthly actions like walking. In addition apart from regular rehabilitation techniques, video games have also proven to be an engaging way of rehabilitation. Video games often require cognitive involvement from players, thus offering an engrossing way to treat stroke rehabilitation patients. MI can be used to control the in game objects and avatars with multiple possible tasks for the patients to perform. This will help promote motor learning and may be less frustrating during the recovery phase of motor function [124].

Motor imagery has proven to be an effective way for post-stroke rehabilitation. MI based BCI-VR methods are shown to provide upper rehabilitation to post-stroke patients with improvements observed on both motor-function as well as neuro-plasticity [146]. By providing a simulated world with which the patients can interact, data can be collected and patients may be monitored in real time. A visual, auditory and haptic multisensory-feedback provision may be provided to make training less monotonous whilst promoting motor learning and enhancing participation [25]. A neurorehabilitation system using MI was developed in [147]. The proposed BCI detected 3 MI produced stimulation that produce virtual stimulation to control the VR environment. Discrete wavelet transforms (DWT) and multi-layer perception (MLP) neural networks were used respectively for preprocessing and classification, miscalculations removed using an expounder.

BCI-FES rehabilitation can lead to significant recovery of motor function and purposeful plasticity due to the activation of efferent (central nervous system (CNS) to limbs) and afferent (sensory organs to CNS) body pathways. [148]. BCI-FES techniques combined with VR were also proposed to empower stroke rehabilitation. Patients were exposed to a VE using an Occulus Rift device where they performed exercises as guided by a therapist. Proper execution of exercises was checked using an electroencephalograph and electrooculograph. The BCI system predicted the intention of the patient. The classification of intent was then converted into a command for controlling the FES device [28,29].

Simulating a prosthetic arm on a virtual-L shape workbench display system with the help of BCI is another useful case of the two technologies [149]. In this experiment, users were evaluated on various criteria like depth recognition and distance recognition. Simulating arms is an excellent way to enter the stream of artificial wearables for people with special needs, since the signals of limbs are comparatively easier to recognize and map. Starting with basic mapping and hand movement, it can be extended to other body parts with a more difficult implementation. In [150], the subject was made to control the arm of a VR avatar, as shown in Fig. 7(a), using a Soft Robotics rehabilitation device with a BCI for upper limb classification. The use of hybrid-BCI for 3D object control in VR is also gaining traction among the research

Table 3
BCI-VR-based rehabilitation studies [125].

Reference	Disorder	Paradigm	VE action	No. subjects	Accuracy
[126]	Nerve injury	MI	Character control	3	97%
[127]	Stroke	MI	Hand control	8	96.7%
[128]	Stroke	MI	Arm control	10	93%
[129]	Stroke	MI	Hand control	3	90.4%
[48]	Disability	MI	Character control	7	90%
[130]	Spinal injury	MI	Navigation	1	67.5%
[131]	Cognitive impairment	SSVEP	Navigation	1	91%
[132]	Stroke	SSVEP	Mole game	5	90%
[133]	Stroke	SSVEP	Character control	3	81.4%
[134]	Alzheimers	P300	Navigation	22	90.%
[135]	Spinal injury	P300	Character control	21	89%
[136]	Cognitive impairment	P300	Navigation	50	87%
[137]	Paralysis	P300	Sequence spelling	18	80.5%
[138]	Autism	P300	Flickering object	17	80%

Table 4
Brain–Computer Interface and Augmented Reality.

Technologies	AR display	Field	Objective	Reference
P300-BCI	Computer Screen	Robotics	Robot Steering	[139]
P300-BCI	HMD	Robotics	Robot Limb Control	[140]
SSVEP-BCI	Computer Screen	Medical	Wheelchair Control	[141]
SSVEP-BCI	HMD	Robotics	Robot Limb Control	[142]
MI-BCI	Computer Screen	Medical	Phantom Pain Therapy	[143]
MI-BCI	Computer Screen	Robotics	Robot Limb Control	[144]
MI-BCI + EMG	Computer Screen	Medical	Phantom Pain Therapy	[143]
SSVEP-BCI + EMG	HMD	Medical	X-ray Vision	[145]

(a) VR-MI Limb Control (b) Virtual Boat Rowing Game

Fig. 7. VR-MI rehabilitation.

groups [151]. Chun et al. use an eye-tracking module to track and select a 3D object in the VE. Users are asked to concentrate their mind on the object to manipulate is using BCI. The manipulations of the objects in the experiment range from basic to complex interactions which help observers gather the right data. A group also developed a multiplayer checkers game in which a robotic arm moves the piece to the square that player wants to move to.

Another game-based real-time rehabilitation BCI was developed in [152]. The 3D VR game was controlled by the BCI after preprocessing, feature extraction and classification of MI signals. A CSP feature extractor and SVM classifier were used. An MI based boat rowing VR game, as shown in Fig. 7(b), for entertainment and rehabilitation was presented in [19].

Using a wheel-chair for injured people is extremely difficult. In this case study, users were put in VE with avatars on the streets [100]. The users need to travel from one point to another. This is a very small application in an extremely resource deprived industry. Patients (especially older ones) find it extremely difficult to adapt to newer technologies that might make their life easier. Such VEs and games along with BCI can be used to train people on the advanced technology as well as also collect surveys and observation on how useful the technology is for patients.

Vision impaired patients are unable to use BCIs based on visual-feedbacks. Auditory methods can act as a good replacement in such cases. A hybrid auditory system of P300-BCI combined with the auditory steady state response (ASSR) was presented in [35]. By providing audio stimuli at different amplitude modulated (AM) frequencies along with a beep sound arbitrarily between sound sources. Different auditory responses lead to different ASSR and the beeps cause P300s. The system is vision independent and provides slightly lower accuracy as compared to the traditional P300 BCI systems available.

4. BCI-AR/MR applications

Augmented and Mixed Reality enables better human–computer interactions due to the new communication channels it offers. BCI is a powerful way to interact with an AR headset in real-time. The Epson Moverio, which acts like a “thinking mouse”, is one such instance [153]. The most common applications used in conjunction with BCI employ optical see through HMDs. Such HMD-BCI systems are well compatible and can be tolerate small head movements using the BCI [154]. Table 4 provides the details of few studies conducted on BCI and AR in the domains of robotics and medicine.

Researchers at the TU-Munich proposed a Superman-like X-ray vision application for doctors to use during surgeries [145]. Switching between normal vision and X-ray vision would traditionally require a UI but the need for this is removed with the use of a BCI employing EMG signals and gaze tracking. Neural Impulse Actuator (NIA) can acquire brain waves (α, β) and signals (EMG, EOG). NIA is traditionally marketed for computer gaming and hands-free computer access to people with disabilities. Due to the importance of gaze position, eye movement could not be used for switching between X-ray and normal vision. Furthermore, the utilizing α and β brain waves to control the system requires learning on the end of the Medical Doctors (MDs). Thus a learning free EMG model with gaze tracking was proposed: Instead of augmenting the entire anatomy onto the patients body, only small windows where the gaze lies are augmented. The augmentation is switched on either as a toggle at a certain muscle tension threshold or it stays on only above the threshold and drops when the muscle is relaxed. Such a system could be improved, adding additional functionalities, if alpha and beta waves are used instead but would require additional training time for the MDs.

BCI-AR system for industrial monitoring was proposed by Angrisani et al. where a smart transducer was used for the required information [155]. This removes any requirement to physically measure the industrial-system parameters saving time and providing safety from potential accidents. An SSVEP based model for which stimulus is provided through AR glasses. AR glasses are semi-transparent and semi-reflexive thus providing the ability to see both real and virtual scenes. AR with a P300-based BCI was employed by Takano et al. to make an environment control system [156]. When the attached camera on the HMD detects an AR marker on the device, the control panel of the device is created in the HMD with flickering visual stimuli, providing the user with the ability to control it. This system does not require much training from the user. Such BCI-AR systems using an HMD may be focal in building intelligent environments.

5. Way forward: Future scope of XR based BCI applications

As we progress further, radical changes are expected in how BCI and VR will be combined, and what problem these will put forth. Experimenting with the synchronization of various modules with BCI can help make VR a completely hands free experience. As a trend setting example, Neuralink by Elon Musk, is creating minimally invasive neural implants that will suit a wider range of future applications. It is first generation N1 implantable sensors claim to provide the real world experience to its immediate target, people without use of their limbs. Neuralink has also teased a neural mesh-like device called the 'Neural Lace' that could give more access to the brain since they would be injected into its capillaries. To put it briefly, the future of the fusion of these technologies looks bright, but still has a long way to go before becoming an integral part of our lives. Following the example of Neuralink, with time, as our knowledge for other modules and BCI increases, so will the possibilities in XR. Having said that, here are some of the suggestive application which can be looked into in the near future.

Google has released its Glass Enterprise Edition 2 [157], a wearable AR device that aims to streamline business processes in different areas. It also aims to help employees work smarter, faster and safer by providing them with voice activated or glance based assistance. Such an AR device can be combined with a BCI and applied to several areas of work including surgery and aviation. We discussed research on X-ray vision with BCI-AR earlier in this paper. If doctors could be provided with a quick retrieval system of crucial information through AR glasses with ocular or EEG based control, it would make surgical operations a lot less prone to error, thereby making operations more precise. Researchers are also interested in moving away from 'head-down displays' in the cockpits (where the pilots need to look down on the screens to see information regarding aircraft path coordinates and upcoming obstacles) towards technologies that provide head-up displays. These project important intelligence on head mounted transparent screens to avoid unnecessary distractions that might be fatal. It also makes retrieval of information faster without the need of unnecessary head movement and enables the pilots to focus better. Adding a very high accuracy BCI-based control to the AR display — for instance searching for an alternative path, or selecting from multiple options, would further reduce the chances of a mishap and improve the quality of operation for the pilots by making information retrieval easier for them. Such BCI-AR (or BCI-MR) devices can also be developed to show details regarding the stores a particular person is interested in, while he/she is on the street. These could be reviews, ratings or even the names and history.

EEG is one of the lowest resolution methods of reading brain activity. Semi-invasive methods as employed by Neuralink can prove to give better results across all current and future application of BCI. This would open up the possibilities of transcending the 5 senses and the limited bandwidth of our brain, and open up the possibilities of achieving symbiosis with AI. Since BCI controlled weapons are already under the radar, BCI-VR based war training for soldiers can be an important application for the future of defense and security. VR and BCI together can make specialized doctors accessible everywhere. They shall be able to perform operations without the need of any physical equipment or movement of their hands. BCI tracked thoughts and signals can potentially open avenues for neuro-marketing, a highly targeted marketing technique that is bound to change the future of interactive and predictive marketing campaigns. BCI-VR can help build inventory-less shopping for users to shop whenever they want. Neurogaming can provide a hands-free, immersive experience of gaming. BCI-VR will enable people to experience immersive environments that are otherwise inaccessible to them either for luxury or immersive entertainment.

6. Conclusions

This paper presented the state of the art combination: BCI and XR, and covered major contributions in this intersection of research domains. It reviews the previous works on the fusion of the stated technologies in navigation, entertainment, rehabilitation, robotics and home control. Combining XR and BCIs is useful in scenarios favoring hands-free interaction, and future works in this domain may look to explore this combination in many more use cases than the ones discussed in depth. This review also gives direction for design of new interaction techniques and feedback modalities that would take advantage of the conjunction of these two technologies. In addition, it also presents some possible future developments that can be pursued in this combination of BCI and XR technologies.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgment

This work is supported by BITS ACRG, India funding under Project Grant File no. PLN/AD/2018-19/6 for the Project titled "Brain Computer Interface Controlled Humanoid".

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