Non-Invasive Brain-Computer Interfaces: State of the Art and Trends

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***Abstract*—Brain-computer interface (BCI) is a rapidly evolving technology that has the potential to widely influence research, clinical and recreational use. Non-invasive BCI approaches are particularly common as they can impact a large number of participants safely and at a relatively low cost. Where traditional non-invasive BCIs were used for simple computer cursor tasks, it is now increasingly common for these systems to control robotic devices for complex tasks that may be useful in daily life. In this review, we provide an overview of the general BCI framework as well as the various methods that can be used to record neural activity, extract signals of interest, and decode brain states. In this context, we summarize the current state-of-the-art of non-invasive BCI research, focusing on trends in both the application of BCIs for controlling external devices and algorithm development to optimize their use. We also discuss various open-source BCI toolboxes and software, and describe their impact on the field at large.**

***Index Terms*—BCI, brain-computer interface, deep learning, electroencephalography, manifold classification, motor imagery, motor-related cortical potentials, neural decoding, neurotechnology, robotic arm, transfer learning.**

I. Introduction

A BRAIN-computer interface (BCI) is a neurotechnology that enables direct brain-based communication between an individual and the rest of the world [1], [2]. While BCIs could have broad applications in various patient cohorts and even the general population, they have specifically targeted users suffering from neuromuscular impairments such as amyotrophic lateral sclerosis (ALS) [3], [4], [5], spinal cord injury (SCI) [6], [7], [8], or stroke [9], [10], [11], but whose cognitive function remains intact. Indeed, clinical applications of BCIs, while still limited to research use, have become more accepted than ever and often complement other therapeutic strategies [10], [12], [13], [14]. This technology has also recently gained recreational popularity (e.g., "brain games") [15], [16] as neural recordings become increasingly accessible due to low-cost systems and open-source toolboxes. As such, the concept of human enhancement and restoration through brain-controlled channels now allows individuals to connect with others on a level not previously achievable.

In its most basic form, a BCI is a system that decodes the user's mental state or intention and maps such information to the action of a device that interacts with the surrounding environment [17], [18]. These interactions can convey information that range from answering simple yes/no questions, to constructing word-based communication, to the navigation and control of devices such as robotic arms, wheelchairs, and more. Nevertheless, the widespread research space of BCI has also facilitated new and creative applications for this technology. For example, rather than decoding an intended sentence from a word or letter bank presented on a computer screen, modern BCIs can now decode handwriting signals directly from the brain [19]. In addition, extra-sensory BCIs have been proposed that detect and in some cases provide closed-loop feedback to alter various affective states [20], [21], [22]. Other interesting avenues of BCIs investigate how sensory feedback, whether provided to the peripheral (i.e., haptic feedback) [23], [24] or central (i.e., intracortical micro-stimulation [25], transcranial electrical stimulation [26], or focused ultrasound stimulation [27]) nervous system, impacts the performance of these systems for completing various tasks.

While these examples represent exciting and innovative avenues for the field of BCI, the direction of BCI subfields is often guided by how easily and robustly mental intention can be decoded from brain recordings. As such, there are various methods available to acquire neural signals, including both non-invasive and invasive approaches that exhibit different signal-to-noise ratios, spatial coverage, spatiotemporal resolution, etc. This

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spectrum of signal acquisition techniques is accompanied by a broad collection of mental states and tasks that can be incorporated into the BCI system. For invasive BCIs, high-resolution recordings provide information regarding detailed brain states and dynamics (often related to motor function), however, these systems are often constrained to a limited number of clinical participants or basic research in rodents and non-human primates (NHPs) [28], [29]. Non-invasive BCIs, on the other hand, minimally impact the user without safety concerns, are easy to use in everyday life, and facilitate long-term performance tracking in a large number of participants. Nevertheless, current non-invasive BCIs exhibit limited performance due to the limited signal-to-noise ratio and information transfer rate that occurs when neural signals transmit from brain tissues, through the skull, and to the scalp. The easy access to many suitable participants, however, offers opportunities that enable non-invasive BCI researchers to push the limits of robust paradigms and decoding techniques to optimize task accuracy, information transfer, and system reliability for human applications.

In the current review, we focus on recent innovations in the field of non-invasive BCI research. We first recount traditional BCI signal acquisition methods and describe various new approaches to measuring information from the brain. We then provide detailed accounts of different non-invasive signal types and highlight how these signals have been utilized to achieve the current state-of-the-art demonstrations of brain-based device control. We further outline various relevant algorithmic trends that enable high-performance EEG-based brain state decoding. Finally, we review different BCI toolboxes and software that are available to aid in performing reliable BCI experiments at a large scale.

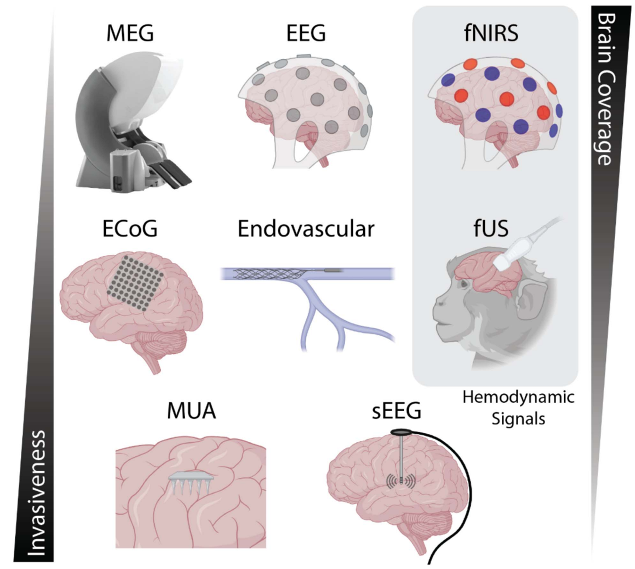

Fig. 1. Neural recording modalities used for brain-computer interface applications. (top) Non-invasive techniques include magnetoencephalography (MEG), electroencephalography (EEG) and functional near-infrared spectroscopy (fNIRS). (middle) Minimally invasive approaches involve electrocorticography (ECoG) and relatively novel technologies such as endovascular electrodes (i.e., the Stentrode) and functional ultrasound (fUS). (bottom) Invasive techniques include stereo-EEG (sEEG) with penetrating electrodes and multi-unit arrays (i.e., the Utah Array). Nearly all these techniques measure electrophysiological signals with the exception of fNIRS and fUS, which measure an indirect hemodynamic readout of neuronal activity.

II. Invasive and Non-Invasive BCI

All BCIs have the common goal of decoding an individual's mental state or intention. However, there exists an implicit dichotomy between invasive and non-invasive BCI technology. A middle ground of minimally invasive techniques that require direct brain access but that do not penetrate neural tissue has also shown promise (Fig. 1). In general, there are notable differences in the complexity of deploying these various techniques, many of which also provide varying levels of brain coverage and signal quality. Currently, invasive BCI technology is limited to patients enrolled in clinical trials and the use thereof involves a lengthy timeline that encompasses surgical planning and task training. While invasive BCIs reach a limited number of individuals, the detail of control has seen significant advancements due to the high-fidelity signals that are available. In this regard, notable achievements include the control of robotic arms and lower limb exoskeletons, speech decoding, and more.

Invasive BCIs that leverage motor-related signals (e.g., motor cortex, posterior parietal cortex, etc.) have traditionally utilized Utah arrays or other multi-site recording probes. These arrays provide detailed multi-unit activity (MUA) from hundreds of recording sites and have enabled the control of robotic arms, patients' own arms, and speech decoding [30], [31], [32], [33], [34]. However, chronic use of these electrodes is hindered by a lack of long-term signal quality and the high power requirements needed for high temporal sampling of the signals of interest. As such, invasive recording methods often require physically wired connections between the brain implant and the decoding hardware, power supply, etc. Therefore, in addition to the need for surgical implantation of the recording device, these technical constraints limit widespread clinical use. Nevertheless, there are ongoing attempts using both lower fidelity signals and more advanced silicone electrodes (i.e., Neuropixels) that may, in the future, enable wireless systems that can be utilized in a larger patient population [35], [36]. Stereo-electroencephalography (sEEG) is an alternative invasive technique that utilizes penetrating electrodes inserted into deep regions of the brain. These electrodes are typically used for monitoring brain pathologies such as epilepsy but are also gaining recognition for closed-loop stimulation [22] and other BCI applications [37].

An alternative to these invasive and penetrating electrode arrays is minimally invasive electrocorticographic (ECoG) grids that record neural activity from the surface of the brain [8], [38]. This approach covers a larger area of the brain than penetrating arrays, records lower fidelity signals, and enables wireless data transfer. ECoG-based BCIs have long shown promise for clinical use, but were often limited to individuals undergoing temporary brain monitoring when a craniotomy was required for other purposes. However, the introduction of self-contained devices such as the WIMAGINE system [39], which consists of an implantable ECoG grid that can be stably mounted to the skull, has been useful for BCI-specific purposes. In fact, using the WIMAGINE device has gained notoriety for facilitating the restoration of walking ability by combining motor-related brain signals with either robotic exoskeletons or spinal cord stimulation [40], [41]. These individual demonstrations have shown significant clinical BCI translation, and the similarity in signal characteristics between ECoG and EEG gives rise to the question of when and if similar achievements can be made completely non-invasively.

Within the past few years, the field of BCI has also seen the rapid rise of two relatively novel approaches to minimally invasive neural recordings. One promising approach to recording signals from the brain is through the use of an endovascular electrode placed within the lumen of large cortical vessels such as the superior sagittal sinus [42]. This type of electrode, termed the Stentrode, resembles a simple stent that also contains several recording/stimulation sites and can be inserted into the brain using standard endovascular medical procedures. However, as this device relies on vessel location in the brain, the recording coverage is limited to tissue within the cleft between the two brain hemispheres, often targeting contact with the precentral gyrus. With the topographic organization of the motor homunculus, these electrodes primarily detect motor commands related to the feet, but may, in the future, incorporate other mental states as well. Nevertheless, the Stentrode received approval for human BCI use from the United States Federal Drug Administration (FDA) and has already shown successful control of computer cursor-related tasks in patients [43], [44].

Functional ultrasound (fUS) has also recently demonstrated feasibility in decoding motor intentions directly from the brain. fUS measures an indirect hemodynamic readout of neuronal activity at a relatively slow temporal resolution (∼2–10 Hz) and requires a cranial window and/or an acoustically transparent skull prosthetic for high-quality signal acquisition [45], [46]. Despite the need for this procedure, fUS offers a potential alternative to chronic electrical recordings that can degrade over time. The use of this technology for BCI applications is still in its infancy, but has already demonstrated the presence of discriminable motor intention signals in the parietal cortex in NHPs that can be detected in real-time [47], [48]. Importantly, fUS has recently also been used to record motor-related signals in a patient with a sonolucent cranial implant [46], indicating that human BCI applications are on the horizon. Nevertheless, transcranial fUS has yet to be realized in healthy adult individuals or patients at a spatio-temporal resolution (and without contrast agents) that would benefit large-scale BCI studies. While matrix mixing and aberration correction approaches [49], [50] show promise for transcranial fUS imaging, these concepts need to be further validated *in vivo*.

Non-invasive BCI technology primarily utilizes EEG recordings that measure electrical potentials from the scalp. Other approaches utilize magnetoencephalography (MEG) or functional near-infrared spectroscopy (fNIRS) that respectively measure magnetic and hemodynamic information from the brain, however, these are less popular. As EEG is cheap, completely non-invasive, easy to set up, and temporary, it can be employed by large studies with as many as thousands of human participants to obtain robust statistical conclusions [51], [52]. Furthermore, non-invasive recording modalities uniquely record whole-brain activity and provide a variety of signal types that can be used individually or in a hybrid fashion to construct a BCI. These signal types (as described in the next section) are often robust and can be extracted for BCI purposes using minimal processing steps. The ease-of-use and low barrier-to-entry have, in turn, led to more creative BCI applications for both research and consumer applications that incorporate mobile use. As such, there are now dozens of wireless and/or dry electrode EEG systems that enable the acquisition of up to 128 channels at > 2 kHz [53], [54]. Importantly, wireless systems avoid artifacts associated with cable movement and facilitate use in ambulatory tasks that will eventually be required to perform neural recordings in naturalistic settings. However, mobile tasks and locomotion also introduce other distortions related to the gait cycle and head movement that must be further characterized and accounted for [55], [56].

III. Non-Invasive BCI Signals

For the remainder of this review we discuss various types of signals used for non-invasive BCIs (see Fig. 2).

A. Visual Evoked Potentials

Visual evoked potentials (VEPs) rely on the conscious recognition of a target in the user's visual field. VEPs depend on external stimuli, which generally consist of lights flickering with different temporal profiles. These profiles fall into five broad categories: 1) frequency modulation (f-VEP), 2) time modulation (t-VEP), 3) code modulation (c-VEP), 4) phase modulation (p-VEP), and 5) motion-onset (m-VEP). In all of these cases, each stimulus carries a unique temporal pattern according to the modulation scheme that can also be detected in the scalp EEG to indicate the selected stimulus. For example, in the case of t-VEPs and c-VEPs, different stimuli are presented at varying delays from trial onset, which can then be detected in the time-domain EEG signal [57], [58], [59]. However, due to noisy time-domain signals, these VEP variations require a high number of trial averages for robust results. By contrast, f-VEP and p-VEP stimuli flicker at different frequencies and/or phases. Attending to a particular target increases the band power of the corresponding oscillation in electrodes covering the occipital cortex. Thus, f-VEPs and p-VEPs are collectively also known as steady-state VEPs (SSVEPs). In practice, SSVEP-based BCIs provide some of the highest information transfer rates as the combination of frequency and phase modulation can be decoded with high accuracy [60]. This combination also now allows for the successful detection of >100 target options [61], [62], which can be further expanded in hybrid systems when complementary signal types are utilized [63]. Finally, the m-VEP stimuli consist of moving lines across a virtual keyboard to induce visual motion-based event-related potentials [64] to form a BCI speller. In particular, the N200 component of these evoked signals is considered to be primarily related to motion-onset visual processing. These fast and high-dimensional BCIs work well with a variety of applications, including spellers and, less

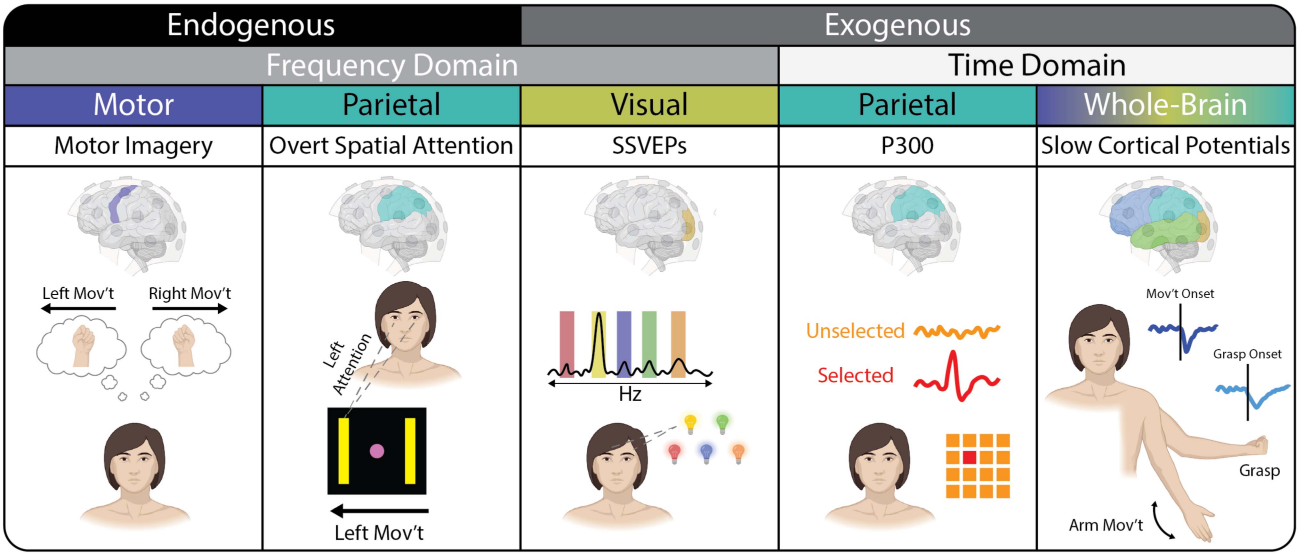

Fig. 2. Overview of neural signals used for noninvasive brain-computer interface control. These signals can be broadly categorized according to being endogenous or exogenous in origin, frequency or time domain, and by the brain region/electrode coverage from which they are acquired. Motor imagery tasks generate an event-related (de)synchronization that can be detected from motor electrodes and which generate a velocity-based signal for end effector control direction. Overt spatial attention refers to a gaze-based action that is detected in electrodes covering the parietal cortex and which drives an end effector in a particular direction. Steady-state visual evoked potentials (SSVEPs) refer to increases in narrow band power in electrodes covering the visual cortices upon attending to a stimulus flickering at the corresponding frequency. The P300 response is elicited during an oddball-type context when a user's choice is selected. Finally, slow cortical potentials refer to electrical potential deflections that are time-locked to movement events or that correspond to limb kinematics.

often, spatial navigation, where individual commands need to be correctly identified during relatively narrow time windows.

B. Overt Spatial Attention

Overt spatial attention (OSA) tasks leverage activity patterns generated in the parietal cortex in response to the user's spatial attention. Similar to motor imagery (MI) tasks, OSA signals do not require external stimuli and generate focal patterns of alpha band activity. This makes OSA tasks well suited to complement other endogenous signals, such as those generated from performing MI tasks [65], [66], by increasing control dimensions without sacrificing overall performance of the BCI. While this relatively new BCI paradigm shows promise for higher dimensional control, users and experimenters must still consider the interaction effects of overt gaze control and other BCI-related tasks [67], [68].

C. P300

The P300 is an endogenous event-related potential (ERP) within the EEG, and is detected in electrodes covering the parietal cortex. P300 signals occur in the context of an oddball paradigm [69], and rely on a user's implicit ability to distinguish a rarely presented target stimulus from other more common non-target stimuli. This structure makes such an event-related response useful for spelling applications where a specific letter must be chosen from a larger set of irrelevant letters. Most P300-based BCIs use the visual row/column paradigm, in which a matrix (e.g., 6×6 cells or variable) containing the alphabet, numbers, and other items is presented to the user for selection [70], [71]. A P300 response is then elicited when the rows and columns of the matrix, flashing in random order, converge on the desired item being attended to. The P300 was documented well before BCI use and has long been implicated as a biomarker of various clinical disorders, including depression [72] and schizophrenia [73]. While these signals can be gaze- and space-dependent, advances in stimulus design such as variations of the rapid serial visual presentation approach have significantly improved information transfer rates as well as task reliability and performance [74], [75].

D. Movement-Related Cortical Potentials

Other broadband time-domain strategies that are favored for the identification of both cued and continuous mental states involve slow cortical potentials, otherwise known as movement-related cortical potentials (MRCPs). When closely examining voluntary movement, changes in low-frequency activity (delta band, $\sim 1-4$ Hz) occur in the movement planning and execution stages and are time- and phase-locked to movement onset [76], [77]. After averaging across numerous trials, a so-called MRCP becomes visible; the main components are the "Bereitschaftspotential" or readiness potential, the motor potential (negative peak), and the positive rebound potential. It has been shown in the literature that such an MRCP occurs after different voluntary actions and can be derived from sensorimotor areas. Over the last decade, MRCP features have been heavily exploited for decoding movement detection [78], [79], [80], [81], [82], [83], [84], but also for the classification of movement-related parameters such as speed [85] and force [79].

While the success rate of the MRCP-based motor control is modest compared to some other signal types, the burden of imagining different types of movement is dramatically reduced. For example, during the MoreGrasp project [86], study participants

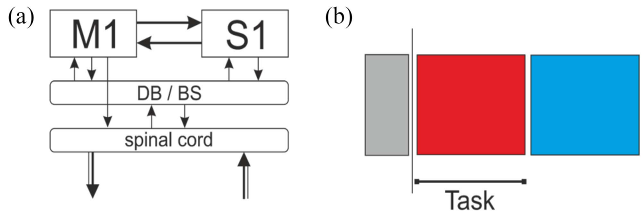

Fig. 3. Neuro-structural model and general trial structure to elicit ERD/ERS. a) Neurostructural model for the description and interpretation of resulting EEG patterns. M1 and S1 symbolize primary motor and somatosensory cortex, respectively, and both carry bidirectional pathways to the deep brain and brainstem (DB/BS). M1 projects directly to the spinal cord, which is also connected to the DB/BS via ascending and descending fibers. Efferent and afferent connections in the peripheral nervous system are indicated by double lined arrows. b) The general structure of a task trial consists of a preparation phase (grey box), followed by the "Task" (red box) and a post-movement phase (blue box). Movement onset is indicated by the vertical black line.

described a low burden during the calibration and use of the BCI, suggesting that a successful transfer of MRCPs towards natural control can be achieved. Nevertheless, the false positive and success rates can still be improved, which is a matter of ongoing and future work (see [87] for a comprehensive review).

E. Event-Related (De)Synchronization

Event-related desynchronization (ERD) or event-related synchronization (ERS) refers to a band power decrease or increase, respectively, relative to a reference period [88], [89], [90]. These phenomena are usually induced in response to a motor task and produce a reliable contralateral ERD and ipsilateral ERS in the alpha/mu (8–13 Hz) and/or beta (14–30 Hz) bands of scalp EEG. Thus, projecting the different ERD/ERS traces into a time-frequency plot for each electrode can further generate so-called ERD maps [91] to identify the spatial, temporal, and spectral characteristics of these signals. These features are based on a traditional neuro-structural model and have been robustly exploited using a simple task paradigm illustrated in Fig. 3 [92].

Fig. S1 provides an overview of the typical ERD/ERS patterns that are generated during various movement conditions for both able-bodied and participants with spinal cord injury (SCI). Here, we differentiate these conditions into: a) active, voluntary movement; b) passive movement and movement induced by functional electrical stimulation (FES); c) complex finger movement and peripheral stimulation; d) continuous finger, hand/arm movements; and e) motor imagery. We also indicate the same conditions for people with SCI, however, due to physical limitations of these individuals, there is no counterpart to c), and f) describes attempted movement instead of real movement.

The most classical ERD/ERS patterns appear in able-bodied participants when performing voluntary hand movements (Fig. S1a, h) [90], [93]. These contexts often produce a mu/beta ERD before and during movement, as well as a post-movement beta ERS (PMBS), also called the beta rebound. Active foot movement (Fig. S1a, f) can also induce a clear beta ERD followed by a PMBS [94], [95], [96]. These oscillatory activities are often also accompanied by an MRCP [97], [98].

During passive hand movements (Fig. S1b, h), there is no pre-movement ERD, however, a mu/beta ERD is present during hand movement (either completely passive, or facilitated by FES), followed by a PMBS [93]. A beta ERD and PMBS are also observed during passive dorsiflexion of both feet (Fig. S1b, f) [95]. A similar pattern occurs in the case of complex finger movement (Fig. S1c, h; cube manipulation) and additional median nerve stimulation. These tasks also induce a contralateral mu/beta ERD; where ipsilateral beta ERS returns quickly to baseline, the mu ERD/ERS oscillates [99]. These tasks also produce sensory evoked potentials that are much larger than the rest condition [100].

In addition to changes in oscillatory activity, movement trajectories (Fig. S1d, h) can be decoded from delta band activity [101]. For example, in [102], a mu ERD and characteristic delta band activity was observed when participants performed rhythmic finger movements (flexion, extension, repetitively). Along these lines, low-frequency time domain (LFTD) signals have been shown to encode hand/arm kinematic movement [103], [104], [105]. Importantly, for these and other works [106], there also exists a mu and beta ERD during movement as well as PMBS after the termination of movement.

Very early after the investigation of executed movements in EEG research, imagined movement or motor imagery (MI) (Fig. S1e, h) played a major role in BCI development. Mu and beta ERD occur during MI [90], [107], and are often followed by a PMBS [96], [108], [109] (Fig. S1e, f). These ERD/ERS signals are often focal phenomena that arise according to the topographic organization of the motor homunculus, similar to what was previously observed for motor execution tasks. For example, multimodal work using EEG source imaging and fMRI has revealed strong co-localization of sensorimotor cortex activation for hand and foot movement execution and imagery tasks [110], [111]. Similarly, common patterns of BOLD elevation observed in fMRI have also been observed using EEG source imaging [112] in the form of ERD in the sensorimotor cortex. Based on these findings, MI tasks involving body parts with spatially separated motor cortex representations often define the number of control signals that can be used. Many online BCI paradigms include four or more MI tasks of different body parts to control an end effector in multiple dimensions. Common tasks include imagining the action of the right hand, left hand, both hands, rest, foot, and tongue.

Studies have shown that the speed of hand movement or imagined hand movement is also correlated to EEG activity [113]. Many of these tasks can be easily detected and separated by a standard set of electrodes covering sensorimotor areas [114], [115], however, including subject-specific features from larger groups of electrodes can improve both offline and online performance [116], [117], [118]. Furthermore, successful discrimination of more specialized MI tasks of the same body part (i.e., hand gestures, limb joints) has shown promise in offline scenarios and may, in the future, be integrated into online control as well [119], [120], [121], [122].

In people with SCI, MRCPs are apparent for different movement attempts (Fig. S1f, h) as well as a beta ERD and, in some cases, a beta ERS [94], [123]. In a study on foot movement attempts, only a slight ERS was visible, which indicates that the PMBS is not solely triggered by afferent input but also by internal processes [95]. Passive foot movement in SCI patients (Fig. S1g, f) exhibits no visible patterns, which makes sense since there is no afferent feedback to the brain in these individuals [95]. In incomplete SCI patients, however, there may exist slight ERD/ERS activity.

Overall, when examining the existence of ERD/ERS patterns in people with SCI, several concerns need to be considered. First, attempting continuous hand/arm movement can lead to activity in sensorimotor and centro-parietal areas (hand-eye coordination). For example, in Pulferer et al. [124], delta band activity could be used for kinematic decoding in a SCI patient. Furthermore, a mu and beta ERD can also be observed in SCI patients performing hand and feet MI (Fig. S1i, f,h) [125], [126], [127], [128], [129], [130]. Finally, these patterns vary widely across patients and depend on the severity of their injury, the time since injury [94], [131] and also whether the individual had previous BCI training experience.

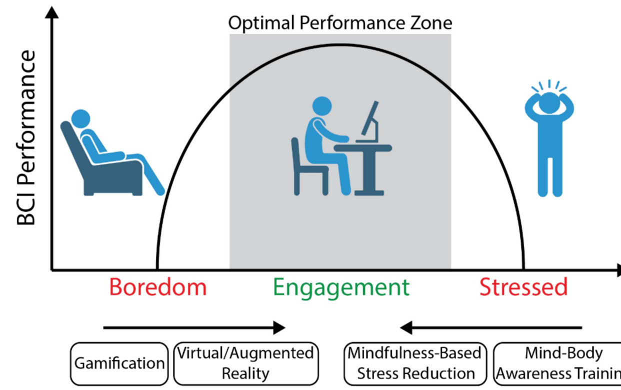

Fig. 4. BCI strategies leverage principles of the Yerkes-Dodson law to improve performance. Virtual and augmented reality paradigms have been integrated into BCI control to increase user engagement. By contrast, various mediation-based practices help reduce anxiety levels. In both cases, the user's mental state is driven towards an optimal performance zone where skill acquisition and execution can be maximized.

IV. Capacity of Non-Invasive BCI

BCIs consist of three main pillars that facilitate the mutual learning of both the user and system with the intent to accomplish a task as easily as possible [132]. Considering and optimizing all three pillars - the user, the application, and the machine – is important to ensure the success of a BCI. While some labs and studies attempt to address all three of these pillars, focusing on a single one is much more common. Here, we will address some promising approaches to these concepts reported recently.

A. The User–Training Strategies

While some non-invasive BCI signals can be inherently produced, others must be learned throughout an often long training period. Some users never learn to successfully control a BCI despite lengthy training experience, which is often referred to as "BCI illiteracy" for a specific BCI paradigm. Thus, it is important to identify human factors that cause illiteracy and formulate strategies that promote BCI skill acquisition and optimal performance. One popular theory within the field posits that user attention plays a key role in the success of user training and achieving BCI control. This is often portrayed in terms of the Yerkes-Dodson law [133], which describes an inverted U-shape relationship between a user's engagement and habit/skill formation. In this sense, tasks or contexts that are too simple can cause boredom, and those that are too difficult can cause stress, both of which negatively impact performance (Fig. 4). To address this, researchers have developed novel or adaptive tasks that appropriately engage subjects and improve BCI training and performance [134].

Along similar lines, many complementary technologies have been employed in BCI research to increase user engagement and avoid reduced performance due to boredom. Traditional BCI tasks that rely on endogenous signals utilize simple visual feedback paradigms involving a computer cursor, however, recent trends show an increased usage of virtual reality (VR) [135] and anthropomorphic feedback using computerized arms [10]. Previous cognitive studies have found that virtual hands and arms can elicit a strong sense of embodiment that is use-dependent [136], and suggest that these tools may also benefit BCI training. In fact, VR feedback with MI tasks has been commonly explored for motor recovery training in stroke patients with overall positive, but still varying levels of success [10], [14], [137]. These studies often focus on motor function rather than BCI performance and must accommodate highly variable brain damage, making it difficult to draw conclusions regarding the efficacy of VR aids.

Nevertheless, the use of VR tools with healthy individuals has shown much more promise by providing immersive contexts that enhance the embodiment of virtual limbs. Many of these studies have shown an increased amplitude of the respective ERD/ERS signals and a further improvement in online BCI performance compared to classic computer cursor feedback [138], [139], [140]. Using VR is currently a relatively low-cost addition to BCI systems; however, its full occupancy of the visual channel makes this technology somewhat impractical for future integration into daily life. By contrast, augmented reality (AR) is more compatible with everyday tasks and has been shown to be compatible with at least SSVEP-based BCIs [141], [142]. However, these contexts can create crowded visual scenes that must be considered so as not to overwhelm and distract the user [143].

At the other end of the spectrum, anxiety has been shown to impart a significant negative bias on BCI learning and performance for both MI and SSVEP-based BCIs [144], indicating that the self-regulation of mental state can lessen these effects. This factor has recently been creatively addressed through the use of meditation practice that can help alleviate elevated anxiety levels. Exemplary meditation-based strategies such as mind-body awareness training (MBAT) and mindfulness-based stress reduction (MBSR) training [145], [146], [147] have improved MI-based BCI performance. Overall, this suggests that acute and chronic stress levels impact BCI performance. Therefore, the ability to control a BCI may scale with the amount of stress-reduction training experience and the improved ability to produce stronger EEG signals associated with MI tasks.

B. The Application–External Device Control

Modern brain-based navigation of external devices includes the control of computer cursors, quadcopters/drones, wheelchairs, and robotic arms. Computer cursor paradigms remain robust testbeds for exploring new decoding algorithms, tasks/signal types, and more. Currently, non-invasive cursor control can be performed in two [107] and three dimensions using MI tasks [116], [148], [149] or hybrid systems that utilize MI and OSA [66]. More sophisticated navigational control has also been achieved using virtual helicopters or drones [150], [151]. However, this application comes with additional complexity as continuous flight often requires an asynchronous control strategy with ongoing commands/tasks rather than discrete trials, such as the center-out paradigm. BCI-controlled continuous flight of a physical quadcopter in three-dimensional space was first demonstrated using ERD/ERS signals corresponding to MI tasks [152]. This feat was achieved using right- and left-hand MI for one dimension of control, and MI of both hands and rest for the second [152]. More recently, a combination of SSVEP and MI tasks was also used to control various aspects of quadcopter flight [153].

Another important application of BCI is the brain-based control of a wheelchair [154], [155]. Such a task allows BCI technology and the use of various brain signals, such as P300 or SSVEP responses, in addition to MI tasks, to assist impaired patients in situations resembling daily life [156], [157], [158]. A recent study demonstrated that tetraplegic patients with SCI can operate a self-paced wheelchair during complex navigation tasks using an MI protocol [155].

In recent years, multiple non-invasive BCI studies have focused on robotic arm control. Controlling robotics is far more complex than the previously described devices, as the increased physical skill required for grasping tasks requires a corresponding mental strategy. Initial demonstrations of robotic arm control via scalp EEG focused on endpoint velocity or position control. However, as more detailed control of reach-and-grasp tasks practical for daily assistance became desired, this work branched into additional threads that focus on individual task segments. These segments can be broadly categorized into navigational robotic device control ("reach") and dexterous hand commands ("grasp"). Along these lines, the reaching aspect was initially demonstrated in three-dimensional movement decoding of center-out and motor execution tasks [159] and has since greatly expanded [160], [161], [162].

Other than movement execution, MI paradigms have been pursued using ERD/ERS signals to control a robotic's arm reach, grasp, and movement. He and colleagues have developed a unique and comprehensive framework for reach and grasp using MI. Along these lines, Meng et al. first demonstrated online non-invasive BCI control of a robotic arm in a group of human subjects, in whom MI tasks were used to reach for and grasp a Lego block (Fig. 5) [163]. Eight subjects completed all tasks and demonstrated well over 80% accuracy for completing reach tasks requiring two-dimensional navigation. Similar performance was achieved for more complex sequences of tasks in three-dimensional space involving grasping blocks off of a shelf, reaching over 70% accuracy. Edelman et al. further demonstrated the continuous reaching of a robotic arm through a combination of source-based decoding and a continuous pursuit control paradigm in a group of six human subjects [164], [165]. This work first demonstrated that the extended target-chasing task significantly improved MI-based BCI learning compared to traditional discrete trial protocols by increasing user engagement throughout training. By integrating real-time electrical source imaging, BCI performance was further enhanced across the skill spectrum in naive and experienced users. These works represent major advancements in the reach and grasp of BCI robotic arm control. When combined, this framework may, in the future, enable individuals with neuromuscular dysfunctions to autonomously perform daily tasks using only MI-based brain signals.

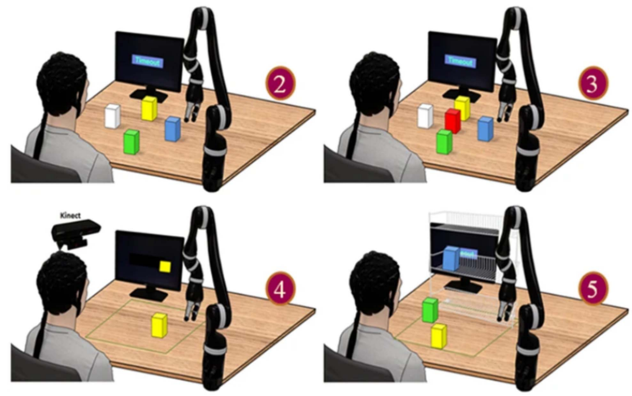

Fig. 5. EEG-BCI based control of a robotic arm using motor imagery tasks. Motor imagery was performed to control the "reach" of a robotic arm in one and two dimensions. Similar motor imagery protocols were also used to perform the "grasping" of a lego block. Task complexity increases from 2 to 5 during subject training. Reproduced from Fig. 1 of [163].

Robotic arm control has also been pursued from decoding movement execution. As such, to decode control initiation, Pereira et al. [166] developed a paradigm for online detection of self-initiated movements in a realistic scenario. EEG signals were time-locked to saccade onset, with participants shifting their gaze during goal-directed reach-and-grasp tasks. This strategy enabled relevant feature extraction and gaze incorporation with careful artifact handling [167]. A hierarchical classification approach utilizing LFTD features achieved a 54% true positive rate (compared to a chance level of 12%). This work expands possibilities for realistic settings, incorporating motor and visual processing in real-world tasks. Kobler et al. [103] further designed an experiment that involved center-out and continuous goal-directed movements, and considered two conditions (observation, execution) to study different volitional states. In either condition, the participants fixated on a target stimulus with their gaze in a 2D workspace. During motor execution trials, participants controlled a cursor by moving their right arm (on a flat surface) in a pursuit tracking task (PTT) to investigate the tuning characteristics of position and velocity. These temporal tuning characteristics indicated that neural activity preceded cursor velocity by approximately 150 ms [103]. These observations from EEG are in agreement with the tuning characteristics of spiking activity of M1 neurons [168].

In a follow-up study, Mondini et al. [105] investigated the feasibility of continuously decoding voluntary hand/arm movement trajectories from EEG to achieve closed-loop online control of a robotic arm. This work also implemented a PTT where the participants were asked to track a moving object on the screen by controlling a robotic arm. Kobler et al. [104] then suggested that integrating information about non-directional kinematics (e.g., distance, speed) in the decoding model can alleviate the amplitude mismatch problem. This non-directional kinematic information has been found in both ECoG [169] and MEG activity [170]. Provided that distance and speed are nonlinearly related to position and velocity, the previously introduced partial least squares Kalman filtering (PLSKF) approach [105] was extended to an unscented Kalman Filter (PLSUKF). Kobler et al. [104] re-analyzed EEG [103] and MEG data [170] to evaluate the performance of the PLSUKF with respect to both the PLS and the PLSKF during both observed and executed movements. Indeed, the correlation between the executed and the decoded trajectories was stronger for PLSUKF compared to other algorithms. Further, with the integration of non-directional kinematics in the decoding model, the amplitude mismatch between recorded and decoded trajectories could be reduced, overcoming the limitations of previous work [105]. Follow-up studies by Müller-Putz et al. and Pulferer et al. investigated the viability of decoding attempted movement, mimicking the limited motor function of SCI patients (by strapping each participant's dominant arm to a chair) [86], [171]. They examined potential learning effects that may arise when a user performs the same motor control task multiple times [171]. Within five days, ten able-bodied participants performed three sessions. The selected timeframe aimed to allow participants to recover from the mental strain of various tasks while ensuring they maintained a distinct memory of previous sessions. After calibration, EEG decoding was gradually included in online feedback until it reached 100% EEG control. Overall, this longitudinal study revealed learning effects across the various days of training, indicating a positive effect of training on decoding performance.

While extensive effort has been dedicated to improving the navigation aspect of robotic arm control, considerable work has also focused on incorporating EEG-based grasping signals into a BCI. First attempts to restore hand movements in paralyzed persons were purely pragmatic in that BCIs were directly connected to an orthosis or the patients' arm using FES [127], [128], [129]. These works demonstrated the possibility of connecting a BCI with closed-loop FES, recording EEG from the scalp, and stimulating a body part. However, they remained proof-of-concept studies. Study subjects were able to switch through pre-defined grasping patterns, but BCI control remained rather artificial in that they used the imagination of different limbs (foot and right hand) [129], or only the left hand [126] to trigger the different neuroprosthesis steps.

Nevertheless, in recognition of the various complexities involved with grasping objects of different sizes, shapes and orientations, further studies have since investigated how relevant grasping actions and features are encoded in scalp EEG. In particular, the use of MRCPs has helped support the hypothesis of natural control of a neuroprosthetic device. MRCPs vary across different types of movements or grasps, which may be useful as a natural control signal for a BCI-based neuroprosthetic. In fact, studies with able-bodied participants have shown that different movement types (right arm: hand open, hand close, pronation, supination, elbow flexion, elbow extension), grasp actions (i.e., palmar, pincer, lateral, rotation), grasp laterality (i.e., unimanual vs bimanual) and grasp force (i.e., power vs precision) can be successfully decoded from scalp EEG using MRCPs [172], [173], [174], [175], [176], [177], [178], [179]. Importantly, similar differences across multiple grasp types at the single-trial level could also be observed in individuals with SCI [123].

While these studies show promise for neurorobotic control, they were primarily employed in offline classification settings. Translating these offline studies into online performance greatly increases the potential utility in patient-oriented BCIs. Working towards this goal, some studies that integrate decoding paradigms that simulate online control, have shown successful above-chance performance for the execution of three different grasp types (i.e., palmar, lateral, wrist supination) [180]. More recent work has successfully moved to complete online control of four grasp types (i.e., cylindrical, spherical, lateral, pincer) using MI tasks [181].

This demonstration indicates that dexterous grasping can be performed in real-time using scalp EEG, however, it is difficult to suppress reaching signals during the grasp portion of the task, and vice versa. In this case, mode switching would be greatly beneficial in informing the BCI whether the user is focusing on positioning the arm or grasping an object. Similar to the previously described movement onset detection, various BCI "switches" have been proposed, but have also yet to be seamlessly integrated into online control paradigms [182]. Therefore, an easier solution to robotic arm control for daily tasks that has been widely adopted by the field is to utilize shared control strategies [183], [184], [185], [186]. In this sense, shared control refers to partial autonomous control by the user and partial automatic task recognition and execution by the BCI [187]. In these cases, such a strategy allows the user to control the BCI in up to three dimensions using a variety of MI and SSVEP signals (often hybrid) to select a pre-established task/action that is then automatically carried out. Nevertheless, the degree and complexity of shared control vary. Some systems utilize custom image processing pipelines for object identification using off-the-shelf camera components such as the now-discontinued Xbox Kinect. However, this approach can be limited to objects with similar shapes consistently viewed in the same orientation [184], [185], [188]. Other strategies utilize depth cameras and more advanced pose estimation methods [189] or simple QR codes [186] to identify objects that may be approached from different angles or perspectives, potentially offering a more versatile solution.

To ensure effectiveness and safety, the user and machine must consider practical considerations when utilizing a real-life robotic arm. Recent work on robotic arm control utilizes SSVEP signals for at least one control dimension. However, the visual attention required for these signals can be distracting when integrating these systems into everyday life. Similar issues have been observed when controlling a robotic arm using MI tasks – while the visual channel is reserved for observing the robotic arm rather than the flickering stimuli, impaired sightlines can still cause a slight drop in performance [165]. It has also been shown that other cognitive distractions accompany the user when controlling an interactive device, which can reduce its effectiveness [190], [191]. Another practical consideration for robotic device control that has been recently addressed is the need to impose physical constraints such as obstacle avoidance or trajectory correction [192], [193] to ensure the user's and others' safety. Controlling a robotic arm is a highly complex cognitive process, and various precautions and aids should be added to BCIs to maximize their effectiveness.

C. The Application–Clinical Use

Non-invasive BCIs have emerged as a transformative technology with significant clinical applications, and carry immense potential for improving the quality of life for individuals with various neurological conditions and disabilities. Using BCI technology for clinical applications can complement traditional strategies for disease diagnosis, treatment, and rehabilitation. For example, BCIs facilitate the early detection of EEG biomarkers for epilepsy monitoring and intervention. In addition, BCIs interact directly with the brain, enabling precise targeting of neural pathways. This can lead to more accurate and effective treatments of specific bodily functions and provide immediate feedback based on brain activity. Finally, the interactive nature of BCIs can be more engaging and motivating for patients than repetitive physical exercises.

BCI technology has two primary clinical applications: 1) assistive BCI and 2) rehabilitative BCI [194]. Assistive BCI seeks to bypass damaged neural pathways, providing a continuous and permanent means of communication and control of external devices. Assistive BCI systems are designed for individuals with severe motor impairments. These systems use SSVEP, P300, or MI signals to control various external devices, such as spellers [195], computer cursors [196], robotic devices [197], or speech synthesizers [198], thereby improving the user's quality of life and independence. Rehabilitative BCI aims to recover damaged neural connections, restoring impaired functional abilities by effectively facilitating neuroplasticity. This approach offers comprehensive and personalized functional, cognitive, and affective rehabilitation therapies. Restoring motor function is one of the most promising clinical applications of BCIs for individuals with SCI, stroke, or neurodegenerative diseases such as ALS. Since conditions like stroke do not affect the ability to form motor intentions, BCIs can decode neural signals related to these activities. This allows for neurofeedback training through assistive devices such as robotic systems, virtual reality, and functional electrical stimulation. Despite the significant attention BCI-based rehabilitation has received for motor function, applications in cognitive training remain underexplored. Evidence suggests that BCI-based neurofeedback training can improve cognitive functions in conditions like attention-related hyperactivity disorder [199] and mild cognitive impairment [200], and may similarly benefit post-stroke cognitive impairments [201]. These findings highlight the potential of neurofeedback-based cognitive training to induce neuroplastic changes essential for rehabilitation. BCI-based interventions have also demonstrated significant potential in emotion and mood regulation, offering solutions to address critical challenges such as depression. By leveraging real-time neural feedback, these interventions enable individuals to consciously modulate their brain activity and promote more positive emotional states. Advanced BCI systems can detect and respond to specific neural patterns associated with mood disorders, providing personalized therapeutic feedback that encourages neural reorganization and emotional resilience. Such interventions not only complement traditional treatments but also offer a non-invasive, self-regulated approach to managing and mitigating depressive symptoms, thus opening new avenues for mental health care. We believe the future of BCI for clinical applications lies in integrating functional, cognitive, and affective rehabilitation into a holistic approach. This comprehensive strategy enhances motor recovery and supports cognitive and emotional health, paving the way for more robust and inclusive rehabilitation solutions.

Compared to BCIs targeted at healthy users, BCIs designed for clinical applications still present several unique challenges. Patients usually show higher individual variability in neurological conditions. Patients may also experience higher levels of fatigue and cognitive load when using BCI systems. Furthermore, neurological impairments can affect the quality of neural signals that the BCI relies on. Many neurorehabilitation patients may have limited mobility or dexterity, making it difficult for them to use BCI hardware comfortably. Consequently, recent advancements propose the use of advanced decoding methods [202], [203], [204], [205] and the integration of other medical interventions, such as transcranial direct current stimulation (tDCS), transcranial magnetic stimulation (TMS), and transcranial focused ultrasound stimulation (tFUS) [10], [26], [27], [206], [207], [208] to develop more robust, calibration-free, and user-friendly BCIs for clinical applications.

D. The Machine–BCI Decoding Algorithms

EEG decoding involves developing algorithms and models to analyze recorded EEG signals, with the aim of understanding and interpreting the underlying neural processes. EEG decoding is crucial for BCIs because it enables the translation of neural signals into actionable commands, realizing communication and control between the human brain and external devices. Brain signal decoding is always a challenging part of BCI, especially for non-invasive EEG. As EEG signals travel from their source in the brain to the scalp surface through the low-conductive skull, they encounter various instances of noise caused by both biological and non-biological factors.

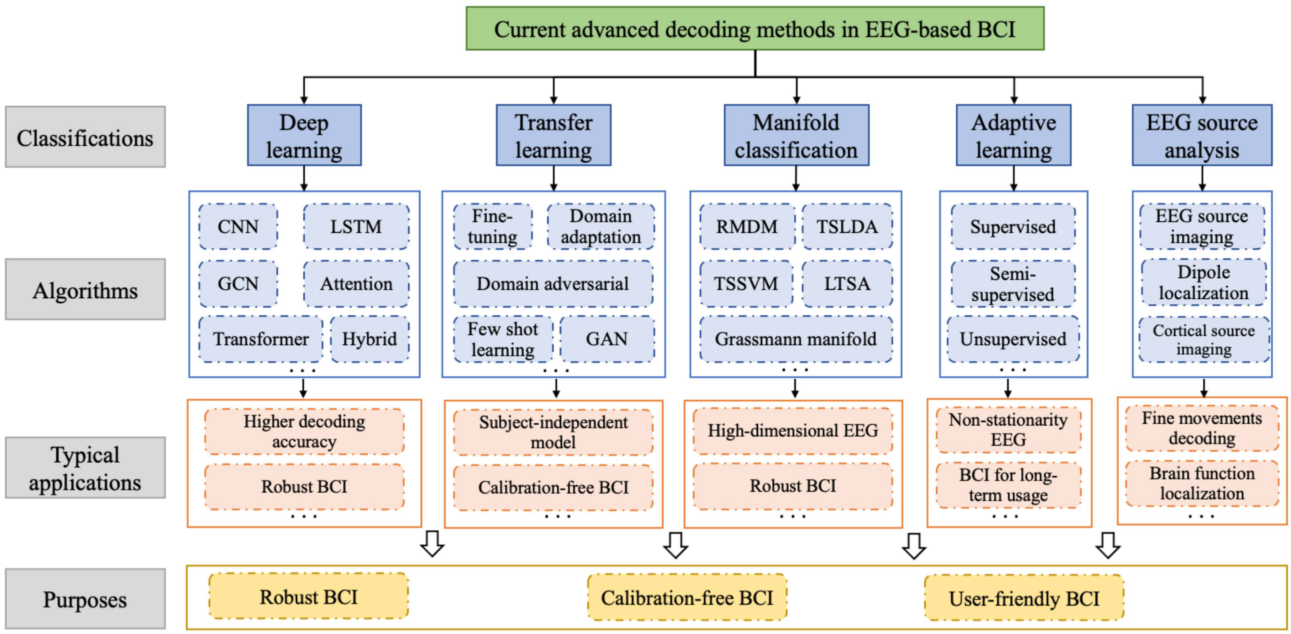

Fig. 6. Overview of recent decoding methods used in EEG-based BCI. These methods can be broadly separated into five main categories: Deep learning, transfer learning, manifold classificiation, adaptive learning, and EEG source analysis. Each of these categories consists of detailed algorithms that aim to improve various aspects of EEG decoding and BCI performance. In the end, all of these approaches aim to develop robust, calibration-free and user-friendly BCIs.

While EEG signal decoding can be viewed as a specific type of classification problem, this topic presents unique complexities. In typical classification tasks, larger datasets enhance performance by providing richer information. However, in EEG classification, more data necessitates longer acquisition times, which can lead to participant fatigue and distraction. This degrades data quality, introduces noise and inconsistencies, and negatively affects model training. Therefore, proper EEG classification needs a balance between data quantity and quality. It is generally recommended to limit EEG recording sessions to 30–60 minutes, with regular breaks, to maintain high data quality. For intra-subject training, a model is trained and tested on data from the same subject. By contrast, inter-subject training involves training a model on data from multiple subjects and testing it on different subjects. This requires a large and diverse dataset to capture the variability in EEG signals across individuals, along with more complex operations to create a model capable of handling EEG data with different distributions.

The traditional classification pipeline in BCI typically encompasses an initial filtering process applied to EEG signals, followed by the classification of the filtered data. This filtering operation is designed to extract pertinent information from temporal, spectral, or spatial dimensions, depending on the specific BCI paradigms. However, traditional methods face many challenges when decoding EEG. First, the feature extraction and classification processes in traditional methods are optimized separately using distinct objective functions. This could result in a suboptimal solution for the decoding process. Second, traditional methods strongly rely on hand-crafted features, a manual selection process that can be time-consuming and subjective. Finally, while these approaches prove effective in a specific subject, their performance tends to decline when applied in subject-independent applications. Therefore, more advanced methods are explored to address these limitations.

In this section, we comprehensively explore recent progress in decoding methods for EEG-based BCI. We outline the principles underlying these methods, how these methods relate to one another, and provide guidance on their appropriate application. The methods discussed in this section are summarized in Fig. 6 and Table I.

1) Deep Learning-Based Methods: Deep learning is a subfield of machine learning that focuses on the development and application of artificial neural networks to solve complex problems such as computer vision, speech recognition, and natural language processing [209]. With their ability to automatically learn hierarchical representations from raw data, deep learning approaches offer a promising alternative for EEG decoding and have achieved state-of-the-art performance.

A convolution neural network (CNN) is among the most popular and successful deep learning methods for EEG decoding. CNNs are designed for signal processing and analysis, especially for those contexts that provide spatial information. The convolutional layer is a fundamental building block of CNN that extracts features by sliding small filters across the input. Each filter is equipped with learnable weights designed to detect specific patterns, and the aggregation of multiple filters results in the creation of a feature map. During the training of a CNN, backpropagation is adopted to calculate the gradients of the loss function with respect to the weights of the network, allowing for weight updates that minimize the overall loss. When adopted into EEG decoding, CNNs are generally initiated with an input layer that accepts the pre-processed EEG data. Then, the CNN extracts spectral and spatial features by deploying a spatial convolution layer along the channel dimension and a temporal

TABLE I
SUMMARY OF CURRENT ADVANCED DECODING METHODS FOR EEG-BASED BCI

Decoding method	Algorithm	Literature
Deep learning	CNN	[210]-[216]
	Graph based methods	[217]-[221]
	LSTM	[222],[223]
	Neural networks with attention mechanisms	[224]-[226]
	Transformer	[227]-[229], [233]
	Hybrid deep learning	[230]-[233]
Transfer learning	Fine-tune	[230],[236]-[242]
	Domain adaptation	[244]-[246]
	Domain adversarial	[247]-[251]
	Few-shot learning	[252]-[257]
Manifold-based classification	Riemannian manifold	[258]-[261]
	Kernel-based nonlinear manifold	[262]
	Grassmann manifold	[263]
Adaptive learning	Supervised learning	[238]
	Unsupervised learning	[264],[265]
	Semi-supervised learning	[266]-[268]
EEG source analysis	EEG source imaging	[110]-[112], [121],[164]-[166],[270]-[276]

convolution layer along the sample dimension. After this step, several layers will be followed to project the feature into higher dimensions. Between two convolutional layers, there always exists one pooling layer to reduce the parameter dimension and eliminate overfitting. In the final phase, the fully connected layer serves as a decision-making layer, mapping the high-level representations to the specific classes related to the decoding task. Many current approaches are completely or partially based on a CNN. In a typical and pioneering work, Cecotti & Graser [210] proposed a CNN-based method for P300 decoding. This network was quite simple yet effective, with only two convolution layers and one fully connected layer. As one of the initial papers to apply the CNN to BCI, Sakhavi et al. [211] designed a framework to learn temporal information from EEG, and achieved the best classification performance on BCI competition IV-2a dataset. Subsequent efforts aim to enhance performance by incorporating structures with varying convolution depths and by employing advanced training strategies. Two CNN-based classifiers named Shallow ConvNets and Deep ConvNets were introduced for MI decoding in Schirrmeister et al. [212]. The Shallow ConvNets were initiated with a spatial convolution layer and a temporal convolution layer to extract features from the spatial and spectral domains, respectively. Deep ConvNets was equipped with three more convolution layers that project outputs into higher dimensions, facilitating the learning of features in more complex spaces. Results showed that Deep ConvNets reached at least as good performance as filter bank common spatial patterns (FBCSP), a staple of the field [213]. The EEGNet proposed by Lawhern et al. [214] demonstrated a high level of versatility of the CNN-based method on four different BCI paradigms, i.e., P300, error-related negativity (ERN), MRCP, and ERD/ERS. This method introduced depthwise and separable convolutions for feature extraction and achieved high classification accuracy while using fewer parameters than other models. In more recent work, Mane et al. [215] proposed a filter-bank convolutional network (FBCNet) to classify MI tasks from EEG for both healthy and stroke subjects. FBCNet employed a multi-view data representation followed by spatial filtering to extract spectro-spatially discriminative features. A similar work introducing multi-scale CNN to learn spatial-temporal features for epileptic seizure detection can be found in [216].

EEG signals are collected by multiple electrodes positioned on the scalp, inherently forming a spatial network. To consider the physical distribution of EEG signals, graph convolutional networks (GCNs) were introduced as an extension of CNN. In a graph, data are represented by nodes and edges, and convolution involves aggregating information from neighboring nodes. The concept of a "neighborhood" holds different meanings for traditional convolution and graph convolution. For traditional convolution, a neighborhood refers to local patches or regions of the input data. For graph convolution, however, it refers to the set of adjacent nodes connected by edges. When decoding EEG using a GCN, the data are first represented as a graph with nodes (electrodes) and edges (relationship between electrodes). This can be realized by calculating the absolute Pearson's matrix of EEG data [217]. Then, the initial feature vectors are assigned to each node in this graph. Finally, graph convolutional layers are implemented to capture relationships between connected nodes. GCNs have been used for MI classification [218], P300 decoding [219], and cognitive analysis [220] by learning the intrinsic relationship between different EEG channels. Recently, a CNN variation that considers the "neighborhood" of EEG electrodes – PointNet – has been introduced to study continuous tracking in MI BCI [221].

A recurrent neural network (RNN) assumes that there are long-term dependencies in sequential data. RNNs capture information from previous time steps by maintaining hidden states [222], are capable of decoding temporal and spectral information from EEG. Long short-term memory (LSTM) is a typical RNN, which was proposed to address the vanishing gradient problem in RNN by incorporating a memory cell and three gates named forget gate, input gate, and output gate. The memory cell is capable of maintaining long-term memory, while the three gates control the flow of information into and out of the memory cell. This structure enables LSTM to handle sequences of varying lengths and retain important information over extended periods. Totora et al. [223] proposed an LSTM network with two separate layers, allowing the network to capture both low-level and high-level gait patterns from brain signals.

Despite the effectiveness of CNNs and LSTM in capturing spectral and temporal features in sequential EEG, they encounter challenges when dealing with long-range dependencies and may experience a long training process to selectively focus on crucial elements in EEG. To address this limitation, attention mechanisms were introduced [224]. In EEG decoding, the relevant information for making a prediction is not equally distributed across the entire trial. Attention mechanisms enable the model to dynamically weigh different parts of the input, giving more importance to relevant regions. In the attention mechanism, the "query" represents the current position or context that the model is focusing on and the "key" represents different positions or elements in the input data. Attention is realized by calculating attention scores, which represent the importance of each key with respect to the current query. The attention mechanism has been used in ERP classification [225] and VEP detection [226]. One typical attention-based method is the transformer, which uses multi-head attention. This involves multiple parallel self-attention mechanisms, allowing each position in the sequence to attend to all positions. Transformers have been used for MI decoding [227], ERP detection [228], SSVEP recognition [229], etc.

The previously presented deep learning methodologies are characterized by singular architectural frameworks. Hybrid deep learning (hDL) methods, on the other hand, combine the diverse strengths of different decoding approaches to effectively integrate temporal, spectral, and spatial features from EEG data, thereby offering a comprehensive solution for EEG decoding. The most common hDL approaches combine homogenous CNNs together, or integrate CNNs with other neural networks, including RNNs, transformers, and other variants. [230] combined a CNN with a multilayer perceptron (MLP) to facilitate epileptic seizure prediction. A CNN-LSTM framework was proposed to extract the spectral, spatial, and temporal features from EEG to address the BCI illiteracy problem in MI paradigms [231] and also to boost the classification of SSVEP paradigms [232]. Song et al. [233] introduced a compact convolutional transformer to enhance the decoding of SSVEPs by encapsulating local and global features in a unified framework. Despite hDL's potential for a more comprehensive analysis of EEG signals, its elevated model complexity and computational costs still pose challenges in BCI.

The appeal of deep learning methods for EEG decoding lies in three main reasons. First, the EEG signal is inherent with high variability across time and subjects, leading traditional methods to fail to generalize well across these diversities. On the contrary, deep learning methods are capable of integrating high-level knowledge directly from raw EEG, significantly reducing the reliance of the decoding algorithm on prior knowledge. Second, deep learning methods are trained in an end-to-end manner rather than the two-step phases employed in traditional methods, ensuring a global optimum during the decoding process. Finally, deep learning methods automatically extract features, avoiding the highly time-consuming and labor-intensive extractor designing process of traditional methods. However, it is important to note that deep learning methods assume the training and testing data share the same distribution, an assumption that may not hold in many real-world scenarios. Furthermore, the challenge of obtaining extensive and diverse labeled training data for training a deep learning model is often not feasible in practical cases like clinical applications. Therefore, despite their advantages, deep learning methods still face challenges, and more advanced methods should be explored.

2) Transfer Learning-Based Methods: Transfer learning is currently a hot topic in machine learning and data mining. Different from deep learning methods, transfer learning assumes that the distribution of training and testing data is different, and tries to utilize knowledge learned in one group to solve problems in another [234]. In transfer learning, the domain comprises the feature space $\mathcal{X}$ and the probability distribution $P(X)$, where $X = \{x_1, x_2, \ldots, x_n\} \in \mathcal{X}$, with n being the number of feature vectors. In a specific EEG decoding problem, X is all available EEG feature vectors in this decoding task with x_i denoting one particular vector extracted from one single EEG trial. n can therefore also be considered as the number of EEG trials, and $\mathcal{X}$ the feature space of all EEG samples. In transfer learning, the domain holding known knowledge is termed the source domain, typically denoted as $\mathcal{D}_\mathcal{S}$. The domain encompassing unknown knowledge to be acquired is termed the target domain, usually represented as $\mathcal{D}_\mathcal{T}$. The learning goal is referred to as a task $\mathcal{T}$, which consists of a label space $\mathcal{Y}$ and the prediction function $f(\cdot)$, and $Y = \{y_1, y_2, \ldots, y_n\} \in \mathcal{Y}$ is the label space in that training dataset. More formally, given a source domain $\mathcal{D}_\mathcal{S}$ with task $\mathcal{T}_\mathcal{S}$ and a target domain $\mathcal{D}_\mathcal{T}$ with task $\mathcal{T}_\mathcal{T}$ ($\mathcal{D}_\mathcal{S} \neq \mathcal{D}_\mathcal{T}$), transfer learning aims to utilize the information learned from $\mathcal{D}_\mathcal{S}$ to facilitate the prediction function $f_T(\cdot)$ [235]. According to the label type of available data, transfer learning can be divided into inductive transfer learning, transductive transfer learning, and unsupervised transfer learning. In inductive transfer learning, the labels of the target domain are known, and the target task and the source task are different ($\mathcal{D}_\mathcal{S} \neq \mathcal{D}_\mathcal{T}$). In unsupervised transfer learning, data from both the source and target domains are unlabeled, and tasks in the two domains are different ($\mathcal{D}_\mathcal{S} \neq \mathcal{D}_\mathcal{T}$). Most BCI research focuses on transductive transfer learning, where $\mathcal{D}_\mathcal{S} \neq \mathcal{D}_\mathcal{T}$, but $\mathcal{T}_\mathcal{S} = \mathcal{T}_\mathcal{T}$. For instance, in the context of a group of subjects performing an identical MI task, the labeled EEG data from some subjects (source domain, $\mathcal{D}_\mathcal{S}$) are used to improve the decoding of the unlabeled EEG signals in naive subjects (target domain, $\mathcal{D}_\mathcal{T}$).

To date, the predominant approach in transfer learning for BCI has largely relied on fine-tuning techniques. In one typical cross-subject fine-tuning application, one subject-independent model $f_S(\cdot)$ will be pre-trained on all of the data from $\mathcal{D}_\mathcal{S}$, and then the data from $\mathcal{D}_\mathcal{T}$ will be used to fine-tune a subject-dependent model $f_T(\cdot)$ on $f_S(\cdot)$ [236]. Zhang et al. [237] demonstrated the efficacy of fine-tuning using a pre-trained model from other subjects in cross-subject applications. Besides this, fine-tuning method can also be used in cross-session scenarios, where the data from the calibration session are pre-trained to initialize a model, while data from the subsequent sessions are adopted to fine-tune a session-specific model [238]. Fine-tuning has been widely used in MI decoding [239], SSVEP detection [240], and P300 recognition [241]. Previous studies with deep learning have shown that fixing some of the initial weights in $f_S(\cdot)$, while adjusting others by the optimizer, will improve the performance of transfer learning. This technique is termed frozen and has been adopted into BCI to enhance the decoding performance of the fine-tuning strategy [242]. Notably, not all subjects from the target group will benefit from the performance of the source group. Coarsely performing a transfer regardless of the dissimilarity between the source and target domain will lead to even worse decoding accuracy. This phenomenon is called "negative transfer" [243]. To tackle this issue, domain adaptation techniques are proposed in EEG decoding.

Domain adaptation techniques are employed to adapt the source domain information to better align with the features of the target domain. This approach was introduced in EEG decoding to help mitigate the variability between different subjects, sessions, or experimental conditions. Domain adaptation can be realized by conditional distribution adaptation and marginal distribution adaptation, i.e., with or without considering the relationship between variables. Conditional adaptation considers the joint distribution of multiple variables, seeking to preserve the relationships that exist in the data. It not only aligns individual feature distributions but also aims to capture the interdependencies and relationships between features. On the other hand, marginal distribution adaptation performs domain adaption without considering the relationship between variables. Chen et al. [244] proposed a multi-source marginal distribution adaption method. First, a common feature extractor was designed to map the sources and target data from the original feature space into a common shared latent space. Then the EEG from the target domain and source domain was combined as pairwise inputs to learn domain-specific features. In order to project the data from the target and source domain as closely as possible, they adopted a maximum mean discrepancy (MMD) loss to obtain domain-invariant features. So far, more and more work on domain adaption concern both marginal distribution and conditional distribution to adapt models to new subjects or datasets while preserving task-specific information [245], [246].

Domain adversarial is a relatively new approach to realize domain adaptation, aiming to learn a model that cannot identify the domain of origin of the input observation. This idea is based on the belief that if an algorithm cannot distinguish the source domain based solely on the transformed representation, it indicates that the representation has effectively abstracted domain-specific information. When performing domain adversarial, data with both class labels and domain labels are initially input into a feature extractor. These representations are then directed towards a label predictor and a domain classifier. The objective is to minimize loss in the label predictor while employing a gradient reversal layer to maximize loss in the domain classifier. This process reduces domain-specific information within the representation space and significantly improves the generalization ability of the label predictor. Inspired by this idea, Li et al. [247] trained subject-independent models by reducing the impact of subject-specific information on the EEG emotion recognition process. Liu et al. [248] proposed a unified multi-source optimization framework to realize multi-source domain adaption by learning the weight distribution and fusion results.

Besides realizing domain adaptation, adversarial training is also adopted to perform data augmentation by generating artificial samples resembling the real data distribution it was trained on. A generative adversarial network (GAN) is another transfer learning method. It consists of a generator to create EEG data and a discriminator to distinguish between the real and artificially generated samples. The training process of a GAN involves a continual back-and-forth struggle between the generator and the discriminator. It succeeds when the generator can produce synthetic data that are indistinguishable from the real data by the discriminator. Typically, this method can be used for EEG data augmentation [249], [250] and artifact detection [251]. Training a GAN using EEG is widely acknowledged as a tough task due to prevalent instability issues. One notable challenge arises when the discriminator quickly reaches an optimal state, effortlessly differentiating between the synthetic samples and the real EEG samples. As a consequence, this will lead to no meaningful gradients and bring no progress for model training.

While improving classification accuracy, transfer learning is also capable of achieving a calibration-free BCI. Few-shot learning is an effective transfer learning tool for achieving this goal [252]. This approach trains models to make accurate predictions or classifications with very few labeled examples, or even without any supervised information (zero-shot learning). There exist three primary approaches to facilitate few-shot learning. The first option is to augment the training dataset. Besides the above-mentioned GAN, data augmentation can be realized by incorporating various representations with temporal EEG trials (such as spatio-temporal features and power spectral density) [253], by designing a sliding window to crop EEG data into smaller segments across the temporal domain [212], by injecting various types of noise (such as Gaussian, Poisson, etc.) into clean EEG to create new EEG trials [254], and by performing oversampling [255] or subsampling [256] on EEG trials. The second option is to constrain the hypothesis space within the model. An et al. [257] proposed a few-shot learning method by using two branches of embedding modules to extract data from support data and query data. This work was applicable to few-shot learning because, instead of learning features within each EEG trial individually, it focused on learning the relationships between EEG trials, which significantly constrained the hypothesis space. The third option is to modify the search strategy within the hypothesis space. The previously mentioned fine-tuning approach serves as a common search strategy, refining existing parameters from source tasks to optimize the parameter for the target task.

BCI datasets typically have limited samples due to the challenges in collecting brain data, making transfer learning an ideal solution for signal decoding. Transfer learning has shown its priority in training subject-independent models. It is worth noting that prior to executing the transfer process, careful consideration of domain adaptation is recommended to prevent negative transfer.

3) Manifold-Based Methods: Manifold approaches are different from the classification algorithms we have discussed until now. The feature space of these algorithms is defined in Euclidean space, which is flat everywhere. Manifold space, on the other hand, exhibits flatness at a specific point and its vicinity [258]. The manifold theory assumes that the higher-dimensional EEG feature space is mapped from a lower-dimensional space. Throughout this mapping procedure, the feature space introduces dimensionality redundancy and interferes with the feature extraction process. Consequently, manifold-based classification aims to unveil the inherent structure or geometry of this high-dimensional data, represent it in a more concise lower-dimensional space, and then perform classification.

Among different manifold-based classification methods, the Riemannian manifold is the most commonly used for EEG decoding [259]. This method aims to pull symmetric positive definite (SPD) features of the same class toward their barycenters and separate other features of different classes farther away in Riemannian space [260]. SPD features are important for calculating the Riemann distance because its symmetry ensures the Riemann distance remains invariant under coordinate transformations and its positive definiteness guarantees the well-defined nature of the Riemannian metric, ultimately resulting in a meaningful distance measure. In EEG decoding, the SPD matrix is typically derived from the covariance matrix of EEG trials, represented as $C = \frac{1}{N-1}XX^T \in \mathbb{R}^{N\times N}$, where N is the number of EEG channels. This SPD matrix characterizes the relationships among various electrodes and serves as an effective tool for capturing the characteristics of EEG signals. Given the two SPD matrices C_1 and C_2, the affine-invariant Riemann distance δ between them can be calculated by [317], [318]:

$$\delta_R\left(C_1, C_2\right) = \|\log\left(C_1^{-1/2} C_2 C_1^{-1/2}\right)\|_F = \left[\sum_{i=1}^{N} \frac{1}{2}\log^2\lambda_i\right]^{1/2} \tag{1}$$

where $\lambda_i, i = 1\ldots N$ are the real eigenvalues of $C_1^{-1/2} C_2 C_1^{-1/2}$. By using the Riemann distance, the centroid of I SPD matrices on a Riemannian manifold (also known as the Riemannian geometric mean point) can be obtained through the following formula:

$$\mathfrak{G}\left(C_1, \ldots, C_I\right) = \underset{C\in C(n)}{\operatorname{argmin}} \sum_{i=1}^{I} \delta_R^2\left(C, C_i\right) \tag{2}$$

where $C(n)$ is the space of the SPD matrices and C is the SPD matrix representing one point in the manifold. When decoding EEG in a Riemannian manifold, all SPD matrices of the EEG trials are first mapped into the Riemannian manifold space. Subsequently, the Riemannian geometric mean points of every class are computed. When new test data are introduced, the Riemann distances between this point and the Riemannian geometric mean points of each class are calculated. The point is then classified into the class associated with the minimum Riemann distance. This method is called Riemannian Minimum Distance to Means (RMDM) [319], and is parameter-free, robust to noise, and therefore exhibits better generalization capability. Other solutions try to introduce traditional classifiers like linear discriminant analysis (LDA), support vector machine (SVM), and neural networks into classification. As these methods rely on Euclidean geometry assumptions (LDA and SVM assume the decision boundaries are linear in the input space, and neural networks heavily rely on optimization using gradient descent based on Euclidean geometry), additional operation projecting data points from Riemannian space into tangent space is employed. The flat and linear nature of the tangent space at a specific point serves as an approximation of Euclidean geometry at that point and thereby meets the assumption of traditional classifiers. This concept has led to the development of Tangent Space LDA (TSLDA) and Tangent Space SVM (TSSVM) for EEG decoding.

Manifolds based on Riemannian geometry have been successfully adopted in EEG decoding. A novel geometric deep learning-based model was proposed in [261] to learn spatiotemporal representations of EEG data fully on a Riemannian SPD manifold. This work was tested on MI, ERP, and SSVEP datasets. Apart from the Riemannian manifold, many other manifolds have been explored in recent years. Gunawardena et al. [262] proposed a kernel-based non-linear manifold classifier to identify important channel inter-relationships within the EEG data. Li et al. [263] extended the low-rank representation method from the Euclidean space to the Grassmann manifold, aiming to investigate subspace information and re-represent EEG signals.

Manifold-based classification can be performed in an unsupervised manner, allowing the decoding of EEG data without the need for labeled examples. Moreover, the robustness of manifold-based methods extends to their ability to handle noise and outliers in the EEG signals, making them more applicable to real-world scenarios.

4) Adaptive Learning-Based Methods: An adaptive classifier is a type of classification algorithm that can adjust its parameters or structure based on the characteristics of the data it is processing. The adaptability of such a classifier allows it to respond to changes in the input data distribution, making it more flexible and potentially better suited for dynamic or evolving environments. Adaptive classifiers can be categorized into three types: supervised adaptation, unsupervised adaptation, and semi-supervised adaptation. For supervised adaptation, all data used for adaptation are supposed to be labeled. Most of the adaptive methods for EEG decoding are based on supervised adaptation. One typical application is cross-session adaptation for the long-term utilization of BCI, which requires the method to continuously adapt to the subjects' mental state with the incoming unlabeled data. In this case, the decoding algorithms aim to retrain a new model to classify the unlabelled data from session i with the data from session 1 to $i-1$ in a supervised manner [238].

On the contrary, for unsupervised adaptation, no labeled data are available in the target domain. In such cases, the model has to rely on domain information or other unsupervised learning techniques to adapt itself to the new domain. Most works using unsupervised adaptation for EEG decoding attempt to learn domain-invariant features by training a domain-adversarial or domain-alignment model [264], [265].

For semi-supervised adaptation, most of the EEG used for model training is unlabeled, while only a fraction of them is labeled. Given that data labeling can be time-consuming and tedious, semi-supervised adaptation may have more potential than supervised adaption in EEG decoding. Pseudo-labeling, self-training, and co-training are three semi-supervised methods used for EEG decoding. In pseudo-labeling, the initial EEG decoding model is trained on the labeled EEG dataset. Then, the trained model is applied to the unlabeled EEG data to generate pseudo-labels. Finally, the labeled and pseudo-labeled datasets are combined together to retrain the model. This process is usually iterated many times to refine the model and update the pseudo-labels [266]. Self-training is similar to pseudo-labeling, except only those predictions with high confidence are added to the labeled set for the next iteration of training [267]. In co-training, multiple models are trained on different subsets of EEG features. The models then vote on the labels for the unlabeled EEG, and the most confident predictions are added to the labeled set [268]. It has been proven that when using the proper method, the semi-supervised method can reach a similar performance as the supervised method [269].

Compared with static methods, adaptive learning-based methods show more advantages in the real-time adjustment and robustness to non-stationarity for EEG decoding. Therefore, they are particularly well-suited for real-world applications.

5) EEG Source Analysis: The adoption of source domain analysis for EEG decoding introduces a departure from the conventions observed in sensor domain analysis that have been previously discussed. Sensor domain analysis deals directly with the signals recorded by EEG sensors on the scalp, focusing on patterns and features at the sensor level. On the other hand, source domain analysis seeks to go beyond the scalp-level signals to estimate the neural sources responsible for those signals, providing more detailed spatial information about brain activity. He and his colleagues have pursued source domain analysis [270], [271], [272] for BCI for years and have achieved equal or superior performance compared to sensor domain analysis [121]. Early work on this topic investigated the performance of using EEG source imaging using cortical current density or equivalent dipole models to classify MI tasks without BCI feedback [121], [273], [274]. EEG source imaging was further used offline to localize and image cortical activation during MI tasks performed during online BCI experiments where the online decoding was based on sensor data only [110], [111], [112]. This approach was also implemented in real-time online MI BCI experiments for continuous cursor and robotic arm control [164], [165], where the online decoding was based on estimated source signals. To perform EEG source imaging, an inverse transform such as minimum norm estimate (MNE) and low-resolution electromagnetic tomography (LORETA) is applied to convert EEG data recorded on the scalp (the sensor domain) into cortical source estimates (the source domain). Second, a region of interest in the brain cortex is selected according to the specific task or by a data-driven approach to realize an adaptive selection [275]. Then, the data can be treated according to traditional decoding methods or deep learning methods [276].

Source domain analysis is well suited for deciphering the precise movements of distinct arm segments. It further enables the decoding of fine MI movements [166] and realizes motor control for a robotic arm through the interpretation of MI tasks. While the computational demands of this approach can be high, source analysis has been successfully deployed in online MI BCI applications [164], [165].

6) BCI Decoding Methods Outlook: Presently, decoding methods prioritize three main goals: elevating classification accuracy, establishing calibration-free BCIs, and enhancing the robustness of BCIs. The need for higher classification accuracy is evident, as it facilitates effective communication, precise control of external devices, and an improved user experience. Calibration-free BCIs contribute to a more user-friendly and efficient experience, particularly crucial for real-world applications where users can swiftly engage with the system without undergoing lengthy calibration sessions. Robust BCIs address session-to-session non-stationarity and inter-subject variability, ensuring consistent performance across sessions and subjects, thereby enhancing overall BCI effectiveness.

While the decoding methods are categorized into distinct sections, it is important to note that these divisions are not strictly separated. Rather, there is often interconnectivity and overlap between these categories. For instance, transfer learning may be equipped with a CNN for intra-subject classification and using a strategy by adaptive learning to realize inter-subject transfer. Compared with offline applications, online evaluations provide a more realistic and dynamic assessment of a decoding method's performance in practical, real-world scenarios. While current decoding methods in BCI research predominantly undergo offline testing using pre-recorded datasets, there is a crucial need to encourage and prioritize online applications, especially for emerging machine learning-based methods. In fact, a recent study implementing EEGNet and PointNet demonstrates the merits of deep learning for continuous tracking of a virtual object using MI paradigms in an online setting [221].

V. BCI Software

As the previous sections demonstrate, there is now ample evidence that non-invasive BCI systems can be used, together with appropriate feedback/conditioning protocols, to replace, restore, improve, enhance, or supplement functions lost due to different neurological disorders [1], [277]. The realization of these possibilities crucially hinges on the effective and efficient implementation and validation of various BCI approaches. Unfortunately, the implementation of any new BCI system involves complex technology and the result may need to support different situations.

BCI systems are technically complex; they acquire signals from the brain and possibly other physiological or behavioral sources, analyze them to produce output commands, and finally realize the output and associated feedback. The acquisition of these signals is accomplished using specialized hardware and requires the implementation of proprietary software interfaces to configure the device and acquire data simultaneously. As an additional complication, the acquisition of all signals often needs to be synchronized. This is technically challenging as different sampling rates and acquisition delays must be accounted for across the different input devices. Finally, all of the involved device interactions and processing functions must occur in real time, with minimal delays and consistent timing. While there is no formal definition of these timing requirements, it is clear that feedback must be perceived as continuous (e.g., must be provided $>$20 times per second). Thus, the BCI software has less than 50 ms to store, visualize, and process the acquired data, and to produce all necessary outputs. These timing requirements necessitate highly optimized coding that minimizes CPU load and latency variation that may be introduced by the operating system or other factors. Implementing and integrating these functions is challenging, time-consuming, and costly.

Large multi-center BCI research or development efforts create additional challenges. These efforts usually involve different personnel who conduct experiments or analyze data in different

TABLE II
OVERVIEW OF BCI TOOLBOXES AND SOFTWARE PLATFORMS

	Language	License	Website
Toolboxes			
Psychophysics	MATLAB	MIT	http://psychtoolbox.org
EEGLab	MATLAB	GPL GNU	http://sccn.ucsd.edu/eeglab
BioSig	MATLAB	GPL GNU	http://biosig.sourceforge.net
Brainstorm	MATLAB	GPL GNU	http://neuroimage.usc.edu/brainstorm
FieldTrip	MATLAB	GPL GNU	http://www.fieldtriptoolbox.org
MNE	MATLAB	BSD	http://martinos.org/mne
BCILAB	MATLAB	GPL GNU	http://sccn.ucsd.edu/wiki/BCILAB
rtsBCI	MATLAB	GPL GNU	http://biosig.sourceforge.net
FieldTrip buffer	C++	GPL GNU / BSD	https://www.fieldtriptoolbox.org/development/realtime/buffer/
g.BCIsys	SIMULINK	commercial	https://www.gtec.at/product/bcisystem/
Craniux	LabView	?	?
BciPy	Python	Hippocratic License	https://github.com/CAMBI-tech/BciPy
pybci	Python	MIT	https://github.com/LMBooth/pybci
MEDUSA	Python	Creative Commons	https://www.medusabci.com
Lab Streaming Layer	Python	MIT	https://github.com/sccn/labstreaminglayer
pySPACE	Python	GPL GNU	https://pyspace.github.io/pyspace/
PsychoPy	Python	GPL GNU	http://www.psychopy.org
pyff	Python	GPL GNU	https://github.com/bbci/pyff
mushu	Python	GPL GNU	https://github.com/bbci/mushu
wyrm	Python	MIT	https://github.com/bbci/wyrm
BCI Software Platforms			
BCI++	C++	GPL GNU	?
xBCI	C++	?	https://xbci.sourceforge.net (outdated)
TOBI	C++	LGPL	https://github.com/tools4BCI/
MindDesktop	?	?	https://www.oriossmy.com/project01
UniPA BCI	C++	GPL GNU	https://github.com/slabua/AugmentedBCIFramework
BCI2000	C++	GPL GNU	http://www.bci2000.org
OpenViBE	C++	GPL Affero	http://openvibe.inria.fr

locations. Thus, such large BCI efforts require the creation of many different BCI systems that all must store the resulting data in a standard format that is properly annotated. This means that all experimental parameters and event markers must be included to make the data practical for analysis by a person who is not intimately familiar with all experimental and technical details of a particular BCI experiment. Thus, there is an important need to facilitate such large BCI research and development efforts that vary in technical or neuroscientific approach, people, site, and are executed over long periods of time.

The following two sections summarize the existing toolboxes and BCI software platforms that can address these relatively simple or more complex needs, respectively (Table II).

A. Toolboxes

Toolboxes relevant to BCI development provide functions that simplify the development of an individual BCI system. BCI toolboxes are usually developed on top of commercial high-level platforms (MATLAB, SIMULINK, or LabVIEW) or, more recently, using scripting languages such as Python.

MATLAB provides the basis for a number of BCI toolboxes for the presentation of behavioral paradigms (e.g., Psychophysics Toolbox [278]) and the post-hoc analysis and visualization of biosignals (e.g., EEGLab, [279]; BioSig [280]; Brainstorm [281]; FieldTrip [282]; and MNE [283]). EEGLab, BioSig and FieldTrip have been extended into toolboxes for rapidly prototyping and evaluating online BCIs, called BCILAB, rtsBCI and FieldTrip buffer, respectively.

SIMULINK provides the basis for g.BCIsys [284], a commercial SIMULINK-based toolbox that provides a front-end interface for rapid BCI research and development to users of g.tec hardware. LabVIEW has been the basis for several BCI demonstrations and has been used to implement the BCI toolbox Craniux [285]. The popularity of Python in the BCI community has increased over the past decade, and quite a few toolboxes have been implemented to facilitate BCI development. They include BciPy [286]; PyBCI [287]; MEDUSA [288]; Lab Streaming Layer [289]; pySPACE [290]; PsychoPy (for presentation of stimuli) [291]; and a set of toolboxes from the Berlin BCI group: Pyff – a framework for feedback applications and stimulus presentation [292]; Mushu – a toolbox for BCI signal acquisition [293]; and Wyrm – a BCI analysis toolbox [294].

B. BCI Software Platforms

Just like BCI toolboxes, BCI software platforms offer functions that facilitate the development of BCI systems. To do this, they contain support for different signal acquisition hardware, signal processing and visualization routines, and different types of user feedback. They also have complete implementations of different BCI approaches that have been validated in different contexts, contain ample documentation, are maintained consistently to adapt to variations in a device's software interface or operating systems, and provide a whole ecosystem of tools to interact online and offline with other tools or programming languages.

BCI software platforms are usually implemented in low-level programming languages (e.g., C++), compiled into native machine code, and executed without dependencies on commercial libraries. Mature platforms also support economical development and deployment across many laboratories and users. While many general-purpose BCI software platforms have been proposed, e.g., BCI++ [295], xBCI [296], TOBI [297], MindDesktop [298], and UniPA BCI [299], only BCI2000 [300], [301] and OpenViBE [302] have been consistently developed for many years, and have enjoyed widespread adoption across many laboratories.

1) OpenViBE: The OpenViBE software platform has been developed since 2007 [302]. OpenViBE is implemented in C++ and can be compiled on Windows and Linux; binaries are provided for Windows. OpenViBE is based on an architecture that facilitates the integration, expansion, and configuration of modular functionality, while the graphical interface makes OpenViBE easy to use for a wide range of investigators, including engineers, scientists, and clinicians. These two factors make OpenViBE well-suited to supporting the implementation of different BCI approaches.

2) BCI2000: The BCI2000 software platform has been developed since 1998 [300], [301]. BCI2000 is implemented in C++ and can be compiled on Windows and Linux; binaries are provided for Windows. Its implementation is based on a model that can describe any BCI system [300], [303]. In accordance with this model, BCI2000 has four modules that communicate with one another: Source (data acquisition and storage); Signal Processing; User Application; and Operator interface. The modules communicate through a documented network-capable protocol based on TCP/IP. The implementation of BCI2000 is highly optimized, so that it can support even very demanding BCI configurations with good timing characteristics [304].

BCI2000 provides interfaces to Matlab, SIMULINK, LabView, and Python. It has extensive scripting functionality that can be used on the command line using various approaches that include Matlab, Python, through a Telnet interface, or with a Windows dynamic link library (DLL). With these capabilities, BCI2000 can be used to implement applications with a completely custom graphical interface.

The BCI2000 data storage format accommodates variations in the digitized signals (e.g., in number of channels, sampling rate), defines the operating protocol, and includes a record of all events (e.g., feedback to user, device control, artifact detection) that occur during operation. BCI2000 has a roster of existing implementations with primarily technical documentation. These implementations can realize different BCI designs and readily usable methods, and employ commercially available and relatively inexpensive hardware components. BCI2000 is described in detail in a book [301], as well as in multiple book chapters [305], [306], [307], [308], [309], [310], [311] and peer-reviewed articles [300], [304], [312].

C. Considerations for Designing BCI Software

The initial and important choice for designing BCI software is whether to implement it from scratch using a particular programming language, or whether to proceed using the existing toolboxes or BCI software platforms described above in order to reduce the time, complexity, and cost associated with BCI software development [313].

Implementing BCI software from scratch can be appropriate (and is only practical) if the technical demands are relatively low, such as, for example, in a student project that aims to use a consumer BCI headset to create simple visualizations/feedback of a particular brain signal. It may also be the best choice for clinical BCI systems that need to pass regulatory approval and whose functionality is relatively fixed.

Using BCI toolboxes can be appropriate when the technical demands are somewhat more complex but when there is an expectation that BCI software design, data collection, and data analysis are performed by the same person. Example situations are the development of a BCI system to support one research study by an individual graduate student.

Using BCI software platforms is most appropriate when the technical demands are complex (such as the simultaneous use of different hardware), and when there is an expectation that over the course of several years, many different BCI systems are needed to support diverse experimentation executed by different people in potentially different locations.

D. Impact of BCI Software

The ultimate purpose of BCI software is to facilitate the implementation and testing of different BCI approaches. Thus, the success of BCI software in achieving this purpose can be measured by the number of scientific studies that they have supported. The illustration in Fig. S2 indicates the number of publications that have been supported by different BCI software packages. The benefit of the use of BCI software platforms is an improvement in practicality or cost associated with BCI system development [313].

VI. Conclusion and Outlook

This review demonstrates that the field of non-invasive BCI research is active and prolific. The substantial progress in BCI research and the increasing availability of affordable and capable hardware, software, and signal processing/AI components have attracted an increasing number of scientists, engineers, and clinicians to participate in the field. Current research incorporates a broad range of neural signals that can be detected non-invasively, various classes of modern decoding algorithms, and different types of output devices such as robotic arms, motor neuroprosthetics, wheelchairs, or spellers. It also successfully transfers and adapts knowledge from other areas such as cognitive neuroscience (e.g., user training) or AI (e.g., sequence-to-sequence learning). Game- or meditation-based training protocols that target a particular mental state can also be combined with virtual and augmented reality technologies to facilitate a more cooperative communication between brain and machine. Despite these creative approaches, BCI illiteracy persists in some participants, calling for further innovations in neuroscientific protocol design and ML/AI algorithms. Moreover, AI algorithms, computer vision techniques, and increasing computer power continue to push the limits of neural decoding and help adapt various BCI applications to scenarios that better represent daily life.

There is no doubt that the field of non-invasive BCI research has made substantive progress in broadening its scientific and technical approaches and is now a mature research enterprise that has produced BCI demonstrations across the world. As the general public has become aware of this increasingly common accomplishment with healthy individuals, commercial technology companies have also become interested in further developing BCI systems. Indeed, companies such as Neuralink, Synchron and Meta have recently invested in similar technologies that may also allow healthy users and various patient populations to one day augment their lives [314], [315]. Ideally, further placing BCI technology in the public eye in this way may open new opportunities for larger collective innovation across the field. As such, additional resources would be greatly beneficial to address various technical problems that will certainly continue to occupy the attention of the BCI community for years to come. These issues include, but are not limited to the construction of deep learning models that can better extract and decode mental intention signals buried within noisy EEG, the development of robust wireless hardware for easy BCI experimentation in naturalistic settings, practical electrodes that can be used without gel but have a research-like impedance, the generalization of BCIs across subjects or tasks, the appropriate integration of large language models, the elimination of eye-blink or ambulation-based artifacts, and the development of more capable and versatile BCI software.

It is evident that publications and participant numbers used to demonstrate and validate technical advances far outnumber those applying such progress to patient populations. This is somewhat counterintuitive as the non-invasive nature of these systems should help facilitate more widespread clinical translation and acceptance. Such phenomena may be a result of the high level of heterogeneity across individual patients and conditions, relatively small effect sizes for neuromuscular rehabilitation metrics, and/or patient compliance. It may also be due to the lack of robust decoding techniques. In the future, integrating BCI technology with on-demand and closed-loop neuromodulation technologies, such as transcranial focused ultrasound stimulation, transcranial electric stimulation, or transcranial magnetic stimulation could enhance feedback directed at the brain and increase the intended effects while further lowering the effort and burden placed on users. The integration of neuromodulation with brain decoding may help bring BCI technology into the clinic for patients that require further facilitation of communication [27] or better control of a computer/robotic device [26], and expand its applications to patient populations extending beyond the neuromuscular realm, such as those suffering from neuropsychiatric disorders [316].

In summary, the field of non-invasive BCI research has witnessed substantial progress over the past decade. Continued research efforts on neuroscientific paradigms, ML/AI algorithm innovation, and the increased attention on BCI by the scientific community and larger society will further stimulate and facilitate research progress on non-invasive BCI. Future research shall be directed at innovating fundamental BCI technology by leveraging recent technological breakthroughs such as AI, improving individual system components and producing technical demonstrations, and by identifying and solving pressing problems of patients and clinicians.

References

[1] B. He et al., "Brain–computer interfaces," in *Neural Engineering*, B. He, ed., Cham, Switzerland: Springer International Publishing, 2020, pp. 131–183.

[2] J. R. Wolpaw et al., "Brain–computer interfaces for communication and control," *Clin. Neurophysiol.*, vol. 113, no. 6, pp. 767–791, Jun. 2002.

[3] F. Nijboer et al., "A P300-based brain–computer interface for people with amyotrophic lateral sclerosis," *Clin. Neurophysiol.*, vol. 119, no. 8, pp. 1909–1916, Aug. 2008.

[4] E. W. Sellers and E. Donchin, "A P300-based brain–computer interface: Initial tests by ALS patients," *Clin. Neurophysiol.*, vol. 117, no. 3, pp. 538–548, Mar. 2006.

[5] M. J. Vansteensel et al., "Fully implanted brain–computer interface in a locked-in patient with ALS," *New England J. Med.*, vol. 375, no. 21, pp. 2060–2066, Nov. 2016.

[6] B. Jarosiewicz et al., "Virtual typing by people with tetraplegia using a self-calibrating intracortical brain-computer interface," *Sci. Transl. Med.*, vol. 7, no. 313, Nov. 2015, Art. no. 313ra179.

[7] G. R. Müller-Putz et al., "Motor imagery-induced EEG patterns in individuals with spinal cord injury and their impact on brain–computer interface accuracy," *J. Neural Eng.*, vol. 11, no. 3, May 2014, Art. no. 035011.

[8] W. Wang et al., "An electrocorticographic brain interface in an individual with tetraplegia," *PLoS one*, vol. 8, no. 2, Feb. 2013, Art. no. e55344.

[9] E. Buch et al., "Think to move: A neuromagnetic Brain-Computer interface (BCI) system for chronic stroke," *Stroke*, vol. 39, no. 3, pp. 910–917, Mar. 2008.

[10] N. N. Johnson et al., "Combined rTMS and virtual reality brain–computer interface training for motor recovery after stroke," *J. Neural Eng.*, vol. 15, no. 1, Jan. 2018, Art. no. 016009.

[11] F. Pichiorri et al., "Brain–computer interface boosts motor imagery practice during stroke recovery," *Ann. Neurol.*, vol. 77, no. 5, pp. 851–865, 2015.

[12] E. López-Larraz et al., "Control of an ambulatory exoskeleton with a brain–machine interface for spinal cord injury gait rehabilitation," *Front. Neurosci.*, vol. 10, 2016, Art. no. 359. [Online]. Available: https://www.frontiersin.org/articles/10.3389/fnins.2016.00359

[13] B. C. A. Osuagwu et al., "Rehabilitation of hand in subacute tetraplegic patients based on brain computer interface and functional electrical stimulation: A randomised pilot study," *J. Neural Eng.*, vol. 13, no. 6, Oct. 2016, Art. no. 065002.

[14] M. Sebastián-Romagosa et al., "Brain computer interface treatment for motor rehabilitation of upper extremity of stroke patients—A feasibility study," *Front. Neurosci.*, vol. 14, 2020, Art. no. 591435. [Online]. Available: https://www.frontiersin.org/articles/10.3389/fnins.2020.591435

[15] M. Li et al., "The mindgomoku: An online P300 BCI game based on Bayesian deep learning," *Sensors*, vol. 21, no. 5, Jan. 2021, Art. no. 1613.

[16] R. R. Subramanian et al., "Multiplayer online car racing with BCI In VR," in *Proc. 5th Int. Conf. Intell. Comput. Control Syst.*, 2021, pp. 1835–1839.

[17] B. He et al., "Noninvasive brain-computer interfaces based on sensorimotor rhythms," *Proc. IEEE*, vol. 103, no. 6, pp. 907–925, Jun. 2015.

[18] H. Yuan and B. He, "Brain–computer interfaces using sensorimotor rhythms: Current state and future perspectives," *IEEE Trans. Biomed. Eng.*, vol. 61, no. 5, pp. 1425–1435, May 2014.

[19] F. R. Willett et al., "High-performance brain-to-text communication via handwriting," *Nature*, vol. 593, no. 7858, pp. 249–254, May 2021.

[20] A. D. Bigirimana et al., "Emotion-inducing imagery versus motor imagery for a brain-computer interface," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 28, no. 4, pp. 850–859, Apr. 2020.

[21] S. K. Ehrlich et al., "A closed-loop, music-based brain-computer interface for emotion mediation," *PLoS one*, vol. 14, no. 3, Mar. 2019, Art. no. e0213516.

[22] K. W. Scangos et al., "Closed-loop neuromodulation in an individual with treatment-resistant depression," *Nature Med.*, vol. 27, no. 10, pp. 1696–1700, Oct. 2021.

[23] N. A. Grigorev et al., "A BCI-based vibrotactile neurofeedback training improves motor cortical excitability during motor imagery," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 29, pp. 1583–1592, 2021.

[24] Z. Wang et al., "A BCI based visual-haptic neurofeedback training improves cortical activations and classification performance during motor imagery," *J. Neural Eng.*, vol. 16, no. 6, Oct. 2019, Art. no. 066012.

[25] S. N. Flesher et al., "A brain-computer interface that evokes tactile sensations improves robotic arm control," *Science*, vol. 372, no. 6544, pp. 831–836, May 2021.

[26] B. S. Baxter et al., "Sensorimotor rhythm BCI with simultaneous high Definition-Transcranial direct current stimulation alters task performance," *Brain Stimulation*, vol. 9, no. 6, pp. 834–841, Nov. 2016.

[27] J. Kosnoff et al., "Transcranial focused ultrasound to V5 enhances human visual motion brain-computer interface by modulating feature-based attention," *Nature Commun.*, vol. 15, 2024, Art. no. 4382.

[28] Q. Zhang et al., "A prototype closed-loop brain–machine interface for the study and treatment of pain," *Nature Biomed. Eng.*, vol. 7, pp. 533–545, 2023.

[29] X. Zhou et al., "Distinct types of neural reorganization during long-term learning," *J. Neurophysiol.*, vol. 121, no. 4, pp. 1329–1341, Apr. 2019.

[30] A. B. Ajiboye et al., "Restoration of reaching and grasping movements through brain-controlled muscle stimulation in a person with tetraplegia: A proof-of-concept demonstration," *Lancet*, vol. 389, no. 10081, pp. 1821–1830, May 2017.

[31] G. K. Anumanchipalli et al., "Speech synthesis from neural decoding of spoken sentences," *Nature*, vol. 568, no. 7753, pp. 493–498, Apr. 2019.

[32] L. R. Hochberg et al., "Reach and grasp by people with tetraplegia using a neurally controlled robotic arm," *Nature*, vol. 485, no. 7398, pp. 372–375, May 2012.

[33] S. L. Metzger et al., "Generalizable spelling using a speech neuroprosthesis in an individual with severe limb and vocal paralysis," *Nature Commun.*, vol. 13, no. 1, Nov. 2022, Art. no. 6510.

[34] S. L. Metzger et al., "A high-performance neuroprosthesis for speech decoding and avatar control," *Nature*, vol. 620, no. 7976, pp. 1037–1046, Aug. 2023.

[35] N. Even-Chen et al., "Power-saving design opportunities for wireless intracortical brain–computer interfaces," *Nature Biomed. Eng.*, vol. 4, no. 10, pp. 984–996, Oct. 2020.

[36] A. C. Paulk et al., "Large-scale neural recordings with single neuron resolution using Neuropixels probes in human cortex," *Nature Neurosci.*, vol. 25, no. 2, pp. 252–263, Feb. 2022.

[37] D. Liu et al., "Intracranial brain-computer interface spelling using localized visual motion response," *NeuroImage*, vol. 258, Sep. 2022, Art. no. 119363.

[38] E. C. Leuthardt et al., "A brain–computer interface using electrocorticographic signals in humans," *J. Neural Eng.*, vol. 1, no. 2, Jun. 2004, Art. no. 63.

[39] C. S. Mestais et al., "WIMAGINE: Wireless 64-Channel ECoG recording implant for long term clinical applications," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 23, no. 1, pp. 10–21, Jan. 2015.

[40] A. L. Benabid et al., "An exoskeleton controlled by an epidural wireless brain–machine interface in a tetraplegic patient: A proof-of-concept demonstration," *Lancet Neurol.*, vol. 18, no. 12, pp. 1112–1122, Dec. 2019.

[41] H. Lorach et al., "Walking naturally after spinal cord injury using a brain–spine interface," *Nature*, vol. 618, no. 7963, pp. 126–133, Jun. 2023.

[42] T. J. Oxley et al., "Minimally invasive endovascular stent-electrode array for high-fidelity, chronic recordings of cortical neural activity," *Nature Biotechnol.*, vol. 34, no. 3, pp. 320–327, Mar. 2016.

[43] P. Mitchell et al., "Assessment of safety of a fully implanted endovascular brain-computer interface for severe paralysis in 4 patients: The stentrode with thought-controlled digital switch (SWITCH) study," *JAMA Neurol.*, vol. 80, no. 3, pp. 270–278, Mar. 2023.

[44] T. J. Oxley et al., "Motor neuroprosthesis implanted with neurointerventional surgery improves capacity for activities of daily living tasks in severe paralysis: First in-human experience," *J. NeuroInterventional Surg.*, vol. 13, no. 2, pp. 102–108, Feb. 2021.

[45] B. J. Edelman et al., "The COMBO window: A chronic cranial implant for multiscale circuit interrogation in mice," *PLOS Biol.*, vol. 22, no. 6, Jun. 2024, Art. no. e3002664.

[46] C. Rabut et al., "A window to the brain: Ultrasound imaging of human neural activity through a permanent acoustic window," *bioRxiv*, Jun. 2023.

[47] W. S. Griggs et al., "Decoding motor plans using a closed-loop ultrasonic brain–machine interface," *Nature Neurosci.*, vol. 27, pp. 196–207, 2024.

[48] S. L. Norman et al., "Single-trial decoding of movement intentions using functional ultrasound neuroimaging," *Neuron*, vol. 109, no. 9, pp. 1554–1566, May 2021.

[49] R. Ali et al., "Distributed aberration correction techniques based on tomographic sound speed estimates," *IEEE Trans. Ultrasonics, Ferroelect., Freq. Control*, vol. 69, no. 5, pp. 1714–1726, May 2022.

[50] F. Bureau et al., "Three-dimensional ultrasound matrix imaging," *Nature Commun.*, vol. 14, no. 1, Oct. 2023, Art. no. 6793.

[51] C. Guger et al., "How many people are able to control a P300-based brain–computer interface (BCI)?," *Neurosci. Lett.*, vol. 462, no. 1, pp. 94–98, Sep. 2009.

[52] J. R. Stieger et al., "Continuous sensorimotor rhythm based brain computer interface learning in a large population," *Sci. Data*, vol. 8, no. 1, Apr. 2021, Art. no. 98.

[53] C. He et al., "Diversity and suitability of the State-of-the-art wearable and wireless EEG systems review," *IEEE J. Biomed. Health Inform.*, vol. 27, no. 8, pp. 3830–3843, Aug. 2023.

[54] G. Niso et al., "Wireless EEG: A survey of systems and studies," *NeuroImage*, vol. 269, Apr. 2023, Art. no. 119774.

[55] Y. He et al., "A mobile brain-body imaging dataset recorded during treadmill walking with a brain-computer interface," *Sci. Data*, vol. 5, no. 1, pp. 1–10, Apr. 2018.

[56] N. S. J. Jacobsen et al., "A walk in the park? Characterizing gait-related artifacts in mobile EEG recordings," *Eur. J. Neurosci.*, vol. 54, no. 12, pp. 8421–8440, 2021.

[57] G. Bin et al., "VEP-based brain-computer interfaces: Time, frequency, and code modulations [Research Frontier]," *IEEE Comput. Intell. Mag.*, vol. 4, no. 4, pp. 22–26, Nov. 2009.

[58] G. Bin et al., "A high-speed BCI based on code modulation VEP," *J. Neural Eng.*, vol. 8, no. 2, Mar. 2011, Art. no. 025015.

[59] M. Spüler et al., "Online adaptation of a c-VEP brain-computer interface (BCI) based on error-related potentials and unsupervised learning," *PLoS one*, vol. 7, no. 12, Dec. 2012, Art. no. e51077.

[60] X. Chen et al., "High-speed spelling with a noninvasive brain–computer interface," *Proc. Nat. Acad. Sci.*, vol. 112, no. 44, pp. E6058–E6067, Nov. 2015.

[61] X. Chen et al., "A spectrally-dense encoding method for designing a high-speed SSVEP-BCI with 120 stimuli," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 30, pp. 2764–2772, 2022.

[62] Y. Chen et al., "Implementing a calibration-free SSVEP-based BCI system with 160 targets," *J. Neural Eng.*, vol. 18, no. 4, Jul. 2021, Art. no. 046094.

[63] M. Xu et al., "Implementing over 100 command codes for a high-speed hybrid brain-computer interface using concurrent P300 and SSVEP features," *IEEE Trans. Biomed. Eng.*, vol. 67, no. 11, pp. 3073–3082, Nov. 2020.

[64] D. Liu et al., "Doubling the speed of N200 Speller via Dual-Directional motion encoding," *IEEE Trans. Biomed. Eng.*, vol. 68, no. 1, pp. 204–213, Jan. 2021.

[65] D. Forenzo et al., "Integrating simultaneous motor imagery and spatial attention for EEG-BCI control," *IEEE Trans. Biomed. Eng.*, vol. 71, no. 1, pp. 282–294, Jan. 2024.

[66] J. Meng et al., "Three-dimensional brain–computer interface control through simultaneous overt spatial attentional and motor imagery tasks," *IEEE Trans. Biomed. Eng.*, vol. 65, no. 11, pp. 2417–2427, Nov. 2018.

[67] B. J. Edelman et al., "Exploring cognitive flexibility with a noninvasive BCI using simultaneous steady-state visual evoked potentials and sensorimotor rhythms," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 26, no. 5, pp. 936–947, May 2018.

[68] J. Meng et al., "Effects of gaze fixation on the performance of a motor imagery-based brain-computer interface," *Front. Hum. Neurosci.*, vol. 15, 2022, Art. no. 773603. [Online]. Available: https://www.frontiersin.org/articles/10.3389/fnhum.2021.773603

[69] E. Donchin and M. G. H. Coles, "Is the P300 component a manifestation of context updating?," *Behav. Brain Sci.*, vol. 11, no. 3, pp. 357–374, Sep. 1988.

[70] L. A. Farwell and E. Donchin, "Talking off the top of your head: Toward a mental prosthesis utilizing event-related brain potentials," *Electroencephalogr. Clin. Neurophysiol.*, vol. 70, no. 6, pp. 510–523, Dec. 1988.

[71] S. Halder et al., "Brain-controlled applications using dynamic P300 speller matrices," *Artif. Intell. Med.*, vol. 63, no. 1, pp. 7–17, Jan. 2015.

[72] N. J. Santopetro et al., "A reduced P300 prospectively predicts increased depressive severity in adults with clinical depression," *Psychophysiology*, vol. 58, no. 4, 2021, Art. no. e13767.

[73] F. Li et al., "Differentiation of schizophrenia by combining the spatial EEG brain network patterns of rest and task P300," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 27, no. 4, pp. 594–602, Apr. 2019.

[74] S. Lees et al., "Speed of rapid serial visual presentation of pictures, numbers and words affects event-related potential-based detection accuracy," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 28, no. 1, pp. 113–122, Jan. 2020.

[75] Z. Lin et al., "A novel P300 BCI speller based on the triple RSVP paradigm," *Sci. Rep.*, vol. 8, no. 1, Feb. 2018, Art. no. 3350.

[76] H. H. Kornhuber and L. Deecke, "Hirnpotentialänderungen beim Menschen vor und nach Willkürbewegungen, dargestellt mit Magnetbandspeicherung und Rückwärtsanalyse," *Pflügers Arch*, vol. 281, no. 1, 1964, Art. no. 52.

[77] H. Shibasaki and M. Hallett, "What is the Bereitschaftspotential?," *Clin. Neurophysiol.*, vol. 117, no. 11, pp. 2341–2356, Nov. 2006.

[78] N. Jiang et al., "A brain–computer interface for single-trial detection of gait initiation from movement related cortical potentials," *Clin. Neurophysiol.*, vol. 126, no. 1, pp. 154–159, Jan. 2015.

[79] M. Jochumsen et al., "Detection and classification of movement-related cortical potentials associated with task force and speed," *J. Neural Eng.*, vol. 10, no. 5, Aug. 2013, Art. no. 056015.

[80] M. Jochumsen et al., "Detecting and classifying movement-related cortical potentials associated with hand movements in healthy subjects and stroke patients from single-electrode, single-trial EEG," *J. Neural Eng.*, vol. 12, no. 5, Aug. 2015, Art. no. 056013.

[81] D. Liu et al., "EEG-based lower-limb movement onset decoding: Continuous classification and asynchronous detection," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 26, no. 8, pp. 1626–1635, Aug. 2018.

[82] E. López-Larraz et al., "Continuous decoding of movement intention of upper limb self-initiated analytic movements from pre-movement EEG correlates," *J. NeuroEngineering Rehabil.*, vol. 11, no. 1, Nov. 2014, Art. no. 153.

[83] I. K. Niazi et al., "Detection of movement intention from single-trial movement-related cortical potentials," *J. Neural Eng.*, vol. 8, no. 6, Dec. 2011, Art. no. 066009.

[84] A. I. Sburlea et al., "Continuous detection of the self-initiated walking pre-movement state from EEG correlates without session-to-session recalibration," *J. Neural Eng.*, vol. 12, no. 3, Apr. 2015, Art. no. 036007.

[85] Y. Gu et al., "Single-trial discrimination of type and speed of wrist movements from EEG recordings," *Clin. Neurophysiol.*, vol. 120, no. 8, pp. 1596–1600, Aug. 2009.

[86] G. Müller-Putz et al., "Non-invasive brain–computer interfaces for control of grasp neuroprosthesis: The European moregrasp initiative," in *Neuroprosthetics and Brain-Computer Interfaces in Spinal Cord Injury: A Guide For Clinicians and End Users*, G. Müller-Putz and R. Rupp, Eds. Cham, Switzerland: Springer, 2021, pp. 307–352.

[87] G. Müller-Putz and R. Rupp, ed.s., *Neuroprosthetics and Brain-Computer Interfaces in Spinal Cord Injury: A Guide For Clinicians and End Users*. Cham, Switzerland: Springer, pp. 307–352, 2021.

[88] G. Pfurtscheller and A. Aranibar, "Event-related cortical desynchronization detected by power measurements of scalp EEG," *Electroencephalogr. Clin. Neurophysiol.*, vol. 42, no. 6, pp. 817–826, Jun. 1977.

[89] G. Pfurtscheller and F. H. Lopes da Silva, "Event-related EEG/MEG synchronization and desynchronization: Basic principles," *Clin. Neurophysiol.*, vol. 110, no. 11, pp. 1842–1857, Nov. 1999.

[90] G. Pfurtscheller and C. Neuper, "Motor imagery activates primary sensorimotor area in humans," *Neurosci. Lett.*, vol. 239, no. 2, pp. 65–68, Dec. 1997.

[91] B. Graimann et al., "Visualization of significant ERD/ERS patterns in multichannel EEG and ECoG data," *Clin. Neurophysiol.*, vol. 113, no. 1, pp. 43–47, Jan. 2002.

[92] G. Pfurtscheller and C. Neuper, "Motor imagery and direct brain-computer communication," *Proc. IEEE*, vol. 89, no. 7, pp. 1123–1134, Jul. 2001.

[93] G. R. Müller et al., "Event-related beta EEG changes during wrist movements induced by functional electrical stimulation of forearm muscles in man," *Neurosci. Lett.*, vol. 340, no. 2, pp. 143–147, Apr. 2003.

[94] K. Gourab and B. D. Schmit, "Changes in movement-related β-band EEG signals in human spinal cord injury," *Clin. Neurophysiol.*, vol. 121, no. 12, pp. 2017–2023, Dec. 2010.

[95] G. R. Müller-Putz et al., "Event-related beta EEG-changes during passive and attempted foot movements in paraplegic patients," *Brain Res.*, vol. 1137, pp. 84–91, Mar. 2007.

[96] T. Solis-Escalante et al., "Cue-induced beta rebound during withholding of overt and covert foot movement," *Clin. Neurophysiol.*, vol. 123, no. 6, pp. 1182–1190, Jun. 2012.

[97] A. Sosnowska et al., "MRCP as a biomarker of motor action with varying degree of central and peripheral contribution as defined by ultrasound imaging," *J. Neurophysiol.*, vol. 126, no. 1, pp. 249–263, Jul. 2021.

[98] R. Xu et al., "Movement-related cortical potentials in paraplegic patients: Abnormal patterns and considerations for BCI-rehabilitation," *Front. Neuroengineering*, vol. 7, Aug. 2014, Art. no. 35.

[99] C. Neuper et al., "ERD/ERS patterns reflecting sensorimotor activation and deactivation," in *Prog. Brain Res.*, vol. 159, pp. 211–222, 2006.

[100] G. Pfurtscheller et al., "Contrasting behavior of beta event-related synchronization and somatosensory evoked potential after median nerve stimulation during finger manipulation in man," *Neurosci. Lett.*, vol. 323, no. 2, pp. 113–116, Apr. 2002.

[101] D. Borra et al., "Decoding movement kinematics from EEG using an interpretable convolutional neural network," *Comput. Biol. Med.*, vol. 165, Oct. 2023, Art. no. 107323.

[102] M. Seeber et al., "EEG Oscillations are modulated in different Behavior-Related networks during rhythmic finger movements," *J. Neurosci.*, vol. 36, no. 46, pp. 11671–11681, Nov. 2016.

[103] R. J. Kobler et al., "Tuning characteristics of low-frequency EEG to positions and velocities in visuomotor and oculomotor tracking tasks," *Sci. Rep.*, vol. 8, no. 1, Dec. 2018, Art. no. 17713.

[104] R. J. Kobler et al., "Distance- and speed-informed kinematics decoding improves M/EEG based upper-limb movement decoder accuracy," *J. Neural Eng.*, vol. 17, no. 5, Oct. 2020, Art. no. 056027.

[105] V. Mondini et al., "Continuous low-frequency EEG decoding of arm movement for closed-loop, natural control of a robotic arm," *J. Neural Eng.*, vol. 17, no. 4, Aug. 2020, Art. no. 046031.

[106] H. S. Pulferer et al., "Getting off track: Cortical feedback processing network modulated by continuous error signal during target-feedback mismatch," *NeuroImage*, vol. 274, Jul. 2023, Art. no. 120144.

[107] J. R. Wolpaw and D. J. McFarland, "Control of a two-dimensional movement signal by a noninvasive brain-computer interface in humans," *Proc. Nat. Acad. Sci.*, vol. 101, no. 51, pp. 17849–17854, Dec. 2004.

[108] G. R. Müller-Putz et al., "Fast set-up asynchronous brain-switch based on detection of foot motor imagery in 1-channel EEG," *Med. Biol. Eng. Comput.*, vol. 48, no. 3, pp. 229–233, Mar. 2010.

[109] G. Pfurtscheller et al., "Beta rebound after different types of motor imagery in man," *Neurosci Lett*, vol. 378, no. 3, pp. 156–159, Apr. 2005.

[110] H. Yuan et al., "Negative covariation between task-related responses in alpha/beta-band activity and BOLD in human sensorimotor cortex: An EEG and fMRI study of motor imagery and movements," *NeuroImage*, vol. 49, no. 3, pp. 2596–2606, Feb. 2010.

[111] H. Yuan et al., "Differential electrophysiological coupling for positive and negative BOLD responses during unilateral hand movements," *J. Neurosci.*, vol. 31, no. 26, pp. 9585–9593, Jun. 2011.

[112] H. Yuan et al., "Cortical imaging of event-related (de)synchronization during online control of brain-computer interface using minimum-norm estimates in frequency domain," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 16, no. 5, pp. 425–431, Oct. 2008.

[113] H. Yuan et al., "Relationship between speed and EEG activity during imagined and executed hand movements," *J. Neural Eng.*, vol. 7, no. 2, Feb. 2010, Art. no. 026001.

[114] S. Ge et al., "Classification of four-class motor imagery employing single-channel electroencephalography," *PLoS One*, vol. 9, no. 6, Jun. 2014, Art. no. e98019.

[115] B. Lou et al., "Bipolar electrode selection for a motor imagery based brain–computer interface," *J. Neural Eng.*, vol. 5, no. 3, Aug. 2008, Art. no. 342.

[116] D. J. McFarland et al., "Electroencephalographic (EEG) control of three-dimensional movement," *J. Neural Eng.*, vol. 7, no. 3, May 2010, Art. no. 036007.

[117] H. Shan et al., "A novel channel selection method for optimal classification in different motor imagery BCI paradigms," *Biomed. Eng. OnLine*, vol. 14, no. 1, Oct. 2015, Art. no. 93.

[118] J. R. Stieger et al., "Benefits of deep learning classification of continuous noninvasive brain–computer interface control," *J. Neural Eng.*, vol. 18, no. 4, Jun. 2021, Art. no. 046082.

[119] D. Achanccaray and M. Hayashibe, "Decoding hand motor imagery tasks within the same limb from EEG signals using deep learning," *IEEE Trans. Med. Robot. Bionics*, vol. 2, no. 4, pp. 692–699, Nov. 2020.

[120] C. Chen et al., "Neural activities classification of left and right finger gestures during motor execution and motor imagery," *Brain-Comput. Interfaces*, vol. 8, no. 4, pp. 117–127, Oct. 2021.

[121] B. J. Edelman et al., "EEG source imaging enhances the decoding of complex right-hand motor imagery tasks," *IEEE Trans. Biomed. Eng.*, vol. 63, no. 1, pp. 4–14, Jan. 2016.

[122] X. Ma et al., "Multi-channel EEG recording during motor imagery of different joints from the same limb," *Sci. Data*, vol. 7, no. 1, Jun. 2020, Art. no. 191.

[123] P. Ofner et al., "Attempted arm and hand movements can be decoded from Low-Frequency EEG from persons with spinal cord injury," *Sci. Rep.*, vol. 9, no. 1, May 2019, Art. no. 7134.

[124] H. S. Pulferer et al., “Continuous 2D trajectory decoding from attempted movement: Across-session performance in able-bodied and feasibility in a spinal cord injured participant,” *J. Neural Eng.*, vol. 19, no. 3, May 2022, Art. no. 036005.

[125] C. Enzinger et al., “Brain motor system function in a patient with complete spinal cord injury following extensive brain–computer interface training,” *Exp. Brain Res.*, vol. 190, no. 2, pp. 215–223, Sep. 2008.

[126] G. R. Müller-Putz et al., “EEG-based neuroprosthesis control: A step towards clinical practice,” *Neurosci. Lett.*, vol. 382, no. 1, pp. 169–174, Jul. 2005.

[127] G. R. Müller-Putz et al., “Brain–computer interfaces for control of neuroprostheses: From synchronous to asynchronous mode of operation /Brain–Computer Interfaces zur Steuerung von Neuroprothesen: Von der synchronen zur asynchronen Funktionsweise,” *Biomed. Tech.*, vol. 51, no. 2, pp. 57–63, Jul. 2006.

[128] G. Pfurtscheller et al., “Brain oscillations control hand orthosis in a tetraplegic,” *Neurosci. Lett.*, vol. 292, no. 3, pp. 211–214, Oct. 2000.

[129] G. Pfurtscheller et al., “‘Thought’ – control of functional electrical stimulation to restore hand grasp in a patient with tetraplegia,” *Neurosci. Lett.*, vol. 351, no. 1, pp. 33–36, Nov. 2003.

[130] G. Pfurtscheller et al., “Discrimination of motor Imagery-Induced EEG patterns in patients with complete spinal cord injury,” *Comput. Intell. Neurosci.*, vol. 2009, 2009, Art. no. 104180.

[131] E. López-Larraz et al., “Evolution of EEG motor rhythms after spinal cord injury: A longitudinal study,” *PLoS One*, vol. 10, no. 7, Jul. 2015, Art. no. e0131759.

[132] S. Perdikis et al., “The cybathlon BCI race: Successful longitudinal mutual learning with two tetraplegic users,” *PLOS Biol.*, vol. 16, no. 5, May 2018, Art. no. e2003787.

[133] R. M. Yerkes and J. D. Dodson, “The relation of strength of stimulus to rapidity of habit-formation,” *J. Comp. Neurol. Psychol.*, vol. 18, no. 5, pp. 459–482, Nov. 1908.

[134] J. Faller et al., “Regulation of arousal via online neurofeedback improves human performance in a demanding sensory-motor task,” *Proc. Nat. Acad. Sci.*, vol. 116, no. 13, pp. 6482–6490, Mar. 2019.

[135] C. G. Coogan and B. He, “Brain-computer interface control in a virtual reality environment and applications for the Internet of Things,” *IEEE Access*, vol. 6, pp. 10840–10849, 2018.

[136] R. O. Maimon-Mor and T. R. Makin, “Is an artificial limb embodied as a hand? Brain decoding in prosthetic limb users,” *PLoS Biol.*, vol. 18, no. 6, Jun. 2020, Art. no. e3000729.

[137] A. Vourvopoulos et al., “Effects of a brain-computer interface with virtual reality (VR) neurofeedback: A pilot study in chronic stroke patients,” *Front. Hum. Neurosci.*, vol. 13, 2019, Art. no. 460405. [Online]. Available: https://www.frontiersin.org/articles/10.3389/fnhum.2019.00210

[138] J. W. Choi et al., “Improving performance in motor imagery BCI-based control applications via virtually embodied feedback,” *Comput. Biol. Med.*, vol. 127, Dec. 2020, Art. no. 104079.

[139] J. W. Choi et al., “Observing actions through immersive virtual reality enhances motor imagery training,” *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 28, no. 7, pp. 1614–1622, Jul. 2020.

[140] F. Škola et al., “Progressive Training for Motor Imagery Brain-Computer Interfaces Using Gamification and Virtual Reality Embodiment,” *Front. Hum. Neurosci.*, vol. 13, 2019, Art. no. 329. [Online]. Available: https://www.frontiersin.org/articles/10.3389/fnhum.2019.00329

[141] Y. Ke et al., “An online SSVEP-BCI system in an optical see-through augmented reality environment,” *J. Neural Eng.*, vol. 17, no. 1, Feb. 2020, Art. no. 016066.

[142] H. Si-Mohammed et al., “Towards BCI-based interfaces for augmented reality: Feasibility, design and evaluation,” *IEEE Trans. Visual. Comput. Graph.*, vol. 26, no. 3, pp. 1608–1621, Mar. 2020.

[143] R. Zhang et al., “The effect of stimulus number on the recognition accuracy and information transfer rate of SSVEP–BCI in augmented reality,” *J. Neural Eng.*, vol. 19, no. 3, May 2022, Art. no. 036010.

[144] H. Y. Zhang et al., “Stress-induced effects in resting EEG spectra predict the performance of SSVEP-based BCI,” *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 28, no. 8, pp. 1771–1780, Aug. 2020.

[145] K. Cassady et al., “The impact of mind-body awareness training on the early learning of a brain-computer interface,” *Technology*, vol. 02, no. 03, pp. 254–260, Sep. 2014.

[146] X. Jiang et al., “Effects of long-term meditation practices on sensorimotor rhythm-based brain-computer interface learning,” *Front. Neurosci.*, vol. 14, Jan. 2021, Art. no. 584971.

[147] J. R. Stieger et al., “Mindfulness improves brain–computer interface performance by increasing control over neural activity in the Alpha Band,” *Cereb. Cortex*, vol. 31, no. 1, pp. 426–438, Jan. 2021.

[148] R. Scherer et al., “An asynchronously controlled EEG-based virtual keyboard: Improvement of the spelling rate,” *IEEE Trans. Biomed. Eng.*, vol. 51, no. 6, pp. 979–984, Jun. 2004.

[149] R. Scherer et al., “Toward self-paced brain–computer communication: Navigation through virtual worlds,” *IEEE Trans. Biomed. Eng.*, vol. 55, no. 2, pp. 675–682, Feb. 2008.

[150] A. J. Doud et al., “Continuous three-dimensional control of a virtual helicopter using a motor imagery based brain-computer interface,” *Plos One*, vol. 6, no. 10, Oct. 2011, Art. no. e26322.

[151] A. S. Royer et al., “EEG control of a virtual helicopter in 3-dimensional space using intelligent control strategies,” *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 18, no. 6, pp. 581–589, Dec. 2010.

[152] K. LaFleur et al., “Quadcopter control in three-dimensional space using a noninvasive motor imagery-based brain–computer interface,” *J. Neural Eng.*, vol. 10, no. 4, Jun. 2013, Art. no. 046003.

[153] X. Duan et al., “Quadcopter flight control using a non-invasive multimodal brain computer interface,” *Front. Neurorobot.*, vol. 13, 2019, Art. no. 23. [Online]. Available: https://www.frontiersin.org/articles/10.3389/fnbot.2019.00023

[154] T. Kaufmann et al., “Toward brain-computer interface based wheelchair control utilizing tactually-evoked event-related potentials,” *J. NeurEng. Rehabil.*, vol. 11, no. 1, pp. 1–17, Jan. 2014.

[155] L. Tonin et al., “Learning to control a BMI-driven wheelchair for people with severe tetraplegia,” *iScience*, vol. 25, no. 12, Dec. 2022, Art. no. 105418.

[156] X. Chen et al., “Clinical validation of BCI-controlled wheelchairs in subjects with severe spinal cord injury,” *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 30, pp. 579–589, 2022.

[157] A. Cruz et al., “A self-paced BCI with a collaborative controller for highly reliable wheelchair driving: Experimental tests with physically disabled individuals,” *IEEE Trans. Hum.-Mach. Syst.*, vol. 51, no. 2, pp. 109–119, Apr. 2021.

[158] L. Kanungo et al., “Wheelchair automation by a hybrid BCI system using SSVEP and eye blinks,” in *Proc. IEEE Int. Conf. Syst., Man, Cybern.*, 2021, pp. 411–416.

[159] T. J. Bradberry et al., “Reconstructing three-dimensional hand movements from noninvasive electroencephalographic signals,” *J. Neurosci.*, vol. 30, no. 9, pp. 3432–3437, Mar. 2010.

[160] J. H. Kim et al., “Decoding three-dimensional trajectory of executed and imagined arm movements from electroencephalogram signals,” *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 23, no. 5, pp. 867–876, Sep. 2015.

[161] R. J. Kobler et al., “Using machine learning to reveal the population vector from EEG signals,” *J. Neural Eng.*, vol. 17, no. 2, Mar. 2020, Art. no. 026002.

[162] J. Lv et al., “Decoding hand movement velocity from electroencephalogram signals during a drawing task,” *Biomed. Eng. Online*, vol. 9, Oct. 2010, Art. no. 64.

[163] J. Meng et al., “Noninvasive electroencephalogram based control of a robotic arm for reach and grasp tasks,” *Sci. Rep.*, vol. 6, no. 1, Dec. 2016, Art. no. 38565.

[164] B. J. Edelman et al., “Noninvasive neuroimaging enhances continuous neural tracking for robotic device control,” *Sci. Robot.*, vol. 4, no. 31, 2019, Art. no. eaaw6844, doi: 10.1126/scirobotics.aaw6844.

[165] D. Suma et al., “Spatial-temporal aspects of continuous EEG-based neurorobotic control,” *J. Neural Eng.*, vol. 17, no. 6, Nov. 2020, Art. no. 066006.

[166] J. Pereira et al., “Online detection of movement during natural and self-initiated reach-and-grasp actions from EEG signals,” *J. Neural Eng.*, vol. 18, no. 4, Jul. 2021, Art. no. 046095.

[167] R. J. Kobler et al., “Corneo-retinal-dipole and eyelid-related eye artifacts can be corrected offline and online in electroencephalographic and magnetoencephalographic signals,” *NeuroImage*, vol. 218, Sep. 2020, Art. no. 117000.

[168] L. Paninski et al., “Spatiotemporal tuning of motor cortical neurons for hand position and velocity,” *J. Neurophysiol.*, vol. 91, no. 1, pp. 515–532, Jan. 2004.

[169] J. Hammer et al., “Predominance of movement speed over direction in neuronal population signals of motor cortex: Intracranial EEG data and a simple explanatory model,” *Cereb Cortex*, vol. 26, no. 6, pp. 2863–2881, Jun. 2016.

[170] R. Kobler et al., “Simultaneous decoding of velocity and speed during executed and observed tracking movements: An MEG study,” in *Proc. 8th Graz Brain-Comput. Interface Conf.*, 2019, pp. 100–105, doi: 10.3217/978-3-85125-682-6-19.

[171] H. Pulferer et al., "Learning effects in 2D trajectory inference from low-frequency EEG signals over multiple feedback sessions," in *Proc. Annu. Meet. Austrian Soc. Biomed. Eng.*, 2021, pp. 83–86 doi: 10.3217/978-3-85125-826-4-22.
[172] I. Iturrate et al., "Human EEG reveals distinct neural correlates of power and precision grasping types," *NeuroImage*, vol. 181, pp. 635–644, Nov. 2018.
[173] G. R. Müller-Putz et al., "From classic motor imagery to complex movement intention decoding: The noninvasive Graz-BCI approach," *Prog. Brain Res.*, vol. 228, pp. 39–70, 2016.
[174] P. Ofner et al., "Upper limb movements can be decoded from the time-domain of low-frequency EEG," *PLoS One*, vol. 12, no. 8, Aug. 2017, Art. no. e0182578.
[175] A. I. Sburlea et al., "Disentangling human grasping type from the object's intrinsic properties using low-frequency EEG signals," *Neuroimage: Rep.*, vol. 1, no. 2, Jun. 2021, Art. no. 100012.
[176] A. Schwarz et al., "Decoding natural reach-and-grasp actions from human EEG," *J. Neural Eng.*, vol. 15, no. 1, Dec. 2017, Art. no. 016005.
[177] A. Schwarz et al., "Unimanual and bimanual reach-and-grasp actions can be decoded from human EEG," *IEEE Trans. Biomed. Eng.*, vol. 67, no. 6, pp. 1684–1695, Jun. 2020.
[178] B. Xu et al., "Decoding hand movement types and kinematic information from electroencephalogram," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 29, pp. 1744–1755, 2021.
[179] B. Xu et al., "Decoding Different Reach-and-Grasp Movements Using Noninvasive Electroencephalogram," *Front. Neurosci.*, vol. 15, 2021, Art. no. 684547. [Online]. Available: https://www.frontiersin.org/articles/10.3389/fnins.2021.684547
[180] A. Schwarz et al., "Decoding hand movements from human EEG to control a robotic arm in a simulation environment," *J. Neural Eng.*, vol. 17, no. 3, Jun. 2020, Art. no. 036010.
[181] J. H. Cho et al., "NeuroGrasp: Real-time EEG classification of high-level motor imagery tasks using a dual-stage deep learning framework," *IEEE Trans. Cybern.*, vol. 52, no. 12, pp. 13279–13292, Dec. 2022.
[182] G. Pfurtscheller et al., "The hybrid BCI," *Front. Neurosci.*, vol. 4, 2010, Art. no. 1283. [Online]. Available: https://www.frontiersin.org/articles/10.3389/fnpro.2010.00003
[183] L. Cao et al., "A brain-actuated robotic arm system using non-invasive hybrid brain–computer interface and shared control strategy," *J. Neural Eng.*, vol. 18, no. 4, May 2021, Art. no. 046045.
[184] Y. J. Kim et al., "Vision-aided brain–machine interface training system for robotic arm control and clinical application on two patients with cervical spinal cord injury," *BioMed Eng OnLine*, vol. 18, no. 1, Feb. 2019, Art. no. 14.
[185] Y. Xu et al., "Shared control of a robotic arm using non-invasive brain–computer interface and computer vision guidance," *Robot. Auton. Syst.*, vol. 115, pp. 121–129, May 2019.
[186] Y. Zhou et al., "Shared three-dimensional robotic arm control based on asynchronous BCI and computer vision," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 31, pp. 3163–3175, 2023.
[187] G. Müller-Putz et al., "Towards noninvasive hybrid Brain–Computer interfaces: Framework, practice, clinical application, and beyond," *Proc. IEEE*, vol. 103, no. 6, pp. 926–943, Jun. 2015.
[188] X. Chen et al., "Combination of augmented reality based brain- computer interface and computer vision for high-level control of a robotic arm," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 28, no. 12, pp. 3140–3147, Dec. 2020.
[189] J. M. Catalán et al., "Hybrid brain/neural interface and autonomous vision-guided whole-arm exoskeleton control to perform activities of daily living (ADLs)," *J. NeuroEngineering Rehabil.*, vol. 20, no. 1, May 2023, Art. no. 61.
[190] W. Fei et al., "Effects of cognitive distraction on upper limb movement decoding from EEG signals," *IEEE Trans. Biomed. Eng.*, vol. 70, no. 1, pp. 166–174, Jan. 2023.
[191] R. Ortner et al., "An SSVEP BCI to control a hand orthosis for persons with tetraplegia," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 19, no. 1, pp. 1–5, Feb. 2011.
[192] P. D. Lillo et al., "BCI-controlled assistive manipulator: Developed architecture and experimental results," *IEEE Trans. Cogn. Devlop. Syst.*, vol. 13, no. 1, pp. 91–104, Mar. 2021.
[193] C. Yang et al., "Mind control of a robotic arm with visual fusion technology," *IEEE Trans. Ind. Informat.*, vol. 14, no. 9, pp. 3822–3830, Sep. 2018.
[194] R. Mane et al., "BCI for stroke rehabilitation: Motor and beyond," *J. Neural Eng.*, vol. 17, no. 4, Aug. 2020, Art. no. 041001.
[195] S. Kundu and S. Ari, "Brain-computer interface speller system for alternative communication: A review," *IRBM*, vol. 43, no. 4, pp. 317–324, Aug. 2022.
[196] R. Abiri et al., "A usability study of low-cost wireless Brain-Computer interface for cursor control using online linear model," *IEEE Trans. Hum.-Mach. Syst.*, vol. 50, no. 4, pp. 287–297, Aug. 2020.
[197] R. Na et al., "A wearable low-power collaborative sensing system for high-quality SSVEP-BCI signal acquisition," *IEEE Internet Things J.*, vol. 9, no. 10, pp. 7273–7285, May 2022.
[198] M. Angrick et al., "Online speech synthesis using a chronically implanted brain–computer interface in an individual with ALS," *Sci. Rep.*, vol. 14, no. 1, Apr. 2024, Art. no. 9617.
[199] T. Y. Kim et al., "Design and Implementation of BCI-based intelligent upper limb rehabilitation robot system," *ACM Trans. Internet Technol.*, vol. 21, no. 3, pp. 1–17, Jun. 2021.
[200] A. Vourvopoulos et al., "Efficacy and brain imaging correlates of an immersive motor imagery BCI-Driven VR system for upper limb motor rehabilitation: A clinical case report," *Front. Hum. Neurosci.*, vol. 13, 2019, Art. no. 244, doi: 10.3389/fnhum.2019.00244.
[201] A. Fusco et al., "Virtual reality and lower limb rehabilitation: Effects on motor and cognitive outcome—A crossover pilot study," *J. Clin. Med.*, vol. 11, no. 9, Apr. 2022, Art. no. 2300.
[202] Y. Miao et al., "BCI-based rehabilitation on the stroke in sequela stage," *Neural Plast.*, vol. 2020, no. 1, 2020, Art. no. 8882764.
[203] K. P. Thomas et al., "Enhancement of attention and cognitive skills using EEG based neurofeedback game," in *Proc. 6th Int. IEEE/EMBS Conf. Neural Eng.*, Nov. 2013, pp. 21–24.
[204] H. Zeng et al., "EMCI: A novel EEG-based mental workload assessment index of mild cognitive impairment," *IEEE Trans. Biomed. Circuits Syst.*, vol. 16, no. 5, pp. 902–914, Oct. 2022.
[205] V. V. Fateeva et al., "Rehabilitation of patients with Post-Stroke cognitive impairments using a P300-based brain–computer interface: Results of a randomized controlled trial," *Neurosci. Behav. Physiol.*, vol. 54, no. 4, pp. 575–580, May 2024.
[206] A. Nagarajan et al., "Transferring a deep learning model from healthy subjects to stroke patients in a motor imagery brain–computer interface," *J. Neural Eng.*, vol. 21, no. 1, Jan. 2024, Art. no. 016007.
[207] S. Zhang et al., "Learning EEG representations with weighted convolutional siamese network: A large multi-session post-stroke rehabilitation study," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 30, pp. 2824–2833, 2022.
[208] H. W. Ng and C. Guan, "Subject-independent meta-learning framework towards optimal training of EEG-based classifiers," *Neural Netw.*, vol. 172, Apr. 2024, Art. no. 106108.
[209] S. Dong et al., "A survey on deep learning and its applications," *Comput. Sci. Rev.*, vol. 40, May 2021, Art. no. 100379.
[210] H. Cecotti and A. Graser, "Convolutional neural networks for P300 detection with application to brain-computer interfaces," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 33, no. 3, pp. 433–445, Mar. 2011.
[211] S. Sakhavi et al., "Learning temporal information for brain-computer interface using convolutional neural networks," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 29, no. 11, pp. 5619–5629, Nov. 2018.
[212] R. T. Schirrmeister et al., "Deep learning with convolutional neural networks for EEG decoding and visualization," *Hum. Brain Mapping*, vol. 38, no. 11, pp. 5391–5420, 2017.
[213] K. K. Ang et al., "Filter bank common spatial pattern (FBCSP) algorithm using online adaptive and semi-supervised learning," in *Proc. Int. Joint Conf. Neural Netw.*, San Jose, CA, USA, pp. 392–396, Jul. 2011.
[214] V. J. Lawhern et al., "EEGNet: A compact convolutional neural network for EEG-based brain–computer interfaces," *J. Neural Eng.*, vol. 15, no. 5, Oct. 2018, Art. no. 056013.
[215] R. Mane et al., "FBCNet: A multi-view convolutional neural network for Brain-Computer interface," 2021, *arXiv:2104.01233*.
[216] P. Thuwajit et al., "EEGWaveNet: Multiscale CNN-based spatiotemporal feature extraction for EEG seizure detection," *IEEE Trans. Ind. Informat.*, vol. 18, no. 8, pp. 5547–5557, Aug. 2022.
[217] Y. Hou et al., "GCNs-Net: A graph convolutional neural network approach for decoding time-resolved EEG motor imagery signals," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 35, no. 6, pp. 7312–7323, Jun. 2024.
[218] B. Sun et al., "Adaptive spatiotemporal graph convolutional networks for motor imagery classification," *IEEE Signal Process. Lett.*, vol. 28, pp. 219–223, 2021.

[219] R. Lu et al., "SAST-GCN: Segmentation adaptive spatial temporal-graph convolutional network for P3-based video target detection," *Front. Neurosci.*, vol. 16, Jun. 2022, Art. no. 913027.

[220] Y. Ding et al., "LGGNet: Learning from local-global-graph representations for brain–computer interface," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 35, no. 7, pp. 9773–9786, Jul. 2024.

[221] D. Forenzo et al., "Continuous tracking using deep learning-based decoding for non-invasive brain-computer interface," *PNAS Nexus*, vol. 3, no. 4, 2024, Art. no. 145.

[222] V. S. Lalapura et al., "Recurrent neural networks for edge intelligence: A survey," *ACM Comput. Surv.*, vol. 54, no. 4, pp. 1–38, May 2021.

[223] S. Tortora et al., "Deep learning-based BCI for gait decoding from EEG with LSTM recurrent neural network," *J. Neural Eng.*, vol. 17, no. 4, Jul. 2020, Art. no. 046011.

[224] W. Tao et al., "EEG-based emotion recognition via Channel-Wise attention and self attention," *IEEE Trans. Affect. Comput.*, vol. 14, no. 1, pp. 382–393, Jan.-Mar. 2023.

[225] Z. Lan et al., "MACRO: Multi-attention convolutional recurrent model for subject-independent ERP detection," *IEEE Signal Process. Lett.*, vol. 28, pp. 1505–1509, 2021.

[226] Z. Gao et al., "Attention-based parallel multiscale convolutional neural network for visual evoked potentials EEG classification," *IEEE J. Biomed. Health Inform.*, vol. 25, no. 8, pp. 2887–2894, Aug. 2021.

[227] J. Xie et al., "A transformer-based approach combining deep learning network and spatial-temporal information for raw EEG classification," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 30, pp. 2126–2136, 2022.

[228] Y. Ma et al., "An N400 identification method based on the combination of Soft-DTW and transformer," *Front. Comput. Neurosci.*, vol. 17, Feb. 2023, Art. no. 1120566.

[229] J. Chen et al., "A transformer-based deep neural network model for SSVEP classification," *Neural Netw.*, vol. 164, pp. 521–534, Jul. 2023.

[230] H. Daoud and M. A. Bayoumi, "Efficient epileptic seizure prediction based on deep learning," *IEEE Trans. Biomed. Circuits Syst.*, vol. 13, no. 5, pp. 804–813, Oct. 2019.

[231] Z. Gao et al., "A deep learning method for improving the classification accuracy of SSMVEP-Based BCI," *IEEE Trans. Circuits Syst. II: Exp. Briefs*, vol. 67, no. 12, pp. 3447–3451, Dec. 2020.

[232] Y. Pan et al., "An efficient CNN-LSTM network with spectral normalization and label smoothing technologies for SSVEP frequency recognition," *J. Neural Eng.*, vol. 19, no. 5, Sep. 2022, Art. no. 056014.

[233] Y. Song et al., "EEG conformer: Convolutional transformer for EEG decoding and visualization," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 31, pp. 710–719, 2023.

[234] K. Weiss et al., "A survey of transfer learning," *J. Big Data*, vol. 3, no. 1,pp. 1–40, May 2016.

[235] Z. Wan et al., "A review on transfer learning in EEG signal analysis," *Neurocomputing*, vol. 421, pp. 1–14, Jan. 2021.

[236] F. Fahimi et al., "Inter-subject transfer learning with an end-to-end deep convolutional neural network for EEG-based BCI," *J. Neural Eng.*, vol. 16, no. 2, Jan. 2019, Art. no. 026007.

[237] K. Zhang et al., "Adaptive transfer learning for EEG motor imagery classification with deep convolutional neural network," *Neural Netw.*, vol. 136, pp. 1–10, Apr. 2021.

[238] S. Zhang et al., "Online adaptive CNN: A Session-to-session transfer learning approach for non-stationary EEG," in *Proc. IEEE Symp. Ser. Comput. Intell. (SSCI)*, Singapore, Singapore, Dec. 2022, pp. 164–170.

[239] S. Pérez-Velasco et al., "EEGSym: Overcoming Inter-Subject variability in motor imagery based BCIs with deep learning," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 30, pp. 1766–1775, 2022.

[240] P. R. A. S. Bassi et al., "Transfer learning and SpecAugment applied to SSVEP based BCI classification," *Biomed. Signal Process. Control*, vol. 67, May 2021, Art. no. 102542.

[241] X. Xiao et al., "Enhancement for P300-speller classification using multi-window discriminative canonical pattern matching," *J. Neural Eng.*, vol. 18, no. 4, Jun. 2021, Art. no. 046079.

[242] S. Raghu et al., "EEG based multi-class seizure type classification using convolutional neural network and transfer learning," *Neural Netw.*, vol. 124, pp. 202–212, Apr. 2020.

[243] Z. Wang et al., "Characterizing and avoiding negative transfer," in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit.*,Long Beach, CA, USA, Jun. 2019, pp. 11285–11294.

[244] H. Chen et al., "MS-MDA: Multisource marginal distribution adaptation for cross-subject and cross-session EEG emotion recognition," *Front. Neurosci.*, vol. 15, Dec. 2021, Art. no. 778488.

[245] M. Jimenez-Guarneros and P. Gomez-Gil, "Custom domain adaptation: A new method for cross-subject, EEG-based cognitive load recognition," *IEEE Signal Process. Lett.*, vol. 27, pp. 750–754, 2020.

[246] J. Li et al., "Domain adaptation for EEG emotion recognition based on latent representation similarity," *IEEE Trans. Cogn. Devlop. Syst.*, vol. 12, no. 2, pp. 344–353, Jun. 2020.

[247] Y. Li et al., "A Bi-hemisphere domain adversarial neural network model for EEG emotion recognition," *IEEE Trans. Affect. Comput.*, vol. 12, no. 2, pp. 494–504, Apr.–Jun. 2021.

[248] D. Liu et al., "Multi-source transfer learning for EEG classification based on domain adversarial neural network," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 31, pp. 218–228, 2023.

[249] F. Fahimi et al., "Generative adversarial networks-based data augmentation for brain–computer interface," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 32, no. 9, pp. 4039–4051, Sep. 2021.

[250] Z. Ni et al., "Improving cross-state and cross-subject visual ERP-based BCI with temporal modeling and adversarial training," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 30, pp. 369–379, 2022.

[251] P. Sawangjai et al., "EEGANet: Removal of ocular artifacts from the EEG signal using generative adversarial networks," *IEEE J. Biomed. Health Inform.*, vol. 26, no. 10, pp. 4913–4924, Oct. 2022.

[252] J. H. Jeong et al., "2020 International brain–computer interface competition: A review," *Front. Hum. Neurosci.*, vol. 16, Jul. 2022, Art. no. 898300.

[253] E. Lashgari et al., "Data augmentation for deep-learning-based electroencephalography," *J. Neurosci. Methods*, vol. 346, Dec. 2020, Art. no. 108885.

[254] E. S. Salama et al., "EEG-based emotion recognition using 3D convolutional neural networks," *Int. J. Adv. Comput. Sci. Appl.*, vol. 9, no. 8, 2018, Art. no. 8.

[255] J. Fan et al., "EEG data augmentation: Towards class imbalance problem in sleep staging tasks," *J. Neural Eng.*, vol. 17, no. 5, Oct. 2020, Art. no. 056017.

[256] C. Rommel et al., "Data augmentation for learning predictive models on EEG: A systematic comparison," *J. Neural Eng.*, vol. 19, no. 6, Nov. 2022, Art. no. 066020.

[257] S. An et al., "Dual attention relation network with fine-tuning for few-shot EEG motor imagery classification," *IEEE Trans. Neural Netw. Learn. Syst.*, pp. 1–15, 2023, doi: 10.1109/TNNLS.2023.3287181.

[258] Y. Chu et al., "Decoding multiclass motor imagery EEG from the same upper limb by combining Riemannian geometry features and partial least squares regression," *J. Neural Eng.*, vol. 17, no. 4, Aug. 2020, Art. no. 046029.

[259] A. Barachant et al., "Multiclass brain–computer interface classification by Riemannian geometry," *IEEE Trans. Biomed. Eng.*, vol. 59, no. 4, pp. 920–928, Apr. 2012.

[260] B. H. Kim et al., "A discriminative SPD feature learning approach on Riemannian manifolds for EEG classification," *Pattern Recognit.*, vol. 143, Nov. 2023, Art. no. 109751.

[261] Y.-T. Pan et al., "MAtt: A manifold attention network for EEG decoding," *Adv. Neural Inf. Process. Syst.*, vol. 35, pp. 31116–31129, Dec. 2022.

[262] R. Gunawardena et al., "Kernel-based nonlinear manifold learning for EEG-based functional connectivity analysis and channel selection with application to Alzheimer's disease," *Neuroscience*, vol. 523, pp. 140–156, Jul. 2023.

[263] X. Li et al., "EEG classification based on Grassmann manifold and matrix recovery," *Biomed. Signal Process. Control*, vol. 87, Jan. 2024, Art. no. 105491.

[264] J. Fan et al., "Unsupervised domain adaptation by statistics alignment for deep sleep staging networks," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 30, pp. 205–216, 2022.

[265] R. Zhao et al., "Unsupervised sleep staging system based on domain adaptation," *Biomed. Signal Process. Control*, vol. 69, Aug. 2021, Art. no. 102937.

[266] E. Eldele et al., "Self-supervised contrastive representation learning for semi-supervised time-series classification," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 45, no. 12, pp. 15604–15618, Dec. 2023.

[267] H. Wang et al., "EEG-based motor imagery recognition framework via multisubject dynamic transfer and iterative self-training," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 35, no. 8, pp. 10698–10712, Aug. 2024.

[268] J. Ye et al., "*CoSleep* : A multi-view representation learning framework for self-supervised learning of sleep stage classification," *IEEE Signal Process. Lett.*, vol. 29, pp. 189–193, 2022.

[269] G. Zhang et al., "PARSE: Pairwise alignment of representations in Semi-Supervised EEG learning for emotion recognition," *IEEE Trans. Affect. Comput.*, vol. 13, no. 4, pp. 2185–2200, Oct.–Dec. 2022.
[270] B. He et al., "Electrophysiological mapping and source imaging," in *Neural Engineering*, B. He, Ed., Cham, Switzerland: Springer, 2020, pp. 379–413.
[271] B. He et al., "Electrophysiological source imaging: A noninvasive window to brain dynamics," *Annu. Rev. Biomed. Eng.*, vol. 20, no. 1, pp. 171–196, Jun. 2018.
[272] A. Sohrabpour et al., "Noninvasive electromagnetic source imaging of spatiotemporally distributed epileptogenic brain sources," *Nature Commun.*, vol. 11, no. 1, Apr. 2020, Art. no. 1946.
[273] B. Kamousi et al., "Classification of motor imagery tasks for brain-computer interface applications by means of two equivalent dipoles analysis," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 13, no. 2, pp. 166–171, Jun. 2005.
[274] L. Qin et al., "Motor imagery classification by means of source analysis for brain–computer interface applications," *J. Neural Eng.*, vol. 1, no. 3, Aug. 2004, Art. no. 135.
[275] R. Sun et al., "Deep neural networks constrained by neural mass models improve electrophysiological source imaging of spatiotemporal brain dynamics," *Proc. Nat. Acad. Sci.*, vol. 119, no. 31, Aug. 2022, Art. no. e2201128119.
[276] Y. Hou et al., "A novel approach of decoding EEG four-class motor imagery tasks via scout ESI and CNN," *J. Neural Eng.*, vol. 17, no. 1, Feb. 2020, Art. no. 016048.
[277] J. Wolpaw and E. W. Wolpaw, *Brain-Computer Interfaces: Principles and Practice*. USA: Oxford Univ. Press, 2012.
[278] D. H. Brainard, "The psychophysics toolbox," *Spatial Vis*, vol. 10, no. 4, pp. 433–436, 1997.
[279] A. Delorme and S. Makeig, "EEGLAB: An open source toolbox for analysis of single-trial EEG dynamics including independent component analysis," *J. Neurosci. Methods*, vol. 134, no. 1, pp. 9–21, Mar. 2004.
[280] C. Vidaurre et al., "BioSig: The free and open source software library for biomedical signal processing," *Comput. Intell. Neurosci.*, vol. 2011, 2011, Art. no. 935364.
[281] F. Tadel et al., "Brainstorm: A user-friendly application for MEG/EEG analysis," *Comput. Intell. Neurosci.*, vol. 2011, Apr. 2011, Art. no. e879716.
[282] R. Oostenveld et al., "FieldTrip: Open source software for advanced analysis of MEG, EEG, and invasive electrophysiological data," *Comput. Intell. Neurosci.*, vol. 2011, 2011, Art. no. e156869.
[283] A. Gramfort et al., "MNE software for processing MEG and EEG data," *NeuroImage*, vol. 86, pp. 446–460, Feb. 2014.
[284] "g.BCIsys - g.tec's brain-computer interface research environment." [Online]. Available: http://www.gtec.at/Products/Complete-Solutions/g.BCIsys-Specs-Features
[285] A. D. Degenhart et al., "Craniux: A LabVIEW-based modular software framework for brain-machine interface research," *Comput. Intell. Neurosci.*, vol. 2011, Apr. 2011, Art. no. e363565.
[286] T. Memmott et al., "BciPy: Brain–computer interface software in Python," *Brain-Comput. Interfaces*, vol. 8, no. 4, pp. 137–153, Oct. 2021.
[287] L. Booth et al., "PyBCI: A python package for brain-computer interface (BCI) design," *J. Open Source Softw.*, vol. 8, no. 92, p. 5706, Dec. 2023, doi: 10.21105/joss.05706.
[288] E. Santamaría-Vázquez et al., "MEDUSA©: A novel Python-based software ecosystem to accelerate brain-computer interface and cognitive neuroscience research," *Comput. Methods Programs Biomed.*, vol. 230, Mar. 2023, Art. no. 107357.
[289] "lab streaming layer (lsl): System for unified collection of measurement time series in research experiments," 2018. [Online]. Available: https://github.com/sccn/labstreaminglayer
[290] M. M. Krell et al., "pySPACE—A signal processing and classification environment in Python," *Front. Neuroinform.*, vol. 7, 2013, Art. no. 40, doi: 10.3389/fninf.2013.00040.
[291] J. Peirce et al., "PsychoPy2: Experiments in behavior made easy," *Behav. Res.*, vol. 51, no. 1, pp. 195–203, Feb. 2019.
[292] B. Venthur and B. Blankertz, "A Platform-Independent Open-Source feedback framework for BCI systems," in *Proc. 4th Int. Brain-Comput. Interface Workshop Training Course*, vol. 2008, 2008, pp. 385–389.
[293] B. Venthur and B. Blankertz, "Mushu, a free- and open source BCI signal acquisition, written in Python," in *Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, San Diego, CA, USA, Aug. 2012, pp. 1786–1788.
[294] B. Venthur et al., "Wyrm: A brain-computer interface toolbox in python," *Neuroinformatics*, vol. 13, no. 4, pp. 471–486, Oct. 2015.
[295] P. Perego et al., "BCI++: A new framework for brain computer interface application," in *Proc. Softw. Eng. Data Eng.*, 2009, pp. 37–41.
[296] I. P. Susila et al., "xBCI: A generic platform for development of an online BCI system," *IEEJ Trans. Elect. Electron. Eng.*, vol. 5, no. 4, pp. 467–473, 2010.
[297] C. Breitwieser et al., "Proposing a standardized protocol for raw biosignal transmission," *IEEE Trans. Biomed. Eng.*, vol. 59, no. 3, pp. 852–859, Mar. 2012.
[298] O. Ossmy et al., "MindDesktop: A general purpose brain computer interface," 2017, *arXiv:1705.07490*.
[299] S. Tramonte et al., "UnipaBCI a novel general software framework for brain computer interface," in *Complex, Intelligent, and Software Intensive Systems*, L. Barolli and O. Terzo, Eds. Cham, Switzerland: Springer, 2018, pp. 336–348.
[300] G. Schalk et al., "BCI2000: A general-purpose brain-computer interface (BCI) system," *IEEE Trans. Biomed. Eng.*, vol. 51, no. 6, pp. 1034–1043, Jun. 2004.
[301] G. Schalk and J. Mellinger, *A Practical Guide to Brain–Computer Interfacing With BCI2000*. London, U.K.: Springer, 2010.
[302] Y. Renard et al., "OpenViBE: An open-source software platform to design, test, and use brain–computer interfaces in real and virtual environments," *Presence*, vol. 19, no. 1, pp. 35–53, Feb. 2010.
[303] S. G. Mason and G. E. Birch, "A general framework for brain-computer interface design," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 11, no. 1, pp. 70–85, Mar. 2003.
[304] J. A. Wilson et al., "A procedure for measuring latencies in brain-computer interfaces," *IEEE Trans Biomed Eng*, vol. 57, no. 7, pp. 1785–1797, Jul. 2010.
[305] B. Z. Allison et al., ed.s., "Towards practical brain-computer interfaces: Bridging the gap from research to real-world applications," in *Biological and Medical Physics, Biomedical Engineering*. Berlin, Germany: Springer, 2013.
[306] C. Brunner et al., "BCI software platforms," in *Towards Practical Brain-Computer Interfaces: Bridging the Gap from Research to Real-World Applications*, B. Z. Allison, S. Dunne, R. Leeb, J. Del R. Millán, and A. Nijholt, Eds. Berlin, Germany: Springer, 2013, pp. 303–331.
[307] P. Brunner and G. Schalk, "BCI Software," in *Brain–Computer Interfaces Handbook*. Boca Raton, FL, USA: CRC Press, 2018.
[308] J. Mellinger and G. Schalk, "BCI2000: A general-purpose software platform for BCI," in *Toward Brain-Computer Interfacing*, G. Dornhege, J. Del R. Millán, T. Hinterberger, D. J. McFarland, and K. R. Müller, Eds. Cambridge, MA, USA: The MIT Press, 2007, pp. 359–368.
[309] J. Mellinger and G. Schalk, "Using BCI2000 in BCI research," in *Brain-Computer Interfaces: Revolutionizing Human-Computer Interaction*, B. Graimann, G. Pfurtscheller, and B. Allison, Eds. Berlin, Germany: Springer, 2010, pp. 259–279.
[310] A. Wilson and G. Schalk, "Using BCI2000 for HCI-centered BCI research," in *Brain-Computer Interfaces: Applying our Minds to Human-Computer Interaction*, D. S. Tan and A. Nijholt, Eds. London, U.K.: Springer, pp. 261–274, 2010.
[311] J. A. Wilson et al., "BCI Hardware and Software," in *Brain–Computer Interfaces: Principles and Practice*, J. Wolpaw and E. W. Wolpaw, Eds. London, U.K.: Oxford Univ. Press, Jan. 2012, pp. 164–188.
[312] J. A. Wilson et al., "Using an EEG-based brain-computer interface for virtual cursor movement with BCI2000," *J. Vis. Exp.*, vol. 29, Jul. 2009, Art. no. 1319.
[313] G. Schalk et al., "Translation of neurotechnologies," *Nature Rev. Bioeng.*, vol. 2, pp. 637–652, May 2024.
[314] S. Abdelghafar et al., "Metaverse for brain computer interface: Towards new and improved applications," in *The Future of Metaverse in the Virtual Era and Physical World*, (Studies in Big Data series), A. E. Hassanien, A. Darwish, and M. Torky, Eds. Cham, Switzerland: Springer, 2023, pp. 43–58.
[315] E. Musk, "An integrated brain-machine interface platform with thousands of channels," *J. Med. Internet Res.*, vol. 21, no. 10, Oct. 2019, Art. no. e16194.
[316] M. M. Shanechi, "Brain–machine interfaces from motor to mood," *Nature Neurosci.*, vol. 22, no. 10, pp. 1554–1564, 2019.
[317] D. Hajhassani et al., "An automatic riemannian artifact rejection method for P300-based BCIs," in *Proc. Eur. Signal Process. Conf.*, 2024.
[318] R. Bhatia and M. Congedo, "Procrustes problems in Riemannian manifolds of positive definite matrices," *Linear Algebra Appl.*, vol. 563, pp. 440–445, 2019.
[319] M. Congedo et al., "The Riemannian minimum distance to means field classifier," in *Proc. 8th Int. Brain-Computer Interface Conf.*, 2019.