A Systematic Review of Bimanual Motor Coordination in Brain–Computer Interface

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***Abstract*— Advancements in neuroscience and artificial intelligence are propelling rapid progress in brain–computer interfaces (BCIs). These developments hold significant potential for decoding motion intentions from brain signals, enabling direct control commands without reliance on conventional neural pathways. Growing interest exists in decoding bimanual motor tasks, crucial for activities of daily living. This stems from the need to restore motor function, especially in individuals with deficits. This review aims to summarize neurological advancements in bimanual BCIs, encompassing neuroimaging techniques, experimental paradigms, and analysis algorithms. Thirty-six articles were reviewed, adhering to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines. The literature search result revealed diverse experimental paradigms, protocols, and research directions, including enhancing the decoding accuracy, advancing versatile prosthesis robots, and enabling real-time applications. Notably, within BCI studies on bimanual movement coordination, a shared objective is to achieve naturalistic movement and practical applications with neurorehabilitation potential.**

***Index Terms*— Brain–computer interface, bimanual coordination, neuroscience, machine learning.**

I. Introduction

BRAIN–COMPUTER interface (BCI) systems capture and translate brain activity into artificial commands, enabling users to control peripheral devices. BCI applications address physical impairments by restoring motor functions through brain signal-controlled prostheses or orthosis, promoting neuroplasticity crucial for motor rehabilitation [1], [2]. However, most studies have focused on decoding motor tasks involving different limbs, which activate distinct cortical regions [3]. Consequently, the available control signals remain limited. Numerous studies have decoded various motor tasks, including hand movements [4], [5], [6], finger movements [7], and reach-and-grasp actions [8], [9] to address this challenge.

Activities of daily living (ADL) necessitate coordinated and synchronized movements involving both hands, i.e., bimanual motor control, for effective completion. Furthermore, bimanual motor training enhances both bimanual and unimanual performance [10], [11]. Notably, bimanual coordination training strengthens interhemispheric communication pathways, promoting symmetrical brain functions through coordinated interactions between hemispheres [12], [13]. Consequently, numerous studies have investigated bimanual training, including inter-subject variability [12], optimizing task design for maximum efficiency [14], and comparing its efficacy to other training paradigms [15], [16], [17], [18]. Moreover, researchers have developed bimanual training devices such as robot-assisted tools and VR-integrated systems to enhance subject performance [19], [20].

Despite the widespread use of bimanual training in neurorehabilitation over several decades, research on BCI-based bimanual training remains limited. Integrating neuroimaging techniques into bimanual coordination training allows for progress monitoring and provides valuable insights into brain activation and neurological perspectives. Desrochers et al. [21] explored the impact of visuomotor perturbation on bimanual motor control by analyzing electroencephalography (EEG) spectral power across both high and low beta bands. Phunruangsakao et al. [13] investigated changes in alpha band EEG connectivity during unimanual and bimanual motor imagery, comparing measurements taken before and after bimanual training. In addition, brain activation differences were investigated using functional near-infrared spectroscopy (fNIRS) across varying complexities of unimanual and bimanual tasks [22]. These studies reveal brain activation differences during unimanual and bimanual tasks of varying complexities. Although these studies offered valuable insights into neural correlates of bimanual coordination, they did not satisfy the primary goal of BCI, which is to utilize neural signals to control peripheral devices.

Despite limited research on BCI-based bimanual training, existing studies have explored diverse directions and objectives. One of the most noticeable trends is the studies aiming for the highest classification accuracy of bimanual predefined

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class, including leftward, rightward, and midward hand motions [23]. These research directions highlight impactful neurological features interpreted via high-performance classification models. Specifically, deep-learning models can benefit from comprehensive feature visualization using explainable artificial intelligence (xAI), enhancing the understanding of neural correlates [24], [25]. However, the practical implementation of these studies is limited by the predefined tasks within the paradigm. Hence, researchers have explored more flexible decoding systems. Instead of decoding predefined classes, some studies have focused on decoding position, velocity, and force trajectories [25], [26], [27], [28], [29], [30]. Additionally, a few investigations have extended motion analysis to 3-dimensional space, aiming for higher degrees of freedom (DOF) [31], [32], [33]. In addition to decoding bimanual tasks, relevant studies exploring bimanual training-related findings were identified. King et al. [34] investigated the impact of bimanual visual feedback on unimanual task performance. Additionally, another study assessed motor-imagery skills in pianist and non-pianist subject groups, representing varying levels of bimanual dexterity [35].

The primary objective of this systematic review was to consolidate knowledge on bimanual training in BCI, compare diverse approaches, and facilitate cross-study knowledge transfer. However, inherent biases make direct comparisons challenging, especially when contrasting experiments involving non-disabled individuals, patients, and non-human primates. Even when recruiting participants with similar criteria, differences in neuroimaging techniques must be considered, as different techniques capture different aspects of neural activities. Task paradigms, including motor execution, motor imagery, motor attempt, and task complexity, must also be carefully considered, as they activate distinct but overlapping cortical regions. Therefore, concluding which decoding model outperforms others based solely on accuracy comparisons is inappropriate. This review contributes to the scientific literature by addressing these challenges as follows:

- It provides an overview of the recent research trends and the state-of-the-art paradigms in bimanual training within the BCI field.
- It classifies and summarizes study details, encompassing participants, neuroimaging techniques, task designs, experimental paradigms, model inputs, feature extraction techniques, and decoders.
- It summarizes important neurological findings, evaluates their transferability and explores potential synergies with corresponding conclusions.
- It examines challenges and proposes future research directions within this context.

The remaining sections of this study are structured as follows: Section II outlines the procedures for identifying relevant references, covering search databases, conducting the screening process, and applying inclusion and exclusion criteria. Section III provides an in-depth analysis of the literature search results, organized by key topics such as study populations, neuroimaging techniques, experimental tasks, input and feature extraction methods, and decoding algorithms. Section IV discusses key findings, current challenges, and areas for future research. Finally, Section V concludes the study.

II. Methods

The identification of relevant references adhered to widely recognized Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines [36], which set the standards for reporting systematic reviews within the scientific community. Figure 1 provides an overview of the guidelines. The search spanned several databases, including PubMed, IEEE Xplore, Scopus, and ISI Web of Science. It specifically targeted article titles, abstracts, and keyword sections of articles up to the search date of November 5, 2024.

During the identification phase, 1999 records from selected databases and three registers were initially included. These records underwent the automatic elimination of 998 duplicate records with exact matches using Zotero (version 7.0.9), a reference management software. Consequently, 1001 unique records remained for further screening.

Further screening focused exclusively on titles and abstracts. Studies not employing neuroimaging techniques were excluded. Additionally, studies centered on unimanual or lower limb tasks were omitted from this study. Furthermore, other non-bimanual tasks, such as linguistic, somatosensory attention, and navigation, were also excluded due to their lack of simultaneous usage of both hands. Moreover, unrelated studies, including those related to sensor development, supernumerary limbs, and teleoperation, were excluded. This screening process resulted in the removal of 868 records, including one without access, leaving only 133 records for subsequent analysis.

During eligibility assessment, full-text articles were accessed to identify relevant studies for reviewing the state of the art. The inclusion criteria during full-text screening encompassed studies involving participants performing upper-limb bimanual tasks that necessitated synchronization of both limbs and experimental paradigms designed to investigate the impact of bimanual training (e.g., bimanual feedback) and discuss neurological findings that may be beneficial for improving bimanual BCI systems. Exclusion criteria included studies that extracted features unrelated to neuroimaging techniques and those that did not entail decoding, classification, or the application of brain signals to external devices.

Finally, in the systematic review, 36 articles met the eligibility criteria. Figure 2 illustrates the distribution of these articles, with 30 from journal publications and six from conference proceedings. Table I summarizes key aspects of the eligible studies.

A. Other Studies on Bimanual BCI

During the eligibility stage, 28 bimanual BCI studies were excluded due to the absence of neurological findings or discussions related to bimanual movements. These studies primarily focused on enhancing classification performance through advanced feature extraction or decoding methods, using bimanual movements to control external devices, or comparing the impact of multimodal signal acquisition on decoding

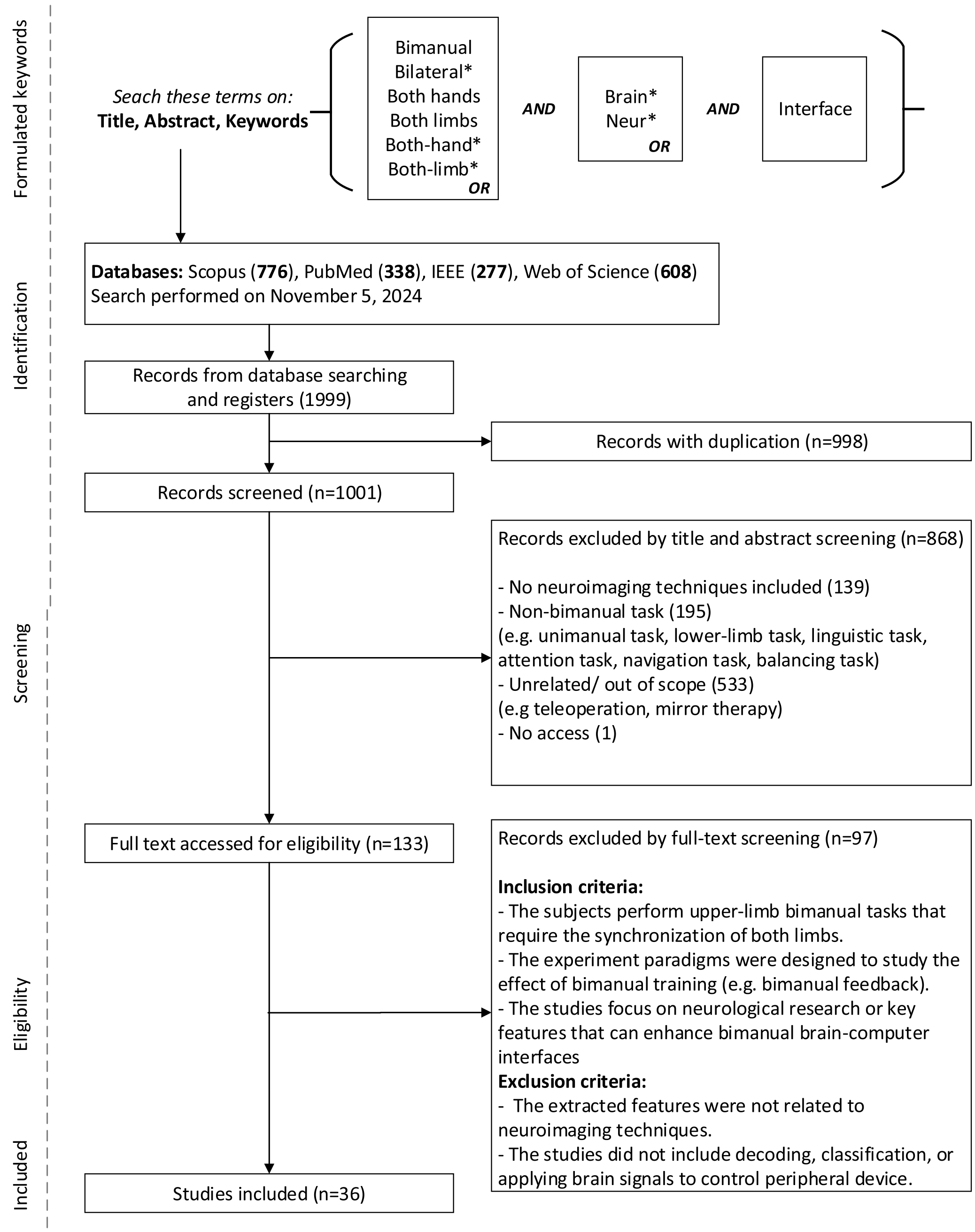

Fig. 1. Crafted search terms for diverse databases, accompanied by the PRISMA [36] flowchart depicting article inclusion and exclusion criteria. The asterisk (*) denotes a wildcard search term.

performance. Although excluded from further review, these studies may still provide valuable insights for researchers in the field. A list of these studies is compiled in Table II, briefly summarizing their objectives, sensors used, tasks performed, and paradigms applied.

B. Existing Review

During the search, two review papers investigating bimanual coordination in BCI systems were identified. One of these papers [37], published in 2022, explores bimanual coordination within the context of motor imagery. It encompasses studies utilizing bimanual tasks with motor imagery to control BCI systems and those focusing on cognitive, behavioral, and neurophysiological analysis underlying imagined bimanual tasks.

Another paper [3], published in 2023, discusses EEG-based motor BCIs for upper-limb movement, covering both unimanual and bimanual tasks. It provides a comprehensive overview of BCI system, including experimental paradigm design, data collection, signal preprocessing, neural activity correlation, feature extraction, movement intention decoding, and online or real application model testing.

The primary distinction between this review and existing literature lies in its comprehensive scope. Unlike prior reviews,

TABLE I
STUDIES ON BIMANUAL COORDINATION IN BRAIN-COMPUTER INTERFACE IDENTIFIED BY PRISMA PIPELINE

Ref.	Year	Population (n)	Sensors (n)	Task	Paradigm	Input	Feature extraction	Decoder
[58]	2013	NHP (2)	8 MEA (96); 8 MEA (48)	L/ R/ B reaching	ME/ MA/ AO	Firing rate	PETH	UKF/ kNN
[63]	2013	Healthy (99)	EEG (64)	L/ R/ B /F opening-closing	MI	ERDS	CSP	LDA
[46]	2013	Healthy (10)	EEG (64)	L/ R/ B/ F/ L+RF/ R+LF/ Re	MI	ERDS	CSP; Multi-GECSP; Multi-sTRCSP	SVM
[57]	2013	Healthy (22); MCS (5); UWS (9)	EEG (32)	B/ Re closing	MI	ERDS	Hjorth parameters; Brainrate; Wackermann; Hurst exponent; FFT; Coherence; GC; PDC; DTF; Entropy; Bhattacharyya distance; Correlation entropy	kNN/ SVM/ DADF
[44]	2014	Healthy (3)	fNIRS (45)	L/ R/ B/ Re ball grasping	ME	ΔOxy-Hb	GLM	SVM
[43]	2016	Healthy (6)	EEG (26)	L/ R/ B/ Re	MI	ERDS	CSP	Stepwise regression
[67]	2017	Healthy (30)	MEG (4)	B finger tapping	ME	ERF	-	Magnitude squared coherence
[59]	2018	NHP (2)	2 ECoG (32)	L/ R/ B/ Re reach-and-press	ME	ERDS	Wavelet transform	LDA + PLS
[47]	2018	Healthy (9)	EEG (8)	L/ R/ B/ F opening-closing	MI	ERDS	-	Autoregression model
[40]	2018	Healthy (10)	MEG (114)	B opening-closing	ME/ MI	ERF	Mean ERF amplitude	SVM
[54]	2018	Healthy (10)	EEG (32)	L/ R/ B waving	ME/ MI	ERDS	CSP; CSPb	LDA
[52]	2019	Healthy (10)	EEG (30)	L/ R/ B/ F	MI	ERDS	OVR-CSP	SVM
[41]	2019	Healthy (15)	EEG (58)	L/ R/ B/ Re palmar/lateral grasp	ME	MRCP	MRCP amplitudes	sLDA
[29]	2019	Healthy (68)	EEG (128); fMRI	L / R/ B/ Re tracking	MI	ERDS	Wavelet transform	Weighted sum of the alpha power
[64]	2020	Healthy (10)	EEG (32)	L/ R/ B/ F	MI	ERDS	CSP; FBCSP	SVM/ RVM/ SNN
[45]	2020	Healthy (8)	EEG (24)	L/ R/ B reaching	ME	MRCP	MRCP amplitudes; power sum	LDA/ SVM

the examination of bimanual coordination in BCI is unrestricted by specific BCI paradigms (such as motor imagery, motor execution, motor attempt, and action observation) or neuroimaging techniques. Additionally, recent advancements are summarized, challenges are identified, and future research directions are proposed. This is particularly significant given

TABLE I
(Continued.) STUDIES ON BIMANUAL COORDINATION IN BRAIN-COMPUTER INTERFACE IDENTIFIED BY PRISMA PIPELINE

Ref.	Year	Population (n)	Sensors (n)	Task	Paradigm	Input	Feature extraction	Decoder
[24]	2020	NHP (1)	2 ECoG (4x8)	L/ R/ B reach-and-press	ME	ERDS	Wavelet transform	DenseNet
[35]	2020	Non-Pianist (4); Pianist (4)	EEG (8)	L/ R	MI	ERDS	CSP	LDA
[53]	2020	SCI (1); SCD (1)	2 MEA (96); 2 MEA (88)	L/ R/ B reaching; reach-and-grasp	MA/ AO	Firing rate	-	OLE with ridge regression
[26]	2021	Healthy (9)	EEG (24); fNIRS (24)	B isometric contraction	ME	ERDS (EEG); HbO/HbR (fNIRS)	Hilbert transform (EEG)	cnnatt-mdn
[60]	2021	NHP (2)	2 ECoG (32)	L/ R/ B reach-and-press	ME	ERDS	Wavelet transform	DenseNet-3D
[31]	2022	C4-C5 injury (1)	2 ECoG (64)	L/ R/ B reach-and-touch and wrist rotations	MI/ MA	ERDS	CCWT	REW-MSLM
[34]	2022	Healthy (14)	EEG (32)	L/ R rotation (B feedback)	MI	ERDS	SB-CSP	LDA
[25]	2022	Healthy (13)	EEG (64)	L/ R/ B reaching	ME	ERDS	-	EEGNet + LSTM
[55]	2022	Healthy (10); C4 injury (2)	EEG (32)	Dominant/ B/Re palmar/ lateral grasp	ME/ MA	MRCP	MRCP amplitudes	sLDA/ SVM/ RF/ NBC
[51]	2022	Stroke (10); Older (10); Younger (10)	EEG (4)	L/ R/ B wrist extension/ flexion	ME/ MA/ AO	ERDS	FFT	Thresholding
[39]	2022	Tetraplegic (1)	2 MEA (96)	L/ R/ B / Re wrist/ elbow	MI	Firing rate	PETH	SVM
[23]	2023	Healthy (8)	EEG (64)	L/ R/ B reaching	ME	MRCP	-	EEGNet + BiLSTM
[65]	2023	Healthy (15)	EEG (8)	L/ R/ B/ F	MI	ERDS	ITD	FNN
[56]	2023	Healthy (18)	MEG (306)	B/ F/ WORD/ SUB	MI	ERF	Linear kernel	SVM/ GPC
[48]	2023	Healthy (8)	EEG (24)	L/ R/ B reaching	ME	MRCP; ERDS	DWT (MRCP); CWT (ERDS)	ME-Net
[50]	2023	C4 injury (1)	2 MEA (96)	L/ R/ B reaching	MI	Firing rate	PETH	SVM
[38]	2023	C4 injury (1)	MEA (96)	L/ R/ B/ Re wrist/elbow	MI	LFP	Average power signal	RF
[30]	2024	C4 injury (1)	2 MEA (96)	L/ R/ B cursor control	MA	Firing rate	-	RNN
[66]	2024	Healthy (100)	EEG (64)	L/ R/ B/ F opening-closing	ME/ MI	ERDS	FD; relative power	SVM/ GB/ kNN/ RF
[49]	2024	Healthy (9)	EEG (32)	L/ R/ B reaching	ME	MRCP	MRCP amplitudes	LSDA

the emerging trend of bimanual coordination in BCI, necessitating a thorough exploration of its complexities.

III. SYNTHESIS OF RESULTS

This section is organized into six subsections, each exploring variations in studies across different stages of the BCI pipeline. As illustrated in Fig. 3, the general BCI framework consists of two main components: signal acquisition and signal analysis. Participants—whether healthy individuals, patients, or non-human primates—perform specially designed bimanual motor tasks, while their brain signals are recorded using non-invasive (e.g., EEG, MEG, fNIRS, and fMRI) or

TABLE II
STUDIES ON BIMANUAL COORDINATION IN BRAIN-COMPUTER INTERFACES EXCLUDED FROM FINAL REVIEW FOR LACK OF NEUROLOGICAL INSIGHTS OR DISCUSSION ON KEY FEATURES IN DECODING BIMANUAL MOVEMENTS

Ref.	Year	Sensors (n)	Task	Paradigm	Objective
[118]	2011	EEG (5)	B/ F opening-closing (MI); flickering visual stimulus (SSVEP)	MI/ SSVEP	Compared ERDS-based, SSVEP-based and hybrid BCI approaches.
[119]	2014	EEG (14)	L/ R/ B	MI	Used EEG signals to control a car racing game simulator and evaluate the performance of different spatial filtering techniques.
[120]	2015	EEG (8); tEEG (8); fNIRS (16)	L/ R/ B/ F	MI	Evaluated multimodal BCI using different sensor combinations.
[121]	2015	EEG (14)	L/ R/ B	MI	Utilized BCI to control the altitude of a quadrotor helicopter.
[122]	2016	EEG (64)	L/ R/ B thumb or fifth finger flexion	MI	Proposed a new spatiotemporal and spectral feature extraction method to classify finger flexion MI.
[123]	2017	2 ECoG (4x8)	L/ R/ B/ Re reach-and-press	ME	Proposed a hybrid method to decode movement conditions and hand trajectories from NHP neural signals.
[124]	2017	EEG (6)	Flickering visual stimulus	SSVEP	Developd an online BCI system using multichannel SSVEP to control a dual-arm robot.
[125]	2017	EEG (24)	L/ R/ B/ Re	MI	Designed a brain-controlled wheelchair with five steering behaviors using a two-stage control strategy that combines sustained and brief MI.
[126]	2018	EEG (20)	L/ R/ B/ F	MI	Integrated collaborative strategies with BCI to enhance the performance.
[127]	2018	EEG (8)	L/ R/ B/ F	MI	Developed feature extraction methods using ITD and FNN to decode MI.
[128]	2018	EEG (3)	L/ R/ B/ Re closing	ME/ MI	Developed a system to control two robotic hands in real-time using Hjorth parameters and FNN.
[129]	2018	EEG (9)	L/ R/ B/ F grasping	MI	Developed a classification scheme for eight types of MI including multitasking tasks such as L+F, R+F, and B+F.
[130]	2018	2 ECoG (N/A)	L/ R/ B/ Re reach-and-press	ME	Developed a CNN for classifying movement states from NHP cortical signals using spectrogram inputs.
[131]	2018	MEG (114)	B opening-closing	ME/ MI	Decoded and controlled a humanoid robot performing simultaneous bimanual movements using MEG amplitudes in real-time.
[132]	2018	MEG (114)	B opening-closing	ME/ MI	Decoded and controlled a humanoid robot executing simultaneous bimanual movements using low-frequency MEG components in real-time.
[33]	2019	2 ECoG (64)	L/ R/ B reach-and-touch and wrist rotations	MI/ MA	Designd a four-limb neuroprosthetic exoskeleton controlled by continuous online epidural ECoG in a tetraplegic patient.
[28]	2019	MEA (164-171)	L/ R/ B reaching	ME	Used LSTM to decode bimanual reaching tasks from single-unit recordings in NHP.

TABLE II
(Continued.) STUDIES ON BIMANUAL COORDINATION IN BRAIN-COMPUTER INTERFACES EXCLUDED FROM FINAL REVIEW FOR LACK OF NEUROLOGICAL INSIGHTS OR DISCUSSION ON KEY FEATURES IN DECODING BIMANUAL MOVEMENTS

Ref.	Year	Sensors (n)	Task	Paradigm	Objective
[133]	2020	EEG (16)	L/ R/ B/ F fisting	MI	Used a CNN with spectrograms of CSP-filtered signals as input to decode MI tasks.
[134]	2020	EEG (128)	L/ R/ B/ Re opening-closing	MI	Identified the spatio-temporal aspects of EEG-based continuous neurorobotics where users control a robotic arm and virtual cursor to track target using MI.
[135]	2020	EEG (16)	B	MI	Decoded the termination of motor imagery to enhance closed-loop MI-BCI system.
[27]	2021	EEG (24); fNIRS (24)	B Isometric contraction	ME	Utilized multimodal BCI to decode continuous bimanual grip force through deep learning.
[136]	2022	EEG (16)	B/ F	MI	Proposed a control system for continuous teleoperation of a robotic manipulator using BCI.
[137]	2022	EEG (24)	B multi-direction reaching	ME	Decoded multi-directional bimanual movements from EEG potential amplitudes and power sums.
[138]	2022	EEG (64)	L/ R/ B/ F opening-closing	MI	Utilized resting-state EEG alpha rythm to predict subject performance in MI-BCI.
[32]	2022	3 MEA (96); 3 MEA (32)	L/ R/ Re hand open; finger pinch; wrist flexion/ extension	MA	Developed a collaborative shared control approach to manipulate prosthetic limbs for performing a bimanual self-feeding task in a SCI patient.
[139]	2023	EEG (64)	L/ R/ B/ F/ Re opening-closing	MI	Proposed a novel method called AutoEncoder-Filter Bank Common Spatial Patterns (AE-FBCSP) for decoding imagined movements from EEG signals.
[140]	2023	EEG (29/ 64)	L/ R/ B/ F opening-closing	ME/ MI	Conducted a study on the performance of a novel implementation of the Riemannian geometry decoding algorithm.
[141]	2024	EEG (15)	L/ R/ B rotation (lateral/medial)	ME	Used a CSP-LR pipeline to decode unimanual, semi-asymmetric bimanual and symmetric bimanual movement.

invasive (e.g., ECoG and MEA) neuroimaging techniques. The acquired signals are processed using various decoding strategies. Decoding may occur simultaneously with signal collection (on-line decoding) or after the complete dataset has been acquired (off-line decoding). Depending on the approach, traditional algorithms, machine learning models, or deep learning techniques are employed to interpret the signal. The decoded outputs can then be utilized to provide real-time feedback—such as visual cues—or to control external devices, including robots and actuators.

A. Study Population

Figure 4a illustrates the distribution of the study population. Thirty-two studies included human participants, with 23 focusing on healthy participants. Notably, this review did not define healthy participants based on demographic factors such as age or sex. Instead, they were defined as individuals without known neurological or psychiatric diseases, without motor deficits, and with normal or corrected-to-normal eyesight. The activation of brain networks and interhemispheric interactions necessary for bimanual movements is influenced by non-pathological factors, including handedness and motor skills [12], [42]. However, interpreting and generalizing these findings poses challenges due to limited reporting of hand dominance in numerous studies. Specifically, while some studies exclusively recruited right-handed participants [23], [25], [26], [30], [31], [34], [35], [41], [43], [44], [45], [46], [47], [48], [49], [50], [51], [52], [53], [54], only studies [55], [56] included both right-handed and left-handed individuals. Furthermore, Riquelme et al. [35] compared BCI control performance between right-handed participants with high bimanual dexterity (pianists) and control participants

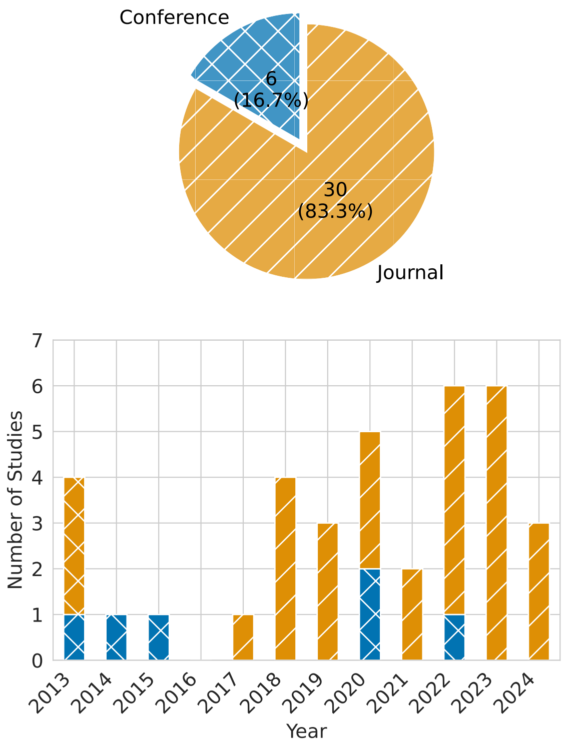

Fig. 2. Visualization of eligible articles by publication type (pie chart) and year (bar graph).

(non-pianists). In contrast, Edelman et al. [29] recruited participants with varying BCI experience, including both right- and left-handed individuals.

Several studies recruited patients exhibiting motor deficits due to spinal cord injury (SCI) or spinocerebellar degeneration (SCD). These conditions often result in permanent changes in strength, sensation, and other bodily functions below the affected site. Four studies focused on patients with SCI [30], [31], [38], [50], except for [53], which included both SCI and SCD patients. The study [39] involved a tetraplegic patient but did not specify the type of disease or injury. In addition, the study described in [51] recruited stroke patients and healthy participants, with the healthy group further divided into older and younger subgroups, to evaluate the effects of age and stroke on neuroplasticity during BCI feedback sessions involving muscle stimulation. A study detailed in [55] compared BCI performance between individuals diagnosed with SCI and healthy control participants, while [57] examined EEG features and classification methods in both healthy individuals and patients with disorders of consciousness (DOC), including patients with a minimally conscious state (MCS), and those with unresponsive wakefulness syndrome (UWS). Furthermore, four studies incorporated non-human primates (NHPs) [24], [58], [59], [60].

B. Neuroimaging Techniques

In this review, six neuroimaging techniques were identified and categorized, as shown in Fig. 4b. These included non-invasive methods such as electroencephalography (EEG), magnetoencephalography (MEG), functional near-infrared spectroscopy (fNIRS), and functional magnetic resonance imaging (fMRI). Additionally, invasive techniques, namely electrocorticography (ECoG) and microelectrode array (MEA), were considered. Each method provides distinct insights into brain function [2], [61], [62]. Among the studies analyzed, 26 employed non-invasive techniques, while 10 utilized invasive methods.

1) Non-Invasive Neuroimaging: Non-invasive brain recording involves monitoring and measuring brain activity without surgical intervention or skull penetration. EEG captures electrical signals via scalp electrodes, providing high temporal resolution but limited spatial resolution. MEG detects magnetic fields generated by neuronal activity, offering high temporal and spatial resolution despite cost and accessibility challenges. fNIRS assesses blood oxygenation level-dependent (BOLD) signals using near-infrared light, providing moderate temporal resolution with spatial constraints. fMRI excels in spatial resolution and detailed brain activity mapping by observing BOLD signals, although it sacrifices temporal resolution.

Among studies employing non-invasive neuroimaging techniques, EEG emerged as the most frequently utilized method, featured in 20 studies [23], [25], [34], [35], [41], [43], [45], [46], [47], [48], [49], [51], [52], [54], [55], [57], [63], [64], [65], [66]. Additionally, MEG was employed in three studies [40], [56], [67], and fNIRS was utilized in one study [44].

Moreover, two studies utilized multimodal non-invasive techniques. EEG and fNIRS signals were jointly employed to decode bimanual isometric contraction tasks and evaluated the efficacy of using either or both methods [26]. In a separate investigation [29], fMRI estimated cortical activity sources and improved EEG signal quality by mitigating volume conduction effects.

2) Invasive Neuroimaging: ECoG records cerebral cortex electrical activity by placing electrodes directly on the brain surface, yielding high spatial resolution compared to non-invasive methods such as EEG. In contrast, MEA achieves high spatial resolution by simultaneously recording multiple neurons, often inserted into brain tissue. ECoG, conversely, captures neural signals with high fidelity and is suitable for mapping cortical activity related to specific functions. Meanwhile, MEA enables the study of neuronal populations and synaptic connectivity within the brain.

All invasive studies were conducted on either NHPs or patients. Specifically, three studies employed ECoG in NHP research [24], [59], [60], while one study focused on patients [31]. Additionally, one study utilized MEA in NHP research [28], [58], and five studies involved patients [30], [38], [39], [50], [53].

Studies [30], [39] have highlighted the use of both invasive and non-invasive methods. However, data from non-invasive techniques, such as fMRI and MEG, were exclusively employed for surgical guidance or electrode placement and were not analyzed.

C. Experimental Task and Paradigm

Bimanual coordination tasks exhibit varying difficulty levels based on the degree of hand symmetry. Both discrete

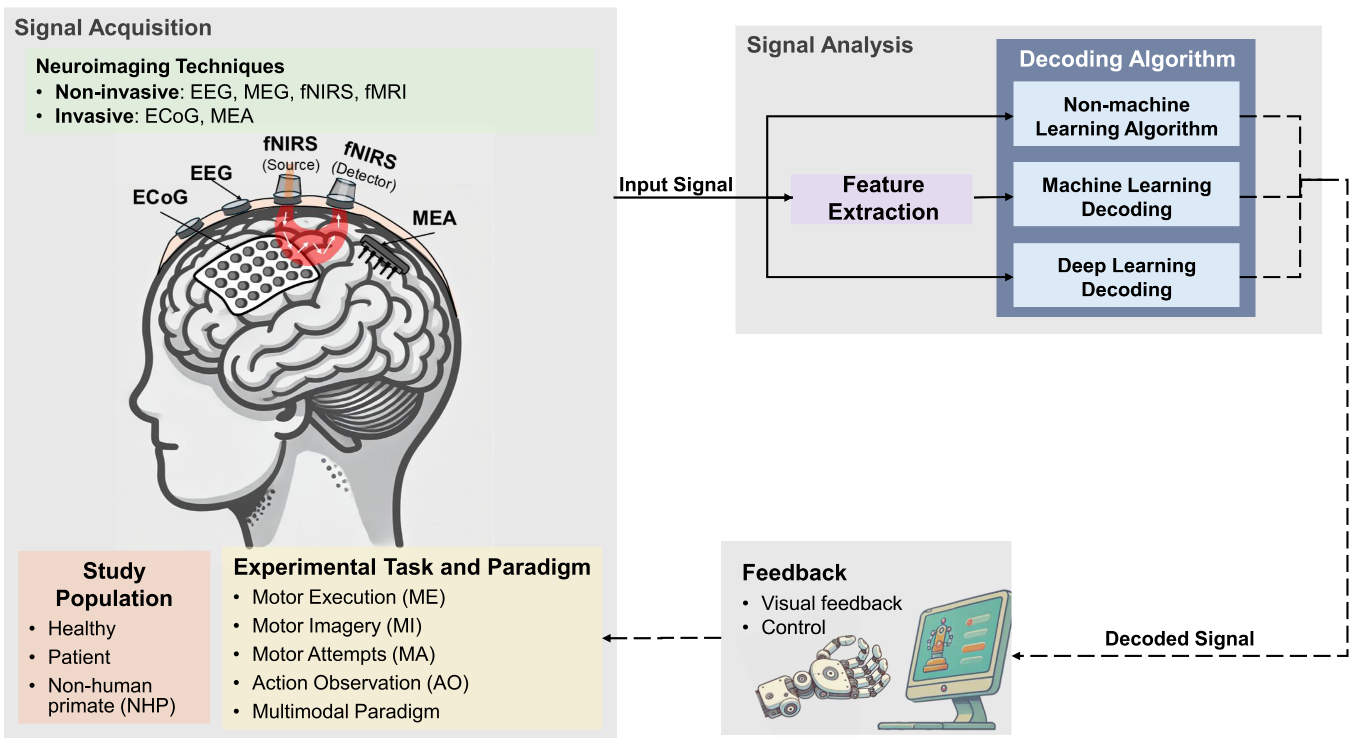

Fig. 3. Generalized BCI pipeline of bimanual motor coordination studies included in this review paper.

and continuous bimanual coordination patterns present challenges when limbs are assigned distinct movement directions, velocities, or amplitudes. In such scenarios, individuals must coordinate their movements across both hands, necessitating precise timing and control. These variations in movement parameters increase task complexity, demanding heightened cognitive and motor control for effective bimanual coordination. This review identified several studies that have incorporated various unimanual and bimanual tasks. These tasks range from simple unimanual left/right-hand (L/R) movements to more complex activities, such as bimanual tapping and tracking.

The experimental tasks employed in these studies encompassed paradigms, such as motor execution (ME), motor imagery (MI), motor attempt (MA), and action observation (AO), as shown in Fig. 4c. Although these paradigms represent different cognitive tasks, the brain activation elicited by each paradigm shares some similarities [68], [69], [70], [71]. Figure 5 presents examples of bimanual motor tasks, with the illustrations adapted from the experimental paradigms of the studies included in this review paper.

1) Motor Execution Paradigm: ME involves overt intentional bodily movements, enabling researchers to study natural brain activity and measure factors such as muscle activation, movement trajectory, and force [72], [73]. Nevertheless, ME paradigms do not apply to patients lacking residual movement.

Sato et al. [44] instructed participants to perform a bimanual ball-grasping task. Kajal et al. [67] utilized a bimanual finger-tapping task with real-time neurofeedback to observe the changes in interhemispheric functional coupling and their impact on motor performance. Additionally, in a study by Ortega et al. [26], noninvasive BCI techniques were employed to decode bimanual grip force. An isometric grip-force tracking task (Fig. 5, *upper right*) was introduced, allowing continuous monitoring and evaluation of force-related brain signals to assess decoding performance.

The reaching task has also received extensive attention. In this task, participants are required to move their hands from one point to another point in space. Zhang et al. [23] decoding reaching direction in one-dimensional space, while Chen et al. [25] focused on reconstructing reaching trajectories, including position and velocity. The researchers in [45] and [48] focused on classifying hand movement directions in a two-dimensional space where the movements are orthogonal. Wang et al. [49] investigated the neural correlates and movement decoding associated with simultaneous and sequential bimanual reaching.

In typical daily scenarios, reaching movements are often combined with other actions to achieve specific goals. Previous research has investigated reach-and-press tasks in NHP studies, where NHPs extended their hands to press buttons [24], [59], [60]. Additionally, Schwarz et al. [41] focused on decoding reach-and-grasp tasks, which involved unimanual lateral or palmar grasp, and bimanual combinations of palmar and lateral grasps or double lateral grasps (Fig. 5, *lower right*).

2) Motor Imagery Paradigm: MI is a cognitive process during which an individual internally rehearses or simulates a given action within their working memory, without movement execution. This practice involves no external motor action or output. The MI paradigm is commonly categorized into two types: kinesthetic MI and visual MI. Kinesthetic MI entails

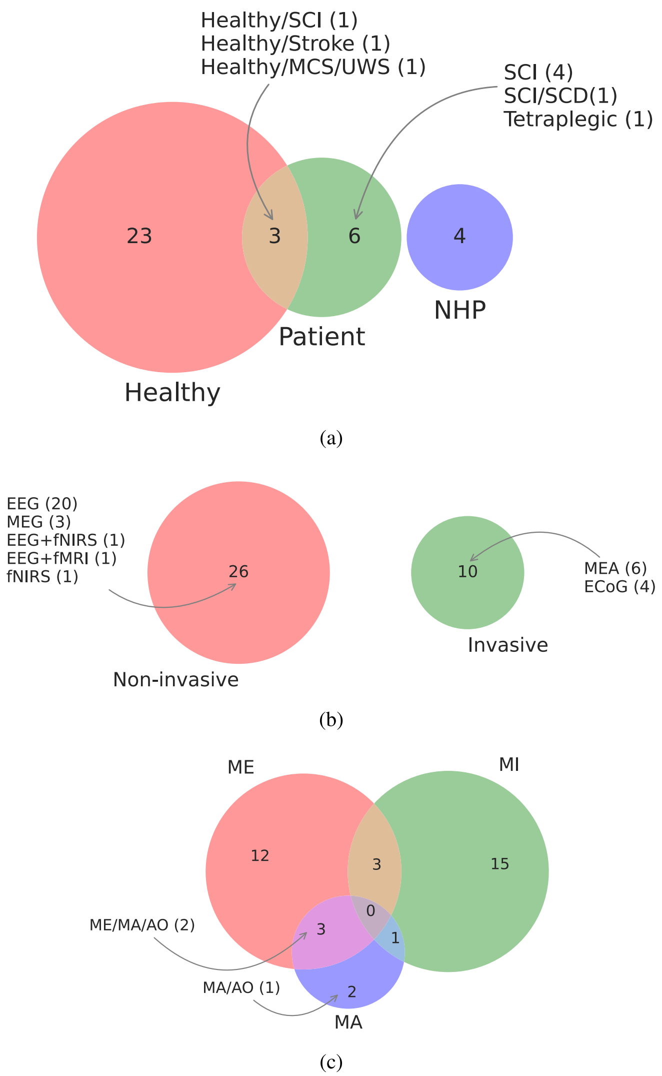

Fig. 4. (a) Distribution of participants across studies, including healthy individuals (23 studies), patients (6 studies), and non-human primates (4 studies). Three studies recruited both healthy participants and patients. (b) Types of neuroimaging techniques utilized across studies, with most employing non-invasive techniques. (c) Studies employed experimental paradigms, predominantly utilizing motor execution (ME) or motor imagery (MI), followed by motor attempt (MA) and action observation (AO). Additionally, some studies explored multimodal paradigms.

participants mentally simulating muscle activities and movements from a first-person viewpoint. In contrast, visual MI involves imagining movement from a third-person perspective, emphasizing action visualization over muscle sensation [69]. All the studies included in this section utilized kinesthetic MI as their approach.

Two studies utilized unimanual MI tasks. King et al. [34] instructed participants to perform unimanual hand-rotation tasks to investigate changes in brain connectivity and MI performance under various neurofeedback conditions, including bimanual rotation neurofeedback. Additionally, Riquelme et al. [35] employed a task involving unimanual finger drumming with swinging wrists to compare MI performance between pianist and non-pianist groups.

The EEG Motor Movement/Imagery Dataset V1.0.0 (MMIDB) [74], [75], [76] comprises recordings of unimanual, bimanual, and foot movements performed under both ME and MI conditions. Kim et al. [63] exclusively utilized the MI data from this dataset to evaluate the classification performance of various task combinations. Similarly, studies such as [47], [52], [64], and [65] employed the same set of tasks, whereas [43], [46] extended their analyses to include resting-state (Re) data, though these studies collected their own datasets.

Additionally, Lin et al. [38] and Wan et al. [39] investigated unimanual and bimanual elbow/wrist flexion from neurons, specifically in the left primary motor cortex (Fig. 5, *upper left*). Lai et al. [50] captured neural signals from the patient's left motor cortex during center-out reaching tasks, quantifying the representational interaction between arms by analyzing the tuning parameters of individual neurons. A study by [56] aimed to map and decode bimanual hands and feet MI movements, as well as mental arithmetic (SUB) and silent word generation tasks (WORD). Additionally, participants were instructed to perform MI involving both hand movements as well as the act of holding both hands still in the study [57]. Edelman et al. [29] employed EEG signals with neurofeedback to facilitate participants in executing target-reaching tasks via a virtual cursor and real-time control of a robotic arm.

3) Motor Attempt Paradigm: MA denotes the endeavor to move a paralyzed hand with minimal or no actual movement, typically observed in patients with motor disabilities. This review identified one study that exclusively focused on MA in bimanual BCI. A study in [30] demonstrated the capacity of neural network decoders to enable patients to simultaneously control two computer cursors by attempting bimanual movements.

4) Action Observation Paradigm: AO entails actively observing actions with the intent to imitate. This process can activate mirror neurons, a distinct class that fires during observation and execution of similar motor actions [77], [78]. While none of the reviewed studies specifically addressed AO, studies [51], [53], [58] included AO as part of their multimodal paradigms, as discussed in the subsequent section.

5) Multimodal Paradigm: Several studies have also incorporated more than one paradigm to compare the performance of the proposed algorithms and neural correlates under different experimental conditions. By including multiple paradigms, researchers can assess the influences of variations in task demands, cognitive processes, and neural activity patterns on the effectiveness of their methods.

In their research, Belkacem et al. [40] focused on decoding neuromagnetic activities within the sensorimotor cortex during MI and ME tasks involving symmetric and asymmetric hand movements (Fig. 5, *lower left*). Their objective was to enhance real-time control of humanoid robots using BCI systems. Conversely, Moaveninejad et al. [66] evaluated their proposed classification algorithms using both ME and MI data from MMIDB. Additionally, Vuckovic et al. [54] aimed to classify unimanual and bimanual hand-waving tasks and investigate the specific brain activity associated with each task during MI and ME.

The experiment detailed in [31] directed patients to perform MI or MA without explicit instructions. These actions were subsequently harnessed to control both an exoskeleton

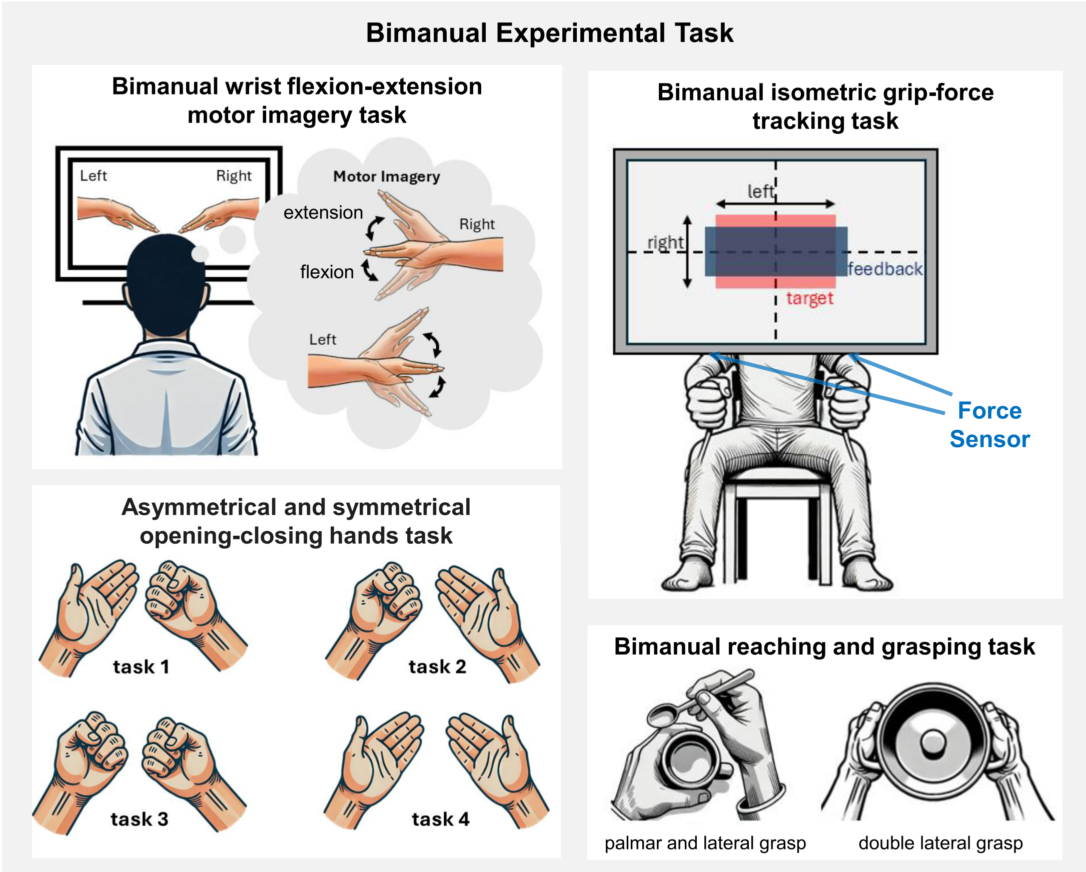

Fig. 5. Bimanual experimental tasks illustrated based on the paradigm explanations of the included studies. *Upper left*: adapted from [38], [39]; *lower left*: adapted from [40]; *upper right*: adapted from [26]; *lower right*: adapted from [41].

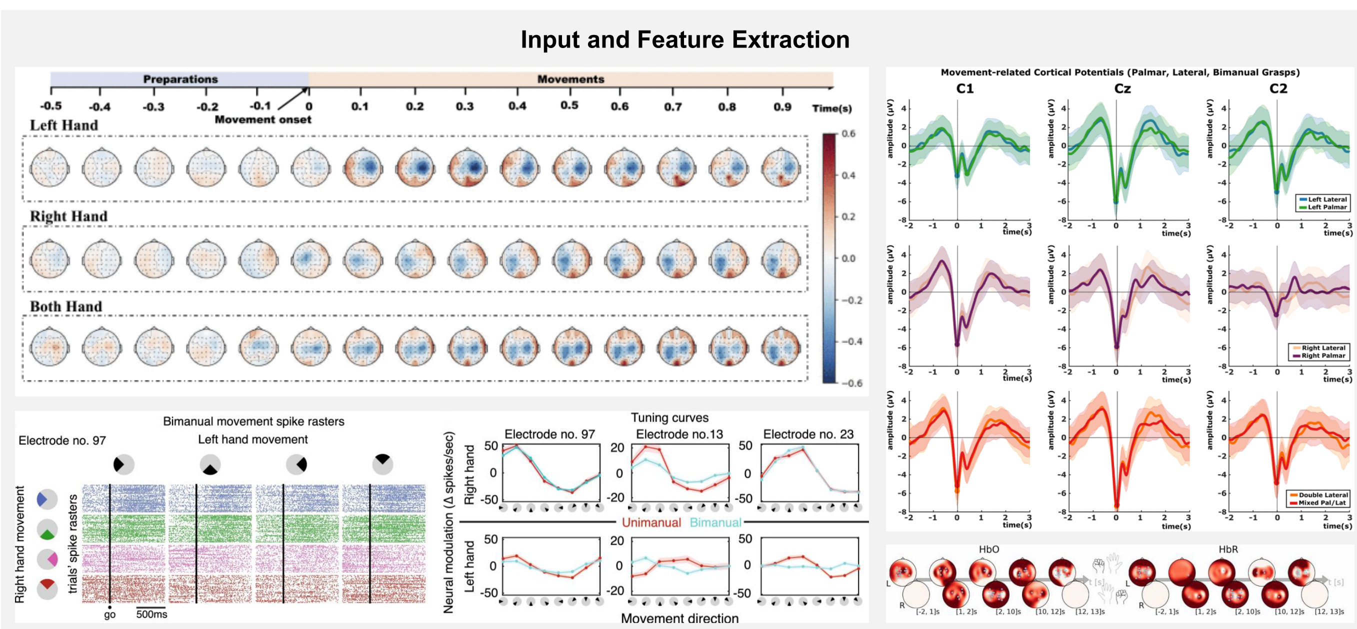

Fig. 6. Input and feature for decoding bimanual motor tasks included review papers. *Upper left*: ERD/ERS (IEEE image credit: [23]); *lower left*: neuron firing rate (Nature image credit: [30]); *upper right*: MRCP (IEEE image credit: [41]); *lower right*: fNIRS (IOP image credit: [26]).

and its virtual counterpart. The tasks involved bimanual three-dimensional reaching and hand rotation, resulting in an eight-dimensional control space. In contrast, the study described in [55] instructed patients and healthy participants to execute reach-and-grasp tasks for the MA and ME paradigms, respectively. The researchers then analyzed movement-related cortical potentials (MRCP) and compared decoding performance between the two groups. Kumari et al. [51] recruited subacute stroke patients, older healthy adults, and younger healthy adults to perform MA or ME combined with AO of wrist extension and flexion. The study aimed to investigate neuroplasticity in bimanual BCI with functional electrical stimulation (FES) feedback. Downey et al. [53] instructed participants to perform MA while observing (AO) a computer executing the same task. The study focused on motor cortical activity associated with unimanual reaching, alternating L/R-hand reach-and-grasp tasks, and bimanual reaching movements.

In their study, Ifft et al. [58] trained NHPs to operate a bimanual BCI without overt movements, utilizing MA. To ensure this, the NHPs' arms were restrained and concealed with an opaque material. This study devised a setup to replicate the real-world challenges faced by paralyzed individuals learning to operate BCIs without overt upper limb movements. The classifiers were trained either through manual control of two joysticks (ME) by the NHPs or by observing avatar arm movements (AO). Additionally, the study investigated neuroplasticity during the NHPs' training with the bimanual BCI.

D. Input and Feature Extraction

Recent advances in deep learning facilitate direct raw data analysis and automatic learning of discriminative representations, reducing reliance on manual feature extraction. EEG studies [23], [25] and the MEA study [30] employed deep learning models without relying on handcrafted feature extraction. In contrast, the EEG-fNIRS study [26] utilized raw fNIRS data (Fig. 6, *lower right*) while incorporating handcrafted feature extraction for EEG signals. In contrast, the EEG study by Abdalsalam et al. [47] utilized an autoregressive model to calculate the frequency spectrum from Laplacian-filtered signals, which was then used to provide visual feedback during MI training.

Nonetheless, many reviewed studies relied on manual feature extraction methods. Moreover, given the diverse aspects of different neuroimaging techniques, the employed feature extraction methods exhibit variation. Brain signals typically encode temporal, spatial, and spectral information relevant to movements. Therefore, feature extraction is crucial for identifying and characterizing these distinct neural aspects.

EEG, MEG, and ECoG studies investigate neural correlates of movements, including movement-related cortical potentials (MRCP) (Fig. 6, *upper right*) and event-related desynchronization/synchronization (ERDS) (Fig. 6, *upper left*). MRCP, referring to low-frequency potentials below 10 Hz, is associated with motor planning and execution processes in the brain [79], [80]. These potentials typically appear approximately 1-2 seconds before voluntary movement onset, enabling the classification of movement intention before its actual execution. In their study, Wang et al. [45] extracted temporal and spectral features from MRCP amplitudes and power sum, respectively. Conversely, studies in [41], [49], and [55] solely utilized MRCP amplitudes feature for their decoding scheme.

ERDS, however, involves time-locked changes in relative power during motor tasks [81]. This analysis typically focuses on the alpha (7–13 Hz) and beta (13–30 Hz) frequency bands, but it may also encompass other frequencies, such as delta (<4 Hz), theta (4-7 Hz), and gamma (>30 Hz). Spatial features were extracted using variations of the common spatial pattern (CSP) algorithm in several studies [34], [35], [43], [46], [52], [54], [63], [64], while spectral features were derived using the Hilbert transform in the work by Ortega et al. [26]. Moaveninejad et al. [66] extracted temporal and spectral features by estimating fractal dimension and calculating EEG relative power across different bands. Wang et al. [48] described a study where they extracted spectral features from both MRCP and ERDS using wavelet transform. Edelman et al. [29] introduced a co-adaptive BCI to enhance user engagement and improve the spatial resolution of noninvasive neural data. They achieved this through a continuous tracking task that utilized the weighted power density of the EEG alpha band for real-time robotic arm control. Additionally, their training approach aimed to enhance spatial resolution using a novel EEG source imaging technique called frequency-domain electrical source imaging. Kumari et al. [51] employed fast Fourier Transform (FFT) to calculate power in specific frequency bands for providing FES feedback. In contrast, Mohamed et al. [65] proposed leveraging subject-specific regions of interest (ROIs) combined with intrinsic time-scale decomposition (ITD) to improve classification performance. The study in [57] compared features extracted using various methods, including Hjorth parameters, Brainrate, Wackermann features, Hurst exponent, FFT, coherence, Granger causality (GC), partial directed coherence (PDC), directed transfer function (DTF), approximate entropy, Shannon entropy, Bhattacharyya distance, and correlation entropy.

In a study by Belkacem et al. [40], MEG amplitudes were extracted from the event-related magnetic field (ERF). To reduce feature dimensionality, they calculated the mean amplitude of single trials for each MEG sensor around the sensorimotor area. A linear kernel was employed to calculate the group cross-similarity of task-related beta-decrements in ERF, which were then used as input features in the study by Youssofzadeh et al. [56]. In another study by Kajal et al. [67], neurofeedback training utilized the ERF magnitude-squared coherence of sensorimotor rhythm between hemispheres. All ECoG studies employed similar feature extraction methods, specifically wavelet transform, to capture spatial-spectral-temporal features of ECoG signals [24], [31], [59], [60].

Sato et al. [44] introduced the general linear model (GLM) to extract features and mitigate scalp hemodynamic artifacts in fNIRS signals, comparing its performance with several alternative methods Conversely, the majority of MEA studies have employed peri-event time histograms or neuron firing rates (Fig. 6, *lower left*) [30], [39], [50], [53], [58]. However, in a specific MEA study [38], the average power signal of local field potentials was used as a feature.

E. Decoding Algorithm

1) Non-Machine Learning Algorithm: Kajal et al. [67] explored the causal relationship between interhemispheric functional coupling and bimanual performance using neurofeedback. Neurofeedback was determined based on dynamically updated neural coherence, calculated over the preceding trials. In a study by Edelman et al. [29], the instantaneous control signal was computed as the weighted sum of alpha powers from a subset of electrodes. In the study by Kumari et al. [51], tactile feedback was controlled using a simple threshold switch, where the power in the selected frequency band needed to stay below the power threshold for a specific duration. Additionally, Ifft et al. [58] utilized an unscented Kalman filter (UKF) to extract motor commands from brain activity. This approach captures both reaching parameters, such as position and velocity, and their nonlinear relationships with neuronal rates.

2) Machine Learning Algorithm: Various machine learning classifiers have been employed in bimanual BCI research, including variations of the Support Vector Machine (SVM) [39], [40], [44], [45], [46], [50], [52], [55], [56], [57], [64], [66], Linear Discriminant Analysis (LDA) [34], [35], [41], [45], [49], [54], [55], [57], [63], Gaussian Process Classification (GPC) [56], and Relevance Vector Machine (RVM) [64]. Additionally, Random Forest (RF) [38], [55], [66], the Naive Bayes Classifier (NBC) [55], and k-Nearest Neighbors (kNN) [57], [58], [66] have been utilized.

Choi et al. [59] devised a two-stage decoder that combines an effector classifier using LDA and a movement trajectory predictor using Partial Least Squares (PLS) regression. Moaveninejad et al. [66] assessed their feature extraction algorithm by employing SVM, kNN, RF, and a Gradient Boosting classifier (GB) to explore diverse model combinations via soft and hard voting techniques.

In a recent study by Moly et al. [31], novel algorithms were introduced, including Recursive Exponentially Weighted Multisource Linear Modeling (REW-MSLM) and Recursive Exponentially Weighted N-way Partial Least Squares (REW-NPLS). REW-MSLM, an online tensor-based fully adaptive mixture of multilinear expert algorithms, integrates a recursive model parameter identification procedure inspired by the REW-NPLS method [82] and inherits the structure of a Mixture of Linear Modeling (MSLM) [83]. Lindig-Leon and Bougrain [43] employed stepwise regression for classification, calculating CSP and training the model separately for each contralateral movement. In contrast, Abdalsalam et al. [47] used an autoregressive filter to compute the frequency spectrum for controlling cursor movement.

Moreover, Downey et al. [53] employed the Indirect Optimal Linear Estimation (OLE) technique, incorporating ridge regression [84], to create a neural decoder based on an encoding model. This decoder establishes the relationship between neural unit firing rates and unilateral arm velocity, leveraging data from observation trials.

3) Deep Learning Algorithm: Deep learning methods are widely used for decoding neural signal movements. Notably, Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) emerge as favored options. CNNs excel at extracting spatial-spectral-temporal features from brain signals, while RNNs capture temporal dependencies and dynamics, facilitating efficient representation learning and classification of mental states or motor intentions [85].

Lim et al. [24] adopted DenseNet [86] to classify NHP arm movements. Meanwhile, Choi et al. [60] extended the DenseNet model to classify three-dimensional ECoG data related to arm movement by incorporating temporal, spectral, and spatial information domains. Similarly, Deo et al. [30] employed Gated Recurrent Unit (GRU), a type of RNN, for movement decoding.

Chen et al. [25] and Zhang et al. [23] combined a well-known CNN architecture, EEGNet, with Long Short-Term Memory (LSTM) for trajectory fitting and decoding, respectively. Additionally, Wang et al. [48] incorporated an attention-based channel-weighting module and CNN to propose ME-NET, which enhances temporal-spectral-spatial feature extraction for movement decoding. In a comprehensive study, Ortega et al. [26] employed CNNs with attention to decoding bimanual force using raw EEG, EEG Hilbert features, and fNIRS. The model was further extended to incorporate diverse architectures, including CNNs with LSTMs, mixture density networks (MDNs), and residual modules with self-attention.

Furthermore, Mohamed et al. [65] employed a simple feedforward neural network (FNN) as their decoding model. In contrast, Tang et al. [64] utilized a spiking neural network (SNN), which closely emulates the structure and function of natural neural networks.

IV. Discussion

A. Toward Practical Bimanual BCI Implementation

Bimanual BCI research aims to enhance movement range and enable complex simultaneous actions, ultimately facilitating patients to perform ADL with greater ease. Consequently, numerous studies have prioritized improving the robustness and real-time performance of the movement decoder.

The key themes in bimanual studies center on achieving high accuracy in movement classification. This pursuit establishes a robust foundation for investigating influential features and models in bimanual decoding and comprehending brain activation during bimanual BCI tasks. However, the limitation of a predefined set of classes may restrict real-world applications. To address this limitation, The decoders providing precise position and velocity trajectories for bimanual movement, and bimanual-controlled cursor trajectory were proposed in studies [25], [30], [58]. Another notable advancement is the continuous decoder developed by Ortega et al. [26] that provides force trajectory information and further enhances the pursuit of a realistic decoder. Moly et al. [31] introduced a highly robust bimanual movement scheme using a Mixture of Expert (MoE) technique. This technique integrates five specialized experts, each responsible for distinct movement tasks: hand translation, hand rotation, and idle movements. These experts collaborate through a gating mechanism akin to a classifier. By applying MoE to this approach, subjects achieve approximately 75% accuracy in controlling virtual avatars and exoskeletons, even in online decoding.

Real-time functionality is pivotal in practical implementation. Belkecem et al. [40] effectively controlled a humanoid robot to execute contralateral and ipsilateral bimanual tasks, achieving average real-time accuracies of 61.25% and 63.5%, respectively, which is deemed acceptable for online decoding. However, when aiming to broaden movement constraints by developing real-time continuous decoders, the performances of these decoders were slightly lower due to the wider movement range. For instance, in studies [31], [53], [58], real-time decoders for virtual avatar and exoskeleton control achieved modest ground-truth correlations. Notably, Handelman et al. [32] introduced an online discrete decoder that enables continuous control via a shared control strategy, mapping subject gestures to specific robot-arm movements. This approach enabled participants to perform real-time self-feeding tasks despite the relatively lower accuracy of the decoder. Furthermore, Deo et al. [30] applied the cursor trajectory decoder in a real-time context. Even though it effectively decoded alternating bimanual task, it struggled to achieve the same performance in simultaneous tasks due to the suppressed left-hand representation in bimanual simultaneous movement. Nonetheless, the efficacy of real-time implementation may vary due to factors such as intersubject variability, fatigue, and emotional state [87].

The main challenge is that most studies focus on either discrete actions or continuous limb translation, which limits generalizability across datasets and populations. This presents an opportunity for future research to integrate both movement types, enabling more naturalistic control in bimanual BCI systems. While collecting large datasets for training decoders is ideal, it is often time-consuming and costly. Adopting transfer learning to generalize motor task variability and address both intrasubject and intersubject non-stationarity may offer a more efficient solution, requiring minimal data collection and model retraining [88], [89]. This approach streamlines development and improves generalization across diverse populations and experimental conditions.

B. Motor Function Restoration in Paralyzed Patient

BCI therapy for post-stroke upper limb paralysis is moderately recommended, with medium evidence support, according to the 2021 Japanese Guidelines for the Management of Stroke by The Japan Stroke Society [90]. This recognition highlights BCI-based therapies' increasing interest and potential in neurorehabilitation. However, most bimanual BCI studies have exclusively focused on SCI patients. Nevertheless, there exists a substantial body of research employing BCI technology for various other conditions that result in motor function impairment, including stroke, cerebral palsy, Parkinson's disease, and multiple sclerosis. Although conclusive evidence of neuroplasticity during bimanual training is lacking, numerous studies have aimed to expand the movement range of paralyzed patients by developing decoding techniques for bimanual tasks. The robust classification accuracies observed in predefined bimanual tasks classification validate the feasibility of simultaneous movement decoding in patients with SCIs [38], [39], [50], [55]. Additionally, advanced continuous bimanual decoders enabled SCI patients to perform target-reaching tasks by controlling virtual avatars, exoskeletons, and cursors, enhancing the potential for motor function restoration [30], [53].

The delta-alpha ratio (DAR) and brain symmetry index (BSI) are commonly used metrics for assessing recovery levels after neurorehabilitation, with lower values indicating stroke recovery [91], [92], [93]. In the study by [51], these indices were used to evaluate the short-term priming effects of unimanual and bimanual BCI-FES feedback across three groups: subacute stroke patients, older healthy adults, and younger healthy adults. However, significant changes in DAR and BSI were observed only in the healthy groups. The authors suggest that injured brains may require longer sessions to induce short-term changes or that gradual improvements could emerge through cumulative effects in long-term studies. They further recommend bimanual BCI-FES as a viable alternative to unimanual BCI-FES.

The inclusion of NHPs, patients, and non-disabled participants in existing bimanual BCI studies presents challenges for transferring domain knowledge across participant categories. Comparing brain activation across patients with different diseases is inherently biased, and even within the same disease, the neurological injury level should be considered. Furthermore, bimanual BCI studies cited in this review likely conform to distinct injury level standards. Nevertheless, interhemispheric interaction, critical for neural activation during bimanual movement, can be influenced by age and sex, as demonstrated by Takeuchi et al. [12]. Similarly, Pfurtscheller et al. [94] observe that ERD strength and lateralization in SCI patients may vary with the recovery course. Chronic complete SCI patients tend to exhibit weaker ERD compared to subacute incomplete SCI patients, leading to inferior BCI performance.

Hence, conducting experiments comparing diverse subject types is essential to explore the transferability of domain knowledge. Currently, only two studies investigate the difference between healthy participants and patients during bimanual activation [51], [55], while another examines an SCI patient and an SCD patient [53]. The scarcity of research in this area invites further exploration, potentially yielding valuable insights into bimanual BCI across various populations.

C. Bimanual Training on BCI Performance and Neuroplasticity

Bimanual motor training has been demonstrated to modulate interhemispheric interactions, promoting symmetrical brain function and enhancing the efficiency of connections between both hemispheres [12]. This facilitates temporally and spatially coordinated movement of both hands. This may be attributed to intermanual transfer, where motor learning in one hand improves performance of the other hand. Amemiya et al. [95] showed that intermanual transfer can occur during both ME and MI tasks. Moreover, both bimanual and unimanual movements benefit from bimanual training, and vice versa [10]. However, the transfer of learning may be limited depending on the type of movement [96].

Riquelme et al. [35] conducted a groundbreaking comparative study on pianists who attained advanced bimanual dexterity through rigorous training, alongside a control group, during MI tasks. They discovered a statistically significant higher BCI performance and lower activation of the bilateral motor cortex in the pianist group during MI. Using brain connectivity analysis, King et al. [34] detected mutual information transfer between prefrontal areas, signifying improved motor preparation and bimanual coordination during bimanual rotational feedback. Additionally, parietal-to-bilateral frontal cortex communication implies that feedback conveys essential spatial location information, critical for motor planning. Study in [31] observed lower bimanual BCI performance in virtual avatar control compared to exoskeleton control, which may be attributed to differences in feedback and perception. Exoskeleton control provides more enriched and realistic feedback, potentially enhancing BCI performance.

The study conducted by Ifft et al. [58] observed performance enhancements in NHPs during real-time BCI control of bimanual movements. Initially, heightened correlated neural activity was observed, likely attributed to the learning process. However, after this initial phase, NHPs consistently exhibited a reduction in correlated neural activity across various cortical areas in both hemispheres as they acquired independent control over both arms. Kajal et al. [67] investigated the causal link between interhemispheric functional coupling and bimanual performance using an out-of-phase bimanual finger-tapping task with neurofeedback. Their findings suggest that stronger functional coupling adversely affects bimanual performance.

Additionally, Edelman et al. [29] compared participant performance in two distinct tasks: discrete center-out cursor control (DT) and continuous pursuit task (CP), both guided by EEG signals during MI. Their findings revealed that CP training outperformed DT, with participants demonstrating superior neural control over both cursor and robotic devices for discrete and continuous target-tracking tasks. Furthermore, higher engagement was demonstrated during training sessions. Moreover, the study investigated the impact of source and sensor neurofeedback on CP training, revealing nearly identical learning effects for both feedback types.

Studies have shown that bimanual BCIs can induce neuroplasticity, but the extent of these changes varies widely among individuals due to factors such as sex, brain disease, and age [12], [97], which poses challenges for achieving consistent neurorehabilitation outcomes. Additionally, different types of activity-based rehabilitation can result in varying levels of brain changes. Personalizing rehabilitation strategies may therefore lead to better outcomes. The brain criticality hypothesis suggests that optimal brain function occurs at or near a critical point between order and disorder, with deviations potentially causing dysfunction [98]. A recent study [99] found that lower brain criticality during resting-state EEG was linked to improved BCI performance in a locked-in patient, while Rocha et al. [100] proposed that personalized brain dynamic models poised near criticality could predict stroke recovery. Future research could potentially employ brain criticality as a metric to tailor bimanual BCI neurorehabilitation, potentially optimizing patient outcomes.

D. Unilateral Cortex Encodes Unimanual and Bimanual Movements

In this review, multiple studies have explored the decoding and neural representation of bimanual movements in the unilateral motor cortex [30], [38], [39], [50], [53], [58]. A consistent finding across these investigations leads to a general inference: neurons within the unilateral motor cortex independently encode both contralateral and ipsilateral movements. Additionally, a significant correlation exists in the representation of movement direction between contralateral and ipsilateral actions. Moreover, their representations exhibit nonlinear changes between unimanual and bimanual movements. The encoding patterns for bimanual movements show a stronger correlation with contralateral movements than ipsilateral movements. Most studies suggest that brain activation patterns during bimanual movements are not simply a superposition of unimanual movements. The observed changes in representations may stem from variations in tuning parameters, such as modulation depths and directional preferences. However, this review found a contradictory finding by Linding et al. [43], who demonstrated effective performance using a stepwise classification strategy, showing that bimanual movements generate similar activity in each brain hemisphere to that produced by simple unimanual motor imagery on the contralateral side.

Notably, Downey et al. [53] observed a correlation in grasping representations between both hands while also identifying distinct representations for hand and arm movements. Previous research [39], [50] identified distinct neural representations for wrist and elbow movements, as well as movement directions. Furthermore, the investigation of unilateral local field potentials revealed distinct representations for bilateral MI, based on average energy across the full array and single-channel power levels [38]. Moreover, considering variations in representations across unimanual, bimanual, and different limb movements within the unilateral motor cortex, it becomes feasible to decode movement types and directions.

Although these studies confirm the involvement of the unilateral cortex in encoding both unimanual and bimanual movements, the underlying mechanisms remain to be fully understood. In unimanual tasks, the ipsilateral hemisphere encodes information distinct from that of the contralateral hemisphere, suggesting its role in both the planning and execution of movements [101]. Potential explanations include balancing interhemispheric inhibition, maintaining an efferent copy of the ipsilateral limb to facilitate bimanual control, and driving proximal muscle activity for posture stabilization. While this remains a topic of debate, investigating the role of both hemispheres in executing unimanual and bimanual movements—especially under task- and time-specific conditions—could significantly enhance the understanding of human motor control mechanisms. This knowledge carries important implications for developing novel rehabilitation strategies for individuals with motor impairments.

E. Important Features for Decoding Bimanual Movements

Studies employing MRCP signals have revealed significant findings. Specifically, they demonstrate a larger negative peak and lateralization of MRCP around movement onset in bimanual movements compared to unimanual movements [23], [45], [48]. Furthermore, a correlation exists between the negative offset maximum of MRCP and torque level, with higher torque tasks exhibiting greater negative offset maximums than lower torque tasks [102]. For example, Wang et al. [45] argued that upward hand movement against gravity yielded the largest negative amplitudes. Kirchhoff et al. [55] also observed a stronger MRCP rebound during bimanual tasks compared to unimanual tasks. Additionally, they identified an optimal decoding time window approximately 0.75 seconds before movement onset. Furthermore, Schwarz et al. [41] reported slower response times for bimanual movements, potentially indicating the additional planning and cognitive effort required for coordinated bimanual tasks. Wang et al. [49] demonstrated that simultaneous bimanual movements exhibited symmetric activations in both hemispheres, whereas sequential bimanual movements showed asymmetric activations with predominant contralateral effects.

The ERDS studies reveal key brain regions for decoding, including the supplementary motor area (SMA), primary somatosensory cortex (S1), posterior parietal cortex (PPC), and primary motor cortex (M1). Additionally, frequency bands such as delta, alpha, beta, and gamma were associated with decoding motor tasks. Studies [44], [46], [47], [52], [54], [63], [64], [65], [66] observed that during bimanual tasks, both hemispheres are actively engaged, with ERD showing a broader distribution over the non-dominant hemisphere, particularly in the parietal cortex, compared to unimanual tasks. Belkacem et al. [40] detected distinct time and frequency distributions in the SMA across bilateral hemispheres for diverse bimanual tasks. Additionally, bimanual movements were associated with bilateral beta ERD in the SMA, precentral/primary motor cortex, as well as in the anterior cingulate gyri and prefrontal regions areas and the frontal pole [56].

The study in [57] compared various feature extraction and classification methods in healthy participants and patients with DOC performing both hands MI. The results showed that coherence features yielded the best classification results in healthy participants, although unexpectedly, coherence was predominantly observed in the frontal regions. In contrast, none of the extracted features showed significant results in DOC patients, possibly due to the degree of disability and neuroplasticity variations among the patients.

Moreover, NHP studies [24], [59], [60] employing class activation mapping, a branch of xAI, have unveiled significant weights in the ipsilateral motor and somatosensory cortex regions. Simultaneously, gamma-band power activation has been observed in contralateral areas during unimanual movement, suggesting that brain signals acquired from the motor cortex encode information about both contralateral and ipsilateral movements. These results corroborate research demonstrating the decodability of both unimanual and bimanual movements from unilateral neural signals [30], [38], [39], [50], [53], [58]. Furthermore, the hand-movement classification system leveraged critical temporal cues during movement onset and offset, emphasizing its accuracy in bimanual movement classification. Additionally, they highlighted the substantial role of alpha and beta bands in decoding, signifying their importance in hand or finger movement planning and execution. Ortega et al. [26] reported a distinct frontal ipsilateral delta band pattern for the left hand, contrasting with a more bilateral pattern observed for the right hand. This discrepancy likely arises from the dominant cortical representation of each hand. Additionally, they noted contralateralization of the alpha band during bimanual tasks, accompanied by a bilateral frontal-parietal pattern, suggesting involvement of a fine motor control network. Conversely, Kirchhoff et al. [55] observed that feature importance for decoding predominately centered around the motor cortex in healthy participants, but in patients, it shifted to the frontal cortex.

Despite successful decoding of bimanual tasks, cortical activation patterns for different bimanual tasks lack strong spatial distinctiveness, particularly when using non-invasive neuroimaging techniques [41], [54]. Consequently, a significant challenge remains in expanding the DOF or the number of tasks that a bimanual BCI can decode. Furthermore, only a limited number of studies in the review employed multimodal neuroimaging techniques. Adopting such an approach could be advantageous, as multimodal neuroimaging provides a more comprehensive assessment of the integrated neural mechanisms underlying complex processes. This methodology allows for more robust comparisons, cross-validation across modalities, and can significantly enhance the overall understanding of brain function in BCI applications.

F. Future Prospects in Bimanual Coordination in BCI

While the reviewed papers offer diverse research directions, their limitations highlight opportunities for future development. The focus of bimanual BCI studies in this review has primarily been on decoding motor intentions during the execution of MI or ME, and translating these intentions into real movements by controlling peripheral devices. However, achieving precise and real-time control requires a deeper understanding of motor planning—the preparatory stage preceding movements. Studies by Hanakawa et al. [103], [104] have shown differences in the distributed motor network during motor planning, MI, and ME. Although brain regions involved in MI are similar to those in motor planning, discerning these distinctions is crucial for refining BCI control algorithms. A comprehensive grasp of motor planning could enable controllers to discern between preparation signals and actual execution signals, enhancing the system's responsiveness and accuracy. Another promising development prospect is implementing a system capable of halting execution upon user request. Bhattacharyya et al. [105] proposed a robot arm's online control scheme that utilizes the error-related potential signal to stop the movement of individual links. Integrating these ideas into the bimanual BCI system can pursue a more realistic movement.

Moreover, the application of BCIs in the spinal cord is an intriguing research topic in the BCI-based neurorehabilitation field. Several studies [106], [107], [108], [109] have demonstrated the potential of restoring communication pathways in the injured spinal cord. Currently, only one study found the potential of utilizing spinal fMRI and electromyography signals from healthy patients to decode bimanual tasks [110]. While this study may not explicitly focus on motor function restoration, its investigation and analysis contribute to a deeper understanding of spinal cord mechanisms related to bimanual motor control. Exploring the integration of bimanual BCIs into spinal cord applications presents an intriguing avenue for future research.

The primary goal of most bimanual BCI applications is to restore motor function in patients with deficits, enabling them to regain natural movements through brain-controlled devices. However, it is crucial to explore whether these technologies can also augment the human body, enhancing task performance and enabling multitasking. One promising application is the development of supernumerary limbs, which aim to expand motor capabilities by adding extra limbs [111], [112]. While this offers exciting prospects for BCI, the application is relatively new and requires further research. Specifically, it is important to address the neural allocation problem, which examines whether the brain can adapt to effectively provide control signals to additional limbs without impairing the function of existing ones [113], [114], [115]. Furthermore, the extra limb must provide sensory feedback that complements natural information and creates a sense of realistic embodiment [116], [117].

V. Conclusion

This review investigated recent trends in bimanual coordination within BCI research. It comprehensively examined participant demographics, neuroimaging methods, experimental tasks and paradigms, and feature extraction and decoding algorithms. Recommendations to enhance bimanual BCI usability and support motor function rehabilitation in individuals with motor deficits are suggested. The review synthesized key neurological findings on bimanual coordination and proposed future research directions. Leveraging advancements in neurological understanding and BCI technology, it anticipates progress in motor BCIs towards more natural and practical applications. Thus, this article serves as a starting point for designing bimanual motor coordination studies in BCI, addressing both engineering and neurological aspects by summarizing recent trends.

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