Noninvasive Brain–Computer Interface

Decoding Arm Movement Kinematics and Motor Control

by Neethu Robinson and A.P. Vinod

Over the last few decades, the advances in disciplines such as neuroscience and engineering have introduced the brain–computer interface (BCI) as a promising tool for neurorehabilitation and neurophysiology research. BCI research primarily aims at development of assistive and rehabilitation strategies for motor-impaired users and, hence, sensorimotor-rhythm (SMR)-based BCIs are widely explored. This type of BCI performs detection and interpretation of the neural activity underlying various user intentions, specifically related to movement, and translates these brain functionalities to the external environment without relying on normal neuromuscular pathways. The interfaced device thus achieves motor control directly from the neural activity. Motor-control BCIs investigate various aspects of human motor skills and have successfully identified neural patterns related to motor execution, imagination, and intention from bilateral limbs. In this article, we provide a summary of recent advances in motor control BCI, specifically in movement kinematics decoding and motor control of localized areas of the limb. We further discuss the research challenges and future scope of work in this area of research.

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Background

The primary focus area of BCI research is the neurological disorders that affect the motor cortex of the brain, leaving the patients with severe motor disabilities and loss of manual dexterity [1]. This has resulted in the development of motor-control BCIs that function depending on the SMRs of the brain [1]–[3]. Human motor abilities and their underlying phenomena are explored using invasive and noninvasively recorded brain activity. SMR-based BCIs focus on characterizing and differentiating the neural features responsible for various motor tasks. The translation of neural activity corresponding to bilateral limb movement execution or imagination is a widely popular motor BCI control output. As indicated in Figure 1, in a BCI system, recorded neural data undergo signal processing and machine learning algorithms that identify neural features that can be translated to commands to control external devices. The demand of continuous and control output with higher degrees of freedom introduced movement kinematics research in BCI, which uses neural activity to decode movement parameters such as speed, direction, position, and force. Furthermore, just as the neural activation patterns differ for various motor tasks and limbs, specific localized areas of the limbs (arm, elbow, shoulder, hip, and knee) also generate discriminative activity. Identifying such cortical activations underlying these tasks from scalp-recorded brain activity can have a huge impact on neuromotor rehabilitation applications.

The objective of these areas of SMR-BCI research is to provide high-precision, continuous, and accurate motor control to the interfaced device. The existing BCI research sets performance goals, including high information transfer rate, low decoding error, high classification accuracy, robustness, portability, and cost efficiency, while designing a system. To attain each of these goals, the major challenge is to identify the neural phenomenon underlying finer movement tasks, using scalp-recorded brain signals. The development of signal processing and machine learning algorithms [98], [106], [107] over the years has enabled BCI to work toward these goals. The various brain data acquisition modalities record neuronal activations appearing at different cortical levels or on the scalp surface, which result in different signal spatial resolution. Specifically, for noninvasive techniques that record extracellular potentials over the scalp, the signal has limited spatial resolution and frequency range, and the technique is highly susceptible to environment interference and muscular or ocular artifacts. As a result, these factors are major challenges in noninvasive BCI research. Recent studies have established the use of noninvasive signals for movement kinematics and finer motor control, despite the assumption that these parameters are encoded in the neuronal firing [4]–[7].

Related Work

BCI for Communication and Control

BCI technology has been introduced with the goal of providing augmentative communication and control for those with severe neuromuscular disorders [1], [7], [8]. However, researchers have also investigated the nonmedical applications of BCI [95], thus developing brain-controlled devices aimed at performance enhancement or entertainment. In this section, an overview

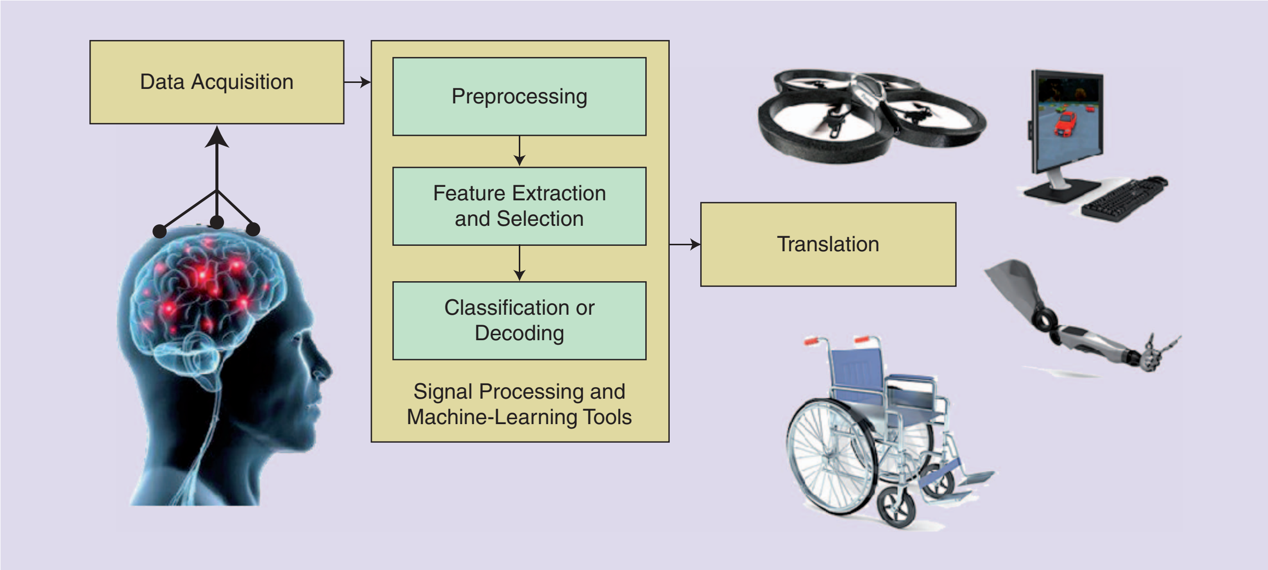

Figure 1. The components of a BCI system.

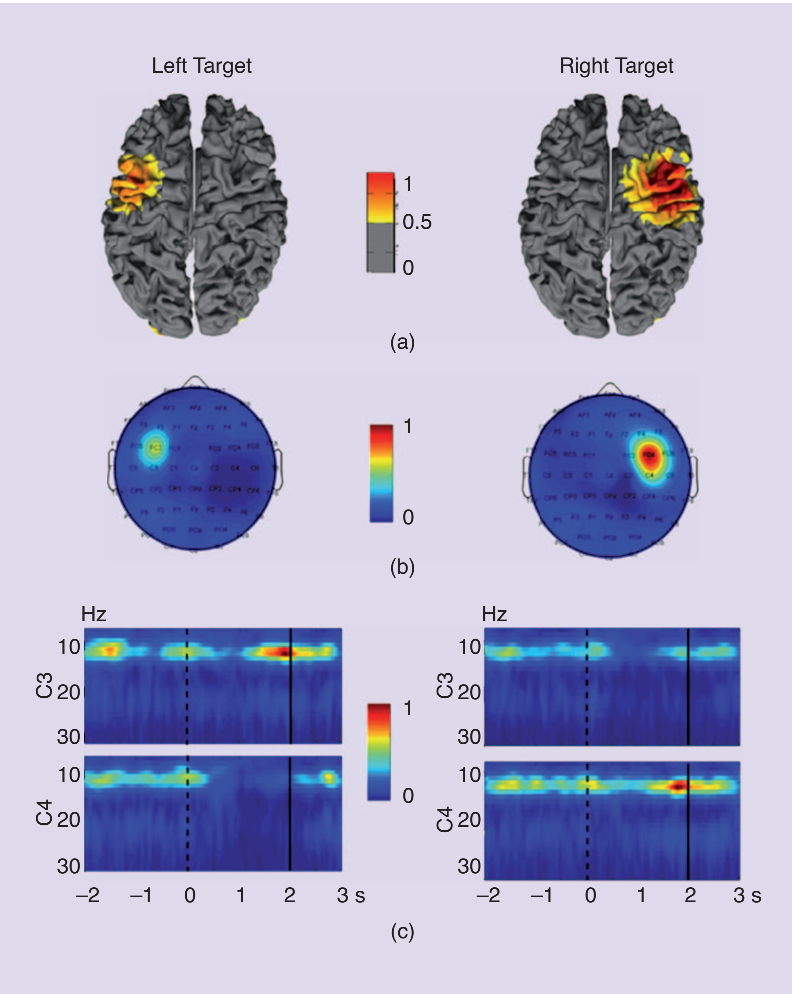

Figure 2. The topologies of a mu-band power for right-/left-hand motor imagery. (a) The cortex and (b) the scalp. (c) Average time-frequency representation maps using minimum-norm estimates in the frequency domain [99].

of existing BCI that provides motor control is discussed.

The pioneering researchers in BCI have reviewed the state-of-art techniques in this area and have reported their findings in [1], [7]–[9], and [99]. The neurophysiological phenomenon observed is the modulation of rhythmic activities (mu, beta, and gamma rhythms) recorded over the sensorimotor cortex, termed *SMR*, by human motor tasks, such as actual movement, motor intention, or motor imagery. In bilateral movement tasks, these modulations are called *event-related (de-) synchronization (ERD/ERS)* of mu (8–13 Hz) and beta (14–26 Hz) rhythms, indicating a decrease in band powers recorded from contralateral sites and its increase in ipsilateral sites. Figure 2 demonstrates these cortical rhythmic modulations associated with bilateral hand motor imagery as reported in [99]. In addition, the neural phenomena reflected in slow cortical potentials (SCP), P300 and event-related potentials with their ability to generate discrete control commands to an interfaced device were reported to have a wide range of usability in BCI. Real-time motor control was achieved by BCI in which users learned to modulate their SMR amplitude [10] and ERD/ERS [11] associated with various limb movement imaginations. The reports in [4], [8], and [12]–[14] highlighted the developments in SMR-BCI and the shift of its goal from single-trial classifications to the design of adaptive, asynchronous BCI systems. BCI research on discriminating limb areas, such as wrist/elbow/shoulder and knee/hip, is relevant since stroke-related impairments affecting movement coordination can be better studied using this approach rather than gross movement activation patterns. Various brain studies have reported the cortical reorganization following stroke, resulting in overlap of cortical areas corresponding to independent joints [15], [16].

Neural Encoding of Movement Kinematics

The investigation of neuronal activation patterns responsible for hand-movement kinematics have been performed using invasive brain recording of primates as well as humans. The goal of these works have been to shed light on the neural encoding and connectivity that enables one to perform coordinated and defined motor tasks. In [6], the authors reviewed the directional tuning of neural signals and the literature on decoding movement direction and trajectory using multiple BCI modalities. Furthermore, the review reported in [5] provided a comprehensive overview of invasive and noninvasive studies in movement kinematics decoding in humans and in primates.

Various studies have demonstrated directional tuning of neuronal parameters, i.e., its variation with the direction of movement. Center-out hand-movement experiments were used in these studies. Single-unit activity and multiunit activity studies in primates showed that the movement direction was found to depend on the neuronal firing rate [17]. More recent studies reported the ability of an ensemble of neuronal activity to control a robotic arm to perform reach/grasp movement [18] and that of localized field potentials to decode movement trajectories and velocity [19]. Further neural data recorded from cortical surface using electrocorticography also provided local motor potential features that demonstrated direction tuning and two-dimensional (2-D) four-target movement decoding [19], [20]. The next sections discuss the state-of-the-art techniques in finer motor control using noninvasive BCIs.

Discrete Classification of Movement Parameters

In implementing a BCI with higher degrees of freedom, the identification of the neural correlates of motor kinematics is of prime importance. The noninvasive research in this area aimed to identify and extract the neural features that are responsible for precise motor control. In this section, we list the recent findings in BCI research that used noninvasive brain data acquisition modalities to discretely classify hand-movement parameters such as direction, arm force, and speed. Some special cases are also mentioned that investigated speed/force imagery, rhythmic imagined movement, and expressive movements.

The tasks adopted by the researchers include center-out and center-in movements that are either visually guided or self-paced. Various studies have even attempted natural movements such as drawing, clenching, and reaching. All this research points toward specific spectral and spatial distribution of neural activity associated with finer movement. The involvement of the motor and parietal cortex has been repeatedly proven in all the studies as well as the neural features from low-frequency (<8 Hz) bands. A wide range of algorithms were reported that use time–frequency (TF)-space localized features to classify the movement parameters. According to the results reported in the literature, spectrally localized neural data and optimized algorithms based on a common spatial pattern (CSP) provide better classification performance and hence are widely explored. The results obtained from these studies are summarized in Table 1, and we will discuss the details.

The foremost study on identifying hand-movement parameter direction using a noninvasive brain signal was reported in [21]. The movement direction was classified on a single-trial basis using magnetoencephalography (MEG) signal power in low-frequency bands. The study simultaneously recorded electroencephalography (EEG) and 3-Hz low-pass-filtered EEG and MEG features were analyzed. Reported in [22] and [23] was that the cortical sources of movement direction were using source-localization methods. Functional near infrared spectroscopy (fNIRS) has been used by various researchers to investigate arm movement force. The hemoglobin concentration changes as the subject performed isometric arm movement were used to discriminate the force direction, and results of classification were reported in [24] and [25]. The direction tuning of fNIRS-based hemodynamic signals recorded over contralateral sensorimotor areas were demonstrated in [26].

The role of posterior parietal cortex in encoding hand-movement direction and intended movement direction was studied in [27] and [28]. The studies [29]–[31] investigated the TF regions that contain optimal movement directional information that can enhance the decoding and classification performance of EEG-BCI systems. The TF bins that provide higher direction-dependent information from specific electrodes were detailed in [29]–[31]. Reported in [31] was a significant ($p < 0.005$) movement direction dependent modulation toward the end of movement at low frequencies (≤6 Hz) from the midline parietal and contralateral motor areas, as shown in Figure 3. In [87], neural activity related to bidirectional hand movement (imagined and executed) was recorded using a low-cost commercial EEG amplifier and decoded. Single-trial classifications of center-out and center-in movements were reported in [32] using CSP-based EEG features (eight classes), [33] with dyadic filter bank CSP-based EEG (<8 Hz) feature (four classes), and in [34] with canonical variance analysis (four classes). In [35], SCP derived from 0.1–1-Hz EEG data was used to predict movement direction on healthy as well as stroke patients (using paretic arm). In [36], movement direction was studied by recording data as the subject traced an infinity shape using his

Table 1. Classification of hand-movement parameters.

Modality	Study	Movement Parameter/Task	Feature/Technique	Result (Classification Accuracy, Remarks)
MEG EEG	[24]	2-D center-out self-chosen target hand movement	Regularized linear discriminant analysis (LDA)	MEG: 67%; EEG: 55% MEG+EEG: 60.2%
MEG	[25], [26]	2-D center-out visually guided four-target wrist movement	LDA and Bayesian classifier, discriminant pattern source localization	67% (overt) and 62.5% (imagined), localized activations for the spectral band of 0–7 Hz
fNIRS	[27]	Isometric arm movement force to four targets	Self-organizing maps	87.5% (binary class)
	[29]		Sparse logistic regression	>95% (binary class)
EEG	[30]	Visually guided four-target wrist movement	Regularized LDA, nonlinear support vector machine (SVM)	65% (left versus down movement)
	[31]	Delayed saccade/reach	Independent component analysis	80.25% (right versus left direction)
	[32]	Visually guided three-target reaching task	Fisher linear discriminant (FLD)	93.91% (right versus left direction)
	[35]	2-D center-out visually guided four-target reaching	Regularized wavelet CSP	80.24% (four-class)
	[36]	Eight-target center-out and center-in movement	CSP	71% (binary)
	[37]	2-D center-out visually guided four-target reaching	Dyadic filter bank CSP	66.08% (four-class)
	[38]	Four-target self-paced center-out movement	Canonical variance analysis	85%
	[39]	Four-target center-out movement	SCP	76% (healthy) and 47% (stroke)
	[40]	Tracing infinity shape	CSP for six-class data	74% (binary)
	[43]	Movement speed	Wavelet CSP	83.71% (binary)
	[44]	Speed and force of clench motor imagery	Alpha band power	67.65% (trained subjects) and 59.68% (nontrained subjects)
	[46]	Imagined grip force	Movement-related cortical potential	24% (SVM) and 27% (k-FLD)
	[97]	Bidirectional center-out visually guided movement	Filter bank CSP	81.3% (movement execution) and 82.4% (movement imagination)

right arm in the vertical plane. Various other tasks studied using EEG include hand-movement speed [37], the parameters of motor imagery, such as speed and force specific to clenching [38], and bilateral imagined grip force [39].

Movement Kinematics Decoding

The BCI research findings that specifically focus on the reconstruction of hand-movement speed/velocity and trajectory are reviewed in this section. The movement trajectory/coordinates as a hand/finger/elbow performs a task are studied using various experiment paradigms. The research has reported significant contribution to linear decoding by low-frequency EEG (<3 Hz) from motor, premotor, and parietal areas. Various nonlinear decoders were also proposed with the goal of including more signal spectrum. The research in this area using EEG is summarized in Table 2. The performance metric, indicated in the results, is the correlation coefficient between recorded and reconstructed movement parameters.

The ability of an MEG signal to decode hand-movement kinematics was explored in [40]–[44]. In [40] and [41], 15-Hz low-pass-filtered MEG was used for decoding, and it was reported that the sensor networks over central and parietal scalp areas contributed more toward this decoding. Further studies have used MEG to reconstruct 2-D fingertip movement trajectory [42] to decode movement velocity [43], [44]. The 2-D or three-dimensional (3-D) center-out movement/reaching tasks were used to reconstruct kinematics using low-frequency MEG. In [45], an fNIRS signal was used to estimate finger pinch forces using a sparse linear regression method. The applicability of EEG in decoding hand-movement kinematics was explored in [46] and [47] using a center-out 3-D hand-movement experiment

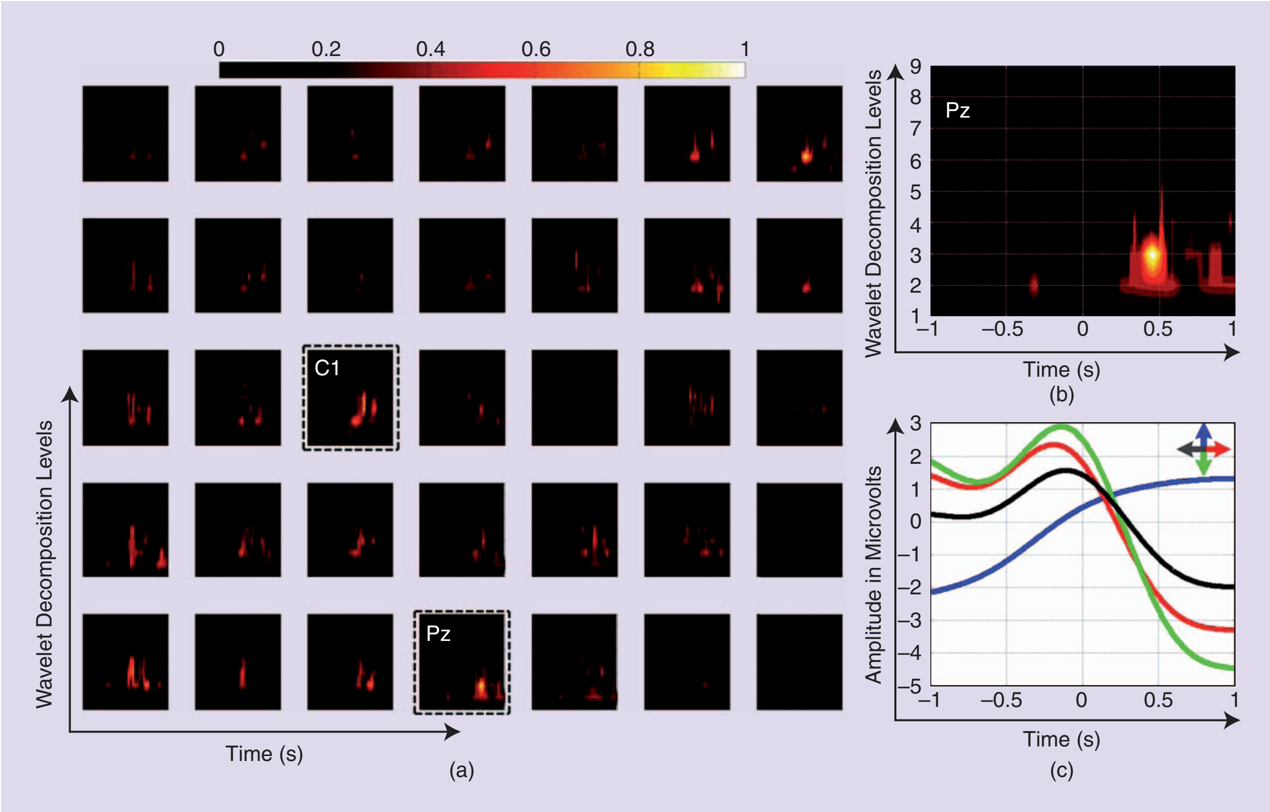

Figure 3. The movement-direction-dependent, normalized SNR. (b) The SNR and (c) the trial-averaged temporal activity for electrode Pz low-pass-filtered at 1 Hz [35].

paradigm. The low-pass-filtered EEG (<1 Hz) was used to reconstruct hand-movement velocity using a linear decoding model, and further source localization analyses indicated the highest contributions to decoding from contralateral precentral gyrus, postcentral gyrus, and inferior parietal lobule, recorded 60 ms premovement, as indicated in Figure 4. In [48], researchers applied a continuous 2-D drawing task experiment to investigate the corresponding EEG activations and reported significant contributions from 0.1–4-Hz, and 24–28-Hz bands in premotor, posterior parietal, and occipital areas was reported.

The kinematics of movement intention using a target-reaching task in virtual 3-D space [49], natural grasping movement [50], center-out hand movements [51], and self-paced and self-initiated reaching movement [52] was studied using EEG. Various modes of EEG signal analysis, such as linear decoding models using low-pass-filtered EEG, phase-locking of low-frequency EEG, and TF information of EEG were explored. The movement kinematics during natural task, such as filling a glass of water, was studied in [53] using filtered EEG (<1 Hz) and (0.5–2 Hz). The 2-D hand-movement speed coordinates and trajectory were decoded using wavelet-CSP-based predictors, and the results were reported in [37] and [55]. An adaptive estimation of the same parameters was reported in [88] using Kalman filters, and the results obtained are indicated in Figure 5. In [55] and [56], the involvement of low-frequency EEG from motor, premotor, and parietal areas pre- and postmovement was indicated. Reported in [57] and [58] was the use of a linear decoder model on low-pass-filtered EEG (<1 Hz) to decode the velocity of the hand and elbow, among others.

The applicability of linear decoding models in stroke patients to reconstruct one-dimensional hand-movement velocity was demonstrated in [59]. The parameters of an imagined rhythmic movement were studied in [60] using the filtered EEG (0.4–0.6 Hz). Nonlinear regression models were also reported in decoding movement kinematics to enable processing of high-frequency EEG and to improve regression performance [61]. In [61], a particle filter model to decode 2-D and 3-D hand-movement position, and in [62] a kernel ridge regression to decode 3-D hand-movement velocities were reported. In [63], the hand joint angular velocities as well as synergistic trajectory during a 3-D reach-to-grasp task were decoded using EEG. The applicability of EEG alpha and beta band powers, from planning, execution, and combined time segments, to predict peak hand-movement speed and acceleration was studied in [64].

Movement of Localized Limb Areas

The noninvasive BCI research on localized areas of upper limbs, such as, elbow, wrist, finger, and shoulder, and lower limbs, such as, hip, knee, and foot, mainly

Table 2. Hand movement kinematics decoding.

Modality	Study	Movement Parameter/Task	Feature/Technique	Result (Correlation Coefficient, Remarks)
EEG	[54], [55]	3-D center-out hand movement	Linear decoding model	(0.19, 0.38, 0.32) (*x, y, z*) axes of speed
	[56]	2-D drawing task	Kalman smoother decoder	0.35–0.83 (horizontal) and 0.11–0.45 (vertical)
	[58]	3-D virtual space target-reaching intention	Stepwise regression	(0.2–0.39, 0.09–0.5, 0.09–0.57) for vertical, horizontal, depth
	[59]	Natural grasping: finger trajectories	Linear decoding model	0.76
	[60]	Eight-target center-out hand movement	Linear multiple regression model	0.76
	[61]	Self-paced and self-initiated movement	Partial least squares and support vector regression	0.2-0.4
	[62]	3-D center-out movement to self-chosen targets	Linear decoding model	0.7, 0.77, 0.62) and (0.7, 0.78, 0.62) for *x, y,* and *z* coordinates of velocity and position
	[63]	Movement kinematics: filling a glass of water	Filter bank CSP and regression models	(0.41, 0.36, 0.48, 0.17) for *x, y, z* and absolute values of speed
	[43], [64], [65]	2-D center-out four-target reaching task at two different speeds	Wavelet CSP, Kalman filters	0.57 (average over six parameters), 76% reduction in number of predictors.
	[66]	2-D target selection task	Linear decoding models	(0.39, 0.47) for (*x, y*) axes of velocity
	[67]	Velocity of hand/elbow during a center-out movement task	Linear decoding models	(0.31, 0.27, 0.15) and (0.31, 0.3, 0.16) for (*x, y, z*) axes of hand and elbow velocity
	[70]	2-D and 3-D hand movement position	Particle filter model	Higher decoding accuracy compared to linear decoders
	[71]	3-D movement velocities	Kernel ridge regression	Significant reduction in decoding error
	[72]	3-D reach to grasp task	Independent component analysis, Wiener filter, multiple kernel learning	(0.59, 0.47, 0.32) for first three kinematic synergies
	[73]	2-D finger movement	Alpha and beta band powers	Coefficient of determination: 0.21–0.31

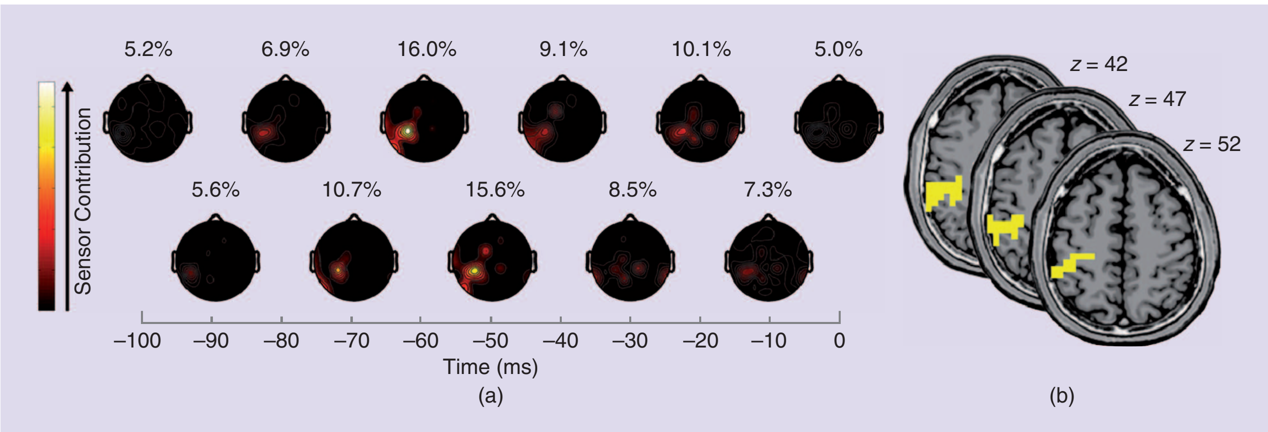

Figure 4. (a) The scalp maps indicating a contribution toward decoding hand-movement velocity. (b) The localized EEG sources from –60 ms overlaid onto magnetic resonance imaging structural images [55].

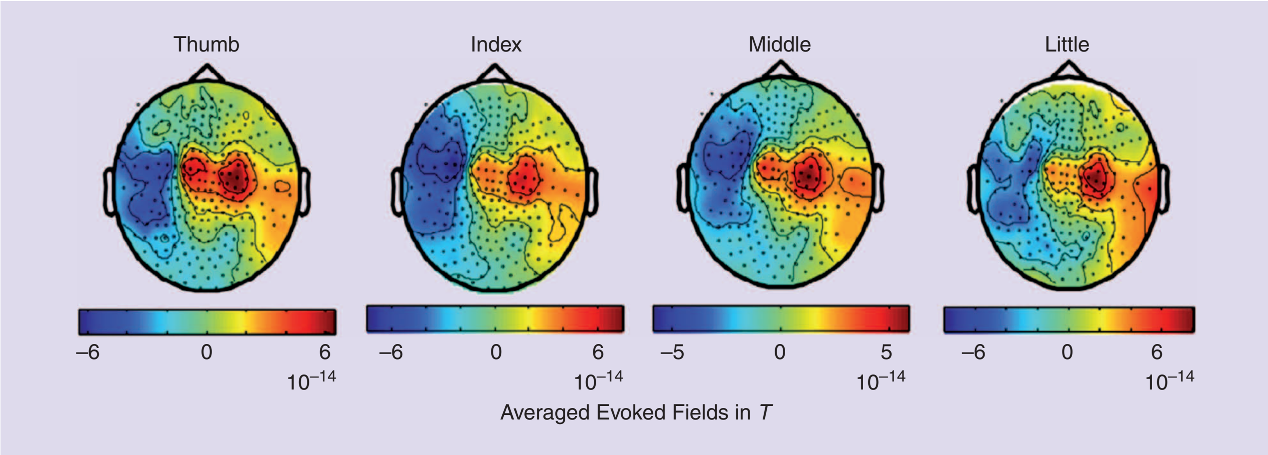

Figure 5. The evoked magnetic fields are shown for movements of the thumb, index, middle, and little finger of the right hand [76].

addresses the challenges of overlapping cortical sources. The investigations in this area focus on movement types executed by different areas of the same limb. Studies have investigated upper limb movement (hand grasping, pinching, and elbow flexion) using MEG [65], finger movement tasks using functional magnetic resonance imaging (fMRI) [66], and combined MEG-EEG [67]. Figure 6 shows the relatively similar activation patterns in terms of average evoked magnetic field recorded by MEG for different finger movements.

A summary of various EEG studies mentioned in this section is given in Table 3:

- classification of imagined fast and slow wrist extension and rotation, elbow versus shoulder torque intention [68]
- imagined movement involving three limbs (left and right index finger and right toe) [69]
- imagined movement of finger and wrist [70]
- imagined wrist flexion and extension of right and left wrists [71]
- self-initiated movement tasks (shoulder abduction, extension and rotation, elbow extension, forearm pronation, wrist extension, and rotation) [72]
- imaginary grasp movements and imaginary elbow movements [73]
- five finger movements of the same hand [74], [75]
- nine index finger position during a key-pressing task [76]
- real and imagined movements using index and thumb fingers [77].

The neural features, such as mu/beta band powers, movement-related cortical potential (MRCP), event-related potentials, and ERD/ERS patterns, are of interest in these BCIs. A wide range of algorithms were employed in these studies, as shown in Table 3, to improve the classification performance of these multiclass BCI systems. Also, studies such as [69] and [75] have reported single-trial classifications of elbow/shoulder/finger movements in disabled subjects as well. The BCI research on lower limb movements was reported in [92], using fMRI to identify cortical source of bilateral foot movement imagery and in [93] and [94] using EEG to perform single-trial classifications of foot movement. The research indicates the feasibility of EEG signals to decode localized limb movements. A less-explored topic in this BCI research seems to be investigation of spatially localized regions responsible for distinct limb areas using EEG. Although the spatial resolution of EEG makes this a challenging task, the significant findings in the literature makes this a promising area for future research.

SMR-BCI Applications

The ultimate objective of all the studies mentioned in the previous sections is to impart higher-dimensional

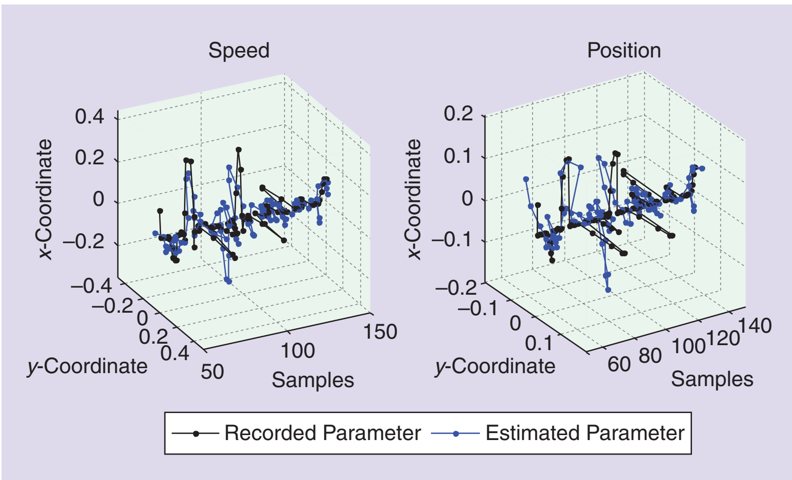

Figure 6. The 2-D hand-movement trajectory parameters reconstructed using Kalman-filter-based adaptive estimator with selected predictors [98].

Table 3. Classification of movement types of the same limb.

	Study	Movement Task	Feature/Technique	Result (Classification Accuracy)
EEG	[77]	Imagined fast and slow wrist extension and rotation	Rebound rate of MRCP and the mu and beta band powers	Average misclassification rate of 21% (binary)
	[78]	Elbow versus shoulder torque intention	Classifier-enhanced TF synthesized spatial pattern	(92%, 75%) and (100%, >80%) accuracy for (healthy, stroke) subjects
	[80]	Motor imagery patterns for finger and wrist	Mahalanobis distance clustering and artificial neural networks	65% and 71%
	[81]	Imagined wrist flexion and extension of wrists	Elman's neural networks	63%
	[82]	Self-initiated seven movement tasks	Bayesian classifier	62.9% (30.2% baseline)
	[83]	Rest, imaginary grasp, and elbow movements	CSP, filter bank CSP, etc.	66.9% (grasp versus elbow) and 60.7% (three-class)
	[84], [85]	Finger movement	Spectral principal component analysis, band powers, and direct temporal data	77.11% over each finger pairs 91.28% (epileptic patients)
	[86]	Nine index finger position during key-pressing	Random forest classifier	12.29% (11.1% chance level)
	[87]	Real and imagined movements using fingers	Symbolic regression-based features	45% (SVM) and 38% (artificial neural networks)

and continuous motor control to an interfaced device directly from brain signals. In this section, a few studies that demonstrate noninvasive BCI systems used to control movement of an interfaced device are listed. It is interesting to note that, in all these studies, continuous control is achieved using discrete motor tasks or combinations of motor tasks, using specific control strategies. The applicability of movement kinematics decoding to achieve higher-dimensional motor control, as an alternative for this strategy, can thus be investigated.

In [78], robotic arm control to execute a multistep grasping task was achieved using EEG and was demonstrated both in healthy and poststroke subjects. Discrete motor tasks (imagine left/right hand open-close, imagine open-close of both hands, imagine tap foot) were performed, and control commands (move right-left, vertical, open/close robot hand) were provided for the robot. In [79], a virtual helicopter control was achieved using EEG. The (left, right, up, down) controls were provided by imagining movement of left hand, right hand, both hands up, and rest, respectively. In [80], an EEG-based asynchronous BCI system was developed that allowed driving a car in a 3-D virtual reality environment. The imagined hand and feet movements were used to determine the direction of the steering wheel and car speed. Similarly, in [81] and [82], continuous 3-D control was achieved using EEG in a virtual helicopter and quadcopter. The SMR-based features were used in [81] to achieve helicopter control and features from selected electrodes and frequency bins were used in [82] to achieve quad copter control.

Limitations and Future Scope

The noninvasive BCI research discussed in this review demonstrated the potentials of scalp-recorded signals to provide higher-dimensional motor control. In this regard, we have provided a comprehensive review of recent studies using noninvasive BCI for classification and decoding of hand-movement parameters and classification of movement types performed by localized areas of a single limb. SMR-BCI that aims to obtain precise motor control using relevant features from spectral, temporal, and spatially localized neural signals recorded by EEG, fNIRS, and MEG were reported in these studies. Most studies report the increase in BCI performance to decode (classify or reconstruct) movement kinematics when low-frequency features (<6–7 Hz) are considered [21]–[23], [29], [31], [33], [35], [37], [44], [48], [50]–[60], [88]. Further, the contribution of parietal and supplementary motor areas along with primary motor cortex is also reported [23], [27]–[31], [46]–[48], [56]. These results introduce novel research areas for BCI research that will look into low-frequency signals and the regions outside motor area and how these correlate with the human motor activity.

It will be interesting to look into the temporal variations in connectivity between regions of the brain for different spectral regions and how it correlates to movement intention, planning, and execution. Research in these directions can help to better understand the neurophysiology of human locomotion and thus contribute to SMR-BCI systems. The results indicate the feasibility of such BCI systems to impart higher degrees of freedom of movement to an interfaced device or allow the user to learn and enhance finer control and coordination of one's limb movement. These can have a significant impact on clinical applications, (neurorehabilitation and neuroprostheses) as well as navigation applications (robot, virtual reality, and games).

Notwithstanding the aforementioned highlights of this area of research, it is worth mentioning its challenges and limitations as well. SMR-BCI investigates different aspects of voluntary movement, namely, preparation, intention, execution, and imagination. The research on finer parameters of movement widely uses movement execution experiments. Even though studies on kinematics of movement intention/imagination can have a significant role in rehabilitation applications, this area is yet to be explored. The major challenges in this area include

1) BCI performance of imagined tasks; the SMR-BCI research reports reduction in decoding accuracy for imagined movement compared to executed movement, owing to globalized activity
2) experiment paradigms that can elicit imagination of finer movements; cues and feedback to ensure that subject performs kinesthetic imagination of such movement will be challenging.

Some studies cited in this review [38], [39], [49], [87], [100] report promising results in decoding imagined movement kinematics, and future research can look into this aspect of SMR-BCI.

The performance of SMR-BCI is often reported in terms of average classification accuracy or a correlation coefficient over a limited number of subjects. However, to ensure generalization of the results, analysis of statistical significance maybe incorporated. Future research may look into acquiring a larger dataset on standardized experiment paradigms to study movement kinematics. The report in [84] raised various concerns regarding the use of linear regressors and a correlation coefficient as the evaluation metric in movement kinematics reconstruction studies. The statistical analyses that can be performed to avoid certain misinterpretations of the results were further suggested. The study pointed out how the usage of a linear regressor can limit the spectral region of the brain signal under investigation and how the correlation metric provided overly optimistic results in lower spectral regions.

The studies in [85] and [86] investigated how the artifacts affect movement parameter decoding in EEG-BCI systems. The effect of a slow trend on EEG signal and proposed adaptive filtering methods to extract the same was examined in [85]. In [86], the effect of eye movement artifacts in the performance of linear decoding models was demonstrated. The article reported significant fall in performance of linear decoders as compared to nonlinear decoders once the electrooculography-related activity was removed. The previously mentioned studies point out the major design considerations in decoding and signal enhancement algorithms and the need to develop efficient alternatives.

Interesting research in this area is the study in [83] that investigated the impact of decoding error in device control using simulations and suggested how remapping decoded parameters to control some other aspects of device movement is a viable option. The study specifically reported that, for the same amount of error for position, velocity, and goal decoding, only the latter two could produce accurate control output. It reported the option of remapping the decoded velocity/goal to control position of the output device or vice versa. As pointed out by the authors, these interesting transformations exist in our everyday skills, e.g., the car velocity being controlled by foot position in the pedal.

Researchers still need to look into the possibility of developing closed loop BCIs, which can provide real-time high-dimensional motor control. Also, decoding of imagined or intended movement trajectory can also be explored through design of proper experiment paradigms and neural feature identification. It will also be interesting to see how the various areas of a single limb contribute to gross movement and its parameters, which essentially combines the goals of the various topics discussed in this review. Also, incorporating a multimodal brain data acquisition system (EEG-fNIRS, EEG-MEG) can enhance the signal resolution and hence provide thorough insights into neurophysiological phenomena involved in these movement tasks.

Present-day BCI is capable of interpreting the electrophysiological or hemodynamic activity of the brain, thereby establishing it as a possible augmentative communication and control technology for disabled people [1]–[4]. However, the major challenges in this research still include unreliability of the BCI performance due to low signal resolution and nonstationary neural activity. The research reviewed in this article suggest that translation of motor intentions into precise control commands is possible with the help of efficient BCI algorithms. Further studies [80], [90] suggest the use of low-cost and user-convenient commercial EEG amplifiers in SMR-BCI. These results encourage research to develop real-life, practical, and user-friendly BCI technology.

We would like to point out that even though the research reported in this article promises feasibility of a higher-dimensional motor control system, applying SMR-BCI as a rehabilitation technology for users who are locked in may encounter several difficulties. The adaptation of BCI systems to account for neural features affected by neuromuscular impairments will be challenging. The review in [91] reports EEG-BCI research in stroke rehabilitation using imagined and executed motor tasks. BCI-based rehabilitation for finer motor control can also have significant impact in motor recovery of the user and, hence, extensive research is required for the same. In conclusion, the SMR-BCI research indicated that finer and precise motor control to an interfaced device could be achieved using noninvasively recorded brain signals. By addressing the various challenges in this area, practical and real-world applications of BCI can be implemented. Further progress in this area of BCI research can thus lead to innovations in BCI technology.

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