In this article, we provide an overview of electroencephalography (EEG) source imaging (ESI) of movement decoding for brain–computer interface (BCI) applications. The current state-of-the-art neuroimaging modality—functional magnetic resonance imaging (fMRI)—is expensive and nonportable and has poor temporal resolution. EEG, however, offers an attractive choice as a portable and cost-effective neuroimaging technique that delivers excellent temporal resolution, especially in reading dynamic human motor behavior.

This article introduces the basics of ESI, followed by a critique of state-of-the-art ESI methods concerning various facets of motor tasks, such as directional decoding, movement kinematics, and localized arm movement decoding in BCI paradigms. We also examine the clinical applications of EEG-based neuroimaging in prognoses of neuromotor diseases. Furthermore, we discuss some of the common pitfalls related to EEG source localization and the necessary measures to circumvent these challenges.
Developments in ESI

With the rapid strides that have been made in machine learning and signal processing techniques, BCI is becoming quite popular, as it allows the translation of human intentions into control commands. While the applications of EEG-based BCI span several domains, the most important are in the field of neuroprosthetics to assist locked-in patients. Nevertheless, even the current state-of-the-art technology in noninvasive BCI systems allows for only a limited degree of control in neuroprosthetics. Since motor functions are somatotopically organized in the human brain and motor control is highly dynamic in nature, it is indispensable to understand the spatiotemporal dynamics of brain activity to produce a greater number of control commands with higher degrees of freedom (DoF) [1], [2].

Although EEG has the advantage of high temporal resolution, its innate limitation of poor spatial resolution makes gathering information from the cortical source arduous. Unfortunately, traditional approaches focusing on increasing the number of scalp electrodes to improve scalp spatial resolution do not address the problem of volume conduction effects. Because ESI addresses this issue to some extent, there is increasing attention toward using this approach. ESI is essentially a model-based neuroimaging technique that uses anatomical constraints to solve the ill-posed problem of identifying the cortical sources that generate electrical potentials recorded from the scalp.

Although there have been several multimodal neuroimaging methods in the literature [3] that incorporate EEG’s high temporal resolution and fMRI’s high spatial resolution to complement each other’s limitations, there are severe practical hindrances concerning the monetary cost and the limited portability of MRI. Discussing the advantages and drawbacks of multimodal neuroimaging is out of the scope of this article, and therefore, we suggest that readers refer to recent review articles on this topic [4], [5]. Another such article gives an excellent overview of ESI in the context of BCI paradigms [6].

In our current work, we aim to equip readers by supplying a nonexhaustive topical review of EEG source localization and associated source domain analysis of motor tasks, thereby complementing the thorough literature survey in [6] and [7] on the challenges and opportunities of ESI. Although the fundamental concept of EEG source localization has been known for some time, its application to the motor imagery (MI) classification of left- versus right-hand movement was pioneered by Qin et al. [8], which paved the way for later studies on source-space EEG for motor decoding. Since then, there have been several studies that use various approaches of inverse modeling to localize and identify the sources involved in movement execution (ME) and/or movement imagination. As different tool boxes to implement ESI—such as BrainStorm [9], FieldTrip [10], minimum-norm estimation (MNE) [11], and statistical parametric mapping [12]—were made open source for reproducible research, ESI has become progressively well known.

ESI Basics

ESI transforms the sensor domain into the cortical source domain. It is an ill-posed problem, because the number of cortical sources vastly outnumbers the number of scalp electrodes. Therefore, several physical constraints, such as the head shape, skull thickness, number of layers in a head model, conductivity values in different layers, and a priori information about the brain atlas, are used to create a forward model, followed by solving an inverse problem to convert EEG data from the sensor domain to the source domain.

Forward Modeling

Forward modeling is a decisive stage in source imaging, as it substantially influences the accuracy of EEG source localization results. Solving a forward problem relates the cortical sources to the sensor-space EEG recordings by a simple transformation using a lead-field matrix. As the electromagnetic signals propagate from cortical sources through a head volume conductor, it is crucial to use effective computational techniques to accurately represent the volume shape and conductivities. Although the spherical head model was popular in earlier days because of its simplicity, it is an inaccurate model compared to state-of-the-art approaches, such as the boundary element method (BEM) [13] and finite element method (FEM) [14].

Although FEM results in a more accurate head model, as it handles the tissue anisotropies and inhomogeneous conductivities within the brain, it is computationally intractable and increases the model complexity. BEM, however, assumes piecewise homogeneous conductivity within different layers (e.g., skull, scalp, and cortex), and thus results in a reasonably accurate head model, in addition to being computationally more efficient than FEM [7]. Irrespective of the type of modeling (BEM or FEM) used, the head model needs an anatomical prior that is obtained by using either

1) multimodal EEG–fMRI, where an individual MRI provides the subject-specific head shape to which EEG can be coregistered
2) the template anatomy, such as Colin 27 (single-subject, multiple MRI scans [15]) or ICBM-152 (a nonlinear average of MRIs obtained from 152 subjects) [16] when there is no subject-specific MRI available.

Inverse Modeling

As ESI is an ill-posed problem, several morphological and anatomical constraints are used to reduce the number of unknown parameters. In that respect, there are different techniques to solve the opposite problem: parametric methods like equivalent current dipole, and non-parametric methods (distributed solutions), such as
current-density techniques—e.g., MNE, standardized low-resolution brain electromagnetic tomography (sLORETA), and local autoregressive average (LAURA)—and beamformer approaches (linear constrained minimum variance and dynamic imaging of coherent sources). Readers can access a detailed literature review of various methods to solve the inverse modeling in [17] and can find a more recent review of ESI’s challenges and opportunities in [7]. Spyrou et al. [18] proposed another inverse modeling technique for cortical source localization corresponding to the event-related potentials that is appropriate for many BCI paradigms. The authors of [19] report the consistency of various inverse methods using different tool boxes.

**BCI for Movement Decoding**

An ideal BCI-mediated control should be as close as possible to natural arm control in terms of motor function. With the advent of the robotic arm and higher-DoFs prosthetics, current assistive technologies (or effectors) are capable of mimicking some basic arm movements, such as holding a bottle, grabbing an object and placing it at a target position, and so on [50]. Nevertheless, the neural decoding of highly dexterous movements is complicated, because the cortical regions responsible for movements with higher DoFs are located extremely close to each other in the motor region of the brain. The classification of these direction-specific cortical sources is not a trivial task, especially through the use of sensor EEG.

Consequently, researchers have looked into various modalities to observe the neural correlates of motion kinematics. The authors of [51] present a review (until 2009) of BCI techniques (mostly invasive) focusing on decoding movement direction and continuous movement trajectories. Since then, there has been an increasing number of noninvasive BCI studies in this direction. So, in the next section, we concentrate primarily on those works that use ESI to study the neural correlates. Various state-of-the-art EEG source-space-based methods for classifying different types of movements are summarized in Table 1.

**Directional Decoding**

In [52], Waldert et al. show that hand movement direction decoding is possible using noninvasive magnetoencephalography (MEG) and EEG with a significant power modulation in the frequency range of <7 Hz and high gamma (62–87 Hz). In another high-density EEG study (128 channels), Wang et al. [53] reported the classification of left-versus right-arm movement intention using the equivalent dipole approach for source localization. Both [52] and [53] reported that the features from the parietal reach region (PRR) result in good decoding accuracy, partially due to the fact the PRR receives a visual cue regarding the movement direction.

Other researchers [54] presented a right-arm MI BCI paradigm in a two-dimensional (horizontal and vertical) plane. Here, they calculated sLORETA-based source-space contributions using partial least squares regression instead of multiple linear regression (MLR), as the weights of an MLR model are not interpretable. Interestingly, the central subareas of supplementary motor area contained the predominant sources, which were consistent across subjects. Shenoy et al. reported similar observations in [34], wherein the cortical sources responsible for right-hand movement in four orthogonal directions were located toward the central sulcus. In [55], the authors used weighted MNE (wMNE) as an inverse model for source localization, followed by feature extraction using supervised factor analysis. In a recent study on goal-directed ME and MI paradigm [40], the researchers reported that the sLORETA-based movement-related cortical potentials revealed significant activation in the posterior parietal cortical lobes in addition to the primary and premotor cortex.

The feedback from the neural decoder to control the movement of a cursor or an end effector is crucial from a BCI perspective. The studies reported in [56] and [57] revealed that the left versus right cursor control using online ESI–BCI is possible. Going further, Bradberry et al. employed sLORETA-based source imaging [33] in which they used the low-frequency EEG signals in a linear decoding model to generate the $x$ and $y$ coordinates of a cursor. They reported the cortical regions, such as the precentral and postcentral gyrus, lateral premotor cortex, superior temporal sulcus, and lateral prefrontal cortex, to be associated with the encoding of the observed cursor velocity. However, it is to be noted that the researchers did not explore as much the ESI with feedback for actual motor control in different directions.

**Decoding of Kinematic Movement Parameters**

In addition to the directional decoding, kinematic movement parameters like speed are also vital for neuroprosthetic control. The work in [58] found different finger-tapping speeds to be associated with the activation of different parts of the primary motor cortex (MI) and premotor cortex. In an MEG-based visuomotor adaptation study [59], sLORETA-based source imaging identified that the contralateral precentral gyrus, postcentral gyrus,
ipsilateral superior parietal lobule, and precuneus were involved in the encoding of the hand velocity in all phases. Although [59] was an MEG-based study, the same source-imaging approach can also be extended to EEG.

In an EEG-based gait speed study [60], independent components clustering, as well as equivalent dipole localization based on brain electrical source analysis (BESA), in a four-shell spherical model revealed that the posterior parietal cortex contains information regarding gait speed. Although an invasive study, we find it worth highlighting [61], which suggests the speed-related information is well represented in the neural activity as compared to direction-related information. It is worth noting that the low-frequency cortical source

<table>
<thead>
<tr>
<th>Study</th>
<th>Type of Experiment</th>
<th>N_{ch}</th>
<th>Inverse Methods</th>
<th>Features and Classifier</th>
<th>Key Findings [Classification Accuracies (CAS)]</th>
</tr>
</thead>
<tbody>
<tr>
<td>[8]</td>
<td>Left- versus right-hand MI</td>
<td>59</td>
<td>EDA, CCD</td>
<td>Complex Morlet wavelets features</td>
<td>CA of 78.9% (EDA), 80.6% (CCD)</td>
</tr>
<tr>
<td>[20]</td>
<td>Left- versus right-hand MI</td>
<td>59</td>
<td>CCD</td>
<td>Von Neumann relative entropy features</td>
<td>CA of 88% (CCD)</td>
</tr>
<tr>
<td>[21]</td>
<td>BCI Competition 2003 Data Set IV [22]: Self-Paced Tapping (SPT)</td>
<td>28</td>
<td>sLORETA</td>
<td>Data-driven spatial-filter plus sLORETA source power in left and right ROIs; classification based on a simple decision tree</td>
<td>CA of 83% (sLORETA plus spatial filter), 78% (sLORETA, no spatial filter)</td>
</tr>
<tr>
<td>[23]</td>
<td>Left- versus right-hand MI</td>
<td>16</td>
<td>FD-MNE</td>
<td>TF combination with lowest p-values</td>
<td>CA of 71% (trained group)</td>
</tr>
<tr>
<td>[24]</td>
<td>Data Set IV [22]: SPT; Data Set IIIa [25]</td>
<td>60</td>
<td>sLORETA</td>
<td>Fuzzy Region of Interest Activity (FuRIA)-based features; classification using OVR-SVM</td>
<td>CA of 84% (Data Set IV), CA of 82.4% (Data Set IIIa)</td>
</tr>
<tr>
<td>[26]</td>
<td>BCI Comp. 2003 Data Set IV: SPT</td>
<td>28</td>
<td>LORETA</td>
<td>Change in power spectral density (PSD) in 1–40 Hz and Bereitschaftspotential features</td>
<td>CA of 84.25%</td>
</tr>
<tr>
<td>[27]</td>
<td>Error-potential paradigm (left-hand versus foot MI)</td>
<td>64</td>
<td>sLORETA</td>
<td>PSD features from sensor-space are classified using a simple Gaussian classifier</td>
<td>CA of 81.8% (correct trials)</td>
</tr>
<tr>
<td>[28]</td>
<td>MI-based cursor control in left versus right (Graz approach)</td>
<td>128</td>
<td>Beamformer</td>
<td>Log-bandpower of 20 frequency bands; spatial filters obtained using static beamformer</td>
<td>Mean CA of 79.8%</td>
</tr>
<tr>
<td>[29]</td>
<td>Left versus right index finger tapping (ME)</td>
<td>128</td>
<td>LAURA</td>
<td>Single-trial discriminative power features classified using LOO-SVM cross-validation</td>
<td>Average CA of 97% over 12 subjects</td>
</tr>
<tr>
<td>[30]</td>
<td>MI-based cursor control</td>
<td>64</td>
<td>LORETA</td>
<td>FuRIA features and adaptive FLD classifier</td>
<td>Average CA of 85%</td>
</tr>
<tr>
<td>[31]</td>
<td>Left- versus right-hand MI</td>
<td>64</td>
<td>MNE</td>
<td>Morlet wavelets-based TF selection (6–30 Hz) followed by ERD/S, Source R &gt; scalp R</td>
<td></td>
</tr>
<tr>
<td>[32]</td>
<td>Self-initiated movement to one of the eight directions</td>
<td>128</td>
<td>sLORETA</td>
<td>Linear decoding model to fit the 3-D coordinates of hand movement with EEG</td>
<td>Continuous decoding of hand velocity from EEG is demonstrated</td>
</tr>
<tr>
<td>[33]</td>
<td>MI-based cursor control in up, down, left, and right</td>
<td>128</td>
<td>sLORETA</td>
<td>Regression weights of the linear decoding model multiplied by time-series of voxels</td>
<td>Continuous decoding of hand MI with minimal calibration</td>
</tr>
<tr>
<td>[34]</td>
<td>Right-hand movement in four directions</td>
<td>118</td>
<td>wMNE</td>
<td>Features from regularized variants of CSP followed by OVR-SVM</td>
<td>Four-class CA of source-space SRCSP (64.98%) &gt; sensor-space (52.20%)</td>
</tr>
<tr>
<td>[35]</td>
<td>Right-hand movement in four directions</td>
<td>118</td>
<td>sLORETA</td>
<td>Features from supervised factor analysis (SFA) followed by OVR-SVM</td>
<td>Four-class CA of source-space SFA features (71%)</td>
</tr>
</tbody>
</table>

Table 1. An overview of the state of the art in EEG source analysis of movement-type classification.

Comp.: competition; EDA: equivalent dipole analysis; CCD: cortical current density; OVR: one-versus-rest; SVM: support vector machine; LOO: leave-one-out; FLD: Fisher’s linear discriminant; ERD/S: event-related desynchronization/synchronization; CSP: common spatial patterns; SRCSP: shrinkage-regularized CSPs.
signals are predominantly used for movement trajectory reconstruction [54].

**Upper-Limb Movement Decoding**

For a more realistic and practical neuroprosthesis, it is important to decode the movement of localized arm parts, such as the finger, wrist, elbow, and shoulder. However, the localization of the cortical sources responsible for the movement of these arm parts is not trivial, as these neural sources overlap in the cytoarchitectural maps of the brain. In that respect, there have been several studies that sought to address this challenge. In a sequential finger-tapping movement imagery versus execution study [41], sLORETA-based source imaging showed significant differences between MI and ME in Brodmann Areas (BAs) 2 and 3. Carrillo-de-la-Peña et al. hypothesized that the neuronal sources involved in localized arm movement imagery would be restricted to the selection of arm part and that an additional set of neurons would engage in parameters such as direction, speed, and force. As the team conducted this study using only 28 EEG channels, with no MRI coregistration, the results interpreted in [41] need further validation.

In another study, a LAURA-based inverse solution revealed that the best discriminating voxels are present in the dorsal premotor cortex. Contradicting the belief that only intracortical recordings can reveal high-frequency oscillations, this study [29] showed that high-frequency oscillations are indeed observable at the scalp level, which needs further investigation.

Seeber et al. studied rhythmic finger movements [62], using individual T1 MRI scans to create a forward model, followed by sLORETA as an inverse model. They showed that the flexion and extension of the finger have different movement phase-related β synchronies. Besides, there are studies that have focused on the decoding of wrist ME and imagination [37], [38], [63]. In [37], a Tikhonov regularized MNE-based inverse solution revealed that the precentral region of interest (ROI) encodes the wrist deviation. This study also cautioned that without kinesthetic feedback, the precise naturalistic motor control commands would be challenging.

Another investigation [63] explored radial–ulnar wrist movement decoding. The researchers reported precentral, postcentral, and premotor areas to have significant activity peaks in the cortical source space modeled using MNE. Furthermore, the work in [38] studied wrist-based MI decoding. In it, Edelmann et al. reported that the source-space EEG outperformed sensor-space EEG in classifying the MI of wrist pronation, supination, flexion, and extension. Source activation based on wMNE showed that the hand knob region near the central sulcus contains discriminative information on different types of wrist MI. Some of the recent works on ESI for localized movement kinematics decoding are summarized in Table 2.

**Cortical Biomarkers to Prognosticate Movement Disorders**

ESI has been extensively explored in epileptic studies in which the seizure location needs to be localized before surgery. Revisiting the literature on ESI studies in epilepsy is currently beyond the scope of this article. To this end, we recommend [64] to readers; it provides a comprehensive overview of ESI methodologies and pitfalls in epilepsy studies. In this section, we shall review the literature concerning ESI in other neurological disorders.

Researchers are currently examining the use of brain connectivity measures as a potential biomarker in stroke, amyotrophic lateral sclerosis (ALS), Alzheimer’s disease (AD), Parkinson’s disease (PD), and Huntington’s disease (HD). Cortical connectivity measures give an idea of the statistical dependencies between the time-series data of different brain regions [functional connectivity (FC)] and the causal interactions of different ROIs (effective connectivity). A detailed review of connectivity measures can be found in [65] and [66]. The research in [44] and [45] reported alpha- and beta-band coherence-based FC measures in a group of ischemic stroke patients. The team used alpha-band synchrony as a prognostic indicator of poststroke cortical plasticity. The findings also concurred with those of a similar MEG-based study [67] that explored connectivity analyses in neurodegenerative diseases like ALS and PD.

In one such study on PD-related dementia and AD, the EEG-based sensor-connectivity analysis revealed that the relative wavelet energy could be used as an indication of healthy versus dementia-affected people, while the wavelet coherence values could be used to differentiate PD-related dementia and AD [68]. In another work conducted on HD patients [49], EEG connectivity analysis using an exact LORETA (eLORETA)-based inverse solution revealed that there was an increased interhemispheric coupling between the motor areas during the wake state in HD patients as compared to healthy controls. The current research trend in ESI-based cortical biomarker studies is shown in Table 3.
### Table 2. An overview of the state of the art in EEG-based localized arm movement and kinematics.

<table>
<thead>
<tr>
<th>Study</th>
<th>Type of Experiment</th>
<th>N_{ch}</th>
<th>Inverse Method</th>
<th>Features and Classifier</th>
<th>Key Findings (Classification Accuracies)</th>
</tr>
</thead>
<tbody>
<tr>
<td>[36]</td>
<td>Lower-limb extension/flexion (ME)</td>
<td>64</td>
<td>sLORETA</td>
<td>Task-related bandpower increase/decrease (TRPI/TRPD)</td>
<td>BA6 and cingulate cortex (BA23, 24, 31) involved in gait movement relative to resting period</td>
</tr>
<tr>
<td>[37]</td>
<td>Radial–ulnar wrist MI and ME</td>
<td>61</td>
<td>Tikhonov regularized MNE</td>
<td>Time-frequency bins classified using Bayes linear classifier</td>
<td>Kinesthetic feedback is essential for good motor decoding performance</td>
</tr>
<tr>
<td>[38]</td>
<td>Right-hand MI of flexion, extension, pronation, and supination</td>
<td>64</td>
<td>wMNE</td>
<td>Morlet wavelet features and Mahalanobis distance-based classifier</td>
<td>Source-space EEG features could classify four types of wrist movement with an accuracy of 79.8%</td>
</tr>
<tr>
<td>[39]</td>
<td>Hand opening and closing (ME)</td>
<td>160</td>
<td>LORETA</td>
<td>Time–frequency synthesized spatial patterns</td>
<td>Contralateral activity (M1, S1) during hand opening, bilateral activity during hand closing</td>
</tr>
<tr>
<td>[40]</td>
<td>Right-hand ME (goal directed versus nongoal directed)</td>
<td>60</td>
<td>sLORETA</td>
<td>Movement-related cortical potential features classified using SRLDA</td>
<td>Source-space EEG can distinguish goal-directed and nongoal-directed movements</td>
</tr>
<tr>
<td>[41]</td>
<td>Sequential finger tapping MI and ME</td>
<td>28</td>
<td>sLORETA</td>
<td>Lateralized readiness potential-based features</td>
<td>Few cortical sources involved in the selection of arm parts, but more for kinematic parameters</td>
</tr>
<tr>
<td>[42]</td>
<td>Elbow ME (short, medium, and long)</td>
<td>128</td>
<td>BESA</td>
<td>ERSP features followed by directed transfer function</td>
<td>M1 uses distinct oscillatory, broad-band activity regionally to make correct decision</td>
</tr>
</tbody>
</table>

S1: somatosensory cortex; SRLDA: shrinkage-regularized linear discriminant analysis; ERSP: event-related spectral perturbation.

### Table 3. Recent works (from 2013 onward) on EEG-based cortical biomarker systems for clinical applications.

<table>
<thead>
<tr>
<th>Study</th>
<th>Type of Disorder</th>
<th>N_{ch}</th>
<th>Inverse Methods</th>
<th>Main Connectivity Findings</th>
<th>Clinical Correlates</th>
</tr>
</thead>
<tbody>
<tr>
<td>[43]</td>
<td>Chronic stroke</td>
<td>128</td>
<td>Beamformer</td>
<td>Resting-state alpha-band coherence with NFT can induce region- and band-specific enhancement of neural synchrony</td>
<td>Motor deficit</td>
</tr>
<tr>
<td>[44]</td>
<td>Ischemic stroke</td>
<td>128</td>
<td>Beamformer</td>
<td>Decrease in alpha-band imaginary component of coherence between lesion-affected brain parts and rest of the brain</td>
<td>Cognitive and motor deficit</td>
</tr>
<tr>
<td>[45]</td>
<td>Ischemic stroke</td>
<td>128</td>
<td>Beamformer</td>
<td>Increase in beta-band WND (graph-theoretic measure) at ipsilesional M1; motor improvement within two to three weeks after stroke onset</td>
<td>Motor and cognitive deficit</td>
</tr>
<tr>
<td>[46]</td>
<td>MTBI</td>
<td>19</td>
<td>sLORETA</td>
<td>Significant increase in short-distance connectivity and decrease in long-distance connectivity</td>
<td>MTBI</td>
</tr>
<tr>
<td>[47]</td>
<td>AD</td>
<td>19</td>
<td>eLORETA</td>
<td>Decrease in CSF beta-amyloid (Ab42) concentration; increase in CSD (right temporal region)</td>
<td>AD pathology</td>
</tr>
<tr>
<td>[48]</td>
<td>AD</td>
<td>19</td>
<td>sLORETA</td>
<td>Increase in lagged linear coherence; decrease in MMSE scores</td>
<td>Cognitive decline</td>
</tr>
<tr>
<td>[49]</td>
<td>HD</td>
<td>19</td>
<td>eLORETA</td>
<td>Increase in lagged phase synchronization in delta (BAs 6–8), theta and alpha (BAs 1–3)</td>
<td>Cognitive decline</td>
</tr>
</tbody>
</table>

NFT: neurofeedback training; MTBI: mild traumatic brain injury; CSF: cerebrospinal fluid; CSD: current source density; MMSE: minimental state exam.
Discussion

Source Localization: Pitfalls and Challenges
There exist some practical concerns regarding source imaging. We recommend having a subject-specific MRI scan to achieve a more reliable head model, which is crucial for better source-imaging results. Although MRI is expensive, only one scan would ever be needed for a subject-specific anatomy, as it can be reused. Furthermore, we advise performing the digitization of the EEG electrode positions to create a coordinate transform between the subject-specific head model and the electrode location in a three-dimensional (3-D) geophysical space. Although it is obvious that the higher the number of EEG electrodes, the better the scalp spatial resolution, the improvement in the source localization accuracy is minimal beyond a certain number of channels [69]. If there is no subject-specific MRI scan available, then the next suggested approach is to use an ICBM-152 template anatomy, coregistering the positions of the EEG electrodes with the aid of a digitizer like Polhemus or ANT-Xensor. In the absence of both an MRI and a 3-D digitizer, the final recourse would be to apply a template anatomy as is, at the cost of less-reliable source localization accuracy.

Recently, Yu et al. proposed the New York head, a precise, standardized head model that can be used in the absence of an MRI [70]. Since the New York head is a highly detailed anatomical model developed using FEM, the source localization accuracy is higher than what one would get by using a BEM of ICBM-152, and it is competitive with individualized BEMs. Furthermore, the transfer learning approach used in [71] has been shown to handle intersubject variabilities by training a BCI classifier using the source-imaging data transferred from other subjects with better accuracy than the standard subject-specific approach.

Remarks on the Identification of ROIs for Movement Decoding
In the previous section, we noted that there are several ROIs involved in the encoding and decoding of motor tasks. However, there is no general consensus regarding the selection of ROIs, as there are studies reporting both brain-atlas-based predefined selection of ROIs (e.g., [28], [35], [71]) and data-driven methods for such selection [24], [26], [38], [72]. In the absence of a subject-specific cortical model, we suggest employing data-driven ROI selection, either by using information theoretic approaches [26], [72] or based on statistically significant voxels, as in [24] and [38].

From a BCI perspective, it is possible that the BCI classification performance may be inferior if we use only the data within a predefined ROI, as there is a risk that the discriminative sources could, as well, be outside ROIs. Nevertheless, in the context of BCI for movement decoding, the neural ROIs are well established, and they can complement the information provided by data-driven ROI selection. It would be interesting to explore the objective comparison of these two approaches in a BCI paradigm, which is another possible future direction for ESI studies.

Future Directions for Practical Applications in ESI-Based Online BCI
Although there has been significant progress in identifying the cortical sources responsible for the movement of arm parts, there is a long way to go toward realizing the BCI-based neuroprosthetics control that is functionally as capable as the real human hand. To this end, future work should aim at real-time source imaging of multiclass BCI with far more DoFs. In Table 2, we have highlighted some of the studies in this direction, most of which are offline data analysis of EEG-based decoding of different DoFs associated with the upper limb. Prompted by a recent work on robotic arm control for reach and grasp using noninvasive scalp EEG [73], the objective of noninvasive BCI-based neuroprosthetics seems to be achievable.

Although it is evident that the online use of ESI decoding is paramount in the practical use of state-of-the-art neural signal processing methods, there are certain hurdles in an online ESI, such as the low signal-to-noise ratio in a single-trial EEG and the limited time available to compute the inverse solution [74]. Because of this concern of computational intractability, there are only a handful of studies that report online source imaging for BCI [56], [57], [75], [76]. One way to address this challenge is to use a smaller lead-field matrix (of the forward model) with appropriate regularization techniques to handle single-trial nonstationarity.

Future studies should aim at leveraging the anatomical information of ROIs and extracting task-relevant features for fast classification of complex movement types. Recently, real-time source-imaging tool boxes have been made available as open source [77], [78], so we hope there will be an increasing number of real-time ESI studies for BCI applications.
Remarks on EEG-Based Cortical Biomarker Studies

Traditionally, connectivity measures are computed using the source-space EEG, as the scalp connectivity measures are not robust against volume conduction effects [79]. With the availability of open-source tool boxes like eConnectome [80] and BrainStorm [9], there is an increasing number of ESI-based connectivity studies. Therefore, researchers can examine the outcomes of source-space connectivity measures and make a reasonable inference about the observed neural correlates.

When it comes to clinical diagnosis, however, we recommend that researchers use EEG-based biomarkers as a secondary standard. Neuroimaging studies with fMRI have reported the causal interpretation of brain connectivity using dynamic causal modeling, Granger causality, and related techniques. As fMRI suffers from poor temporal resolution, it limits the interpretation in effective connectivity analysis, where temporal information is vital. We urge readers to weigh in the advantage of either multimodal EEG–fMRI or EEG-based source imaging before interpreting the connectivity measures. As we noted in the “Cortical Biomarkers to Prognosticate Movement Disorders” section, EEG-based cortical biomarker studies are gaining momentum in diagnosing various movement-related disorders, the exception being ALS. Therefore, ESI for source-level connectivity analysis of ALS patients could be a future research direction.

Conclusions

In this article, we have spotlighted some of the EEG inverse methods being used in movement decoding, followed by cortical biomarkers for neurorehabilitation applications, cautioning readers about certain interpretational caveats. Further advances in robust machine learning and signal processing techniques for ESI-based BCI can result in a more visible impact on our daily lives.

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