EEG Source Imaging of Movement Decoding

The State of the Art and Future Directions

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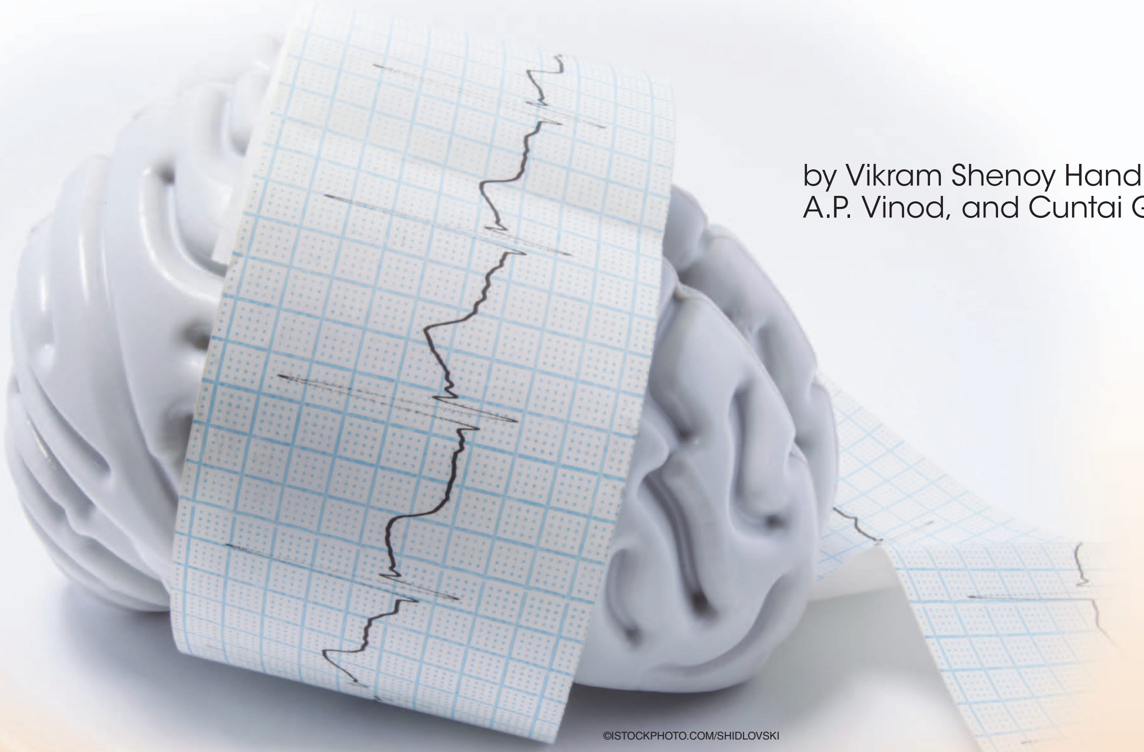

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In this article, we provide an overview of electroencephalography (EEG) source imaging (ESI) of movement decoding for brain–computer interface (BCI) applications. The current state-of-the-art neuroimaging modality—functional magnetic resonance imaging (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.

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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-place 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 nonparametric 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 lobule in addition to the primary and premotor cortex.

In addition to the directional decoding, kinematic movement parameters like speed are also vital for neuroprosthetic control.

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 (M1) and premotor cortex. In an MEG-based visuomotor adaptation study [59], sLORETA-based source imaging identified that the contralateral precentral gyrus, postcentral gyrus,

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

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

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.

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 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.

> **ESI has been extensively explored in epileptic studies in which the seizure location needs to be localized before surgery.**

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.

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

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.

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

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.

Future studies should aim at leveraging the anatomical information of ROIs and extracting task-relevant features for fast classification of complex movement types.

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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References

[1] L. M. Rueda-Delgado, E. Solesio-Jofre, D. Mantini, P. Dupont, A. Daffertshofer, and S. P. Swinnen, "Coordinative task difficulty and behavioural errors are associated with increased long-range beta band synchronization," *NeuroImage*, vol. 146, pp. 883–893, Oct. 2017.

[2] M. P. Branco, Z. V. Freudenburg, E. J. Aarnoutse, M. G. Bleichner, M. J. Vansteensel, and N. F. Ramsey, "Decoding hand gestures from primary somatosensory cortex using high-density ECoG," *NeuroImage*, vol. 147, pp. 130–142, Dec. 2017.

[3] A. M. Dale and M. I. Sereno, "Improved localization of cortical activity by combining EEG and MEG with MRI cortical surface reconstruction: A linear approach," *J. Cognitive Neurosci.*, vol. 5, no. 2, pp. 162–176, 1993.

[4] F. Biessmann, S. Plis, F. C. Meinecke, T. Eichele, and K. R. Müller, "Analysis of multimodal neuroimaging data," *IEEE Rev. Biomed. Eng.*, vol. 4, pp. 26–58, Oct. 2011.

[5] B. He and Z. Liu, "Multimodal functional neuroimaging: Integrating functional MRI and EEG/MEG," *IEEE Rev. Biomed. Eng.*, vol. 1, pp. 23–40, Oct. 2008.

[6] M. Wronkiewicz, E. Larson, and A. K. Lee, "Incorporating modern neuroscience findings to improve brain-computer interfaces: Tracking auditory attention," *J. Neural Eng.*, vol. 13, no. 5, pp. 056017, Sept. 2016.

[7] B. He, L. Yang, C. Wilke, and H. Yuan, "Electrophysiological imaging of brain activity and connectivity: Challenges and opportunities," *IEEE Trans. Biomed. Eng.*, vol. 58, no. 7, pp. 1918–1931, July 2011.

[8] L. Qin, L. Ding, and B. He, "Motor imagery classification by means of source analysis for brain computer interface applications," *J. Neural Eng.*, vol. 2, no. 4, pp. 65–72, Aug. 2005.

[9] F. Tadel, S. Baillet, J. C. Mosher, D. Pantazis, and R. M. Leahy, "Brainstorm: A user-friendly application for MEG/EEG analysis," *Comp. Intell. Neurosci.*, vol. 2011, Jan. 2011. doi: 10.1155/2011/879716.

[10] R. Oostenveld, P. Fries, E. Maris, and J. M. Schoffelen, "FieldTrip: Open source software for advanced analysis of MEG, EEG, and invasive electrophysiological data," *Comp. Intell. Neurosci.*, vol. 2011, Jan. 2011. doi: 10.1155/2011/156869.

[11] A. Gramfort, M. Luessi, E. Larson, D. A. Engemann, C. Brodbeck, L. Parkkonen, and M. S. Hämäläinen, "MNE software for processing MEG and EEG data," *NeuroImage*, vol. 86, pp. 446–460, Feb. 2014.

[12] K. J. Friston, A. P. Holmes, K. J. Worsley, J.-P. Poline, C. D. Frith, and R. S. J. Frackowiak, "Statistical parametric maps in functional imaging: A general linear approach," *Human Brain Map.*, vol. 2, no. 4, pp. 189–210, Oct. 1994.

[13] M. S. Hamalainen and J. Sarvas, "Realistic conductivity geometry model of the human head for interpretation of neuromagnetic data," *IEEE Trans. Biomed. Eng.*, vol. 36, no. 2, pp. 165–171, Feb. 1989.

[14] Y. Zhang, L. Ding, W. van Drongelen, K. Hecox, D. M. Frim, and B. He, "A cortical potential imaging study from simultaneous extra- and intracranial electrical recordings by means of the finite element method," *NeuroImage*, vol. 31, no. 4, pp. 1513–1524, July 2006.

[15] C. J. Holmes, R. Hoge, L. Collins, R. Woods, A. W. Toga, and A. C. Evans, "Enhancement of MR images using registration for signal averaging," *J. Comput. Assisted Tomog.*, vol. 22, no. 2, pp. 324–333, Mar. 2015.

[16] J. C. Mazziotta, A. W. Toga, A. Evans, P. Fox, and J. Lancaster, "A probabilistic atlas of the human brain: Theory and rationale for its development: The international consortium for brain mapping (ICBM)," *NeuroImage*, vol. 2, no. 2, pp. 89–101, June 1995.

[17] R. Grech, T. Cassar, J. Muscat, K. P. Camilleri, S. G. Fabri, M. Zervakis, P. Xanthopoulos, V. Sakkalis, and B. Vanrumste, "Review on solving the inverse problem in EEG source analysis," *J. Neuroeng. Rehabil.*, vol. 5, no. 1, pp. 25, Jan. 2008.

[18] L. Spyrou and S. Sanei, "Source localization of event-related potentials incorporating spatial notch filters," *IEEE Trans. Biomed. Eng.*, vol. 55, no. 9, pp. 2232–2239, Sept. 2008.

[19] K. Mahjoory, V. V. Nikulin, L. Botrel, K. Linkenkaer-Hansen, M. M. Fato, and S. Haufe, "Consistency of EEG source localization and connectivity estimates," *NeuroImage*, vol. 152, pp. 590–601, May 2017.

[20] B. Kamousi, A. N. Amini, and B. He, "Classification of motor imagery by means of cortical current density estimation and Von Neumann entropy," *J. Neural Eng.*, vol. 4, no. 2, pp. 17–25, 2007.

[21] M. Congedo, F. Lotte, and A. Lécuyer, "Classification of movement intention by spatially filtered electromagnetic inverse solutions," *Phys. Med. Biol.*, vol. 51, no. 8, pp. 1971–1989, Mar. 2006.

[22] B. Blankertz, K.-R. Müller, G. Curio, T. M. Vaughan, G. Schalk, J. R, A. Schlögl, C. Neuper, G. Pfurtscheller, T. Hinterberger, M. Schröder, and N. Birbaumer, "The BCI Competition 2003: Progress and perspectives in detection and discrimination of EEG single trials," *IEEE Trans. Biomed. Eng.*, vol. 51, no. 6, pp. 1044–1051, June 2004.

[23] H. J. Hwang, K. Kwon, and C. H. Im, "Neurofeedback-based motor imagery training for brain-computer interface (BCI)," *J. Neurosci. Meth.*, vol. 179, no. 1, pp. 150–156, Apr. 2009.

[24] F. Lotte, A. Lecuyer, and B. Arnaldi, "FuRIA: An inverse solution based feature extraction algorithm using fuzzy set theory for brain-computer interfaces," *IEEE Trans. Signal Process.*, vol. 57, no. 8, pp. 3253–3263, Aug. 2009.

[25] A. Schlögl, F. Lee, H. Bischof, and G. Pfurtscheller, "Characterization of four-class motor imagery EEG data for the BCI-Competition 2005," *J. Neural Eng.*, vol. 2, no. 4, pp. L14–L22, Aug. 2005.

[26] Q. Noirhomme, R. I. Kitney, and B. Macq, "Single-trial EEG source reconstruction for brain-computer interface," *IEEE Trans. Biomed. Eng.*, vol. 55, no. 5, pp. 1592–1601, May 2008.

[27] P. Ferrez and J. Millán, "EEG-based brain-computer interaction: Improved accuracy by automatic single-trial error detection," in *Advances Neural Information Processing Systems*, 2008, pp. 441–448.

[28] M. Grosse-Wentrup, C. Liefhold, K. Gramann, and M. Buss, "Beamforming in noninvasive brain-computer interfaces," *IEEE Trans. Biomed. Eng.*, vol. 56, no. 4, pp. 1209–1219, Apr. 2009.

[29] R. Grave de Peralta, T. Landis, and S. Gonzalez Andino, "Electrical neuroimaging of single trials to identify laterality and brain regions involved in finger movements," *J. Physiol. Paris*, vol. 103, no. 6, pp. 324–332, Nov. 2009.

[30] M. Dyson, E. Thomas, L. Casini, and B. Burle, "Online extraction and single trial analysis of regions contributing to erroneous feedback detection," *NeuroImage*, vol. 121, pp. 146–158, Nov. 2015.

[31] Y. Han, A. Doud, A. Gururajan, and B. He, "Cortical imaging of event-related (de) synchronization during online control of brain-computer interface using minimum-norm estimates in frequency domain," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 16, no. 5, pp. 425–431, Oct. 2008.

[32] T. J. Bradberry, R. J. Gentili, and J. L. Contreras-Vidal, "Reconstructing three-dimensional hand movements from noninvasive electroencephalographic signals," *J. Neurosci.*, vol. 30, no. 9, pp. 3432–3437, Mar. 2010.

[33] T. J. Bradberry, R. J. Gentili, and J. L. Contreras-Vidal, "Fast attainment of computer cursor control with noninvasively acquired brain signals," *J. Neural Eng.*, vol. 8, no. 3, pp. 036010, Apr. 2011.

[34] H. V. Shenoy, A. P. Vinod, and C. Guan, "Multi-direction hand movement classification using EEG-based source space analysis," in *Proc. 38th Annu. Int. Conf. IEEE Engineering Medicine and Biology Society (EMBC)*, Orlando, FL, Aug. 2016, pp. 4551–4554.

[35] H. V. Shenoy, A. P. Vinod, and C. Guan, "EEG source space analysis of the supervised factor analytic approach for the classification of multi-directional arm movement," *J. Neural Eng.*, vol. 14, no. 4, pp. 046008, May 2017.

[36] M. Wieser, J. Haefeli, L. Bütler, L. Jäncke, R. Riener, and S. Koeneke, "Temporal and spatial patterns of cortical activation during assisted lower limb movement," *Experimental Brain Res.*, vol. 203, no. 1, pp. 181–191, May 2010.

[37] F. Galán, M. R. Baker, K. Alter, and S. N. Baker, "Degraded EEG decoding of wrist movements in absence of kinaesthetic feedback," *Human Brain Map.*, vol. 36, pp. 643–654, Oct. 2014.

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

[39] J. Yao, C. Sheaff, C. Carmona, and J. P. Dewald, "Impact of shoulder abduction loading on brain-machine interface in predicting hand opening and closing in individuals with chronic stroke," *Neurorehabil. Neural Repair*, vol. 30, no. 4, pp. 363–372, May 2016.

[40] J. Pereira, P. Ofner, A. Schwarz, A. Ioana Sburlea, and G. R. Müller-Putz, "EEG neural correlates of goal-directed movement intention," *NeuroImage*, vol. 149, pp. 129–140, Jan. 2017.

[41] M. T. Carrillo-de-la-Peña, S. Galdo-Álvarez, and C. Lastra-Barreira, "Equivalent is not equal: Primary motor cortex (MI) activation during motor imagery and execution of sequential movements," *Brain Res.*, vol. 1226, pp. 134–143, Aug. 2008.

[42] J. W. Chung, E. Ofori, G. Misra, C. W. Hess, and D. E. Vaillancourt, "Beta-band activity and connectivity in sensorimotor and parietal cortex are important for accurate motor performance," *NeuroImage*, vol. 144, pp. 164–173, Jan. 2017.

[43] A. Mottaz, M. Solcà, C. Magnin, T. Corbet, A. Schnider, and A. G. Guggisberg, "Neurofeedback training of alpha-band coherence enhances motor performance," *Clin. Neurophysiol.*, vol. 126, no. 9, pp. 1754–1760, Sept. 2015.

[44] S. Dubovik, R. Ptak, T. Aboulafia, C. Magnin, N. Gillabert, L. Allet, J. M. Pignat, A. Schnider, and A. G. Guggisberg, "EEG alpha band synchrony predicts cognitive and motor performance in patients with ischemic stroke," *Behav. Neurol.*, vol. 26, no. 3, pp. 187–189, 2013.

[45] P. Nicolo, S. Rizk, C. Magnin, M. D. Pietro, A. Schnider, and A. G. Guggisberg, "Coherent neural oscillations predict future motor and language improvement after stroke," *Brain*, vol. 138, no. 10, pp. 3048–3060, July 2015.

[46] C. Cao and S. Slobounov, "Alteration of cortical functional connectivity as a result of traumatic brain injury revealed by graph theory, ICA, and sLORETA analyses of EEG signals," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 18, no. 1, pp. 11–19, Feb. 2010.

[47] M. Hata, T. Tanaka, H. Kazui, R. Ishii, L. Canuet, R. D. Pascual-Marqui, Y. Aoki, S. Ikeda, S. Sato, Y. Suzuki, H. Kanemoto, K. Yoshiyama, and M. Iwase, "Cerebrospinal fluid biomarkers of Alzheimer's disease correlate with electroencephalography parameters assessed by exact low-resolution electromagnetic tomography (eLORETA)," *Clin. EEG Neurosci.*, vol. 48, no. 5, pp. 338–347, Aug. 2016.

[48] F. Vecchio, F. Miraglia, C. Marra, D. Quaranta, M. G. Vita, P. Bramanti, and P. M. Rossini, "Human brain networks in cognitive decline: A graph theoretical analysis of cortical connectivity from EEG data," *J. Alzheimer's Disease*, vol. 41, no. 1, pp. 113–127, Jan. 2014.

[49] C. Piano, C. Imperatori, A. Losurdo, A. R. Bentivoglio, P. Cortelli, and G. Della Marca, "Sleep-related modifications of EEG connectivity in the sensory-motor networks in Huntington Disease: An eLORETA study and review of the literature," *Clin. Neurophysiol.*, vol. 128, no. 7, pp. 1354–1363, July 2017.

[50] V. Maheu, P. S. Archambault, J. Frappier, and F. Routhier, "Evaluation of the JACO robotic arm: Clinico-economic study for powered wheelchair users with upper-extremity disabilities," in *Proc. IEEE Int. Conf. Rehabilitation Robotics (ICORR)*, Zurich, 2011, pp. 1–5.

[51] S. Waldert, T. Pistohl, T. Ball, A. Aertsen, and C. Mehring, "A review on directional information in neural signals for brain-machine interfaces," *J. Physiol. Paris*, vol. 103, no. 3-5, pp. 244–254, Sept. 2009.

[52] S. Waldert, H. Preissl, E. Demandt, C. Braun, N. Birbaumer, A. Aertsen, and C. Mehring, "Hand movement direction decoded from MEG and EEG," *J. Neurosci.*, vol. 28, no. 4, pp. 1000–1008, Jan. 2008.

[53] Y. Wang and S. Makeig, "Predicting intended movement direction using EEG from human posterior parietal cortex," in *Foundations of Augmented Cognition, Neuroergonomics, and Operational Neuroscience*, D. D. Schmorrow, I. V. Estabrooke, and M. Grootjen, Eds. Lecture Notes in Computer Science, vol. 5638. Berlin, Heidelberg: Springer-Verlag, 2009, pp. 437–446.

[54] P. Ofner and G. R. Müller-Putz, "Using a noninvasive decoding method to classify rhythmic movement imaginations of the arm in two planes," *IEEE Trans. Biomed. Eng.*, vol. 62, no. 3, pp. 972–981, Mar. 2015.

[55] H. V. Shenoy, A. P. Vinod, and C. Guan, "A novel supervised locality sensitive factor analysis to classify voluntary hand movement in multi direction using EEG source space," in *Proc. IEEE Int. Conf. Systems, Man, and Cybernetics (SMC)*, Oct. 2016, pp. 2795–2800.

[56] M. Besserve, J. Martinerie, and L. Garnero, "Improving quantification of functional networks with EEG inverse problem: Evidence from a decoding point of view," *NeuroImage*, vol. 55, no. 4, pp. 1536–1547, Apr. 2011.

[57] E. Florin, E. Bock, and S. Baillet, "Targeted reinforcement of neural oscillatory activity with real-time neuroimaging feedback," *NeuroImage*, vol. 88, pp. 54–60, Mar. 2014.

[58] L. Jäncke, K. Lutz, and S. Koeneke, "Converging evidence of ERD/ERS and BOLD responses in motor control research," *Progress Brain Res.*, vol. 159, pp. 261–271, Dec. 2006.

[59] T. J. Bradberry, F. Rong, and J. L. Contreras-Vidal, "Decoding center-out hand velocity from MEG signals during visuomotor adaptation," *NeuroImage*, vol. 47, no. 4, pp. 1691–1700, Oct. 2009.

[60] G. Lisi and J. Morimoto, "EEG single-trial detection of gait speed changes during treadmill walk," *PLoS ONE*, vol. 10, no. 5, pp. 1–28, May 2015.

[61] J. Hammer, T. Pistohl, J. Fischer, P. Kršek, M. Tomášek, P. Marusič, A. Schulze-Bonhage, A. Aertsen, and T. Ball, "Predominance of movement speed over direction in neuronal population signals of motor cortex: Intracranial EEG data and a simple explanatory model," *Cerebral Cortex*, vol. 26, no. 6, pp. 2863–2881, Mar. 2016.

[62] M. Seeber, R. Scherer, and G. R. Muller-Putz, "EEG oscillations are modulated in different behavior-related networks during rhythmic finger movements," *J. Neurosci.*, vol. 36, no. 46, pp. 11671–11681, Nov. 2016.

[63] M. Witte, F. Galán, S. Waldert, C. Braun, and C. Mehring, "Concurrent stable and unstable cortical correlates of human wrist movements," *Human Brain Map.*, vol. 35, no. 8, pp. 3867–3879, Aug. 2014.

[64] K. Kaiboriboon, H. O. Luders, M. Hamaneh, J. Turnbull, and S. D. Lhatoo, "EEG source imaging in epilepsy: Practicalities and pitfalls," *Nature Rev. Neurol.*, vol. 8, no. 9, pp. 498–507, Sept. 2012.

[65] A. M. Bastos and J.-M. Schoffelen, "A tutorial review of functional connectivity analysis methods and their interpretational pitfalls," *Frontiers Syst. Neurosci.*, vol. 9, pp. 175, Jan. 2015.

[66] A. Sohrabpour, S. Ye, G. A. Worrell, W. Zhang, and B. He, "Noninvasive electromagnetic source imaging and Granger causality analysis: An Electrophysiological Connectome (eConnectome) approach," *IEEE Trans. Biomed. Eng.*, vol. 63, no. 12, pp. 2474–2487, Dec. 2016.

[67] T. W. Wilson, A. Fleischer, D. Archer, S. Hayasaka, and L. Sawaki, "Oscillatory MEG motor activity reflects therapy-related plasticity in stroke patients," *Neurorehabil. Neural Repair*, vol. 25, no. 2, pp. 188–193, Feb. 2011.

[68] D.-H. Jeong, Y.-D. Kim, I.-U. Song, Y.-A. Chung, and J. Jeong, "Wavelet energy and wavelet coherence as EEG biomarkers for the diagnosis of Parkinson's disease-related dementia and Alzheimer's disease," *Entropy*, vol. 18, no. 1, pp. 8, Dec. 2015.

[69] J. Song, C. Davey, C. Poulsen, P. Luu, S. Turovets, E. Anderson, K. Li, and D. Tucker, "EEG source localization: Sensor density and head surface coverage," *J. Neurosci. Meth.*, vol. 256, pp. 9–21, Dec. 2015.

[70] Y. Huang, L. C. Parra, and S. Haufe, "The New York Head: A precise standardized volume conductor model for EEG source localization and tES targeting," *NeuroImage*, vol. 140, pp. 150–162, Oct. 2016.

[71] M. Wronkiewicz, E. Larson, and A. K. C. Lee, "Leveraging anatomical information to improve transfer learning in brain-computer interfaces," *J. Neural Eng.*, vol. 12, no. 4, pp. 046027, Aug. 2015.

[72] R. G. De Peralta Menendez, S. González Andino, L. Perez, P. W. Ferrez, and J. D. R. Millán, "Non-invasive estimation of local field potentials for neuroprosthesis control," *Cognitive Process.*, vol. 6, no. 1, pp. 59–64, Mar. 2005.

[73] J. Meng, S. Zhang, A. Bekyo, J. Olsoe, B. Baxter, and B. He, "Noninvasive electroencephalogram based control of a robotic arm for reach and grasp tasks," *Scientific Rep.*, vol. 6, no. 1, pp. 38565, 2016.

[74] C. Dinh, D. Strohmeier, M. Luessi, D. Güllmar, D. Baumgarten, J. Haueisen, and M. S. Hämäläinen, "Real-time MEG source localization using regional clustering," *Brain Topog.*, vol. 35, no. 10, pp. 771–784, Nov. 2015.

[75] M. Grosse-Wentrup and B. Schölkopf, "A brain-computer interface based on self-regulation of gamma-oscillations in the superior parietal cortex," *J. Neural Eng.*, vol. 11, no. 5, pp. 056015, Aug. 2014.

[76] F. Cincotti, D. Mattia, F. Aloise, S. Bufalari, L. Astolfi, F. De Vico Fallani, A. Tocci, L. Bianchi, M. G. Marciani, S. Gao, J. Millan, and F. Babiloni, "High-resolution EEG techniques for brain-computer interface applications," *J. Neurosci. Meth.*, vol. 167, no. 1, pp. 31–42, Jan. 2008.

[77] C. Dinh, M. Luessi, L. Sun, J. Haueisen, and M. S. Hamalainen, "Mne-X: MEG/EEG real-time acquisition, real-time processing, and real-time source localization framework," *Biomed. Eng./Biomedizinische Technik*, vol. 58, no. 1, Aug. 2013. doi: 10.1515/bmt-2013-4184.

[78] L. Pion-Tonachini, S.-H. Sheng-Hsiou Hsu, S. Makeig, T.-P. Tzyy-Ping Jung, and G. Cauwenberghs, "Real-time EEG Source-mapping Toolbox (REST): Online ICA and source localization," in *Proc. 37th Annu. Int. Conf. IEEE Engineering Medicine and Biology Society (EMBC)*, Aug. 2015, pp. 4114–4117.

[79] C. Brunner, M. Billinger, M. Seeber, T. R. Mullen, and S. Makeig, "Volume conduction influences scalp-based connectivity estimates," *Frontiers Computational Neurosci.*, vol. 10, pp. 121, Nov. 2016.

[80] B. He, Y. Dai, F. Babiloni, H. Yuan, and L. Yang, "eConnectome: A MATLAB toolbox for mapping and imaging of brain functional connectivity," *J. Neurosci. Meth.*, vol. 195, no. 2, pp. 261–269, Feb. 2011.

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