Inferring hand movement kinematics from MEG, EEG and intracranial EEG: From brain-machine interfaces to motor rehabilitation

Décoder la cinématique d’un mouvement de la main à partir d’enregistrements MEG et EEG: des interfaces cerveau-machine à la réhabilitation motrice

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Abstract

The ability to use electrophysiological brain signals to decode various parameters of voluntary movement is a central question in Brain Machine Interface (BMI) research. Invasive BMI systems can successfully decode movement trajectories from the spiking activity of neurons in primary motor cortex and posterior parietal cortex. It has long been assumed that non-invasive techniques do not provide sufficient signal resolution to decode the kinematics of complex time-varying movements. This view stems from the hypothesis that movement parameters such as direction, position, velocity, or acceleration are primarily encoded by neuronal firing in motor cortex. Consequently, the fact that such signals cannot be detected using non-invasive techniques such as Electroencephalography (EEG) or Magnetoencephalography (MEG) has led to the claim that fine movement properties cannot be decoded with non-invasive methods. However, this view has been proven wrong by numerous studies in recent years. First, a growing body of research over the last decade has shown that the local field potential (LFP) signal, which represents the summed activity of a neuronal population, can encode movement parameters at a level comparable to unit recordings. These findings were confirmed in humans by the successful use of electrocorticography (ECoG) to achieve continuous movement decoding via invasive human BMI approaches. Very recently, a number of non-invasive studies were able to provide striking evidence that even surface-level MEG or EEG data can contain sufficient information on hand movement in order to infer movement direction and hand kinematics from brain signals recorded using non-invasive methods. Here we provide a brief review of this recent literature and discuss its importance on the future of BMI research and its implications on the development of novel motor rehabilitation strategies.

Keywords: Hand velocity; Movement decoding; Brain-computer interface (BCI); Brain-machine interface (BMI); Non-invasive BMI; EEG; MEG; ECoG; SEEG; Motor rehabilitation; Neural prosthesis

Résumé

Décoder les paramètres d’un mouvement volontaire à partir de l’activité cérébrale électrophysiologique est un enjeu majeur pour les recherches dans le domaine des interfaces cerveau-machine (ICM). Les ICM invasives permettent déjà de décoder la trajectoire d’un mouvement à partir du taux de décharge des neurones du cortex moteur primaire et du cortex pariétal postérieur. En revanche, il a été longtemps admis que la résolution offerte par les ICM non invasives était insuffisante pour permettre de décoder les paramètres de cinématique d’un mouvement complexe. Cette affirmation découle de l’hypothèse que ces paramètres tels que la direction, la position, la vitesse ou encore l’accélération sont principalement

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1. Introduction

Elucidating the neural basis of hand movement parameters in humans will not only shed more light on the neurobiology of motor control, but will open avenues for identifying alternative ideas for efficient brain-computer interfaces (BCI). Optimizing the way a neuroprosthetic arm is controlled in order to grasp an object largely relies on our understanding of the neural substrate of voluntary movements. In other words, the quality and efficiency of the decoding process in brain-machine interface (BMI) development is intricately related to our understanding of the neuronal encoding process. Yet, a large portion of BMI research focuses on finding neural signals that can be endogenously modulated by the subject and thereby indirectly used to communicate a command to an external device. Such BMI features do not necessarily need to be related to the intended final actions. For instance, motor imagery has been used to achieve cursor control in non-invasive BMI systems [1–3]. Although such systems have been relatively successful they also have several limitations. For instance, they rely on the endogenous control of sensorimotor rhythms through states of mental imagery that have little to do with the goal. Furthermore, BMI approaches based on voluntary control of sensorimotor brain rhythms [1,4] require a non-negligible amount of subject training. In addition, these approaches require signal classification that only provides limited degrees of freedom for the output device (e.g. up, down, left, right). Such limitations may be considered less critical in the context of laboratory experiments with healthy volunteering subjects, but they might be crucial when it comes to implementing the BMI device in a clinical environment. Next generation BMI applications aspire to provide continuous decoding of movement intentions. Such an endeavor requires identifying, as precisely as possible, the neural patterns that mediate actual movement parameters. An intuitive BMI control based on these natural neural encoding patterns inherently leads to shorter training periods and increases the user-friendliness of the system. A further conceptual benefit of this framework is that it narrows the gap between BMI research and basic physiology and confronts BMI research with fundamental neuroscience questions about how the human brain mediates motor intentions and how it encodes movement kinematics. Beyond the fact that the close interaction between BMI research and basic neurophysiology is likely to be mutually beneficial for the two fields, it seems that it is the only way to ultimately achieve high precision continuous brain-control of a prosthetic hand.

In this paper, we review the state of the art of the neural decoding of hand movements. Although we will briefly mention major findings from animal studies as well as invasive recordings in humans, we will focus the discussion on very recent findings achieved with Magnetoencephalography (MEG) and electroencephalography (EEG). Moreover, given that decoding movement direction has been thoroughly reviewed elsewhere [5] we will spend more time on the feasibility of using non-invasive techniques to infer kinematic parameters such as hand velocity. Finally, we will discuss this recent literature in the context of future non-invasive BMI research paths and the possible implications of current findings on the future development of BMI-based rehabilitation strategies that aim to enhance motor recovery.

2. Inferring movement parameters from invasive recordings

2.1. Directional tuning

Studies in non-human primates have shown that, during center-out tasks, the direction of arm movements can be inferred from the firing pattern of individual neurons in the primary motor cortex [6,7]. Interestingly, primary motor cortex (M1) neurons were shown to display a “directional tuning”, in other words, the firing rate (defined as the mean number of spikes over time) of each neuron depended on the direction of the arm movement that was performed. A directionally-tuned neuron exhibits maximum firing rates when the arm is moved in its “preferred direction” and gradually lower rates for other directions. The firing rate modulation of such neurons plotted as a function of movement direction (i.e. its direction dependency profile) resembles a cosine function that peaks around the preferred direction. This has lead to the now standard concept of “cosine tuning”. Evaluating the tuning of a population of neurons thus allows for the computation of a global “population vector” which points in the direction of the performed movement [7]. While most studies have used single unit activity (SUA) to decode movement parameters, a growing body of research in recent years suggests that
multi-unit activity (MUA) and Local Field Potential (LFP) signals (see Fig. 1 for an overview of these signals) might be equally suitable to infer movement directions from monkey motor cortex [8,9]. The latter studies provided crucial evidence that LFPs in particular could be a very useful signal for BMI research. Indeed, a major advantage of LFP signals compared to unit activity is that while it is difficult to ensure long-lasting recordings from a single neuron, LFP signals could provide reasonable signal longevity [10]. Furthermore, the findings of several studies suggest that LFPs recorded in parietal cortex can provide critical information on the onset of movement execution [11,12]. Such a feature could potentially be crucial for a robust control of a cortical motor prosthesis. Additionally, further evidence for the putative utility of LFP signals in decoding motor intention comes from a series of studies in macaques that reveal task-related LFP modulations during planning and execution of arm movements (reaching) and eye movement (saccades) recorded in posterior parietal cortex [13,14].

Taken together, microelectrode recordings in animals have shown that various measures of neural activity (SUA, MUA and LFP) can be used to decode intended movement directions. While the decoding power of SUA has been widely established, the fact that MUA and LFP may contain comparable directional information has only been demonstrated in the last decade. In particular, the putative suitability of LFP as a feature signal for motor control has opened new opportunities for BMI research since comparable signals can also be acquired without microelectrodes. As a matter of fact, directional tuning has since been investigated with electrocorticography (ECoG) data. These intracranial recordings are generally obtained in the context of presurgical evaluation in patients with drug-resistant epilepsy. These clinical recordings are either performed via subdural grids and strips of electrodes (ECoG) or by stereotactically implanting multiple multi-lead depth electrodes, a procedure known as stereo-EEG (SEEG) [15]. Because of the type of electrodes and amplifiers generally used in this clinical setting, the recorded signals do not capture the SUA and MUA of the neuronal populations but rather the LFP signal (ca. < 200 Hz). Both techniques allow for the investigation of task-related changes in signal power in various frequency bands ranging from delta (2–4 Hz), theta (4–7 Hz), alpha (8–12 Hz), beta (15–30 Hz) to gamma (up to ∼200 Hz) frequencies [16]. A large body of intracranial EEG (iEEG) research has shown that movement execution leads to significant power modulations in multiple frequency components of the LFP signal in motor cortex [17–20]. More recently, a number of invasive studies with epilepsy patients report that iEEG recordings from the human motor cortex show directional tuning [21–24]. Interestingly, when comparing the decoding power achieved by the different frequency components of the ECoG signal, the latter studies show that the highest directional tuning (and hence decoding power) was found in the low-pass filtered signals (e.g. < 4 Hz) and in the amplitude modulation of the so-called high gamma band (approx. 60–140 Hz). This observation is in agreement with data on directional tuning reported previously in monkeys [5,9,22] and non-invasively in humans [25] (Section 3).

2.2. Limb movement kinematics

In the previous section we briefly discussed invasive recordings in animals and humans that investigate the neural correlates of movement direction at various spatial levels and in multiple cortical areas. We will now focus on the neural correlates of movement trajectory and limb kinematics as revealed by a large body of studies based on invasive techniques.

2.2.1. Animal research

Research in non-human primates has shown that the neural activity in primary motor cortex is correlated with various parameters of limb movement including hand speed [26–28].
Interestingly, reports of velocity-related neural discharges are not limited to M1 but have also been reported in other brain areas, including posterior parietal cortex [29,30], premotor cortex [31,32], the cerebellum [33–35], and globus pallidus and subthalamic nucleus [36]. In addition, simultaneous multielectrode recordings from large neuronal ensembles used in the context of brain machine interfaces further support the notion of a distributed representation of limb kinematics in multiple cortical areas [37–40].

2.2.2. Invasive studies in humans

Although scarce, a few human studies have used spiking activity recorded via microarray electrodes implanted in human cortex for the purpose of developing an invasive BMI system. These direct recordings of single unit activity in the primary motor cortex of tetraplegic patients have shown that the direction and kinematics of intended movements can be decoded and used to control an external device [41–43]. At a more mesoscopic spatial scale, electrocorticography has also been used to assess the feasibility of predicting continuous movement trajectory from ongoing brain signals. Indeed, in addition to revealing directional tuning (as described above), ECoG recordings in humans have shown that two-dimensional decoding of movement trajectory can be achieved from direct recordings from the surface of the motor cortex [23,44]. For instance the study by Pistohl et al. [44] used a Kalman filter to predict the trajectory of random two-dimensional movements performed by the patients.

3. Inferring movement parameters from non-invasive recordings: MEG and EEG

What about non-invasive modalities such as MEG and EEG? It is possible to infer precise movement parameters uniquely from surface level measurements of the electrical or magnetic fields generated by the motor cortex in the process?

It has generally been largely assumed that non-invasive recordings cannot decode limb movement directions and trajectories because of the relatively low signal-to-noise ratio and bandwidth limitations of the surface-level signals. For instance, until very recently, most MEG and EEG researchers considered it very unlikely that surface measurements could allow us to differentiate between hand movements towards the right or the left. Motor-related signals and modulations measurable by EEG and MEG, such as the Bereitschaftspotential [45,46] and event-related (de)synchronization (ERD/ERS) of oscillatory components [47] are known to be globally modulated by preparation, execution and imagination of a motor task. Typically, such motor states or tasks are associated with oscillatory power suppressions in the so-called mu (≤10 Hz) and beta (15–30 Hz) frequency ranges [47]. Such power suppressions can be used (and even trained) in order to allow for decoding of motor states or motor imagery (of moving the left versus the right hand for instance). Yet, it has been widely accepted that the neural representation of fine movement details (such as direction or velocity) cannot be extracted from surface recordings. This view has been proven wrong by recent non-invasive studies that show directional tuning, as well as trajectory and kinematics coding of limb movements [25,48–52].

3.1. Decoding arm direction via low (<7 Hz) and high (>60 Hz) frequency components

Waldert et al. [25] were the first to demonstrate the feasibility of decoding hand movement direction from single-trial MEG and EEG data. They used a standard center-out paradigm in which the subjects were instructed to manipulate a joystick to reach a target in any of 4 directions in a self-paced manner. The authors found significant modulations of movement-related oscillatory cerebral activity in various frequency bands, with prominent power increases in a low frequency-band (≤7 Hz) and a high-gamma band (62–87 Hz), as well as a power decrease in the beta band (ca. 10–30 Hz). Strikingly, the frequency range that provided the best movement direction decoding was the low-frequency range (≤7 Hz). A finding that was even more clear-cut when using straight-forward low-pass filtered data (below 3 Hz) in the time domain. These findings are in line with other studies by the same group reporting on center-out or continuous movement decoding with invasive recordings [8,9,22,44]. In addition, the prominent role of the low-frequency component in movement decoding reported by Waldert et al. [25] is also in agreement with results from an MEG source imaging study of continuous visuomotor control by Jerbi et al. [48] who report a significant coupling in the 2–5 Hz range between time-varying hand speed and single-trial activity in contralateral primary motor cortex.

The finding that movement direction and limb trajectory are better decoded via slow frequency components (<5 Hz) of the neural activity than by using its higher frequency components, might appear to be intriguing at first. Despite strong movement-related power suppressions observed in the beta band and power increases in the high gamma band, signals in these frequency ranges are less efficient than the low (<5 Hz) frequency component when it comes to movement decoding [5,25]. Crucially, insight into this issue has come from the fact that even better decoding was achieved using simple low-pass filtering of the signal. This can be taken as an indication of the importance of the “phase” information in the low frequency component and links in these studies with the putative role of motor-related potentials (MRPs) in encoding movement parameters [5,22].

Directional decoding has also been reported in a study by Hammon et al. [53] who demonstrate the feasibility of using EEG to infer target location during both planning and execution phases of a reach movement. Moreover, non-invasive signals from posterior parietal cortex (PCC) have also shown to be useful to infer movement intention. Wang and Makeig [54] recorded EEG data during a delayed saccade-or-reach task and found direction-related modulation of event-related potentials (ERPs) in PPC. The authors used independent component analysis (ICA) to extract relevant PPC components that yield an average decoding accuracy of approximately 80% in a binary single-trial EEG classification (left versus right) across 4 subjects.
3.2. Decoding continuous movement trajectories with MEG and EEG

A recent study [48] provides evidence that cortical representations of time-varying hand speed are detectable non-invasively with MEG. Jerbi et al. [48] used single-trial source reconstruction techniques to estimate the time series of brain-wide cortical activations mediating motor control in a continuous visuomotor tracking task. By computing the coherence (a frequency-domain correlation measure) between the cortical sources and the ongoing hand speed, this study reveals a significant task-related coupling between primary motor cortex and hand speed in the 2–5 Hz range which was prominent during the task and absent during a rest control condition (Fig. 2). This low-frequency coupling is best illustrated by filtering the two signals in the time-domain and superposing them to reveal the close correlation between the two at this low frequency range (Fig. 3). These findings are in agreement with studies in humans [25] and in monkeys [9], which found that the best movement decoding accuracy was achieved with the low-frequency (< 7 Hz) components of the signal in motor cortex.

Two further recent studies used MEG [51] and EEG [52] to non-invasively decode continuous two-dimensional (2D) and three-dimensional (3D) movement trajectories respectively.
the MEG study the authors acquired data during a visuomotor adaptation task that consists of a center-out drawing task with an imposed hand-cursor rotation. The authors used the MEG signals to decode the velocity profile for the horizontal and vertical components of the movement across various phases of the visuomotor adaptation experiment (pre-exposure, early-exposure, late-exposure and post-exposure to the hand-cursor rotation). The authors used a linear decoding algorithm comparable to the one implemented in the study by Georgopoulos et al. [49] combined with n-fold cross-validation. In other words, n-1 data segments were used for training and the obtained decoder was applied to the remaining segment, this is done for exhaustive combinations and at each fold the correlation between decoded and measured hand velocity is computed. For the pre-exposure phase the grand mean correlation coefficients between the decoded and measured velocity (across a total of five subjects) was 0.48 and 0.32 for the x and y velocity components respectively. The authors found that the decoding performance showed a notable drop in accuracy for the y-velocity component when they accounted for eye movement artifacts in the data. This highlights the importance of precise monitoring of eye movements in future studies of EEG and MEG movement decoding paradigms. The study by Bradberry et al. [51] provides additional insights into the neural correlates of the velocity encoding involved in the center-out task. Using source estimation analysis they report velocity-related activity in contralateral precentral gyrus, ipsilateral parietal lobule and precuneus in all phases of their experiment, with additional involvement of the supplementary motor area and inferior parietal lobule in all phases except pre-exposure to hand-cursor rotation.

A further EEG study by the same group addresses the decoding of hand velocity in a 3D self-paced center-out task [52]. Again using linear decoding, cross validation and correlation analysis (Pearson’s r between measured and reconstructed hand velocity component) the authors report correlations that peaked at 0.19, 0.38 and 0.32 for x, y and z-velocity components respectively. An interesting observation in this study is the fact that, although a total of 55 channels were available, the decoding accuracy peaked when 34 electrodes were used, and dropped when more electrodes were used for the linear decoding. The authors relate this to over-fitting the model to the training data. This issue might be crucial when it comes to identifying the optimal sensors to keep in the case of a real EEG-based application in patients with spinal cord injury unable to provide a training set based on real movements. Several other issues may prove to be equally (or even more) important when it comes to achieving online decoding of 3D movement intentions via motor imagery for instance. These include neural adaptation to visual or haptic feedback, which is expected to substantially improve decoding performances through closed loop training.

Moreover, Jun and Yuanqing [55] decoded hand movement velocities during a two-dimensional drawing task by combining spatial filtering of multi-channel EEG in different frequency bands with a Kalman smoother. The mean correlation coefficients between measured and decoded velocities reported in their study ranged from 0.35–0.83 for the horizontal dimension and 0.11–0.45 for the vertical dimension. In a remotely related study, Yuan et al. [56] examined EEG activity during real and imagined hand clenching at various rates (i.e. number of clenches over time). The authors found a parametric modulation of alpha and beta power modulations as a function of (executed and imagined) hand clenching rates. Yuan et al. [56] also propose a linear equation that models the relationship between EEG activity and hand clench parameters aimed at decoding motor imagery (i.e. mental representation of motor task execution) via linear regression. Whether decoding techniques based on the actual neurophysiological processes that mediate limb movements will provide a higher BMI performance for external device control than those based on indirect features such as visual imagery, endogenous control of motor rhythms (without internal representations of movement kinematics), or endogenous engagement in cognitive tasks such as mental calculation [57] still remains to be investigated. While this does seem to be the case for invasive BMI approaches that decode unit activity in human cortex [41], it is not yet clear whether intuitive motor control based on trajectory intentions or planning will be achievable with EEG or MEG.

3.3. Comparing the utility of MEG and EEG for movement decoding

It is critical to compare the relative performance of MEG and EEG in terms of movement decoding accuracy in order to evaluate their significance for future BMI research. The study by Waldert et al. [25] used simultaneous MEG and EEG recordings, which allowed for a reasonably direct comparison between the decoding accuracy of each of the two techniques using recordings from the same areas. The authors found that the decoding accuracy and decoded information measures did not differ significantly between MEG and EEG. Yet, when assessing the temporal profile of the decoding accuracy, they found that it was slower to pick up and exceed a significance threshold with EEG than with MEG. The latter provided better decoding accuracy prior to movement onset (computed over a [−20 050] ms time interval with respect to movement onset at 0 ms). Interestingly, this time window corresponds to the period for which MEG topographies depict increases in decoding performance at medial motor areas, most likely representing supplementary motor area involvement in movement planning. This was followed by an increase in directional information in primary motor cortex in the [50 300] ms interval. More generally, although the study by Waldert et al. [25] suggests that MEG might carry a slight advantage when predicting the direction of an upcoming movement, evidence is still scarce and it is difficult to reliably assert which method provides the most reliable and efficient decoding.

More studies have been conducted with EEG than with MEG and direct comparisons are difficult to achieve. Magnetoencephalography might carry a stronger potential for the development of real-time source reconstructions, which could further improve existing decoding algorithms. On the other hand, portable EEG systems are a major asset for BMI research and allow for BMIs to be implemented and tested outside the laboratory setting in daily life situations. Ultimately, rather than competing, both technologies are expected to play a crucial role in BMI method developments and application in various clinical contexts.
4. The future of non-invasive BMIs: from communication to neural rehabilitation

4.1. Future trends

Notwithstanding the promising non-invasive studies discussed in this review, to our knowledge, no study to date has reported full closed-loop two-dimensional and three-dimensional online control based on decoding actual motor goal, i.e. the intended movement trajectory (in the absence of real movement). So far, two-dimensional and three-dimensional control strategies that have achieved reasonable success have been based on self-regulation of sensorimotor rhythms recorded with EEG [1–4,58]. With the advent of closed-loop EEG or MEG-based motor control experiments (i.e. with visual feedback depicting the output of the decoder in real-time) a merge between the two strategies is likely to occur. In a hybrid system the distinction between endogenous control of motor rhythms and mental encoding of limb trajectories might become less obvious as the subject develops individual strategies of adapting to the online system. This has been reported in invasive BMI approaches based on direct recordings in animals [59] and will most probably occur in advanced non-invasive systems with human subjects as well. Besides, it is highly likely that dealing with the neural representation of the motor goal might become increasingly important in BMI research and that incorporating internal models of action might play a key role in future conceptual advances in the BMI field [60].

Additionally, an increasing number of studies have begun probing the suitability of signals from regions other than motor cortex for the decoding of movement parameters. Numerous animal studies have shown that the signals from the posterior parietal cortex (PPC) may contain sufficient information (in SUA, MUA and LFP) to decode saccade and upper limb trajectories [11,12,14,29,30], only very few studies have investigated the use of posterior parietal signals for non-invasive BMI control [61]. Interestingly, animal studies that have examined the role of the PPC in motor planning and execution have revealed prominent motor information content in the gamma frequency range (>30 Hz) of the parietal LFP signal [11,12,14]. One is thus entitled to ask whether gamma-band signals can be recorded using non-invasive methods [16,62,63]. A few MEG studies have successfully detected gamma-band power modulations in posterior parietal cortex during preparation and execution of saccades and reaching movements [64–66]. This said, it is important to note that attempts to record gamma-band power modulations using surface recordings need to carefully monitor eye movement effects using simultaneous electro-oculogram (EOG) recordings or eye-tracking systems. Several studies have shown that saccadic eye movements are associated with spike potentials that originate in extraocular muscles and that translate into gamma-range artifacts on the EEG electrodes [67–69]. By contrast, intracranial bipolar recordings are by and large immune to such eye movement artifacts. However, occasionally, if an implanted electrode happens to be in the direct vicinity of an extraocular muscle, as is the case for electrodes at the tip of the temporal pole, gamma-range iEEG signal contamination can occur as shown in a recent study by our group [70]. A further comparison of signal quality in simultaneously recorded surface EEG and implanted electrode grids reports the detection of eye movement and blink artifacts in iEEG data under certain conditions [71].

Another current trend that is likely to rapidly gain momentum in the BMI field is the use of neural signals that reflect higher-order cognitive processes instead of motor intentions, trajectory encoding or imagery. For example, novel BCI studies have been able to achieve cursor control based on covert attention [72–74]. Mental calculation is another example of higher-order mental process that could be used for cursor control in a cognitive BCI application. One advantage of mental calculations (and tasks that activate working memory networks in general) is that the subjects (whether healthy or with motor impairments) can voluntarily engage in such activity. Most proofs of concept for such mental calculation based BCI control have so far been based on invasive recordings [75,76], but its evaluation non-invasively in humans is surely just around the corner. Meanwhile, insight from invasive recordings in humans are poised to continue to play an important role in the search for novel features of higher-order cognitive processes and thus provide proofs of concept (at optimal spatial, temporal and spectral resolution) for the feasibility of endogenous control of the underlying cerebral features [75,77,78].

A further exciting path for future research consists of implementing hybrid BCI systems that combine multiple signal types (EEG, electrocardiography, gaze signals, etc.) or various features obtained from the same EEG signals (sensorimotor rhythms, P300 signal, error-related negativity, covert or overt attention, etc.) in order to increase the degrees of freedom and practical utility of a BCI system [79–81]. For instance, adding a “Brain switch” to any intention decoding strategy can be extremely useful. The typical example is implementing a brain-controlled computer mouse: while 2D movement decoding strategies translate neural signals continuously into cursor displacements, a further signal (i.e. equivalent to a button press) is needed to make selections. Similarly, new generations of BCI systems that implement the P300 speller approach [82–85] will increasingly include additional signals that allow the subject to perform simple operations such as a ‘reset’ or a ‘correction’ at any time during spelling. The brain-controlled mouse operation and the P300 speller application are two examples that highlight the need for hybrid systems that incorporate a “brain switch” via asynchronous BCI control capability [86–88].

From a methodological perspective, future studies will focus on improving non-invasive BCI approaches by improving the decoding algorithms and classification methods for MEG and EEG data [89,90] and by applying various spatial filtering techniques and inverse-solution approaches that allow for BCI investigations in MEG or EEG source space [91–98]. Finally,
freely available BCI platforms will continue to play a pivotal role in the community’s effort for joint developments and the exchange of methodological and neuroscience expertise, for example, through open software projects such as OpenViBE [99], FieldTrip (http://fieldtrip.fcdonders.nl) or BCI 2000 [100].

4.2. BCI-based motor rehabilitation

To date, non-invasive BMI approaches are predominantly designed with the objective of restoring a degree of mobility and communication to severely impaired patients who have lost all motor control, for instance as a result of spinal cord injury (SCI) or who suffer from the locked-in syndrome (LIS). In parallel to this important endeavor, an increasing number of clinical research centers have now begun investigating the potential of BMIs as a more general neurological rehabilitation tool to enhance recovery in a range of impairments [101–107].

Numerous studies have examined the therapeutic use of real-time EEG training, which is often referred to as neurofeedback training (NFT). For instance, training patients to gain control over specific EEG features was tested as an intervention to decrease seizure frequency in epilepsy patients, or as a treatment for attention-deficit hyperactivity disorders [108–111]. These studies have focused mainly on producing long-term changes, such as a lasting increase or decrease in a given EEG feature rather than training the patients to rapidly change features of their ongoing brain activity as is needed for the real-time control of a BMI system. The past several years have witnessed a growing interest in the application of BCI for therapeutic purposes. One promising field is BCI-based improvement of volitional motor control following movement impairments resulting from trauma or disease.

Achieving motor re-learning intervention after brain injury relies on one of the brain’s most fascinating properties: its plasticity. Activity-dependent plasticity is not limited to the healthy nervous system and can occur with trauma or disease. For instance, stroke has been shown to be followed by extensive plasticity in the cortex [112–115]. This provides an important framework for neural rehabilitation that has been used for decades with standard-rehabilitation methods such as physical therapy and that is now seen as a great opportunity for the implementation of innovative BMI-based rehabilitation approaches. As pointed out in an excellent review by Daly and Wolpaw [103], two main types of BMI approaches are under consideration for motor rehabilitation. The first strategy is to train patients to produce more normal brain activity. The hypothesis is that by promoting cerebral plasticity such as to reduce pathological activity and enhance normal activity, a more normal brain function will be restored and, as a result, motor control will improve. The second strategy is based on training the patient to gain endogenous control over brain signals that allow him to activate a device that assists movement, such as a hand orthosis [105,116]. By improving motor function, this movement is also expected to enhance sensory input that induces cerebral plasticity. The combination of assistive technology and closed-loop BCI training could ultimately lead to restoration of normal motor control.

Interestingly, although most BCI-based motor rehabilitation approaches aim at using EEG to record brain signals, a few highly promising MEG studies have been reported in recent years. An MEG-based BMI study by Mellinger et al. [106] assessed the feasibility of using real-time analysis of MEG signals as a BMI training environment aimed at enhancing participant’s ability to rapidly learn to modulate his sensorimotor mu (10–12 Hz) and beta (20–24 Hz) brain rhythms. After 32 min of feedback training, the participants were able to communicate binary decisions by imagery of limb movements. The results provided by this study provide the first evidence that MEG-based BMI can be used for user training. Additionally, using a combination of “phase decorrelation analysis” (a principal component analysis (PCA) related technique) and least-squares equivalent dipole (ECD) fit, Mellinger et al. [106] were able (in three out of six subjects) to localize the origin of the mu rhythms (which the subjects were able to modulate for cursor control) to motor cortex. While this finding is not particularly surprising, it is important to localize the origin of the self-controlled mu rhythm as it might not necessarily have the exact same neural substrate as the untrained (i.e. spontaneous) sensorimotor mu rhythm.

A further pioneering real-time MEG study was conducted by Buch et al. [104] in stroke patients with chronic hand plegia. The authors tested the utility of closed-loop BMI-based training to enhance volitional control of neuromagnetic activity features recorded over central cerebral areas in these patients. Most importantly, the participants were able, thanks to real-time BMI training, to self-regulate their sensorimotor mu rhythm allowing them to control grasping actions through a mechanical hand orthosis. Overall, the patients participated in 13–22 training sessions with the objective of achieving voluntary modulations of mu rhythm amplitude. The mu rhythm modulations in turn raised or lowered the position of a cursor in the direction of a target displayed on the screen. Performance feedback was provided visually in real-time and successful trials (in which the cursor made contact with the target) resulted in opening/closing of the orthosis attached to the paralyzed hand. While the training did not lead to improvement from a clinical perspective (the plegic hand remained paralyzed), it does provide evidence that a brain-controlled orthosis can become a viable assistive technology solution that restores a minimal level of hand control in such patients. It is not completely unrealistic to imagine that the next generation of this technique could be based on more complex mechanical orthosis that allow for individual finger control. Individual finger kinematics could ultimately be controlled by continuous decoding of fine-tuned motor intentions.

5. Conclusion

As noted in a recent review the proof-of-concept phase for BMI research is gradually coming to an end: “Time is now ripe to focus on the development of practical BMI technologies that can be brought out of the lab and into real world applications” [107]. Combining BCI technology with existing assistive technologies is an extremely promising field which will change the life of many disabled people [107,117] and which will teach us as much about the injured brain as about normal brain function.
Conflict of interest statement

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References


