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Characterizing Motor System to Improve Training Protocols Used in Brain-Machine Interfaces Based on Motor Imagery

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Additional information is available at the end of the chapter

<http://dx.doi.org/10.5772/intechopen.72667>

Abstract

Motor imagery (MI)-based brain-machine interface (BMI) is a technology under development that actively modifies users' perception and cognition through mental tasks, so as to decode their intentions from their neural oscillations, and thereby bringing some kind of activation. So far, MI as control task in BMIs has been seen as a skill that must be acquired, but neither user conditions nor controlled learning conditions have been taken into account. As motor system is a complex mechanism trained along lifetime, and MI-based BMI attempts to decode motor intentions from neural oscillations in order to put a device into action, motor mechanisms should be considered when prototyping BMI systems. It is hypothesized that the best way to acquire MI skills is following the same rules humans obey to move around the world. On this basis, new training paradigms consisting of ecological environments, identification of control tasks according to the ecological environment, transparent mapping, and multisensory feedback are proposed in this chapter. These new MI training paradigms take advantages of previous knowledge of users and facilitate the generation of mental image due to the automatic development of sensory predictions and motor behavior patterns in the brain. Furthermore, the effectuation of MI as an actual movement would make users feel that their mental images are being executed, and the resulting sensory feedback may allow forward model readjusting the imaginary movement in course.

Keywords: motor system, forward model, inverse model, brain-machine interfaces, training protocols

1. Introduction

Electroencephalography (EEG) has become a standard brain imaging tool due to its viability for recording the brain activity. Typically, EEG has been analyzed by quantifying and qualifying neural oscillations. In broad terms, “neural oscillations” can be defined as spatial, temporal, and spectral patterns that are associated with particular perceptual, cognitive, motor, and emotional processes [1]. A large and growing body of literature has investigated neural oscillations as EEG feature in all directions: from neurological to technological perspectives. In terms of Neurosciences, research into brain response has a long history. Brain responses have been traditionally studied on the basis of event-related experiments, where time-locked and phase-locked responses (i.e., event-related potentials) along with time-locked but not necessary phase-locked responses (i.e., event-related (de) synchronization) have been essentially analyzed [2, 3]. In the case of technology, research into neural interfaces has taken a leading role. A neural interface is a system that permits to reintegrate the sensory-motor loop, accessing directly to brain information. There are three main types of neural interfaces: (1) sensory interfaces, which artificially activate the sensory system; (2) cognitive interfaces, which try to re-establish the communication of the neural networks; and (3) motor interfaces, which translate neural oscillations into control commands for a device of interest [4]. In particular, motor interfaces are known as brain-machine interfaces (BMI).

BMIs are technology under development that modify users’ perception and cognition in order to decode their intentions from their neural oscillations, and thereby bringing some kind of activation. See **Figure 1**. Human perception and cognition can be manipulated actively through

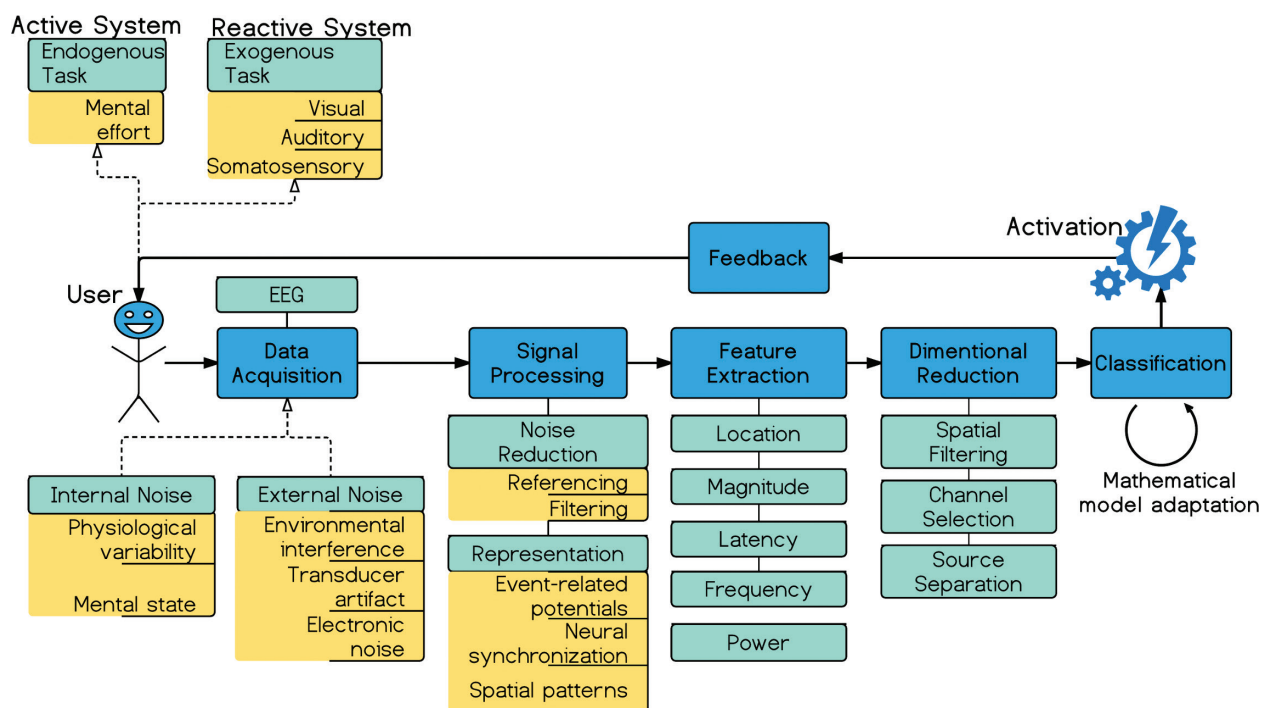


Figure 1. Structure of a brain-machine interface (BMI). The basic structure of a BMI is based on user, control task (endogenous or exogenous), data acquisition, signal processing, feature extraction, dimensional reduction, classification, activation (e.g., neuro-feedback, neuro-prosthesis, domotic environments), and feedback.

mental tasks, or reactively by applying external stimulation (visual, auditory, or somatosensory). Users' intentions are typically decoded by reducing EEG signal noise, extracting neurophysiological features associated with the mental task or the external stimulus in use, and adapting a mathematical model by using those features [5]. Once a model has been calibrated, the BMI attempts to predict users' intentions so as to bring activation in different ways, including neuro-rehabilitation, communication, neuro-prosthesis, domotic environments, or neuro-feedback [6]. In a nutshell, BMI has been the operationalization of Neuroscience research advances.

Although BMI investigation was firstly undertaken in the 60s, these systems are still laboratory prototypes because (1) it is unknown how EEG features are linked to perception and cognition (human side); (2) users have been not involved in the system design, are usually not well instructed, and not guided during the user-system adaption (human-machine interaction); and (3) computational decodification of EEG signals is not enough efficient (system side). In particular, active systems have been much more challengeable to set up since they depend on the user mental effort, rather than spontaneous neural responses as reactive systems do [7]. However, active systems can be controlled by "real" users' intentions since they do not depend on external stimulation as reactive systems do. Furthermore, mental tasks strengthen other neural mechanisms, apart from those related to mental task per se. A case in point is motor imagery (MI). MI refers to the generation and maintenance of imaginary movements. As MI is motor activity, mental tasks related to MI activate the central and peripheral nervous system almost to the same extent that actual movements do it [8–10]. This property of MI-related tasks increases the technical and clinical applicability of BMIs, as well as our interest to define the scope of the present chapter to MI-based BMIs.

Over the past few years, the user has been identified as the main component of the MI-based BMI structure, but who has been frequently ignored in the BMI design [11, 12]. According to [13, 14], there are three factors and three conditioners that directly influence the user performance in an MI-based BMI. See **Figure 2**. On one hand, *factors* have been categorized into (1) user state, (2) user traits, and (3) user conditions. A *user state* can be regarded as the result of many physiological and psychological processes that regulate brain and body in an attempt to put the individual in an optimal condition to meet the environment demands [15]. User state includes emotions such as mood, and cognition such as motivation, mastery, confidence, competence, self-efficiency, and fear. *User traits* refer to behavior, capabilities and abilities that define a person, including personality (tension and self-reliance), and cognitive profile (attention span, attentional abilities, attitude toward work, memory span, visual-motor coordination, learning style, and abstractedness). *User conditions* are associated with demographic information such as age and gender, and lifestyle such as playing music instruments, practicing sports, playing video games, typing, and full body movement either for working or entertainment. On the other hand, *conditioners* have been grouped in (1) user-technology relationship, (2) attention, and (3) spatial abilities. *User-technology relationship* is the level of computer anxiety and sense of agency that a user poses. Computer anxiety refers to the fear and tension produced by the use of technology, while sense of agency is the belief and feeling of being the entity who is causing an action. *Attention system* is responsible for maintaining a state of vigilance (alerting function), selecting information (orienting function), and managing mental resources, which are moreover limited (executive control). Finally, *spatial abilities* are considered the skill to generate, maintain, scan, and manipulate mental images. Spatial

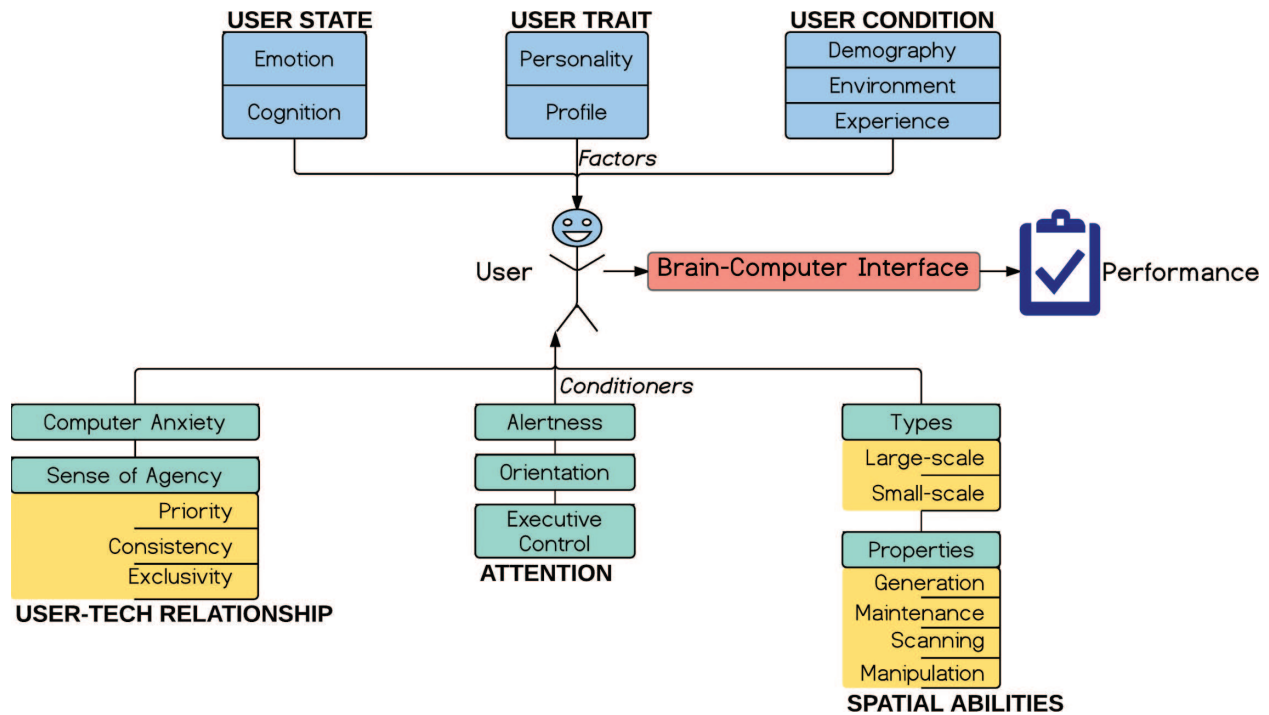


Figure 2. Factors and conditioners that directly influence the user performance during a brain-machine communication. This model has been constructed on the basis of the theoretical framework presented in [13, 14].

abilities can be of two types: small-scale and large-scale. Small-scale abilities refer to generate and transform small shapes and easy-to-handle objects, whereas large-scale abilities refer to spatial navigation [14].

As can be seen, evolutionary genetics, skill acquisition along lifespan, and sensory-cognitive information and resources determine the production quality of motor mental images, which in turn determines the modulation level of EEG signals used to decode user intentions. The modulation level of EEG signals due to MI activity defines if a good or poor brain-computer communication is established. On this basis, the present chapter gives an account of movement production (Section 2), provides an overview of neural oscillations associated with movement production (Section 3), and explores the ways in which humans produce movements (Section 4) so as to propose new training protocols based on how human learn, predict, and act (Section 5). MI is a skill that must be acquired, and possibly, an optimal way to fulfill this task is to lay down the same rules followed by humans when they interact with their environment.

2. Movement production

2.1. Generating movements

Most of the human behaviors involve motor function, which implies the complex and coordinated functional participation of several anatomic structures. The brain integrates the information from different sensory systems in order to construct specific internal representations

of the environment. These representations allow the individual to organize, coordinate, and execute purposefully designed motor plans aimed to maintain internal stability and achieve different specific goals.

The motor plan is conceived in the cerebral cortex. The primary motor cortex, or M1, is located in the frontal lobe of the brain, and its main role consists in generating neural impulses that control the performance of movement on the contralateral side of the body. This is possible as M1 has a particular somatotopic representation of the body parts, in which those parts with more complex movements—e.g. hands—have larger representations. Moreover, the posterior parietal cortex, the premotor cortex, and the supplementary motor area also participate by using the visuospatial information to plan the complex movements and build a complex sensory guidance of each movement. These brain regions, commonly known as secondary motor cortices, send information to both primary motor cortex and brainstem motor structures in order to control the motor performance. They accomplish this goal acting on corticofugal neurons that give rise to corticospinal projections, the corticospinal tract, which ultimately end at striated muscle [16, 17].

On the other hand, the “basal ganglia” (striatum and globus pallidus) and related nuclei (subthalamic nucleus, substantia nigra, and pedunculopontine nucleus) constitute a group of subcortical nuclei primarily engaged in motor control, also playing important roles such as motor learning, executive functions and behavior, and emotions. These complementary pathways control posture and balance, coarse movements of the proximal muscles, and coordinate head, neck, and eye movements in response to visual targets. See **Figure 3** for illustrative purposes [18].

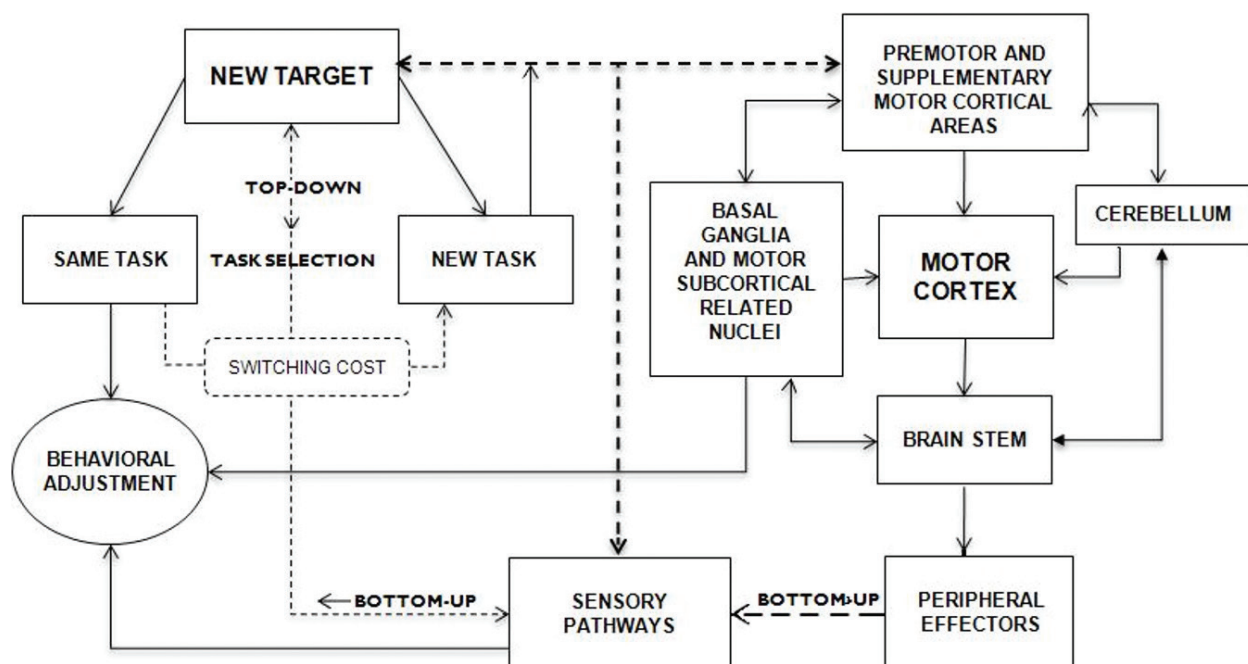


Figure 3. Schematic and simplified representation of the dynamic underlying a goal-directed movement, highlighting the most relevant neural substrates involved in this complex process. The term “switching cost” refers to the cost of adjusting the mental control setting to novel demands.

Despite the concurrence of multiple parallel loops and re-entering circuits that functionally engage complex temporary associations on an extended repertoire of neural structures, a regular movement is effortlessly carried out by healthy adults, due to the continuous converging streaming of visual, somatosensory, and postural information to the cerebral systems underpinning motor acts. In fact, the motor system is hierarchically organized in a way in which the primary motor cortex and several premotor areas crucial for planning and coordinating the sequence of movements are directly related with brain stem and spinal cord structures via neural projections. These relationships allow the upper brain structures to dynamically control the peripheral muscles, whereas several feedback circuits provide useful ascending information with the aim to maintain or adjust the motor commands if the situation demands it.

2.2. Categorizing the movements

In general, movements have been categorized as a) *reflexive*: involuntary coordinated patterns of muscle contraction and relaxation, predominantly based on spinal cord mechanisms; b) *rhythmic* (e.g. quadrupedal locomotion): repetitive motor patterns involving spinal cord and brain stem circuits, and c) *voluntary*: goal-directed mechanisms involving extended motor cortical areas, brain stem, cerebellum, basal ganglia, the pyramidal and extra-pyramidal pathways, among many others [19].

Learning refines the motor programs underlying voluntary movements. Several studies have shown significant changes in the anatomic maps of the motor programs through learning, usually referred as “implicit”, a term used to define changes that cannot be explicitly described in general statements (e.g. to verbally explain the learning process of riding a bicycle).

2.3. Motor intention

During the last few years, generous empirical evidence has been gathered on the fact that goal-directed and non-goal-directed movements have different neural correlates. This simple distinction has enormous implications at the understanding of behavioral actions, and neuro-rehabilitation in general.

An essential challenge in the area of perception and motor control has been to identify the sensory-motor and cognitive processes associated with accurate goal-directed movements. In this context, it is important to note that motor behaviors are based on strategies developed over a lifetime of interacting with objects in the environment and that they are not always conscious strategies. They almost instantaneously ponder variables as body posture, cognitive evaluation, emotional attributes, and position of the target at movement initiation, trajectory and speed of the movement, gravity effect, among several others.

The meaningful goal-directed movements have been studied in several contexts, sensory pathways, and using a wide variety of experimental tasks. However, a clear timeline delineating brain functional engagement to support these movements seems to be far from delineated.

Briefly, information from the spatial senses converges within the parietal cortex, where it is integrated and transformed into motor-relevant reference coordinates. This information is sent

to the premotor cortex and integrated with information from prefrontal cortex about action goals and contexts before final motor output is sent to primary motor cortex, transmitted via the corticospinal tracts, and then modulated by the cerebellum and basal ganglia [20, 21].

The premotor regions have an important role to play in motor planning and the outlining of the motor sequence of the forthcoming goal-directed action. In this sense, a decreased activity in the parietal operculum has been correlated with activity in the lateral premotor cortex, the medial cingulate motor cortex, and supplementary motor cortices. In addition, the left dorsolateral prefrontal cortex, the anterior cingulate motor cortex and bilaterally, the insular cortices are also functionally involved [22, 23].

The cerebellum is another important region that is thought to represent the timing of our goal-directed actions. The neocerebellum has been found to relate with the control and planning of voluntary movements while the intermediate cerebellum seems to be involved in regulating the quality of the movement. It has been argued that the cerebellum is a key predictive component in the conceptualization of the internal models of motor control, probably due to its extensive projections, through the thalamus, to the premotor and prefrontal cortices [24].

2.4. Imagining a movement

Mental imagery is a multimodal construct supporting the formation and maintenance of inner representations of either previously perceived images or feelings, or foreseeing upcoming events in the absence of external sensory input. Within this framework, MI alludes to the dynamic state or mental representation of a given motor action that is rehearsed in working memory without any explicit motor act [25].

There is enough empirical evidence pointing out that imagined stimuli are treated in the same way as other direct sensory stimulations because they engage in multisensory interactions with stimuli directly perceived. In this regard, during real and imagined movements, brain functional activity seems to focus on related neural networks. It is not surprising then that MI draws on the similar neural circuits that are used in actual perception and motor control, involving networks associated with memory and emotion.

Depending on the MI task used, multiple neuroimaging studies have revealed the functional participation of motor, premotor, and supplementary motor cortices, which are consistently activated during motor imagery and are also major components of the interconnected network for motor intention. In addition, other structures play an important functional role in motor imagery as it occurs with the cerebellum, the basal ganglia, the superior and inferior parietal lobules, and the precuneus. Therefore, several authors have concurred in the notion that when performing MI, main differences with motor performance probably lie in the inhibition of some motor commands triggering movements [26].

2.5. Observing a movement

MI and movement observation (MO) have traditionally been studied as separate processes that activate the motor system without any actual motor execution. However, motor and perception

action representations are closely interrelated to such a degree that perceiving another person's action triggers comparable representations as performing the action. This effect has been called "motor resonance."

In terms of neural substrates, evidence indicates that when observing a movement, there is a significant activation on caudal supplementary motor area, bilateral cerebellum and precuneus, but also involving the basal ganglia, the inferior parietal cortex, ventral premotor cortex, and left insula. On this subject, cortico-motor activity is significantly increased while combining MI and MO, compared to either MI or MO independently. This has led to the theory that they are both concurrent processes, in which action representation might be implemented by the dynamic interaction between perception and executive brain networks, thus opening interesting possibilities for practitioners in motor learning and rehabilitation settings [27–29].

2.6. Motor disabilities

Motor impairment—or physical disability—is a common outcome from a wide range of diseases and health conditions that affects almost one of eight adults in America. In broad terms, disability is understood as the inability to engage in any substantial gainful activity in view of confirmable physical or mental impairment(s), lasting for not less than 12 months. Physical disability encompasses limitations in individual physical functioning, mobility, dexterity, or stamina. They are rarely confined to a particular disturbance of motor capabilities and also impact psychological, social, economic, and the quality of life of the affected individuals [30].

Motor disabilities can be broadly divided into two major groups, according to their inflicting conditions: a) traumatic injuries and b) congenital conditions and diseases.

2.6.1. Traumatic injuries

There are several limitations subsequent to traumatic injuries that not only include motor impairments. Neurological sequelae can also involve cognitive impairments or sensory disabilities such as deafness and blindness post-neurotrauma, limb deformations or amputation, paralysis subsequent to spinal cord injury that can affect both arms and legs—quadriplegia, both legs—paraplegia, or a more unusual combination of the limbs.

2.6.2. Congenital conditions and diseases

Several congenital conditions such as cerebral palsy, muscular dystrophy, etc., can lead to different types of motor disabilities. In addition, several degenerative nerve diseases (e.g. Parkinson's disease, multiple sclerosis, amyotrophic lateral sclerosis/Lou Gehrig's disease, etc.), and other neurological conditions (e.g. stroke, central nervous system vascular accidents, peripheral neuropathies, etc.) can also produce different degrees of motor disabilities, even including an extreme form of motor impairment termed as "locked-in syndrome," in which voluntary control of almost all muscles is lost, yet retaining a normal cognitive functioning.

3. Neural oscillations in movement production and beyond

3.1. Overview

Sensory stimulation, cognitive activities, and motor behavior result in amplitude suppression or in amplitude enhancement of the EEG signals, depending on the degree of synchronization of the neural oscillations. Such degree of synchronization is reflected in various frequency bands. Moreover, the synchronization mechanism of the neural oscillations does not only reflect processing of physical and psychological events, but it also appears prior to the event occurrence. The association of this EEG modulation with specific events is known as event-related oscillation (ERO). EROs can be of two types: event-related synchronization (ERS) and event-related desynchronization (ERD). If EEG rhythms increase their synchrony and thus their amplitude, an ERS arises. Otherwise, an ERD appears. ERS reflexes awake-restful states, inhibition processes, rebound events, attention-related demands (e.g., attentive expectation of relevant stimulus omission, working memory activation, and episodic short-term memory task), and cognitive-mnemonic processes. Oppositely, ERD is involved in the processing of sensory and cognitive information, and production of motor behavior [31, 32].

EROs are characterized by four parameters: spatial location, magnitude, latency, and reactive frequency band. Among those parameters, the frequency is the key parameter to understand how humans interact with their environment. Historically, neural oscillations have been studied into five frequency bands: delta, theta, alpha, beta, and gamma [33].

3.1.1. Delta band oscillations

Delta band oscillations (below 4 Hz) are indicative of deep sleep in adults and appear during long attention tasks [34]. They have been also found to carry information pertaining to different movements around a joint, such as extension and flexion of the wrist [35].

3.1.2. Theta band oscillations

Theta band oscillations resonate at the frequency band 4–8 Hz and emanate from the frontal midline due to audio-visual information encoding, attention demands, memory retrieval, and cognitive load. Moreover, these oscillations enhance after practice on the cognitive tasks at hand. They are more prevalent when the individual is focused and relaxed, and prolonged activity is related to selective attention [33, 36]. The upper theta band (6–8 Hz) is also known as lower-1 alpha band and generally reflects levels of alertness [31].

At a neurophysiological level, anticipating sensory events resets the phase of slow, delta-theta (2–8 Hz) activity before the stimulus occurs [32].

3.1.3. Alpha band oscillations

Alpha band rhythms oscillate at frequencies between 8 and 12 Hz and may come from frontal, temporal, parietal, and occipital regions. Overall, enhancement and suppression of alpha band rhythms are respectively associated with top-down and bottom-up information processing [37].

According to the functional roles of the alpha band rhythms, they can be categorized into mu, occipital, and tau rhythms. Mu-rhythms (or sensory-motor rhythms) arise from the sensory-motor cortex at both bandwidths 8–12 and 16–24 Hz. Enhancement and suppression of mu rhythms are due to sensory stimulation, motor activity, cognitive processes, and emotional influences [31]. Particularly, synchronization of mu rhythms increases in line with attention demands, sensory encoding, inhibition processes, and rebound events. On the other hand, suppression of mu rhythms responds to complexity, level of difficulty, and relevance of the tasks in progress. The nature of the task is reflected on the bandwidth reactivity. For example, general tasks associated with arousal, attention, effort, and expectancy produce lower alpha (8–10 Hz) desynchronization widespread over the whole scalp. In contrast, specific tasks related to information processing, selective attention, and motor activity elicit upper alpha (10–12 Hz) topographically restricted desynchronization [31, 38, 39]. Note that “information processing” refers to feature extraction, stimulus identification, and response preparation. Occipital alpha rhythms respond to mental effort expended on the processing of visual relevant stimuli. Maximum suppression of occipital alpha rhythms is expected between 200 and 300 ms after stimulus onset. The ERD effect moves toward parietal regions, reaching a longer duration than the one reached over occipital regions, particularly within the lower alpha frequency band [33]. Tau alpha rhythms (or mid-temporal third rhythms) have been associated with auditory stimulation, and are obviously expected over the temporal lobe. However, these rhythms are hardly recorded over the scalp owing to the anatomical limitations [31].

3.1.4. Beta band oscillations

Beta band oscillations function as a resetting mechanism, which permits neural networks to work repeatedly. These oscillations also play an important role in the top-down process that takes place during predictions [32]. According to their topographical origin, they can be identified as central, frontal, and occipital beta band oscillations. *Central beta band oscillations* are related to cognitive-motor tasks, and relaxation states preceded by strong activations. *Frontal beta band* mainly oscillates around 19 Hz, are post-stimulus events, and are associated with stimulus assessment, level of difficulty, and decision making. Finally, the *occipital beta band rhythms* occur in response to visual stimulation followed by mental relaxation [33].

3.1.5. Gamma band oscillations

Gamma band rhythms oscillate near 30 Hz during linguistic processing of meaningful words and near 40 Hz during sensory encoding, perceptual-cognitive functions, and motor behaviors. With regard to 40 Hz-rhythms, these are phase-locked to the stimulus and short-lasting, and appear 100 ms post-stimulus in sensory-motor tasks. In contrast, these are induced and late-appearing oscillations that might achieve maximum synchrony over the fronto-central region in perceptual-cognitive tasks [36, 40, 41].

According to [32], while predicting when predominantly involves low-frequency oscillations, predicting what points to a combined role of gamma and beta oscillations.

3.2. EROs in voluntary movements

Voluntary movements are produced in three phases: planning, execution, and recovery. During the three phases, voluntary movements provoke EROs within alpha, beta, and gamma bands. These EROs are also generated in the course of imaginary movements to some extent. In this section, the generation of EROs during voluntary movement is first explained, and then how these EROs are reproduced during MI is described.

3.2.1. ERD within the upper alpha band

Voluntary movements result in a somato-topically specific and topographically restricted desynchronization of the upper alpha band over the sensory-motor cortical area. This desynchronization starts around 2 seconds prior to movement onset over the contralateral side and becomes bilaterally symmetrical immediately before execution of movement. This ERD shows a slow recovery in the period of 2 or 3 seconds following the movement [42].

3.2.2. ERS within the upper alpha band

During movement preparation and execution, desynchronization of the upper alpha band is often accompanied by ERS over occipital areas. This ERS can also appear after movement over areas that displayed ERD before. It has been hypothesized that this ERS is produced by deactivated cortical areas. The ERD/ERS effect within the upper alpha band is known as focal ERD/surround ERS [43].

3.2.3. EROs within the Rolandic beta band

Desynchronization of the Rolandic beta band starts around 1 second prior to movement onset over the contralateral sensorimotor area, becoming bilaterally symmetrical during movement execution. This beta ERD recovers in less than 1 second, much faster than upper alpha ERD. After the beta ERD recovery, an ERS around 20 Hz appears. Note that this beta ERS occurs while the upper alpha ERD exists. This post-movement beta ERS is a relatively robust phenomenon because it has been found after finger, hand, arm, and foot movements. However, it is larger in hand movements. The beta ERS is dominant over the contralateral primary sensorimotor area and has a maximum around 1 second post-movement [43].

3.2.4. ERS within the gamma band

It has been found that voluntary movements also provoke ERS within the gamma band. Gamma reactivity is predominantly generated over the primary sensorimotor area. The location of gamma ERS varies with type of movement, i.e., it is somato-topically distributed. Gamma ERS appears as a sharp power increase around 36 Hz shortly before movement-onset. However, this is rarely found in the human EEG. Gamma ERS also reveals a maximum around 40 Hz during execution of movement. This ERS is considered as a stage of active information processing [44].

3.3. EROs in imaginary movements

As MI relies on the same mechanism as actual movements, it is not surprising to observe similar EROs during imaginary movements. Specifically, upper alpha ERD during MI is very similar to upper alpha ERD observed during the planning phase of motor executions, i.e., it is locally restricted to the contralateral sensorimotor areas. In both cases, ERD may reflect a type of readiness or pre-setting of neural networks in sensory-motor areas. Similarly, Rolandic beta ERD appears during MI as it does during movement preparation. After the MI activity, the Rolandic beta ERS found post-movement over the pre-central region of the brain is reflected as well [43, 44]. These EROs are illustrated in **Figure 4**.

3.4. Neural oscillations in BMI

As was aforementioned, a BMI is an emerging technology that aims to achieve interaction between humans and their environment by making use of their neural oscillations. In order to establish brain-machine communication, systems can employ MI-related mental tasks to modulate user neural oscillations, and thus extracting wealthy information to generate an action. As was discussed in this section, MI activity produces well-established ERD/ERS patterns, which have been moderately used to control BMIs. However, it is also well-known that MI-based BMIs require long training sessions and are not suitable for all people [45–47].

From **Figure 2**, it can be clearly seen that the level of synchronization of neural oscillations depends on a wide variety of factors and conditioners. The human-environment interaction through BMI engages a large number of sensory, cognitive, and motor processes, which modulate neural oscillations beyond the MI-related mental tasks. Typically, BMI users are rigorously trained to dominate MI skills, so as to magnify the ERD/ERS effects on the scalp, regardless of evolutionary genetics, skill acquisition along lifespan, and sensory-cognitive information and resources at a time (**Figure 2**). BMI is not only associated with the analysis of EEG signals prior to, during and after MI activity [48–50], but it is also related to previous knowledge of user, current user state, user profile, and environmental conditions: factors that determine the level of synchrony of neural oscillations as well.

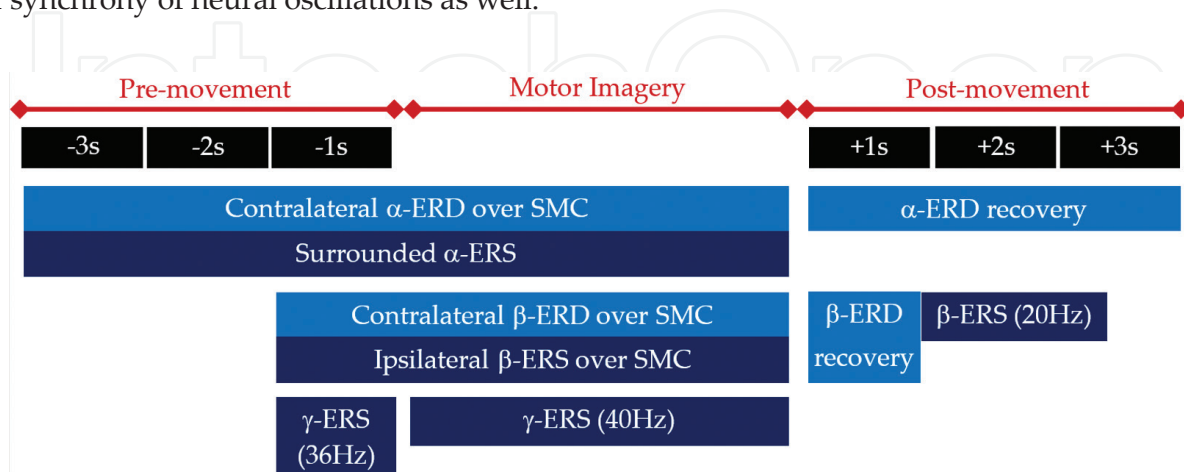


Figure 4. Neural oscillations in MI activity. Similar to voluntary movements, MI is produced in three phases: planning, execution, and recovery. During the three phases, MI modulates neural oscillations in alpha, beta, and gamma bands.

4. Sensory-motor system in motor skill acquisition

Movement is the means whereby individuals interact with other individuals and their environment. Most of motor information is gathered along the human lifetime, but there are also few motor skills genetically and evolutionarily inherited. In general, movements are skills acquired by learning, and are the result of transforming sensory and cognitive inputs into motor outputs. As motor system is a complex mechanism trained along lifetime, and MI-based BMI attempts to decode motor intentions from neural oscillations in order to put a device into action, motor mechanisms should be considered when prototyping BMI systems. Understanding motor processing and control, and including thereafter such motor mechanisms in the BMI architecture could lead to solve BMI drawbacks at the source. On this basis, the main issues addressed in this section are: (1) how humans execute movements, (2) relevance of somatosensory information in movement processing and control, and (3) the role of MI in sensory and motor systems.

4.1. Modular selection and identification for control (MOSAIC) model

Movements are skills that humans need to acquire along with their life-time through an error-and-trial process, which depends on the reduction of kinematic (geometry and speed) and dynamic (force) error detected through somatosensory channels, primarily visual and proprioceptive ones. Eventually, movements become habitual behaviors.

To produce a movement, prediction (forward model) turns motor intentions into expected sensory-cognitive consequences, whereas control (inverse model) turns desired consequences into motor commands. This model is known as modular selection and identification for control (MOSAIC) model. The transformation from sensory-cognitive into motor signals according to MOSAIC model is as follows. Firstly, motor behavior patterns are predicted according to previously acquired knowledge (memory), and simultaneously, sensory predictions are made by scanning the working environment (context). Secondly, motor behavior patterns and sensory predictions are used to make a motor prediction. Thirdly, those predictions are turned out to be movements, and thereby modifying the working environment. Finally, environmental changes cause sensory feedback used to adjust motor behavior [51, 52].

Motor system depends on several forward models that run simultaneously. Each of those forward models is paired with a corresponding inverse model as is illustrated in **Figure 5A**. Note that the controller of the inverse model weights its output in accordance with the matching between sensory feedback and motor prediction. In this way, every forward-inverse model pair contributes correspondingly to motor execution, and depending on the environmental demands [53].

4.2. Sensory feedback in the motor system

Sensory feedback, result of environmental changes caused by motor execution, is not only compared with motor prediction to readjust motor execution. Sensory information collected from the working environment also leads to perceptual learning. From **Figure 5A**, it can be seen that sensory information feed forwards the forward model. This means that sensory

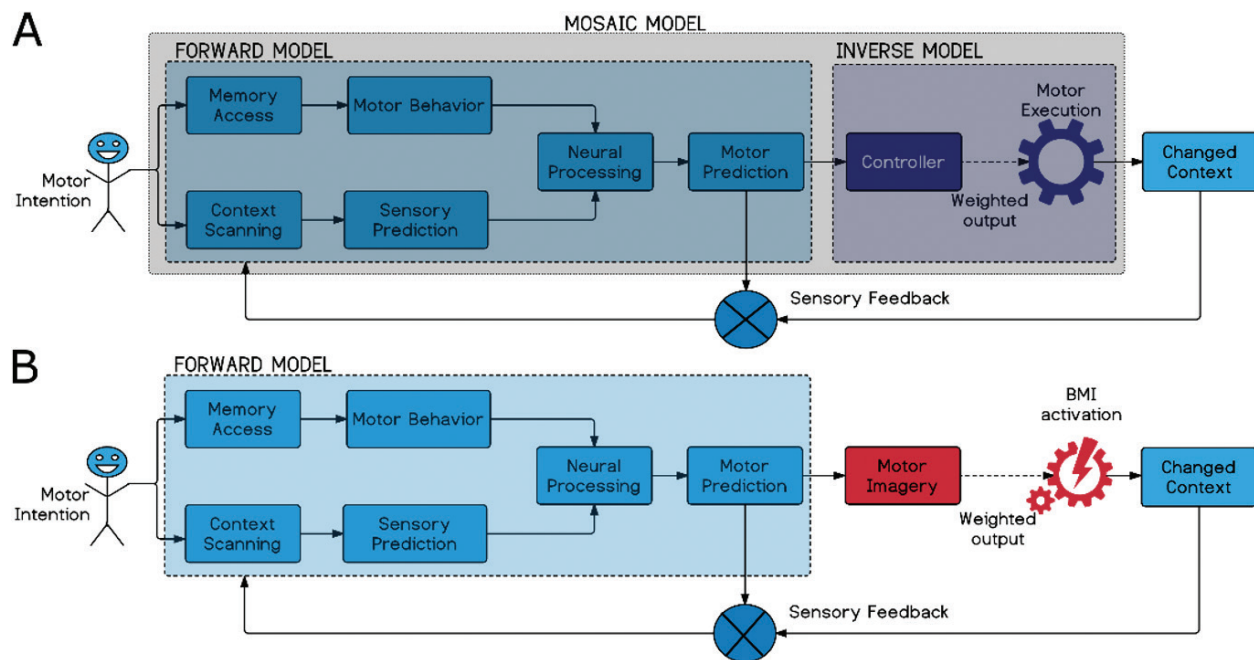


Figure 5. Motor system according to the modular selection and identification for control (MOSAIC) model, and sensory feedback. (A) System diagram to execute actual movements. (B) System diagram to achieve interaction with the environment through MI-based BMI by both sensory and motor systems.

feedback is used to make new sensory predictions, and it influences motor behaviors. As learning is a process that involves changes in behavior that arise from interaction with the environment [52], it means that sensory feedback does not only confirm or contradict motor prediction, but it also promotes perceptual learning.

Recent neuroimaging evidence suggests that perceptual learning promotes neural plasticity over sensory-motor cortices, and increases connectivity between such areas of the brain. Furthermore, the effect of perceptual learning is durable [54, 55]. This means that somato-sensory function plays a vital role in motor (re) learning. As motor skill (re) acquisition is determined by sensory and motor systems, MI-based BMIs should be designed in terms of both systems. At present, only motor system is considered in the BMI architecture. However, if sensory feedback is properly given, perceptual learning will be gained, which in turn will achieve the acquisition of MI skills.

4.3. Motor imagery as a result of sensory and motor systems

Up to now, MI as control task in BMIs has been seen as a skill that must be acquired, but neither user conditions nor controlled learning conditions have been taken into account. Only recently, when MI-based control has not been achieved by anyone at any time [7, 11], those two conditioners started to be investigated [14].

Turning now to **Figure 5B**, it can be seen that MI is managed by forward models, fact that has been shown in previous neurophysiological studies [56, 57]. This indicates that MI depends on sensory predictions and motor behavior patterns, proceeding respectively from context scanning and previous knowledge. As is illustrated in **Figure 2**, previous knowledge of users

(encompassed under the user condition category) influences directly user performance. To date, user ability to produce motor mental images has been somehow quantified psychologically and neuro-physiologically to evaluate the user potential to control a MI-based BMI [13]. However, the role of context, along with sensory prediction, has been overlooked. Based on **Figure 5B**, the production of imaginary movements depends on both motor repertoires built along lifetime and environmental conditions. Furthermore, if a MI-based BMI attempts to put into action MI tasks, the resulting environmental changes will necessarily produce sensory feedback that must be collected, and then, provided to the forward model in order to readjust MI activity. That is, MI is a mental rehearsal that proceeds from forward motor model, which is intended to be effected through BMI, and which should be readjusted by sensory feedback. Following this line of thought, it is proposed to restructure current training paradigms used to train BMI users on the basis of forward model, sensory feedback, and perceptual learning.

5. Toward training paradigms based on how human learn, predict, and act

The interest on MI-based BMIs has been growing exponentially. Although the idea of direct brain-machine communication is very attractive stand alone, BMIs as a tool in Neurosciences to investigate sensorimotor transformations of the nervous system has magnified BMI research [58]. So far, the major issue to debate in BMI research has been system performance. As has been herein discussed, user conditioners and factors are closely associated with system performance (**Figure 2**), and in turn, all those conditioners and factors are related to the acquisition of MI skills. If imaginary movements became automatic, brain-machine communication would be natural and efficient. It is hypothesized that the best way to acquire MI skills is following the same rules humans obey to move around the world. Hereunder, new training paradigms based on the sensory-motor system are proposed.

5.1. How to design new paradigms based on the sensory-motor system functioning to achieve MI skill acquisition?

Similar to actual movements, imaginary movements are predicted in line with motor repertoires built along lifetime, and sensory predictions made through context scanning (**Figure 5B**). Therefore, the first step to design a training paradigm is to create a favorable and familiar environment, which provides at a first glance the sufficient sensory information about which imaginary movements are needed to interact with such environment. This first step refers to the creation of an *ecological environment*. The second step is to identify the necessary imaginary movements in line with the nature of the working environment. Note that the selected imaginary movements are used to modulate EEG signals, and thus getting control of the system. For this reason, the selected imaginary movements are known as *control tasks*. The third step is to modify the working environment as if imaginary movements were being actually executed. This achieves consistency between what is imagined and how that mental image is effectuated. Frequently, the set of imaginary movements that user performs to establish brain-machine communication is not strongly related to the control panel of the

system. For example, imaginary movements of mouth, foot, left hand and right hand are often mapped respectively to move forward, move backward, turn left and turn right. This kind of mapping causes confusion, and makes difficult the user-system adaptation, since not only MI skill acquisition is necessary, but also the correlation between mental rehearsal and control panel. The consistency between imaginary movements and control mechanisms is referred to as *transparent mapping*. Finally, the last step is to provide *sensory feedback* to obtain perceptual information about the environmental changes effected by the MI activity in use.

By way of illustration of this MI training paradigm, the following scenario is constructed. If the working environment is a photo album on a mobile, and the interaction task is to slide photos, the control task should be to imagine sliding the index finger from left to right. With respect to sensory feedback, this can be given in three modalities: (1) auditory, playing a sweeping sound while the current photo is being replaced by the next one; (2) visual, sliding from one photo to another; and (3) tactile, producing a vibration in the hand of interest, similar to the one perceived from mobile devices. The MI training paradigm, along with this exemplification, has been outlined in **Table 1**. The complete picture (forward model, MI process, neural oscillations, and sensory feedback) of this scenario is provided in **Figure 6**.

It is worth noting that there are several neural oscillations related to MI process (**Figure 4**); however, in **Figure 6**, only those previously estimated to improve BMI performance were considered. In [48, 49], it was found that pre-stimulus sensory-motor rhythms can predict user performance, and can lead to better classifiable EEG patterns as well. In [50], it was demonstrated that the most optimal features to differentiate MI tasks were post-MI period, rather than peri-MI period. Nevertheless, the signal analysis is not limited to this proposal.

5.2. Why should these paradigms increase MI-based BMI performance?

These new MI training paradigms take advantages of previous knowledge of users since they supply meaningful contexts. These paradigms can facilitate the generation and maintenance of mental image due to the automatic development of sensory predictions and motor behavior

Step		Description	Exemplification
①	Ecological environment	Create a favorable and familiar environment, which provides at a first glance the sufficient sensory information about which imaginary movements are needed to interact with such environment.	Photo album on mobile.
②	Control task	Identification of control tasks according to the ecological environment.	Slide index finger from left to right.
③	Transparent mapping	Consistency between imaginary movements and control mechanisms.	Slide photo from left to right.
④	Sensory feedback	Multisensory feedback in order to perceive environmental changes.	Sweeping sound, tactile sensation, virtual hand.

Table 1. Motor imagery training paradigm based on motor prediction mechanisms (forward model of motor system) and sensory feedback.

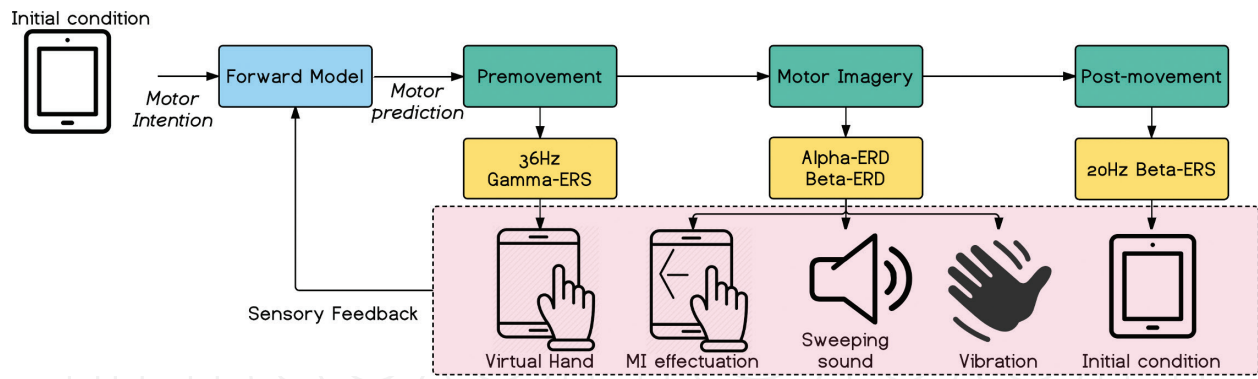


Figure 6. MI training paradigm based on the forward model of the motor system, MI process, neural oscillations, and sensory feedback.

patterns in the brain. Furthermore, the effectuation of MI as an actual movement will make users feel that their mental images are being executed, and are changing their working environment. The external changes give sensory feedback to users, which allows forward model readjusting the imaginary movement in course.

On the other hand, the present MI training paradigms can help to reduce *computer anxiety* since users are interacting with commonly used devices inside a familiar context. They can also increase *sense of agency* since what they imagine is what is executed, and even more, they feel it. *Attention* could increase as well, since users are doing what they like to do. Moreover, if the ecological environment is personalized for each user, attention could be even higher. Finally, at the time of selecting small-scale *spatial abilities* related to activities of daily living, the generation and maintenance of mental images can be facilitated.

6. Conclusion

The interest on MI-based BMIs has been growing exponentially. Although the idea of direct brain-machine communication is very attractive stand alone, BMIs as a tool in Neurosciences to investigate sensorimotor transformations of the nervous system has magnified BMI research. Of particular interest is the neural mechanism behind the motor system, because movement is the only way human beings have for interacting with the world. When this system is malfunctioning, people eventually or suddenly lose their autonomy, what leads to overcome several socio-economical pitfalls. Only in Mexico, around 15.9 million people have some kind of limitation, either mental or physical. This means that 6% of the total population in the country has a poor quality of life. According to the National Institute of Statistics and Geography (2014), mobility restrictions are the most recurrent disability and they are typically associated with aging process, traumatic injuries or congenital conditions.

Unfortunately, MI-based BMIs are still a laboratory prototype since not anyone at any time can control the system. The system functionality greatly depends on the modulation of EEG signals by means of MI-related tasks. MI as control task in BMIs has been seen as a skill that must be acquired, but neither user conditions nor controlled learning conditions have been taken into

account. In this chapter, it has been proposed new training protocols based on how human learn, predict, and act. Possibly, an optimal way to master MI tasks is to lay down the same rules followed by humans when they interact with their environment. This can reduce computer anxiety, increase sense of agency and attention, and facilitate the acquisition of small-scale spatial abilities.

Conflict of interest

No conflicts of interest are declared by authors.

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