Advances in User-Training for Mental-Imagery Based BCI Control: Psychological and Cognitive Factors and their Neural Correlates

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Abstract

While being very promising for a wide range of applications, Mental-Imagery based Brain-Computer Interfaces (MI-BCIs) remain barely used outside laboratories, notably due to the difficulties users encounter when attempting to control them. Indeed, 10 to 30% of users are unable to control MI-BCIs (so-called "BCI illiteracy") while only a small proportion reach acceptable control abilities. This huge inter-user variability has led the community to investigate potential predictors of performance related to users' personality and cognitive profile. Based on a literature review, we propose a classification of these MI-BCI performance predictors into three categories representing high-level cognitive concepts: (1) users' relationship with the technology (including the notions of computer-anxiety and sense of agency), (2) attention and (3) spatial abilities. We detail these concepts and their neural correlates in order to better understand their relationship with MI-BCI user-training. Consequently, we propose, by way of future prospects, some guidelines to improve MI-BCI user-training.

Keywords

Brain-Computer Interfaces · Inter-User Variability · User-Training · Predictors of Performance · Neural Correlates · Sense of Agency · Computer-Anxiety · Attention · Spatial Abilities · Improving Training Protocols

Introduction

Brain-Computer Interfaces (BCI) are communication systems that enable their users to send commands to computers by means of brain signals alone (Wolpaw and Wolpaw, 2012;). These brain signals are usually measured using ElectroEncephaloGraphy (EEG), and then processed by the BCI. For instance, a BCI can enable a user to move a cursor to the left or to the right of a computer screen by imagining left- or right- hand movements, respectively. Since they make computer control possible without any physical activity, EEG-based BCI have promised to revolutionize many application areas, notably to control assistive technologies (e.g., control of text input systems or wheelchairs) for motor-impaired users (Millán et al., 2010, Pfurstcheller et al., 2008) and rehabilitation devices for stroke patients (Ang and Guan, 2015) or as input devices for entertainment and human-computer interaction (Graimann et al., 2010), to name but a few (van Erp et al., 2012). Despite this promising potential, such revolutions have not yet been delivered, and BCI are still barely used outside research laboratories (Wolpaw and Wolpaw, 2012; van Erp et al., 2012). The main reason why current BCI fail to deliver is their substantial lack of reliability and robustness (Wolpaw and Wolpaw, 2012; van Erp et al., 2012). In particular, BCI too often fail to correctly recognize the user's mental commands. For example, in a study with 80 users, the average classification accuracy was only 74.4%, for a BCI using two imagined movements as commands (Blankertz et al., 2010). Moreover, it is estimated that between 10% and 30% of BCI users, depending on the BCI type, cannot control the system at all (so-called BCI illiteracy/deficiency) (Allison and Neuper, 2010).

BCI, as the name suggests, require the interaction of two components: the user's brain and the computer. In particular, to operate a BCI, the user has to produce EEG patterns, e.g., using mental imagery tasks, which the machine has to recognize using signal processing and machine learning. So far, to address the reliability issue of BCI, most research efforts have been focused on EEG signal processing and machine learning (Allison and Neuper, 2010; Bashashati et al., 2007; Makeig et al., 2012). While this has contributed to increased performances, improvements have been relatively modest, with classification accuracy being still relatively low and BCI illiteracy/deficiency still high (Allison and Neuper, 2010; Wolpaw and Wolpaw, 2012). To make BCI truly reliable and thus useful, it is also necessary to ensure the user can produce clear, stable and distinct EEG patterns. Indeed, BCI control is known to be a skill that must be learned and mastered by the user (Wolpaw and Wolpaw, 2012). This means that 1) the BCI performances of a user become better with practice and thus that 2) the user needs to learn how to produce these stable, clear and distinct EEG patterns to successfully control a BCI (Neuper and Pfurtscheller, 2010; Lotte et al., 2013a). This need for training is particularly salient for BCI based on mental-imagery (MI) tasks. With the so-called MI-BCI, users send mental commands by performing mental imagery tasks, e.g., movement imagination or mental mathematics, which are then recognized by the BCI and translated into commands for the application. In this paper we focus on this type of BCI which is prominent in many BCI applications such as stroke rehabilitation (Ang and Guan 2015), the control of wheelchairs or prosthetics (Millán et al., 2010) and entertainment applications (Lotte et al., 2013b), among many others.

Designing a reliable MI-BCI thus requires that the MI-BCI user has been properly and specifically trained to control that BCI. Current training approaches have been rather similar across the different MI-BCI designs so far, and can be divided into two main families: the operant conditioning approach (Wolpaw et al., 1991) and the machine learning approach, (Millán et al., 2002). While these two training approaches differ in the way the classifier is defined (manually defined vs optimized on EEG data), both approaches require to provide feedback to user. Such feedback is generally visual, indicating both the mental task recognized by the classifier together with the system's confidence in the recognized task. A typical and very popular example is the Graz BCI protocol (Pfurtscheller and Neuper, 2001). In this protocol, users are instructed to perform kinesthetic imagination of left- or right-hand movements following the on-screen display of an arrow pointing either left or right respectively. They then receive visual feedback in the form of a bar extending towards the left or the right, depending on whether a left- or right-hand movement was recognized by the BCI. The length of the bar is proportional to the classifier output. Users are typically trained with such an MI-BCI protocol over several sessions (i.e., on several days), each session being composed of 4-6 runs, and a run comprising about 15-20 trials per mental task.

However, even with state-of-the-art signal processing and classification algorithms, a tremendous inter- and intra-subject variability has been observed in terms of performance (command classification accuracy) in virtually every MI-BCI paper, both with the machine learning and the operant conditioning approaches (Allison and Neuper, 2010; Wolpaw and Wolpaw, 2012; Kübler et al., 2013). Thus, it is now clear that one of the major aspects contributing to MI-BCI control performances is the individual characteristics of the BCI user (Kübler et al., 2013). However, it is neither entirely clear which characteristics do impact BCI performances, why they have such an impact nor what the extent of this impact is. This has led the BCI community to look for predictors of MI-BCI performance, i.e., individual characteristics that correlate with the command classification accuracy. Indeed, identifying such predictors would allow BCI designers to find the most suitable BCI for a given user. Alternatively, or additionally, identifying such predictors would enable BCI researchers to identify what makes some users fail to control MI-BCI and thus to work on designing specific solutions. In particular, a promising research direction would be to propose MI-BCI training approaches that are adapted to users, according to their characteristics (Lotte et al., 2013a; Lotte and Jeunet, 2015a). Interestingly enough, a number of neurophysiological predictors have been identified, as reviewed in Ahn and Sun (2015). Some psychological predictors have also been identified for P300-based BCI and BCI based on SensoriMotor Rhythms (SMR) (Kleih and Kübler, 2015). However, to the best of our knowledge, there is no comprehensive and up-to-date review that surveys the psychological and cognitive factors that impact MI-BCI performances, presents some cognitive mechanisms that could explain why they have such an impact, sheds light on the underlying neural correlates of these factors and proposes theoretical solutions that could take these factors into account to improve MI-BCI training. This is therefore what this chapter sets out to offer.

First, this chapter surveys the BCI literature in order to identify the psychological and cognitive factors that correlate with MI-BCI performance (*Section 1)*. This survey allowed the identification of different predictors that can be organized into three main categories, each representing a higher-level cognitive concept. In particular, it was found that existing predictors of MI-BCI performance were mostly related to the relationship between users and technology, their attention and their spatial abilities. Thus, the following sections define each of these concepts in more detail, and describe their neural correlates: the user-technology relationship is dealt with in *Section 2*, attention is discussed in *Section 3* and spatial abilities are attended to *Section 4*. Finally, *Section 5* proposes some future prospects and theoretically promising levers to improve MI-BCI training by taking into account each of these three high-level factors.

1. Psychological and Cognitive Factors related to MI-BCI Performance

This first section offers a review of the latest developments in our understanding of the psychological and cognitive factors reported to influence MI-BCI performance (i.e., control accuracy). These factors can be divided into three groups. The first group includes the factors associated with the *States* of the user. Users' states are described by Chaplin et al. (1988) as "temporary, brief, and caused by external circumstances". The second group gathers the factors related to the users' *Traits*, characterized as "stable, long-lasting, and internally caused" with respect to one's environment and experience (Chaplin et al., 1988). Finally, the third group comprises the factors that can be qualified neither as *Traits* nor as *States*, i.e., demographic characteristics, habits and environment-related factors.

1.1 Emotional and Cognitive States that Impact MI-BCI Performance.

Some aspects of users' states, and more specifically of their cognitive and emotional states, have been reported to influence their MI-BCI performance in terms of control accuracy. First, Nijboer et al. (2008) have shown that mood (measured using a subscale of the German Inventory to assess Quality of Life - Averbeck et al., 1997 -) correlates with BCI performance. On the other hand, both attention (Daum, 1993; Grosse-Wentrup et al., 2011; Grosse-Wentrup and Scholkopf, 2012), assessed for instance by means of digit spans or block taping spans (Daum, 1993), and motivation (Hammer et al., 2012; Neumann and Birbaumer, 2003; Nijboer et al., 2008) levels have repeatedly been shown to positively correlate with performance, both in the context of Slow Cortical Potential (SCP) and SMR based BCI. Furthermore, in their study, Nijboer et al., (2008) suggested that higher scores in mastery confidence, i.e., how confident the participant was that the training would be successful, were correlated to better SMR regulation abilities, whereas higher rates of fear of incompetence were correlated to lower SMR regulation abilities. This last point has also been suggested in Kleih et al. (2013) for stroke patients taking part in BCI-based rehabilitation. More generally speaking, fear of the BCI system has been shown to affect performance (Burde and Blankertz, 2006; Nijboer et al., 2010; Witte et al., 2013). In the same vein, control beliefs (Witte et al., 2013), i.e., participants' beliefs that their efforts to learn would result in a positive outcome, and self-efficacy (Neumann and Birbaumer, 2003), which can be defined as participants' beliefs in their own abilities to manage future events, have been suggested to play a role in BCI performance, in an SMR and an SCP paradigm, respectively. Mastery of confidence, control beliefs and self-efficacy can be classed as context-specific states, i.e., states triggered each time a person faces a specific situation.

1.2 Personality and Cognitive Traits that Influence MI-BCI performance.

On the one hand, several aspects of the cognitive profile have been related to BCI control ability. Memory span and attentional abilities have been shown to correlate with the capacity to regulate SCP in patients with epilepsy (Daum et al., 1993). Hammer et al., (2012) also showed that attention span played a role in one-session SMR-BCI control performance. In addition, active learners seem to perform better than reflective learners (Jeunet et al., 2015a) in a context of MI-BCI control. This dimension, active vs. reflective, is one of the four dimensions of the Learning Style which can be assessed using the Index of Learning Style test (Felder and Spurlin, 2005). Abstractness, i.e., imagination abilities, has also been shown to correlate with classification accuracy in an MI-BCI experiment (Jeunet et al., 2015a). Furthermore, Hammer et al. (2012) have proposed a model for predicting SMR-BCI performance – which includes visuo-motor coordination (assessed with the Two-Hand Coordination Test) and the degree of concentration (assessed with the Attitudes Towards Work) - that reaches significance. More recently, Hammer et al. (2014) tested this model in a 4 session experiment (one calibration and three training sessions) within a neurofeedback based SMR-BCI context (i.e., involving no machine learning). Their results showed that these parameters explained almost 20% of SMR-BCI performance in a linear regression. However, the first predictor, i.e., visual-motor coordination, failed significance. With this model, the average prediction error was less than 10%. Moreover, kinesthetic imagination and visual-motor imagination scores have both been shown to be related to BCI performance by Vuckovic and Osuagwu (2013). Finally, a strong correlation [r=0.696] between mental rotation scores and mental-imagery based BCI performance has been reported (Jeunet et al., 2015a) in a 6 session experiment, during which participants had to learn to perform 3 mental-imagery tasks (motor-imagery of the left-hand, mental subtraction and mental rotation of a 3D shape). This finding has recently been replicated in an experiment based purely on motor-imagery (imagination of left- and right-hand movements) in which mental rotation scores correlated with participants' peak performance [r=0.464] (Jeunet et al., *submitted*).

On the other hand, concerning personality traits, Burde and Blankertz (2006) have obtained a positive correlation between a Locus of control score related to dealing with technology and the accuracy of BCI control. More recently, tension and self-reliance (i.e., autonomy towards the group) were related to MI-BCI performance (measured in terms of classification accuracy) in a model also including abstractness abilities and the active/reflective dimension of the learning style (Jeunet et al., 2015a). This model enabled prediction of more than 80% of the between-participant variance in terms of performance with an average prediction error of less than 3%.

1.3 Other Factors impacting MI-BCI Performance: Demographic Characteristics, Experience & Environment.

Some other factors that have also been related to the ability to control a BCI, cannot be classified as either traits or states. These factors can be divided into three categories: (1) demographic characteristics, (2) experience/habits and (3) environment. Concerning the first point, demographic characteristics, age and gender have been related to SMR-BCI performance (Randolph, 2012): women being more capable than men and over 25 year-olds being more competent than their younger counterparts. On the other hand, some habits or experiences have been shown to increase SMR-BCI control abilities (Randolph, 2012; Randolph et al., 2010). More specifically, playing a musical instrument, practicing a large number of sports, playing video games (Randolph, 2012), as well as spending time typing and the ability to perform hand and arm or full-body movements (Randolph et al., 2010) positively impact SMR-BCI performance. However, the consumption of affective drugs seems to have the opposite effect (Randolph et al., 2010). Finally, the user's environment, and more particularly the quality of caregiving for patients, has been suggested in an anonymous report to play a role in SMR-BCI performance (Kleih and Kübler, 2015).

STATES	EMOTIONAL STATE	♣ Mood (Nijboer et al. 2008)
	COGNITIVE STATE	♣ Attention level (Grosse-Wentrup et al., 2011; Grosse-Wentrup and Scholkopf, 2012) ♣ Motivation (Hammer et al., 2012; Neumann and Birbaumer, 2003; Nijboer et al., 2008) ♠ Mastery confidence (Nijboer et al., 2008) ♠ Fear of the BCI (Burde and Blankertz, 2006; Nijboer et al., 2010, Witte et al., 2013) ♠ Control beliefs (Witte et al., 2013) ♠ Fear of incompetence (Kleih et al., 2013; Nijboer et al., 2008) ♠ Self-efficacy (Neumann and Birbaumer, 2003)
TRAITS	PERSONALITY	♠ Locus of control for dealing with technology (Burde and Blankertz, 2006) ♠ Tension (Jeunet et al., 2015) ♠ Self-reliance (Jeunet et al., 2015)
	COGNITIVE PROFILE	♣ Attention span (Hammer et al., 2012) ♣ Attentional abilities (Daum et al. 1993) ♣ Attitude towards work (Hammer et al., 2012) ♣ Memory span (Daum et al., 2013) ♦ Visual-motor coordination (Hammer et al., 2014, 2012) ♦ Learning style: active vs. reflective learners (Jeunet et al., 2015) ♦ Kinaesthetic imagination score (Vuckovic and Osuagwu, 2013) ♦ Visual motor imagination score (Vuckovic and Osuagwu, 2013) ♦ Mental rotation scores (Jeunet et al., 2015) ♦ Abstractness (Jeunet et al., 2015)
OTHER FACTORS	DEMOGRAPHIC DATA	• Age (Randolph, 2012) • Gender (Randolph, 2012)
	EXPERIENCE	♦ Playing a music instrument (Randolph, 2012) ♦ Practicing sports (Randolph, 2012) ♦ Playing video-games (Randolph, 2012) ♦ Hand & arm movements (Randolph et al., 2010) ♦ Time spent typing (Randolph et al., 2010) ♦ Full body movements (Randolph et al., 2010) ♣ Consumption of affective drugs (Randolph et al. 2010)
	ENVIRONMENT	• Quality of caregiving (Kleih and Kübler, 2015)

Table 1: This table summarizes the different predictors (state, trait and others) which have been related to MI-BCI performance in the literature. The predictors related to the user-technology relationship are associated to orange spades, while those related to attention are associated to green clubs and those related to spatial abilities are associated to blue diamonds.

1.4 *To Summarize* - MI-BCI Performance is Affected by the Users' (1) Relationship with Technology, (2) Attention and (3) Spatial Abilities.

To summarize, the predictors of MI-BCI performance can be gathered into the three following categories, as depicted in Table 1:

- Category 1 - ***The user-technology relationship & the notion of control*** (in orange – spades, see Table 1): indeed, based on the literature, it appears that people who apprehend the use of technologies (and more specifically the use of BCIs) and who do not feel in control, experience more trouble controlling BCIs.
- Category 2 - ***Attention*** (in green - clubs, see Table 1): this category includes both attentional abilities (trait) and attention level (state). The latter can fluctuate with respect to different parameters such as environmental factors, mood or motivation. Both these aspects of attention have been repeatedly evoked as being predictors of BCI performance.
- Category 3 - ***Spatial Abilities*** (in blue - diamonds, see Table 1): many predictors depicted in the previous brief review are related to motor abilities (e.g., 2-hand coordination, sports or music practice) or to the ability to produce mental images (e.g., kinesthetic imagination scores or abstractness abilities). These predictors can be gathered under the label of "spatial abilities".

It is noteworthy that in the vast majority of the experiments during which the predictors were computed, users were BCI-naïve and thus novices. Indeed, as stated earlier, predictors were generally computed during the first training session, whereas learning to control an MI-BCI requires several training sessions (Neuper and Pfurtscheller, 2010; Pfurtscheller and Neuper, 2001; McFarland et al, 2010). In the next paragraph, we will argue that the involvement of the predictors in Category 1, i.e., *the User-Technology Relationship & the Notion of Control*, can be explained by the fact that users were BCI-naïve while the involvement of the predictors in Categories 2 & 3, i.e., *Attention* & *Spatial Abilities*, can be explained by the fact they were novices.

First, when confronted with a new technology, and even more so when this technology is associated with a new interaction paradigm (as is the case here with MI), users are likely to experience anxiety and a related low feeling of control during their first interaction attempts. Yet, the level of control perceived by a user (i.e., to what extent they consider being responsible for the perceived outcome of their actions) has been shown to positively correlate with motivation, performance and general skill acquisition (Achim and Al Kassim, 2015; Saadé and Kira, 2009; Simsek, 2011). These elements, which will be described in further detail in *Section 2*, both explain why the notions of anxiety and control are involved in BCI performance and how they are related to other predictors.

Second, the definition of attention and spatial abilities as two major categories of MI-BCI performance predictors is consistent with *Phase # 1* of the Ackerman model of inter-individual differences during skill acquisition (Ackerman, 1988). In his model, Ackerman argues that skill acquisition is divided into three phases and that inter-individual differences are explained by different factors according to the phase in which the user is (Neumann and Birbaumer, 2003):

- Phase #1: Slow and error prone performance - During this phase, inter-individual differences are mainly explained (1) by task-appropriate abilities and (2) by "cognitive-intellectual general ability, involving a strong demand on the cognitive attentional system" (Neumann and Birbaumer, 2003).
- Phase #2: Redefinition and strengthening of the stimulus-response connections of the skill - During this second phase, speed of perception plays a major role in inter-individual differences.
- Phase #3: Automatic phase - During this third phase, non-cognitive psycho-motor abilities are mostly responsible for inter-individual differences (Wander et al., 2013).

As stated earlier, BCI users were in an early stage of learning, i.e., in Phase #1 of the Ackerman model, when the predictors were computed. This is coherent with the fact that BCI literature reports a strong involvement of (1) spatial abilities and (2) attention. Spatial abilities correspond to the ability to produce, transform and interpret mental images (Poltrock and Brown, 1984). Thus, they can be defined as "task-appropriate abilities" for an MI-BCI control task. On the other hand, the involvement of attentional state and trait is consistent with the second factor responsible for inter-individual differences in Phase #1, namely, "cognitive-intellectual general ability" and the "cognitive attentional system".

The concepts associated with each of the three categories of predictors, i.e., relationship with technology, attention and spatial abilities are introduced, and their neural correlates are described in the following sections.

2. The user - technology relationship: introducing the concepts of Computer-Anxiety and Sense of Agency - *Definition & Neural Correlates*

In the previous section, we stated that some predictors of MI-BCI performance could be gathered under the label "user – technology relationship". These factors can be divided into 2 categories: (1) the apprehension of the use of technology and (2) the notion of control.

On the one hand, the fear of the BCI system (Burde and Blankertz, 2006; Nijboer et al., 2010; Witte et al., 2013), the fear of incompetence (Kleih et al., 2013; Nijboer et al., 2008) and tension (Jeunet et al., 2015a), all having been shown to negatively impact MI-BCI performance, reflect a certain apprehension of the user towards BCI use. This apprehension can be defined as *computer-anxiety*.

On the other hand, the locus of control related with dealing with the technology (Burde and Blankertz, 2006) will influence the extent to which users feel in control while using the BCI. In the same vein, levels of mastery confidence (Nijboer et al., 2008), control beliefs (Witte et al., 2013) and self-efficacy (Neumann and Birbaumer, 2003) will impact the experience of control of the technology. An experimental study (Brosnan, 1998) suggested that self-efficacy would determine the way the person attempts to solve the task and that it would explain around 50% of the variance in the task performance. Besides, self-efficacy has been suggested to be related to motivation, work engagement and performance (Achim and Al Kassim, 2015). This would be consistent with the MI-BCI literature as both self-efficacy and motivation were involved in MI-BCI users' control abilities. It appears that people with high a self-efficacy level perceive failure as a challenge, and not as a threat (Achim and Al Kassim, 2015) which could explain why they are prone to persevere, and thus more likely to reach good performances. Furthermore, Vlek et al. (2014) indicate that when users feel in control, their attitude towards the BCI system is more positive which enables them to replenish mental resources and increase motivation which in turn induces a better task engagement. Both these studies and the predictors stress the importance of the notion of control to reach better MI-BCI control abilities. This notion of control can be conceptualized as the *sense of agency*.

These two aspects of the user – technology relationship, namely the apprehension of the technology and the notion of control, are much related. In the following sections, we will further detail these two phenomena and the neural correlates associated to the sense of agency (indeed, to our knowledge, no studies have investigated the neural correlates of the specific concept of computer anxiety). We will notably see that the *sense of agency* (i.e., the feeling of being in control) actually mediates *computer anxiety* (i.e., the apprehension of the technology).

2.1. Apprehension of technology: the concept of Computer Anxiety - *Definition*

Computer Anxiety (CA), also called “Tech-Stress” (Achim and Al Kassim, 2015), can be classed as a *context-specific anxiety*, i.e., a transitory neurotic anxiety ranging between anxiety trait and anxiety state (Saadé and Kira, 2009). Indeed, it is a kind of anxiety specifically associated to one context: the use of a computer or of a computer-based technology.

Brosnan (1998) has shown that CA has a direct influence over performance when an unforeseen or unknown event occurs during the interaction process. Moreover, CA has been shown to impact the perceived ease-of-use of the technology, i.e., high computer anxiety will result when perceived difficulty is high. Both these elements explain why CA plays a major part when people are first exposed to new technologies, especially when the paradigm of interaction is new for them, as is the case for MI-BCI control. Brosnan (1998) insists on the fact that even those who do not usually experience it, may undergo CA when confronted with a piece of technology that is new to them. Besides, around one third of the population is thought to experience CA to some degree: from preferring not to use the technology to palpitations while using it (Brosnan, 1998). The relationship between anxiety and performance could be explained, according to Brosnan (1998), by the fact that anxious people devote more cognitive resources to “off-task” efforts (such as worrying about their performance), which induces shifts in attention between task and “off-task” considerations. As a consequence, the focused attention level dedicated to the task is decreased and fewer resources are available to perform the task. Thus, the task takes longer to complete, and performances drop in the case of tasks in which a limited amount of time is allocated. Furthermore, Simsek (2011) identifies CA as being an affective response due to one's beliefs about one's lack of ability to control the technology. This perception of the level of control that one can exert on the task corresponds to the concept of self-efficacy. Simsek (2011) argues that decreasing CA, and thus increasing self-efficacy, would lead to a better skill acquisition.

To summarize, based on empirical and theoretical studies, it seems that CA levels could enable to predict one's level of self-efficacy, which in turn could enable prediction of one's performance. More specifically, self-efficacy mediates the impact of CA on performance (Saadé and Kira, 2009).

2.2 "I did that!": The concept of Sense of Agency - *Definition*

The sense of agency can be defined as "the sense that I am the one who is causing or generating an action" (Gallagher, 2000). The sense of agency is of utmost importance when a person is controlling an external device, since it will influence their affect towards the technology, and thus their commitment to the task and their performance (Vlek et al, 2014). However, in the context of MI-BCI, experiencing this sense of agency is not straightforward. Indeed, as a component of the "who" system (De Vignemont and Fourneret, 2004; Farrer and Frith, 2002), *i.e.* a mechanism which allows one to attribute one's own actions to oneself, the sense of agency depends on the sensory feedback resulting from the action. In other words, it depends upon a bodily experience (Damasio, 1999). Yet, the absence of proprioceptive feedback when performing mental imagery tasks prevents this bodily experience from occurring (Haselager, 2013), and should theoretically inhibit the sense of agency. However, evidence exists that the sense of agency does not only depend on the outcome of an action, but also that it is triggered before the action takes place (Gallagher, 2012; Synofzik et al., 2008) which explains why mental imagery, under certain conditions, can be associated with a sense of agency (Perez-Marcos et al., 2009).

The sense of agency can be divided into 2 components (Farrer and Frith, 2002; Gallagher, 2012; Synofzik et al., 2008): (1) the feeling of agency and (2) the judgement of agency (also called feeling of ownership). The feeling of agency is pre-reflective, implicit, low-level and non-conceptual while the judgement of agency is reflective, explicit, high-order, belief-like and conceptual. In other words, the feeling of agency precedes the action, and triggered during the preparation of the action, while the judgment of agency results from the computation of the comparison between the predicted and actual outcomes of the action. Synofzik (2008) explains that a feeling of agency must be conceptually processed for a judgement or an attribution of agency to occur. The judgement of agency has been investigated in more depth than the feeling of agency in the literature (Chambon et al., 2013).

In order to experience a judgement of agency, three principles must be respected (Vlek et al., 2014): (1) the priority principle: the conscious intention to perform an act must immediately precede the action, (2) the consistency principle: the sensory outcome must fit the predicted outcome and (3) the exclusivity principle: one's thoughts must be the only apparent cause of the outcome (i.e. one must not believe there to be an outside influence). Moreover, several indicators influencing the judgement of agency have been proposed (Wegner, 2003; Wegner et al., 2004): bodily and environmental cues ("Where am I?"), bodily feedback (proprioceptive and kinesthetic information), bodily feedforward (*i.e*., the predicted sensory feedback), sensory feedback, social cues, action consequences and action-relevant thoughts (thinking about doing beforehand, in other words: the feeling of agency). On the one hand, the absence of some of these markers can lead to "a case of automatism" (Wegner, 2003), that is to say to the absence of judgement of agency: the agent is "doing without feeling". On the other hand, the manipulation of the same markers can lead to "an illusion of agency/ownership" (Wegner, 2003): agents who are "feeling without doing", and thus think they are in control although they are not.

2.3 "I did that!": The concept of Sense of Agency - *Neural Correlates*

As stated by Ehrsson et al. (2004), the neural correlates underlying the sense of agency remain poorly understood. However, some brain regions have been repeatedly associated with this phenomenon. More specifically, here we will focus on the premotor cortex (PMC), and more precisely on its ventral part i.e., the supplementary motor area (SMA), as well as on the Angular Gyrus (AG) which is part of the posterior parietal cortex (PPC), on the anterior insula and on the cerebellum. All of the aforementioned brain areas have been reported to be involved in sensorimotor transformation and motor control as well as in the sense of agency (David et al., 2008).

Self-agency has been shown to be underlain by an increased activity in the PMC (Farrer and Frith, 2002; Ehrsson et al. 2004) and more specifically in its ventral part, the SMA (Farrer and Frith, 2002; Kühn et al., 2013). The neural populations in the ventral PMC (SMA) and parietal PMC have been stated to represent both the seen and felt position of the limbs (Ehrsson et al., 2004). Thus, it is thought that the PMC enables a multisensory integration and thus provides a mechanism for bodily attribution (Ehrsson et al., 2004). Farrer and Frith (2002) have also suggested that the insula may play a role in the experience or agency. More specifically, they measured an increase in activity in the anterior insula when a person was aware of causing an action. The authors justify this implication by the fact that the insula's role is to integrate all the concordant multimodal sensory signals associated with voluntary movements. This result seems very consistent with the literature, since the activation of both these regions has been linked to awareness and execution of self-generated actions, to action preparation and to subjects' own intention to act (David et al. 2008).

Contrariwise, the activation of the posterior parietal cortex (PPC) has been shown to negatively correlate with the sense of agency: the more a person tends to attribute the action to another person, the more the PPC is activated (Farrer and Frith, 2002). In other words, the activity in the PPC - and more specifically in the AG - increases when discrepancies are noticed between the predicted and the actual sensory outcomes of the action (Chambon et al., 2013). Indeed, PPC activation is linked to the processing of visual-motor incongruence during self-generated actions (David et al. 2008). In this process, the cerebellum acts as a relay to inform about the sensorimotor discrepancies between the predicted and actual outcomes of the action (David et al. 2008). But it seems that the AG also monitors the signals linked to action selection in the dorsolateral Pre-Frontal Cortex (dlPFC) to prospectively provide information about the subjective feeling of control over action outcomes (Chambon et al., 2013). Thus, the online monitoring of these signals by the AG may provide the subject with "a subjective marker of volition, prior to the action itself" (Chambon et al., 2013). While consistent, these correlates are still discussed. For instance, Kühn et al. (2013) report no correlation between AG activation and their subjective measure of agency.

The fact that these brain areas belong to different functional brain networks could explain their role in self-agency. For instance, the insula and the PPC have been shown to be involved in complex representations of the self (Farrer and Frith, 2002). Farrer and Frith (2002) suggested that the relocation from the insula (when experiencing self-agency) to the PPC (when attributing the outcome to another person) could correspond to a shift in the attentional process from the egocentric to the allocentric point of view. In a similar vein, the PPC and the SMA are the key nodes in the human mirror neuron system: they encode motor aspects of actions performed by oneself or by another person (David et al., 2008).

To summarize, the sense of agency seems to be related to complex interconnections between several brain areas enabling one to experience (1) a feeling of agency before the action outcome (through the involvement of the PMC/SMA and cerebellum among others) but also (2) a judgement of agency by comparing the predicted and perceived outcomes (notably through the activation of the insula and the AG/PPC). However, the neural processes involved in each of these phenomena, namely the feeling and judgement of agency, as well as the differences between both, require further investigation (David et al., 2008).

3. Attention - *Definition & Neural Correlates*

The second category of factors that have been found to correlate with BCI performances contains attention-related predictors. Indeed, both attentional traits, i.e., the BCI user's intrinsic attentional capacities, and attentional states, i.e., the amount of the user's attentional resources dedicated to the BCI task, were found to be correlated to BCI performances. To summarize (see Table 1), the attentional traits predicting BCI performances include attention span (Hammer et al., 2012), attentional abilities (Daum et al., 1993), attitude towards work (Hammer et al., 2012) which also measures the capacity to concentrate on a task, and memory span (Daum et al., 2013) which measures the ability to maintain attention (Engel et al., 1999). The higher the attentional abilities of BCI users, the better the BCI classification accuracy they will reach. There is also some evidence that the attentional state of BCI users seems to be correlated to their BCI performances. Indeed, two different neurophysiological markers based on neural correlates of the attentional state were defined and measured in single-trial EEG signals. They were both found to be significantly correlated to the classification accuracy obtained for these trials (Grosse-Wentrup et al., 2011; Grosse-Wentrup and

Scholkopf, 2012; Bamdadian et al., 2014) (see section 3.2 for more details on these two EEG predictors based on attentional states).

Another factor, which is not a result of attention alone but is however related to it, is the user's motivation for a given BCI session, which has also been found to be predictive of their BCI performances (Hammer et al., 2012; Neumann and Birbaumer, 2003; Nijboer et al., 2008). Indeed, attention appears to be a critical factor in many models of motivation (Keller, 2008; Keller, 2010).

Finally, there are a number of other factors that have been found to be correlated to BCI performances that are not related to attention *per se*, but that are likely to impact the attentional resources that users devote to the BCI task. These include mood (Nijboer et al. 2008), the consumption of affective drugs (Randolph et al. 2010), as well as environmental factors for patients such as room temperature, sleep quality or headaches (Neumann and Birbaumer, 2003).

The following sections define and describe in more detail some of the cognitive mechanisms of attention, their associated neural correlates and their relevance to BCI control.

3.1 Attention - *Definition*

Attention could be defined as the "the ability to focus cognitive resources on a particular stimulus" (Frey et al., 2014). According to Posner and Petersen (1990), the attention system can be divided into three main sub-systems, each of which corresponds to a major attentional function. These three sub-systems are the alerting system, the orienting system and the executive control system. The alerting function is responsible for maintaining a state of vigilance over long periods of time, i.e., it is responsible for sustained attention. Sustained attention (or vigilance) is necessary to perform long and usually tedious tasks. The orienting function is involved in selecting information among different information streams, such as different modalities (sounds, images) or different spatial or temporal locations. It is implicated in ignoring distracting events, and is thus involved in what is known as selective attention. The third function, executive control, is involved in the awareness of events and in the management of attentional resources, which are limited. Indeed, two tasks competing for attention will interfere with each other, thus possibly reducing performances for these tasks. Executive control is therefore involved in what is known as focal attention. For further details concerning the different components of attention, the interested reader can refer to (Posner and Boies, 1971; Posner and

Petersen, 1990; Petersen and Posner, 2012). It is also important to note that attentional abilities and resources vary between individuals (Petersen and Posner, 2012).

Attention has been known for many years to be necessary in ensuring successful learning (Nissen and Bullemer, 1987). Indeed, if learners do not assign enough attentional resources to a given learning task, e.g., because they have to perform dual-attentional tasks (i.e., split their attentional resources between two tasks), their learning performance will be greatly reduced, or they may even fail to be aware of relevant learning material and fail the learning task altogether (Nissen and Bullemer, 1987). Keller even stated that “attention is a prerequisite for learning” (Keller, 1987). This gave birth to the ARCS model of instructional design, a well-known model used to design learning material and training tasks (Keller, 1987; Keller, 2008). ARCS stands for Attention, Relevance, Confidence and Satisfaction, which are the four main components of human motivation that are necessary to ensure successful learning. In order to ensure an efficient instruction and training, the ARCS model states that it is necessary to get the attention of students on the relevant learning stimulus (thus ignoring distractors), and to sustain this attention over the duration of the instruction, in order to focus the attentional resources on training-relevant problems (Keller, 1987). We can see here that the three sub-systems of attention (sustained attention, selective attention and focal attention) are therefore involved in the learning process. Since BCI control requires training, it therefore makes sense that it also requires the user’s attentional resources, and thus that attention and motivation are predictors of BCI performance.

3.2 Attention - *Neural Correlates*

Interestingly enough, the attention system corresponds to specific anatomical structures in the brain that are different than those dedicated to information processing (Posner and Petersen, 1990). Each of the three attention subsystems (alerting, orienting and executive control) corresponds to a specific brain network (Posner and Petersen, 1990; Petersen and Posner, 2012). The alerting network, although still not fully understood, seems to primarily involve the right hemisphere (frontal and parietal lobes), including the right inferior parietal lobule with the AG and thalamic areas (Seghier, 2014; Petersen and Posner, 2012). The orienting network notably involves the Frontal Eye Fields, the intraparietal sulcus and the superior parietal lobe, the temporo-parietal junction, the AG and the ventral frontal cortex (Seghier, 2014; Petersen and Posner, 2012). Finally, the Executive Network involves multiple brain areas, including the medial frontal cortex, the Anterior Cingulate Cortex (ACC), the dorsolateral prefrontal cortex, the anterior prefrontal cortex, the precuneus, the thalamus, the anterior insula, the intraparietal sulcus and the intraparietal lobule. There is large inter-individual variability in the efficiency of these networks which explains, at least in part, the inter-individual variations in attentional abilities, i.e., attentional traits (Petersen and Posner, 2012).

There are also a number of electrophysiological neural correlates, in particular spectral variations in EEG signals that are related to change in attention levels. Regarding the alerting system, decreased vigilance levels are associated with a slowing of EEG frequencies, i.e., in an increased power for low frequency EEG rhythms (delta - ~1-4z, theta ~4-7Hz, low alpha ~7-10Hz), and a decreased power for higher frequency EEG rhythms (Frey et al., 2014; Roy, 2015). The amplitude of Event Related Potentials such as the P300 or the parietal N100 also decreases with lower vigilance. Concerning the orienting system, alpha activity (~8-12Hz) has also been shown to be related to selective attention, with higher alpha power indicating lower attention, and occipital alpha providing information on the location of spatial visual attention (Frey et al., 2014). A delta (3-8Hz) over beta (16-24Hz) power ratio has also been used as a marker of sustained attention (Bamdadian et al., 2014). Finally, it seems that the Gamma (55-85Hz) power in attentional networks related to the executive control system also correlates with the attentional level (Grosse-Wentrup et al., 2011).

Consistent with the cognitive literature stressing the impact of attention on success in task-learning, the BCI community has also identified a number of neural correlates of attention that are related to BCI performance. For instance, variation in Gamma power, notably in executive control attentional brain networks, have been found to be correlated to SMR-BCI performance and can be used to predict successful or unsuccessful classification both for SMR-BCI (Grosse-Wentrup et al., 2011; Grosse-Wentrup and Schölkopf, 2012) and for general MI-BCI (Schumacher et al., 2015). Moreover, the extent of activation of the dorsolateral prefrontal cortex (involved in executive control as seen above), was also found to differ between SMR-BCI users with high performances and SMR-BCI users with low performances (Halder et al., 2011). Finally, an EEG predictor based on frontal Theta, occipital Alpha and midline Beta power, which are all neural correlates of sustained attention (thus involving the alerting system) as described previously, has been shown to correlate with SMR-BCI performances (Bamdadian et al, 2014).

4. Spatial abilities - *Definition & Neural Correlates*

As already seen, many studies have highlighted the role of spatial abilities on BCI performance variation across subjects. The general hypothesis is that low BCI performers have less-developed abilities to generate or maintain mental images.

For example, Vuckovic and Osuagwu (2013) relate the results of kinesthetic and visual motor imagery questionnaires to performances obtained with a BCI based on object oriented motor imagery. They show that the kinesthetic score could be a relevant predictor of performance for an SMR-BCI. Moreover, the physical presence of the object of an action facilitates motor imagination in poor imagers. It is important to note that the impact of imagery abilities on BCI performances might be mediated by differences in brain activation. Guillot et al. (2008) attempted to identify the functional neuroanatomical networks that dissociate able versus poor imagers. They used functional magnetic resonance imaging (fMRI), to compare the pattern of cerebral activations in able and poor imagers during both the physical execution and mental imagery of a sequence of finger movements. Results show that good imagers activated the parietal and ventrolateral premotor regions to a greater degree, both having been shown to play a critical role in the generation of mental images.

Another spatial skill which has been shown to be related to MI-BCI performance is mental rotation ability. Mental rotation scores (measured using a mental rotation test) are a robust measure of spatial abilities, particularly for mental representation and manipulation of objects (Borst et al., 2011; Poltrock & Brown, 1984). Mental rotation scores have been shown to be correlated with scores obtained with other tests of spatial abilities such as space relation tests or spatial working memory (Just & Carpenter, 1985; Kaufman, 2007; Reuhkala, 2001), suggesting that they may be related to more general spatial skills (Thompson et al., 2013). Jeunet et al. (2015a) have explored the relationships between MI-BCI performance and the personality and cognitive profile of the user. The main result is a strong correlation between MI-BCI performances and mental rotation scores.

In the same vein, Randolph (2012) has shown that video game experience is likely to enhance BCI performance. Many studies have noted a link between video game experience and spatial abilities. For example, spatial abilities can be improved through playing action video game (Dorval and Pepin, 1986; Subrahmanyam and Greenfield, 1994). Feng et al. (2007) observe that performances in a mental rotation test are enhanced after only 10 hours of training with an action video game. More remarkably, these authors found that playing an action video game can decrease the well-known gender disparity in mental rotation tasks (see also Ventura et al., 2013). All these elements strongly suggest that the link between video game experience and BCI performance could be mediated by spatial ability levels.

Moreover, Randolph (2012) showed that using hand-and-arm movements, or full body movements (such as playing sports or musical instruments) also favors BCI performances. Many authors have also observed a link between spatial abilities and motor processes (Hoyek et al., 2014). For example, Moreau et al. (2011) compared elite and novice athletes and found a significant relationship between sports performance, activity, sport-specific training and mental rotation abilities. In the Hoyek et al. (2014) study, the motor performance of 7 to 8 year old and 11 to 12 year old children was measured in a steeple chase and an equivalent straight distance sprint. Data revealed that the time taken to complete the chase was influenced by speed and sex, but also by the individual mental rotation ability. These links between motor performances and spatial abilities are also attested by neuroimaging studies which provide evidence that motor areas are involved in mental rotation (e.g., Lamm et al., 2007). Thus, it can be assumed that the relationship between BCI performance and motor processes are mediated by spatial ability levels.

Finally, Hammer et al. (2012) found that visual-motor coordination abilities constitute a predictor of BCI efficiency, and Scordella et al. (2015) showed a relationship between motor coordination and visual-spatial skills (measured by a visual-constructive task). We can again assume that the link between visual-motor coordination and BCI efficiency is mediated by visual-spatial abilities.

4.1 Spatial Abilities - *Definition*

As mentioned above, spatial abilities embody the ability to produce, transform and interpret mental images (Poltrock and Brown, 1984). Lohman (1993) greatly highlighted the pivotal role of spatial abilities and particularly mental imagery in all models of human abilities. This author reports that high levels of spatial abilities have frequently been linked to creativity in many domains (arts, but also science and mathematics) (see also Shepard, 1978). He also indicates that Albert Einstein, as well as other well-known physicists (such as James Clerk Maxwell, Michael Faraday and Herman von Helmholtz) and inventors, have been reported to have had high spatial abilities, and that these abilities played an important role in their creativity. Furthermore, studies on developmental cognitive skills have consistently shown that spatial aptitude and mathematical aptitude are closely related (Geary, et al., 2000). Moreover, the importance of spatial ability in educational pursuits and in the professional world was examined by Wai et al. (2009), with particular attention devoted to STEM (science, technology, engineering, and mathematics) domains. Participants (Grades 9-12, N=400 000) were tracked for 11 years. Results showed that spatial abilities were a significant predictor of achievement in STEM, even after taking into account possible third variables such as mathematical and verbal skills (see also Humphreys et al., 1993; Shea, et al., 2001).

The key role of mental imagery in human cognition has also been highlighted by the fact that it is involved in certain pathological situations such as Posttraumatic Stress Disorders (Brewin et al., 1996), schizophrenia (Oertel et al., 2009), depression (Rogers et al., 2002) social phobia (Clark and Wells, 1995) and bipolar disorder (Holmes et al., 2008) (for a review, see Pearson et al., 2013). For example, impairment in image generation or in mental rotation of letters has been shown in unipolar major depression (Rogers et al., 2002).

Furthermore, the potential role of imagery for motor skill learning has been demonstrated in many situations, such as learning new skills in sports (Murphy, 1994), improving performance both in novice and expert surgeons (Cocks et al., 2014) and in Paralympics athletes (Martin, 2012).

Today, it is common to distinguish between large scale and small scale spatial abilities (Hegarty et al., 2006). Large scale abilities refer to the notion of wayfinding (or spatial navigation) defined as “the process of determining and following a path or route between origin and destination” (Golledge, 1999). Wayfinding is assessed by tasks such as search, exploration, route following, or route planning in contexts including outdoor and urban environments, indoor spaces and virtual reality simulations (Weiner et al., 2009).

By contrast, small-scale spatial abilities are usually assessed by paper-and pencil tests which involve perceptually examining, imagining, or mentally transforming representations of small shapes or easy-to-handle objects (Hegarty et al., 2006). These abilities also refer to the notion of mental imagery consisting of several component processes. For example, the classical model of Kosslyn (1980, 1994) proposes a distinction between four components, namely image generation (the ability to form mental images), image maintenance (the ability to retain images over time), image scanning (the ability to shift one's attention over an imaged object), and image manipulation (the ability to rotate or otherwise transform images) (see also Marusan et al., 2006).

4.2 Spatial Abilities - *Neural Correlates*

The neural correlates of visual mental imagery are subject to much debate. Some authors claim a functional equivalence between visual perception and visual mental imagery, with the retinotopic areas in the occipital lobe acting as common substrate (for a review, see Bartolomeo, 2008). However, some brain lesion studies indicate that visual imagery is possible without the involvement of primary visual areas (Chaterjee and Southwood, 1995). Nevertheless, the frontal eye fields and the superior parietal lobule seem to play a crucial role in generating visual mental images (Mechelli et al., 2004). These results have been confirmed by Zvyagintsev et al. (2013) showing that the visual network comprises the Fusiform Gyrus bilaterally and a fronto-parietal network involving the Superior Parietal Lobule and Frontal Eye Field bilaterally.

Motor imagery is a particular case of mental imagery defined as the mental simulation of a specific action without any corresponding motor output (Jeannerod, 1994). The neural substrate that underlies motor imagery has also been subject to many debates. Miller et al. (2010) measured cortical surface potentials in subjects during overt action and imagery of the same movement. They demonstrated the role of primary motor areas in movement imagery and showed that imagery activated the same brain areas as actual motor movement. In their study, the magnitude of imagery-induced cortical activity was reduced compared to real movement, but this magnitude was largely enhanced when subjects learned to use imagery to control a cursor in a feedback task. It is important to note that a distinction has been made between two types of motor imagery depending on the point of view adopted to imagine an action: the third-person perspective point-of-view consists in selfvisualizing an action, whereas the first-person point of view perspective implies somesthetic sensations elicited by the action. Some evidence suggested that visual (third person) and somesthetic/kinesthetic (first person) motor imagery recruit distinct neural networks. Guillot et al. (2004) showed that visual imagery predominantly activated the occipital regions and the superior parietal lobules, whereas kinesthetic imagery preferentially activated the motor-associated structures and the inferior parietal lobule. Finally, Ridderinkhoff and Brass (2015) specify that activation during kinesthetic mental imagery is not just a subliminal activation of the same brain areas involved in the real action. For these authors the activation during kinesthetic imagery is similar to the activation associated with the preparatory planning stages that eventually lead to the action (Jeannerod, 2006). Interestingly enough, it has been shown that kinesthetic motor imagery leads to better MI-BCI performances than visual motor imagery (Neuper et al, 2005). Nevertheless, the distinction between these different forms of mental imagery, their neural correlates and their relationships with the neural circuits involved in motor processes remain to be elucidated.

To conclude this section, spatial skills play a crucial role in human cognition as they are involved in many activities including art, music, mathematics, engineering, literature, etc. Jeunet et al. (2015a) demonstrated that spatial skills and particularly mental rotation scores are a relevant predictor of BCI efficiency. Moreover, many skills related to spatial abilities (such as playing sports, musical instruments, action video games, etc.) have been shown to be likely to improve BCI performance. It is an attractive hypothesis to consider that imagery abilities could contribute to explaining the “BCI illiteracy” phenomenon, but further investigations are needed to make a more systematic study of the relationship between certain cognitive and personality predictors, spatial abilities and BCI efficiency.

5. Perspectives: the user-technology relationship, attention and spatial abilities as three levers to improve MI-BCI user-training

5.1 Demonstrating the Impact of the protocol on Computer Anxiety & Sense of Agency

In *Section 2*, we stressed the impact of the notion of control on performance, notably through its mediating role on computer anxiety. The notion of control can be conceptualized as a *Sense of Agency*, i.e., “the sense that I am the one who is causing or generating an action” (Gallagher, 2000). Given the strong impact that the sense of agency has on performance, it seems important to increase it as far as possible. Yet, in the context of MI-BCI control, it is not straightforward. Indeed, the sense of agency is mainly based on a bodily experience, whereas performing MI tasks does not provide the participant with any sensory feedback. Thus, here we would like to insist on the importance of the feedback, especially during the primary training phases of the user (McFarland et al., 1998; Coyle et al., 2015). Indeed, in the first stages, the fact that the technology and the interaction paradigm (through MI tasks) are both new for the users is likely to induce a pronounced computer anxiety associated with a low sense of agency. Providing the users with a sensory feedback informing them about the outcome of their “action” (MI task) seems necessary in order to trigger a certain sense of agency at the beginning of their training. This sense of agency will in turn unconsciously encourage users to persevere, increase their motivation, and thus promote the acquisition of MI-BCI related skills, which is likely to lead to better performances (Achim and Al Kassim, 2015; Saadé and Kira, 2009; Simsek, 2011). This process could underlie the (experimentally proven) efficiency of biased feedback for MI-BCI user-training. Indeed, literature (Barbero and Grosse-Wentrup, 2010) reports that providing MI-BCI users with a biased (only positive) feedback is associated with improved performances while they are novices. However that is no longer the case once they have progressed to the level of expert users. This result could be due to the fact that positive feedback provides users with an illusion of control which increases their motivation and will to succeed. As explained by Achim and Kassim (2015), once users reach a higher level of performance, they also experience a high level of self-efficacy which leads them to consider failure no longer as a threat (Kleih et al., 2013) but as a challenge. And facing these challenges leads to improvement.

However, to be efficient, this feedback must follow certain principles (Vlek et al., 2014). First, the priority principle, i.e., the conscious intention to perform an act must immediately precede the act: here, the feedback must appear after the users become conscious they have to perform the act and have started to do it. Second, the consistency principle, i.e., the sensory outcome must fit the predicted outcome. And third, the exclusivity principle, i.e., one’s thoughts must be the only apparent cause of the outcome. This last point suggests that the user should not think that another person is controlling the feedback. Thus, if the feedback is biased, it has to be subtle enough so that the user is not aware of it. Otherwise, the user will not feel in control anymore. The two latter principles could explain why biased feedback is efficient for novices but not for experts. Indeed, experts develop the ability to generate a precise predicted outcome that usually matches the actual outcome (when the feedback is not biased). This explains why when the feedback is biased, and therefore the predicted and actual outcomes do not match, expert users attribute the discrepancy to external causes more easily. In other words, it can be hypothesized that experts might be disturbed by a biased feedback because they can perceive that it does not truly reflect their actions, thus decreasing their sense of being in control.

Furthermore, Beursken (2012) tested the impact of the concept of transparent mapping in a pseudo-BCI experiment. A protocol is said to be transparent when the task and the feedback are consistent. In the experiment, the sense of agency of the participants was tested in two conditions: one transparent and one non-transparent. The participants had to imagine movements of their left and right hands. In the transparent condition, a virtual left or right hand moved on the screen when left or right hand imagination was recognized, respectively. In the non-transparent condition however, the same tasks were associated with both hands making “thumbs-up” or “okay” movements. Participants felt more in control in the transparent condition and reported that less effort was required to understand the instructions and remember the meaning of the feedback. Consequently, more resources were available to perform the task. This result means that when designing the feedback, researchers must be careful to propose a feedback that fits the mental task. Yet, in standard training protocols such as Pfurtscheller and Neuper’s (2001), MI-tasks are associated with a bar extending in a specific direction. Although the direction of the bar is consistent with the task when participants are asked to perform left- and right-hand motor imagery, it is not particularly natural. In a recent study (Jeunet et al., 2015b), we showed that an equivalent tactile feedback provided on users’ hands was more efficient. With reference to the Ackerman model (1988), when the outcome (the feedback) is consistent with the task, during the Phase #1 the “task-appropriate” abilities, here spatial abilities, decrease in influence and thus the between-subject variability in terms of performance also decreases. However, when the outcome is inconsistent with the task, the requirements for information processing are important and the impact of the user-profile, here in terms of attentional abilities and spatial abilities, remains constant (Neumann and Birbaumer, 2003) which makes the between-subject variability due to these factors stable even in advanced phases of the training.

To summarize, we can derive three guidelines for MI-BCI protocol design that could enable users to experience a better sense of agency. First, providing the users, especially novices, with a sensory feedback is essential as it will increase their potential sense of agency. While positively biasing the feedback can improve novice users' sense of agency, motivation and will to succeed, this is not the case for expert users who can be disturbed by biased feedback. Second, in order to be efficient the feedback must follow the principles of priority, consistency and exclusivity. And finally, transparent protocols, i.e., protocols in which the feedback fits with the MI-task, should be associated with better MI-BCI performance as (1) they induce a greater sense of agency and (2) they require less workload to be processed and thus grant more cognitive resources to be devoted to the task.

5.2 Raising and Improving Attention

As mentioned previously, attention is a major predictor of BCI performances, and it has been shown that the better the users' attentional abilities and the more attentional resources they devote to BCI training, the better their BCI performances. Therefore, BCI performances could be improved by designing BCI training protocols that 1) train users to increase their attentional abilities and 2) ensure the attentional resources of users are directed towards and maintained on the BCI training tasks.

A first suggestion to improve BCI training is to include attention training tasks, to improve users' attentional abilities and thus their BCI performance. A number of approaches may be used, but recently researchers have identified meditation and neurofeedback as promising approaches for attention training (Brandmeyer and Delorme, 2013). Indeed, it has been shown that meditation is actually a successful form of attention training that improves the ability of practitioners to focus their attentional resources on a given task, possibly for long periods of time, as well as their ability to ignore distractors. Expert meditators have been found to show different activation levels than non-meditators in the fronto-parietal and the default mode networks, in functional Magnetic Resonance Imaging (fMRI) studies (Braboszcz et al., 2010). The Gamma EEG power in these areas also differs between expert meditators and non-meditators (Lutz et al., 2008). Such brain networks are notably involved in sustained attention. Interestingly enough, these areas, and gamma activity originating from there, have both been identified as being related to BCI performance (Grosse-Wentrup and Schölkopf, 2012; Halder et al., 2011). The promising usefulness of meditation practice for BCI training is further supported by research from a number of groups who have found that meditation increases SMR-BCI performances (e.g., Eskandari and Erfanian, 2008; He et al., 2015). In other words, meditation improves attentional abilities, which in turn improves BCI performances.

Attentional capabilities can also be improved using neurofeedback training, e.g., by providing users with games in which they have to increase an EEG measure of their attentional level to win (Lim et al., 2010; Lim et al., 2012). For instance, in Lim et al. (2012), children with Attention Deficit Hyperactivity Disorder (ADHD) were asked to play a game in which the speed of the character they were controlling was directly proportional to their attentional level, as measured by EEG. Thus, they had to focus as much attention as possible on the game in order to move fast enough to complete it in the allotted time. This was shown to be a successful form of attention training which reduced the children’s ADHD symptoms (Lim et al., 2010; Lim et al., 2012). Gamma neurofeedback was also shown to be useful in improving visual attention abilities (Zander et al., 2013). To the best of our knowledge, such neurofeedback training of attentional capabilities has not been explored with the aim of MI-BCI control abilities, and thus could be a promising direction to investigate.

A second suggestion to improve BCI training is to design BCI training tasks, feedbacks and environments that capture and maintain the attention of the user on the BCI training. In the ARCS model for instructional design, Keller suggests a number of approaches to get and maintain users’ attention (Keller, 1987). In particular, this includes ensuring the active participation of the learners, adding game-like training, having a variety of supports, training materials and tasks, ensuring concrete training tasks and feedbacks as well as encouraging inquiry and curiosity from the learners (Keller, 1987). In practice, for MI-BCI, this could be achieved by having BCI users control video games or Virtual Reality (VR) applications with their BCI, hence ensuring game-like training, active user participation and concrete training tasks. The fact that VR and game-based BCI training were actually shown to improve BCI performances (Lotte et al., 2013b) further supports this suggestion. Moreover, rather than using the same standard training protocol continuously and repeatedly, variety in training can be obtained by adding other training tasks, with different objectives. For instance, users can be asked to practice each MI task separately, or to perform a given MI-task as fast as possible as in

(Ramsey et al., 2009) for instance. Finally, to encourage enquiry and add concreteness to the training, BCI users could be provided with richer and more motivating visualization and feedbacks that enable them to see the impact of a given MI-task on their EEG signals in real-time, thus motivating them to explore different strategies. This could be achieved using recently proposed EEG visualization techniques such as Teegi (Frey et al., 2014). With this approach, users can see their own brain activity and EEG features in real-time, displayed in a user-friendly way on the head of a physical puppet they can manipulate.

Other considerations could be taken into account to ensure users assign an appropriate amount of attentional resources to the BCI training. For instance, the training protocol should avoid requiring split attention, i.e., requiring users to divide their attentional resources between two different subtasks, especially if these tasks involve the same modality, e.g., two visual processing tasks. This would indeed deplete the user's cognitive resources and lead to poorer performances and lower learning efficiency for any training task (Sweller et al., 1998). This is a relevant point to consider as BCI feedback is often provided on the visual modality, while the controlled BCI application generally also requires visual processing, e.g., to control a game or a visual speller. Interestingly enough, it has been shown that providing tactile instead of visual feedback in such a split-attentional task leads to improved BCI performance (Jeunet et al., 2015b). Thus, it would be worth studying as well auditory feedback, see, e.g., (McCradie et al., 2014), in similar contexts. Finally, since it is possible to measure users' attentional level from EEG signals, this could be used in real-time to detect whether they are paying enough attention, and warn them to refocus their attention, if necessary, as suggested in Schumacher et al. (2015).

5.3 Increasing Spatial Abilities

If it appears that the training of spatial abilities could improve BCI performance, it is necessary to review the studies that have tried to better understand the effects of training on spatial skills.

For instance, it is well known that men perform better than women in spatial perception and mental rotation tests (see for example, Linn and Peterson's, 1985). In a meta-analysis, Baenninger and Newcombe (1989) found that improvements in men and women remain parallel in response to practice and training, so that gender differences remain constant. However, others studies have shown greater performance improvement in women than in men (Okagaki and Frensch, 1994), or a waning of gender differences (Kass et al., 1998).

In a meta-analysis of training studies, Uttal et al. (2013) indicated that spatial skills are highly malleable and that training in spatial thinking is effective, durable, and transferable (to skills that have not been subject to specific training). The authors outline that many studies in which transfer effects were present administered large numbers of trials during training, which allowed to conclude that such a transfer is possible if sufficient training or experience is provided. The meta-analysis did not show a significant effect of age or a significant effect of the type of training on the degree of improvement. Finally, the initial level of spatial skills affected the degree of malleability. Participants who started at lower levels of performance improved more in response to training than those who started at higher levels (Uttal et al., 2013).

Terlecki et al. (2008) confirmed the impact of long-term practice or repeated testing, and training capacity to improve mental rotation performances. However, neither mental rotation practice nor video game training reduced gender differences. It is also important to note that these effects can last over several months and the effects of video game experience are transferable to tasks that have not been trained for.

All these results are extremely interesting as they show that training and practice can improve spatial skills. Mental training has been used to improve performances in many domains such as sports, surgical performances, music, etc. However, very few studies have focused on BCI practice.

Erfanian and Mahmoudi (2013) have investigated the role of mental practice and concentration on a natural EEG-based Brain-computer interface for hand grasp control. The imagery task used was the imagination of hand grasping and opening. For imagery training, the authors used a video based method where subjects watched themselves performing hand-closing and -opening while undertaking imagery. The results showed that mental and concentration practice increased the classification accuracy of the EEG patterns. Moreover, mental practice more specifically affected the motor areas. This study shows very promising results on the way spatial training could improve BCI performances.

In the study of Jeunet et al. (2015a), participants followed a standard training protocol composed of 6 identical sessions during which they had to learn to perform 3 mental imagery tasks: mental rotation, mental subtraction and left-hand motor imagery. On the one hand, no improvement in performance was noticed between the 1st and 6th session on average, suggesting that participants did not learn despite the large number of sessions. On the other hand, the BCI performance appeared to be strongly correlated to participants' mental rotation scores. In the near future, the authors propose to test the impact of spatial training and particularly mental rotation training on BCI efficiency. The authors also considered applications in the context of patients suffering from motor impairments, since mental imagery abilities can be preserved after brain injury. In any case, it is a challenging project to study the impact of spatial training on reducing the "BCI illiteracy" phenomenon, and thus enabling BCI to be more systematically used outside laboratories.

Conclusion

In this chapter, we performed a literature survey in order to identify the psychological and cognitive factors related to MI-BCI performance. This survey enabled us to classify most of the predictors into three categories representing higher-level cognitive concepts: (1) the user - technology relationship (comprising the notions of anxiety and control during the interaction), (2) attention and (3) spatial abilities. These three categories appear to be extremely relevant in the context of MI-BCI training. Indeed, the predictors were computed during the early stages of training, i.e., during the first or first few sessions. Moreover, most studies were performed on BCI-naïve users who were confronted with a BCI for the first time. Yet, the literature suggests that this situation (early training phase and first exposition to the technology) can induce an important level of anxiety associated to a low sense of agency, both having potential negative repercussions on performance (Achim and Al Kassim, 2015; Saadé and Kira, 2009; Simsek, 2011). This first point justifies the involvement of the *category 1* predictors, i.e., those related to the users' relationship with the technology. Besides, the Ackerman model (Ackerman, 1988) suggests that during the early stages of learning (phase #1), the inter-user variability in terms of performance in mainly due to (1) differences in “task-appropriate” abilities and (2) high-level cognitive abilities such as attention. These two aspects correspond to the two other predictor categories that we identified. Indeed, spatial abilities (*category 3*), i.e., the ability to produce, transform and interpret mental images (Poltrock and Brown, 1984) can be considered as “task appropriate” abilities in the context of MI-BCI training, while attention (*category 2*) clearly corresponds to the second parameter influencing inter-user variability in Ackerman’s model. Hence the elaboration of these three categories: the inclusion of the predictors in different categories was justified, the associated cognitive models were introduced and the neural correlates related to each concept were described. This work was intended to provide a better understanding of the different factors impacting MI-BCI training and thus to provide, in the Prospects section, a discussion about how these factors could be taken into account when designing future protocols in order to optimize user-training. More specifically, the impact of the training protocol on users’ computer anxiety and sense of agency was demonstrated. It has been suggested that a biased positive feedback could increase novice users’ sense of agency and thus increase their performance. Also, the significance of respecting the principles of priority, consistency, exclusivity and a transparent mapping between the task and the feedback was emphasized. Furthermore, it should also be possible to increase BCI training efficiency by considering the user’s attention. In particular, attention capabilities can be improved using meditation or neurofeedback. Moreover, attentional resources can be optimally directed towards BCI training by using gamified BCI training tasks, varied tasks, rich and friendly feedback as well as multimodal feedbacks. BCI efficiency could also be improved by using training procedures of spatial skills, since spatial training has proved to enhance performances in many domains (sport, music, surgical practice, etc.). Moreover, this improvement has been shown to be effective, durable, and transferable (to skills that have not been subject to specific training) when the training duration is long enough. Finally, the user’s mental rotation ability seems to be a very good candidate to be trained, since this ability has been identified as a relevant predictor of BCI performance and since the consequences of mental rotation training on spatial and more general skills have been clearly identified.

To conclude, we hope that this work will be useful to guide the design of new protocols and improve MI-BCI user-training so that these technologies become more accessible to their end-users. Nevertheless, it is important to note that improving training protocols is not enough. The roles of the researcher and experimenter are also of utmost importance, notably concerning: (1) the demystification of the BCI technology to reduce *a priori* computer anxiety, through scientific mediation and communication with the media, (2) the writing of informed-consent forms and explanations, that should be clear and informative, and provide an objective estimation of the benefit on risk balance and enable to regulate any form of hope that may be generated (Nijboer et al., 2013), and (3) the social presence and trust relationship with the user, which are essential in facilitating the learning process (Kleih et al., 2013).

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