Brain-computer interfaces (BCIs) based on sensorimotor rhythms

Evaluating practical interventions to improve their performance and reduce BCI inefficiency

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I would like to dedicate this thesis to my loving parents,
who gave everything they had for the education and happiness of my two brothers and me.

Eidesstattliche Erklärung

Hiermit versichere ich, Loïc Botrel, an Eides statt durch meine Unterschrift, dass ich die nachfolgende Arbeit selbständig und ohne fremde Hilfe angefertigt und alle Stellen, die ich wörtlich oder dem Sinne nach aus Veröffentlichungen entnommen habe, als solche kenntlich gemacht habe und mich keiner anderen als der angegebenen Literatur oder sonstiger Hilfsmittel bedient habe. Ich erkläre ferner, dass die Regeln der Universität Würzburg über gute wissenschaftliche Praxis eingehalten wurden und diese Dissertation, vollständig oder teilweise, keiner anderen Prüfungsbehörde vorgelegt worden ist.

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Abstract

Brain computer interfaces based on sensorimotor rhythms modulation (SMR-BCIs) allow people to emit commands to an interface by imagining right hand, left hand or feet movements. The neurophysiological activation associated with those specific mental imageries can be measured by electroencephalography and detected by machine learning algorithms. Improvements for SMR-BCI accuracy in the last 30 years seem to have reached a limit. The currrent main issue with SMR-BCIs is that between 15% to 30% cannot use the BCI, called the "BCI inefficiency" issue. Alternatively to hardware and software improvements, investigating the individual characteristics of the BCI users has became an interesting approach to overcome BCI inefficiency. In this dissertation, I reviewed existing literature concerning the individual sources of variation in SMR-BCI accuracy and identified generic individual characteristics. In the empirical investigation, attention and motor dexterity predictors for SMR-BCI performance were implemented into a trainings that would manipulate those predictors and lead to higher SMR-BCI accuracy. Those predictors were identified by Hammer et al. (2012) as the ability to concentrate (associated with relaxation levels) and "mean error duration" in a two-hand visuo-motor coordination task (VMC). Prior to a SMR-BCI session, a total of n=154 participants in two locations took part of 23 min sessions of either Jacobson's Progressive Muscle Relaxation session (PMR), a VMC session, or a control group (CG). No effect of PMR or VMC manipulation was found, but the manipulation checks did not consistently confirm whether PMR had an effect of relaxation levels and VMC on "mean error duration". In this first study, correlations between relaxation levels or "mean error duration" and accuracy were found but not in both locations. A second study, involving n=39 participants intensified the training in four sessions on four consecutive days or either PMR, VMC or CG. The effect or manipulation was assessed for in terms of a causal relationship by using a PRE-POST study design. The manipulation checks of this second study validated the positive effect of training on both relaxation and "mean error duration". But the manipulation did not yield a specific effect on BCI accuracy. The predictors were not found again, displaying the instability of relaxation levels and "mean error duration" in being associated with BCI performance. An effect of time on BCI accuracy was found, and a correlation between State Mindfulness Scale and accuracy were reported. Results indicated that a short training of PMR or VMC were

insufficient in increasing SMR-BCI accuracy. This study contrasted with studies suceeding in increasing SMR-BCI accuracy Tan et al. (2009, 2014), by the shortness of its training and the relaxation training that did not include mindfulness. It also contrasted by its manipulation checks and its comprehensive experimental approach that attempted to replicate existing predictors or correlates for SMR-BCI accuracy. The prediction of BCI accuracy by individual characteristics is receiving increased attention, but requires replication studies and a comprehensive approach, to contribute to the growing base of evidence of predictors for SMR-BCI accuracy. While short PMR and VMC trainings could not yield an effect on BCI performance, mindfulness meditation training might be beneficial for SMR-BCI accuracy. Moreover, it could be implemented for people in the locked-in-syndrome, allowing to reach the end-users that are the most in need for improvements in BCI performance.

Résumé

Les interfaces cerveau-ordinateur (angl. *brain-computer interfaces, BCIs*) basées sur les rythmes sensorimoteurs (angl. *sensorimotor rhythms, SMR*) permettent d'émettre des commandes par l'imagination de mouvements des mains ou des jambes. Dans le cas des BCIs non-invasifs, les manifestations neurophysiologiques liées á l'imagination motrice peuvent être mesurées par électroencephalographie (EEG) á la surface du cuir chevelu, puis détectées á l'aide d'algorithmes d'apprentissage. Après 30 années de progrès dans l'implémentation des BCI basées sur les SMR, il devient de plus en plus difficile d'obtenir un gain significatif de performance, alors qu'il est estimé qu'entre 15% et 30 % des utilisateurs ne peuvent pas utiliser une BCI basée sur les SMR. On parle d'inefficacité de la BCI (angl. *BCI inefficiency*). Une alternative aux avancées matérielles et logicielles réside dans l'investigation de caractéristiques propres à l'utilisateur. Dans ce travail de thèse, j'ai d'abord procédé à une revue de littérature sur les sources individuelles de variation de la performance SMR-BCIs, sous la forme de caractéristiques psychologiques, neurologiques et neuroanatomiques propres à l'utilisateur. Pour l'étude empirique, je me suis basé sur deux prédicteurs – l'attention et la dextérite motrice – que j'ai expérimentalement manipulés par des protocoles d'intervention. Ces deux prédicteurs ont été identifiés par Hammer et al. (2012) en tant que capacité à se concentrer (*ability to concentrate*) et durée moyenne d'erreur dans une tâche de coordination visuo-motrice (*mean error duration in a visuomotor coordination task, VMC*). La première étude comprend N=154 participants recrutés dans deux villes allemandes (Würzburg et Berlin). Avant de procéder à une session de BCI basée sur les SMR, les participants ont été aléatoirement répartis en trois groupes d'intervention d'une durée de 23 minutes. Le groupe PMR a pris part à une session de relaxation musculaire progressive de Jacobson, censée relaxer le participant ; le groupe VMC a pris part a une session de coordination visuo-motrice des deux mains, censé augmenter la dextérité motrice ; le groupe controle CG ayant eu pour tâche de lire un texte. Les résultats, analysés indépendemment pour chaque lieu de mesure, indiquent que l'entraînement PMR ou VMC n'ont pas provoqué d'amélioration significative de la performance BCI. L'effet des interventions sur leurs variables témoins respectives (PMR sur le niveau subjectif de relaxation ; VMC sur la durée moyenne d'erreur) sont inéquivoques. Il n'est donc pas possible d'interpréter l'absence d'effet d'entraînement sur la performance

BCI. Les corrélations entre les variables témoins et la performance BCI répliquent les deux prédicteurs à l'origine de l'étude, mais ces résultats sont restreints à l'un des deux lieux de mesure. La seconde étude a été menée sur N=39 participants pour lesquels la durée d'entraînement (soit PMR, VMC ou CG) a été prolongée sur quatre sessions étalées sur quatre jours successifs. Cette seconde étude a été conçue selon un modèle pré-test post-test permettant de réduire la sensibilité aux variations inter-individuelles de la performance, ainsi que de tester la présence d'une relation causale entre entraînement et performance BCI. Les variables témoins – relaxation et durée d'erreur VMC– ont evolué de maniere positive validant les entraînements. Cependant, les entraînements PMR et VMC n'ont eu aucun effet positif sur la performance BCI basée sur les SMR. Les prédicteurs n'ont donc pas de nouveau été répliqués, démontrant l'instabilité des niveaux de relaxation et la performance VMC dans leur association avec la performance BCI. L'effet de temps sur la performance BCI, constaté dans de nombreuses études a été répliqué. De manière plus inattendue, une correlation entre l'échelle d'attention consciente (*state mindfulness scale, SMS*) et la performance BCI a été révélée. Globalement, Les résultats de ces deux études empiriques indiquent que de courts entraînements PMR ou VMC ont été insuffisants pour améliorer la performance BCI. Ces études contrastent donc avec les précédentes études qui au contraîre ont montré un effect positif d'un entraînement en relaxation Tan et al. (2009, 2014), notamment marqués par leur durée s'étalant sur plusieurs mois ainsi que leur forme de relaxations basées sur la méditation de pleine conscience (angl. *Mindfulness*). Mes deux études se démarquent cependant par la présence de tests de manipulation, l'approche expérimentale basée sur l'implémentation du potentiel des prédicteurs et corrélats de la performance BCI. La prédiction de performance SMR-BCI par des caractérisiques individuelles reçevant une attention croissante ces dernières années, il est nécessaire pour contribuer efficacement au domaine des sources de variation des BCI, d'opter pour une approche expériementale englobant les résultats existants, notamment par l'effort de réplication, et de comparaison d'études. En conclusion, Alors que de courts entraînements PMR et VMC n'ont pas eu d'effets sur la performance BCI basée sur les SMR, la piste de l'entraînement de méditation pleine conscience présente un potentiel qu'il est nécessaire de confirmer. De plus, il pourraît être mis en place pour des patients paralysés moteur (angl. *locked-in syndrome, LIS*), permettant de fait d'atteîndre la population pouvant le plus profiter des améliorations de la performance BCI.

Zusammenfassung

Gehirn-Computer Schnittstellen (engl. brain-computer interfaces, BCIs), basierend auf der Modulation sensomotorischer Rhythmen (SMR), erlauben Menschen, Befehle an eine Schnittstelle zu übermitteln, beispielsweise durch die Vorstellung von Bewegungen der Hände oder der Füße. Die neurophysiologische Aktivität, die mit den Bewegungsvorstellungen assoziiert ist, kann mittels Elektroenzephalographie gemessen und durch Algorithmen aus dem Bereich des maschinellen Lernens detektiert werden. Die Fortschritte in Bezug auf SMR-BCIs, die es in den letzten 30 Jahren gab, scheinen an eine Grenze zu stoßen. Das Hauptproblem liegt darin, dass 15 bis 30% der Nutzer keine Kontrolle über SMR-BCIs erlangen. Dieses Phänomen wird als „BCI Ineffizienz“ bezeichnet. Neben Verbesserungen der Hard- und Software ist die Untersuchung individueller Charakteristika der BCI Nutzer ein vielversprechender Ansatz, um die BCI Ineffizienz zu überwinden. Im Rahmen dieser Dissertation habe ich zunächst durch eine Literaturstudie zu den Ursachen der Variation der SMR-BCI Genauigkeiten individuelle Charakteristika identifiziert. In der experimentellen Untersuchung wurden Aufmerksamkeit und Feinmotorik als Prädiktoren für die Leistung mit einem SMR-BCI in ein Trainingsparadigma aufgenommen, das zum Ziel hatte, die SMR-BCI Genauigkeiten zu verbessern. Diese Prädiktoren wurden von Hammer et al. (2012) als die Konzentrationsfähigkeit (assoziiert mit Entspannungsniveau) und „mittlere Fehlerdauer“ in einer beidhändigen visuomotorischen Koordinationsaufgabe (engl. two-hand visuo-motor coordination task, VMC) identifiziert. In der ersten Studie der vorliegenden Dissertation nahmen insgesamt n=154 Studienteilnehmer an zwei verschiedenen Standorten teil. Im Vorfeld einer SMR-BCI Sitzung nahmen diese entweder an einer 23-minütigen Sitzung mit Progressiver Muskelrelaxation nach Jacobson (PMR), einer Sitzung mit VMC oder einer Kontrollgruppe (KG) teil. Es zeigten sich keine Effekte auf die Genauigkeiten des SMR-BCI als Folge der Versuchsbedingung (VMC, PMR oder KG). Jedoch konnte auch durch Manipulationschecks nicht konsistent bestätigt werden, dass PMR eine Auswirkung auf das Entspannungsniveau und VMC auf die „mittlere Fehlerdauer“ hatte. In dieser ersten Studie konnten Korrelationen zwischen dem Entspannungsniveau oder „mittlerer Fehlerdauer“ und der Genauigkeit mit dem SMR-BCI aufgedeckt werden, jedoch nicht an beiden Standorten. In der zweiten Studie dieser Dissertation mit n=39 Teilnehmern wurde das Training durch die

Steigerung auf vier Sitzungen intensiviert, die an vier aufeinanderfolgenden Tagen entweder mit PMR, VMC oder KG durchgeführt wurden. Der Effekt dieser Manipulation auf SMR-BCI Genauigkeiten wurde mittels eines Pretest-Posttest-Studiendesigns untersucht. Die Manipulationschecks validierten den positiven Effekt des Trainings sowohl für Entspannung als auch die „mittlere Fehlerdauer“. Es gab jedoch keine spezifische Wirkung des Trainings auf die BCI Genauigkeiten. Entspannungsniveau und „mittlere Fehlerdauer“ konnten nicht als zuverlässige Prädiktoren für SMR-BCI Leistung bestätigt werden. Es gab einen Effekt der Zeit auf die BCI Genauigkeit und eine Korrelation zwischen der State Mindfulness Scale und der Genauigkeit. Die Ergebnisse deuten darauf hin, dass ein kurzes PMR oder VMC Training nicht ausreichten, um SMR-BCI Genauigkeiten zu steigern. Diese Studie steht im Widerspruch zu Studien von Tan et al. (2009, 2014), die erfolgreich die SMR-BCI Genauigkeit steigern konnten, unterscheidet sich von diesen jedoch auch durch die kürzere Trainingsdauer und dem Fehlen von Achtsamkeitskomponenten beim Entspannungstraining. Weitere Unterschiede liegen in dem verwendeten Manipulationscheck und dem umfassenden experimentellen Ansatz der aktuellen Studie mit dem Ziel, zuvor ermittelte Prädiktoren oder Korrelate von SMR-BCI Genauigkeit zu replizieren. Die Vorhersage von BCI Genauigkeit durch individuelle Charakteristika erhält steigende wissenschaftliche Aufmerksamkeit, bedarf aber Replikationsstudien und eines umfassenden Ansatzes, um die Beweislage hinsichtlich Prädiktoren für SMR-BCI Genauigkeit zu verbessern. Während für kurze PMR und VMC Trainings kein Effekt auf die SMR-BCI Genauigkeit aufgedeckt werden konnte, könnte sich achtsamkeitsbasiertes Meditationstraining als vorteilhaft für die Leistung mit einem SMR-BCI erweisen. Darüber hinaus könnte es auch für Personen mit Locked-In-Syndrom implementiert werden, um so diejenigen Endnutzer zu erreichen, die am meisten von Verbesserungen der BCI Leistung profitieren würden.

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Chapter 1

Introduction

Brain-computer interfaces (BCIs; for review, see Wolpaw and Wolpaw (2012)) are systems that interpret activity from the brain into output commands. The "non-invasive" BCIs uses external sensors such as scalp electroencephalography (EEG). The particularity of BCIs is that they – in principle – do not rely on traditional muscular control, but only on neurophysiological processes. Sensorimotor rhythms (SMR; for review, see Pfurtscheller and McFarland, 2012) are frequencies in the range of $8\,\mathrm{Hz}$ to $13\,\mathrm{Hz}$ (μ) and $16\,\mathrm{Hz}$ to $24\,\mathrm{Hz}$[1] (β) present in the surface EEG of motor and somatosensory areas. The strength of SMR rhythms is associated with motor preparation or execution, following relatively generic patterns concering time and scalp locations. SMR-based BCI requires user to perform motor imagery of a limb to lead to SMR modulation, which can be translated into output commands. Its first implementation was made by Wolpaw et al. (1986).

Improvements for SMR-BCI accuracy in the last 30 years seem to have reach a limit, that can be described as a glass ceiling (McFarland et al., 2011). The currrent main issue with SMR-BCIs is that between $15\,\%$ to $30\,\%$ (Allison and Neuper, 2010) cannot use the BCI. Those people have initially been called BCI "illiterate". Researchers, such as Kübler et al. (2011a); Grosse-Wentrup and Schölkopf (2013) have proposed that instead of mainly looking for hardware and software improvements, individual characteristics (e.g. relaxation or motivation states) of the BCI users have been overlooked, and that their investigation and implementation could lead to further improvements. The change of perception on the issue was also marked by a reversal in how "BCI illiterate" (i.e. people not able to learn the BCI) were labeled. The authors named them "BCI inefficient" (Kübler et al., 2011b), putting the blame on the BCI to not be able to interpret the brain activity of the users.

At the very beginning of this doctoral work (i.e. in 2011), only a few studies had investigated and reported individual characteristics for SMR-BCI, such as motivation (Nijboer

[1] The frequencies often vary from $1\,\mathrm{Hz}$ to $2\,\mathrm{Hz}$ depending on the source or author.

et al., 2008), locus of control (Burde and Blankertz, 2006), attention levels (Grosse-Wentrup et al., 2011), age and full-body movements (Randolph et al., 2010), resting SMR rhythms (Blankertz et al., 2010), and ability to concentrate and proficiency in a visuo-motor task (Hammer et al., 2012).

1.1 Aim of the dissertation

In this dissertation, the approach was to investigate the individual dimension of the BCI user in relation with SMR-BCI accuracy. To proceed I collected and identified variables that explained variation in SMR-based BCI accuracy, supported by empirical evidence. Having identified these source of variation, the objective was to propose and evaluate trainings that could increase SMR-BCI accuracy. Those trainings were based on the manipulation of the identified predictors, and aimed at investigating a causal relationship between training and BCI accuracy.

1.2 Structure of the dissertation

In the structure of this dissertation, I had a bottom-up approach that starts from the neuronal origin of the brain activity. While this chapter (1) contains a short introduction of the topic of the dissertation, the chapter 2 describes the origin of the motor activity of the brain. This can only be understood by taking into account the the specific neuroanatomical organization of the motor cortex brain (section 2.1) and its neurophysiological processes (section 2.3), which can be measured via different means (section 2.2).

Having introduced in chapter 2 the existence of specific patterns of brain activity, I described in chapter 3 the methods allowing these patterns to be instrumentally extracted via EEG and translated into commands. After evoking the origins of how the modulation of those patterns was conditionned via neurofeedback (section 3.1), I then concisely report how it was implemented into communication systems via different EEG based BCI paradigms (section 3.2). Focused only on SMR-BCIs, I introduced the methods to conduct SMR-BCI, (in section 3.4), from EEG setup (section 3.4.1), reduction of the artifacts (section 3.4.2), to signal processing (section 3.4.4) and experimental trial feedback (section 3.4.5). This method section allows to evoke the complexity of SMR-BCI (as compared to neurofeedback), particularly by the use of machine learning in spatial derivation and co-adaptive calibration (i.e. between the user and the BCI), therefore positing SMR-BCI as the dynamical combination of spatial, temporal and oscillatory properties of SMR modulation. Having described SMR-BCIs, I introduce the different applications they are – or anticipated to be – used for (section 3.5).

This section particularly describes the accidental or pathological conditions that lead to the locked-in-state (LIS; section 3.5.1). As people in the LIS are the one who need – functional – BCI the most, I provide a description of BCI-based implementations for assistive technology (section 3.5.1) and the benefits the BCI can provide.

In chapter 4, I introduced the current models and guidelines for investigating variation in SMR-BCI performance. This chapter first posits the issue of BCI inefficiency (section 4.1) that motivated this dissertation, then provide guidelines and models of BCI control (section 4.2) to better categorize and interpret the sources of varitation in the BCI.

The empirical investigation can be found in chapter 6. I provide a list and description of individual predictors – and correlates – of BCI performance, sub-classified by their generic subtypes (one per section, e.g. psychological, visuo-motor and spatial, neurophysiological, anatomical). In the following section (5.5), I evoke the limitations of these predictors. In the next section, I listed the – scarce – findings that, similarly to the aim of this dissertation, successfully implemented specific training to increase SMR-BCI accuracy (section 5.7).

The original contribution in chapter 6 describes the empirical experimentation work in two studies in which investigated the effect of relaxation and visuo-motor coordination based training on SMR-BCI accuracy. The first study consisted in an intervention prior to SMR-BCI training (section 6.1), while the second extended the training duration on four consecutive days (section 6.2). Those two studies are retrospectively introduced with respective summaries, research gap and research questions. Both studies are described following a substructure of hypotheses, method, results and discussion.

In Chapter 7, a general discussion encompasses the findings of both studies and integrates them in the state-of-the art review of the literature concerning individuals variation of SMR-BCI performance. The limitations section (7.1) evokes the main issue that can limit the generalization of the empirical investigation. The next section (7.2) concludes this dissertation and provides a general interpretation of this dissertation. An outlook (section 7.3) provides my future plans following this doctoral dissertation work.

Chapter 2

Motor activity in the brain

2.1 The motor cortex

The motor cortex refers to dorsal areas of the frontal lobe, involved in the planning and execution of movement. It is defined in smaller areas called (from anterior to posterior): premotor cortex (PMC), supplementary motor area (SMA); primary motor cortex (M1); primary and secondary somatosensory cortex (S1,SSA); the posterior parietal cortex (PPC, see Figure 2.1). The primary motor cortex is anterior to the central sulcus ("anterior central gyrus"), while the somatosensory cortex is located posterior to the central sulcus ("post central gyrus"). An anatomical specificity of these cortices is their point-to-point mapping with areas of the body, or "somatotopic arrangement". The discovery of this arrangement was found by stimulating the motor cortex with weak electric discharges over the motor cortex which would trigger movements, contralateraly from the stimulated side. Experimentations led researchers to map these areas, by dogs (Fritsch and Hitzig, 1870), then on the brain of apes (Ferrier, 1874, 1875) and later by humans (Campbell, 1905; Vogt and Vogt, 1919; Foerster, 1936). After a meticulous investigation, Penfield and Boldrey (1937); Penfield and Rasmussen (1950) provided a yet iconic drawing of the brain's representation of the body on a slice of the cortex called "motor homunculus", noting that the representation of the arm and the fingers were disproportionately big in relation to other parts of the body. He also provided somatosensory mapped body parts ("somatosensory homunculus"), with the particularity that the two homunculus are slides of the cortex located side by side along the central gyrus, with the position of the motor and somatosensory mapped areas roughly matching. The somatosensory homunculus comprises additional representations of body parts that are linked with only few to no muscles such as the nose, internal organs, the pharynx and genitals. Yet, while it looks well organized, the brain is renowned for its complexity, and limitations of this model have been evoked by (Penfield and Rasmussen, 1950, p. 56), mentioning the homunculus: *"A figurine of this sort cannot give an accurate indication of the specific joints in which movement takes place, for in most cases movement appears at more than one joint simultaneously [...]"*. Recent studies confirm these early findings (e.g. Asanuma and Rosén, 1972), demonstrating that there is an overlap and a wide distribution of smaller body across arm, leg and face representations.

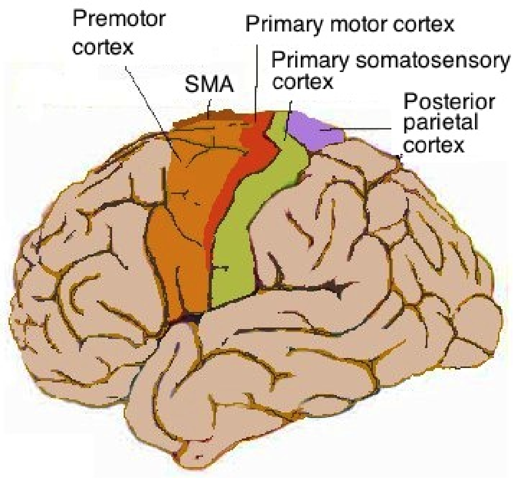

Figure 2.1 Representation of the motor areas on the Human cortex.The upper part shows the area between the right and left cortices, in the longitudinal fissure. SMA: supplementary motor area; PMC: premotor cortex; MI: Primary motor cortex; SI: somatosensory cortex (Source: Iamozy/Pancrat, Wikimedia CC BY)

The particularity of the somatotopic areas (M1,S1) lies in the fact they are mapped in a way that enables to roughly locate and discriminate the representation limbs, making them interesting for BCIs. For example, the somatosensory representation of both feet can be found on the central midline of the cortex (called Cz in electroencephalography); and the somatosensory representation of the hand can be found laterally on the side of the motor cortex (C3 for left cortex, C4 for the right cortex, EEG montage is described in section 3.4.1).

There are in the brain several types of neurons with different functions. The cortex is notably known to be populated with a high amount of pyramidal neurons. Those neurons were named after the conic shape of the cell body (soma) and can be found in several layers of the cortex. They have the particularity of having their apical (upper) dendritic tree projecting directly and perpendicularly below the surface of the cortex (see Figure 2.2).

2.2 Measuring neuronal activity

2.2.1 Invasive recordings

An invasive and most specific method to measure neuronal activity is to insert a very small needle shaped microelectrode in the cortex, with its conductive end either in contact with the neuron, or in its vicinity. The methods allow to measure the electrical activity of the neuron with a very good time resolution, and is visualized on a time axis as a succession of spikes. Intserting the electrode directly inside the somatotopically mapped areas (see section 2.1) alows to measure neurons associated with the sensorimotor function. An invasive study with apes conducted by Georgopoulos et al. (1986) found that the direction of the arm movement could be decoded by summing the spike activity of a population neurons in the motor cortex mapping the arm. To do such a measurement, the author used a device called a microelectrode array, which is composed by a grid of microelectrodes (see figure), greatly increasing the number of input channels. The analysis is conducted on spike trains (see "rate coding theory"; Adrian and Zotterman (1926); or "temporal coding theory"; Theunissen and Miller, 1995). Alternative to spike measurements, instruments can measure the summed up neural activity directly at the surface of the cortex via electrocortigraphy (ECoG) or scalp electroencephalography (EEG), allowing for measuring oscillatory patterns.

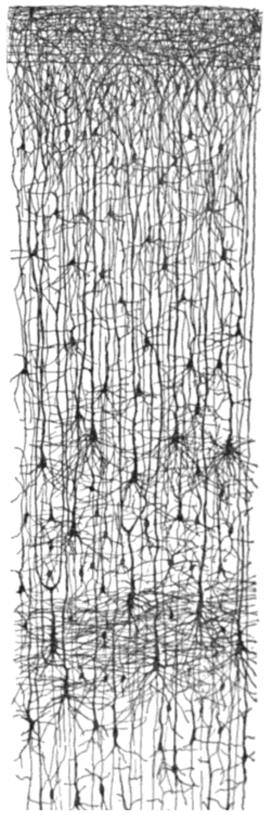

Figure 2.2 Drawing of golgi-stained cortex, representing pyramidal neurons (from y Cajal, 1899; p. 363, public domain)

2.2.2 EEG oscillations

The beginning of EEG measurements by Humans dates back to Hans Berger, a German psychiatrist who measured EEG activity of the brain using Einthoven's string galvanometer (Moise et al., 2008; see Figure 2.4). The existence of such electrical potentials produced by the brain was already proven by intra-cranial animal measurements by Caton in 1875, who reported *"fluctuations of the electric current often occured coincidently with some movements of the animal's body or changes in its mental condition;"* (Caton, 1877). The first frequency Berger identified was named alpha wave (α see Figure 2.5) and had a frequency of 8–12 Hz which could be observed when participants were resting (Berger, 1929). He then identified beta (β) for 12–30 Hz frequencies when his participants were in an attentive state of mind. He subsequently named gamma (γ, 30 to 100 Hz) and delta (δ, below 4 Hz) frequency bands. Walter et al. (1964) investigated tumoral lesions in the thalamus of apes, and observed a frequency in the 4 to 7 Hz range, which was called as theta (for thalamus; θ, see Figure 2.5).

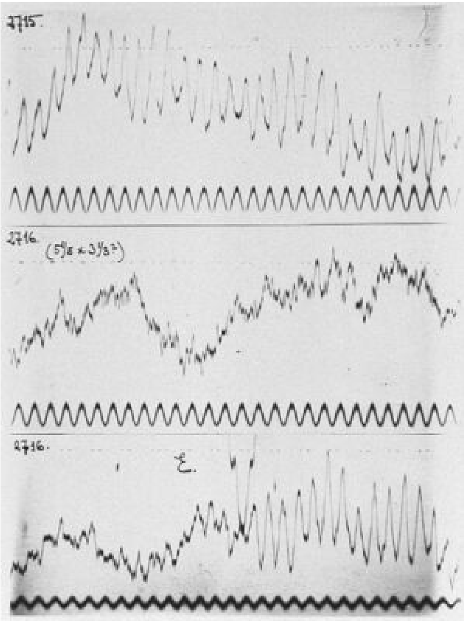

Figure 2.3 EEG recordings from Berger, showing α beta β EEG wave. A 10 Hz sinusoidal wave was inserted as a reference below. (public domain)

While the role of lower γ waves (<60Hz) has been hypothesized to "bind" different areas of the brain, there is no strong evidence of such a claim (Vanderwolf, 2000; Jerbi et al., 2009). The γ band oscillations, as noted by Engel and Fries (2010), are involved in several cognitive processes such as feature integration (Engel et al., 1992; Singer, 1995), stimulus selection (Engel et al., 2001), attention (Jensen et al., 2007) and sensorimotor processing (Grosse-Wentrup et al., 2011; Grosse-Wentrup and Schölkopf, 2013). A better consensus was reached in lower frequency bands due to their activity reflecting cognitive processes or states of wakefulness. The β band is observed during the active, busy or concentrating state of the brain (Baumeister et al., 2008). The α band identified by Berger is known to be prominent in the resting state or the absence of sensory input, and a more recent theory show that α band relates to a disengagement of task-irrelevant brain areas or to the function of short-term memory (Palva and Palva, 2007). θ activity has been extensively studied in both animals and humans (Bland and Oddie, 2001) for its role in memory integration during wakefulness and REM sleep. This θ activity is however found in the hippocampus, which is the main subcortical substrate for memory. Yet, animal models did not transfer to Humans, as was demonstrated that Human cortical θ is not directly synchronized with hippocampal activity (Cantero et al., 2003). Instead, it reflects focused attention and is called

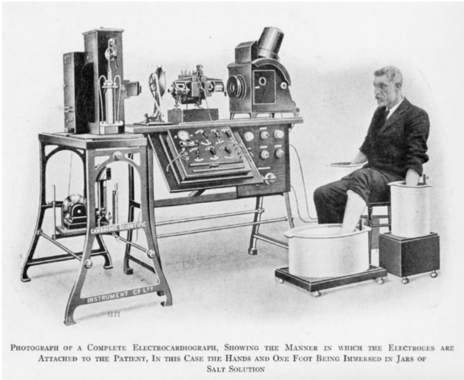

Figure 2.4 Commercial ECG machine, built in 1911 by the Cambridge Scientific Instrument Company (from Burch and DePasquale, 1964) to measure the human electrocardiogram according to the standards developed by Einthoven. (Source: Norman publishing, http://www.historyofscience.com/norman-publishing/, accessed 11/20/2017, with permission)

"frontal midline θ" (Ishihara and Yoshii, 1972). Frontal-midline θ is more prominent during inattentive (Gevins et al., 1997), drowsy, meditative, or in shallow sleep ("hypnaogic") states of mind (Schacter, 1976). Yet, frontal-midline θ oscillations were also found to be linked with dispositional anxiety (Osinsky et al., 2016), working memory (Raghavachari et al., 2001), in short phases of about 1-2 seconds and time-locked to the cognitive event (Rizzuto et al., 2003). θ oscillations were also found to be anticorrelated with α (Klimesch, 1999). Finally, the lowest frequency brain oscillations, called Delta (δ), are predominant during deep sleep. Their functional significance is not well understood, but Knyazev (2012) links δ with autonomic and metabolic processes representing homeostasis. The author proposes an evolutionary approach, associating δ with "evolutionary old basic" processes, that are in adults "overshadowed by more advanced processes". Such old processes concerns the reward system and defense mechanisms (Knyazev, 2007; Steriade et al., 1993).

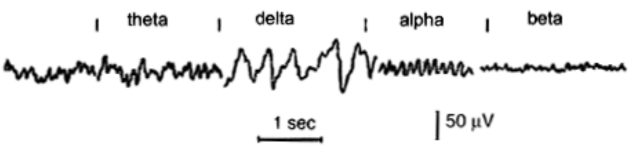

Figure 2.5 Stereotypical EEG shape of cortical theta θ, delta δ, α and beta β. (Source: The McGill Physiology Virtual Lab, https://www.medicine.mcgill.ca/physio/vlab/biomed_signals/eeg_n.htm, accessed 11/20/2017, with permission)

2.2.3 Recording the EEG activity

Oscillatory activity in the brain is the result of the combined activity of large populations of pyramidal neurons. Instead of directly recording the individual activity of neurons from within, it is also possible to measure the activity of a large population of neurons from the surface of the cortex or from the scalp. From outside the cortical tissue, action potentials cannot be measured in term of axonal potentials of neurons, due to their random directions, myelin sheath insulation and fast latency. A rather viable candidate can be found in the excitatory and inhibitory post synaptic potentials (IPSPs) occurring on the synapses of the dendritic trees. Due to their particular anatomical properties, pyramidal neurons produce electrical dipoles. At the individual level, the polarity of each dipole depends on the type of synaptic stimulations, and whether they occur superficially or deep near the cell body (soma, for review on the source of EEG, see Kirschstein and Kohling, 2009). The aggregated synaptic activity of large quantities of neurons creates electrical dipoles that are measurable at the surface of the cortex. Electrocorticography (ECog) is when an electrode is placed directly on the surface of the cortex, (more commonly a patch several of electrodes). It requires surgery to saw off a part the skull, and is used for a medical intervention that locates the neuronal tissue responsible for epilepsy. Researchers which are unlikely to obtain an ethical approval to perform such a surgery can however be allowed to perform measurements while the ECoG is in place. Due to these non-optimal conditions of invasive recordings, non-invasive surface EEG is the most commonly used method to measure brain activity. In this method, the electrodes are placed at the surface of the scalp, extending the spatial resolution to several centimeters while the signal to noise ratio is strongly reduced, due to the several layers of brain tissues, bone and cerebrospinal fluid that attenuate the signal source and the electrode. While the tension at the membrane of individual neurons ranges between -70 and 40 mV, the EEG cap record neuronal currents with an amplitude of 80 μV. Moreover, surface EEG contains a lot of noise originating from non-cerebral physiological and other environmental sources called artifacts (described in section 3.4.3). Another common recording methods exist, such as magnetoencephalography (MEG) that provides bettwer spatial resolution due the non-interference of brain tissues with electromagnetic waves the device measures. Yet, MEG requires a very strict setup, as experiments must be conducted in a magnetically shielded room and the superconductors coils of the device requires super-cooling.

2.2.4 Why use EEG?

BOLD states for blood oxygenation level dependent. It is dependent on the hemodynamic response that follows localized neuronal activity. Variations in the blood opacity can measured using Near Infrared spectroscopy (NIRS). The device sends infrared light though the skin using small infrared (IR) emitters and measures it back using light sensors. The size of the device and the spatial resolution are comparable to EEG, and can measure localized activity, but suffers from its poor temporal resolution of several seconds. The magnetic resonance imagery (MRI), records the magnetic resonance of the molecules that compose the brain tissue. A variation of MRI called functional MRI (fMRI), allows to distinguish oxygenated to deoxygenated blood, but the subsequent variations in blood flow are better discriminated. It can measure activity at the surface and in deep areas of the brain with a spatial resolution of a few millimeters. The high complexity of the device, using an assembly of strong magnets precisely calibrated, with moving parts requires the participant to remain still in a small chamber and endure loud noises. Diffusion weighted MRI (DWI) is a MRI based method that maps the diffusion of water mollecules in the brain. A variant of this technique called diffusion tensor imagery (DTI) makes possible to map the white matter tracts in the brain, in addition to estimate their anisotropy (whether they all in line) and their orientation.

While all methods presented in this section can be used efficiently to extract information from the brain, only the EEG – and NIRS to some extent – has been miniaturized and offer an innocuous, easy to apply device that can be used outside a laboratory, justifying why it is widely used.

The use of EEG and fMRI devices for research purposes in the 20$^{\text{th}}$ centrury has made possible to precisely locate and detect patterns of activations in the brain associated with behaviors or mental states. In this thesis, I specifically investigate activations in the motor cortex linked to motor imagery retrieved by EEG. The voluntarily modulation of BOLD activity while being supervised in real time by an fMRI (rt-fMRI), is anticipated to potentially lead to BCI applications (Weiskopf et al., 2004), as it was shown to work in neurofeedback applications (for a review see Sulzer et al., 2013), and can reach acceptable BCI control accuracies (e.g. $80\,\%$; Sorger et al., 2012; Luhrs et al., 2017) while being still hard to achieve (Sepulveda et al., 2016; for a review, see Ruiz et al., 2014). Nevertheless, it is yet limited by its high cost and heavy setup constraints, and no recent breakthrough, or any improvement in miniaturization or portability are on the horizon. Still, the NIRS allows for trading spatial resolution for portability and price, and can therefore be used to measure hemodynamic responses in the cortex.

2.3 Motor function of the brain

2.3.1 Neural substrate of voluntary movements

Initially thought to be the source of voluntary movements, motor neurons (known also as "Betz neurons") are large pyramidal neurons which have their axon projecting directly into the spinal cord. This is called the direct pathway of motor movements (see Figure 2.6). But to produce voluntary movement, there are far more areas than M1 alone recruited in the process. The decision to trigger movements, their sequencing and coordination comes from indirect pathways. One of the indirect pathways involves excitatory and inhibitory connections between MI and the Basal Ganglia, including the Caudate Nucleus, the Putamen, both Globus Pallidus and the Substantia Nigra. The second involves the SMA and the SI area interacting with the cerebellum via the pontine nuclei. In addition to regulating balance and muscle tonus, the role of the cerebellum is to coordinate sequences of movements. These "motor loops", involving the basal ganglia, the cerebellum and the motor cortex is considered to be the substrate for voluntary movement, the cerebellum coordinating sequences of movements while basal ganglia inhibit the movements for preparation and then providing the "Go" for movement execution. Higher order commands are transmitted down the spinal cord to the interneurons and lower motor neurons (LMN) controlling the muscles. Upper motor neurons (UMN) is used to label neurons from the cortex or in the brainstem.

From this model, we see that not only the primary motor cortex is involved in movement preparation and execution, but also the SMA and S1, which are implied in secondary pathways, and are important in the localization of brain areas associated with movement preparation and execution.

2.3.2 Rhythms and components in the EEG

In this section, I provide a description of the different EEG patterns of activity in the brain that are association with the motor function. Those are reported via the scope of EEG measurements to provide a direct insight in how they could later be used in BCI paradigms.

Sensorimotor rhythms (SMR)

In their survey studies of occipital and central rhythms of the brain, Jasper and Andrews (1938) reported that certain tactile or light stimulations affected α and β rhythms on the central region. Despite the unsuccessful attempt of Bates (1951) in finding any change in α or β oscillations in the motor areas preceding voluntary movements, Gastaut et al. (1952) described the presence of arch-shaped waves ("rythme en arceau") of a frequency between

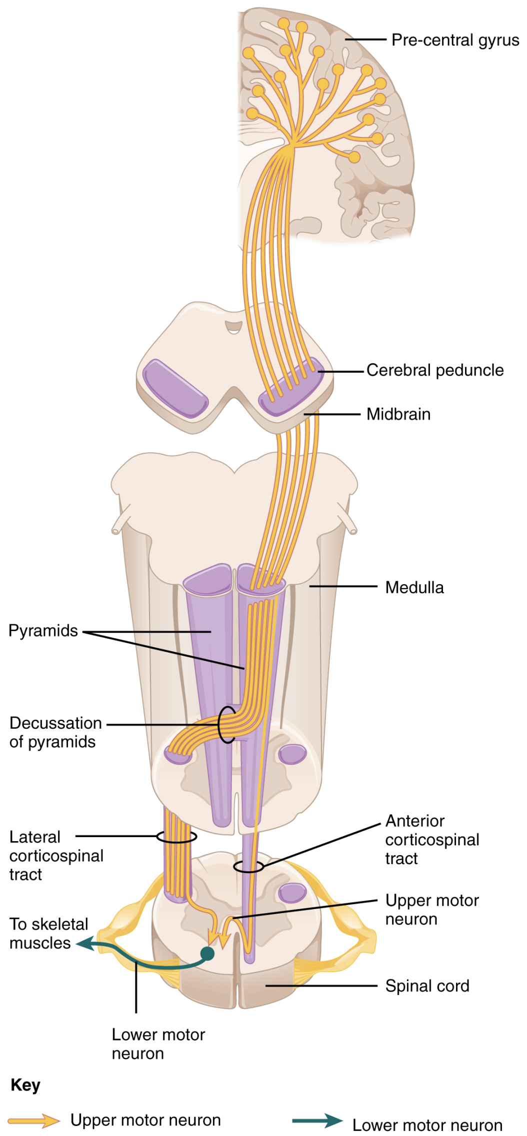

Figure 2.6 Direct pathway of motor control from the cortex to the spinal chord, showing the position of upper and lower motor neurons. (Source: OpenStax College, Anatomy & Physiology, Connexions Web site. CC BY 4.0 https://cnx.org/contents/FPtK1zmh@8.108:8_Ye-vQ3@6/Motor-Responses accessed 11/20/2017)

7-11 Hz recorded over the motor cortex. Movements of the arm and thumb, whether they were passive, reflex or voluntary were marked by contralateral activations or activations on both hemispheres. Moreover, the contralateral blocking of the rhythms occurred a few seconds before the onset of voluntary movements. These 9 Hz oscillations, also called rolandic wickets were later on solely referred to as mu (μ). Pfurtscheller et al. (1976) investigated the contingent negative variation (CNV, see) paradigm, a shift in the EEG amplitude occuring 1 second before moment onset ("expectancy wave"; Walter et al., 1964; or "readiness potentials"; (Deecke et al., 1976)) matching with the somatotopic mapping of the limbs. During this investigation, Pfurtscheller et al. (1976) found a reduction in the α range concurrently to the negative shift of the CNV. In the year that followed, Pfurtscheller (1977) described the blocking of μ oscillations preceding the pressing of a button, which he called event-related desynchronization (ERD), he found a similar effect, that he called ERD for "event-related desyncrhonization" in the low β range (16-20 Hz) a few years afterwards (Pfurtscheller, 1981). Over the years, Pfurtscheller (1992) refined a proper definition of the μ ERD: "*not only an electrophysiological correlate of cortical activation related to stimulus processing or motor output, but is also characteristic for cortical areas or neural structures preparing to process sensory information or ready and prepared to execute a motor command.*". Pfurtscheller then introduced the event related synchronization rebound ("secondary ERS") in the μ range that follows the offset of a movement, and hypothesized to represent the inhibition of cortical areas (Pfurtscheller, 1992).

Still, the ERD/ERS patterns described so far were restricted to the α frequency range, a comprehensive review of these patterns was provided by Pfurtscheller and Lopes Da Silva (1999). The authors evoked the presence of low β (14-19 Hz) and high β (20-24 Hz) in the motor areas while μ rhythms in the somatosensory areas (Pfurtscheller et al., 1994; Salmelin et al., 1995). As for the frequencies, the description of the topographic properties of SMR ERD/ERS are scattered in several publications; Pfurtscheller et al. (2000) describe that during motor preparation, a lower-frequency μ (8-10 Hz) ERD appears widespread over the motor cortex, while a task-specific, higher-frequency μ (10-13 Hz) ERD remains topographically restricted, especially in term or laterality. Pfurtscheller and McFarland (2012) specifically evokes the presence of a β band ERD similar in location and topography to the μ. But β band displays a typical ERS occurring on movement offset, which was called "β rebound".

Later, and with the use of MEG and EcoG for the detection of SMR rhythms, Pfurtscheller and McFarland (2012) also report the presence of high γ associated with movements (Miller et al., 2009; He et al., 2010). Lopes da Silva et al. (1976), using simulation data, demonstrate that averaging the common activity a larger zone of neurons decreased the frequency while increasing the amplitude, but it is unclear whether it alone explains the inter-individual variation in observed and reported frequencies, especially due to their different dynamics.

The origin in the brain of SMR rhythms has not yet been completely elucidated, but Pfurtscheller and McFarland (2012) evoke that areas such as the thalamus, the subthalamic nucleus and the pedunculopontine area display μ and β-range activity (Androulidakis et al., 2008; Williams, 2002) and that specific ERD/ERS are reflected in those subcortical areas. Klostermann et al. (2007) showed that with movement, μ ERD occurred in the cortex, while μ ERS occurs in the subthalamic nucleus; β ERD occurs in both cortex, thalamus and subthalamic nucleus.

It must be also indicated the presence of θ oscillations associated with the motor function. More than being an indicator of drowsiness and inattention, θ oscillations have also been found to be involved in sensorimotor processing. For example, cortical θ activity correlates with performance in memory taks (Guderian et al., 2009; Kahana et al., 1999). More importantly in the context of this thesis, Bland and colleagues' research, based on rodents, proposed a model in which θ oscillations integrate sensory and motor information with the hippocampus during sensorimotor behavior (Bland and Oddie, 2001; Bland, 2009), acting as a carrier wave (Jensen, 2001). The hippocampus is known to be a major component of short, long-term memory and spatial memory both in rats (Winson, 1978) and in humans (Lega et al., 2012). As transferring animal models to human model is not without discrepancies, Mitchell et al. (2008) argues that unlike rodents, the θ rhythms in the frontal cortex are not directly coupled with hippocampal activity, and that such oscillations are not directly and exclusively generated in the hippocampus, but originate from other sources in the neo-cortex (Cantero et al., 2003). In transfering this model to human, Caplan et al. (2003) found that θ activity, increased during virtual movement as opposed to stillness, when sensory information and motor planning were in flux. Cruikshank et al. (2012) reported higher θ oscillations during movement initiation and execution as compared to stillness; adding that θ band had been overlooked by researchers which were more interested in studying μ activity.

Chapter 3

SMR-BCI and its applications

As the origin of oscillatory activity in the motor cortex has been introduced. In this chapter, we will see how EEG activity can be modulated, first by operant conditionning (i.e. "neurofeedback" section 3.1), then in BCI paradigms (section 3.2). A detailed method SMR BCI is provided, indicating how to translate raw EEG signal into voluntary commands (section 3.4). At last, the section "BCI Applications" (3.5) comprises a desription of the end-user population of BCIs, with the emphasis on locked-in syndrome, their requirement for assistive technology and how BCI answer to those needs.

3.1 Neurofeedback

Biofeedback is a method that utilizes operant conditioning (Thorndike, 1911; Skinner, 1948) to increase or decrease the occurence of a behavior that cannot or is insufficiently supervised by proprioception, and require the participant to build control strategies. Those strategies are meant to persist after the conditioning phase. Neurofeedback, in particular, is a type of biofeedback that solely rely on brain activity. Operant conditioning of SMR rhythms was first demonstrated on cats by (Wyrwicka and Sterman, 1968) and shown to increase sleep quality (Sterman et al., 1970). Interestingly, both monkeys and cat who underwent the SMR training had higher threshold in resisting drug induced seizures (Sterman et al., 1969), therefore suggesting an inhibitory effect of SMR synchronization training. The SMR EEG training was shown to produce similar inhibition in treating epilepsy seizures by Human (Sterman and Friar, 1972).

The development of BCIs, evoked in the next section (3.2), is intertwined with the development of neurofeedback. While both SMR neurofeedback and BCI rely on SMR modulation as an input signal, neurofeedback attempts to provide a therapeutic or behavioral effect, and BCI attempts to provide control over the interface. BCIs for rehabilitation focus on both aspects.

3.2 BCI paradigms

A brain computer interface (BCI) is a device that translate activity produced in the brain into output commands. The term was first advanced by Vidal (1973). Alternatively, brain-machine interface" (BMI, Joseph, 1985) has also been used to characterize such systems, particularly when involving the use of invasive microelectrodes arrays. BCIs are driven by a "paradigm", which is the ensemble of experimental protocols and trainings, combined with the use of specific mental strategies from the user, allowing the system to extract voluntary commands from EEG. The most common EEG paradigms are

- the **P300** paradigm, based on the eliciting of P300 event-related potentials (EEG amplitude)
- the **SCP** paradigm, based on the voluntary shifting the polarity of cortical activity (EEG amplitude)
- the **SMR** paradigm, based on voluntarily modulate the frequency of SMR rhythms (μ and β oscillations in the EEG)
- the **SSVEP** paradigm, in which the frequency of the attended stimuli (with the eyes) is reflected in the occipital cortex (elicited oscillations in the EEG)

The diversification and the introduction of new BCI paradigms, including those that do not strictly rely on CNS activity, led Wolpaw et al. (2002) to advance the term "dependent" and "independent" BCI, term attributed on whether or not the BCI relied on muscular activity. This is for example the case for SSVEP-BCI that relies on neural activity but is by design inherently dependent on muscular control of the eyes. The term "hybrid", was introduced by Graimann et al. (2010) to describe a BCI relying on two different paradigms, but as noted by Wolpaw and Wolpaw (2012), can alternatively be used to describe a BCI relying on both dependent and independent paradigms, therefore casting doubt about its independence. The independence from muscular activity appears to be important for BCIs, at least for most researchers, as shown in the report of a survey of the BCI community stakeholders, in which Nijboer et al. (2013) report that $83.3\,\%$ of the respondents answered that a BCI "must detect brain activity directly (without using signals from peripheral nerves or muscles)".

3.2.1 Characterizing the BCIs

Bitrate

The first characterization of a BCI is it's performance. An estimation of the operational capabilities of BCIs was proposed by evaluating the information transfer rate (ITR; Shannon and Weaver, 1949) or bitrate (estimated in bits/minute; Obermaier et al., 2001), which combines the number of possible choices with the output speed. This is the potential bitrate, but due to the amount of selections required to cancel out false classifier predictions, the bitrate or ITR correct for individual level of control. The criterion for "BCI efficiency" (Kübler et al., 2011b) posits that in a binary classifier, a minimum of 70 % accuracy is required to be able to transmit information and correct errors. Below 70 % the number of false classifier predictions prevents participants to reliably correct for mistakes.

Synchronous vs Asynchronous

There are several classifications for BCI, we already mentioned hybrid and non-hybrid , and mentioned the asynchronous based control (see introduction of section 3). Asynchronous control means that the control over the BCI is self-initiated in opposition to external. But BCIs can fall in each of the classes depending on the design. For example, while modulation of SMR is autonomously produced by the user, a SMR BCI can be in one case "self-paced" if the BCI relies on rest vs motor imagery. It is commonly designed to emit a command after several contingent conditions are reached, such as exceeding a threshold for several seconds ("asynchronous"). In a second case, it can be "externally-paced", when an output is produced every few seconds, with timing restrictions imposed by the BCI ("synchronous"). Such a distinction cannot be found with ERP based BCIs since they are synchronous by essence. They are indeed time-locked to an event and the events are produced externally. The synchronous/asynchronous distinction raises a bigger issue encountered with BCIs in general. In most setups and paradigms, indistinctively from the synchronous or the asynchronous nature of a BCI, connected a user to a BCI forces the user to constantly interact with the device, even in times the interaction is not wanted.

Invasive vs non-invasive

Also it is important to note that in parallel to EEG solutions, invasive BCIs (iBCIs) have been developed. It was first demonstrated by Kennedy and Bakay (1998) that a person with ALS could manipulate spikes in the motor cortex to move a cursor on a unidimensional axis. A significant leap was done when Chapin et al. (1999), using a microelectrode array, enabled a monkey to control a 3-dimensional prosthesis, plus and additional dimension for grasp. The proof-of-concept technology was later on successfully transferred to humans (Hochberg et al., 2006). Long-term studies showed that invasive BCI could work for years, even after the scaring process of brain tissue, which was expected to restrict the long-term operability of the devices (Bartels et al., 2008). Outside from the significant issues related to safety (discussed by Wong et al., 2009) when dealing with iBCIs, non-invasive BCIs have advantages, notably in the field of portability (Zich et al., 2015) and easiness of use (Debener et al., 2012); moreover it is argued that their performance can compete with their invasive counterparts, according to Wolpaw and McFarland (2004).

3.3 SMR BCI

Vidal (1973) had anticipated techniques that bypass the normal output channels to issue commands. Using electromyography (EMG, detection of potentials generated by muscle fiber depolarization), Loeb (1989) developed a system that could send command to a prothesis; yet, this was based on muscle control in the first place. Keirn and Aunon (1990) suggested that a BCI system was feasible by exploiting the various rhythms detected in the brain such as δ, θ α and β oscillations. In fact, a conjunction of factors led to the development to SMR based BCI; it was found that SMR were linked with movement preparation (Pfurtscheller et al., 1976, described in section 2.3.2), that they were measurable on most healty adult participants (Pfurtscheller, 1989), and that such rhythms could be increased through biofeedback (Kuhlman, 1978). Wolpaw and colleagues combined those into a system that could issue commands, introducing the "Wadsworth BCI" (Wolpaw et al., 1986, 1991). Named after their research laboratory ("The Wadsworth Center"), the BCI could detect voluntary modulation of μ rhythms, using bipolar electrodes placed over C3 (or C4 if the participant was left-handed). The feedback on a TFT monitor displayed a ball moving up or down. The height of the ball was defined by the participants' μ activity, and the participants were told to attempt to move ball up or down in a target direction for every trials. No particular instruction else that avoiding muscle artifact was given to the participants, meaning they were expected to implicitly learn the association between feedback and EEG modulation. Having ruled out any contribution from EEG artifacts, Wolpaw et al. (1991) reported various strategies used by the participants to control their μ rhythms (*"thinking about activities (e.g lifing weights) to move the cursor down and thinking about relaxing to move it up"*). The system was calibrated such that producing desyncronizing μ activity steered the ball down while synchronizing μ activity steered it upwards. Interestingly, the authors also report that as training progressed, several participants did no longer need to use mental imageries, but instead just though about moving the ball up or down, showing the success of the implicit learning. The wadsworth BCI then integrated a time dimension, restricting the duration of each trial, and allowing to evaluate BCI performance. The time was represented by the continuous horizontal movement of the ball that took three seconds to move from left to right.

Concurrently, Pfurtscheller and colleagues started in 1991 to develop their own BCI, they named after their laboratory "Graz BCI" (Pfurtscheller et al., 1993). The paradigm and methods were very similar to the first Wadsworth BCI, but instead of opposing mental imagery against rest, it differentiated between two movements imageries, respectiveley left or right finger movements. For this purpose, the feedback was different: a fixation cross appeared in the center of the screen, then the target was cued for 1 second by a rectangle on the right or on the left side of the screen. For the 2 seconds of provided feedback, a cross moved in real-time on the horizontal axis depending on classified EEG signals. Their early results were such that the cursor was in the correct direction at the end of 70 % of the trials.

Since two MI classes restricted the range of possible actions, several attempts have been made to distinguish more than two classes by relying on three dimensions (Kalcher et al., 1996; Scherer et al., 2004; Doud et al., 2011) and even five dimensions (Anderson et al., 1998). The use of more than two motor imagery classes was used to allowed for the design self-paced or "asynchronous" use of the BCI (Lotte et al., 2010), and it and considered by Hema et al. (2011) as a viable option for the control of a wheelchair. A different,but nonetheless potent asynchronous interface was proposed by Blankertz et al. (2006); Müller and Blankertz (2006) called the "Hex-o-spell", allowing to periodically select one out of 6 choices by a one class movement imagery (movement imagery vs rest).

3.4 Methods for SMR BCI

I present here an up-to date description on how to produce outputs from the modulation of SMR in the context of a BCI. This section indirectly refers to concepts introduced in the preceding sections.

3.4.1 EEG setup

Electrode arrangement

In its early findings, SMR rhythms associated with arm and thumb movements were performed with bipolar recordings over C3 and C4 (Jasper and Andrews, 1938; Gastaut et al., 1952), meaning that the amplifier recorded the difference between two electrodes. Currently, electrode caps can have from 8 to 256 electrodes following layouts proportional to the dimensions of the head. Such proportion can be ensured by the use of the 10-20 system, 5-10 or 5-5 systems (Oostenveld and Praamstra, 2001). The electrodes can be regularly dispatched on the head of the user or be more concentrated on certain areas of interest. The electrodes are named after the cortex they are placed over (FP: frontal-pole, F: frontal, C: central, P: parietal, O: occipital, T: temporal), and with a number that increases from the longitudinal fissure. Over the fissure (i.e. the center), the position is coded with the letter "z", then electrodes on the left side are coded with odd numbers and electrodes on the right side are coded with even numbers. For example, the electrode over the motor cortex on the center is named "Cz", then "C3" and "C4" correspond to the left and right cortex somatotopical representation of the arms. The presence of a ground electrode (GND) helps to cancel out electrostatic and electromanetic noise. As EEG recorded signals correspond to small currents traveling through the amplifier, it is important to note that the recorded current travels from electrodes to one reference electrode ("REF"). Positioning the REF electrode has an influence on the recordings (McFarland et al., 1997), and most common positions for the REF are either the nose, earlobes, or mastoid (bone behind the ears). These locations were chosen because they are less sensitive to artifacts and therefore maximize the signal-to-noise ratio (SNR). Nose reference, since it is place exactly in the middle is particularly interesting to compare overall activations between the right and the left cortex. However, using a nose REF comes with practical constraints, since it can obstruct vision and eventually prevent participants to carry glasses. In P300 designs, earlobe electrode can be preferred since the use of a clamp shaped electrode makes it easy to apply. Preferably for SMR-BCIs, the REF is placed on the mastoid electrode, and re-referenced on the opposite mastoid to obtain what we call "linked mastoids".

Increasing the number of electrodes allows to increase the SNR. Since the cortical activity is very diffused when recorded from scalp; using specific cap montage which cover certain areas of interest can be beneficial to increase SNR. The specific methods of spatial filtering are described in section 3.4.3.

Electrode prepping

When applying the electrodes on the skin, a gel is required to ensure a stable conductivity between the skin and the electrode and prevents artifacts or loss of contact produced by movements. The prepping duration is commonly acceptable for 8 to 32 electrodes because its practice is does not exceed 30 min, but since the prepping time is proportional to the number of electrodes, it becomes cumbersome when prepping 64 to 256 electrode caps, requing a significant amount of time prior to an EEG recording.

3.4.2 Acquiring and filtering the EEG

3.4.3 Artifacts in the EEG

Since it records electrical activity, EEG catches currents originating from non-cerebral sources. Some of those sources are produced by activity of the body, in particular muscle activity. As muscle contractions result from muscular fiber membrane depolarization and that these produce strong dipoles, muscle contractions from the shoulder, jaw, mouth, head and face muscles generate strong noise into the EEG signal. The alignment of the sensory cells on the retina generates a dipole which direction changes when the eyeball moves, strongly impacting EEG signal. Mechanically, the eyes also tend to move upward when closing the eyelids, generating blinking artifacts. By placing EOG (for "electrooculographic") electrodes around the eyes can help detect or cancel such influence on cortical EEG. In BCI setups, it is therefore recommended to the participants to remain immobile, reduce as much as possible their muscle activity, especially facial, and to inhibit (or avoid excessive) eye blink reflex during recordings. Transpiration also produces slow drifting of the EEG baseline that can easily filtered out using a high pass filter on low frequencies (e.g. most common are 0.1 and 0.5 Hz). Non-bodily artifacts can be elicited by static, and most importantly electromagnetic noise. The 60 Hz (American continent) or 50 Hz (rest of the world) frequencies in power lines induces electromagnetic currents during recording. The common applied solution is to either apply a low pass below the frequency (e.g. below 45 Hz), or to exclude specifically those frequencies (i.e. a "notch" filter between 48 to 52 Hz).

Signal processing

The raw EEG signal has to follow multiple treatments to be interpreted by machine learning algorithms; thus, what we call "EEG features" are transformation of the signal that are sent to the classifier, allowing training and classification. Krusienski et al. (2012) lists 3 phases for the extraction of features: **1)** signal conditioning **2)** feature extraction **3)** feature conditioning.

Signal conditioning

The raw EEG might contain a certain amount of noise that needs to be removed. Therefore, frequencies that are not of neuronal origin are usually filtered out. Such frequencies can be low frequencies such as signal drift or frequencies over 40 Hz, that have low SNR (Krusienski et al., 2012), are produced by muscular artifacts or relates electromagnetic noise from power lines (50 or 60 Hz, artifacts are detailed in section 3.4.3). In SMR based BCI, the frequencies of interest are μ and β SMR (assuming high-γ is not investigated), the filter would therefore band pass filter the signal between 0.1 Hz and 40 Hz. A narrower band can be selected (e.g. 8-35 Hz for μ to high-β range), but can still be performed in further stages of the analysis. Using a wide filter allows the data to remain interpretable when plotted in average or spectrum.

Artifact rejection, which is part of the signal conditioning can be done directly by identifying the source of the artifacts. For example, many EEG studies place electrode next to the eyes to record eye-movements and eye blink artifacts. Using a threshold on those specific electrode allows to filter out trials or part of trials that are contaminated with eye artifacts. There are other sources of artifacts such as movements or head muscles, a common method is to use a threshold for amplitudes that exceed the neuronal activity (e.g. > 80 uV). Blankertz et al. (2007) also provide methods based on within and between channels variability during trials. This part of the design, should not be overlooked, as it reduces for example the contribution of eye or muscular movents in the EEG, increasing the SNR.

Spatial filtering

Due to the distance and the amount of tissue that separate the source of neuronal activity and the scalp electrode, each electrode records signals from a broad area around its location. Many artifacts also tend to apply noise on several electrodes. In certain cases, the SNR can be increased by using spatial filtering extracting the features from EEG channels.

Historically, the very first EEG measurements were bipolar (two electrodes). With several electrodes connected to one reference, it is possible to perform simple operations on the channels to increase the SNR. McFarland et al. (1997) provide a very informative comparison between a channel referenced to the ear, and multiple spatial filters that are commonly applied. In the context of a SMR modulation paradigm, a clear increase in signed r^2 significance can be obtained by the use of a common average reference ("CAR", subtracting the mean of all channels) or a small or large Laplacian (subtracting the mean of the four surrounding electrodes, small or large referring to the distance separating the electrodes). According to the authors, the best r^2 are obtained (from best to worst): **1)** large Laplacian **2)** CAR **3)** small Laplacian **4)** no spatial filter. Another method for filtering is called "Local average reference" (LAR; Binias and Palus, 2016) consisting in subtracting the average of all surrounding channels in a certain radius around the concerned channel.

There is a different way to proceed to spatial filtering, by performing analysis on the data instead of the electrode location. Those types of filter are called "data-dependent spatial filters". It includes principal component analysis (PCA) and independent component analysis (ICA). Both methods rely on statistical methods to transform the EEG channels into new channels that account for the maximum variance from the original signal, while being uncorrelated to one another (and also independent for ICA). Common spatial patterns (CSP) design is close to the PCA but takes into account the class of the signal (e.g. motor imagery vs rest, left hand vs right hand), and attempts in each transformed channel to maximize the variance of one class while reducing the variance of the other class. In other words, while Laplacian spatial filters attempt to filter EEG signal based on its topographic origin, data-dependent spatial filters create a set of artificial EEG channels that attempt to isolate the different sources of correlated signal. Data-dependent filters have the particularity of not specifically labeling the correlated sources of signal. Yet, those sources can be guessed, and are most likely representing heart rate, eye blinks or more valuably, localized ERS/ERDs. The advantage of using CSP filter lies in the supervised fashion of the algorithm, which allows to maximize the variance of one source in each transformed channel, meaning that it implicitely distinguish the sources on a class-wise fashion (and therefore tied to the MI classes).

3.4.4 data extraction and classification

Feature extraction

In SMR based BCIs, features depend on the number of channels, on time intervals and frequency bands. Depending on the type of pre-existing knowledge on the MI classes and the participants, the features' frequency bands and time interval can be optimized and selected before being sent to the classifier for calibration.

The squaring or the envelope transformation of EEG signal is essential for the detection event-related desychronization or synchronization (ERD/ERS; see section 2.3.2). Unlike ERPs, they are not defined on a time-locked EEG amplitude at a certain time (i.e. 100ms after stimulus onset). ERD/ERS are increase or decrease in amplitude of certain wavelengths, which is progressive and occurs during several seconds. As the obtained signal is oscillating, it is neither possible to take the amplitude at a certain point, which would return random values; nor possible to average them on a certain period, which would return a mean amplitude of zero. To measure the amplitude of a certain frequency, the signal is band-passed to only retain this particular frequency range. As an example, mu waves range between 9-13 Hz, and the channels are band-pass filtered in this frequency. To obtain the band power, there are two methods, an easy method is to square the signal. Another more accurate method is the calculation of the "signal envelope". The signal envelope uses the Hilbert transform with a sliding epoc (e.g. 200ms) to average the amplitude maxima (positive) and minima (negative). The difference between positive and negative envelope provides the frequency amplitude. The feature is obtained by averaging the resulting value in a predefined period (e.g. 1 second) and applying a logarithmic transformation is then applied to reduce normalize the values for machine learning algorithms.

Features range preselection

Using the mean envelope of a channel for the whole duration of a trial can be problematic, because both ERD and ERS can both occur at different times in trials, counterbalancing one another (e.g. ERD followed by an ERS during the same trial). The easy solution is to not do any pre-selection to force the user to choose one by feedback conditioning . A proper method can be applied by restricting the time interval used for averaging to the most significant ERS/ERD. Blankertz et al. (2008) implemented an automatic time interval selection that starts from the most discriminative single frequency, calculated by classwise r^2 calculation, and broadens the band to both sides as long as there is a substantial gain, thus preventing ERD and ERS in the same trial to cancel each other.

Classification

There are two types of approach in the BCI classification. The first approach is a manual classification requiring the experimenter to pick specific features and set a threshold while. All features are analyzed in single factor regressions of the class (e.g. target vs non-target; right hand vs left hand, used in e.g. Lafleur et al., 2013). It provides a signed r^2 value for every feature. Plotting those r^2 plots in topographic heat maps helps the decision. Using such a method made sense in neurofeedback protocols but is currently outdated, and outperformed by algorithm-based or machine learning based methods.

The second approach is to use machine-learning based methods to train a classifier that enables the prediction of the class of the provided features. Before predicting the class, the classifier has to be trained using supervised data. Most SMR-based BCIs use a linear discriminant analysis (LDA) which in many comparisons has been proven to be the most robust to variance in the data (e.g. back to Farwell and Donchin, 1988). Non-linear classifiers such as support-vector machines can also be used, but comparative studies show that the gain in performance and robustness is low for a higher computational cost (for a concise review of pre-processing and classification methods, see Ilyas et al., 2015). With recent improvements, LDA classifiers can also be adapted after classification to better fit variability in the signal using for example pooled mean adaptation Vidaurre et al. (2010). For more than two classes, more complex algorithms can be used (see for example: Lotte et al., 2010). Yet, only in rare cases are the participants able to control a 3-class classifier with a sufficient level of control.

Zero-training classification

Due to the lack of subject-specific knowledge about BCI users, the EEG requires an initial recording of supervized data, otherwise no reliable prediction can be done on the data. Such data is required for training the classifier, and in most BCI protocols requiring the user to initially perform motor imageries without feedback for a certain duration. Training a classifier in these conditions is not optimal, as it was shown that there was a difference between EEG acquired with feedback and without feedback (e.g. Elbert et al., 1991). The use of subject unspecific pre-trained classifiers has been implemented by Blankertz et al. (2007). Since they collected the data of several participants in similar conditions with the same EEG cap, they could train a subject-unspecific classifier from aggregated data of those participants. After a few selections, the real-time adaptation could provide participant with a reliable control over the BCI. The possibility of retraining the classifiers based only on subject-dependent signal allowed to make this initial period a transition phase. Yet, the authors did not report any increase in the performance of the BCI, and that the subject-independent classifiers did not benefit at all for certain individuals. In principle, allowing the user to have feedback from the start reduces the lack of focus of the participants during the calibration phase. Another zero-training classification can be the usef of positively biased feedback. In a study from Acqualagna et al. (2016), the participants received positively biased feedback during the calibration runs. The authors did not find any significant improvement in using this method.

3.4.5 Feedback

The feedback a key element of a BCI. It must remain as clear and simple to reduce sources of confusion or distraction. The initial Wadsworth BCI translated the classifier ouput on the veritcal position of a ball on the monitor, with the time axis from left to right. In the Graz BCI, the classifier output was translated in the position of the ball which could either go left for left hand, right for right hand and up for feet. The main goal of these feedbacks is to organize 3 to 4 seconds periods of BCI control (after the average duration of ERS/ERD). In a trial, a BCI participant receives an initial signal that indicates the beginning of a trial, for about one second. A target cue is provided, indicating the position to reach, or the direction to follow, but in any case, clearly indicating which motor imagery the participant has to perform. The feedback lasts about 3 to 4 seconds and stops. During "classical" calibration trials, no feedback indicating classifier's prediction is provided. a few seconds mark the end of a trial and the beginning of the next one. Those trials are time-restricted, but there are also SMR-BCIs that work based on threshold based methods, in which the ERD or the ERS crosses a threshold for a predetermined number of seconds. For example the "Hex-o-spell" from Blankertz et al. (2006); Müller and Blankertz (2006) or the virtual museum walk by Lotte et al. (2010).

Most BCI interfaces have relied in the visual modality, while it is admitted that Human perception and cognition in the neocortex is essentially multisensory (Ghazanfar and Schroeder, 2006). In a review, Wagner et al. (2013) report that the main secondary modality that has been used is auditory, and more rarely somatosensory. The possibitly to reach other modalities can be critical for providing the system to people in the locked-in-state. The sonification of the classifier's output could be done by changing the pitch of the sound instead of moving a ball on an horizontal or vertical axis. Nijboer et al. (2008) made a comparison between visual and auditory BCI, but instead associated ERD with a "bongo sound" and ERS with a "harp sound". While the accuracy was inferior in the auditory modality in the first session, there was no difference after three sessions, suggesting that auditory feedback requires more learning. Cincotti et al. (2007) used vibrotactile "tactors" placed on the neck and shoulders of their participants, and found that the accuracy in the SMR-BCI was comparable to the auditory and visual modalities. Chatterjee et al. (2007) placed the tactors on different locations and found that the accuracy was higher when the tactor was placed on the limb ipsilateral to the motor imagery, therefore demonstrating an interaction between somatosensory feedback and motor imagery.

3.5 SMR-BCI Applications

In this section, I present the different applications of BCI systems, with a particular emphasis on patients with motor disabilities. BCI systems offer additional output channels on our environment, those additional output channels could have several applications. In an effort to broadly cover the range of applications of BCIs, Wolpaw and Wolpaw (2012) discriminate between five applications of a brain computer interface:

- **Replace**: the BCI can replace a natural output that was lost as the result of injury or disease
- **Restore**: the BCI can restore the output in the case of an injury that affected the nerves, using stimulations electrodes on a non-innervated but functional muscle.
- **Enhance**: the BCI can enhance a natural output, for example by detecting and providing a sound to prevent a lapse of attention while driving
- **Supplement**: adding an additional control output (e.g. a brain switch)
- **Improve**: Interpreting CNS activity could improve the movement of a partially disabled limb.

The *replace*, *restore* and *improve* applications draw the most attention of researchers who attempt to provide solution for people with motor disabilities, while *enhancing* and *supplementing* the motor output are yet gaining more attention, notably from healthy audience. Due to the underlying mechanism of BCIs, and despite strenuous efforts to increase the bitrate of BCIs, the artificial neural channel provided by BCIs has not yet been able to exceed any muscular output channels of a healthy human body (Wolpaw and Wolpaw, 2012; Hart et al., 1998). I will further introduce the condition of people with motor impairements specifically those leading to the locked-in-state. Such people in the LIS can yet truly benefit from BCI development, I thereafer describe wich BCI applications have been reported for use as assisitive technology.

3.5.1 Locked-in syndrome (LIS) and motor disabilities

The term "locked-in-syndrome" (LIS) was first introduced by Plum and Posner (1966); Posner and Plum (2007), which regroup forms of quadriplegia associated with anarthria (inability to speak), and is due to lesions in the brain stem, in the corticospinal and in corticobulbar tracts (see figure 2.6). LIS is used to describe people who cannot communicate with the external world, by moving their limbs or by producing speech. Those people yet retain good cognitive abilities. The LIS is often precised into stages or level, that better describe the patient's situation. Bauer et al. (1979) proposed the following classification:

- **Classical LIS**: total immobility except for vertical eye movements and blinking; preserved consciousness.
- **Incomplete LIS**: when remnants of voluntary motion (excepted eyes and blinking) are present.
- **Total LIS**: Total immobility (including eye movements); with normal EEG during wake or sleep, assuming that consciousness is preserved, since it is not possible to interact with the person.

Additionnaly to this classifcation that is a standard in characterizin the level of LIS, Bauer et al. (1979) also emphasizes their observation that LIS can be either chronic or have a transient character, in which case motor recovery can occur.

To better understand LIS, I provide an overview of the different causes that lead to LIS, and their neurological and physiological consequences on the body.

Stroke and trauma

The most common cause LIS is observed as a consequence of an ischemic or hemorrhagic stroke in the basilar or vertebral arteries, provoking lesions in the ventral pons. A similar effect can result from traumatic injuries leading to the dissection of vertebral or basal arteries (Rae-Grant et al., 1989), or a dissection of the vertebrobasilar axis (Patterson and Grabois, 1986). The consequences of a stroke or trauma are tied to the affected brain area(s). For example affect the damage in the Wenicke or Broca area can impair the understanding and the production of language (Aphasia). In the case of strokes, a comatose episode can occur for several weeks then a recovery to a locked-in state (Laureys et al., 2005).

Motor neuron diseases (MNDs)

The motor neuron disease (MND) subsumes several neurodegenerative disorders of the motor neurons. The most common is Amyotrophic lateral sclerosis (ALS) named by Charcot and Joffory in 1869 (Souza et al., 2009; Kiernan et al., 2011; Mitchell et al., 2008), who reported two cases of lesions in the corticospinal tract associated with muscular palsy. ALS is marked by the degeneration of upper motor neurons (UMN) and lower motor neurons (LMN; Salameh et al., 2015). LMN degeneration leads to weakness and atrophy of the muscles while UMN degeneration leads to stiffness and uncontrolled movements or reflexes of the muscles. Nevertheless, it is important to note that sensation is preserved in ALS (Laureys et al., 2004). When diagnosed, ALS is described depending on its onset location (Mitchell and Borasio, 2001) which can be **1)** bulbar (as described in progressive bulbar palsy and pseudobulbar palsy) **2)** cervical (upper limbs) **3)** lumbar (lower limbs). Modern neuroimagery and genetic evidence support the overlap between ALS and fronto-parietal degeneration (Goldstein and Abrahams, 2013). It was reported by Phukan et al. (2012) that frontotemporal dementia (FTD) is observed in up $14\,\%$ of a sample of 160 ALS patients, while non-demential cognitive impairments could be observed on $40\,\%$ of the sample, although the authors did not use specifically validated scales for ALS such as the ALS Cognitive Behavioral Scale ("ALS CBS", Woolley et al., 2010)) or the Edinburgh Cognitive and Behavior ALS Screen (ECAS; Abrahams et al., 2014. According to statistics conducted for the year 2012-2013, the ALS prevalence rate (per year) is evaluated to 4.7 per $100{,}000$ (Mehta et al., 2016), but when combined with a life expectancy in the US of 79.3 years (The Global Health Observatory, 2016), it provides a lifetime expectancy of 1/270 which is superior to Al-Chalabi et al. (2016)'s estimation of 1/350 for 2013. Additionally, ALS is more common among whites, males (ratio is 1.5 male to 1 female), and persons aged 60-69 years (Mehta et al., 2016). The median survival of patients with the classical form of ALS is about 2 to 3 years from symptom onset (Ohry, 1990; Byrne et al., 2012; Lee et al., 2013), knowing that the diagnosis often requires several months. In the last stages if ALS, respiratory function cannot autonomously be ensured and requires the use of mechanical ventilation. It can be non-invasive, extending life expectancy up to 9 months (Bourke et al., 2006). Later on, invasive ventilation can be required, inplying tracheotomy, which was found to extend life expectancy from about two weeks to 6-17 months (Mustfa et al., 2006; Spataro et al., 2012). Yet, most patients with ALS die due to respiratory failure (Hardiman, 2011).

Other variants of neuron diseases differ from ALS, such as primary lateral sclerosis (PLS) affecting upper motor neurons; progressive muscular atrophy (PMA; D'Amico et al., 2011), affecting lower motor neurons. Two localized variants (sometimes called "bulbar ALS"), that affect the motricity innervated by the medulla oblongata (IX, X and XII, controlling chewing, swallowing and gag reflex), are the progressive bulbar palsy (PBP; Collins, 1900), affecting lower motor neurons, marked by slurring in speech (dysarthria) and difficulty swallowing (dysphagia), progressively leading to a loss of these functions. The other bulbar variant is called pseudobulbar palsy, and affect upper motor neurons, marked by emotional lability (i.e. pathological laughing or crying). Since those MNDs concern only upper or lower motor neurons, the prognosis is better than for ALS, who concern both.

Several other neurological autoimmune diseases can lead to LIS, such as multiple sclerosis (MS), affecting neurons in the brain and in the spinal cord (Goldenberg, 2012); and acute motor axonal neuropathy (AMAN; Mckhann et al., 1993) an acute form a Guillain-Barré syndrome (GBS).

Muscular dystrophy

Muscular dystrophy (MD; Pearson, 1963) is a group of myopathic diseases that are due to genetic mutations. The prevalence for all forms of MDs is estimated between 19.8 to 25.1 per $100\,000$ (Theadom et al., 2014). Duchenne muscular dystrophy is the most common form with a prevalence of $3.2 - 4.6$ per $100\,000$. While MD causes progressive weakness in the musculoskeletal system, depending on the form of a disease it may be mild and progress over a lifetime, or can lead to severe weakness and disabilities over a few years, requiring the use of assistive respiration or pacemaker support.

Cerebral Palsy

Unlike the other conditions evoked, Cerebral palsy (CP) is neither solely accidental nor neurodegenerative. CP describes group of neuromotor disorders that appear during early childhood, affecting principally movements, but that do not further worsen (Rosenbaum et al., 2007); it is marked by abnormal development of the fetal or infant brain, due to prenatal or post-natal injuries, stroke, infection or exposition to toxic substances. In 2007, the prevalence or CP was estimated of $2.4/1\,000$ (Hirtz et al., 2007) and was raised to $11.2/1\,000$ in case of a preterm infancy (Himpens et al., 2008). According to Kent (2013), the symptoms of

CP can be spastic diplegia (muscle stiffness) or spastic tetraplegia (jerking, motor issues); CP present comorbidities, such as epilepsy (28 %), communication issues (58 %) and visual problems (42 %) that the author assumes to be underreported. The level of disability vary from one individual to another, but due to the high prevalence, several patients have strong motor disabilities, and could benefit from BCI technology.

BCI for LIS

Between the first iteration of the P300 speller (Farwell and Donchin, 1988) and the introduction of the speller to patients with MND (Sellers and Donchin, 2006; Nijboer et al., 2008; Hoffmann et al., 2008), its variants enabling virtual painting (Münßinger et al., 2010) or web-browsing (Mugler et al., 2010), it took about 20 years for BCI paradigm to reach its target population (Kübler, 2017). We had to wait a few years for the technology to be transfered at the home of the end-user (Sellers et al., 2010; McCane et al., 2014; Holz et al., 2015; Botrel et al., 2015). Those few studies in which BCIs were installed at the end-user's home, have been reported to increase the quality of life (QoL) of the patient through productivity and with the ability to communicate with the external world. In parallel, SCP based solutions have also been implemented for communication with patients with ALS (Kübler et al., 2001) and later on for web-browsing (Karim et al., 2006; Bensch et al., 2007). As there were already neuroprosthetic assistive technology (AT) relying on EMG, researchers attempted to transfer this non-BCI technology to the field of BCI. For example, Pfurtscheller et al. (2003) showed that hand grasp could be restored based on a combination of SMR-BCI and fonctional electrical stimulation (FES). It was also shown that communication via SMR-BCI was possible with four patients with ALS (Kübler et al., 2005), allowing to maintain quality of life. Another solution could be found via the use of hybrid BCIs. As Rupp et al. (2014) specifies, non-invasive BCI control of a neuroprosthesis is low compared to their non-BCI counterparts (e.g. Hart et al., 1998), since activation of the muscles can be controlled with precision. A meta-analysis from Tai et al. (2008), based on data acquired up to 2006, compares the benefits and limitations of non-BCI assistive technologies as compared to BCI and iBCI-driven solutions. The authors posit that the use of simple mechanical switches has been demonstrated for their clinical relevance, while the use of BCIs as an assistive technology, mostly rely on single-case studies or uncontrolled experiments. It is nowadays still the case since we haven't seen a broad dissemination of the BCI in the hands of it's end-user base. It could first be explained by several factors, such as the BCI inefficiency issue, the cost of the EEG devices (that is now becoming affordable, e.g., OpenEEG[1], OpenBCI[2]), the perpetual evolution of the algorithms

[1]http://openeeg.sourceforge.net/ - Open source project, Accessed March 2017.
[2]http://openbci.com/ - Accessed March 2017

that restrict BCI applications to hightly specific and incrementally developped softwares that can only be maniputated by BCI experts, and more importantly the lack of user-based methods (i.e. UCD; Kübler et al., 2014). Yet another factor is that training patients in using BCI represents a financial and practical efforts from both researchers, patients and families (Neumann and Kübler, 2003). To cite a few, there are additional costs that already weight on patient's families, such as the requirement of caregivers, life-maintaining equipment and treatment. All those factors prevented such devices to be disseminated out of the lab, but as it was observed by Kübler (2017), a growing effort is being made to transfer the technology from the lab to the end-users.

The paradoxal and yet unsatisfying fact for BCI researchers is the fact that BCI efficiency (>70 %) could be reach with classical LIS patients but not with CLIS patients (Birbaumer (2006)). A meta-analysis by Kübler and Birbaumer (2008), reported a total of 29 patients who used BCI to ask yes/no questions using SCP, P300 or SMR based BCIs. In the study, 2 out of 7 CLIS patients were over chance level, for a performance of 59 % and 62 % meaning that no control can be obtained in regard to the minimum level of control ("criterion level", Neumann and Kübler, 2003). These results showed that CLIS could not directly benefit from BCI. As CLIS patients cannot produce voluntary output for days and months, Kübler and Birbaumer (2008) hypothesize patients may "*loose the perception of the contingency between the required physiological behavior and its consequences*", or in other words to the "extinction of goal directed thinking". This hypothesis has recently been challenged by Chaudhary et al. (2017), who could find above chance level response of four patients with CLIS, using fNIRS. Larger studies targeted at CLIS patients, and the dissemination of BCIs to LIS patients might both provide the possibility, yet unfortunate, to observe the communication possibilities through the course of ALS, such that we can better identify and design the best mean of communication for them. SMR-BCIs in particular are investigated for their potential in rehabilitation after brain stroke or trauma, as it might increase the efficacy of rehabilitation protocols by fostering neuroplasticity (e.g. Clerc et al., 2016; Cincotti et al., 2012; Daly and Wolpaw, 2008).

Chapter 4

Variations in SMR BCI performance

After 30 years of constant effort, there have been significant advances in increasing SMR BCI accuracy. Put in relation to the technologic advances that have been made in the field of informatics or genetics, the result is perceived as unexpectedly low. Principally, we could not solve the BCI inefficiency issue, casting applications further away to bringing BCIs to their target sample – end-users. In this chapter, I list the identified predictors and correlates found to explain of variation in BCIs based on SMR rhythms.

4.1 BCI inefficiency

Since the introduction of the first SMR BCIs, the detection equipment and algorithms for non-b constantly refined, but it is estimated that there are a constant percentage of users, estimated between $15\,\%$ and $30\,\%$, who cannot gain control of the BCI (Allison and Neuper, 2010), even after a long learning process. This issue was initially called "BCI illiteracy" (Andrea and Müller, 2007; Vidaurre et al., 2010; Blankertz et al., 2010), but a more accurate expression "BCI inefficiency" was coined (Kübler et al., 2011b) to redirect the cause on the system rather than on the user.

4.2 Models of BCI control

In an effort to provide a global model of the inter-individual variance in the efficiency of BCIs, (see Figure 4.1) Kübler et al. (2011b) proposed a general model that enumerate the four aspects contributing to the control of a BCI:

1. **Individual characteristics** of the BCI user, which includes all dimensions that range from anatomical and neurophysiological to psychological and personality aspects. For

example, it was found that BCI accuracy correlated with strength of resting state μ activity in the motor cortex (Blankertz et al., 2010), correlated with motivation and fear of failure (Kleih and Kübler, 2013; Nijboer et al., 2008), or was predicted by whether persons play a musical instrument (Randolph et al., 2010). Due to the amount of individual characteristics that have been identified, I provide a state-of-the art list and description of performance predictors in SMR-BCI in chapter 5.

2. **Characteristics of the BCI** that encompasses the hardware and the software involved in the system. Providing a decent level of control depends on the choice of a correct BCI amplifier and electrodes setup, combined with software and algorithms that extract relevant information from the acquired EEG signal. The choice of design also weights on the resulting performance. This is best illustrated by the use of co adaptive learning designs, that considerably reduced the training duration (Krauledat et al., 2008), including the adaptation of the system to the user (i.e. "co-adaptive calibration", Vidaurre et al., 2011b).

3. **Feedback and instructions** that are an essential (and often overlooked) part of the BCI control. Instruction directly impact the user's understanding of the BCI output. In combination with a good feedback, it can reduce miscommunication issues. For this purpose, one can suggest the use of user centered design (UCD: Kübler et al., 2014), minding the target population which can either be healthy individuals as well as LIS. The time aspect of the feedback is concerned, whether the feedback is provided in real time, continuously or periodically depending on the paradigm; but also whether the interface adapts properly to specific cases such as the detection of errors or responding to the user's attention levels.

4. **The Application** of the BCI-controlled system. In this sections falls several criteria such as the number of possible outputs. It is obvious that increasing the number of classes in a SMR paradigm greatly increases the difficulty to control the BCI (i.e. Doud et al., 2011). Another criteria is the nature of the output commands; Wolpaw and Wolpaw (2012) accurately formulate an essential problematic in designing applications for BCIs: "*Goal selection or process control?* "This question can be developped as following: should the BCI user control every little step of an action, (e.g. by sending direction to a robot arm for pressing a button) or should the user only send higher order commands (such as "press the button") and have those little step automatically covered.

This model indeed attempts to gather all the elements that can explain the inter-individual variance in the BCI users' performance. Such characteristics can fall in one of the four aspects.

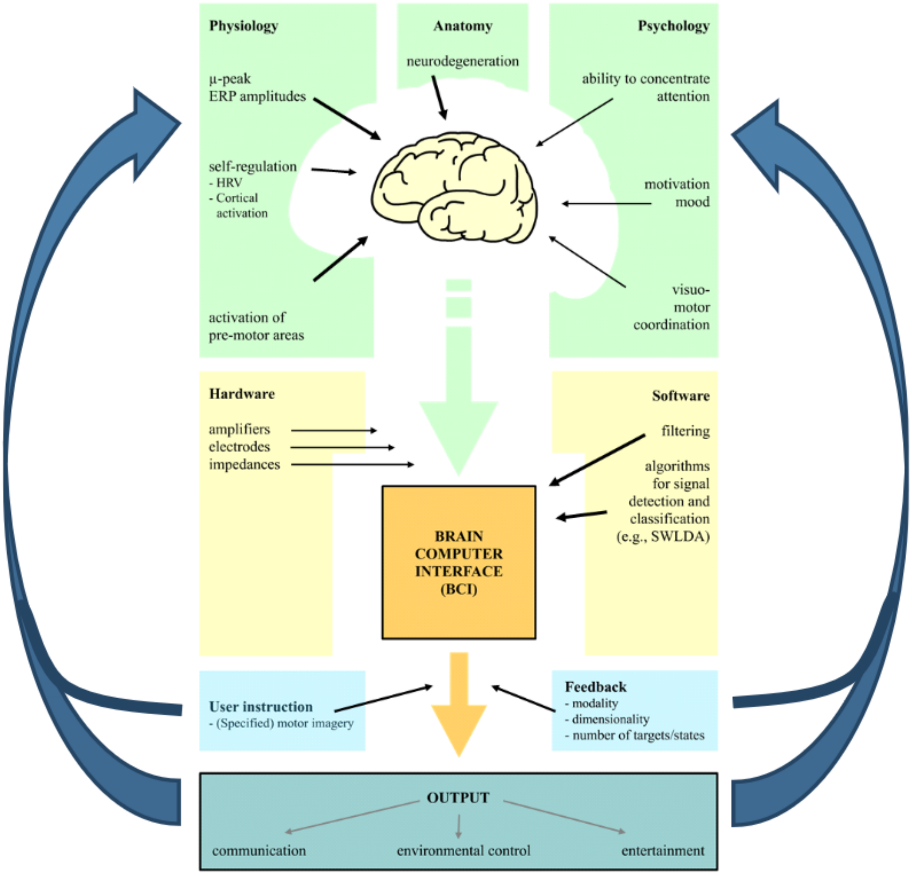

Figure 4.1 A model of BCI-control comprised of 4 aspects: individual characteristics, BCI characteristics, feedback and instruction, BCI-controlled application. Colours serve for distinction of categories only. Boldness of black arrows indicates possible strength of influence on BCI control (from Kübler et al., 2011a)

While previous research thoroughly investigated individual or BCI characteristics, there is less emphasis put on the feedback and instructions and even less on the application. It was yet shown that in SMR-BCI design, the instructions do matter (e.g. kinesthetic motor imageries Neuper et al., 2005) and the application (e.g. virtual environments Leeb et al., 2007) are both related with higher performance.

To refine future or past investigation of the variables explaining the variance in BCI accuracy, Grosse-Wentrup and Schölkopf (2013) proposed to assess those variables following four different angles or characterization:

1. The **type of explanatory variable**. By describing whether the variable is for example neuroanatomical or psychological, whether they are subject to change or whether they are stable over time. It is important to attempt to well identify the properties of the variables, such that it can be known whether they could potentially be modulated in further experimental setups.

2. Whether it **causes or correlates** with performance. By this, Grosse-Wentrup and Schölkopf stresses the importance of not confounding causality and correlation, which is an important issue when reporting sources of variations of SMR-BCI accuracy.

3. The **Inter- or Intra-subject variation**, which are two dimensions that, according to Grosse-Wentrup and Schölkopf (2013) should be both reported, as they lead to different strategies in respectively approaching paradigms and participants in a BCI. The inter-subject variation explain variance over all participants globally, implicitly assuming there are invariant traits associated with SMR-BCI accuracy. The intra-subject variation focuses on individual changes occurring over time, such as between the BCI sessions or the BCI trials.

4. Whether the study concerns **healthy participants or patients**, which present different conditions, constrains and expectations of the BCI.

By using this approach, the authors firstly suggest that the variables explaining variability of the BCI should be clearly identified in both their nature, whether they are stable or evolving over time, which can be short-term or long term. A correct identification of those variables might therefore help. The second distinction given suggests that researchers should be precise on whether any newly found variable causes the variability, whether they are a consequence or that both are related in a more complex relationship. The third distinction between inter- and intra-individual variability allows for a better design of SMR-BCI learning strategies. For example, we could hypothesize a variable (e.g. hypothetically: δ band power) that predicts intra-individual performance, but that only applies on 10 % of the participants. It is likely that researchers could overlook the importance of this variable if only one of the inter- or intra-individual analysis is performed. Finally, it is possible to consider the approach from Grosse-Wentrup and Schölkopf (2013) as guidelines to properly describe different predictors, as they additionnaly stress the fact that the predictors should mention whether they concern healthy participants or patients, especially since the physical, mental and environmental conditions of the target patient population of the BCI strongly differ when compared to our common sample of healthy undergraduate students. Those guidelines were strictly followed in elaborating the cross table of SMR Predictors and correlates for SMR BCI accuracy (in the next chapter).

4.3 How to do we learn to control the BCI?

An important characteristic of both instructions and feedback for SMR-BCI is that they are carefully designed to allow for the learning of SMR modulation. According to Lacroix and Gowen (1981); Lacroix (1986), learning comes in a dual-process model, based on feeding forward a strategies and validating them by feedback, in a co-dependency loop. When the feedback is negative, the participant must find a new strategy, whereas a positive strategy motivates to keep the current strategy. This model underlines the importance of the instructions given to the BCI before starting a session, and may condition the leaning of an effective strategy. It also supports that participants should have a mindset that foster the elaboration and testing of accurate strategies. Moreover, in this process, there is a transfer of existing strategies (e.g. Schmidt and Young, 1986). From those two inferences from the dual-process model, it could be hypothesized be that individual characteristics of BCI participants, such as personality traits, level of physical activity or proficiency in certain motor or cognitive skills might contribute to the learning of a BCI. This questions motivated the conduct of this dissertation which revolves around individual predictors for SMR-BCI performance.

Chapter 5

Individual Predictors for SMR-BCI Performance

The goals that foster BCI research comprises the wish to increase the BCI performance to reduced or prevent BCI inefficiency. I present here the current predictors that have been found to significantly predict or correlate with SMR-BCI accuracy. There are several other studies that reported performance predictors of P300-BCI (e.g. Attention; Riccio et al., 2013) and SCP-BCIs (e.g. Kübler and Birbaumer, 2008). While those studies are of great interest, it must be stressed that P300 and SCP paradigms are strictly different paradigms, and that assuming predictors indiscriminately to apply to all paradigms would lead to wrong assumptions, further damaging the studies attempting to base their experimental on this knowledge. Therefore, I omitted from this review the predictors that correlated with other paradigms of BCI.

The studies collected during literature review could be characterized after on the origin or the reported variables, temporal magnitude, participant sample, and so forth. Similar characteristics of the predictors could be observed and led me to draw categories based on the "type of explanatory variable" of the predictors (in bold):

- **Psychological** or **behavioral** factors, which should be interpreted in their respective temporal dimension (transitional/state or durable/trait).
  - Task engagement (attention levels)
  - Locus of Control
  - Motivation and affective variables
- **Visual**, **kinesthetic** and **spatial** characteristics systematically linked with **motor function**

- **Neurophysiological** factors, complex or simple, principally involving μ, θ, β and γ oscillations obtained by **EEG** or by **functional MRI**.
- **Neuroanatomical** properties of motor-related or subcortical areas of the cortex, acquired by MRI imagery
- One of the variable was not related to the participant itself but by the voluntary and reversible effect of external forces (i.e. drug intake), this specific factor was labeled **environmental**.

Certain studies, report predictors that fall into several categories. For example, the study of Jeunet et al. (2015) approached different predictors from different angles (psychology, spatial abilities and neurophysiology). In this chapter, those studies will thus appear in different categories represented by the following sections, but will only be fully described once:**1)** Psychological factors **2)** Visual, Kinesthetic and spatial characteristics **3)** Neurophysiological oscillatory patterns **4)** Anatomical and functional MRI

5.1 Psychological factors

Pychological variables ranged from the transitional time level to the durable time level. We might be inclined to attempt to define them as either state or traits. (Chaplin et al., 1988) provide a very meaningful description of twose two concepts. *"Prototypical traits are stable, long-lasting and internally caused. Prototypical states are temporary, brief and caused by external circumstances"*. By "prototypical" Chaplin and colleagues mean that both *traits* and *states* are defined in ideal attribute value. While the boundary between a *state* and a *trait* is fuzzy in practice, the authors note that those concepts are defined to serve a specific goal: *states* are behaviors that are linked to the situation and can be manipulated; *traits* allows us to predict the behavior from previous knowledge. Providing this definition, it is not possible to accurately label all *transitional-psychological* variables as states and all *durable-psychological* variables as traits. For example, the "attention level" predictor could be labeled as a trait; the "locus of control" as a trait; the "fear of incompetence in the BCI" falls into a grey area in which it is both a trait and a state. Indeed, the "fear of incompetence" could be both manipulated and used predict the outcome. I thus believed that labelling the variables as states or traits was not inherently required for the classification of the predictor variables.

5.1.1 Task engagement and attention

It is evident that a certain degree of attention is required to operate a SMR BCI, as an inattentive individual not even paying attention to the interface, or not trying to modulate his SMR rhythms would naturally dramatically reduce the outcome performance. When in this section I mention attention levels, it should be naturally assumed that the participants in the reported studies actively attended to the tasks, meaning that the definition of *attention* can be estimated between *mildly* attentive to *very* attentive, or from *attentive with some disruptions* to *attentive without interruption*.

The first large scale investigation of psychological predictors was done by Hammer et al. (2012), measuring total of 83 participants in two locations (Tübingen and Berlin, Germany). Prior to conducting a SMR-BCI session, all participants filled a number of psychometric tests, including personality, cognitive, learning and motor performance tests. In two-hands visuo-motor coordination task (2HAND, Schuhfried; in this dissertation called VMC), participants used two joystick controllers, then two knob to controllers to steer a ball through narrow two-dimensional paths. The "mean error duration" refers to the time the ball was outside the path. The authors found that the "mean error duration" in a two hand visuo-motor coordination task and the ability to concentrate on a task (AHA) predicted the $11\,\%$ of the BCI performance. "Mean error duration", was positively correlated ($r = .42$) with BCI performance , and since the variable was standardized by the experimentation software, a positive correlation indicated that people who made fewer mistakes had higher performance. AHA was also positively correlated ($r = .50$) with BCI performance, and also intercorrelated with "mean error duration" ($r = .49$). Age was correlated with BCI accuracy ($r = -.23$). To account for non-normally distributed age, the authors created two age groups, below or over 40 years old. In a logistic regression analysis, the authors found that "mean error duration" predicted $11\,\%$ of the variance and AHA predicted $19\,\%$ of the variance (AHA was calculated in a smaller group $n = 40$). No correlation was reported for SMR Predictor but including it in the model with "mean error duration", AHA and age group allowed for a prediction of $64.3\,\%$ of the variance. The AHA test measured the "attitudes towards work" (from German *"Arbeitshaltungen"*) can be interpreted as a "very long and fastidious task" (personal communication with Kleih, S. in 2015). The authors yet noted that the AHA score reflected the ability to concentrate. The study provided new evidence that attention was positively related with SMR-BCI performance. In a replication study with N = 32 participants, Hammer et al. (2014) found a moderate ($r = .36$) correlation between "mean error duration" (ranked and standardized) and BCI accuracy but no correlation with AHA. Instead they found a negative correlation ($r = -.41$) with the "attentional impulsivity" subscale of the Baratt impulsiveness scale (BIS-15, Spinella, 2007, German translation from Meule et al., 2011) which did not pass Bonferonni correction and was, interrestingly, negatively intercorrelated $r = -.39$ with the mean error duration. Yet, a regression model including "mean error duration" and "attentional impulsivity" explained $20\,\%$ of the variance and $8\,\%$ of the variance without "attentional impulsivity". While the study did not replicate the correlation with attentional levels it successfully replicated mean error duration as a predictor for BCI performance.

In another study directly investigated the attentional levels, Grosse-Wentrup (2011) found the presence of γ oscillations concurrently activated with μ rhythms in a SMR paradigm. After demonstrating a casual inference of the γ oscillations on the SMR modulation, the author suggested that the presence the shift of theta activity from centro parietal to frontal reflects attentional processes. Further on, Grosse-Wentrup and Sch??lkopf (2012) hypothesized that the presence of γ power predicted whether a subject is in a state of mind beneficial for operating the BCI and implemented it into a pilot study (Grosse-Wentrup, 2011), and found that two out of the 3 participants (the third participant being discarded for muscular artifacts) were able to learn to modulate their theta activity. A decrease in frontal theta lead to increased resting μ over the SMR. More than showing that γ can predict SMR BCI performance, it shows that attention, expressed by frontal theta activity, plays a casual role, yet undefined, in the modulation of SMR.

The predictor related to meditation practice cannot really placed within a psychological component and neither in a visual, kinesthetic and spatial characteristics due to the fact that the meditation methods are heterogenous. For the example of Yoga, there are different forms that include more or less physical practice and visualization. But such practices are known to reduce stress and increase attentional abilities (Jensen et al., 2012). Also the authors of the studies did not report any standardized variables to evaluate the effect of meditation on any dimension other than SMR-BCI. Mind-body awareness training (MBAT) has been found to correlate with SMR-BCI accuracy, in a study with N = 36 healthy participants by Cassady et al. (2014). The authors recruited in locals yoga club n = 12 participants who practiced diverse forms of MBAT training at least two times per week for at least one year. The forms of MBAT were various and included different ranging from "as Yoga Nidra and Vinyasa in addition to Reiki (ed. a visualization healing method), Mindfulness, and Transcendental Meditation". The other n = 24 participants were healthy controls (CG) who had in their lifetime experienced less than ten MBAT sessions. The authors found that the MBAT participants achieved higher performances in the left vs right hand MI-BCI at the end of four BCI sessions ($82\,\%$), as compared to the CG ($63\,\%$). The authors associated this difference to the practice of yoga and meditative techniques, which is known to alter the resting alpha and beta frequencies (Hebert et al., 2005; Aftanas and Golocheikine, 2002; Mason et al., 1997). The authors further suggested that the effect was due to the process of learning particular mental techniques that *"provide subjects with the experience and practice of modulating their sensorimotor rhythms prior to even participating in a BCI task"* (Cassady et al., 2014). While the relationship between SMR and meditative practice was not further detailed by the authors, we can see that meditation practitionners performed dramatically better than the CG. All the MBAT group ($n = 12$) could reach the criterion of BCI efficiency, while the mean of CG was under the criterion. Nevertheless, the study pose a few methodological problems, since the experimenters did not mention whether the participants were matched for age and sex. The authors also chose to report t-tests without accounting for the time (for example using an ANOVA with repeated measures), and therefore, it is not possible to know whether the samples were significantly different on session 1. Yet, the result showed that MBAT practice offered a very promising direction of intervention for reducing BCI inefficiency. The conduction of well controlled studies or the MBAT training of participants might provide additional evidence for the identification of related predictors.

5.1.2 Locus of control

The locus of control (LOC) ("generalized expectancies of internal versus external control of reinforcement", Rotter, 1966) is a concept tied to the contingency between a behavior and the associated reward. If an individual perceives that a reward is contingent with his or her own behavior, the control is considered as being dependent on self-produced actions; the locus of control is internal. But if the reward is independent from his or her own actions, then the individual perceives that the reward is attributed by external forces such as bad luck or coincidence; the locus of control is external. In the case of a BCI, the perception of the LOC can be defined on a scale from external to internal depending on the probability of success of the BCI. The LOC has consequences on reinforcement scenarios, such as the leaning of new skills (for further details, see Rotter, 1966). The LOC is a concept very close to the concept of sense of agency. While the LOC is tied to a reward, the sense of agency is the sense of experiencing self as the agent of our own actions (Gallagher, 2000). A well known experiment that illustrates the sense of agency is the "alien hand" experiment (Nielsen, 1963), in which participants had to draw lines while receiving deceitful feedback of their hands using a set of mirrors. After a practice period, the mirror would be secretely flipped and the participants instead saw the hand of the experimenter who would produce intentional mistakes by drifting the hand on the right. While the participants made unconscious appropriate movements with their own hand to the left to correct the perceived mistakes, they still genuinely believed the hand they saw to be theirs. This experiment revealed that the visual representation of the hand dominated its kinesthetic representation. It shows that the sense of agency is a representation built upon different modalities and that can in this study could be intelligently manipulated by the experimenters. As it is typical in cases of schizophrenia to observe disturbances in the sense of agency with individuals failing to properly attribute themselves as the source of their actions, Synofzik et al. (2008) investigated the sense of agency based on a model that would integrate mistakes in attribution. The authors proposed a "comparator model" of agency, which is built upon a feed forward loop (error monitoring of the expectation) and feedback (sensory feedback) loop. The comparator model provided by the authors can also explain the "self despite mismatch argument" which is a recurring pattern in SMR-BCI training of BCI novices. During the first runs with feedback, the experimenters must convince the participants that they are in control of the feedback. This truth being more virtual than actual in many cases, as it can take several sessions for the participant to obtain more than random control over the BCI; and some never reach significance. The neural substrate for the sense of agency is widely distributed in the brain, David et al. (2008) reviews areas implied in the sense of agency, located using fMRI and positron emission tomography (PET), listing the supplementary motor area (SMA), the ventral premotor cortex, (vPMC; Jeannerod, 2004) the dorsolateral prefrontal cortex (dPFC), the posterior parietal cortex (PPC; Fink et al., 1999), the cerebellum (Blakemore et al., 2001; Leube et al., 2003) and the insula (Farrer and Frith, 2002; Farrer et al., 2003). David et al. (2008) suggest a classification of these areas into two groups: the first group is a network of sensorimotor transformations and motor control (vPMC, SMA, cerebellum), representing the executive function; the second group containing the PFC representing the supervisory functions. The LOC can be interpreted as an inference of the sense of agency associated with the notion of control and projected on a dimension that ranges between internal and external. Based on the neural substrate of sense of agency, we can suggest that, similarly, the LOC, in the context of SMR, implies the interaction the neural substrate of motor control with frontal executive evaluation to adjust whether the LOC is internal or external.

Burde and Blankertz (2006) evaluated $N = 17$ participants who filled questionnaire assessing the LOC using IPC questionnaires (Krampen and Levenson, 1981) for internal and external LOC. They also filled the KUT ("Kontrollüberzeugungen im Umgang mit Technik", German for "locus of control in dealing with technology"; Beier, 2004). In the subsequent SMR BCI session, they found a one-sided correlation ($r = .59$) between KUT and BCI accuracy, suggesting that people with self-confidence in technology perform better.

Witte et al. (2013) found another relation with KUT in a study involving neurofeedback training. The authors asked $N = 10$ participants to fill the KUT scale, then modulate their μ power on Cz during six runs of three minutes. A negative correlation of $r = -.69$ between KUT and μ band power was found, which led the authors to conclude that participants with higher confidence might use additional cognitive resources, which then became counterproductive in performing better with the BCI. The authors concluded that in SMR-BCI setups, the participants should be instructed to relax and avoid forcing mastery.

Jeunet et al. (2015) assessed 18 participants in 6 mental imagery (MI) BCI sessions. The type of BCI was meant to broadly cover the range of possibilities in using MI-BCIs, and used an unusual combination of three different types of MIs: **1)** left hand motor imagery **2)** mental rotation **3)** mental subtraction. The authors spread the assessement of tests and scales in between the sessions, in a pseudo-random fashion. Among those test were the 16 Personality Factors ("16-PF-5", Cattell and P. Cattell, 1995), the learning style inventory ("LSI", Kolb, 1999) and a mental rotation test (Vandenberg and Kuse, 1978). They found that "tension", "abstractedness ability", "self-reliance" (dimensions of the 16-PF), "learning style (active/reflective learners)" and "mental rotation score" to correlate with SMR-BCI accuracy. The authors noted that both "self-reliance" and "tension" were predictors of a person's ability to acquire new skills Jeunet (2016), while "self-reliance" has been associated with LOC and mediated with psychological adjustment to life stress (Funch and Marshall, 1984).

Interestingly, the results about the LOC and the self-reliance point in the direction of learning. It appears that previous beliefs and expectations of performance in the accuracy of the BCI have an effect on the learning of SMR modulation. No particular hypothesis can yet be advanced, but further investigations could attempt to explain why people with higher self-confidence in BCI are better able to perform better in SMR- or MI-BCI (Burde and Blankertz, 2006; Jeunet et al., 2015) and people with lower self-confidence are better able to synchronize their μ rhythms (Witte et al., 2013).

5.1.3 Motivation and affective variables

Motivation is what leads our behavior and provide the mental energy to achieve goals (Heckhausen, 1977). We can distinguish between an intrinsic form and extrinsic form of motivation. The first, intrinsic, means that the individual is energized by the interest of doing the activity, as the reward lies in the activity itself. Extrinsic motivation describes a task for which the motivation is acquired by external rewards such as money or status. The interesting part of this distinction is that intrinsically motivated individuals show more interest, confidence and a higher persistence on the task leading to higher performance (Heckhausen, 1977). In the case of BCIs, those two forms of motivation can be simply illustrated by evoking the case of healthy students who have to modulate their SMR modulation in experimental studies that can last several hours spread over several days. Those are recruited for a monetary reward and might show different motivation as compared to patient samples with paralysis who perceive the BCI as a mean to acquire a new control output, or participate to the research effort by empathy for other patients. Kleih and Kübler (2013) manipulated participants in their "motivation-to-help", by preceding the P300 BCI session with **1)** either a technical presentation on the BCI or **2)** a presentation focused on how important BCI volunteers were for the development of BCI benefiting for paralyzed end-users. The authors, who then separated the sample in "highly able to take others' perspective" (HAPT) aptitude and "less able to take others' perspective" (LAPT), found that the high aptitude group also showed a higher empathetic concern, but not a higher motivation. Partcipants in the LAPT group had higher P300 amplitude. The authors suggested that the empathetic concern determined the participants' emotional involvement and was therefore reducing the allocated attention on the task. These results did not allow to conclude on motivation, but suggested that a non-emotional state of mind could be recommended to increase allocated attention to the BCI task.

To address patient populations with visual impairments or a loss of motor control of the eyes, Nijboer et al. (2008) compared a visual and an auditory feedback for $N = 16$ participants in three sessions of SMR-BCI. Although they did not find an effect of modality on performance, they found interesting results in the questionnaire for current motivation (Rheinberg et al., 2001, adapted for BCI). The motivation contained several subscales: **1)** "mastery confidence", indicating whether the session would be successful **2)** "fear of incompetence" **3)** "interest" in the training **4)** "challenge", whether the participant considered his current experience being challenging **5)** "mood". The authors found through multiple regressions that "mood" and "mastery confidence" predicted positively the performance in the visual modality of the SMR-BCI, while "fear of incompetence" predicted it negatively. The results were partially replicated in a study relying on a bigger sample. Kleih and Kübler (2013) collected an impressing sample of $N = 51$ healthy participants and $N = 11$ stroke which practice SMR-BCI patients in 4 to 8 sessions. The authors found a positive Spearman correlation between SMR-BCI performance and "interest" $\rho = .53$, and a negative correlation for "incompetence fear" $\rho = -.43$ in healthy sample. For the patient sample, the authors reported positive correlation of SMR-BCI performance with "mastery confidence" $\rho = .80$, and with "challenge" $\rho = .83$. Those two studies on motivation indicated that there is an importance of motivational aspects in the learning of a SMR-BCI, showing that a higher motivation is associated with better performance and that other components of motivation such as interest, challenge or the fear of incompetence also relate with performance. Additionaly, it must be noted that "interest" correlated with SMR-BCI accuray in the healthy sample, showing that intrinsically motivated participants performed better in the BCI. Nonetheless, it must be stressed that the scales were systematically filled between runs in both studies, an that no independence between the predictors and dependent variable (BCI performance) can be assumed from these results.

Investigating the motivational aspect of feedback characteristics, not in term of modality, but in term of virtualization, Leeb et al. (2007) trained 10 participants in SMR-BCI sessions. The participants attended three cue based sessions using smileys on a monitor (CF) and two sessions in which the BCI allowed the exploration of an apartment either in on a monitor (TFT) or in a 3D interactive virtual environment (iVE). The performance was higher in the iVE as compared to TFT, which was marginally higher to CF ($p = .050$). The authors concluded that participants were more motivated during the virtual apartment task (+5 % TFT and +10 % iVE) and therefore more engaged in the task. It is possible that the participants were intrinsically motivated in the task, which was engaging, in comparison to a non-engaging task that reward the participant with smileys.

Jeunet et al. (2015) in their MI-BCI study found among their results (that were previously introduced in section 5.1.2) that the "active/reflective" dimension of the learning scale (ILS) predicted the BCI performance. The "active/reflective" was present in the regression models and showed that active learners were more efficient in controlling the BCI. Jeunet (2016) mentions Felder and Silverman (1988), according to which "active/reflective" dimensions are closely related to extravert/introvert according to the Jung-Myers-Briggs model (Briggs and Myers, 1962). Active learners experiment and practice while reflective learners need to passively think of their experience. According to this distinction, the lower performance of "reflective" learners could be explained by the fast pace of the BCI trials, that prevent times of reflexion (e.g. 4 seconds of SMR modulation control every 10 sec), that may favor practice oriented "active" learners.

5.2 Visual, kinesthetic and spatial characteristics of the motor function

In the previous sections we have seen that the SMR rhythms can be found over the motor cortical areas (see section 2.3.2) and that the SMR-BCI was built on exploiting SMR rhythms (see section 3.3). As we saw that controlling the BCI requires the use of efficient motor strategies, as explained in the dual-process model by Lacroix and Gowen, 1981, the iterative strategies elaborated when attempting to modulate the SMR appear decisive in its learning. The motor loop (section 2.3.1) shows that the prepartion of a voluntary movement involves two secondary loops. It was demonstrated (for review, see Andersen et al., 1997) that the sensory information from different modalities (visual, sensory, auditory) converge in the PPC, allowing to code the spatial locations that are involved in movement.

A differentiation between different motor imagery strategies was done by Neuper et al. (2005) with $N = 14$ participants. The authors gave different motor imagery strategies to the participants **1)** kinesthetic motor imagery (MIK)[1] **2)** visual motor imagery (MIV) **3)** motor execution (ME) and **4)** observation of a movement (OOM). Besides the fact that ME return the best prediction accuracy ($80\,\%$), the authors found MIK ($67\,\%$) returned higher performance as compared to MIV ($56\,\%$). Due to the low number of runs per class (i.e. $n = 40$), the true chance level was high (using Müller-Putz et al., 2008, I estimated the true chance level as $64.8\,\%$)[2], meaning that MIV did not perform better than chance. Yet, the authors recommended to perform kinesthetical motor imageries.

Vuckovic and Osuagwu (2013) attempted to verify the recommendations of Neuper et al. (2005). To proceed the other compared kinesthetic motor imageries to visual motor imageries (KVIQ) in the context of an SMR-BCI. The authors gave kinesthetic (KI) and visual (VI) motor imagery questionnaires before starting a SMR-BCI which alternated simple-imageries or goal-oriented imageries. The differences between simple imageries and goal oriented imageries were quite similar (i.e. SI: grasp a mug laterally; GOI: grasp a mug and remove it from the table) and the difference in the results were minor. The KVIQ (Malouin et al., 2007) asked the participant to perform a contraction of a group of muscles showed by the experimenter (e.g. raise the arm vertically), then repeat it mentally, and then rate the vividness of the imagery on a visual or kinesthetic a scale ranging from 0 to 5. The questionnaire involved 17 different group of muscle. Vuckovic and Osuagwu (2013) found a moderate-strong correlation $r = .53$ between kinesthetic imagery score and the performance in the simple imagery task, while the correlation was lower for visual imagery $r = .17$. Moreover, the authors add that comparatively to using SI, using GOI was detrimental for good performers, while GOI was beneficial for low performers.

This disctinction between visual and kinesthetic motor imageries can be approached from a neurophysiological point of view. A recent fMRI study by Guillot et al. (2009) showed that kinesthetic motor imagery yielded more activity in motor ares and the inferior parietal lobule, while visual motor imagery recruited occipital and superior parietal lobules. I will later evoke the functional and anatomic association with motor areas in the context of SMR (sections 5.3 and 5.4). The association between kinesthetic motor imagery and motor areas may supports the evidence of Neuper et al. (2005) a MIK on SMR rhythms.

[1] In this dissertation, the abbreviation MI was used for "mental imagery", and therefore, "motor imagery" was not abbreviated

[2] Using $\alpha = 0.05$, $n = 40$, $p = .5$, using "norminv" for Matlab or "qnorm" for R

chance thresholds = $p \pm \sqrt{\frac{(p \cdot (1-p))}{(n+4)}} \cdot norminv(1-(\alpha)/2)$

A distinction between visual and kinesthetic can also be found in education for providing tools to better identify stereotypical learning types. Gardner (1993) proposed a "theory of multiple intelligence" that initially described seven distinct types of skills that are more or less expressed by individuals. Among the seven, there was the "bodily-kinesthetic" (learning though physical interaction) and "spatial" (learning through visualization). While the theory that was revised multiple times in a decade (Gardner, 2006) and had influence on education guidelines in the US, found dissonant voices denoting its absolute lack of empirical support (Waterhouse, 2006), we can nevertheless estimate that kinesthetic and the spatial abilities are can be considered as different psychological characteristics.

Fitts (1951) noted a difference between interoceptive and exteroceptive feedback, noting that visual control is important when learning a new "perceptual-motor-task", while later on, when the skill is integrated, the kinesthetic modality becomes more prevalent. Based on this statement, Fleishman and Rich (1963) showed a very interresting relationship in a study with $N = 40$ participants who performed 10 runs of two-hand coordination (THC), aerial orientation (Guilford and Lacey (1947)) and kinesthetic sensitivity (estimating the weight of cylinders while blindfolded). The authors found that on run one, the THC correlated with the aerial orientation test ($r = .36$) but was not significant after run 3. In opposition, kinesthetic sensitivity became positively correlated from run 7, reaching a highest correlation on run 10 ($r = .40$). Interestingly, this study showed that the association of the THC correlate was different on different time periods, showing that those characteristics could also apply in investigating the SMR predictors.

Jeunet et al. (2015), found that mental rotation score and abstractedness (imaginative, absent minded, impractical opposed to practical and solution oriented) correlated positively with MI-BCI accuracy. The mental rotation test is a task in which a cue 3 dimensional (3D) shape and four rotations are displayed on the screen. Out of the four selectable shapes, two are rotations of the shape (correct answer) and two others are mirror images of rotations of the shape (distractors). The test is performed using five different sets of four items (Vandenberg and Kuse, 1978). A link between mental rotation and spatial abilities can clearly be established when accounting for the involvement of the dorsal premotor cortex (dPM) during mental rotation task (Lamm et al., 2007). Under the scope of fMRI and PET investigations, the activations of the dPM can be viewed under two group of hypotheses. The first group is that the dPM is linked to motor simulation, when hands or other body parts are involved (e.g. Ehrsson, 2003), and that those are triggered by simulation of movements (e.g. Chao and Martin, 2000) following Gibson's theory of affordance (Gibson, 1979), or by the anticipation of the consequences of the movement (e.g. Wolpert and Kawato, 1998). The second hypothesis, is that the dPM activation is simply caused by eye movements (e.g. Carpenter et al., 1999).

Assuming the hypotheses of the first group, it shows a connection between spatio-motor imagination abilities and MI based BCI, with the possible involvement of motor simulations produced by the hands in both the left hand imagery or the mental rotation tasks. Jeunet (2016) link spatial abilities and mental rotation by first stating that spatial abilities are better when having experience in playing video games (Subrahmanyam and Greenfield, 1994). Another study from Randolph (2012, described later in this section) found a moderate correlation of $r = .42$ between video game experience and SMR-BCI performance, and Dorval and Pfipin (1986) found that visuo-spatial abilities could be improved by playing a 3D video game. Feng et al. (2007) found that mental rotation scores were increased after playing 10 hours of an action first-person shooter video game; the effect was stronger for women such that it cancelled the gender difference found in baseline. It is important to notice that the type of game matters, since no increase was found in playing a 3D maze game for the same duration, and that perhaps the simple exposition to virtual 3D environments does not account alone for this effect on mental rotation. Mental rotation and spatial abilities appears to be closely related, and via the example of video game training, they present a real potential to be evaluated in the context of predicting or training SMR-BCI

For the correlate "abstractedness", Jeunet (2016) describe it as reflecting creativity and imagination abilities, and cite that "creative people frequently use mental imagery for scientific and artistic productions" (LeBoutillier and Marks, 2003).

As Jeunet et al. (2015) combined three different motor imageries in the same BCI paradigm: left hand motor imagery, mental rotation imagery or the mental subtraction task. The BCI accuracy was calculated from all three task, and was predicted by mental rotation, but it is not possible to know which MI the mental rotation score predicted. Unfortunately, no supplementary content was provided by the authors that could selectively compare those predictors in a (MI-)class wise fashion. Therefore, the predictors cannot be disentangled from one another. In other words, mental rotation predicted the performance in the MI of *left-hand* OR *mental rotation* OR *mental subtraction*. Although no evidence gives more weight to any of MI classes, it should be noted that one of the MI classes was a mental rotation imagery, and one of the scale was "mental rotation score", therefore adding a degree of confusion in the interpretation of the results due to the following design: the variable "mental rotation score" was performed after at least one BCI run. The BCI runs contained "mental rotation" MI runs with feedback, and there could possibly be a reverse effect from BCI feedback of performance to the mental rotation scale.

Another study from Randolph et al. (2010) revealed demographic predictors. The authors asked N = 55 healthy participants about their age, time spent typing per day and the time spent on full-body activities per day, then performed a 35 min session of actual movement executions of the hand and of the feet. The trials were not movement imageries, but performed in a way that did not produce artifacts on the BCI. I already cited studies that compared executed movements (Neuper et al., 2005), finding a lower performance in imagined movements. Yet, it is admitted that imagined movements, although they are strictly required for a SMR-BCI, do represent an attenuated version of actual movements in its α and β rhythms modulations and topographies (Fleming et al., 2010). Performed movements can therefore be mentioned along with other predictors, but it must be noted that proprioception, such as haptic feedback "closes the sensorimotor loop" (Gomez-Rodriguez et al., 2011) and lead to better decoding of motor imagery. Randolph et al. (2010) computed two significant predictive models, the first model showed that age predicted the ability to modulate they μ rhythms, and the second showing that the interaction between age and the amount of full-body movement in a day predicted the ability to modulate their μ rhythms. These results imply that the older the participant are, and the more they practice full body activities, the better the SMR modulation is. In a second experiment, Randolph (2012) repeated its setup with $N = 80$ participants, who were yet asked to produce hand or foot motor imageries vs rest two sessions of Wadsworth-BCI-like feedback using BCI2000. Unsurprisingly, the number of the session predicted the accuracy, but more importantly they found that whether the participants played an instrument predicted positively the performance in modulating SMR rhythms, while the consumption of affective drugs and age predicted negatively their ability to modulate SMR rhythms, explaining $40.2\,\%$ of the variance (note that session number was also included in the model). A model containing experience in video games alone predicted $17.5\,\%$ of the variance. In those two studies, Randolph revealed that the regular practice of activities involving fine movements, including playing and instrument or performing full-body movements predicts the ability to modulate the ability to modulate one's own ability to modulate SMR.

Another source of variance in the BCI can be found in variables that relate to visuo-motor tasks assessed by psychomotor evaluations. The "mean error duration" in a visuo-motor coordination task predicted subsequent BCI performance (Hammer et al., 2012, 2014; introduced in section 5.1.1) the results also suggested a potential link between SMR-BCI accuracy and two-hand coordination "mean error duration" (representing a standardized duration of steering error), in the direction that fewer errors in the VMC was associated with a higher BCI performance. The positive correlation between "VMC error duration" and "ability to concentrate" and the negative correlation between "VMC error duration" with "attentional implusivity", although they were not replicated, seem to both refer to attention.

While the association between motor abilities such as VMC error duration, playing an instrument, playing video games, or performing full-body movements, it might be challenging or even impossible to put such predictors into practical instructions or interventions for patients in need for BCI. First, those predictors or correlates were based on samples of healthy participants and moreover, if transferred to a LIS patient sample, there is no possible guideline involving fine, full-bodied and regular motor activity actually possibe.

5.3 Neurophysiological oscillatory patterns

During the conduct of BCI paradigms, the μ and β frequencies are measured within specificly timed trials in which the important information should be evoked by the participant. Yet, the neural activity can also be measured outside those specific BCI trials, and can provide additional information and signals to help explain the variability in the performance. Blankertz et al. (2010) measured the resting SMR activity of $N = 80$ participants before the BCI session for a two minutes recording, during which they alternated for 15 seconds either closing the eyes ("eye closed"), or fixate a shape in the center of computer monitor ("eye open"). The authors found that the difference between the maximum difference between μ or beta power spectral density (a measure of power) and the floor noise correlated ($r = .61$) with subsequent SMR-BCI accuracy. This effect was only significant in the "Eye-Open" conditions, presumably due to interferences from occipital α that reduces the SNR. The method used a new method using the noise floor of the PSD which estimates the shape of the EEG spectrum curve from 1 to 35 Hz. As the spectrum curve usually show frequency increases, using the noise floor function allowed to simulate a baseline of the EEG spectrum in which resting μ and β waves are theorically absent. The noise floor also adapted to inter-individual differences; using this method instead of simply using PSD peaks, the authors increased the correlation with BCI accuracy from moderate to high. Blankertz et al. (2010) called it the neurophysiological predictor and is referred to as the "SMR predictor" (e.g. Geronimo et al., 2016). The SMR predictor could be replicated by Jeunet et al. (2015) with a marginally correlation of $r = .43$ ($p = .087$), or a correlation of $r = .29$ (Zhang et al., 2015; evoked in this secion). The important outcomes of Blankertz et al. (2010)'s findings is that a 3 minutes recording can reveal whether participants' resting SMR are strongly synchronized, in which case it can partially predict how they may succeed in using SMR BCI. Even more interestingly, it allows to suggest certain forms of training for participants with low SMR control, such as neurofeedback with the aim of increasing resting state SMR synchronization.

To extend the number of frequency bands, Ahn et al. (2013) proposed a factor that includes both θ, α (μ), β, and γ frequencies. The authors assembled a subset of $N = 52$ participants who performed a total of 200 to 240 left vs right hand motor imagery trials. They separated their participants in 3 classes: "illiterate" (true chance level); "in-between" (BCI inefficient, below $70\,\%$ criterion but higher than chance level); "literate" BCI efficient (over the criterion). By looking at the inter-individual differences of $n = 21$ BCI efficient and the $n = 16$ participants at chance level, they found differences in frequencies 2 seconds before the directional cue was indicated in each trial. The BCI efficient group had higher θ in the frontal and posterior-parietal regions, an overall lower α power, and slightly lower β power. Following these results, they combined the frequencies in the following formula:

$$\text{PPfactor} = \frac{\alpha + \beta}{\theta + \gamma} \tag{5.1}$$

The *PPfactor* was significantly correlated with SMR BCI performance $r = .59$. While the authors report that their correlate has a superior correlation than the *SMR predictor*, it must be noted that their correlate was assessed during the trials while the SMR predictor was performed before any BCI trial. The authors suggest that the factor represented attention, motor-related memory load processes and the preparation to receive the cue for the motor imagery. Yet, correlates measured between BCI trials should be carefully compared to other predictors, as they can potentially be mediated by effects of attention (e.g. disengagement from the motor imagery task due to low performance or lack of challenge).

It could be argued that the Ahn et al. (2013) study and the study that follows (Bamdadian et al., 2014) could be classified into the "task engagement and attention" section (5.1.1) because the authors claim that their results demonstrate the involvement of attentional levels. Moreover, as they use pre-trial EEG measurements, one could argue that they are they display a transitional variation of the BCI performance. However, the authors average the measurements and do not provide an intra-individual measurement that allows to assess the short term characteristics of the runs.

Bamdadian et al. (2014) found an involvement of the attentional levels on the SMR-BCI accuracy on a study based on 17 participants. To proceed, they calculated a ratio from the EEG in the 2 sec pre-cue duration of motor imagery trials. The normalized power of θ was divided by the normalized power of α and β, following this formula:

$$\text{Bambadian Predictor} = \frac{\theta}{\alpha + \beta} \tag{5.2}$$

The use of such ratio was inspired from previous findings showing that a θ/β ratio can be found by children with hyperactivity attention deficit disorder (ADHD; for review see Arns et al., 2013). The Bambadian predictor correlated with BCI accuracy ($r = .53$), and it is worth mentioning that the proportion of α to β could be adjusted, showing a larger statistical power by using a ratio of α below 0 to $20\,\%$. Yet if Bamdadian et al. (2014) had added the γ

power in their equation, their equation would be the inverse of the *PPfactor*

$$\text{Bambadian Predictor} = \frac{\theta}{\alpha+\beta} \qquad \frac{1}{\text{PPFactor}} = \frac{\theta+\gamma}{\alpha+\beta} \tag{5.3}$$

While they are almost the inverse of each other, both *PPfactor* and the *Bambadian* predictors correlate positively with SMR BCI accuracy, in line by their opposite findings of pre-cue θ and α in good vs bad performers. From this mixed results, we cannot really interpret the role of motor attention in pre-cue SMR BCI trials.

The study from Weber et al. (2011) reported the results of a neurofeedback training of μ SMR. The authors trained $N = 27$ participants in two similar neurofeedback studies for a total of 25 training sessions (or days). The goal was to identify a neurophysiological indicator of the participants' ability to learn to significantly modulate their μ band power. They calculated a predictor using the average change in μ power between the three first days and days 8-11. If the difference showed an increase in μ power, then participants were identified as non-performers. This could predict whether 26 out of 27 participants were able to learn to modulate their SMR at the end of the 25 sessions. The result showed that the ability to increase μ rhythm in a neurofeedback can be quite reliably predicted after 11 sessions of 25 min.

Zhang et al. (2015) measured a total of $N = 40$ subjects, including $n = 26$ who came back for a second SMR-BCI session. Sessions were preceded by two minutes of eyes-open/eyes-closed EEG baseline sessions (similar to Blankertz et al., 2010). The authors calculated their own predictor (*SE*) using spectral entropy. They used the power spectrum density of the EEG signal of electrodes covering the motor cortex (F3, F4 ,FC3, FC4, C5, C3, Cz, C4, C6, CP3, CP4, P3, P4, O1, O2), in the range of .5 to 14 Hz. After normalizing the power spectrum density (PSD) of the frequency spectrum into bins of .5 Hz, they calculated the spectral entropy. They also computed the *Bambadian predictor*, and the *SMR Predictor* for comparison. The highest reported correlations reported were of SMR-BCI accuracy of *SE* ($r = .65$) on C3 (eyes closed); *Bambadian predictor* ($r = .51$) on FC3, eyes closed; *SMR predictor* ($r = .29$) eyes open. The *SE* was found as the best predictor when compared with PPfactor and the SMR predictor. Although it can be argued that the conditions of calculations were unfit to compute the SMR predictor (i.e. impossibility in their choice of electrodes to compute a Laplacian, no mention of the original frequency range of determination of 5 to 35 Hz), the *SE* showed a great potential to predict SMR-BCI performance. The authors additionally found that the *SE predictor* could reliably high and low BCI performers between two sessions, although authors note that the number of session to determine whether a participant can modulate their SMR was estimated to about 8 sessions (citing Kübler et al., 2011b), while we previously reported that Weber et al. (2011) required about 11 sessions.

5.4 Anatomical and functional neural properties

Searching for neuroanatomical predictors for SMR BCI, Kasahara et al. (2015) found very interesting results by making a MRI scan of the brain of N = 30 healthy participants before proceeding to a SMR-BCI session. During the BCI session, the participants performed left vs right hand motor imageries. The authors correlated voxel-based-morphometry data and SMR-BCI accuracy, and used correction for multiple comparisons. They found a significant correlation between the performance in the SMR-BCI and the volume of the grey matter in the following areas **1)** supplementary motor area (SMA, $r = .72$) **2)** the secondary somatosensory area (S2, $r = .71$) **3)** the dorsal premotor cortex (PMd, $r = .59$). The correlated areas were all linked with the motor function, and lateralized (right: SMA, SSA; left: PMd, all participants were right-handed).

Halder et al. (2011) compared fMRI assessed data of $N = 20$ healthy participants who alternated performing motor imageries, actual motor movements or observing 10 seconds videos of hands squeezing. Then the participants performed a SMR-BCI session. The authors separated high and low BCI performers and compared their brain activity. The fMRI revealed that good performers had a higher activation in the SMA for motor imagery and motor observation. The number of activated voxels in the SMA was correlated with SMR-BCI accuracy ($r = .53$). A stronger correlation was found ($r = .65$) in the right precentral gyrus ("motor strip") associated with motor imagery. The strongest correlation ($r = .72$) was found in the middle frontal gyrus during the observation task, showing the importance the neural substrate of task monitoring and working memory in the control of a SMR-BCI. Halder et al. (2013) continued researching the prediction participants using MRI and DTI of the motor imagery of $N = 20$ participants. The authors referred to the region wise fractional anisotropy values according to the ICBM DTI-81 Atlas, while correcting their α level for multiple comparisons. The authors found high correlations between individual performance and the Corpus Calossum ($r = .54$), the right cerebral Peduncule ($r = .52$), the posterior Corona Radiata ($r = .51$), the Cingulum (Hippocampus) ($r = .63$) and the superior fronto-occipital Fasciculus ($r = .54$). The Corpus Calossum is the point of junction between the hemispheres. Importantly, the correlated cerebral white matter areas identified in this study could differentiate high to low aptitude users with $93.75\,\%$ correct prediction.

Another neuroanatomic study conducted by Kasahara et al. (2015) evokes that grey matter density in specific motor areas (SMA, SSA, dPM) correlates positively with SMR-BCI performance, revealing a relation of neuroanatomical nature. We can therefore imagine trainings that focalizes on increasing the grey matter density on those specific areas. It has been shown, in rupture with the traditionally held views that anatomical properties of the brain can be changed via cortical plasticity (Draganski et al., 2004), and that this plasticity is stronger when learning new tasks (Driemeyer et al., 2008). A very interesting study of motor training, by Taubert et al. (2011), showed neuroanatomical effects on $N = 28$ participants. Half of the participants ($n = 14$) were trained on a balancing task once a week for 5 weeks. The other half were used as control. An increased functional connectivity could be observed on the first session. In the same areas that had increased activity (in fMRI contrast), the authors observed neuroanatomical changes in the grey matter occuring in the balancing group from the 3rd week onwards. The concerned areas were the SMA, pre-SMA (bilaterally) and the right ventral PMC (vPMC). The results also found that intrinsic functional connectivity was increased between the prefrontal cortex, SMA, pre-SMA and parietal areas that persisted for more than a week after training, showing different levels of plasticity. As an example of potential training, such an effect or grey matter alteration was shown by Hölzel et al. (2011) who trained their participants in mindfulness meditation (MM), increasing grey matter density in a priori identified areas of the hippocampus, but also in broader cortical areas.

Those interesting prospects of MRI based studies may nevertheless encounter difficulties when being transferred to patients. In a meta-analysis of DTI screenings by ALS patients, Li et al. (2012) report serious alterations of the white matter in the Cingular gyrus and the posterior limb of the internal capsule. Reviewing five studies of $N = 81$ ALS patients, Chen and Ma (2010) reported a loss of grey matter in the whole brain by ALS patients, with $25\,\%$ presenting an atrophy of the right precentral gyrus (PMC). Those two meta-analyses show that ALS is often associated with lesions in both the white and grey matter in motor areas. While it does not specifically overlap with the areas associated with SMR-BCI as found by Halder et al. (2011, 2013) and Kasahara et al. (2015), it nevertheless limits the prospect of transferring observations from healthy participants' samples to patients. Experiments from patient populations, despite heavy underlying constraints, might provide additional data on the feasibility.

5.5 Limitations of the predictors

The experimental protocols and the study designs of BCI predictor studies tend to sensibly vary a lot from one study to the other, and no particular effort is made to replicate previous findings. Firstly because of the progressive adoption of improved algorithms and methods, but also due to common practice and the background of the researchers (e.g. psychologists, bioinformaticians, neurologists). This situation is similar for P300 BCIs, in for which studies report isolated designs or predictors for BCI performance, but rarely attempt to use a common standardized evaluation that would make the comparison easier (Kübler, 2017). With only a few predictors in the field of SMR-BCI, there is also the difficulty to interpret predictors of different types (and criteria, as introduced by Grosse-Wentrup and Schölkopf, 2013 in section 4.2). To include a maximum of predictors and correlates while taking into account their different nature, and avoid overlooking those who do present limitations, I chose to integrate them in the list, but then evoke their respective limitations:

I) Firstly, certain studies **did not report specifically SMR-BCI**. Concerning neurofeedback of SMR rhythms, it does not pose any particular problem, since a SMR neurofeedback session is a BCI in which participants attempt to control the feedback (e.g. a cursor or gauge on the monitor) via SMR modulation, implying a strategy to achieve control over the interface. Yet, to avoid confusion, the quantification of the performance or efficacy of the NF should be precised, whether it describes "online control" (BCI control) or the increase in resting SMR oscillations (effect of NF training; e.g. difference between PRE and POST baselines). Another study from Jeunet et al. (2015) proposed interesting predictors for a three-class MI-BCI that distinguished between left-hand motor imagery, mental rotation and mental subtraction. Whatever the implications of the predictors on BCI performance, particularly mental rotation, we cannot dissociate those predictors from the motor imagery tasks.

II) Secondly, due to the low amount of predictors, it was convenient to introduce the predictors that were **marginal** $.10 < \alpha < .05$, or that did not pass **Bonferonni** correction. Marginal, or alpha-corrected-"discarted" predictors are yet worth being cited to be able to possibly converge similar patterns of findings (e.g. motivation, attention, LOC). It was the case for all the predictors of Jeunet et al. (2015). Also, I reported one study containing one-sided hypothesis but that was not driven by any preliminary knowledge: *"we focus on the [...] LOC [...] which has so far not been considered in a BCI context"* (Burde and Blankertz, 2006). Importantly, the classification between low aptitude and high aptitude users provided by Weber et al. (2011) is **arbitrary** ("*Using* $8\,\%$ *is somewhat arbitrary, but was based on [...] (unpublished) data of earlier experiments*") and no correction for multiple comparison was provided in detecting that a significant classification could be established on the 11th neurofeedback session.

III) Thirdly, certain results presented the risk of a **two-way causal relationship**. In their experimental design, the independence between the dependent variable and predictor cannot be ensured, since participants rated their current motivation prior to multiple sessions with feedback. Nijboer et al. (2008) and Kleih and Kübler (2013) reported that "motivation" and "fear of failure" were correlated with the BCI accuracy, but it is reasonably obvious that those variables could be directly influenced by performance. Yet, the authors did not claim to have predicted SMR-BCI performance, but instead, the experimental design was meant to follow the variables (e.g. "fear of incompetence") along several BCI runs, and study the evolution of those variables over time. These correlations by the authors lead to encourage a certain approach of motivation during the training of SMR, which can be source of within-subject variation. Yet, it raises awareness, as Grosse-Wentrup and Schölkopf (2013) questionned, on whether variation is causally predicted or not.

In the choice of design adopted by Jeunet et al. (2015), participants completed the different evaluations in a counterbalanced fashion in-between the 6 BCI runs, which might also lead to the possibility of reverse-causality. Yet, their predictors were found on personality trait scales, and therefore should in theory not be subject to such effects. Nonetheless, the mental rotation predictor could fall into this category, since its performance could have been increased by mental imagery practice, and that participants did practice mental rotation imagery with variable success during the BCI sessions.

Despite their limitations, the contribution of all those predictors is strongly valuable for the better understanding of the causes of variance and the possible applications in increasing SMR-BCI accuracy. They should naturally not be overlooked based on those evoked limitations, and I therefore introduce them along with the other predictors in table 5.1, but labeled with specific mentions.

5.6 Classification of the predictors

Jeunet et al. (2015); Jeunet (2016) provided a list of predictors for MI-BCI that were classified in three different categories. Which distinguished individual characteristics between "states" (i.e. cognitive and emotional states), "traits" (personality and cognitive profile) and other factors (i.e. demographic data, experience and environment). This distinction was notably tied to her thesis investigation and distributed in three sub categories depending on their "type of explanatory variable": **a)** technology and notion of control **b)** attention **c)** and spatial abilities.

Alternatively, I propose here a classification of all the predictors and other variables that have been shown to be related with SMR-BCI accuracy, in the following cross-table 5.1. For each major type (i.e. Psychological, Visual-motor-spatial, neurophysiological, Neuranatomical, Demographic and environmmental), I identified subtypes that allow to regroup similar findings (e.g. attention, motivation, control beliefs, affective of cognitive for psychological characteristics). I provided for each predictor, the type of relation (Correlation or Regression) and the variables associated with – BCI – accuracy, the sample size (per group), the statistic and the p-value. To conform with the guidelines of Grosse-Wentrup and Schölkopf (2013), I specifically indicated whether the sample was healthy individuals or patients, and I also estimated whether the study design assessed within-participant variability or between participant variability (coded by "W" or "B"). Importantly, I estimated the causal independence of the assessed variable from the level of BCI accuracy. This distinction was based on whether the variable was assessed before or after the measurement of BCI accuracy. In the case of the *PPfactor*, (Ahn et al., 2013), the authors claimed they predicted BCI accuracy from 2 sec pre-trial recording, but I reality this 2 sec pre-trial factor was averaged over several trials, therefore indicating a possible[3] causal relationship of BCI accuracy influencing the *PPfactor*. In the table, if the causal independence is positive ("Y" for yes), the variable or factor could be considered as a predictor that is not influenced by BCI accuracy, otherwise, it would require – a replication study – to assess its causal independence from BCI accuracy. In the table, the last column included notes to provide important information about the study design or the results of the study.

[3]By possible, I mean that the causal relationship of BCI accuracy on the *PPfactor* is "not impossible" until the contrary is proven.

Type	Subtype	Study	Test	Within / Between	Causal-indep	Sample	Statistic	Sig.	Note
Psychological	Attention	Grosse-Wentrup (2011)	Corr. γ and SMR quality score (SMRq)	W	N	10	$\rho = .08$	***	
		Grosse-Wentrup and Sch??lkopf (2012)	Corr. SMRq predicted and measured	W	Y	14	$\rho = .10$	***	two individuals had $\rho = .4$, forward prediction
		Hammer et al. (2012)	Corr. AHA (ability to concentrate) and accuracy	B	Y	40	$\rho = .50$	**	
		Cassady et al. (2014)	log-rank-test of accuracy between MBAT > 1 year and CG	B	Y	12	na	*	
	Motivation	Leeb et al. (2007)	Paired t-test of Accuracy between virtual reality and simple feedback	B	Y	10	$t(8) = 3.2$	*	
		Kleih and Kübler (2013)	Corr. interest and accuracy	W	N	51+11 S	$\rho = .53$	***	bidirectional corr
			Corr. challenge and accuracy	W	N	11 S	$\rho = .83$	*	bidirectional corr
	Control beliefs	Witte et al. (2013)	Corr. KUT and SMR power during feedback	B	Y	10	$r = .69$	*	Neurofeedback
		Burde and Blankertz (2006)	Corr. KUT and number of hits	B	Y	17	$r = .59$	*	1-sided
		Jeunet et al. (2015)	Self-reliance	B	Y	18	$r = .51$	*	mixed BCI, ns. after Bonferonni
		Nijboer et al. (2008)	Regr. accuracy by mastery confidence	W	N	16	$b = .58$	*	bidirectional corr
		Kleih and Kübler (2013)	Corr. mastery confidence and accuracy	W	N	11 S	$\rho = .80$	*	bidirectional corr.
	Affective	Nijboer et al. (2008)	Regr. accuracy by mood	W	N	16	$b = .498$	*	bidirectional corr.
			Regr. accuracy by fear of incompetence	W	N	16	$b = -.62$	*	bidirectional corr.
		Kleih and Kübler (2013)	Corr. fear of incompetence and accuracy	W	N	51+11 S	$\rho = .53$	***	bidirectional corr
		Jeunet et al. (2015)	Corr. Tension and accuracy	W	N	18	$r = -.57$	*	mixed MI-BCI, ns. after Bonferonni
	Cognitive	Jeunet et al. (2015)	Corr. Abstractedness and accuracy	W	N	18	$r = -.53$	*	mixed MI-BCI, ns. after Bonferonni
Visual, motor and spatial	Dexterity	Hammer et al. (2012)	Corr. VMC error duration and accuracy	B	Y	80	$r = .42$	**	
		Hammer et al. (2014)	Corr. VMC error duration and accuracy	B	Y	32	$r = .36$	*	Replication, ns after Bonferroni
		Randolph (2012)	Regr. accuracy by experience in typing, playing instruments, sport and video-games	B	Y	80	$r^2 = .35$	all *	time factor also included in the regression
		Randolph et al. (2010)	Regr. interaction accuracy by age and full body movements	B	Y	55	$b = .0075$	*	
	Mental imagery	Vuckovic and Osuagwu (2013)	Corr. accuracy and KVIQ-K (Kinesthetic)	B	Y	30	$r = .53$	***	correlates more with simple motor imagery
			Corr. accuracy and KVIQ-V (visual)	B	Y		$r = .21$	*	correlates more with goal oriented motor imagery
		Jeunet et al. (2015)	Corr. mental rotation and accuracy	W	N	18	$r = .70$	**	mixed BCI, bidirectional corr.
Neurophysiological	Rest activity	Blankertz et al. (2010)	Corr. Accuracy and SMR Predictor	B	Y	80	$r = .53$	*	
		Zhang et al. (2015)	Corr. Accuracy and SMR Predictor	B	Y	40	$r = .29$	*	replicated the SMR predictor
			Corr. accuracy and Spectral Entropy 2min rest	B	Y	40	$r = .65$ on C3	*	
		Ahn et al. (2013)	Corr. Accuracy and PPFactor	W	N	61	$r = .70$	***	2 sec pre-trial
	Modulated activity	Witte et al. (2013)	μ band power increase after 11 sessions predicts learners and non learners after 25 sessions	W	N	13	na	na	predictor is dependent variable
		Halder et al. (2011)	t-test of Activation in the Supplementary Motor Area (SMA) during MI by low and high BCI aptitude users	W	N	10	$r = 0.59$	*	
Neuroanatomical		Kasahara et al. (2015)	Corr. accuracy and Grey Matter volume in SMA, SSA, PMd	B	Y	10	$r = .72$ to $.59$	*	
		Halder et al. (2013)	Corr. accuracy and Fractional Anisotropy in right Cingulum, left sup. fronto-occipital Fasciculus, Corpus Callosum, right posterior Corona Radiata	B	Y	10	$r = .63$ to $.51$	*	
Demographic		Randolph (2012)	Regr. accuracy by age and other factors	B	Y	80	$b = -0.6$	***	age was either over or below 25 yo
			Regr. accuracy by sex and other factors	B	Y	80	$b = -0.29$	†	marginal, Women>Men
		Randolph et al. (2010)	Regr. accuracy by sex	B	Y	55	$r^2 = 0.0001$	*	Trivial predictor
Environmental		Randolph (2012)	Regr. accuracy by drug intake and other factors	B	Y	55	$\rho = -.311$	*	

Table 5.1 Cross table of the predictors. (B)etween subject design variables; (W)ithin subject design; (Indep)endence with outcome variable. Sample contains healthy participants when unspecified, or (S)troke patient.

5.7 Increasing SMR-BCI performance

In the previous section, I discriminated several different types and subtypes of predictors for BCI performance. The first group revealed psychological variables, notably the modulation of attention, the LOC and motivation. The second group comprised predictors that are linked with visuo-motor and spatial abilities. The third and fourth groups predictors that were neurophysiological and neuroanatomical for which links with psychological or viso-motor-spatial characteristics were suggested by the authors, but was not established through experimentation. Additional demographic and environmental predictors were also cited as fith and sixth groups.

Having listed these predictors, defined their type and causal independance, it is therefore possible to know which expected direction could be preferential for such predictors. One first argument that was made by Blankertz et al. (2010) after finding the *SMR predictor* which was that, provided a variable that can partially predict BCI accuracy, researchers would be able to predict whether the participants would be able to acquire good performance with a SMR-BCI. The idea was that such a procedure implying predictors could identify potential non-learners. The participant could either be presented with neurofeedback methods (similar to Witte et al., 2013) to increase the resting SMR power. McCane et al. (2014) proposed such a screening to determine whether ALS patients could use a visual P300 speller, another solution, would be to instead direct the user to another alternative such as a P300 based BCI.

There is yet no defined protocol to differentiate potentials BCI learners to non-learners, and every studies advanced their own predictor, with few or no overlapping between those variables across studies. It could therefore be beneficial to elaborate such a screening protocol before starting the training of an SMR-BCI, which can take up to a dozen of sessions.

On the individual level, meaning that if we take apart the improvements on the characteristics of the BCI, on the feedback and on the instructions, there are yet a very limited number of studies, to my knowledge, that have been able to experimentally increase the performance in an SMR-BCI.

Those studies also have the particularity to imply the use of relaxation methods. The first study which exploited the use of relaxation intervention to improve SMR-BCI was reported by Mahmoudi and Erfanian (2006). In this study, the authors recorded 14 healthy participants in three SMR-BCI sessions at day 0, 10 and 20. After the first BCI session, half of the participants were trained on mindfulness meditation (MM) session while the other half did nothing (CG). The authors reported that MM participants had higher mean performance ($day_1 = 77\,\%$, $day_{30} = 77\%$) as compared to the control group ($day_1 = 61\%$, $day_{30} = 56\%$). According to the formula proposed by (Müller-Putz et al., 2008), the true chance levels thresholds were: $low = 36.7\%$, $high = 63.3\%$, meaning that the accuracy of CG participants was random from the beginning.

Although the ANOVA with repeated measures returned a significant difference, it must yet be stressed that the MM participants maintained the same performance, and that the effect of training comes from the reduction of CG accuarcy. Despite the dubious methods, this study showed negative results concerning an effect of meditation training, and was the first attempt to use a relaxation training intervention to increase SMR-BCI accuracy.

Tan et al. (2009) published the results of a pilot study with $N = 9$ healthy participants. They were trained during four weeks with either mindfulness meditation training (MM), musical education training (MS) and a control group (CG). The BCI accuracy was evaluated pre and post intervention, knowing that the participants had no musical education (more than school requirements) and neither had previous formal education in relaxation techniques. The authors found that after four weeks, the participants in the mindfulness meditation group had better BCI performance. The study could be criticised for its small group and the fact that they decided to only show the results of $N = 9$ participants while the sample they possessed was $N = 30$, invoking time restrictions.

A few years afterwards, the authors finally published a study (Tan et al., 2014) with $N = 63$ participants, and replicated the effect of MM on BCI, for which BCI accuracy after the training in the MM group was higher than MS and CG, marked with an increase of $10.2\,\mathrm{pp}$ as compared to CG. It is worth repeating that an increase of 10 percent points is considered as a huge improvement in the field of SMR-BCI. The authors conducted a pre-study in which they demonstrated that the influence of non-specific effects were mitigated, first because there was a training group, and second because the expectation of influence on BCI accuracy was not significantly different between MM and MS. By choosing a musical training group, the authors addressed the fact that neuroplasticity and cognitive transfer effects occured due to MM training (e.g. Hölzel et al. (2011), and so did the guitar training (Rabipour and Raz, 2012). The authors suggested that the significantly high increase in BCI accuracy could have been caused by the beneficial effect of mindfulness meditation on improving selective attention (Jensen et al., 2012). Tan et al. provided a detailed description of the MM sessions, including: *"Participants were guided by the instructor to sit quietly and focus on the flow of their breath, with their eyes closed, and to non-judgmentally become aware of their thoughts, senses, and feelings. They were told to not look for any thought or remain alert waiting for any thought to come but to notice the content of each thought when it arises, accept it, and allow it to go. They were also told to gently focus back on the breath when they noticed that their mind had wandered"*. In addition, participants were also asked to perform body scans.

Bishop et al. (2004) proposes a definition of MM, chraracterizing it as a metacognitive process that require the control of cognitive processes (i.e. attention, self-regulation) and monitoring of the stream of consciousness. In SMR-BCI, as for neurofeedback, there is no proprioceptive feedback that can indicate whether the motor imagery is correct or not. The learning is also complex since the participant has to rely on a feedback that is provided externally, sensitive to artifacting or noise, and present a certain temporal "lag" (Often, the sliding windows of the BCI classifier uses features from the previous second). Bishop et al. (2004) further describes mindfulness as following: *"Mindfulness can thus be further conceptualized as a process of investigative awareness that involves observing the ever-changing flow of private experience. The term investigative refers to an intentional effort to observe and gain a greater understanding of the nature of thoughts and feelings"*. The hypothesis that mindfulness meditation provides better interoceptive perception has also been supported by recent studies (e.g. Farb et al., 2013). MM trainings is also known to enhance attention skills (e.g. (Semple, 2010)), and the sustainability of those skills on a prolonged period (note: this reflects Hammer's AHA predictor).

The MM participants of Tan et al. (2014) had to practice 20 min of daily MM for 12 weeks, including a weekly session, it shows that the training was intense for MM. Apart from registering the attendance of the participants to the MM and MS trainings, the authors did not control for the effect of their intervention by any means.

In the perspective of these three studies (Tan et al., 2009, 2014; Mahmoudi and Erfanian, 2006), we can note that the experimenters trained the attentional abilities of the participants using MM. Interestingly, the musical training did not improve their SMR-BCI accuracy, while evidence for an association between musical expertise and spatial abilities has been shown (Brochard et al., 2004). Also, it must be noted that the musical experience was found as a predictor for SMR-BCI (Randolph, 2012). The authors explained that the duration of the musical training might have been too short to equal the life-long acquired skill of musicians.

By combining the findings from Tan et al. (2009, 2014); Mahmoudi and Erfanian (2006), we can see that there is a potential for meditation based studies in increasing SMR-BCI. These trainings are supported by the *MBAT predictor* (Mind Body Awareness Training), in which MBAT predictors perform better in a BCI (Cassady et al., 2014). Nevertheless, the need for stricter evaluation methods, that check for the effect of meditation based interventions, and more replications studies are required to fully convince researchers to use for example MM or MBAT interventions to improve the accuracy of BCI inefficient individuals. The ability to translate those interventions to patients is not evoked by the researchers, restricting the range of meditation techniques to those that are non-motor, or non-respiration based in case the patients receive assisted ventilation.

The low amount of studies investigating whether interventions can increase SMR-BCI accuracy, and the lack of studies reporting non-results show that there is the need to conduct such experiments in well-controlled designs, with more participants, as it is the case in this thesis.

Chapter 6

Empirical investigation

To recall the aim of this dissertation, the approach was to investigate the individual dimension of the BCI user in relation with SMR-BCI accuracy. To proceed I collected and identified variables that explain variation in SMR-based BCI accuracy, supported by empirical evidence. Having identified these source of variation, the objective was to propose and evaluate trainings that could increase SMR-BCI accuracy. Those trainings were based on the manipulation of the identified predictors.

During the course of the investigation work I conducted in the context of this dissertation (2011 to 2017), the number of predictor variables grew (e.g., Vuckovic and Osuagwu, 2013; Bamdadian et al., 2014; Cassady et al., 2014; Jeunet et al., 2015; Kasahara et al., 2015) and several replication of exisiting predictors studies were published (e.g., Randolph, 2012; Grosse-Wentrup and Schölkopf, 2013; Hammer et al., 2014; Zhang et al., 2015). A study even concurrently found an effect of mindfulness meditation training on SMR-BCI (Tan et al., 2014). In the reporting of the studies, I respected the chronological context (i.e. study I in 2011, Study II in 2015) to evoke the summaries and research questions. A global discussion is provided in the next chapter (7) to integrate the knowledge into the current state-of-the art research.

6.1 Study I - Effects of PMR and VMC training on performance in an SMR-BCI

6.1.1 Initial summary

At the time study I was designed (i.e. winter 2011), only the effect of meditation training – specifically mindfulness – had been reported in a preliminary study by (Tan et al., 2009;

described in section 5.7). The amount of predictors was also scarce, but I had access to the – accepted but – yet unpublished results of Hammer et al. (2012) that identified the ability to concentrate and the "mean error duration" in two-hands visuo-motor coordination task (VMC) as predictors for SMR-BCI performance. Other findings also suggested the importance of motor and sensorimotor loops in maximizing BCI performance at different levels. On the instruction level, the Neuper et al. recommended performing kinesthetic motor imagery instead of visual motor imagery; on the psychological level, Grosse-Wentrup (2011) evoked the implication of attention networks (γ band oscillations) with the modulation of SMR rhythms; on the neurophysiological level, where Blankertz et al. reported that resting SMR μ rhythms over the motor cortex (the SMR predictor) correlated with subsequent BCI performance. This evidence was also supported by fMRI, showing a higher activation of the SMA for high aptitude BCI users (Halder et al., 2011).

6.1.2 Research gap

The observations in those studies (see previous paragraph), when compared for similarities, suggested two generic sources of variation in SMR-BCI performance. The first one was attention levels, which was positively associated with SMR-BCI performance; the second one was the activation of motor related areas, also showing a similar positive relation.

When considering that the Wadsworth BCI dates back to Wolpaw et al. (1986), after 25 years of improvement in BCI software and hardware technology, a "performance ceiling" was reach (McFarland et al., 2011), and it was not possible to overcome the issue of BCI inefficency. (Kübler et al., 2011a) proposed a model of BCI extending the investigation area of BCI performance, to other characteritics that had been overlooked, such as instructions, feedback, applications and user's individual characteristics.

Hammer et al. (2012) were the first to assess a large number of participants ($n = 80$) with an extended panel of standardized and validated psychological questionnaires (including the KUT of Burde and Blankertz, 2006) and psychometric tests to find predictors for SMR-BCI performance. Concurrently, Randolph et al. (2010) also found that daily motor activity and age predicted BCI performance. Both authors then replicated and refined their findings (Hammer et al., 2014; Randolph, 2012).

The research gap concerned in the scope of this dissertation the individual predictors and correlates for SMR-BCI performance, that I characterized earlier (see chapter 5) under the "attentional" or "motor dexterity" subtypes. Empirical investigation could be performed in two complementary directions. On one hand, there was a need for more replication studies, most preferably from independent sources, that would allow to better identify those predictors. On the other hand, there was the need to find a way to implement these predictors to directly benefit BCI users. Such implementations of the predictors have been evoked under the following form:

1. As guidelines in BCI setups, practice and instructions that ensures the best conditions to obtain the highest BCI performance (e.g. Neuper et al., 2005).

2. As interventions that would allow to increase BCI performance (e.g., Tan et al., 2009).

3. As evaluation instruments that could predict and BCI performance (e.g., SMR predictor, proposed by Blankertz et al., 2010). This would allow to:

   - propose interventions before learning SMR-BCI – as evoked in point 2.

   - propose the potentially best BCI paradigm and device needed for the user.

Those three implementations all represent tangible and potential ways to counter BCI inefficiency, while the third implementation is a diagnostic tool that does not *per se* increase BCI accuracy. The guidelines represent a inferential process resulting from empirical finding, replicating and intepreting predictors for BCI performance.

In this dissertation, I focused on the second implementation, *increasing BCI performance*. Secondarily, but essentially for answering this "gap" comes the necessity to *further investigate predictors* of SMR-BCI performance by attempting to replicate them.

6.1.3 Research questions

The initial research question of this dissertation is, *what are the factors and variables that can predict SMR-BCI accuracy, and can they be clearly identified*? Provided the evidence showing that BCI performance is positively associated with attention and motor function (see in summary 6.1.1), a more specific question is refined under the scope of attention levels and precision in a visuo-motor task, as provided by Hammer et al. (2012). More specifically, the initial research question be refined as: "*Are attention levels and mean error duration in a VMC task reliable predictors for SMR-BCI accuracy*". To answer this second question, experiments should be conducted attempting to replicate the conditions of the predictor studies.

The third question in this dissertation concerns the implementation of those predictors into non-BCI interventions or trainings. It can be posited as follows: "*By manipulating those predictors in the direction of their association with SMR-BCI accuracy, can this SMR-BCI accuracy be consequently improved?*". To answer this question, efficacious interventions should performed prior to a BCI session. By comparing BCI accuracy after interventions, any causal effect of training on BCI accuracy could be empirically proven.

6.1.4 Hypotheses

In this study it was hypothesized that prior training (i.e. PMR or VMC) would improve subsequent BCI accuracy. The hypotheses were formulated as follows:

- **Main hypotheses**: Interventions increase BCI accuracy.
  - **(H_1)** Participants in the PMR group have higher subsequent BCI accuracy as compared to the CG.
  - **(H_2)** Participants in the VMC group display higher subsequent BCI accuracy as compared to the CG.
- **Secondary hypotheses**: replicating existing predictors[1].
  - Relaxation level (an indicator of attention) correlates with BCI accuracy.
  - VMC "mean error duration" correlates with BCI accuracy.
  - KUT correlates with BCI accuracy.
  - BIS correlates with BCI accuracy.

The primary and secondary hypotheses were all tested during the conduct of study I. The main hypotheses were bound to the assumption that their respective training would be efficacious. A manipulation check was therefore performed for each training condition to ensure that the effect could be quantified and validated experimentally:

- manipulation check for (H_1): PMR intervention increases relaxation levels **(MC_1)**.
- manipulation check for (H_2): VMC intervention reduces "mean error duration" **(MC_2)**.

6.1.5 Introduction

To implement those hypotheses, the study design was performed in conditions similar to those of Hammer et al. (2012). As the software develelopment of this study was made by researchers in Berlin, and that a large sample was needed, the large number of measurements was distributed in Berlin and Würzburg, which allowed for maximizing the statistical power and reliability of the findings. While my main motivation was the investigation of predictors and trainings for SMR-BCI, the implementation of a co-adaptive BCI in the study design was ensured by the research group in Berlin, and further reported in Acqualagna et al. (2016). For increasing the attention level, a reliable and proven relaxation technique was chosen, called progressive muscle relaxation (PMR; Jacobson, 1925). It was shown to foster inhibitory processes (Jacobson, 1938) and globally reduces tension (for meta-analysis, see Carlson and Hoyle, 1993); PMR has often been used as an intervention in the field of psychopathology,

[1] found until winter 2011

for example in anxiety reduction (e.g. Lolak et al., 2008). Despite the fact that PMR, as designed by Jacobsen, can be delivered in a program that lasts several days and, according to its author, involves learning, it can nevertheless display an effect after a single session. As stated by Friedrich et al. (2014), a relaxed state might be beneficial in any BCI setup:"*a state of positive but not emotionally involved attentive and effortless relaxation might be the optimal state for both neurofeedback and BCI*". Preliminary but direct evidence showed that a relaxation technique (i.e. mindfulness meditation) was shown to have a positive effect on BCI performance (Tan et al., 2009). Indirectly, it was shown to increase sustained attention (Valentine and Sweet, 1999). By performing an intervention right before a subsequent BCI session, the aim was to induce a more relaxed state for participants in the PMR group. For increasing the "mean error duration" in the VMC task, a similar VMC training as the one used by Hammer et al. (2012) was chosen. The VMC was an intervention based on two-hand visuomotor coordination that implied acquiring fine motor skills via learning and constituted a challenging task.

6.1.6 Methods

Participants and data collection

In a joint study that took place in two different labs Würzburg (WÜ) and Berlin (BE), $N = 168$ participants were recruited. Due to a mistake in the VMC intervention in WÜ, $n = 28$ participants were dropped and $n = 22$ new participants were again recruited; the reported sample was therefore different from Acqualagna et al. (2016). In addition to using the same EEG hardware and BCI software in both labs, protocol and instructions were written down to ensure the same conditions. From this initial sample were also removed the participants who did not comply with the instructions ($n_{\text{BE}} = 3$), and those who, during questionnaire review, were found to be diagnosed with psychological disorders or taking CNS affecting drugs (depression: $n_{\text{BE}} = 3$, $n_{\text{WÜ}} = 1$; schizophrenia: $n_{\text{BE}} = 1$). The final sample comprised $N = 154$ participants ($n_{\text{WÜ}} = 78$, $n_{\text{BE}} = 76$). By accident, $= 23$ participants in BE did not rate their relaxation levels. Therefore, analyses that concern the relaxation level were based on $n = 131$ participants and all the other were based on the base sample of $n = 154$. The participants were recruited either on university campus, or by the means of Internet ads. The participants were in a vast majority young undergraduate students, aged $M = 24.7$ ($SD = 5.8$) and in majority female ($n = 99$). The study was conducted in accordance with the declaration of Helsinki, approved by the Ethical Review Board of the Medical Faculty (University of Tübingen), and written informed consent was obtained prior to experimentation.

Procedure

In a random fashion, participants were assigned to three different intervention groups (description of these groups further in section 6.1.6). Those groups were either progressive muscle relaxation (PMR), visuo-motor coordination training (VMC) or control group (CG). The timeline of the experiment was as follows:

1) Informed consent and questionnaire for general information

2) Psychological questionnaires during EEG setup

3) Intervention training

4) SMR-BCI session

For visual representation of this timeline, see Figure 6.1.

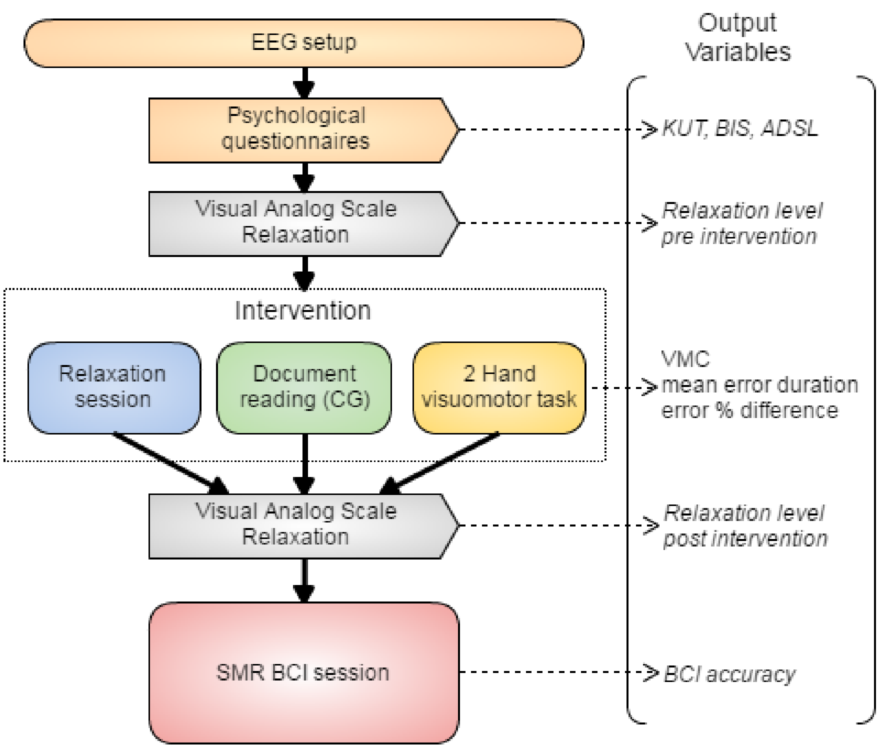

Figure 6.1 Timeline of the experiments and the variables collected

Questionnaires

The reported relaxation level was measured before intervention and immediately before the BCI session (i.e. after intervention) using a 10 cm visual analog scale (VAS) ranging from 0 (not at all) to 10 (maximally). Participants answered by placing a cross on the scale with a pen. Other psychological tests were conducted during the EEG setup:

1. Control convictions in dealing with technology ("*Kontrollüberzeugungen im Umgang mit Technik*", KUT, German version; Beier, 2004). It assess how difficult the participant think his interaction with common technological or mechanical devices in daily situations is. The scale is a measurement of the external locus of control (LOC, introduced in section 5.1.2). The scale uses a 5 points likert scale rating ranging from 0 ("not at all") to 10 ("absolutely").

2. General depression scale ("*Allgemeine Depressionsskala Lang*", ADS-L; Hautzinger and Bailer, 1993; German version from CES-D Radloff, 1977). A self-reported 20 items scale in which participants estimate how often situations occurs that are associated with depression (e.g. crying, loosing appetite, concentration difficulty) on a 4 points Likert-type scale ranging from 0 ("never or rarely") to 3 ("often or always").

3. Baratt Impulsiveness Scale (BIS-15; Spinella, 2007; German translation by Meule et al., 2011, described in section 5.1.1). The scale measures the construct of impulsivity with 15 items comprising three different subscales: non-planning impulsivity (BIS-np), motor impulsivity (BIS-m), attentional impulsivity (BIS-a). The items present situations or statements (e.g., "I am inattentive"), an the participants rate how often they these situation occur on a Likert-type scale from 1 ("never or rarely") to 4 ("always or almost always").

Since study I was designed to train participants, the "ability to concentrate" questionnaire (AHA), found as a predictor by Hammer et al. (2012), was not assessed due to the fastidious task it represents and its variable duration. It must be precised that the duration of the whole experiment was already very long and tiring. Summing up the prepping of 64 electrodes, the 23 min interventions and a 320 trials BCI session, the whole experiment cumulated of about 3 to 3.5 hours.

EEG recording

Participants sat in a comfortable chair, facing a $1280 * 1024$ px 17" monitor placed at approximately 1 m. Two loudspeakers were placed on both sides of the monitor. A 63 electrodes active cap was used (Acticap[2]) with left mastoid (A1) as reference. Ground was placed on FPz. It conformed to a standard 32 electrodes setup according following the 10-20 system (Jasper, 1958). To increase the coverage of the sensorimotor areas, 31 additional electrodes

[2] Brain Products GmbH, Germany

were placed following the 5-10 system (Oostenveld and Praamstra, 2001). The signal was digitized at a sampling rate of $1000\,\mathrm{Hz}$ and band pass filtered between $0.016\,\mathrm{Hz}$ and $250\,\mathrm{Hz}$, and impedances were kept under $5\,\mathrm{k}\Omega$.

Intervention prior to BCI session

1. In the progressive muscle relaxation group (PMR), a Jacobson PMR audio session was conducted, following a 23 minutes script (taken from Hinsch and Pfingsten, 2002) previously recorded by a professional psychotherapist, therefore ensuring the same instruction was provided to all participants. Participants were asked to follow the instructions, which first asked them to relax and breathe deeply. Then, in a repetitive fashion, instructions were to contract distinct groups of muscles (e.g., those of the face, jaw, neck, arms, hands, legs, feet) for a few seconds, then relax and focus on the bodily sensations.

2. In the visuo-motor coordination group (VMC), participants were given a two-hand VMC task, which consisted of steering a virutal ball along narrow paths ("tracks") dipslayed on the monitor. Each of knobs controllers respectively provided control over an orthogonal dimension. Spinning the left knob modified the vertical position of the ball, and spinning the right knob modified the horizontal position of the ball. Sound stimuli and color of the ball provided a feedback of manipulation errors. As depicted in Figure 6.2, if the ball was in the path the color of the ball was *green*; if the ball touched the edge or was about 1 cm outside of the path, it was considered a steering "error", an alarm sound (i.e. single beep) was emitted, and the color of the ball turned *red*; if the ball was completely out, it was considered "out", another alarm sound (i.e. double beep) was emitted, and the color of the ball turned to yellow. After a steering "error", the track could still be continued, but in the "out" condition, the participant had to start again the track from the beginning. As an indicator of the participant's precision (Hammer et al., 2012, 2014), the mean duration of steering errors was used ("mean error duration", expressed in seconds). Another variable "error percentage difference", was calculated by subtracting the error percentage in the 5 first VMC tracks (baseline) and the remaining ones (practice), The "error percentage" was obtained by dividing the "mean error duration" by the "mean track duration" for the corresponding tracks.

3. In the control group (CG), participants were instructed to read a text in German about BCI technology (i.e. book chapter from Kübler and Neuper, 2012). To ensure task compliance, experimenters told the participants that five questions would be asked after reading.

BCI trials

During the motor imagery trials, participants were asked to kinesthetically perform motor imageries of either left hand (and limb; e.g. hand grasp of an object, involving arm movements), right hand or both feet (e.g., tapping both feets on the floor). To reduce sources of noise in the EEG, participants were asked to reduce movements that generate artifacts (i.e. eye-blinks, eye-movements, jaw clenching, muscles of the face and neck).

The BCI consisted of 120 trials in the calibration phase and 320 BCI trials, all providing online feedback. The calibration phase consisted of three runs (1-3) with 40 trials each, using subject-unspecific classifiers, co-adaptive classification and positively biased feedback (all described in the next section). At the end of the calibration phase, classifier training occurred, selecting the participant's two best motor imageries (i.e. right-left, right-foot or left-foot). Using subject-specific classifiers, four online runs (4-7) of 80 trials, totalizing 320 trials were used to calculate participant's BCI accuracy.

BCI trials were similar to the Graz BCI paradigm. In a trial, a fixation cross appeared for 2 seconds, then a red arrow cue appeared for 1 second, determining which motor imagery had to be performed (pointing: left for left hand; right for right hand; and top for both feet). The online feedback appeared 1 second afterwards (i.e. cross changing color and moving according to the classifiers' output) and lasted for 3 more seconds. The position of the cross at the end of the trial determined its success. A 2 seconds break followed every trial. An additional 15 seconds break was provided every 20 trials (see Figure 6.3).

The feedback provided during online runs consisted of the cross starting from the center of the monitor and moving in the direction predicted by the classifier. During classification runs, the feedback was positively biased and the cursor either moved on the direction predicted by the classifier (i.e. classifier's output predicting the cued motor imagery) or returned to the center of the monitor (i.e. classifier's output not predicting the cued motor imagery). The positively biased feedback, that was based on a sample of "BCI efficient" participants, was meant to cue the participants into using successful SMR modulation strategies. It was part of the co-adaptive calibration design, that only lasted for the first three calibration runs. Then, a subject-specific classifier was trained to exploit the best features for SMR-BCI control.

Calibration and classification

All signal acquision and processing was done using the Berlin BCI system (BBCI, Blankertz et al., 2007), and following a co-adaptive classifcation approach (see Figure 6.4). The calibration runs followed a novel "kickstart calibration" method (fully described in Acqualagna et al., 2016), with three classifiers (one for each motor imagery) trained on a generic model

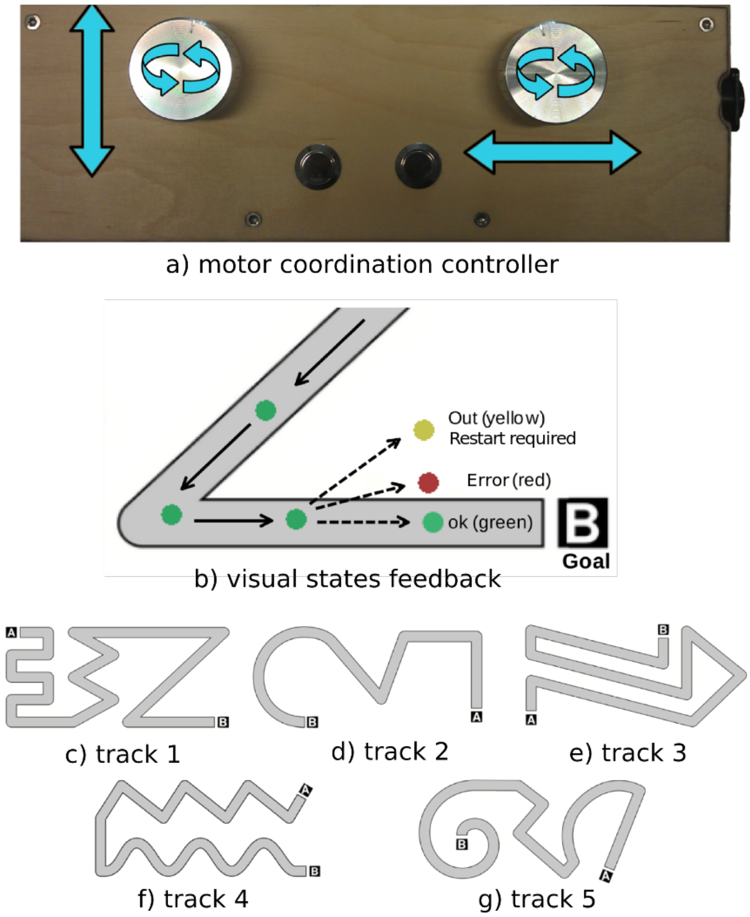

Figure 6.2 Visuo-motor coordination training setup. (a) shows a photograph of the two hands knob controller. As straight blue arrows indicate, the left knob controlled vertical movement of the ball while the right knob controlled horizontal movement. A good coordination of left and right hand on the basis of visual feedback was required to direct the ball along the track. (b) Description of feedback: the goal was to steer the ball from A to B through the path without leaving its outline. When on track the ball remained green. When out of track the ball turned red but was allowed to come back on track. When the basll was too far away from the track, it turned yellow and needed to be brought back to point A to restart the track once again. (c,d,e,f,g) show the 5 tracks in the order of presentation. Each track increased in difficulty, i.e. the easiest to perform was track 1 and track 5 was the most difficult one. (Source: Botrel et al., 2017)

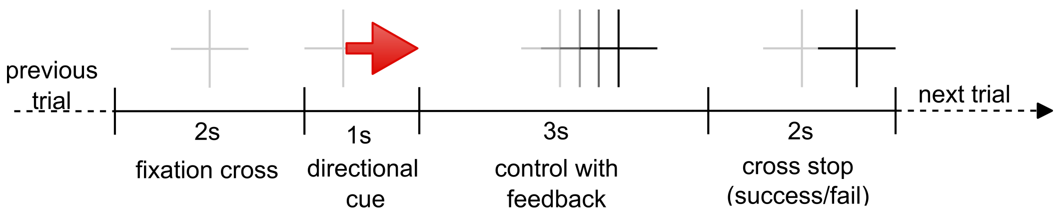

Figure 6.3 Trial description during the BCI session. The user could estimate trial success by comparing the cue direction to the position of the stopped cross. (Source: Botrel et al., 2017)

of participants (i.e. previoulsy recorded participants in the same conditions), and returning positively biased feedback. The subject-independent classifier was trained using three small Laplacian derivations at C3, Cz and C4. Individually, α ($8-15$ Hz) and β ($16-32$ Hz) bands were extracted, resulting in a total of 6 features provided to the LDA classifier. After each calibration trial, the classifier was adapted with "adaptive mean estimation" and "adaptive inverse covariance matrix" algorithms allowing to better fit the participant's individual features (a description of the algorithms Vidaurre et al., 2011a). The positively biased feedback was only provided during the first three runs of classification.

At the end of the calibration runs (1-3), the most discriminative pair of motor imagery classes was selected to train a binary classifier, that was utilized in the runs 4 and 5. This classifier used subject-specific optimized α and β frequency ranges and subject-specific trial time ranges (the optimization of frequency and temporal ranges described in section 3.4.4) for the six laplacian filters and common spatial patterns (CSP) analysis (see Blankertz et al., 2008) based on 24 EEG channels. Log band power (Hilbert envelope) features were extracted from Laplacians and CSP derivations and used to train the LDA classifier. After each trial, the six Laplacian channels were reselected and the LDA classifier was retrained (see Vidaurre et al., 2011a).

Before run 6 and 7, another LDA classifier was trained using the data from the last 160 online runs (i.e. from runs 4 and 5). After optimization of the frequency and trial time ranges, a CSP analysis was performed on 47 EEG channels, and this time, Laplacian derivations were not used. The LDA classifier was trained on the log band power features. To test a newly developed method, the adaptive classification algorithm ignored the supervized nature of the data, using adapted pooled mean adaptation of the LDA classifier (PMEAN; see Vidaurre et al., 2011a).

The final BCI accuracy was calculated by averaging the percentage of correct selections in the 320 online trials (runs 4-7)).

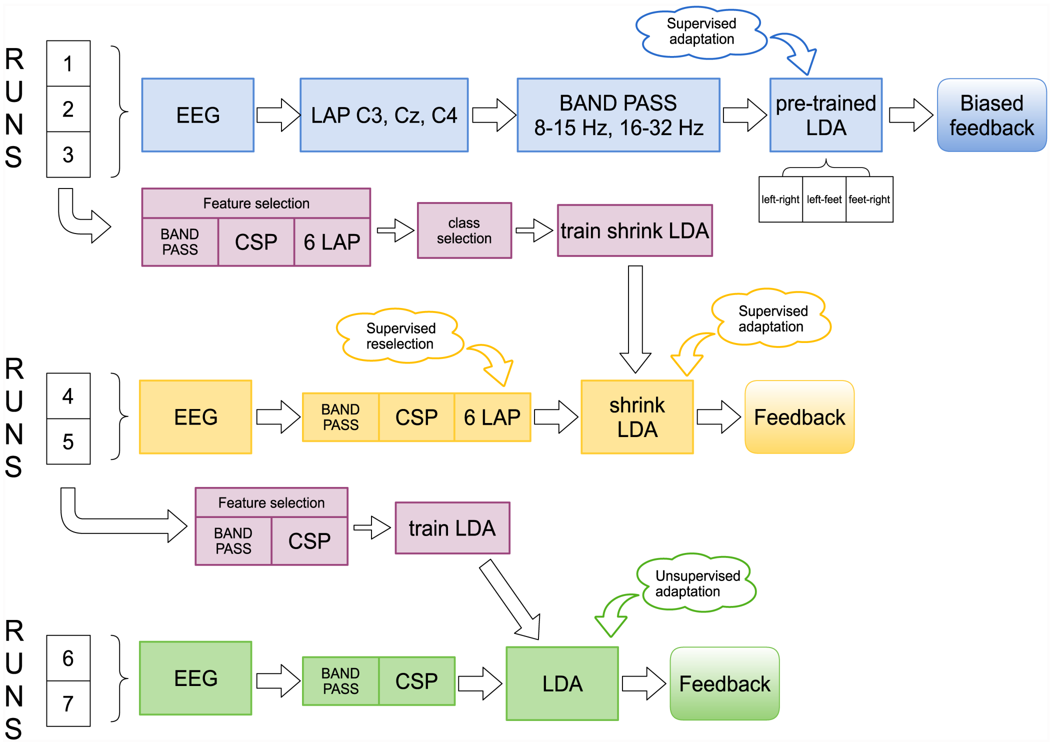

Figure 6.4 This diagram describes the co-adaptive calibration design of Study one. [initial caption:] The EEG processing and adaptation protocol during runs 1–3 with positive biased feedback are depicted in blue, in yellow the processing and adaptation during runs 4–5 with real feedback, in green the processing and adaptation during runs 6–7 also with real feedback. The adaptation applied in runs 1–3 and 4–5 uses supervised methods, the adaptation of runs 6–7 uses unsupervised methods. In magenta are depicted the phases of subject-specific features selection (e.g. frequency band, CSP filters, etc) and training of the classifier that happened two times, i.e. after runs 1–3 and after runs 4–5. (source: Acqualagna et al., 2016., http://dx.doi.org/10.1371/journal.pone.0148886.g001, CC BY PLOS One)

Neurophysiological data analysis

Due to our joint-study with Berlin, the neurophysiological data analysis was performed in Berlin, and further published in Acqualagna et al. (2016). This analysis was based on the initial sample, before $n = 28$ participants were removed from the VMC group and re-recorded, and did not take into account the issue of linked electrodes. Nevertheless, this analysis specifically reported the ERD/ERS time course on C3 and C4 and head topographies of left hand vs right hand motor imagery classes by intervention and lab, complemented with signed r^2 values.

In addition, I followed the methodology from Blankertz et al. (2010) to compute the SMR predictor from the twenty segments of 15 seconds alternating Eye-Open and Eye-Closed. A Eye-closed and an Eye-Open SMR Predictor value was computed for every participant. The preprocessing included artifact rejection based on variance of two-seconds epochs, the a local average reference filtering of C3 (C4 was excluded from calculation), the application of a bandpass filter between 2 and 34 Hz. The power spectrum density (PSD) was computed and smoothed, then the noise floor $1/f$ was computed. The highest peak of $smoothed\ PSD - noise\ floor$ was retrieved and used as SMR Predictor value. A graphical representation of the algorithm is demonstrated in Figure 6.5.

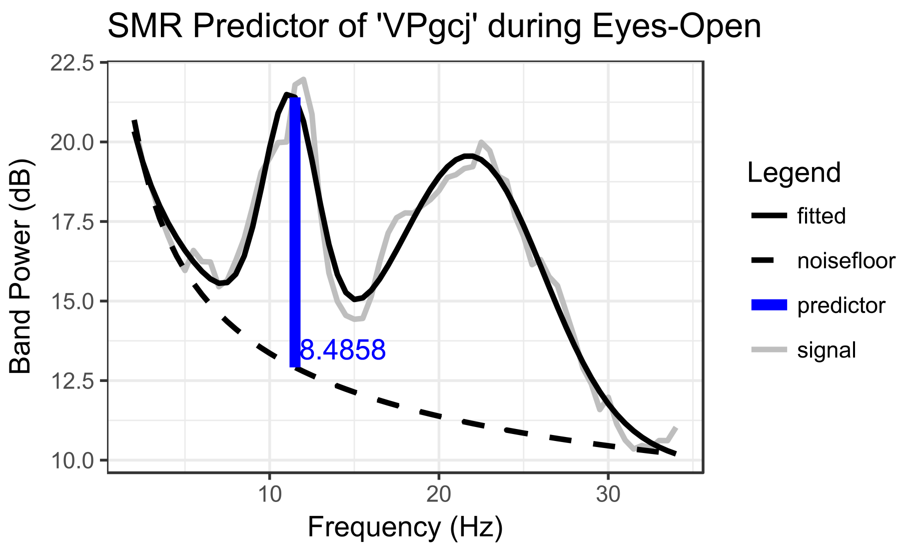

Figure 6.5 Power spectrum density plot, representing the determination of the SMR predictor for participant VPgcj, Eye-Open condition. (Source: Botrel et al., 2017)

Statistical analysis

To check whether the analyzed data was normally distributed, Shapiro-Wilk tests were used, in determining whether or not non-parametric equivalents of ANOVA had to be used (Kruskal-

Wallis test), ANOVA with repeated measures (rm-ANOVA with permutation), independent t-tests (Mann-Whitney-Wilcoxon rank sum test), paired t-tests (Wilcoxon signed rank test), Pearson correlation (Spearman correlation). Prior to calculating correlations, outliers were systematically removed, using two standard deviations of the mean as exclusion criterion. Based on the formula provided by Müller-Putz et al. (2008), the chance level was estimated, based on $N = 320$ trials, with $\alpha = .05$, and a binomial distribution of the motor imagery classes of $1/2$. The calculated chance level considered mean BCI accuracy between $45.44\,\%$ and $55.56\,\%$ to be due to chance with an probability of $\alpha = .05$.

In correlations analyses with BCI accuracy, variables from scales assessed during the PRE BCI session were correlated with the BCI accuracy PRE, BCI accuracy POST, the average BCI accuracy and BCI accuracy $POST - PRE$, for a correction – applied in the results – of $\alpha = 0.125$. When variables were assessed both during the PRE and the POST BCI sessions, the value assessed during the PRE session was correlated with BCI PRE, and the value assessed during the POST session with BCI POST, those were used for correlation of the PRE-POST average and difference $POST - PRE$, for an $\alpha = 0.125$. Concerning the variables acquired during the four training sessions, only the values from the first and the last BCI session were used, and were calculated in the same way that the variables assessed during the PRE and POST BCI sessions, for an $\alpha = 0.125$.

6.1.7 Results

Effect of lab, intervention and BCI runs on accuracy

Firsly, a full factorial type III 2x3x4 ANOVA with repeated measures was computed, using BCI accuracy as dependent variable, lab and intervention as between subject factors, and BCI run as within subject factor. An interaction $lab*run$ was found ($F(3, 444) = 3.51, p = .015$), main effects of lab ($F(1, 148) = 11.04, p = .001$) and run ($F(3, 444) = 4.27, p = .005$) were also significant; the effect of intervention was not significant ($F(2, 148) = 2.38, p = .096$) and no further significant interaction were found (for averaged and run-wise accuracy plots, see Figures 6.6 and 6.7).

BCI Accuracy was significantly higher in BE ($M = 78.2\%$, $SD = 15\%$) in comparison with WÜ ($M = 70.6\%$, $SD = 14.1\%$). Post-hoc pairwise comparisons for the effect of run (online runs 4 to 7) showed that the BCI accuracy increased between runs 4 and 6 ($M_{\text{diff}} = 2.5$, $SD = 10.1$, Wilcoxon signed rank $W = 3796.5$, $p = .003$, Bonferroni adjusted $p_{\text{adj}} = .019$). Accuracy decreased marginally between runs 6 and 7 ($M_{\text{diff}} = -1.6$, $SD = 7.1$, $W = 6240$, $p_{\text{adj}} = .066$). Post-hoc pairwise comparisons for the interaction between run and lab showed that accuracy was higher in BE than in WÜ in run 4 ($M_{\text{diff}} = 9.2$, $SD = 21.6$, $W = 2000$,

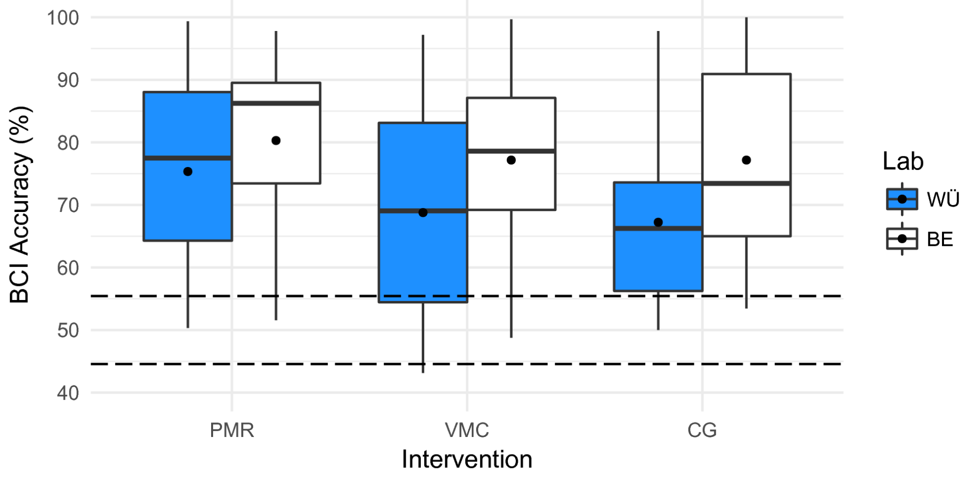

Figure 6.6 BCI accuracy boxplots depending on the lab and intervention, representing quartiles, median (line inside the box) and mean (dot). Dashed lines indicate upper and lower true chance levels. (Source: Botrel et al., 2017)

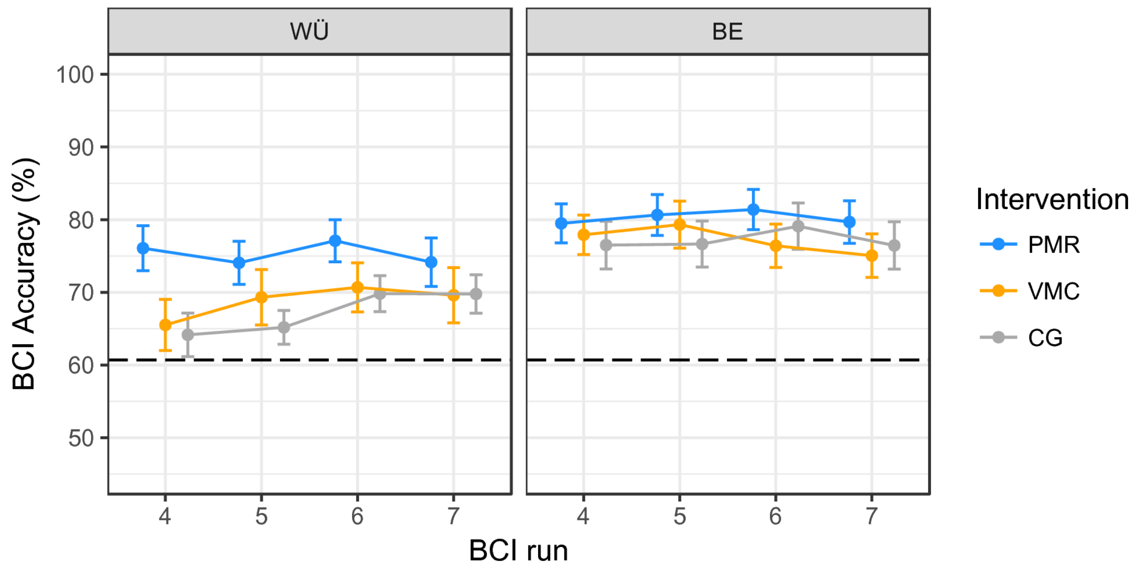

Figure 6.7 Mean accuracy per intervention and run for WÜ and BE with standard error bars. Dashed lines indicate the upper true chance level (with n=80).

Lab	N(*)	Group	BCI Accuracy		VAS relax PRE		VAS relax POST		Wilcoxon PRE-POST	
			$M(\%)$	SD	$M(\%)$	SD	$M(\%)$	SD	W	p
WÜ	28	PMR	75.3	15.5	6.3	1.9	8.2	1.7	12	<.001
	22	VMC	68.8	16.2	8.0	1.4	7.7	1.4	157.5	.322
	28	CG	67.2	12.5	7.2	1.8	7.2	1.8	146.5	.676
BE	27(19)	PMR	80.3	13.5	7.6	2.3	8.3	2.0	41	.097
	24(17)	VMC	77.2	13.8	7.2	2.3	7.0	2.0	59.5	.683
	25(17)	CG	77.2	15.2	6.9	2.3	6.4	2.3	71.5	.532

**: reduced number of participants with relaxation levels measured with visual analog scales. The VAS pre-post values are from these reduced sample sizes; BCI accuracy is from the full samples.*

Table 6.1 Number of participants, mean BCI accuracy, Relaxation levels pre and post intervention, and Wilcoxon signed rank test W per group and condition.

$p_{\text{adj}} < .001$), run 5 ($M_{\text{diff}} = 9.4$, $SD = 22$, $W = 1943.5$, $p_{\text{adj}} < .001$) and run 6 ($M_{\text{diff}} = 6.4$, $SD = 20.4$, $W = 2249$, $p_{\text{adj}} = .039$).

Difference between labs

The ANOVA with repeated measures for mean BCI accuracy revealed a difference between labs. This unexpected difference was further investigated by looking for explanatory variables. Since a few studies found age to predict and BCI accuracy (e.g. Randolph et al., 2010), this was investigated. A correlation between BCI performance and age was found (Spearman $\rho = -.167$, $p = .042$, $n = 151$, $n_{\text{outlier}} = 3$), but the mean age did not differ between labs ($M_{\text{WÜ}} = 24.3$, $SD = 3.5$, $M_{\text{BE}} = 25.1$, $SD = 7.5$, $W = 3127.5$, $p = 0.375$), suggesting there was no effect of age between labs. In further investigations, it was found that $n = 55$ participants in WÜ, accounting for $70\,\%$ of the WÜ sample, presented an error internally linking C4 and T8 at the hardware level. The issue was neither visible during the impedance check nor during the online BCI runs. As C4 (along with C3 and Cz) was one of the most important electrodes in the SMR modulation paradigm, further tests were conducted by assessing the effect of the hardware error on classification results. The negative effect was expected to be the strongest during classification runs 1 to 3, during which the features were calculated with Laplacian derivations of electrodes C3 , Cz and C4. During the following runs 4 to 7, the inclusion of CSP filters may have compensated for the linked electrodes since the method is based on variance and not on location. All VMC runs were recorded using the "bad" EEG cap and were not included in the comparison, but PMR and CG groups were measured with both "good" and "bad", allowing to analyze the difference. The effect of EEG cap on accuracy in the PMR and CG groups was assessed using Wilcoxon rank sum test. No significant difference in accuracy was found ($W = 369.5$, $p = .874$, visualization of the effect in Figure 6.8). Since age, and the use of "bad" or "good" EEG cap could not explain the difference of accuracy between labs, these were not further investigated. Due to the presence of a significant difference without explanation, the samples were analyzed separately for WÜ and for BE.

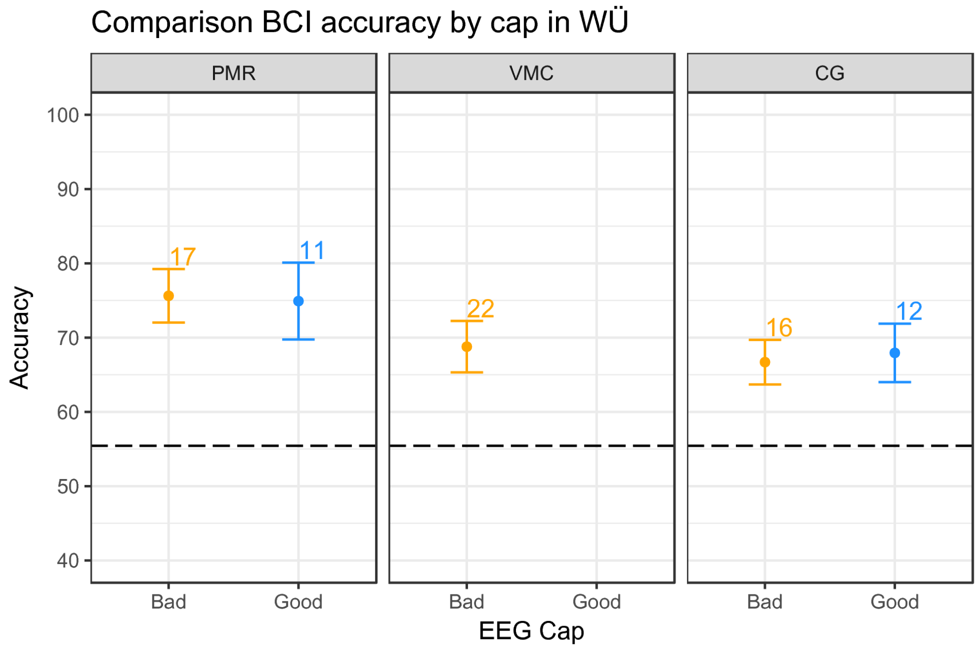

Figure 6.8 Comparison of BCI accuracy mean (dot) and standard error (bars) between lab, intervention and cap. The number indicate the number of cases.

Results for the WÜ sample

Effect of intervention There was no effect of intervention on BCI accuracy, as revealed by Kruskall-Wallis test ($H = 4.0749$, $df = 2$, $p = 0.130$). The manipulation check for PMR and VMC trainings were then performed. To evaluate the effect of training on relaxation levels, a type III rm-ANOVA was conducted with relaxation levels as dependent variable, intervention as between-subject factor and assessment time as within-subject factor. It returned a significiant interaction $intervention * time$ ($F(2, 75) = 22.07$, $p < .001$) and a main effect of time ($F(1, 75) = 11.44$, $p < .01$). Effect of intervention was not significant ($F(1, 75) = 1.31$, $p = .27$). Post-hoc pairwise comparisons revealed that reported relaxation increased in the PMR group from $M = 6.3$ to $M = 8.2$ after intervention (Wilcoxon signed rank $W = 12$, $p_{\text{adj}} < .001$), while it did not change significantly in the other intervention conditions (VMC: from $M = 8$ to $M = 7.7$; CG: from $M = 7.2$ to $M = 7.2$). To assess the effect of VMC on "mean error duration", a paired t-test between "error percentage" between the five first runs and the following runs was computed. The "error percentage" did not differ significantly over time ($M_{\text{diff}} = -0.35$ pp, $SD = 1.42$, $t(21) = -1.17$, $p = .253$) .

Correlations with BCI performance BCI accuracy was not correlated with relaxation levels before intervention ($\rho = .133$, $p = .257$, $n = 78$, $n_{\text{outlier}} = 3$) or after intervention ($\rho = .094$, $p = .421$, $n = 78$, $n_{\text{outlier}} = 3$, see Figure 6.9a). The correlation between BCI

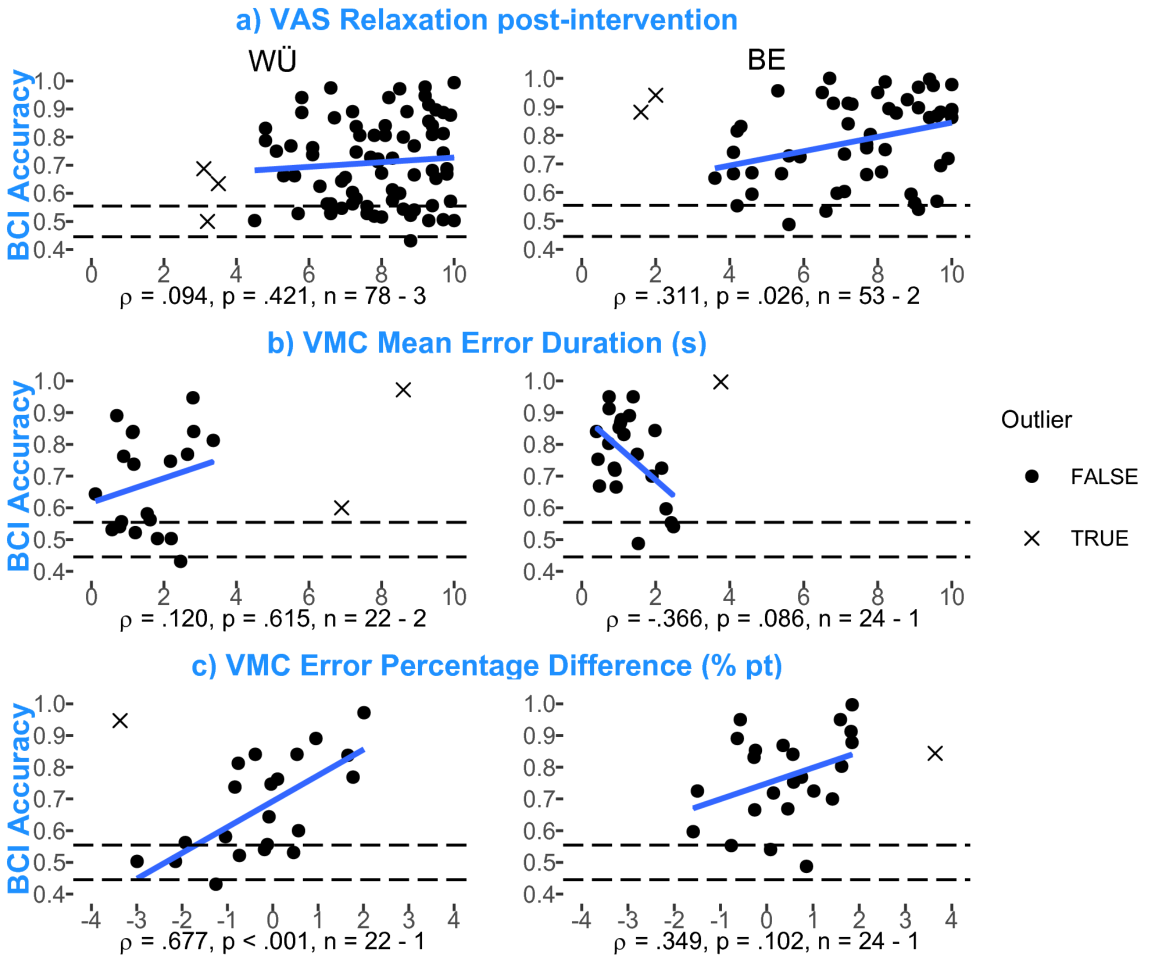

Figure 6.9 Correlation plots of relaxation level or VMC variables with BCI accuracy, Blue lines indicate linear regression. Dotted lines indicate true chance level. Outliers are marked with crosses. a) BCI accuracy and perceived relaxation level after interventions (obtained from visual analogue scales). b) BCI accuracy and two-hand coordination mean error duration. c) BCI accuracy and two-hand coordination error percentage difference expressed in percent points. (Source: Botrel et al., 2017)

accuracy and VMC "mean error duration" was not significant ($\rho = .120$, $p = .615$, $n = 22$,

$n_{\text{outlier}} = 2$, see Figure 6.9b). The VMC "error percentage difference" correlated positively with BCI accuracy ($\rho = .677$, $p < .001$, $n = 22$, $n_{\text{outlier}} = 1$, see Figure 6.9c), showing that a higher value (i.e. a higher reduction in VMC "error percentage" compared to baseline) was associated with higher BCI accuracy. The SMR Predictor in the Eye-Open condition was significantly correlated with BCI accuracy ($\rho = .24, p = .0451$, $n = 72$, $n_{\text{outlier}} = 4$) while the SMR Predictor in the Eye-Closed condition was not correlated with BCI accuracy ($\rho = .04, p = .77$, $n_{\text{outlier}} = 2$). BIS scale (comprising subscales) and KUT did not correlate significantly with BCI accuracy.

Results for the BE sample

Effect of intervention There was no effect of intervention on BCI accuracy, as revealed by Kruskall-Wallis test ($H = 0.8769$, $df = 2$, $p = 0.645$). The manipulation check for PMR and VMC trainings were then performed. To evaluate the effect of training on relaxation levels, a type III repeated measures ANOVA was conducted with relaxation levels as dependent variable, intervention as between factor and assessment time as within-subject factor. No interaction or main effect on relaxation were found, $intervention * time$ ($F(2, 50) = 1.89$, $p = .17$), time ($F(1, 50) = 0$, $p = .99$), intervention ($F(1, 50) = 1.87$, $p = .16$). To assess the effect of VMC on mean error duration, a paired t-test between error percentage between the five first runs and the following runs was computed. The error percentage significantly decreased ($M_{\text{diff}} = 0.53\,\text{pp}$, $SD = 1.21$, $t(23) = 2.16$, $p = .041$).

Correlations with BCI performance Reported relaxation levels assessed before intervention were not correlated with BCI accuracy ($\rho = .041$, $p = .775$, $n = 53$, $n_{\text{outlier}} = 3$). Yet, relaxation levels after intervention were positively correlated with BCI accuracy ($\rho = .311$, $p = .026$, $n = 53$, $n_{\text{outlier}} = 2$, see Figure 6.7a). A marginal negative correlation was found between BCI performance VMC "mean error duration" ($\rho = -.366$, $p = .086$, $n = 24$, $n_{\text{outlier}} = 1$ see Figure 6.8b). A higher "mean error duration" (in seconds) was related with lower BCI accuracy. The "error percentage difference" was not correlated with BCI accuracy ($\rho = .349$, $p = .102$, $n = 24$, $n_{\text{outlier}} = 1$, see Figure 6.8c). The SMR Predictor in the Eye-Open condition was significantly correlated with BCI accuracy ($\rho = .38, p = .002$, $n = 65$, $n_{\text{outlier}} = 3$), the SMR Predictor in the Eye-Closed condition was also correlated with BCI accuracy ($\rho = .35, p = .004$, $n_{\text{outlier}} = 1$). BIS scale (comprising subscales) and KUT did not correlate significantly with BCI accuracy.

Neurophysiological ERD/ERS data

Acqualagna et al. (2016) compared the left hand vs right hand classes ERD/ERS patterns based on the initial sample that I provided them[3]. According to their results, the PMR group showed more pronounced class-wise ERD as compared to the two other groups, for a higher discriminability. Interestingly, the VMC group showed great ERD in both classes. This symmetrical effect reduced the ability to benefit from those deeper ERDs for higher classification accuracy. I included in this dissertation tte plots for ERD/ERS and topographical maps for WÜ (see Figure 6.10) and BE (see Figure 6.11). The evolution of the ERD/ERS is further discussed in Acqualagna et al. (2016)

6.1.8 Discussion

This study investigated whether short interventions trainings of two predictors of BCI accuracy would subsequently increase BCI accuracy. Results did not indicate any effect of PMR (H_1) nor VMC (H_2) interventions on BCI accrurracy. The manipulation checks for the effect of training on SMR-BCI predictors were not systematically validated. In detail, the PMR increased relaxation levels only in WÜ and the VMC decreased the "error percentage" only in BE. Only in those same cases (MC_1 and MC_2 validated), the variables used for manipulation check (i.e. relaxation levels and error percentage difference) were not correlated with BCI accuracy (see Table 6.2). Since that in both labs, all possible outcomes of manipulation check were displayed (Both MC_1 and MC_2 validated and invalidated), and that it resulted in all cases in no effect for SMR-BCI accuarcy, the ability to influence the SMR-BCI accuracy could not be explained by the success of the PMR and VMC manipulations. This observation suggests

Lab	Interv-ention	Predictor	Manipulation check validated	Correlated with BCI accuracy	Variable for Manipulation check
WÜ	PMR	Ability to concentrate	**YES**	NO	Relaxation level
	VMC	VMC error	NO	**YES**	Error % diff
BE	PMR	Ability to concentrate	NO	**YES**	Relaxation level
	VMC	VMC error	**YES**	NO	Error % diff

Table 6.2 When the manipulation check were validated, the variables used for manipulation check (based on the SMR predictors) were not correlated with BCI accuracy.

that the efficacy of training may have reduced the predictive power of the predictors. This

[3]The sample used by the authors of this neurophysiological analysis included the n=28 participants of the VMC that I excluded and replaced (see participants in section 6.1.6).

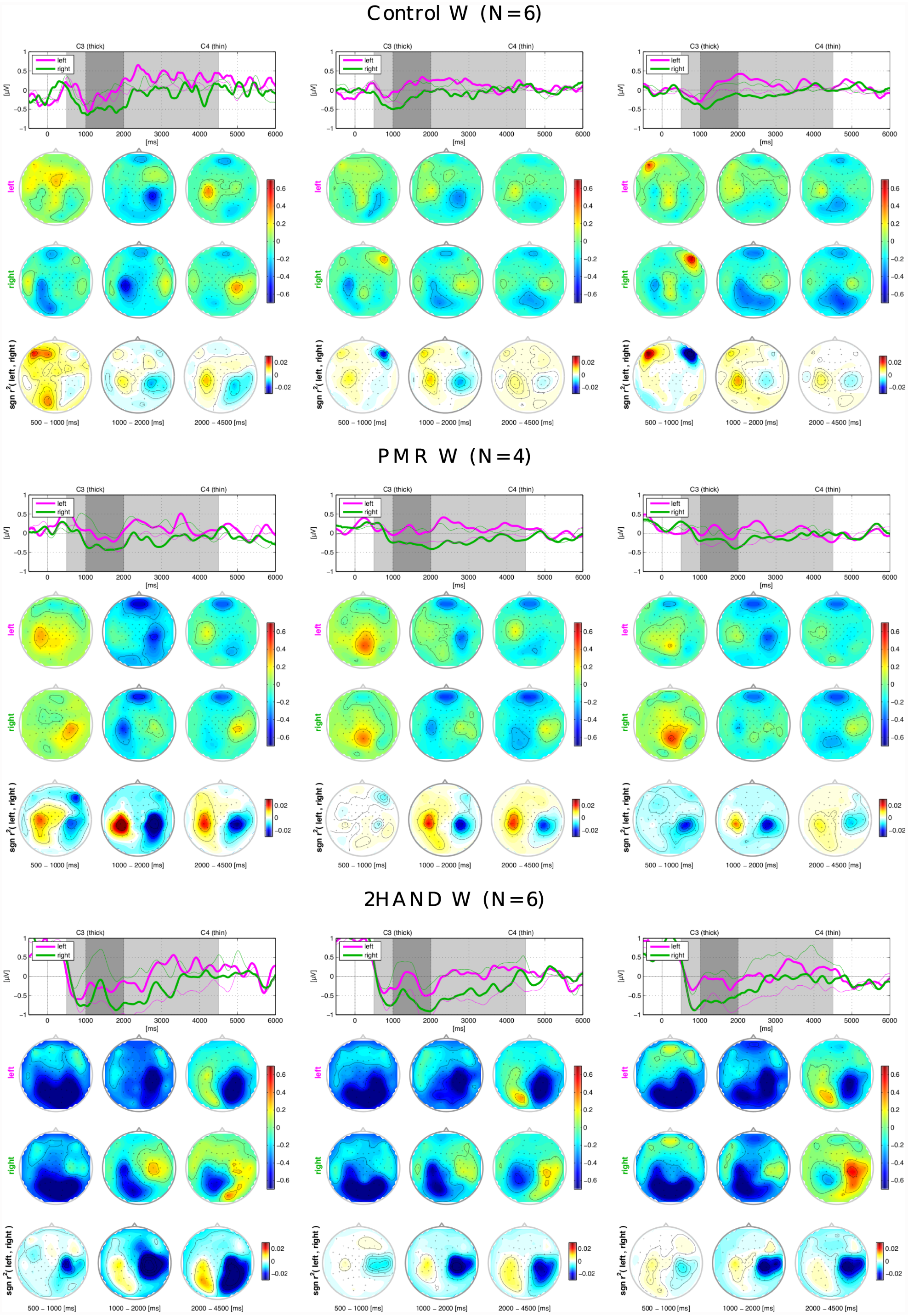

Figure 6.10 **Grand average ERD/ERS for class combination left-right and intervention groups in Würzburg.** 'N' is the number of participants of each group. From left to right: runs 1-3, runs 4-5, runs 6-7. The time plots in the first rows picture the evolution of the ERD/ERS for about 6000 ms at C3 (thick lines) and C4 (thin lines). At time 0 is the onset of the cue, at times 1000–4000 the display of the feedback. Magenta lines refer to left MI trials, green lines to right MI trials. The scalp plots underneath refer to the shaded areas of the time plots and show the distribution of the ERD/ERS. In the second rows, the scalp plots of the left MI trials, in the third rows the scalp plots of the right MI trials and in the fourth the scalp plots of the $signr^2$. From Acqualagna et al. (2016), http://dx.doi.org/10.1371/journal.pone.0148886.g005, CC BY PLOS One

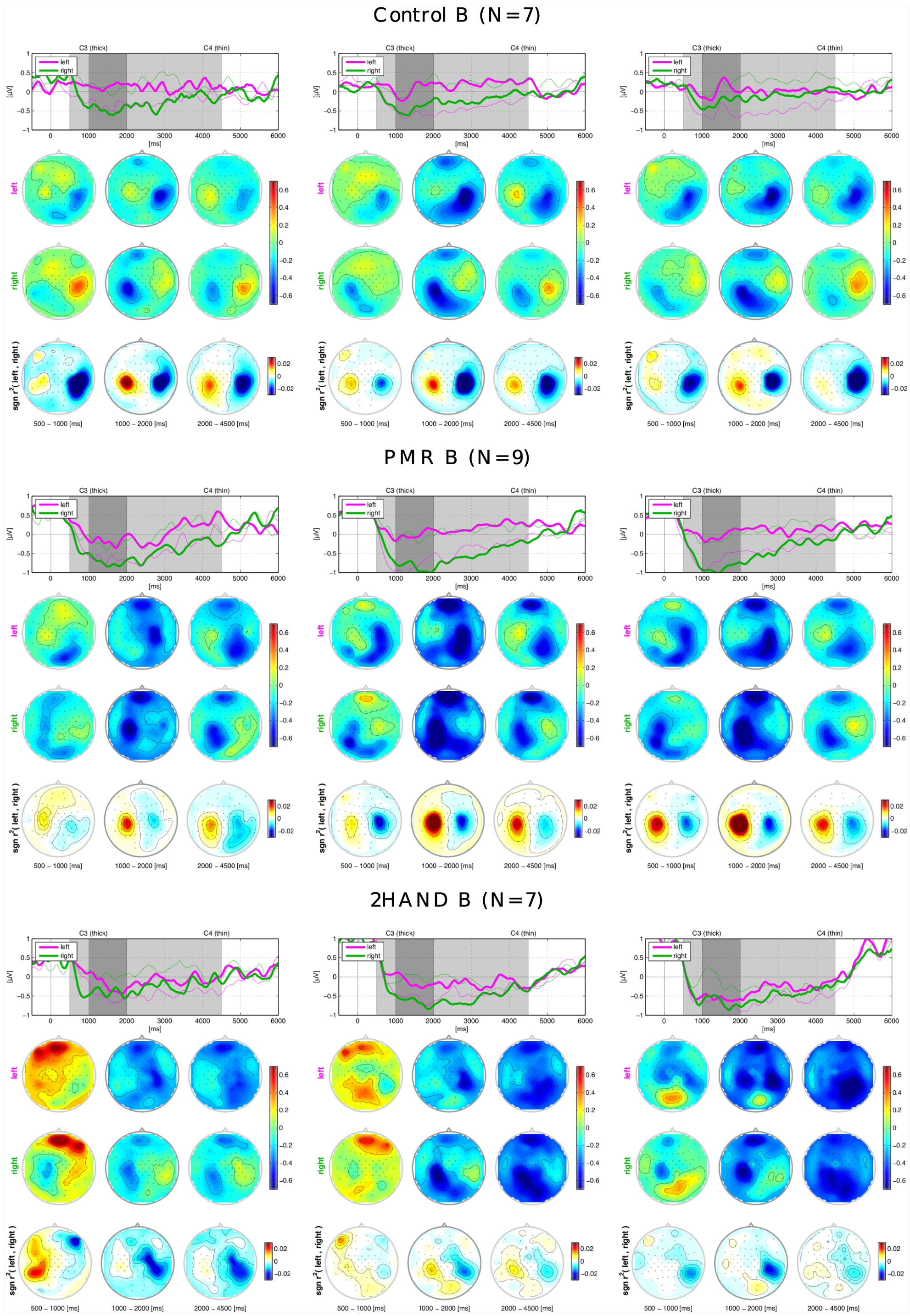

Figure 6.11 **Grand average ERD/ERS for class combination. left-right and intervention groups in Berlin.** 'N' is the number of participants of each group. From left to right: runs 1-3, runs 4-5, runs 6-7. The time plots in the first rows picture the evolution of the ERD/ERS for about 6000 ms at C3 (thick lines) and C4 (thin lines). At time 0 is the onset of the cue, at times 1000–4000 the display of the feedback. Magenta lines refer to left MI trials, green lines to right MI trials. The scalp plots underneath refer to the shaded areas of the time plots and show the distribution of the ERD/ERS. In the second rows, the scalp plots of the left MI trials, in the third rows the scalp plots of the right MI trials and in the fourth the scalp plots of the $signr^2$. From Acqualagna et al. (2016), http://dx.doi.org/10.1371/journal.pone.0148886.g005, CC BY PLOS One

hypothesis would nevertheless require a dedicated experimental design to be determined, as this observation might just be coincidental.

Two of the investigated predictors were not replicated. No relation was found with the Locus of Control in dealing with Technology (KUT), and neither for the BIS impulsiveness scale, even when checking for the "non-planning" subscale (found in Hammer et al. (2014)), showing a lower reliability of those predictors.

The results confirmed both predictors from Hammer et al. (2012), although none of the results were found equivocally in both labs. The post-intervention relaxation level was positively correlated in BE, but not in WÜ. The positive association, although not consistently found, was in line with previous literature (Grosse-Wentrup et al., 2011) and concurrent findings (Grosse-Wentrup and Sch??lkopf, 2012; Bamdadian et al., 2014) associating attention levels with BCI accuracy. The other predictor, "mean error duration" in a VMC task could explain in Hammer et al. (2012) up to 11 % of the variance, but we only found a marginal correlation in BE. It must be precised that the "mean error duration" obtained in study I was a "raw" value without standardization. Therefore, the negative correlation reported in results means that participant with fewer steering errors had higher BCI accuracy. This equated the positive correlation reported by Hammer et al., which was based on standardized results, and that was later replicated (Hammer et al., 2014). The significant positive correlation in "error percentage difference" showed that participants in WÜ who reduced the most their steering errors during manipulation had higher BCI accuracy.

The failure to increase SMR-BCI indicates that the duration of the intervention training could matter. Tan et al. (2009) initially performed a pilot investigation of four weeks to increase BCI accuracy, and then conducted a large scale study on an extended duration of twelve weeks to reveal the effect of mediation training on BCI accuracy (Tan et al., 2014). Most studies investigating the effect of relaxation training on attention (e.g., Tang et al., 2007), anxiety (e.g., Zhao et al., 2012, local brain connectivity (e.g, Luders et al., 2011) or neuroplasticity (e.g., Davidson and Lutz, 2008) typically expose their participants to much longer training durations as compared to the one chosen in this study. Accordingly, and supported by the fact that the assumptions of PMR training success was not always validated, it might be the case that the duration of the PMR training was insufficient to produce a consistent increase in the predictors for SMR-BCI accuracy.

The same reflexion can be applied for the VMC training that was also very short. Studies reporting inter-individual differences mostly compare athletes or highly skilled individuals with novices. The findings from Zapala et al. (2015) show there is much potential to be obtained in training novice. The authors showed that a kinesthetic hand training increased α band power in C3 and C4 measured right after training; and the effect could be observed on novice jugglers but not on experts. Babiloni et al. (2009) provided a similar view on the topic, finding that elite karate practitioners had lower α ERD when watching karate videos in comparison with non-athletes. While opposite effect has also been observed by dance experts observing people dancing (Orgs et al., 2008), Del Percio et al. (2010) provided more evidence of lower ERD by elite fencers. The authors supported the hypothesis of neural efficiency and expertise, according to which non-skilled individuals display intermediate cortical activity as compared to skilled individuals who have a higher neural efficiency. In their fMRI based investigation of motor imagery of sports practitioners, Wei and Luo (2010) posited that this process of neural efficency resulting from learning, is bound to the motor skills of expertise. This increased of α ERD/ERS or activation in motor areas associated with novice learning fine motor skills showed much potential for implementation, as higher amplitude ERD/ERS are better classified in SMR-BCIS, but it nonetheless does not answer as to whether the α ERD/ERS can better be modulated in the context of a BCI. Evidence toward this possibility has been established in the reversed direction, as it was shown by Cheng et al. (2015) that eight sessions of α neurofeedback training increased the accuracy of golfers (yet skilled) in using the putter.

Despite the non-consistent correlation of VMC predictors with BCI accuracy, those were nonetheless replicated in Hammer et al. (2014). The additional evidence (cited above) showing the motor training of novice to be increase motor related EEG activity allowed to consider the VMC training as a potential training for increasing BCI accuracy. Finally, the explanation about the lack of effect of VMC training could be that the duration of the motor training was too short to produce neurophysiological changes, and it could be speculated that an effect may arise from an intensified training, extended in duration.

The SMR Predictor was replicated in this study, by a correlation with BCI accuracy. The results showed, as posited by Blankertz et al. (2010), that the Eyes-Open condition was more associated with BCI accuracy than the Eyes-Closed condition, particularly by the non-significant correlation between Eyes-Closed in WÜ and BCI accuracy. The high number of failure to calculate the SMR Predictor ($n = 14$ participants) was essentially due to the missing C4 electrode. It can be pointed that this study did not offer the best conditions to evaluate the SMR predictors, due to the missing C4 and that motor imagery of the feet that was based on electrode Cz, not included into the SMR Predictor calculation.

Conclusion Study I

The results indicate a positive association between relaxation and BCI performance. The VMC ability (mean error duration) could not be replicated as a predictor of BCI accuracy. The increase in VMC proficiency (reduction of error percentage) was associated with higher

BCI accuracy, but the increase of the predictor linked with intervention was not followed by a significant increase in BCI accuracy. While these relations with BCI accuracy show that both attention levels and VMC coordination ability may be related with SMR-BCI performance, it could not be clearly established whether a training of these factions would lead to higher BCI accuracy. This investigated effect could possibly develop by intensifying the training duration, but yet, the results of this study indicate that a single non-BCI training was insufficient to increase SMR-BCI accuracy.

6.2 Study II - Effect of four days VMC and PMR trainings on SMR-BCI

6.2.1 Summary update, revisiting research questions

The second study was designed during summer 2015. Since study I, which did not success into implementing short PMR or VMC intervention trainings to increase BCI accuracy, new elements had been reported in the literature. The replication of Hammer et al. (2014) had been published showing a replication of VMC "mean error duration" in predicting 11 % of the variance in SMR-BCI performance. The other predictor "ability to concentrate" was not replicated, but instead, Hammer et al. found a correlation between the "non-planning" subscale of the Baratt Implusiveness Scale (BIS). The predictors described in the literature review (see chapter 5) providing heterogeneous but empirically supported relation with SMR-BCI performance that could be globally be classified into three generic classes.

1. Attention levels
2. motivational aspects
3. Visuo-motor and spatial abilities

I chose not to investigate the motivational aspects, firstly because evidence revealed correlations with BCI performance that were very likely to be bidirectional (i.e. Nijboer et al., 2008; Kleih et al., 2010, and secondly because the motivational aspects have been in several reports suggested to potentiate attention levels (e.g. Leeb et al., 2007), in particular via the distinction between intrinsic and extrinsic motivation (see section 5.1.3).

The study from Tan et al. (2014) demonstrated that a twelve week mindfulness meditation (MM) training could lead to an increase in SMR BCI acccuracy compared to a musical training and a control group. Additional empirical evidence showed that relaxation and meditation practice predicted BCI performance. Cassady et al. (2014) showed that weekly mind-body awareness practice (i.e. attending courses twice a week in a yoga club) for at least one year was associated with higher SMR-BCI accuracy. While the authors relate to relaxation or mindfulness, none of the concerned experiments were accompanied with manipulation checks that would experimentally support their claims.

Study I was unsuccessful in increasing SMR-BCI accuracy by a single short training. The neurophysiological and neuroanatomical changes (described in section 5.4) resulting from relaxation and – motor – skill training, and studies that showed a relation between BCI accuracy and longer training (i.e. Tan et al., 2014; Cassady et al., 2014) oriented the research questions of study II to focus on a longer time span. By evoking the extension of the non-BCI training duration, it must be kept in mind that the SMR-BCI training, which can be apparented to neurofeedback, has been shown to produce positive changes over at least three weeks (i.e. Taubert et al., 2011), but in the case of BCI training, increase in ERD/ERS patterns have been reported in only two BCI sessions (e.g. Kaiser et al., 2014). Therefore, if any potential non-BCI training fails to provide better or comparable results in terms of training duration, such a training could only be useful if its effect were shown to be complementary to the BCI training.

6.2.2 Research questions

The research questions for this study were therefore similar to those of study I, but incorporated the added information from study I and other sources from empirical scientific literature. The first question was, provided the evidence (see summary 6.2.1 and study I) showing that BCI performance has been found to be predicted by several variables, "*Are attention levels and proficiency in a VMC task reliable predictors for SMR-BCI accuracy?*" To answer this question, experiments should be conducted in the perspective of repeating the conditions of study I, but this time ensuring the effect of training on the predictors. The question that motivates this implementation could be posited as follows: "*By influencing those predictors in the direction of their association with SMR-BCI accuracy, can this SMR-BCI accuracy be consequently improved?*". To answer this question, specific and efficacious interventions, notably ensured by a longer training duration, should be investigated and tested for their relation with SMR-BCI performance. Taking into account the new studies that revealed new variables associated with increased SMR-BCI accuracy, an additional research question can be posited: *Are kinesthetic motor imagery and mindfulness associated with higher BCI accuracy?* Additional questionnaires for kinesthetic motor imagery and mindfulness could be assessed in a new design with no particular effort, in an attempt to replicate other researcher's findings.

6.2.3 Hypotheses

In this study, the PMR and VMC interventions were intensified into trainings that were conducted on several days. It was hypothesized that training (i.e. PMR or VMC) would improve BCI accuracy. The effect of PMR training on SMR-BCI accuracy was conditioned by the assumption that PMR training increased relaxation levels. For the effect of VMC training, the assumption was that VMC training produced an effect of motor learning, reducing the number of steering errors, and had been associated with higher SMR-BCI performance.

- **Main hypotheses**: There is a positive effect of training on BCI accuracy
  - **(H_1)** PMR training leads to higher BCI accuracy.
  - **(H_2)** VMC training leads to higher BCI accuracy.

  For assessing the specificity of the trainings in causally increasing BCI accuracy, it was necessary proceed to manipulation checks:
- **(MC_1)**: PMR intervention increases relaxation levels:
  - on the short term, before and after each training.
  - on the long term, when assessed right before the BCI sessions (PRE and POST).
- **(MC_2)**: Skill learning occurs during the VMC training:
  - steering errors reduced overall ("mean error duration").
  - difference in steering errors reduced during runs ("error percentage difference").

In an effort to contribute to or validate predictors and correlates for SMR-BCI performance, previous predictors (i.e. previously mentioned in litterature) were assessed in directed correlation analyses[4]. It was therefore assessed whether BCI accuracy correlates:

- positively with reported relaxation VAS (see Hammer et al., 2012; study I in WÜ sample).
- negatively with VMC "mean error duration" (see Hammer et al., 2012, 2014; study 2 in BE sample).
- positively with VMC "error percentage difference" (see study I in WÜ sample).
- positively with Kinesthetic (and Visual) Imagery Questionnaire (KVIQ; Vuckovic and Osuagwu, 2013).
- positively with the SMR predictor eyes-open (Blankertz et al., 2010).

An additional explorative correlation analysis was performed, in which correlations between BCI accuracy and State Mindfulness Scale (SMS), Self-regulation (SR) or Self-efficacy (SWE) were assessed.

[4] Two-sided tests were used

In this study, individual differences in baseline BCI accuracy were controlled by the use of a PRE-POST design; moreover, the training was prolonged such that the training duration totalized two hours over four consecutive days.

6.2.4 Methods

Participants

$N = 39$ healthy participants were recruited by announces on the university campus or via internet ads. The measurements took place at the University of Würzburg (Germany). A financial compensation of €50 was offered for the experiment that spread over five days for a total duration of 6.5 hours. Alternatively, participants could receive hourly credit in a psychology student participation program. All BCI measurements were performed in an EEG cabin designed to attenuate sounds from external sources while providing artificial and indirect lighting conditions. Participants sat on a comfortable armchair, facing a $1024 * 768$ px, 17" monitor, placed at about 1 m from the monitor. Loudspeakers were placed on both sides of the monitor. The study was conducted in accordance with the declaration of Helsinki, approved by the Ethical Review Board of the Medical Faculty (University of Tübingen), and written informed consent was obtained prior to experimentation.

Questionnaires

Different types of questionnaires were given to the participants before and during the course of the experiment

1. The kinesthetic and Visual imagery questionnaire (KVIQ; Malouin et al., 2007) was performed on a chair outside of the EEG cabin to offer enough space for arms and leg extension. The experimenter sat in front of the participant. The origninal questionnaire KVIQ-20 comprises 20 items that concerns groups of muscles from the neck and arms to the feet. We restricted the questionnaire to only consider the four items that included upper limb movements: shoulder shrugging, forward shoulder extension, elbow flexion, thumb to finger tips. The items were assessed for the visual modality (KVIQ-V), then for the kinesthetic modality (KVIQ-K), providing two subscales. For each item, the experimenter performed every movement once, that were repeated once by the participant. Then, the participants were instructed to imagine the same movement without moving. Afterwards, participants were asked to firstly rate the visual vividness of the movement on a scale from 1 (no image) to 5 (image as clear as seeing); secondly

to rate the kinesthetic vividness of the movement from 1 (no sensation) to 5 (as intense as executing the action). The score was averaged for the four items.

2. Visual analog scale (VAS) for relaxation was presented on a respective 10 cm horizontal line that ranged from 0 (not at all) to 10 (maximally). Participants were asked to estimate their current level by crossing the line with a pen.

3. the State Mindfulness Scale (SMS; Tanay and Bernstein, 2013) assessed mindfulness in the present moment, more specifically, in the 15 minutes that preceded the test. The questionnaire items assessed two different forms of mindfulness: mindfulness of bodily sensations (e.g., "*I changed my body posture and paid attention to the physical process of moving*") or mindfulness of mental events (e.g., "*I was aware of different emotions that arose in me*"). A total of 21 items accompanied with the question "*how well each statements describes your experiences*" were answered in a Likert-type scale ranging from 1 (not at all) to 5 (very well), with higher scores indicating a mindful experience. The questionnaire was translated from english and backtranslated by bilingual native german or english and doctor in psychology, but was not methodically validated using statisitcal methods. The scale was provided to the participants 15 min after the beginning of the first BCI run, and therefore evaluated mindfulness during a SMR-BCI control task (i.e. it could not be used to predict BCI accuracy).

4. The self-regulation questionnaire (SR, German version from Lehmann et al., 2014) evaluated the participant's "*general tendency to uphold an action even if influences arise that impair their motivation and attention*". The 10 items were statements that were rated on a Likert-type scale from 1 (disagree) to 4 (agree)

5. The self-efficacy questionnaire (SWE, German version from Jerusalem and Schwarzer, 1999) assessed the generalized persuation of self-efficiency and the competence to cope with unexpected situations. The 10 items were statements rated on a Likert-type scale that ranged from 1 (disagree) to 4 (agree).

6. The Mindful Attention Awareness Scale (MAAS, Brown and Ryan, 2003; German version from Michalak et al., 2008) assessed participants' mindfulness in the form of attentiveness. The definition of mindfulness provided by the authors was "paying attention in a certain way: on purpose, in the present and non-judgementally". The questionnaire comprised 15 items, for which participants answered how often statements or daily life situations described in the sentences occured in their every day life. The rating was done in a 6 points Likert-type scale ranging from 1 (almost always) to 6 (almost never). Sentences refered to the ability to pay attention or to mundane events

or remember about them; they also refered to feelings of being fully aware of "running on automatic" during those daily experiences.

7. The Locus of Control in dealing with technology (KUT; Beier, 2004; introduced in 5.1.2) assessed the difficulty of the participant to deal with electronic or mechanical objects in ordinary life situations (e.g., using the microwave, assembling furniture kits). The questionnaire comprised 8 items, that are statements to be rated on a 5 points Likert-type scale ranging from 1 (not at all) to 5 (absolutely).

Training

The participants were assigned to one of the three groups in a pseudo-random fashion. Depending on their assigned group, participants took part in training sessions four times on four consecutive days (see timeline Figure 6.12). Each training session lasted 23 minutes.

1. a progressive muscle relaxation group (PMR), similar to study 1 (see 6.1.6). The audio file was played inside the EEG cabin offering better insulation from potential sources of distraction.

2. a visuo-motor coordination group (VMC), similar to study 1 (see 6.1.6), in which participants steered a virtual ball through narrow paths using two know controllers. In addition to the setup from study I, a scoreboard was presented after each track completion, allowing participants to monitor their individual track performances during the session. The scoreboard was meant to implicitly motivate participants to improve their own performance during the four training sessions. As in study one, same variables "mean error duration" and "percentage error difference" were extracted, for each of the four training sessions.

3. a control group (CG) in which participants were asked to choose and read a book from a selection of three German novels while remaining seated in the cabin. The choice to use a book instead of a BCI book chapter as in study I was meant to provide non-repetitive and engaging material to read. Although no particular effect pointing in this direction had been demonstrated in study I, this choice was also meant to reduce stress and exertion resulting from reading scientific material with subsequent control questions. In the CG, no control questions were asked to the participants.

Study timeline

Participants took part in two SMR-BCI sessions, separated by five days (day1 and day5). Between the BCI sessions, participants had four training sessions on four consecutive days.

The study therefore had two BCI blocks, assessed in a PRE-POST design and four training blocks. On day 1, the BCI block was followed by a training block. On days 2 to 4, the three remaining training sessions occured. On day 5 only the POST BCI session occurred (for timeline see Figure 6.12). The two BCI blocks were identical between the PRE and the POST condition, at the exception of a few – trait – questionnaires. No subject-specific information was transmitted between BCI blocks and between training blocks.

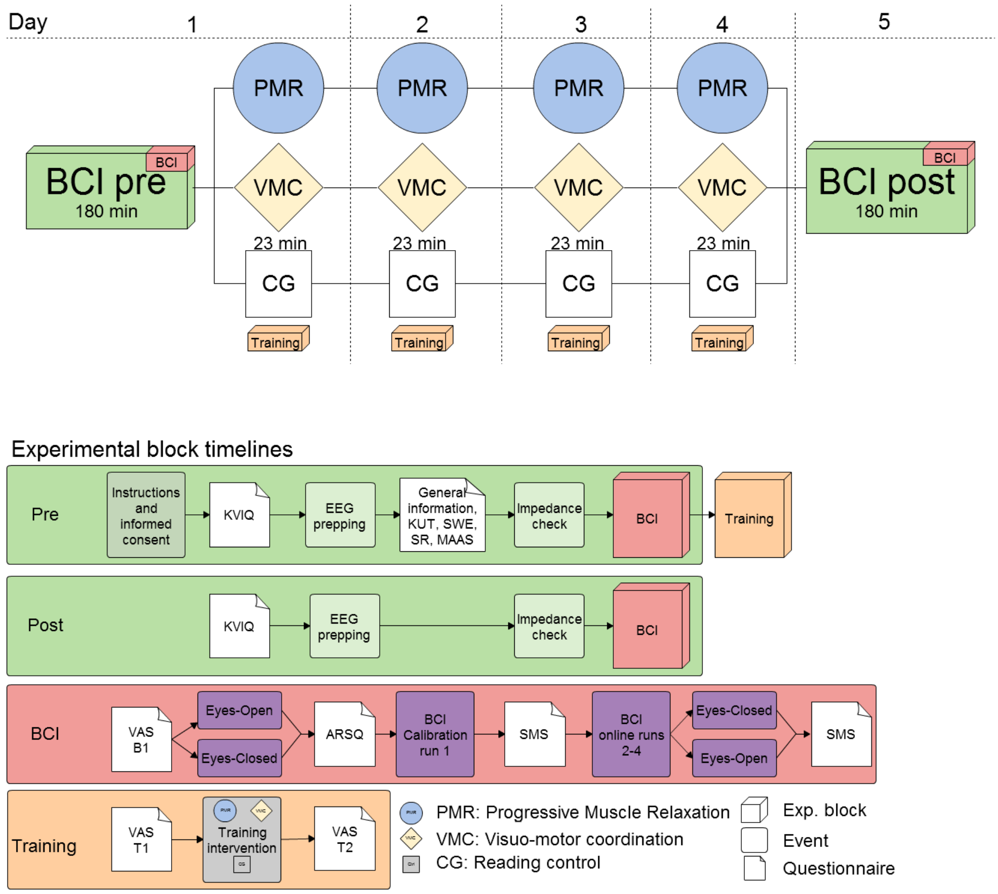

Figure 6.12 Timeline of the experiment over five days, comprising two PRE-POST BCI blocks and the four training blocks (top). A description of PRE and POST sessions, the BCI blocks and the training blocks with the respective questionnaires (bottom).

BCI block After providing informed consent, participants immediately started with the KVIQ test outside the EEG cabin. Inside the cabin, during EEG prepping of the 64 electrodes cap in the PRE session, participants answered trait questionnaires KUT, SWE, SR and MAAS. In the POST session, only KVIQ was filled prior to EEG prepping. In study I, the effect of training relaxation levels was evaluated on the short term, by ensuring that the intervention immediately preceded the BCI session. Similarly in this study, the EEG cap was set on the head of the participant before training, therefore preventing the relaxation effect to dissipate. Following the methodology of the SMR predictor Blankertz et al. (2010), a 2 minutes eye-open/closed session was recorded for offline anaylysis of the resting SMR rhythms (described in the following BCI subsection). After reading instructions about BCI trials (i.e. artifacts, motor imagery and trial organization), participants filled in the VAS for relaxation and immediately started the "zero-training" calibration runs, which were provided with feedback. Unlike in study I, the feedback from the subject-unspecific classifier was unbiased. No subject-specific data was reused in the POST BCI block; thus, participant started calibration using a subject-unspecific classifier. At the end of the 80 trials of the calibration run (run 1) that lasted about 15 minutes, the SMS scale was answered by participants, assessing their mindfulness state. A subject-specific classifier was trained and participants performed three online SMR blocks (runs 2 to 4) for a total of 240 trials. After BCI runs were completed, participants performed another 2 minutes eyes-open/closed session.

Training block The first training block occurred after the PRE-BCI block. In-between, participants were allowed a 5 to 30 min break to rest and remove the EEG gel. During the training block, participants were placed in the cabin, then filled the VAS for relaxation immediately before the training started (Relax_{t1}) and right after it ended (Relax_{t2}). Depending on their assigned group, participants performed identical trainings that lasted 23 min, and were conducted as described in section 6.1.6.

BCI

Setup The EEG acquision setup was identical to study I. The EEG was acquired with 63 active electrodes active (Acticap[5]) with left mastoid (A1) as reference and the 64$^{\text{th}}$ electrode on the right mastoid (A2) to compute linked mastoids reference. Ground was placed on FPz. We conformed to a standard 32 electrodes setup according following the 10-20 system (Jasper, 1958). To increase the coverage of the sensorimotor areas, we placed 31 additional electrodes following the 5-10 system (Oostenveld and Praamstra, 2001). The signal was digitized at a sampling rate of $1000\,\text{Hz}$ and band pass filtered between $0.016\,\text{Hz}$ and $250\,\text{Hz}$, and impedances were kept under $5\,\text{k}\Omega$.

BCI Trial Prior to performing BCI trials, participants read a text at the screen (similar to study I) informing them about the timeline and requirements of the BCI runs and trials. In this text, participants were also instructed to reduce artifact producing movements, principally eye, muscle and jaw artifacts, and received specific instructions to produce kinesthetic motor

[5]Brain Products GmbH, Germany

imagery of either left or right hand – and arm (as recommended in Neuper et al., 2005) for four seconds after receiving a directional cue.

A trial, based on Graz BCI design, lasted 8 seconds and was identical with study I, except that it only comprised left and right hand motor imageries (see trial timeline in Figure 6.13). The removal of the foot motor imagery was meant to reduce the number of trials required for the SMR-BCI, therefore reducing the burden for the participants. Also, since the VMC task did not include feet movements, it would be possible to directly estimate the effect of two-hand VMC training with two-hand motor imagery.

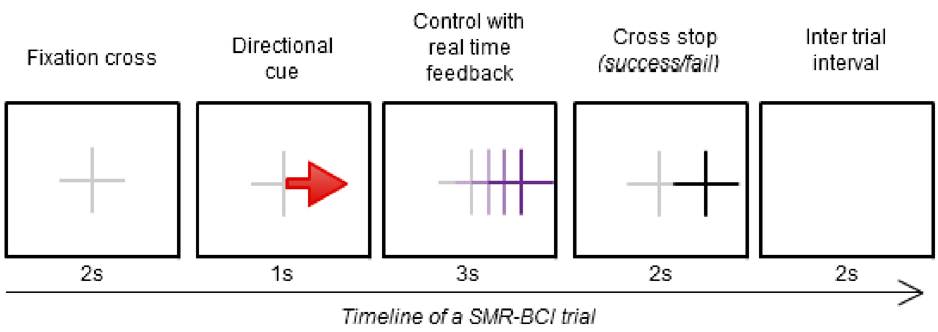

Figure 6.13 Trial description during the BCI session. The user could estimate trial success by comparing the cue direction to the position of the stopped cross

In a trial, a fixation cross appeared for 2 seconds, then an arrow cue appeared for 1 second, determining which motor imagery had to be performed (pointing: left for left hand or right for right hand). The online feedback started to appear 1 second afterwards (i.e. cross changing color and moving according to the classifiers' output) and lasted for 3 more seconds. The success of the run depended on whether the cross stopped in the cued direction in reference to the center. A counter on the top was incremented to indicate the number of successful trials. A 2 seconds break followed every trial. An additional 15 seconds break was provided every 20 trials.

Eyes-open / eyes-closed baseline The two minutes baseline recording, occuring before and after each SMR-BCI session was meant to calculate the SMR predicor (Blankertz et al., 2010). The SMR predictor was calculated by subtracting the maximum peak of the spectrum between $5\,\mathrm{Hz}$ and $35\,\mathrm{Hz}$, by the noise floor $(1/f)$ of this power spectrum (see Figure 6.14). The recording lasted two minutes in which participants had to close the eyes for the entire duration (Eye-Closed), or fixate an animated geometrical shape on the center of the monitor for the entire duration (Eye-Open). The beginning of the recording was indicated with an audio instruction followed by an onset audio beep). Differently to study I, each session was a unique Eye-Open or Eye-Closed situation, but the order of presentation was inverted as follows:

- PRE session: Eye-Open, BCI session, Eye-Closed
- POST session: Eye-Closed, BCI session, Eye-Open

Since the order was inverted, Eye-Open and Eye-Closed recording were merged for analysis.

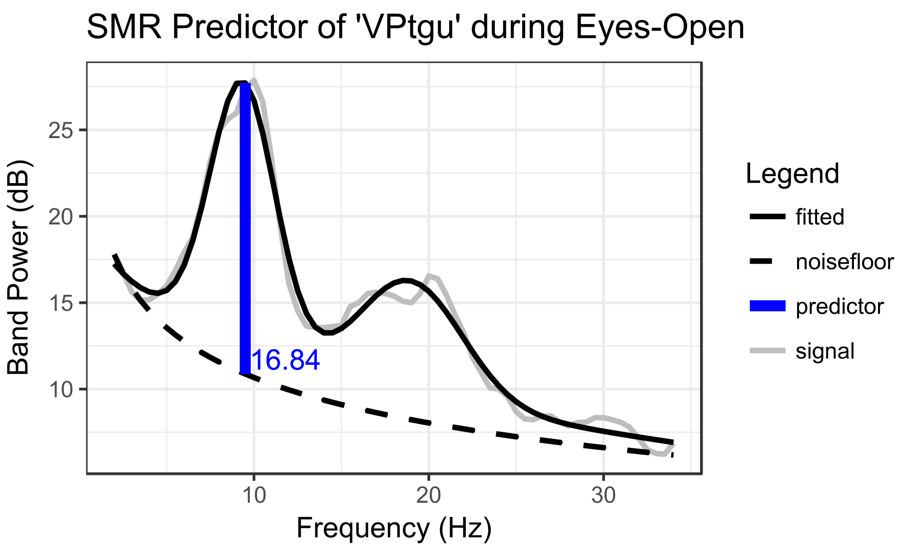

Figure 6.14 Power spectrum density plot, representing the determination of the SMR predictor for participant 'VPtgu' in this study, Eye-Open condition.

Signal processing and classification Signal acquision and processing were done using the Berlin BCI system (BBCI[6], Blankertz et al., 2007), and following a co-adaptive classifcation approach very close to the setup of study I, but with a different method for calibration runs called "zero-training" calibration (see Krauledat et al., 2008). Instead of three motor imageries in study I, participants in this study had to perform either left or right hand – or arm – motor imagery, reducing the number of classification trials to $n = 80$ (run 1). A subject-unspecific binary classifier was trained on two small Laplacian derivations at C3 and C4. The log band power in α $(5 - 15\,\text{Hz})$ and β $(16 - 32\,\text{Hz})$ bands were extracted, resulting in a total of 4 features provided to the LDA classifier. After each calibration trial, the classifier was adapted with "adaptive mean estimation" and "adaptive inverse covariance matrix" algorithms allowing to better fit the participant's individual features (a description of the algorithms

[6]Based on Matlab

Vidaurre et al., 2010). The feedback indicated (via the cross moving) the predicted motor imagery without bias.

At the end of the calibration run 1, a classifier was trained based on subject-specific optimized α and β frequency ranges and subject-specific trial time ranges (identical to study I) for the four laplacian filters and common spatial patterns (CSP) analysis based on 16 EEG channels. Log band power features were extracted from Laplacians and CSP derivations and used to train the LDA classifier. After each trial, the four Laplacian channels were reselected and the LDA classifier was retrained. This classifier was used for runs 2 and 3, for 160 online trials.

Before run 4, a new classifier was trained based on the 160 online trials (runs 2 and 3). After optimized frequency and temporal ranges selection, a CSP analysis was conducted on 47 EEG channels, but no Laplacian derivation was added. Log band power features were provided to a LDA classifier. During run 4, the classifer was adapted after each trial using PMEAN adaptation (introduced in section 6.1.6).

The BCI accuracy was the percentage of successful trials in the n=240 online trials (runs 2,3 and 4). No run-wise accuracy was computed, allowing to better estimate the true chance level. Based on the formula provided by (Müller-Putz et al., 2008), we estimated the chance level of $n = 240$ trials, with $\alpha = .05$, and a binomial distribution of the motor imagery classes of $1/2$. The calculated chance level considered accuracies between $43.73\,\%$ and $56.27\,\%$ to be due to chance with an probability of $\alpha = .05$.

Linked electrodes

While the error was not detected while conducting the experiment, it was found during offline data analysis that all N=39 participants presented an hardware error that internally linked electrodes C4 and T8. In the analysis of study I, that was also concerned by this issue, the effect of the hardware issue was not statistically supported by comparing accuracies with measurements made with fully functional hardware. In the case of this study, the issue affected all participants in all groups during online BCI trials. The C4 electrode was used for Laplacian derivations used in the classifier run 1. Due to the introduction of CSP filters, the effect of the linked electrodes might have been mitigated for runs 2-4. The C4 and T8 electrodes were removed from offline data analysis, comprising averaged ERD/ERS time plots (see Figure 6.14), head topographies (see Figure 6.23) and the calculation of the SMR predictor. Due to the C4 electrode malfunction, the SMR Predictor only relied on C3. The multiple eye-open and eye-close resting state SMR recordings were averaged after analysis, allowing to avoid non-results observed in Study I, and returning one respective value for Eye-Closed and Eye-Open.

Offline analyis In a session, there were 4 runs of 80 trials each. Although feedback was provided to participants from the beginning using a 0-training classifier, run 1 was used for subject specific classifier training only, thus, BCI accuracy was calculated base on runs 2 to 4, for a total of 240 trials.

For calculating averaged online ERD/ERS plots, the data of all $N = 39$ participants acquired in the run 4 of the BCI session PRE and POST, respectively and was band-pass filtered between 8 and 15 Hz, artifacts were removed based a variance criterion. Band power was calculated using Hibert envelope curve with a moving average of 100 ms was calculated for each trial. Then the determination coefficient signed r^2 for left and right hand motor imagery classes was calculated. Due to the missing C4 electrode, only maximum signed r^2 value at C3 electrode for each participant and each session were extracted. As for the analysis of behavioral data (i.e. BCI accuracy), this neurophysiological indicator was assessed in an 2x3 ANOVA of C3 max_r^2 by session and group.

Statistical Analysis

All ANOVA were based on a full-factorial model and used type III Sum of Squares. To check whether the analyzed data was normally distributed, the Shapiro-Wilk test was systematically performed. According to the outcomes of normality tests, non-parametric equivalents of ANOVA were used (Kruskal-Wallis test), repeated measures anova (rm-ANOVA with permutation), independent t-tests (Mann-Whitney-Wilcoxon rank sum test), paired t-tests (Wilcoxon signed range test), Pearson correlation (Spearman correlation). Prior to calculating correlations, outliers were removed, using two standard deviations of the mean as exclusion criterion. Regression lines – in figures – were also calculated without outliers.

6.2.5 Results

Mean accuracy in condition was $M_{\text{PRE}} = 67.8\%$, $SD = 15.9$ and $M_{\text{POST}} = 71.2\%$, $SD = 16.3$. Out of the $N = 39$ recorded participants, $n = 31$ (79.5%) were over the true chance level, and only $n = 17$ (44 %) were BCI efficient by reaching the – 70 % by Kübler et al. (2001) – accuracy criterion (see Figure 6.15).

Effect of training on BCI accuracy ($H_{1,2}$)

The effect of training on BCI accuracy was evaluated using two-way rm-ANOVA, computed with BCI accuracy as dependent variable, group as between-subject factor, and BCI session (time; PRE or POST) as within-subject factor. The ANOVA did not yield an effect of group ($F(2, 36) = 1.73$, $p = .191$) but yielded a significant effect of time ($F(1, 36) = 4.34$,

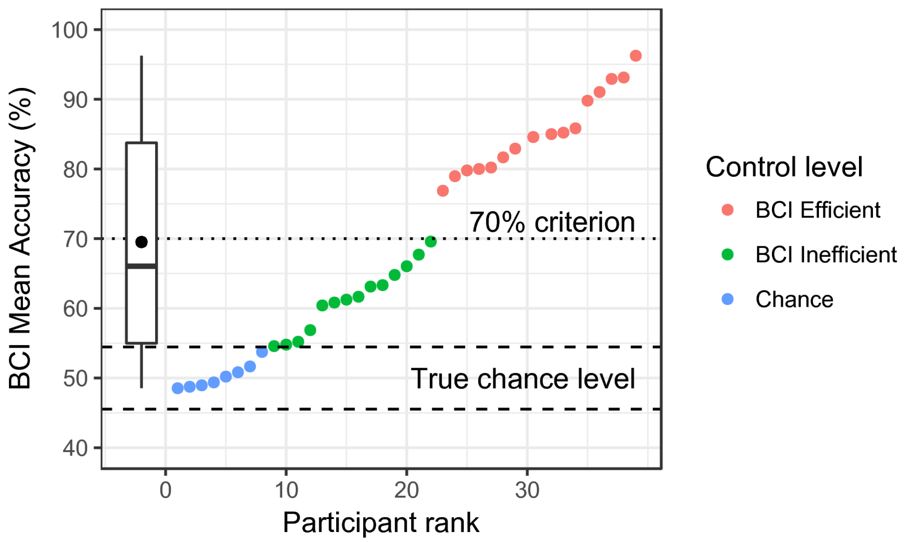

Figure 6.15 Level of control of the participants. Box-plot showing $25\,\%$ percentiles, and point representing the mean BCI accuracy (left). Distribution of the ranked by level of control (right), showing the proportion of users displaying chance level of control (blue), BCI inefficient (green) and BCI efficient users (red).

$p = .044$). The interaction $group * time$ was not significant. Due to non-normal distribution of the BCI accuracy, non-parametric alternative in assessing BCI accuracy. The robust rm-ANOVA (with $n_{\text{perm}} = 1\,000$) returned a significant effect of time ($p < .05$), validating the results of the ANOVA. Post-hoc comparison using Wilcoxon signed rank test showed an increase between PRE and POST BCI sessions ($M_{\text{POST-PRE}} = 3.3\,\text{pp}$, $SD = 10.1$, $W = 227$, $p = .038$, see Figure 6.16).

Validating the intervention

Effect of training on relaxation levels (A$_1$)

Short-term effect A three-way rm-ANOVA was used to investigate the short-term effect of training group on relaxation levels during the training blocks. The rm-ANOVA was computed with relaxation level as dependent variable, intervention was used as between-subject factor, day (days 1 to 4) and training block completion (relaxation assessed before "t_0" or after "t_1" the training block) as within-subject factors. The ANOVA returned an interaction $group * day$ ($F(6, 108) = 22, 89$, $p = .012$) and an interaction $group * training\ block\ completion$ ($F(2, 36) = 17, 28$, $p < .001$). A main effect of training block completion was found ($F(1, 36) = 65.86$, $p < .001$) showing an increase of relaxation between t_0 and t_1 ($M_{\text{t1-t0}} = 1.02$, $SD = 1.72$.). No further interaction or main effect were significant.

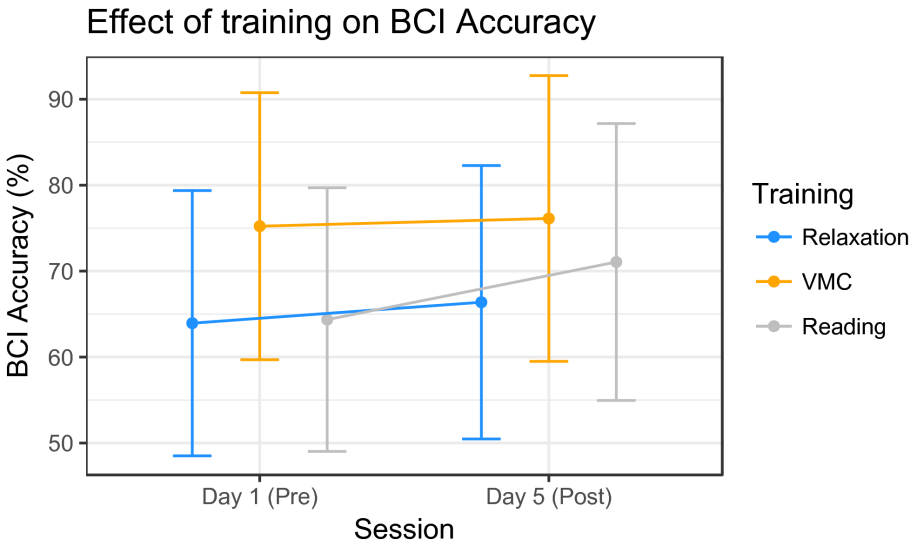

Figure 6.16 BCI accuracy by training between PRE and POST sessions. Error bars indicate standard deviation.

Post-hoc pairwise comparisons using paired t-tests yielded an increase in relaxation between t_0 and t_1 in the PMR group ($t(51) = 9.77$, Bonferroni adjusted $p_{adj} < .001$) and in in the CG ($t(51) = 4.31$, $p_{adj} < .001$). No difference was found in the VMC group ($t(51) = .624$, $p_{adj} = .535$). Another post-hoc pairwise comparison compared the averaged relaxation difference $t_1 - t_0$ between intervention groups. The indepdendent samples t-tests showed that relaxation levels increased more in the PMR group ($M_{t1\text{-}t0} = 1.95$, $SD = 1.44$) than CG ($M_{t1\text{-}t0} = .97$, $SD = 1.61$, $t(21.9) = 3.27$, $p_{adj} = .010$) and VMC ($t(23.9) = 5.42$, $p_{adj} = .010$). Relaxation levels increased more in the CG than in the VMC ($M_{t1\text{-}t0} = .14$, $SD = 1.64$, $t(22.5) = 2.85$, $p_{adj} = .027$, see Figure 6.17a).

Long-term effect The long-term effect of training on relaxation levels was evaluated using a two-way rm-ANOVA, computed with relaxation level as dependent variable, group as between-subject factor, and BCI session (time; PRE or POST) as within-subject factor. The ANOVA did not return any significant main effect of group ($F(2, 36) = 1.98$, $p = .15$), time ($F(1, 36) = .510$, $p = .47$) or interaction $group * time$ ($F(2, 36) = .251$, $p = .77$, see figure 6.17b).

Effect of VMC training on VMC (A_2)

VMC mean error duration The effect of VMC training on VMC "mean error duration" was assessed using a one-way rm-ANOVA, using "mean error duration" as a dependent

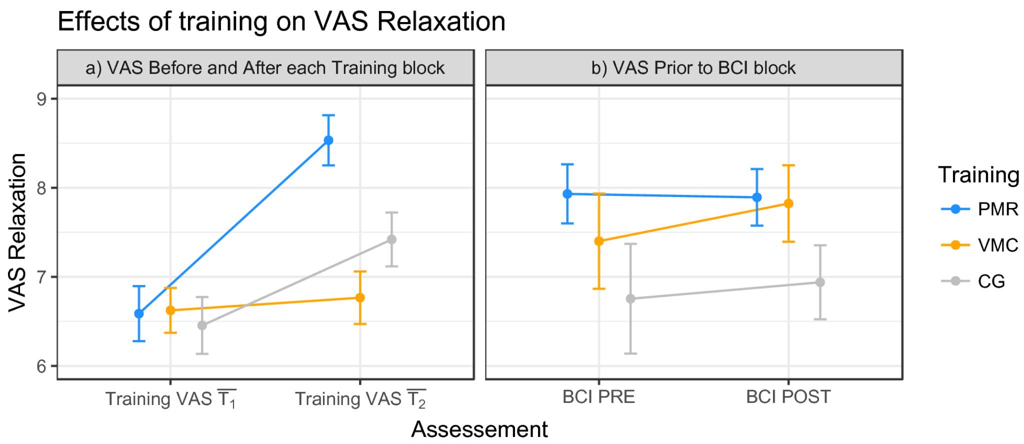

Figure 6.17 Effect of training on relaxation displaying mean and standard error of the mean for each training group. a) average of VAS for relaxation before and after the four training blocks. b) VAS for relaxation right before BCI session in the PRE and POST session.

variable and day (time; days 1 to 4) as within-subject factor. The effect of time was significant ($F(3, 36) = 10.17$, $p < .001$). Post-hoc multiple comparisons using paired t-tests showed that the individual score on day 1 ($M_1 = 2.01$, $SD = 1.51$) was significantly higher than on day 2 ($M_2 = .95$, $SD = .73$, $t(12) = 3.19$, $p_{\text{adj}} = .046$), day 3 ($M_3 = .81$, $SD = .78$, $t(12) = 3.47$, $p_{\text{adj}} = .028$) and day 4 ($M_4 = .84$, $SD = .76$, $t(12) = 3.23$ $p_{\text{adj}} = .044$). No further difference in "mean error duration" was found between runs 2, 3 and 4. The tendency showed a decrease of errors during the first VMC training session (see Figure 6.18).

VMC error percentage difference The effect of VMC training on VMC "error percentage difference" was assessed using a one-way rm-ANOVA, using "error percentage difference" as a dependent variable and day (time; days 1 to 4) as within-subject factor. The effect of time was significant ($F(3, 36) = 2.93$, $p < .046$).

Post-hoc pairwise comparison for the main effect of time using Wilcoxon signed rank test showed that the "error percentage difference" was significantly higher during day 1 ($M_1 = .27$, $SD = 2.11$) than day 3 ($M_3 = 1.64$, $SD = 1.56$, $W = 83$, $p_{\text{adj}} = .037$) and marginally higher than day 4 ($M_4 = 2.72$, $SD = 0.36$, $W = 81$, $p_{\text{adj}} = .066$, see Figure 6.18).

Directed correlation analysis with BCI accuracy

Relaxation levels Spearman correlations between BCI accuracy and VAS relaxation before BCI sessions were calculated, but did neither yield significant correlations in the PRE BCI session (Spearman $\rho = -.242$, $p = .143$, $n_{\text{outlier}} = 1$) nor in the POST BCI session ($\rho = -.074$, $p = .657$, $n_{\text{outlier}} = 1$).

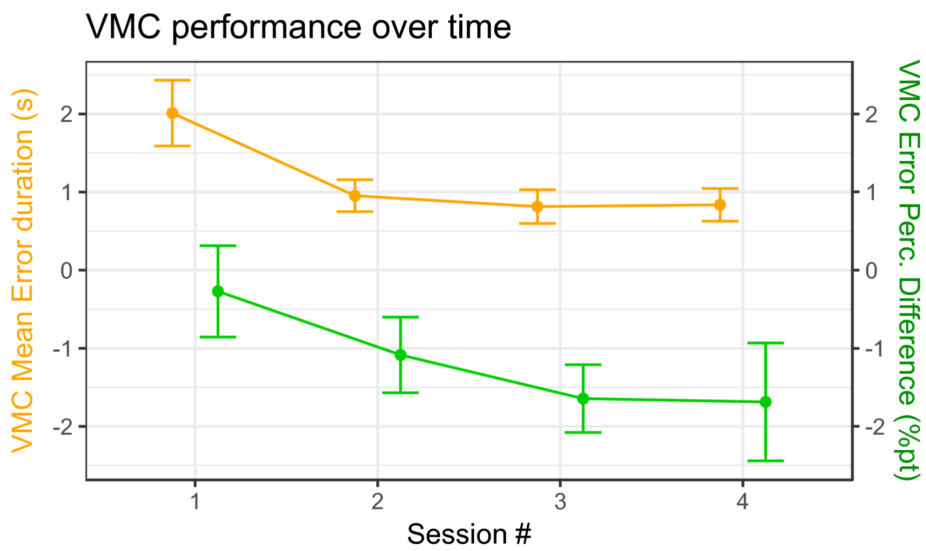

Figure 6.18 Mean VMC performance over the four training sessions. Error bars indicate standard error of the mean. Mean error duration of the VMC, expressed in seconds (orange). VMC error percentage difference (in pp).

VMC mean error duration and error percentage difference The VMC "mean error duration" measured in day 1 did not correlate with BCI accuracy PRE (ρ = .242, p = .449, $n_{\text{outlier}} = 1$). VMC "mean error duration" on day 4 did neither correlate with BCI accuracy POST (ρ = .461, p = .134, $n_{\text{outlier}} = 1$). The VMC "error percentage difference" measured on day 1 did not correlate with BCI accuracy PRE (ρ = .038, p = .901), but VMC "error percentage difference" on day 4 was significantly correlated with BCI accuracy POST (ρ = .622, p = .035, $n_{\text{outlier}} = 1$) but was not correlated after correction for multiple comparison (p_{adj} = .14), see Figure 6.19).

KVIQ The KVIQ did not correlate with BCI accuracy, even when specifically comparing the kinesthetic (KVIQ-K) or at the visual (KVIQ-V) subscales.

SMR Predictor Spearman correlation test between BCI accuracy and "SMR predictor eyes-open" was marginal (ρ = .386, p_{adj} = .066, $n_{\text{outlier}} = 1$), but the correlation between BCI accuracy and "SMR predictors eyes-closed" was significant (ρ = .459, p_{adj} = .019, $n_{\text{outlier}} = 2$). Merging all eye-closed and eye-open recording (M = 6.75 dB, SD = 3.09) yielded the highest and most significant correlation (ρ = .534, p_{adj} = .003, $n_{\text{outlier}} = 1$, see Figure 6.20). The SMR predictor computed during the the Eye-Closed condition (M_{EC} = 7.62, SD = 3.19) was significantly higher than during the eye-open condition (M_{EO} = 5.89, SD = 3.53, paired t-test $t(35) = 1.49$, p = .012).

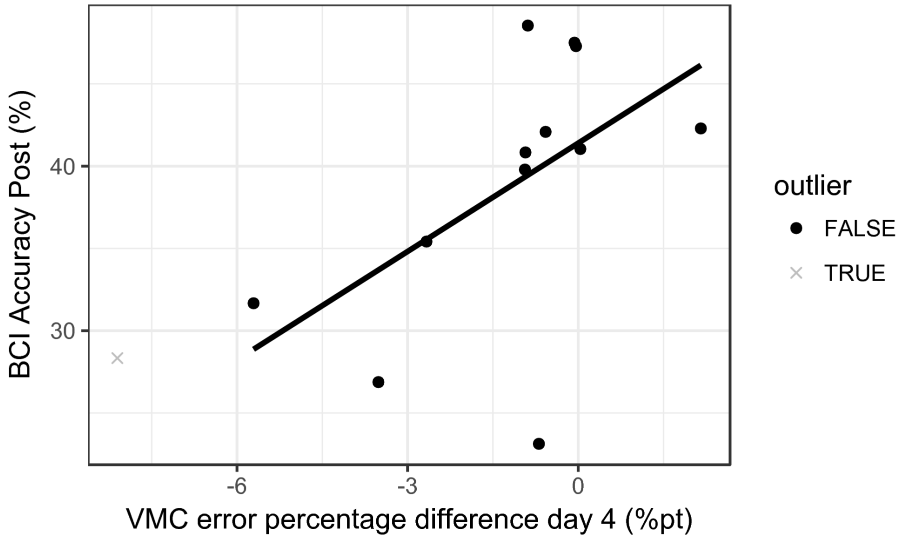

Figure 6.19 Correlation VMC error percentage difference with BCI accuracy. $\rho = .622$, $p = .035$, $p_{\text{adj}} = .14$. Outlier were removed using two standard deviation from the mean criteria.

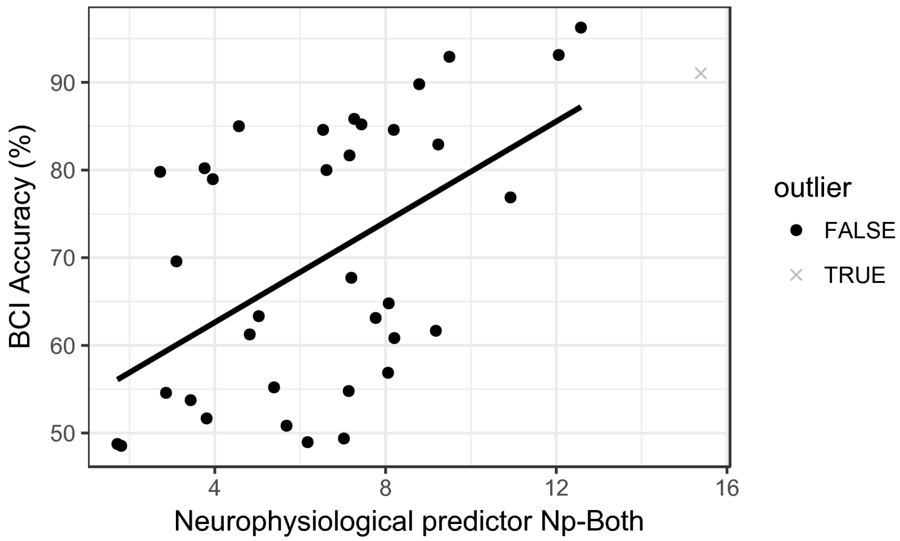

Figure 6.20 Correlation plot between SMR predictor in both Eye-Open and Eye-Closed conditions and BCI accuracy($\rho = .534$, $p_{\text{adj}} = .003$, $n_{\text{outlier}} = 1$).

Explorative analyses

SMS Spearman correlation analysis between SMS PRE and BCI accuracy PRE was not significant ($\rho = .167$, $p = .338$, $n_{\text{outlier}} = 3$), but there was a significant correlation between SMS POST and BCI accuracy POST ($\rho = .418$, $p = .011$, $n_{\text{outlier}} = 2$). Further analysis of the SMS subscales revealed that only the "mindful" items (and not the "body" items) of the SMS correlated with BCI accuracy POST ($\rho = .382$, $p_{\text{adj}} = .043$, $n_{\text{outlier}} = 2$; see Figure 6.21).

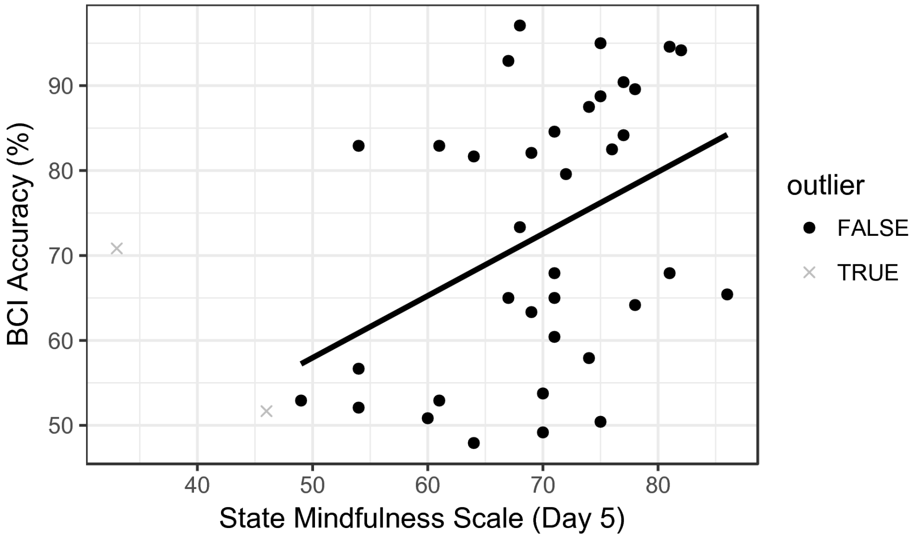

Figure 6.21 Correlation plot between State Mindfulness Scale and BCI accuracy, both assessed during the POST BCI session ($\rho = .382$, $p_{\text{adj}} = .043$, $n_{\text{outlier}} = 2$).

Other correlations The correlations between BCI accuracy and MAAS, SWE or SR did not reach significance.

6.2.6 Discussion

While $80\,\%$ of the participants performed better than chance, only $44\,\%$ were BCI efficient, even though a co-adaptive calibration BCI system was used. The BCI accuracy increased between BCI session PRE and POST. The BCI block, and in particular the classifier training procedures, were identical in both BCI sessions. Since no subject-specific data was transmitted from PRE session to POST session, this result demonstrated that a learning occured between the two BCI sessions, which was quantified to an increase of $3.3\,\text{pp}$ (percent points), but yet with a relatively high standard deviation $SD = 10.1\,\text{pp}$. This result was consistent with litterature showing that SMR-BCI performance globally increases through a learning process (e.g., Pfurtscheller and Neuper, 2001; Nijboer et al., 2010; Zich et al., 2015).

Both hypotheses H_1 and H_2 have to be rejected by the results, since no significant effect of training group on BCI accuracy was found, meaning that neither PMR (H_1) nor VMC (H_2) training lead to increased BCI performance based on a sample of $n = 13$ participants per group. The success of the PMR training in increasing relaxation levels, which was required as a Manipulation Check (MC_1) was only partially validated. The results showed a significant increase in relaxation following the PMR training (during training), but yet, the PMR training did not produce a long-lasting effect, since relaxation did not differ between the PRE and the POST BCI sessions. Studies that found an effect of training on SMR-BCI accuracy (i.e. Tan et al., 2014; Cassady et al., 2014) did not report any questionnaire that would allow to describe or quantify any expected effect. It must yet be noted that the training duration was at least three times longer that in this study (i.e. 3 months for Tan et al.; 1 year for Cassady et al.). The preliminar results from Tan et al. (2009) also reported a shorter training of only four weeks. This duration closely matches with the recent findings of the effect of learning on neuroplasticity, more precisely evoked in changes in cortical grey matter (GM) or white matter (WM). Those studies observed GM density increase associated with the 3-week learning of a balancing task (Taubert et al., 2011), or WM density increase associated with a eight week mindfulness practice (Hölzel et al., 2011).

The design from study II differed from Study I by the separation between intervention and BCI blocks, assessed on different days. The effect of the PMR intervention on relaxation remained significant during the training but could not be sustained until the BCI POST session. This shows on one hand a success in relaxation training, but on the other hand no measurable long-term effect of PMR training.

Concerning the studies that showed a relation between relaxation trainings and BCI accuracy, (Tan et al., 2009, 2014; Cassady et al., 2014), it can be noted that the training of mindfulness was included; which encouraged me to assess the state mindfulness in Study II using SMS. The SMR training, despite being efficacious in relaxaing participants, did not include mindfulness training, as participants focused their attention on bodily sensations. In opposition, the given instruction of MM is to freely monitor the entire range of perception (i.e. sensations, thoughts and feelings; see Lutz et al., 2008) and avoid focusing on any of them in particular. Since MM has been shown to have positive effect on attention (Valentine and Sweet, 1999), it could be influencing the ability to concentrate. The positive correlation of SMS with BCI accuracy in the POST session of this study tells that participants who were mindful during the post BCI session obtained higher classification accuracy. However, the interpretation of this result is limited because the SMS was evaluated after receiving calibration feedback, thus possibly influenced by BCI feedback result. It could also be added that the MAAS scale trait mindfulness was not related with BCI accuracy. The viability of using MAAS in this context is limited, since it was criticized for restricting the concept of mindfulness by opposing it to a mindless “autopilot” attention on our daily activities (van Dam et al., 2010). For a proper evaluation of SMS, I suggest that future experiments should ensure to assess mindfulness scales before any performance feedback is provided, such that it could be confirmed for its potential predictive value.

According to the hypothesis H_2, the success of VMC training in increasing BCI accuracy was tied to the manipulation check stating that the "mean error duration" or the "error percentage difference" would decrease. The result yielded toward a better proficiency (reduction in "mean error difference") and a stabilization in the learning ("error percentage difference" decreases between run 1 and 2, indicating increased learning, but does not differ in further sessions). Both variables indicated that the VMC manipulation was successful in establishing motor learning. In a review of MRI studies investigating the effect of learning, Dayan and Cohen (2011) compared fast an slow learning and describe the performance increase in both as an asymptote that either range in a time magnitude of minutes (for fast learning) or in months (for slow learning). Our results demonstrated a similar asymptotic shape of both VMC variables (see Figure 6.18) acquirement over the cumulated 92 minutes of training, therefore associated a "fast" skill acquision. The other "slow" learning, as posited by Dayan and Cohen, is represented by the music training of Tan et al. (2014), which was neither found to be associated with an increase in SMR-BCI performance. Despite evidence that year-long practice in sports, playing instruments, typing and playing video games (Randolph, 2012), implying slow skill acquision of fine and properly-timed visuo-motor coordination , no effect of training on BCI accuracy was found to result from a fast visuo-motor learning (this study) or slow instrument learning (Tan et al., 2009, 2014).

None of the predictor variables (i.e. relaxation level, "mean error duration" and "error percentage difference") correlated with BCI accuracy. The explorative correlation analysis did not return any significant correlation of state Mindfulness (MAAS), kinesthetic and visual motor imageries (KVIQ), self-efficacy (SWE) or self-regulation (SR). The eyes-open SMR predictor was only marginally correlated with BCI accuracy. Blankertz et al. (2010) originally suggested that the contribution of occipital alpha during EC baseline deteriorated the predictive value of the SMR predictor, which substantially relied on peaks in α band power. But in this study, both the correlation coefficient and the significance were increased in the Eye-Closed condition. Moreover, it was also found that averaging Eye-Closed and Eye-Open values returned a stronger and more significant correlate with BCI accuracy. Nevertheless, by being correlated with BCI accuracy, the SMR predictor was replicated once again.

While the C4 electrode could not be included in the ERD/ERS plots (see Figure 6.22), the C3 electrode on one side, and the electrodes near C4 (i.e. CFC4, C2, CCP4) on the other side, both show distinct ERD contralateral to the side concerned by the motor imagery, while showing ipsilateral ERS (see head topographies in Figure 6.23). While the analysis of max_r^2 C3 did not yield significant effect of session, the detailed plots in the POST session indicates (observation not corroborated with statisitcs) higher signed r^2 values in electrodes that are directly adjacent to C3 and C4 as compared to the PRE session (see Figures B.1 and B.2).

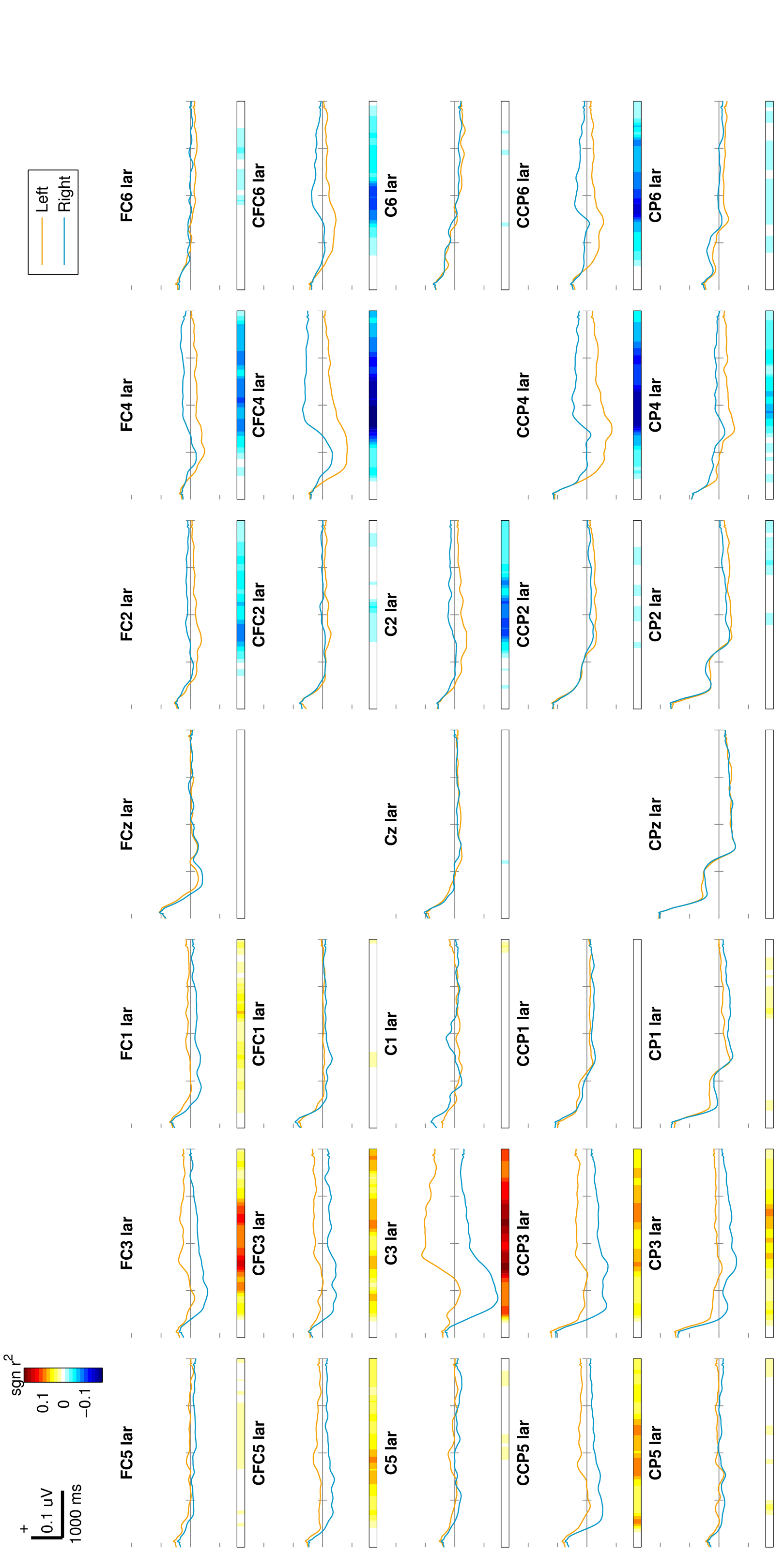

Figure 6.22 ERD/ERS time plots representing relative band power between 8 Hz and 15 Hz from signal envelope in the left and right hand motor imagery. The plot averages the data from all $N = 39$ participants in online run 3.

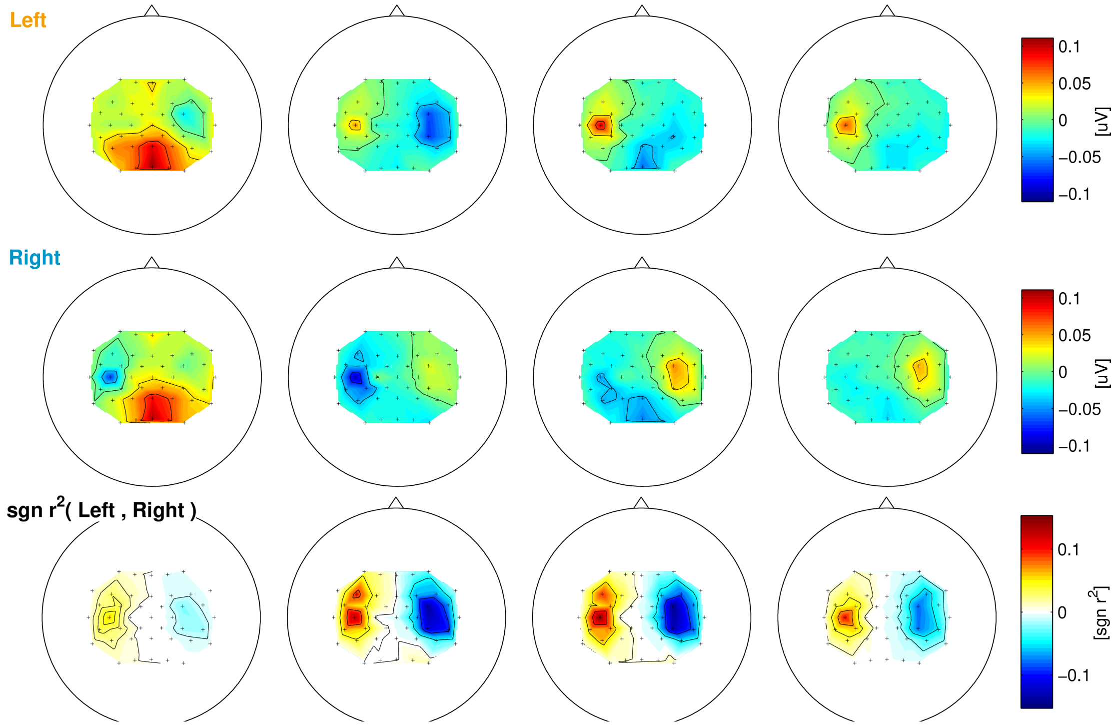

Figure 6.23 ERD/ERS head topographies representing relative band power between 8 Hz and 15 Hz from signal envelope in the Left and right hand motor imagery tasks averaged for every second of online BCI control. Signal was spatially filtered by Local Average Reference. The plot averages the data from all $N = 39$ participants in online run 3. The third line represents the signed r^2, computed to illustrate the classwise contrast of ERD/ERS patterns.

6.2.7 Conclusion Study II

Except for an effect of time, there was no significant effect of training on BCI accuracy, showing that intensifying the intervention trainings was not efficient to increase BCI performance. Particularly in the PMR, the lack of effect on accuracy can be imputed to the failure to increase relaxation levels on the long term, despite the short term efficiency of PMR. This study also revealed the instability of the VMC "mean error duration" predictor and the the "error percentage difference", which were not replicated, and thus reveal both a poor predictive value, and not potential in increasing SMR-BCI performance. The study failed to show a relation between relaxation and BCI accuracy but instead revealed state mindfulness as a positive correlate, reinforcing the evidence about the benefit of mindulness trainings. Unlike the PMR and the VMC trainings, the effect of BCI practice between was significant, and marked by a significant increase between the BCI session PRE and POST. Therefore, four day long training of PMR and VMC are unlikely to be beneficial for the participants and thus not good candidates to address the issues of BCI inefficiency.

Chapter 7

General discussion

The global research aim of this doctoral dissertation was to first identify individual predictors for SMR-BCI performance and then attempt to increase this performance by proposing specific non-BCI interventions or trainings for the participants. The two generic predictors, identified in literature, were attention levels and visuo-motor-spatial abilities. In the course of the studies of this thesis, I attempted to replicate the existing predictors for SMR BCI performance, specifically those found by Hammer et al. (2012, 2014), which were the relaxation levels and the proficiency in a VMC task.

The study I concentrated on a single training session right before using SMR-BCI. This joint-study conducted both in Berlin and Würzburg allowed to acquire a large sample, with the aim of producing generalizable results. Due to lab differences, the samples had to be spitted, but nevertheless, both presented decent sample size as compared to other studies presenting predictors or correlates for SMR-BCI accuracy. Predictors were replicated under the form of correlation with BCI accuracy. PMR training was correlated with BCI accuracy in BE, and VMC "error percentage difference" was correlated with BCI accuracy in WÜ. Those correlations were nevertheless not found equivocally in both labs, and the manipulation of the predictors did not lead to an improvement in SMR-BCI accuracy in Study I.

The study II was designed with PRE-POST BCI measurements, therefore allowing to account for inter-individual differences in BCI accuracy presented by the participants. A global effect of BCI practice could be reported, by a modest increase of 3 percent points in BCI accuracy between PRE and POST. The physiological ERD/ERS marker max_r^2 on C3 did not increase. The aim of Study II was to produce a positive effect on BCI accuracy by the manipulation of the predictor variables in an intensified training. The training of Study II was therefore conducted during four sessions on four consecutive days. Manipulation Checks for VMC and PMR both successfuly validated the effect of training on manipulating the predictor variables in the correct direction, but none of those variables (Relaxation level, VMC "mean error duration" and VMC "error percentage difference") correlated with SMR-BCI accuracy, either PRE, POST for the difference between PRE and POST. No specific training, either VMC or PMR was found to influence BCI accuracy as compared to the CG.

The studies that reported such association between relaxation and SMR-BCI accuracy proposed much longer training durations, for a minimum of twelve weeks (i.e. Tan et al., 2014). The relaxation trainings that were found to be associated with higher SMR-BCI accuracy were "mindfulness meditation" (Tan et al., 2009, 2014) or diverse relaxation and meditative – even healing – methods assembled under the name of mind-body awareness training (MBAT; Cassady et al. (2014). The fundamental distinction between those techniques and PMR, is that they are the result of a century old traditions infused with religion and spirituality, essentially practiced by individuals that embrace the practice of meditation as a lifestyle. While PMR offers an efficacious and temporary release of muscular (and mental) tension by the practitioner, the other methods depicted here train the participant to sustain modified states of consciousness (Tart, 2000) for prolonged durations, and to extend them into daily life. I described in section 5.4 the neuroanatomical effects of mindfulness meditation, which, as shown previously, has been associated with higher SMR rhythms. In terms of meditation techniques, Lutz et al. (2008) discriminate two types of meditation techniques. The first meditation type named "focused attention", consists in inhibiting completely the range of awareness of the meditator, which concentrate his attention on one unique target. This was specifically the case in the PMR training, in which participants were asked to concentrate on the sensation produced by contractions and release of group of muscles. The authors name the second type of meditation "online monitoring", for which the instruction is to freely monitor the entire range of perception (sensations, thoughts and feelings). The authors yet specified that the "online monitoring" is a difficult state to maintain, and that "mindfulness meditators", when too attached and distracted by the course of their thoughts must "stabilize" by returning to a focused attention (e.g, concentrating on respiration, similar to the instructions in Tan et al., 2014). MM requires time and practice, and MRI based studies have shown that the neural efficiency was increased in mindfulness meditation experts (i.e. decreased activity in the prefrontal-cortex associated with lower need for top-down inhibition).

Since mindfulness meditation was found to be associated with accuracy in study II, and has also been shown to have positive effect on attention (Valentine and Sweet, 1999), it could be hypothesized that mindful meditation is a good candidate for increasing SMR BCI accuracy. The state mindulness is yet contradicted with the trait scale (MAAS), which did not return any correlation with BCI accuracy (for further reading on MAAS scale, see van Dam et al., 2010; Rapgay and Bystrisky, 2009). It should therefore be evaluated whether mindfulness meditation can be integrated into a short training, as it is essential that the use of a non-BCI training should be superior to the BCI training itself.

In study I, The VMC "mean error duration" variable was only marginally correlated with BCI accuracy in BE. The effect of VMC intervention on "error percentage difference" was only found in BE, indicating a reduction of errors during VMC training). This manipulation check variable, was thereafter tested for its correlation with BCI accuracy, and yielded a significant association in WÜ. The results were unequivocal in indicating a relation between VMC proficiency and BCI accuracy, but also in validating the VMC training. This ambiguity dissipated in study II, were the training in VMC led to improvement in motor proficiency indicator variables (both "mean error duration" and "error percentage difference"). The VMC manipulation did nonetheless not affect the BCI performance. The VMC practice, displayed an asymptotical evoluation of the VMC variables over the four days, conform to the description of a short skill learning by Dayan and Cohen (2011). This learning was supported in the literature by neurophysiological effects in the sensorimotor areas (e.g., Halder et al., 2011) but the studies indicating neuroanatomical effects were based on a longer duration of at least three weeks (i.e. Taubert et al., 2011), referring instead to an advanced skill acquisition, as posited by Dayan and Cohen (2011). The VMC learning was not associated with increased $signed\ r^2$ values in C3 reported study II.

Yet, concerning Study I, scalps maps of ERD/ERS (by Acqualagna et al., 2016, Figures 6.10 and 6.11) displayed stronger ERDS on both C3 and C4 for participants in the VMC group. The concurrent ERD/ERS pattern on both hemispheres should theorically make it harder for the classifier to discriminate between right hand and left hand motor imageries. This symmetric ERD increased can be compared to the simultaneous use of right and left hand during the VMC and illustrated that the strength of the ERD/ERS alone may not systematically lead to higher BCI accuracy, and that participants, for a better classification might have benefited from more localized ERD/ERS patterns. Such localization of ERD/ERS patters is pushed forward by Babiloni et al. (2010), and typical from – expert – skill learning (e.g. Del Percio et al., 2010; Wei and Luo, 2010; Zapala et al., 2015). It could then be hypothesized that participants may benefit of an motor learning that prevents the simultaneous execution of right and left hand movements (e.g. right or left but never both at the same time), but such an experimental design would require to also take into account time-related constraints to account for the temporal elicitation of ERD/ERS patterns. Apart from this hypothesis, it could be suggested that expert VMC performers, following a longer training might obtain more localized ERD/ERS thus leading to higher BCI accuracy.

Secondarily from the predictors that were manipulated, I also contributed to the identification of SMR-BCI predictors or correlates, by attempting to replicate those reported in literature, comprising the non-planning impulsivity or the Baratt Impulsiveness Scale (BIS-np) found in Hammer et al. (2014), the Locus of Control in dealing with technology (KUT; Burde and Blankertz, 2006), the kinesthetic imagery vividness (KVIQ-K; Malouin et al., 2007) and the SMR predictor (Blankertz et al., 2010) (SMS and MAAS were already reported in this section). The SMR predictor, was replicated in Study I, with similar correlation coefficient, and the suggestion by Blankertz et al. concerning the lesser association in the Eye-Closed condition due to the contribution of occipital α. In study II, organized in separate 2 min blocks – instead of alternations 15 sec – of Eye-Open and Eye-Close, the effect was opposite, showing a stronger correlation coefficient for the Eye-Closed condition. No explanation could be provided to explain this difference, but results yet indicated that SMR Prediction during the Eye-Open condition systematically correlated with SMR-BCI accuracy. Other predictors or suspected correlates (KVIQ,BIS-np,SR and SWE) were not associated with BCI accuracy.

The growing evidence on different levels that suggest links between motor practice or meditation and SMR-BCI accuracy might encourage future investigations in implementing such practice as trainings for increasing SMR-BCI accuracy. Such further investigations should consider that there is no possibility of transferring motor-based trainings for people in the LIS. The relaxation/meditation trainings could therefore be preferred for a patient population. But what appears a the first glance to be easily implementable, displays major constraints. Meditation methods based on concentrating on respiration might be experienced completely differently by patients with artificial respiration. All motor-based relaxation, including PMR, cannot be performed. Thus, in the optic of transferring potential findings to LIS end-users, I would strongly recommend any further investigation of relaxation or meditation training for SMR-BCI accuracy to use relaxation trainings that do not integrate motor execution.

7.1 Limitations

I identified three major limitations that might impact the quality of the findings and the ability to answer the research questions that were posited prior to formulating the hypotheses of studies I and II.

Translating predictors into training The first limitation concerns the viability of the process that translated the identified predictors into training to increase SMR BCI accuracy. The identified predictors were namely: **1)** the "relations towards work", interpreted by Hammer et al. as the ability to concentrate **2)** the "2HAND overall mean error duration", also reported by Hammer et al. (2012) and following a standardization process. The meaning of "ability to concentrate" by Hammer et al., which was not directly replicated, could be contested from its direct link with the "relaxation levels" variable, that I chose to associate to in the frame of this dissertation. Despite this distance between the "AHA" predictor and the "relaxation levels" variable, a pragmatic reflection justified this pairing. By increasing relaxation levels, the ability to concentrate would be positively influenced. It could be hypothesized that the "ability to concentrate" translated self-regulation abilities. In such a scenario, increasing relaxation would also lead to higher self-regulation. Specifically, to investigate any association with self-regulation, I introduced a Self-Regulation questionnaire during Study II. The impossibility to replicate the variable AHA was justified by its laborious and exhausting characteristics (Personal Communication with Hammer et al.'s study co-author), that would lead to unspecific and uncontrolled efects during the BCI session which were unwanted. The Study I reported unconclusive results about the relaxation level, and both studies implying PMR training did not produce an effect on BCI accuracy. Since attention was cited several times in other SMR-BCI predictor literature, and acknowledging the contribution from cognitive components such as mindfulness, it might be beneficial to attempt to more precisely define the temporal, and cognitive characteristics of attention in further investigations.

Concerning the "2HAND overall mean error duration" predictor being translated into VMC "mean error duration" and "error percentage difference", it must be first noted that the initial testing by Hammer et al., 2012 included both joystick and knob controller control. The effect of the predictor was replicated later in Hammer et al., 2014, showing the stability of the predictor. It must first be noted that those were standardized by the assessment software (Schuhfried GmBH) against a larger sample. Therefore, it could be that the predictive value of BCI accuracy would only be significant by proceeding to this specific standardization. Using the "mean error duration" from knob controllers in both studies I and II was fairly similar to the initial assessment of the predictor. The use of Spearman correlation, which proceeds to ranking, was also beneficial in reproducing the initial conditions of the predictor. I attempted to utilize the "error percentage difference" to better translate the short adaptation of steering errors in the VMC task, and provide another explanatory variable. This second correlate and the "mean error duration" both yielded unconclusive significant correlations in Study I, but were not replicated in Study II. As for the attention levels, the "motor dexterity" characteristic and motor learning are a redundant subtypes of predictors of SMR-BCI performance, and replication studies could help refine these predictors.

Causality of the predictors A second limitation to this study, is that causality was not specifically evoked. Study I was specifically designed to have interventions precede the

BCI session, therefore reducing the possibility of BCI accuracy influencing predictor values (and therefore ensuring the independence). The Study II introduced a BCI accuracy session before assessing the predictor, but this session was used as a baseline in a PRE-POST design. Participants were not aware of their assigned training during this BCI run. Strictly, it cannot be rejected that BCI session did not have a causal effect on the predictor, but this effect was yet equal in all three group. In proving that the predictors were influenced by variations in BCI accuracy, this to assume a causal independence for the predictive value of the predictors (yet not significant).

The lack of specific distinction between predictors and correlates of BCI performance spread confusion in the interpretation of such variables. While these terms respectively refer to statistical instruments for assessing linear associations, the regression analysis allows to use one or several independent factors to predict a dependent variable, while the correlation analysis report whether two sets of variables are linearly related, and in which direction. Yet, squaring the r-value of a correlation allows to specify the variance explained of a correlate by the other, and has therefore a predictive value. Yet, the word predictor introduces in its etymology a notion of time "PRE", and the specific vocabulary of regession uses the word "independent variable". Yet, a predictor in a regression is not necessarily temporally older and neither independent. In the scope of specifying interventions to increase SMR-BCI accuracy, it is essential to discriminate variables that, in terms of causality, predicted BCI accuracy before it was even measured, and variables that were measured during of after BCI accuracy was provided, for which independence from SMR-BCI accuracy cannot be proven without rigorous argumentation (e.g. Grosse-Wentrup, 2011). In my table of SMR-BCI predictors, I examined for causal independence of every predictor variable from the associated BCI accuracy. I invite the readers to refer to the updated table of predictors and correlates (Table A) and check whether the variable is estimated either by a regression or a correlation. In conclusion for this limitation, the issue of causal independence invites researchers in the field of neurophysiology and BCI to define a proper terminology to prevent logical fallacies.

Relatively short trainings A third study limitation is the short duration of the training, which lasted 30 min in Study I, and which totalized 2 h on four consecutive days in Study II. This short training duration is by no means comparable to the extended trainings of at least twelve weeks in Tan et al. (2014) and even a year in Cassady et al. (2014). Firstly, the trainings were based on influencing the predictors, and the duration of Study II was found to be sufficient to influence both variables representing the PMR and the VMC predictors. Secondly, the effect of BCI practice itself leads to significant improvement in SMR-BCI accuracy (e.g. Witte et al., 2013), that is comparable in duration and performance to the increase obtained by Tan et al. (2014). The keystone to this reflexion is therefore whether non-BCI trainings can offer and improvement complementary (and not "similar") to BCI training. Since only few studies support an effect of non-BCI training on BCI learning (i.e Tan et al., 2009, 2014), it is too early to conclude on the specific effect of training, but it should be kept in mind when elaborating new study designs.

7.2 Conclusion

The findings of studies I and II showed that the predictors for BCI accuracy could not be consolidated across replications studies. Moreover, the implementation of short trainings based on those predictors did not lead to an improvement in BCI accuracy. The most plausible reason could be the limited duration of the trainings, which could be intensified further than four days to – for example – twelve weeks, in an attempt to replicate existing literature.

The growing base of evidence of predictors for SMR-BCI would benefit from well-thought replication studies, methodologically assessing and refining such predictors, and avoiding the temptation to only push forward "new" or "better" predictors, but rather attempting to have a comprehensive approach that overall benefit to the field of BCI. Publishing, negative results is being recognized more globally, and may help provide essential information for researchers who try to identify predictors for SMR-BCI.

As much as three studies point towards of mindfulness meditation (Tan et al., 2009, 2014; Cassady et al., 2014), representing a potential and interresting topic to further investigate. Alternatively the physiological observations from Study I pointed towards elaborating specific visuo-motor coordination trainings that would exclude simultaneous use of both hands in an attempt to maximize the contrast in topographical ERD/ERS activations.

7.3 Outlook

This dissertation provided groundwork for further scientific contributions. My project for further actions is to firstly extend and consolidate the list of predictors for SMR-BCI that is yet actualized with the results from studies I and II (see Table A). In addition, and due to the importance of also identifiying variables that do NOT predict performance despite theoretical links to motor imagery based BCIs, I would like to compile an exhaustive list of variables predicting SMR-BCI performance, and provide evidence for consolidation or rejection of such predictors.

Closely related to the field of SMR-BCI, I would also like to apply the same methodology to the predictors of P300-BCI, for which Kübler (2017) called for more replication studies and comprehensive reviews (e.g. Bougrain et al., 2012).

Another aspect worth investigating is the effect of Mindfulness Meditation training on BCI performance, for which there is the need to replicate the existing and more importantly properly assess their outcome variables. The potential as stake is tremendous, considering the 10 percent point increase that was reported by respective authors. Importantly, mindfulness trainings would be available for end-users in the locked-in-state, therefore allowing to transfer the technology to those who really could benefit from improvements in SMR-BCI accuracy.

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Appendix A

Updated table of predictors

Type	Subtype	Study	Test	Within / Between	Indep	Sample	Statistic	Sig.	Note
Psychological	Attention	Grosse-Wentrup (2011)	Corr. γ and SMR quality score (SMRq)	W	N	10	$\rho = .08$	***	
		Grosse-Wentrup and Sch??lkopf (2012)	Corr. SMRq predicted and measured	W	Y	14	$\rho = .10$	***	two individuals had $\rho = .4$, forward prediction
		Hammer et al. (2012)	Corr. AHA (ability to concentrate) and accuracy	B	Y	40	$\rho = .50$	**	
		Cassady et al. (2014)	log-rank-test of accuracy between MBAT > 1 year and CG	B	Y	12	na	*	
		Study I (BE)	Corr. accuracy and relaxation VAS	B	Y	53	$\rho = .311$	*	only in Berlin sample
	Motivation	Leeb et al. (2007)	Paired t-test of Accuracy between virtual reality and simple feedback	B	Y	10	$t(8) = 3.2$	*	
		Kleih and Kübler (2013)	Corr. interest and accuracy	W	N	51+11 S	$\rho = .53$	***	bidirectional corr
			Corr. challenge and accuracy	W	N	11 S	$\rho = .83$	*	bidirectional corr
	Control beliefs	Witte et al. (2013)	Corr. KUT and SMR power during feedback	B	Y	10	$r = .69$	*	Neurofeedback
		Burde and Blankertz (2006)	Corr. KUT and number of hits	B	Y	17	$r = .59$	*	1-sided
		Jeunet et al. (2015)	Self-reliance	B	Y	18	$r = .51$	*	mixed BCI, ns. after Bonferonni
		Nijboer et al. (2008)	Regr. accuracy by mastery confidence	W	N	16	$b = .58$	*	bidirectional corr
		Kleih and Kübler (2013)	Corr. mastery confidence and accuracy	W	N	11 S	$\rho = .80$	*	bidirectional corr.
	Affective	Nijboer et al. (2008)	Regr. accuracy by mood	W	N	16	$b = .498$	*	bidirectional corr.
			Regr. accuracy by fear of incompetence	W	N	16	$b = -.62$	*	bidirectional corr.
		Kleih and Kübler (2013)	Corr. fear of incompetence and accuracy	W	N	51+11 S	$\rho = .53$	***	bidirectional corr
		Jeunet et al. (2015)	Corr. Tension and accuracy	W	N	18	$r = -.57$	*	mixed MI-BCI, ns. after Bonferonni
	Cognitive	Jeunet et al. (2015)	Corr. Abstractedness and accuracy	W	N	18	$r = -.53$	*	mixed MI-BCI, ns. after Bonferonni
		Study II	Corr. accuracy and State Minfdfulness	W	N	39	$\rho = .38$	*	SMS assessed after 15min BCI, only in POST
Visual, motor and spatial	Dexterity	Hammer et al. (2012)	Corr. VMC error duration and accuracy	B	Y	80	$r = .42$	**	
		Hammer et al. (2014)	Corr. VMC error duration and accuracy	B	Y	32	$r = .36$	*	Replication, ns after Bonferroni
		Study I	Corr. VMC accuracy and error perc. difference	B	Y	22	$r = .677$	***	
		Study II	Corr. VMC accuracy and error perc. difference	W	Y	13	$r = .622$	*	Replication, only in POST
		Randolph (2012)	Regr. accuracy by experience in typing, playing instruments, sport and video-games	B	Y	80	$r^2 = .35$	all *	time factor also included in the regression
		Randolph et al. (2010)	Regr. interaction accuracy by age and full body movements	B	Y	55	$b = .0075$	*	
	Mental imagery	Vuckovic and Osuagwu (2013)	Corr. accuracy and KVIQ-K (Kinesthetic)	B	Y	30	$r = .53$	***	correlates more with simple motor imagery
			Corr. accuracy and KVIQ-V (visual)	B	Y		$r = .21$	*	correlates more with goal oriented motor imagery
		Jeunet et al. (2015)	Corr. mental rotation and accuracy	W	N	18	$r = .70$	**	mixed BCI, bidirectional corr.
Neurophysiological	Rest activity	Blankertz et al. (2010)	Corr. Accuracy and SMR Predictor	B	Y	80	$r = .53$	*	
		Study II	Corr. Accuracy and SMR Predictor	W	N	38	$\rho = .53$	**	replication, using PRE and POST recordings
		Zhang et al. (2015)	Corr. Accuracy and SMR Predictor	B	Y	40	$r = .29$	*	replicated the SMR predictor
			Corr. accuracy and Spectral Entropy 2min rest	B	Y	40	$r = .65$ on C3	*	
		Ahn et al. (2013)	Corr. Accuracy and PPFactor	W	N	61	$r = .70$	***	2 sec pre-trial
	Modulated activity	Witte et al. (2013)	μ band power increase after 11 sessions predicts learners and non learners after 25 sessions	W	N	13	na	na	predictor is dependent variable
		Halder et al. (2011)	t-test of Activation in the Supplementary Motor Area (SMA) during MI by low and high BCI aptitude users	W	N	10	$r = 0.59$	*	
Neuroanatomical		Kasahara et al. (2015)	Corr. accuracy and Grey Matter volume in SMA, SSA, PMd	B	Y	10	$r = .72$ to $.59$	*	
		Halder et al. (2013)	Corr. accuracy and Fractional Anisotropy in right Cingulum, left sup. fronto-occipital Fascilulus, Corpus Callosum, right posterior Corona Radiata	B	Y	10	$r = .63$ to $.51$	*	
Demographic		Randolph (2012)	Regr. accuracy by age and other factors	B	Y	80	$b = -0.6$	***	age was either over or below 25 yo
			Regr. accuracy by sex and other factors	B	Y	80	$b = -0.29$	†	marginal, Women>Men

	Randolph et al. (2010)	Regr. accuracy by sex	B	Y	55	$r^2 = 0.0001$	*	Trivial predictor
Environmental	Randolph (2012)	Regr. accuracy by drug intake and other factors	B	Y	55	$b = -0.48$	*	

Table A.1 Cross table of the predictors. (B)etween subject design variables; (W)ithin subject design; (Indep)endence with outcome variable. Sample contains healthy participants when unspecified, or (S)troke patient.

Appendix B

Additional physiological data

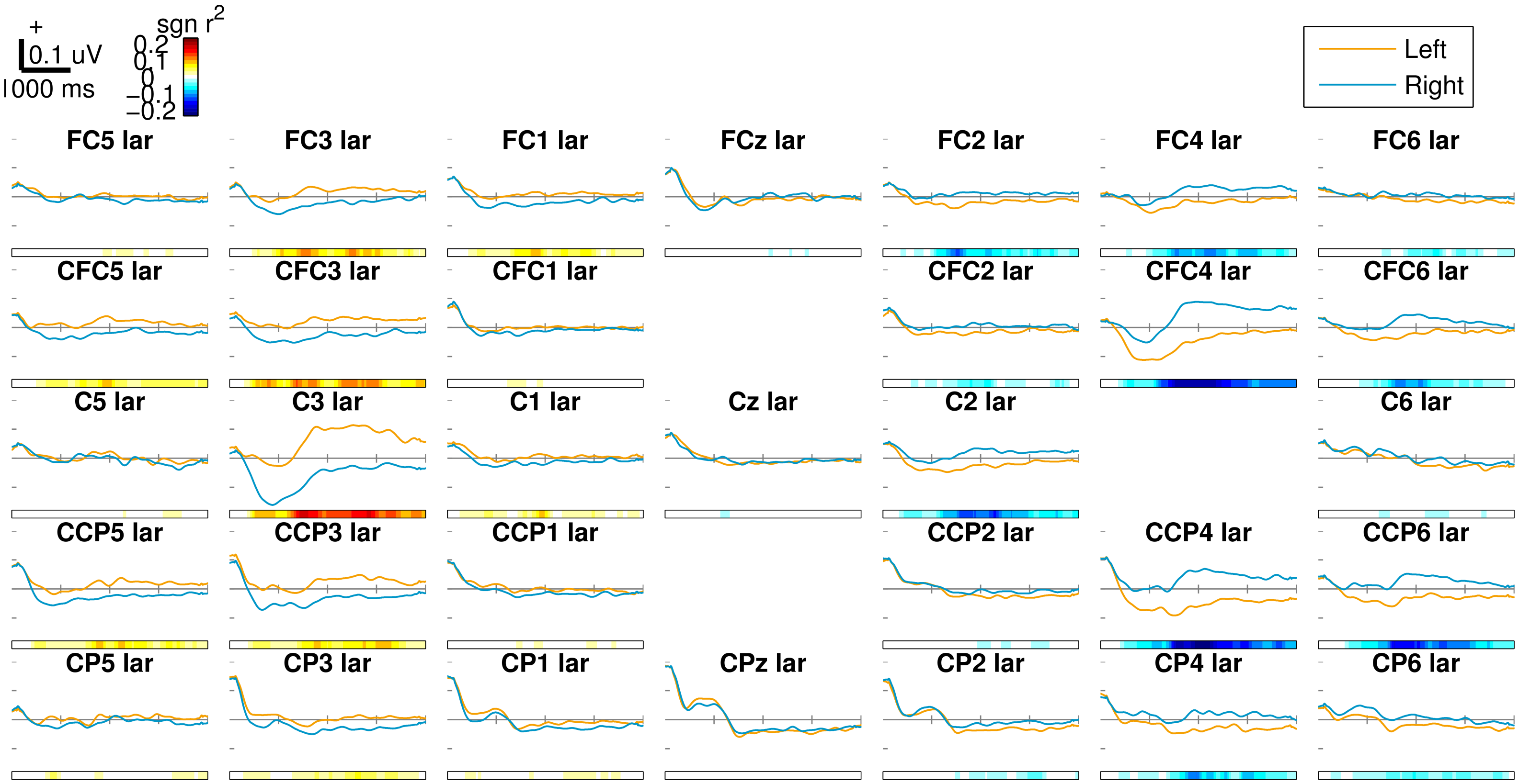

Figure B.1 **PRE** Grand average ERD/ERS time plots representing relative band power between 8 Hz and 14 Hz from signal envelope in the left and right hand motor imagery. The plot averages the data from all $N = 39$ participants in online run 2,3 and 4 of the BCI PRE session.

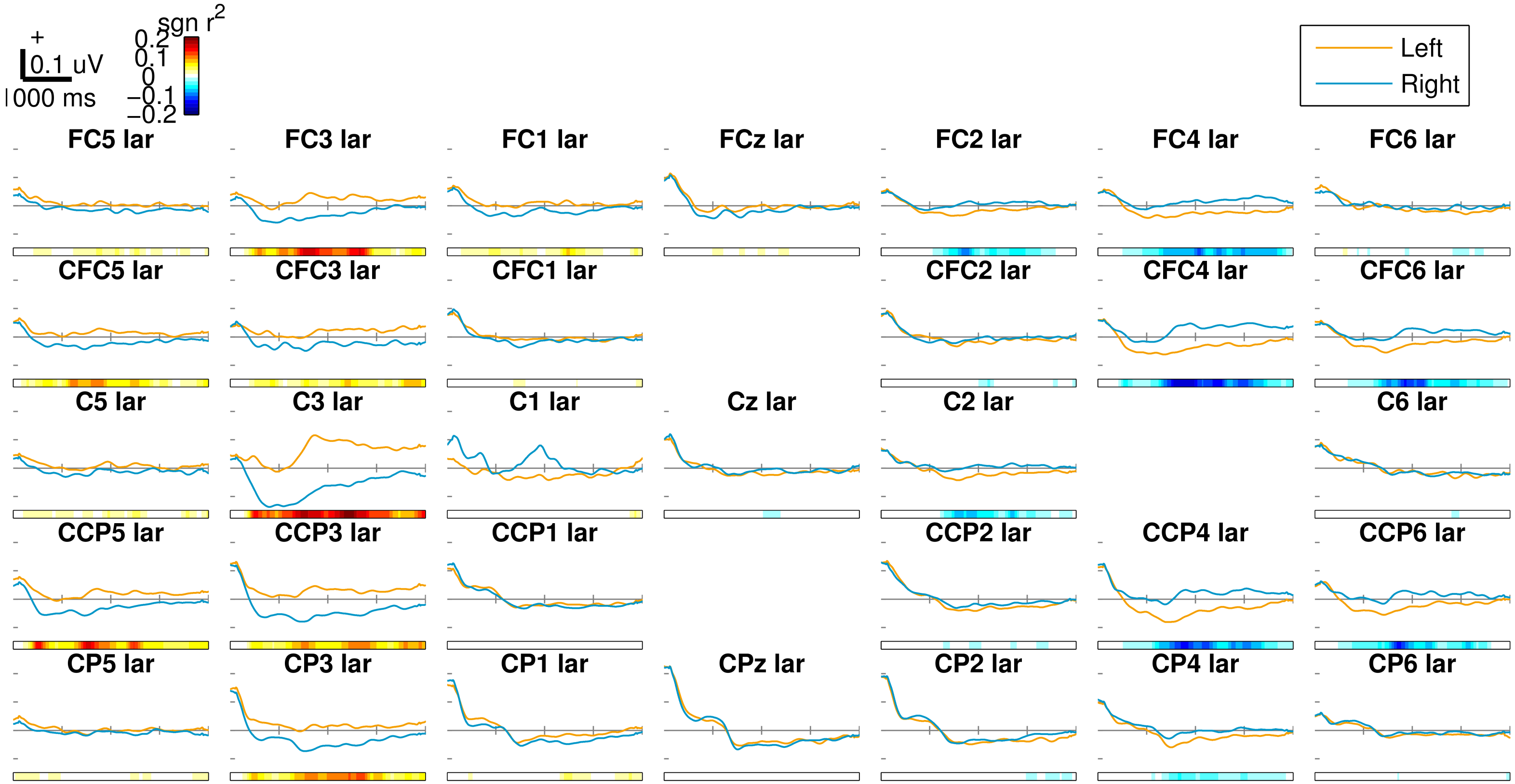

Figure B.2 **POST** Grand average ERD/ERS time plots representing relative band power between 8 Hz and 14 Hz from signal envelope in the left and right hand motor imagery. The plot averages the data from all $N = 39$ participants in online run 2,3 and 4 of the BCI POST session.

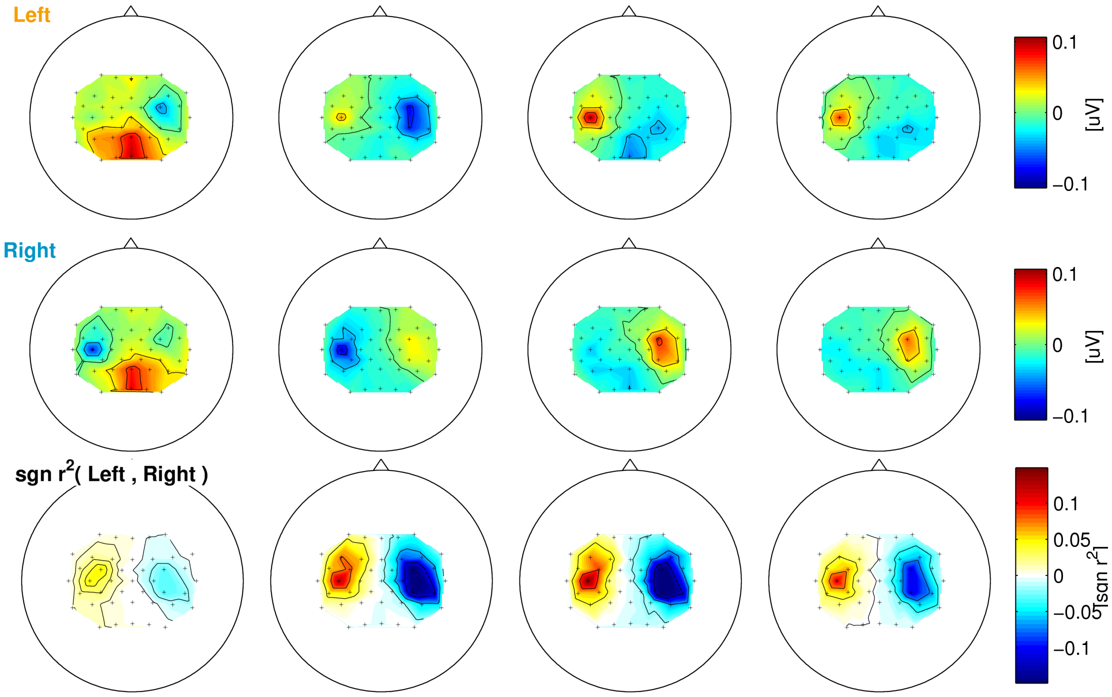

Figure B.3 **PRE** ERD/ERS head topographies representing relative band power between 8 Hz and 14 Hz from signal envelope in the Left and right hand motor imagery tasks averaged for every second of online BCI control. Signal was spatially filtered by Local Average Reference. The plot averages the data from all $N = 39$ participants in online run 2,3 and *4 of the BCI PRE session. The third line represents the signed r^2, computed to illustrate the classwise contrast of ERD/ERS patterns.

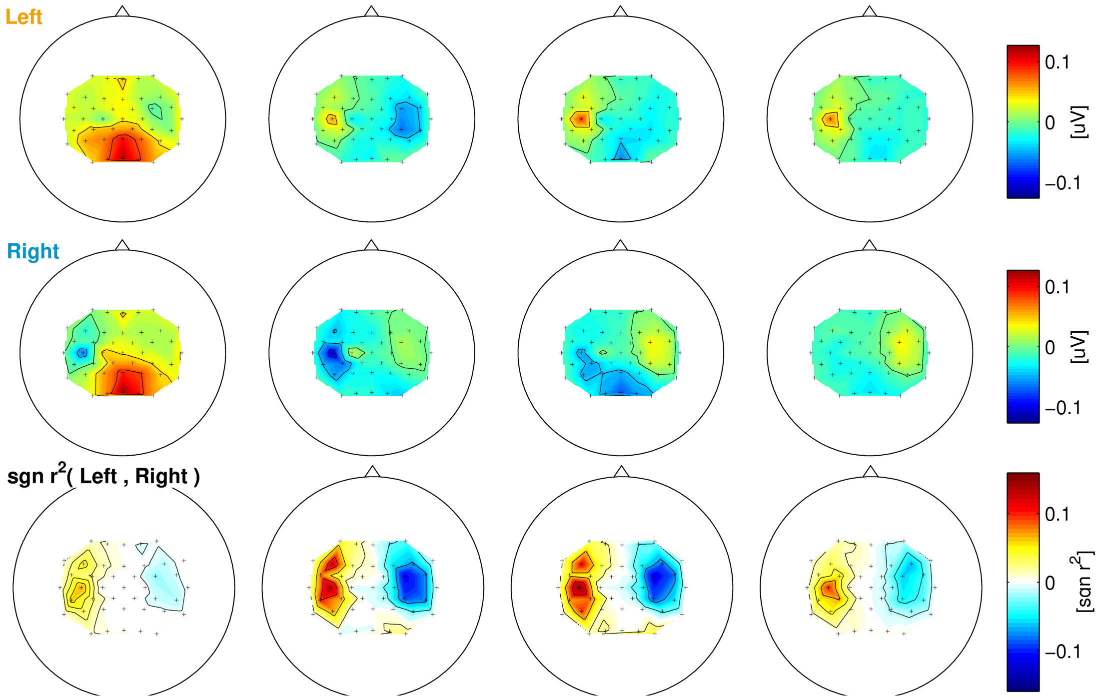

Figure B.4 **POST** ERD/ERS head topographies representing relative band power between 8 Hz and 14 Hz from signal envelope in the Left and right hand motor imagery tasks averaged for every second of online BCI control. Signal was spatially filtered by Local Average Reference. The plot averages the data from all $N = 39$ participants in online run 2,3 and *4 of the BCI POST session. The third line represents the signed r^2, computed to illustrate the classwise contrast of ERD/ERS patterns.