Identifying factors influencing the outcome of BCI-based post stroke motor rehabilitation towards its personalization with Artificial Intelligence

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Abstract—**Stroke is the leading cause of complex disability in adults. The prevalence of motor deficit and cognitive impairment after stroke is high and persistent. The most common consequence is the hemiparesis of the contralateral upper limb, with over 80% of stroke patients suffering from this condition acutely and over 40% chronically. Brain-Computer Interfaces (BCI) based on motor imagery have shown promising results in post-stroke motor recovery. However, this approach does not work for all patients, and even when it works, shows vastly different effectiveness across patients. It thus needs to be improved. This could be achieved by personalizing the BCI-based Motor Rehabilitation (MR) program to each patient, notably by personalizing the employed Artificial Intelligence (AI) models used. To do this, it is necessary to first identify the predictive factors of successful BCI-based motor rehabilitation. In fact, very little research has addressed the question of factors that influence post-stroke BCI-based MR. Thus, in this paper, we present a survey of the literature about the factors related to successful use of BCIs in general and then the factors that are associated to post-stroke motor recovery, to identify the various factors that could influence BCI-based post-stroke MR. We then discuss how such factors could be taken into account in order to develop new AI algorithms for personalized post-stroke BCI-based MR.**

Index Terms—**BCI, stroke motor rehabilitation, Performances predictors, Training personalization, Artificial Intelligence**

I. INTRODUCTION

Stroke, or cerebrovascular accident, which is also defined as a brain dysfunction due to a cerebral blood flow disturbance, is the second most common cause of death and of adult disability around the world. The prevalence of both motor deficit and cognitive impairment after stroke is high and persistent. The most common one is hemiparesis of the contralateral upper limb, with more than 80% of stroke patients experiencing this condition acutely and more than 40% chronically [1]. Improving post-stroke recovery and quality of life for patients is therefore a major public health issue. In this context, new therapeutic approaches are being explored, including brain-computer interfaces (BCI), to improve motor rehabilitation.

Brain-computer interface (BCI) for post-stroke motor rehabilitation (MR) is a promising tool that has already shown better MR results than traditional exercises [2]. BCI is a computer-based system that acquires brain activity signals - typically electroencephal-ogram (EEG), analyzes them, and translates them into commands that are relayed to an output device. BCI can notably identify executed or imagined hand movements from EEG [3], which can be used for MR therapies. Motor Imagery (MI) therapies consist for the patients in imaging a movement of their affected limb to elicit sensorimotor activity in the damaged brain area. During the execution of a hand movement, a desynchronization of the contralateral sensorimotor cortex notably between 8-13 Hz (Mu rhythm), called an event related desynchronization (ERD), and then an increase of the amplitude at the end of the movement in the beta rhythm ($\approx$16-24 Hz), called an event related synchronization (ERS), is observed. Now, research has shown a neurofunctional equivalence between imagining a movement and performing the same movement [4]. In both cases, the execution times are identical and the same brain areas are activated. This overlapping activity of brain regions during MI and motor execution explains the effectiveness of MI in post-stroke motor recovery. In addition, BCI provides the patient with feedback on the imagined movement, which reinforces the intention-action loop and thus improves motor recovery (compared to motor imagery alone) [5]. It has also been shown that feedback increases patient engagement and motivation which contributes to post-stroke improvement [5].

However, there are still several limitations that need to be overcome to enable optimal BCI-based MR procedures. They include long calibration times, the relatively poor classification accuracy of MI tasks and the fact that about 20% of users are not able to control BCIs [6]. Moreover, the proposed BCI-based MR exercises are the same for all patients, without taking into account individual characteristics such as possible sensory or cognitive deficits, the patient's mental states, the number of sessions already completed, etc. These factors should ideally be taken into account to allow for better effectiveness of BCI-based MR. Some of those limitations can be overcome by using artificial intelligence (AI), such as intelligent tutoring systems [7] that could select and present the best sequence of training MR exercises, dynamically, according to the patient's characteristics (workload, motivation, level of impairment, etc.). Interestingly, some of these characteristics, mainly mental states, can be measured from spontaneous brain activity using so-called passive BCIs [8].

However, this approach to designing personalized and adaptive BCI protocols requires to first identify the set of factors that are associated to BCI performance and post-stroke MR outcome, in order to then use them for personalization towards improving both of them. This is what we proposed in this paper. In particular, we conducted a literature survey in order to synthesize the user-related factors (e.g., mental states or traits) that are associated to either BCI performances (in terms of MI decoding accuracy), post-stroke MR outcome (e.g., motor recovery) or both. This survey is based on articles cited in recent literature review papers on predictors of BCI performances [9], MI-BCI for stroke rehabilitation [2] and predictors of stroke MR [10]. We then present some ways in which such factors could theoretically be used, in the future, to personalize BCI-based post-stroke MR, based on AI approaches, in order to improve it.

This paper is organized as follows: In Section II we present the factors identified based on a review of the literature, and in Section III we discuss how we could include these factors into AI algorithms in order to create personalized BCI training. Finally, Section IV concludes the paper.

II. FACTORS OF MR WITH BCI-BASED THERAPY

To our knowledge, very little research has examined the question of factors that influence post stroke MR using a BCI procedure. In this context, we present below a survey of the literature on the factors that are associated to the performances of BCI use in general and then the factors that relate to or influence post-stroke motor recovery, with or without being based on BCI.

Psychological and cognitive factors are usually divided into states, traits and demographic characteristics [11]. States are defined by Chaplin et al. [12] as "temporary, brief, and caused by external circumstances" as opposed to traits that are "stable, and enduring, and caused by internal circumstances", and demographic characteristics are neither states nor traits, and correspond to personal characteristics (age, gender, etc.), habits, environment-related factors, etc. We synthetize in Table 1 the research on the potential factors (mental states, traits and demographic data) that may influence the efficacy of BCI based motor rehabilitation. Little research has been made on this specific topic of BCI-based post-stroke MR factors, but we added related works that should be relevant to consider, such as the literature on psychological and cognitive factors that are associated with BCI control performance for neurotypical users and demographic/medical factors that are predictors of the motor recovery after a stroke, independently of BCI use.

A. Factors influencing BCI performances in neurotypical users[1]

In her review on factors that could predict users performance in controlling a BCI, Jeunet et al. [11] identified three main families of factors in neurotypical users: the user's relationship with technology, spatial abilities and attentional abilities. The user's relationship with the technology corresponds to anxiety and in particular to the user's level of tension in front of the computer [9], their locus of control towards technology [13], fear of incompetence [14] [15], the fear of the BCI system [13] [15] [16] and the lack of feeling of control over the BCI [16]. So it is important that BCI participant feel confident in themselves [9], in their own abilities [15] and that they are motivated to learn this new ability that BCI control is [15] [17] [18]. The ability of controlling a BCI based on motor imagery is positively correlated to the subject's spatial abilities (i.e., their ability to produce, manipulate and transform mental images) assessed with the vividness of visual imagery questionnaire [19] [20] or the mental rotation test [11] [9] [21]. The practice of sport can also be associated to higher performances in controlling MI-BCI [22]; specially training that focus on mind body awareness (MBAT) (e.g., Yoga and Meditation) [23]. Similarly, the visuomotor coordination, that can be improved with sport activity, is a factor correlated to BCI performances [17] [24].

Attention capacities, defined as the "the ability to focus cognitive resources on a particular stimulus", are also a predictor of performance [25]. This skill can be considered as a trait (attentional span [17]) or also as a mental state (attentional state [26]) that can be measured directly with passive BCI observing the high gamma oscillation in the fronto-parietal cortex.

In addition, Darvishi et al. [27] identified a correlation between users' reaction time and their performances in controlling the BCI with a feedback update interval of 16 ms and 96 ms. However, this correlation was not present with a feedback update interval of 24 ms and 48 ms. Also, by dividing the participant between good and bad performers, they have shown that good performers perform better with short feedback update (16 ms) and bad performer with a long feedback update (96 ms). Blankertz et al. [6] proved that with 2 minutes of EEG data at rest, they can identify a correlation (R=0.53) between Mu rhythm amplitude at rest and subsequent MI-BCI performances. To do so, they measured the amplitude of the sensorimotor Mu rhythm using a power spectral density analysis in the motor cortex with two Laplacian channels in C3 and C4.

B. Factors influencing motor rehabilitation without BCI

With regard to motor rehabilitation after stroke without BCI, few articles focus on psychological aspects that predict motor rehabilitation potential. The literature focuses mostly on predicting MR from demographic and medical informations. In their review of the literature, Stinear and Byblow [10] indicated that the best predictors are the level of disability immediately after the stroke. Stiner et al. showed that their PREP algorithm was able to predict the level of recovery with 64% accuracy [28] by measuring 72 hours after the stroke the abduction of the shoulder, the extension of the fingers, the presence of motor evoked potentials (induced

[1] Neurotypical users are defined as the population that does not suffer from any neurological disability, i.e., neither a developmental brain disorder nor a brain injury such as a stroke. This is a more inclusive term than healthy users.

Predictors	How they are measured	Reference
	BCI performances with neurotipical users	
Spatial abilities	mental rotation test	Jeunet et al., 2016
Apprehension, self reliance, visual and verbal learning, spatial abilities	16pf5, Learning style inventory, mental rotation test	Jeunet et al., 2015
Locus of control for dealing with technology	Locus of control reinforcement (LOC)	Burde and Blankertz, 2006
Fear of incompetence	Questionnaire of current motivation (QCM)	Kleih et al., 2013/ Nijboer et al., 2010
Fear of the BCI	QCM	Burde and Blanketz, 2006/ NIjboer et al. 2010/ Witte et al., 2013
Control beliefs	Kontrollueberzeugug im Umgang mit Technik (KUT)	Witte et al., 2013
Mastery confidence	QCM	Nijboer et al., 2010
Motivation	QCM	Hammer et al., 2012 / Neumann and Birbaumer, 2003 / Nijboer et al., 2010
Self efficacy	Theoretical	Neumann and birbaumer, 2003
gender, emotional stability, orderliness, vividness of visual imagery, visuo-spatial ability	Demographic questionnaire, Five factor personality inventory, mental rotation test, design organisation test, vividness of visual imagery questionnaire	Leeuwis et al., 2020, 2021
Block design test, matrix reasoning, visual puzzles, mental rotation test,	Block design, matrix reasoning (wais IV), visual puzzles (WAIS IV dimension)	Pacheco et al., 2017
Interaction of age and daily amount of hand and arm mouvement	Age, Time spent typing per day, times spent on activities requiring hand and arm movement per day , time spent on activities requiring most of the body per day	Randolph et al., 2012
Mind- body awareness training	Mind- body awareness training	Cassady et al., 2014
Visuomotor coordination ability Attentional impulsivity	Two hand coordination, Attitudes toward work	Hammer et al., 2012, 2014
Neural correlates of attention level (γ-oscillations originating in fronto-parietal networks)	EEG	Grosse wentrup et al., 2012
Reaction Time	Simple Reaction Test	Darvishi et al, 2018
EEG activity in motor areas at rest	EEG	Blankertz et al., 2010
	Stroke Rehabilitation without BCI	
Shoulder Abduction and Finger extension, Motor evoked potential, NIHSS score, age	Medical Research Council, Transcranial magnetic stimulation, National institute of health stroke scale, demographic data	stinear et al., 2012, 2017
type of stroke, visual inattention, urinary incontinence, motricity in the upper limb, sitting balance	Bamford Classification , National institute of health stroke scale, barthel index, motricity index / Fulgl Meyer Assesment (FMA), trunk control test	Nijland et al., 2013
Motor function, sensibility	FMA-Upper Extremity (FMA- UE), sensory section of the FMA-UE	Ghaziani et al., 2020
	Stroke Rehabilitation with BCI	
BCI performance	Best trial and mean of trials	Frolov et al., 2017
Somatosensory abilities	Erasmus modified Nottingham Sensory Assessment for the upper limb	Pillette et al., 2020
Neural correlates of fatigue (Beta power)	EEG	Foong et al., 2020
Functional connectivity at rest	fMRI	Vartuki et al., 2013
Alpha band connectivity	EEG	Mottaz et al., 2018
Coherence index in the motor cortex	EEG	Tung et al., 2013

Fig. 1: Potential factors influencing the efficacy of BCI-based MR for stroke patients, divided between factors from neurotypical users' ability to control BCI and factors of stroke recovery from conventional or BCI-based therapy

by transcranial magnetic stimulation) and diffusion-weighted magnetic resonance imaging data. In 2017, they published an update of their model [29] achieving better prediction (75% of accuracy) considering only shoulder abduction and finger extension, the age of the participant, the severity of stroke (assessed with the national institute of health stroke scale) and the presence of motor evoked potentials. Nijland et al. [30] identified other markers of stroke severity that correlate with motor rehabilitation outcome including the type of stroke (classified with the Banford classification), the visual inattention, the urinary incontinence, the sitting balance and the motricity index. In addition, Ghaziani et al. [31] showed that arm recovery can be predicted based on the initial Fugl-Mayer Assessment of Upper Extremity (FMA-UE) considering the sensory and the motor function modalities.

C. Factors influencing motor rehabilitation with BCI

Furthermore some studies using MI-BCI in recovery after stroke report factors influencing MR outcome even though this was not the primary objective of the experiment. Frolov et al. [32] found a correlation between classification accuracy and motor improvement (action reach arm test and FMA score). At least two explanations for this correlation can be offered: first, the ability to induce specific motor brain activity may be impaired by stroke, making it more difficult for a patient with a higher level of impairment to control the BCI ; second, the ability to induce the specific patterns at the basis of classification, ERD on the contralateral motor cortex, improves neural plasticity and therefore upper limb motor function.

The loss of somatosensory skills is also inversely correlated with motor rehabilitation. This result has been largely neglected in previous BCI-based MR studies, insofar as 77% of them do not report measuring somatosensory abilities before BCI motor rehabilitation [33].

Fatigue, which is strongly linked to the attentional state of the participant, is also a factor that is associated to BCI performances. After a stroke, many people suffer from an increased level of fatigue and are less willing to participate in physical or cognitive activities. The frequency of post-stroke fatigue ranges from 29% to 77% [34]. In their experiment, Frolov et al. reported that most of their stroke participants started to feel fatigue after 20-30 min of BCI exercise [32]. The decrease of beta power has been reported as an indicator of fatigue. Indeed, Foong et al. [35] identified a correlation in BCI based stroke rehabilitation between relative beta power and BCI performance, in the frontal and central brain regions. This led to the conclusion that neural correlates of fatigue may be a predictor of performance in controlling a BCI.

Other identified factors include neurophysiological changes indicating neural plasticity measured with fMRI brain functional connectivity observed in the resting state [36], in the EEG alpha band in the motor cortex [37] or in the coherence of the signals from the lesioned hemisphere between the motor cortex and the other cortical areas [38].

III. TOWARDS INCLUDING ARTIFICIAL INTELLIGENCE APPROACHES

After having identified the factors that could potentially influence BCI-based motor rehabilitation, we propose in this section a discussion on how they could be taken into account to improve MR using BCIs. Artificial intelligence approaches indeed make it possible to use prior knowledge to adapt, personalize and optimize training. However, not all factors can be considered in the same way to provide adaptive training.

For example, it is possible to distinguish at least 2 types of factors: those that are invariant and those that can evolve over time. Invariant factors (i.e., factors that will be approximately constant during MR retraining), such as the severity of the stroke, user characteristics, or demographic information can be used as prior knowledge prerequisites for proposing an appropriate training sequence. For example, if the patient has an attention deficit (diagnosed before training), it will be appropriate to offer shorter but more recurrent training, or if he has a somatosensory deficit, we need to focus the feedback on the visual modality and not on the tactile modality. On the other hand, evolving factors, such as mental states or EEG signals, can be monitored during MR and be used to continuously adapt the training protocol. In the following sections, we will discuss on how these factors may be included in AI models. First by presenting the algorithms of intelligent tutoring systems and how they could be used to adapt BCI-based MR therapy, and then by highlighting the current limitations of MI classification algorithms used in BCI-based MR and presenting ML models that could help overcome them.

A. Intelligent Tutoring Systems

To personalize MR, we could propose a sequence of training exercises inspired from Intelligent Tutoring Systems (ITS) [7]. Intelligent Tutoring Systems (ITSs) are computer systems that aim to provide personalized instruction, task and feedback to users, often through the use of AI technology and without a human teacher. ITSs could constitute an optimized approach to MR training sequences taking into account the characteristics of the learner/patient and in particular the various factors identified as having an influence on BCI performance and MR outcome. ITSs have been used in many fields, for instance to teach young students mathematical concepts when manipulating currencies [39]. To do so, a set of exercises is created by an expert who designs the order in which these tasks must be carried out for the student to progress (addition must be mastered to perform subtractions and manipulating round numbers must be understood to work with decimal numbers). During the training, the task is chosen by a Multi-Arm Bandit algorithms that have for reward function, and therefore optimize, the learning progress of the student. This excludes task too difficult that would induce boredom or too complex that would induce frustration. The two scientific and technical points to be investigated in order to use ITS as BCI-based therapy are 1) to identify the reward function to be given to the ITS algorithm (e.g., a bandit algorithm in [39]) to select the most suitable exercise at a given time; and 2) to determine the set of possible exercises to be proposed to the patient.

Regarding the reward function, it needs to be correlated to the long-term motor rehabilitation outcome (i.e., motor recovery) and be able to be estimated on the short term, for each exercise. There are a few potential candidates that could satisfy these constraints, that were presented in section II. These notably include BCI performances [36] and the evolution of brain connectivity (alpha band [37], functional connectivity at rest [37] or connectivity index [38]). However, these potential factors were identified as being correlated with motor recovery, which does not mean that they have a causal influence on motor recovery. Thus, optimizing one factor may not change the rehabilitation outcome. For instance, such correlations could be due to the fact that these factors are also factors of stroke severity. There will be a need to thus assess the most suitable reward function.

Regarding the sequence of training exercises, different parameters could be manipulated to create BCI exercises that are either easier or harder, such as the type of feedback, its update interval [27], the duration of the MI task or the type of classification algorithm used (e.g., ”left-hand MI vs right-hand MI” or ”MI vs rest”) [40]. The interested reader may also refer to [41] for a more in-depth taxonomy of BCI training exercises.

Additionally, invariant factors could be used to focus the therapy on achievable goals as has been proposed by Stinear et al. [28]. These authors have divided the target level of recovery into 4 categories and proposed corresponding objectives. For instance, if a limited recovery is expected, they recommend that the therapy should focus on reducing impairment by strengthening the paretic upper limb and improving active range of motion, whereas if a complete recovery is expected rehabilitation could focus on task-specific therapy [28]. We could propose different types of MI exercises, focusing on range of motion or on task-specific training, in function of the expected motor recovery, as predicted from the factors.

B. Improving Machine Learning techniques

More generally, the use of BCIs poses two recurring problems which are the long duration of the calibration procedure and the lack of robustness of the classification algorithms [42]. These two issues could be overcome - at least to some extent, by improving Machine Learning (ML) techniques, notably by implementing, for example, transfer learning techniques [43]. Transfer learning involves training the ML model on a large number of participants or sessions and then applying it to another session or participant. This is particularly useful with Deep Learning models that need a large amount of data to learn correctly the relevant features to extract [44].

Transfer learning is not yet widely adopted, but may be relevant in some cases. For example, if the patient is unable to generate ERD during calibration, perhaps due to brain damage, the subsequent training phase may not be therapeutically effective. Indeed, the feedback provided will not reflect ERD quality, as such ERD were missing from the training data used to calibrate the classifier providing this feedback. Calibrating the ML model using another participant, who can produce ERD, could then be a promising way for therapeutic improvement and better control of BCI. It has indeed been shown that transfer learning between participants can produce better results compared to a participant-specific calibration if the latter is of poor quality [45]. Some invariant factors identified in Section II could be included in ML models in order to perform patient-to-patient transfer between similar patients in terms of such invariant factors, e.g., in terms of age or stroke location.

Another way to improve the robustness of EEG classification algorithms is to make them invariant to certain evolving factors, which lead to dynamic changes of EEG characteristics and BCI performances, such as fatigue or attention for instance. This may consist in creating machine learning using a custom loss function that takes into account these factors so that the optimized classifier output does not change when the evolving factors change (e.g., to create an MI classifier whose decoding performance does not change when the patient's fatigue changes). Such algorithms that are invariant to some sources of noises have already been developed with, as noise sources, overall alpha variance [46] or overall EEG variance at rest [47]. However, these noise sources are very broad and not very specific, which makes it necessary to develop new algorithms that can take into account the specific evolving factors that influence BCI-based MR.

IV. CONCLUSION AND FUTURE WORKS

In this article, we have surveyed the literature in other identify the different factors that may have an influence on post-stroke motor recovery with BCI. These factors, collected from the literature on factors associated to BCI performance in neurotypical users, and the literature on predictors of post-stroke motor recovery (with or without BCI), can be divided into evolving and invariant factors. We also discussed how these two types of factors could be taken into account in order to improve AI methods for BCI based MR in the future. We presented some methods, including ITS, transfer learning and invariant classifier to specific factors and discussed the possible contributions of these methods and the limitations they can overcome.

In order to be able to apply these new AI methods with strong scientific evidence in the future, more research needs to be conducted to validate the identified factors in actual BCI clinical trials. The AI methods used must also be optimized in order to allow an optimal adaptation of the rehabilitation procedures to the individual characteristics of the patients. Hopefully this could contribute to a new generation of personalized BCI-based MR, enabling effective improvement of post-stroke motor performance.

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