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Towards a model-based personalization approach for driving a BCI

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***Abstract*—A Brain-Computer Interface (BCI) translates a person's intent, derived from brain signals, into control commands for various applications. This work focuses on Motor Imagery-based BCI (MI-BCI), specifically emphasizing sensorimotor-rhythm (SMR) and MI as the relevant task. While improvements have been made in classification algorithms and signal acquisition, human factors influencing user-BCI compatibility remain underexplored. User performance in MI-BCI systems is impacted by personal, psychological, and neurophysiological factors, leading to a phenomenon termed "BCI illiteracy". In this work, we aim to address BCI illiteracy through a systematic, standardized study, incorporating various human factors to enhance user performance by developing a neural network model predicting a trainability score and a training regime. To achieve this, the MI-BCI systems use population-specific indicators and task-based modulators, integrating anatomical, psychological, and neurophysiological information (EEG, biosignals). The proposed model-based personalization approach offers reproducible, innovative, and open-source training protocols to boost BCI performance avoiding prolonged and ineffective training sessions. The ultimate goal is to eliminate BCI illiteracy as a barrier to compatibility between users and BCI systems.**

***Index Terms*—BCI-Illitaracy, Deep learning, individualization**

I. Introduction

Past research has identified predictors of performance in Motor Imagery (MI)-based Brain-Computer Interface (BCI) systems, primarily focusing on neurophysiological and psychological factors. Noteworthy neurophysiological predictors were extensively reviewed by [1], with studies like [2] highlighting the predictive value of resting sensorimotor-rhythm (SMR) amplitudes. Psychological factors, such as mood, motivation, focus of control, and fear, have also been linked to MI-BCI performance [3][4]. Additional studies established correlations between attention span, personality, motivation, spatial abilities, and MI-BCI performance [5]. Recent work by [6] associated Event-Related Desynchronization (ERD) with age, education level, management impression, and anxiety, emphasizing the need to consider such factors in designing ERD-based MI-BCIs. A comprehensive review by [7] proposed strategic approaches to address performance variations and enhance BCI reliability. In a distinct effort,[8] investigated the impact of the Most Discriminant Frequency Band (MDFB) selected during MI-BCI calibration. Their findings suggested a correlation between user-specific frequency band characteristics and classification accuracy, emphasizing the importance of understanding the learning characteristics of both human users and machines. Despite these individual efforts, a systematic approach integrating all identified factors is currently lacking in the pursuit of improving overall user performance in BCI systems.

Extensive research has already concentrated on identifying specific factors that impact the accuracy of performance in Motor Imagery (MI)-based Brain-Computer Interface (BCI) systems. While some investigators have explored potential reasons for suboptimal BCI performance from the user's perspective, others have dedicated their efforts to enhancing machine learning algorithms or diversifying hardware types. Nevertheless, the question regarding the underlying causes of user incompatibility with BCI systems remains unresolved. Therefore, it is imperative to undertake a systematic, standardized, and well-operationalized research project to address inquiries pertaining to the influence of specific human factors on BCI performance. The primary objective of the proposed framework is to embark on this research endeavor, ultimately aiming to establish a person-specific trainability score that can be employed in subsequent studies to enhance BCI performance from its inception. Specifically, our focus is on the development of a neural network model capable of predicting a trainability score for MI-based BCI systems. This prediction will be based on population-specific indicators and task-based modulators. The significant advantage lies in the potential to create an individualized BCI paradigm for each person, leveraging their unique features to ensure optimal outcomes with minimal training time. Essentially, the proposed model represents a groundbreaking step toward innovative activation protocols, introducing a model-based personalization approach for driving a BCI.

II. Gaps in MI-BCI Research

Researchers identified some critical aspects affecting MI-BCIs correct operation in general[9]. These aspects (referred to as components of MI-BCI) include signal measurement (acquisition hardware), classification and recognition algorithms, and user-BCI compatibility. A holistic approach is used to compute the performance in a MI-BCI system, which captures

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the resultant of performances of each of its components. Thus, the failure or inefficiency in any individual component could significantly affect the efficiency of the MI-BCI system. Researchers have attempted to identify the problems associated with each of these components and, further, worked towards addressing them to improve the efficiency of a MI-BCI system. Specifically, a great deal of research has been directed towards (1) improving the EEG acquisition system by developing cost-effective, portable, wireless, and easy mounting EEG devices to operate in low power setting, and (2) developing state-of-the-art methods for processing and decoding information from EEG signal. However, the efforts made towards understanding and improving user-BCI compatibility are still very sparse. The pictorial representation of these components are given in Figure.1.

A. Poor understanding of BCI-Illiteracy and its influencers

The BCI illiteracy could come under the umbrella of ”user-BCI compatibility” and is defined as a condition where users of BCI technology fail to reach proficiency in using a BCI with in a standard training period. According to the literature, nearly 15–30% of BCI users could be labeled as BCI illiterate [10][11]. The cause behind the incompatibility due to BCI-illiteracy may not be always because of the deficit innate to the user, rather could also be driven by the incapability of the system to tailor its functionality according to the user. For example, the poor performance of the user can be a result of (1) user being unable to receive input from the system (stimulus, feedback, or information about the state of the BCI) or being potentially scared by the stimulus, (2) user being unable to focus on the required mental task because of a high mental workload or an increase in fatigue, (3) variability in user-centric factors such as mood, stress, engagement, and level of attention etc. Thus, it is imperative to include these fast performance predictors, based on anatomical, psychological, and neurophysiological information of the user, to estimate likelihood of incompatibility. Then a user-specific training protocol could be proposed to alleviate incompatibility situation in case of MI-BCI. As suggested by recent literature [12][13][14][15][16], a BCI paradigm that is compatible with all participants does not exist. Moreover, it must be adapted to the users' needs by following a user-centered design and individual features (e.g., personality, age, mood, motivation, etc.) which should be taken into account.

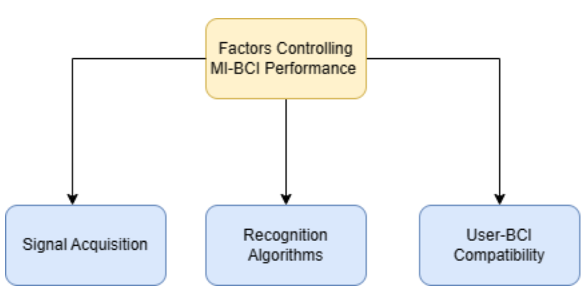

Fig. 1. Components of MI-BCI

B. Adherence to a single training protocol for all the participants

Conventionally, the MI-BCI training paradigm adapts a fixed training protocol that is administered uniformly to all subjects. However, considering the significant individual differences in the ability of skill training, necessary for MI-BCI adaptation, it is expected that performance outcomes may vary among individuals when subjected to a fixed training regimen. Thus, an individualized approach in defining training regime could be a viable solution to avoid poor performance in using MI-BCI systems. According to literature, the skill training is often linked to the demographics (e.g., age, gender), cognitive ability and prior experience [7][17]. Thus, it is important to take these factors into consideration for defining an individualized BCI-trainig approach.

The main goal of this work is to design a framework (1) to predict the likelihood of user incompatibility for a MI-BCI paradigm (referred as trainability score) and (2) to define the intensity of MI-BCI-training in a user-specific manner for maximizing the user performance (and avoiding incompatibility). (3) By collecting data of more than 100 participants, establishing a publicly open database.

III. Proposed Method

This work proposes a personalized framework for addressing MI-based BCI training problems by predicting the possibility of incompatibility and then pre-deciding the intensity of training paradigm for the user while considering its demographics and physiological factors into consideration for optimizing his/her MI-BCI performance. The framework, a neural network architecture, takes demographics, neurophysiological, psychological factors as input, and gives trainability score and the personalized training paradigm for user. The pictorial representation of the framework is given in Figure.2.

Here, we will consider a participant pool of 80-100 healthy individuals in the age group of 18-60 years, including all genders. These participants will be exposed to multiple trials over a period of 4 weeks during with their neurophysiological data (EEG, EMG, HR), demographics and psychological information will be collected. Their performance in all the trials will be recorded. All the data collected during the trials will be used to train the neural network model that can take the demographic information, psychological states, physiological measurements and performance in a trial to predict the performance of a subsequent trial. This data collection protocol, given in Fig.3, will be performed over different sessions divided into runs of approximately 7 minutes each [18][19]. To record enough data samples for the DL model one session will include 8 runs, and each run itself is divided into trials, with 30 per class (i.e., per MI-task). One trial typically lasts 8s. Figure 3 illustrates the timings and parts of one trial. The MI task will include 3 classes namely, imagination of foot, right hand and left hand. The study will be conducted with a prior approval from local ethics committee of the University of Technology Graz. The participants will give their written and informed consent prior to their enrollment in the study.

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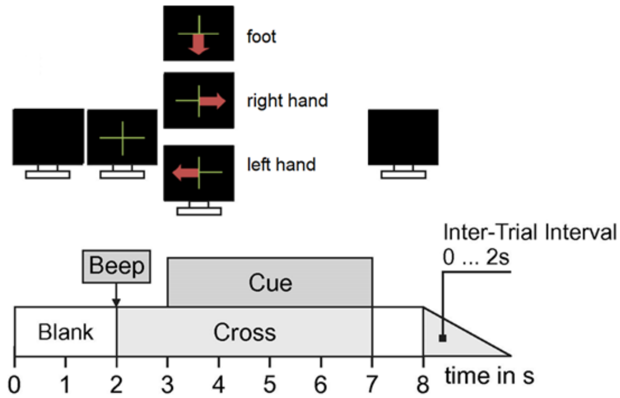

Fig. 2. Data collection paradigm

A. Modulators influencing MI-BCI performance

As evident from the literature, several modulators act simultaneously to influence the MI-BCI performance of the user. In this study, we categorize these modulators into three classes, (1) demographic factors, (2) psychological factors and, (3) neurophysiological factors (Figure 3). In demographic factors,

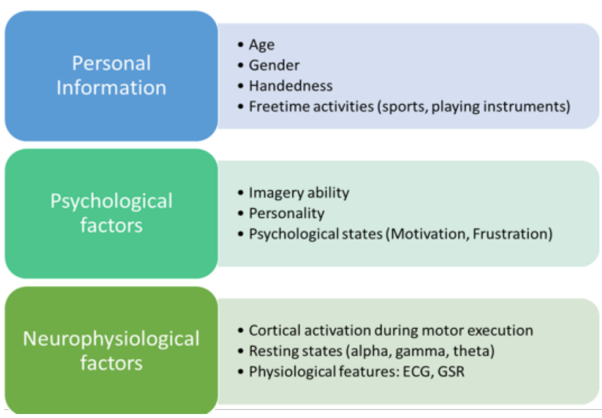

Fig. 3. Modulators of User-BCI compatibility in MI-BCI

age and gender have already been identified to have an impact on driving BCIs or even on the ability to perform a motor imagery task. In a recent study [20], we investigated how handedness impacts brain activity in motor-related areas and found significant differences in brain activity between left- and right-handed participants during MI. In psychological factors, attention, memory load, fatigue, and competing cognitive processes [21][22] [23][24]]influence instantaneous brain dynamics. In addition, states like empathy might influence BCI performance as shown by [15]. Motivation is also related to P300-BCI performance [3]. Hammer et al. [25] for example found that abilities in visuo-motor coordination and the ability to concentrate on a task were correlated with BCI performance. Others [26] reported on the correlation between motor imagery ability (measured by questionnaires) and following BCI performance. Psychological information will be collected through different questionnaires. For example, to evaluate the imagery ability of persons the "Vividness of Movement Imagery Questionnaire (VMIQ-2)" will be used. Personality factors will be retrieved by "B5T Big Five personality test" and with the "STADI", anxiety and depression can be recorded both as a state and as a trait. Furthermore, the "Intrinsic Motivation Inventory (IMI)" assesses participants' interest/enjoyment, perceived competence, effort, value/usefulness, felt pressure and tension, and perceived choice while performing a given activity, thus yielding six subscale scores. The Perceived Stress Scale (PSS) will be used for measuring the perception of stress. It is a measure of the degree to which situations in one's life are appraised as stressful. In neurophysiological factors, physiological predictors such as spectral entropy and power spectral density, derived from resting state EEG recordings are correlated with BCI performance [27][28][29][30]. In addition, the baselines of resting state networks (RSNs) are dynamic and modify any cortical signature instantaneously [31]. An efficient BCI system must be robust to such inherent physiological fluctuations over time to enable more generalized systems [32]. Ahn et al. [13] for example reported that high theta and low alpha is the pattern for BCI-illiteracy and that frontal gamma correlated with BCI performance. Another important neurophysiological predictor for a participant's performance in operating an MI-based BCI was developed by [10]. They found that the alpha rhythm shows a positive correlation with online BCI performance. This so-called Blankertz SMR-predictor is currently one of the most replicated and reliable neurophysiological predictors of MI-BCI performance. Furthermore, Halder et al. [33] observed a correlation between structural integrity and myelination quality of deep white matter structures and BCI performance. We will integrate the execution task to compare related ERDS patterns with those of MI as a further possible predictor from neurophysiology based on EEG.

B. Model and training objective

A data-driven exploration of individual information and physiological data will be carried out with the help of sequential processing deep learning methods. We will use neural network model which are designed to process sequential data such as time series, natural language etc. Different variants of the deep neural network will be considered in the study. These architectures can learn from input data and predict values for the future steps. We will train these models to predict performance scores of a participant of MI tasks from the modulators and performance scores of previous tasks. The effects of motor imagery training can be maximized by personalized experimental designs based on the outcome of the NN model. For example, designing individual schedules, choosing adequate task complexity, instructions, and, in clinical populations, adapting the models for individual impairment.

IV. Conclusion and Future Work

In this work, we introduced a novel theoretical framework for addressing MI based BCI user training problems by pre-

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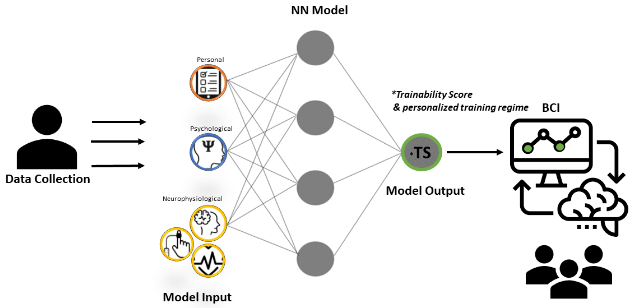

Fig. 4. Flowchart of personalized model for MI-BCI training

dicting the possibility of incompatibility and then pre-deciding the intensity of training paradigm for users. The framework will be a neural network-based architecture and considers demographics, neurophysiological, psychological factors of the user as input to decide a personalized training regime for the user. In the course of execution of this work, we will cover a large sample size with varying age, gender, cognitive ability, handedness and physiological activation. The data collected during the implementation phase will be made available in an open-source platform. Moreover, in future, this endeavor might lay the groundwork for crafting a personalized training paradigm that is both efficient in time utilization and does not compromise user performance.

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