The Intersection of EEG Technology and Brain-Computer Interfaces in Medicine: A Review

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Abstract: Brain-computer interfaces (BCIs) that read electroencephalography (EEG) give people a way to control external devices with brain activity alone and without surgery. Over the past two decades the most active medical use of this idea has been stroke rehabilitation, where a BCI can reward a patient for imagining or attempting a movement that the paralysed limb cannot yet perform. This paper reviews the field with that application in mind. We describe how an EEG-based BCI is built, from signal acquisition and artifact removal to feature extraction and classification, and we compare the three training approaches used most often after stroke: motor imagery, movement attempt and sensorimotor-rhythm neurofeedback. We then summarise other clinical uses, including communication for people who are locked in, detection of awareness in disorders of consciousness, and EEG- based seizure detection. Controlled studies and meta-analyses suggest that BCI-assisted therapy can improve upper-limb function, but the trials are small and the benefit differs a great deal from one person to the next. we conclude with the practical hurdles to clinical implementation and the pathways that appear most promising: hybrid systems, adaptive decoders and home training.

Keyword: Brain-computer interface, electroencephalography, stroke rehabilitation, motor imagery, neuroplasticity, neurofeedback, assistive technology

I. INTRODUCTION

1.1 Evolution of Brain Computer Interfaces

The human brain consists of about 86 billion neurons [1], and all a person does – from picking up a glass to formulating a sentence – can be expressed in terms of neural electrical activities. BCI is an attempt to detect some of those activities in order to translate them into commands. The most popular definition of BCI was suggested by Wolpaw et al., according to which a BCI represents a communication or control channel independent of the brain's default means of conveying its signals through peripheral nerves and muscles [2]. This difference for the one whose nerves and muscles are damaged makes a BCI a very different kind of device when compared to a keyboard or a joystick.

An electroencephalography (EEG) is the most popular technique for detecting a BCI signal. The activity of large populations of cortical neurons is registered using electrodes that are placed on the skull, and the technique features millisecond temporal resolution. The technology of EEG monitoring, the hospital staff's experience and the track record of the technique are well known since hospitals have been employing EEGs for decades in order to monitor seizures and people's sleep states. In addition, an EEG technique is cheap and mobile when compared to most other brain imaging techniques.

However, stroke serves as the best example of this issue. According to the Global Burden of Disease study conducted in 2019, there were more than 12 million first-time strokes globally, while stroke is among the leading causes of permanent disability [3]. Patients often experience a loss of control over one hand and arm. While conventional rehabilitation requires extensive repetition of purposeful movements, a person that cannot move his/her hand will not be able to do any repetitions. Brain-computer interfaces could provide an alternative solution for this problem as they enable the recording of brain activity when the patient is trying to make a movement with the paralyzed arm, which allows producing a certain response in form of a visual or tactile stimulus, such as opening and closing of a robotic hand orthosis. Such approach with a help of "brain intention + feedback" is assumed to be promoting brain rewiring [4].

The present literature review starts with an introduction of the EEG-BCI technology and its current place within the spectrum of brain activity monitoring technologies. Signal processing approach is discussed along with the comparison between the existing post-stroke training protocols and the results achieved via placebo-controlled trials. The other clinical applications of the technology are briefly reviewed before moving on to the numerous limitations and research directions.

1.2 EEG AND BCI LOOP

For any application, the BCI uses a similar sequence of steps represented in a loop shown in Fig. 1. The user executes a mental strategy (such as imagining moving one’s hand). The computer captures and analyzes the brain activity and determines the intent of the user and generates output accordingly. The importance of this step is that it helps the user evaluate their mental strategy

through feedback from the output generated. Such a closed-loop design is essential for a BCI to become an interface rather than just a brain decoder.

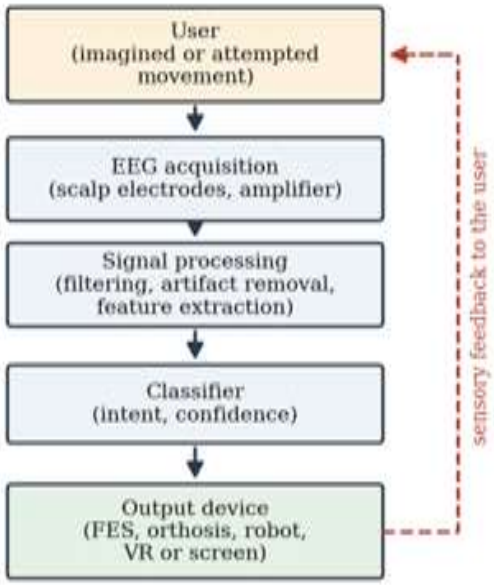


Fig. 1. The closed loop of an EEG-based BCI. Feedback from the output device lets the user adapt their mental strategy.

A. Methods of recording and their pros and cons

Recording of brain activity can be performed using different degrees of invasiveness, and selection of degree depends on the trade-off between quality of signal and danger for the patient (Figure 2). The EEG, magnetoencephalography (MEG) and functional near-infrared spectroscopy (fNIRS) are non-invasive. Even though the EEG provides signal with high temporal resolution, its spatial resolution is relatively poor because the skull and scalp distort the electrical field and allow to determine sources only within a few centimeters [5], while MEG requires magnetically shielded room, and is not applicable in routine therapy. In case of fNIRS, several seconds are needed to see changes in blood oxygenation due to neural activity [6].

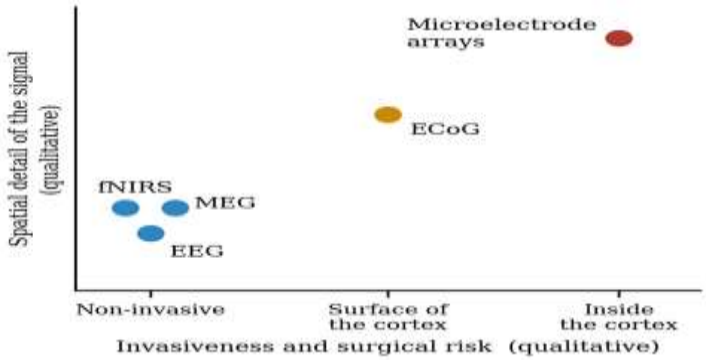


Fig. 2. Schematic comparison of recording methods. Positions are qualitative and meant only to show the general trend, not measured values.

Electrocorticography (ECoG) is the next step, with the electrodes being placed on the brain surface underneath the skull. The information gained by this technique is richer and more precise, but it involves a neurosurgical procedure. Even further, the microelectrode arrays are able to monitor single neuron activity. These techniques enabled patients with tetraplegia to operate a robotic arm [7] and very recently, even to interpret attempted speech from a paralytic patient at 60 words per minute [8]. These achievements are certainly far ahead of any current scalp EEG techniques, but they involve both risks and costs, and in the case of a rehabilitation process, when the patient might use the technology repeatedly for several weeks, safety and costs play the decisive role.

B. Control signals

As a rule, EEGs for BCI systems do not cover a wide range of information due to the fact that they involve a small set of signals known to scientists. The most famous BCI speller system [9] utilized P300 event-related potential (an approximately 300-msec

peak occurring after some rare or attended event) as its main signal. Steady-state visual-evoked potentials (SSVEP) can be considered a stimulus-based method. These techniques fit better for spelling tasks but what if we consider BCIs that would be useful for rehabilitation? We will require an increase in sensorimotor wave power. When the movement itself, preparation of the body to make a movement, or even planning of the movement occurs, the mu rhythm (approximately 8-12 Hz) and beta rhythms (13-30 Hz) of the motor cortex weaken. The process is called the event-related desynchronization (ERD) whereas the following increasing of power is called event-related synchronization (ERS) [10]. As a matter of fact, the phenomena is lateralized and, therefore, thinking about the movement of the left hand produces different scalp topography than thinking about the right one [11].

1.3. SIGNAL PROCESSING CHAIN

The methodologies described in this section are the ones most frequently employed within the literature on motor BCI systems. Such methodologies are standard tools but not standard configuration and are varied by the different studies.

A. Acquisition

Placement of electrodes happens with the use of the 10-20 electrode placement system. As concerns motor activity, the optimal place for placement are sensorimotor areas C3 C4 and Cz, and several electrode arrangements exist with the inclusion of adjacent channels so that some data can be filtered in space. Wet electrodes with the use of the gel are most suitable for achieving good contact although they take more time for placement and create more noise than dry electrodes. Inexpensive, compact research setups are made possible thanks to the appearance of cheap hardware; however, decoding of information depends on the quality of amplifiers and of the contact between electrodes; surface EMG from the forearm is sometimes used in BCI setups for furtive movement detection.

B. Preprocessing and artifact removal

EEG recorded on the scalp is microvolts in magnitude, and it is always contaminated with unwanted signals. We can simplify these contaminations to give $x(t) = s(t) + n(t)$, where $s(t)$ is the particular brain activity we are after, and $n(t)$ is everything else: eye blinks and eye movements, muscle activity, cable movement, 50 or 60 Hz mains powered signal. A band-pass filter (generally around 1 Hz to 40 Hz) gets rid of slow drift and high frequency muscle activity, and a notch filter is often used to get rid of the mains frequency.

The filter output signal is $y(t) = x(t) * h(t)$.

Eye blinks and movement occur at the frequency of the signal under measurement and cannot simply be filtered out without corrupting the brain signal. The usual solution: independent component analysis (ICA) separates the recording into statistically independent elements so that those for eye or heart activity are identified and discarded [12]. Artifact subspace reconstruction (ASR) is a more automated approach, which identifies transient high-variance bursts and replaces them with good reference activity; a technique promising for home and real-time applications [13].

C. Feature extraction

The signal then undergoes transformation in terms of a few numerical values that indicate the state of the user. When we talk about sensorimotor BCIs, the most common way of quantification is the estimation of band power in the mu and beta bands, using a brief interval in time. After the N samples of a band-pass filtered x[n], P will be,

$P = (1/N)\ x[n]$ (1)

and the ERD% value can be calculated based on the rest baseline R using the expression ERD% = (A R)/R 100. Here an denotes the power during the task [10]. One of the well-known ways of spatial analysis is known as common spatial patterns (CSP). Using CSP we can extract a linear combination of the channels that maximizes the variance of the signals in one of the classes while minimizing the same for the other class [14], [15].

D. Classification

The classification component that translates features to the desired movement. Linear discriminant analysis (LDA) remains a common classifier choice in system development due to its cost-effectiveness simplicity, ease of training even from small amounts of data, and capacity for delivering high accuracy in short calibration sessions. Other approaches include comparison to the support vector machines, Riemannian-geometry-based algorithms, and recently, to deep networks [16]. For instance, the EEGNet convolutional neural network extracts relevant features on its own and could be applied in different BCI architectures [17]. A sufficiently large dataset could allow a deep network approach to outperform the classical approaches, but such data is not always available.

For a therapeutic system, an output of the classifier and a confidence measure is usually presented, and only when this value passes a certain threshold the actuator takes action. This prevents incorrect triggering, as it could be counterproductive, since the misleading feedback would confuse a patient and break the entire training system altogether. The typical percentage threshold for

binary classification control systems is roughly 70% accuracy, below which the communication becomes frustrating [18], but in therapy it could be important to minimize the feedback delay relative to the event being reflected.

1.4. BCI TRAINING PROTOCOLS AFTER STROKE

A. Rationale

Overall, the stroke-affected hemisphere generates fewer sensorimotor rhythms when attempting to move the affected hand. The theoretical basis behind the use of a BCI lies in its capacity to provide an association between the patient's motor commands with a sensor feedback at the moment of their manifestation, for example, by actuating a robotic orthosis or a functional electrical stimulation system at the moment of manifestation of ipsilesional ERD. This coupling of the output signal and input signal is supposed to enhance the pathway due to the Hebbian type of plasticity [4], [19]. This is a theoretical notion without empirical basis, which the results presented below could confirm. There are three main protocols considered.

B. Motor imagery BCIs

Motor Imagery Brain-Computer Interfaces (MI-BCIs): the user imagines an action, for example, hand opening, without doing the action. Neural networks used in the imaging tasks coincide with the neural networks used in motor actions and generate mu and beta ERD over the scalp EEG. The user gets feedback using an image of a hand on a screen or a bar and a mobile device. Randomized trials conducted among subacute stroke patients showed that MI-BCI training together with regular rehabilitation was more effective for the recovery of the upper limb and brain connectivity [20].

The most important advantage of MI-BCIs is that they can be started regardless of any motor capacity of a patient. However, one of the major drawbacks is that motor imagery is a trained technique. There are people who cannot perform such task, and it depends on various factors such as cognitive abilities, neural state, and feedback method of MI [21]. A considerable number of users, often mentioned as 15–30% of them, cannot perform motor imagery tasks.

C. Movement-attempt BCIs

MA-BCIs tell the patient to make the utmost effort to move the paralyzed limb irrespective of whether the limb actually moves or not. This approach is predicated upon the notion that a real attempt at moving would stimulate the motor system in a more natural way than imaginary movement and the device would provide the movements that the patient fails to generate. Through a well-designed experiment conducted on stroke patients with chronic hand paralysis, Ramos-Murguialday et al. demonstrated that training using MA-BCI feedback along with physical therapy yielded better results in terms of Fugl-Meyer score than sham-feedback training [22].A preliminary study had suggested that chronic patients who had no finger movement could acquire the ability to control sensorimotor rhythms to open and close an orthosis [23].

D. Sensorimotor-rhythm neurofeedback

Another type of neurofeedback is the sensorimotor rhythm (SMR). In place of a specific motor task, the patient is shown his/her own mu and beta activity levels and learns how to regulate them through self-regulation training. The SMR technique of neurofeedback is widely used beyond stroke [24] despite the fact that the differences between it and imagery and attempt are somewhat unclear as the protocols for both measure the same types of brain activity in the same brain areas; the only difference is in instructions to the patient.

E. What the evidence shows

In the framework of the meta-analysis of randomized and controlled studies regarding the impact of the BCI training on stroke patients, positive effects were reported on the upper limb motor function post-stroke for both subacute and chronic stroke patients using BCI in combination with FES and robotic devices [25]. The following review reached similar conclusions regarding the overall impact of the technology, but it discussed other applications of the BCI as well [26]. However, in both reviews, small sample sizes and significant differences in protocols, devices and outcomes measurements have been reported.

The most commonly used instrument is the Fugl-Meyer Assessment (FMA) for the upper extremities [27], which can take from 0 to 66 points on the motor impairment scale. In order to understand the reported results, one should keep in mind that the minimal clinically important difference of FMA score for the chronic stroke is approximately 4-7 points [28], and therefore the statistically significant effect is not necessarily clinically significant. Moreover, the benefit of the BCI training in addition to the physical therapy, which is applied in parallel to the BCI training, has remained controversial due to the design of most studies.

1.5. OTHER MEDICAL APPLICATIONS

A. Communication

The first practical use of BCI technology was in the hope of making spoken language available to people who could not speak or move. It was demonstrated by Farwell and Donchin that selection of a letter using a P300 spelling system does not require any muscle movement [9], and by Birbaumer et al. that paralyzed individuals can learn how to spell with the help of slow cortical

potentials [29]. Contemporary P300 or SSVEP EEG spellers may be very slow (up to a few characters per minute up to a few tens), and they need sustained concentration from the users; however, they are valuable for patients with late stages of amyotrophic lateral sclerosis or locked-in syndrome where it may be the only possible way of communication [30]. The mentioned invasive systems are far more efficient, although still experimental [8].

B. Disorders of consciousness

There are some patients who have an unconscious state caused by serious brain damage; however, some of them are actually conscious although they do not display any evidence of that. For example, according to Cruse et al., in a group of patients with a diagnosis of vegetative state, the researchers asked them to imagine the movement of their hands and toes while their EEG readings were taken, and some of them had the expected reaction [31].

C. Diagnosis and monitoring

Various machine learning algorithms are being developed to analyze EEG data for diagnostic purposes such as epilepsy seizure detection. While this is clearly connected with the field of BCI research and uses many of the same techniques, it cannot be considered BCI research since there is no output device being controlled by the algorithm. Deep learning techniques have shown great success in many tasks involving the classification of EEG data; however, they have proven to be less accurate when using a pre-trained model on one group of patients with a new group of patients [32].

II. CHALLENGES AND LIMITATIONS

There are several barriers that stand between lab results and practical application in clinical practice. First, it is the problem of variability. Signals from EEGs differ among individuals, change over different days, and also change depending on whether users get tired or distracted during the course of the experiment [21]. Thus, non-stationarity in such cases will mean that classifiers trained in the morning will become useless in the afternoon and some users will not be able to control the system at all.

The next barrier is the problem of practicality. Using gel-based electrodes takes much time, calibration sessions might require much energy which might be useful for therapy instead, as well as trained personnel to operate the device. For home usage, the device should be easy enough to apply by the user or caregiver and should include artifact handling and signal quality detection tools.

Next comes the problem of quality of evidence. Trials are too small, too heterogeneous in terms of participants or protocols, and sham controls are hard to come up with because the patient knows if he or she really has the control over the feedback or not. Long-term follow-up is rare and although there are evidences of the positive effect at the beginning, it is unknown how long it lasts. Besides, there is lack of data on cost-effectiveness. The last but definitely not the least barrier is the issue of vulnerability of the medium. The data on the brain are very private and could reveal much more than what has been actually entered into it, creating serious problems of consent and storage as BCIs go out of labs [33].

III. FUTURE DIRECTIONS

Hybrid BCI systems employ more than one source of information, say, two different forms of brain waves or EEG and EMG, in order to increase robustness in case information is not sufficient from one particular channel [34]. An example of such an approach was using ERD and SSVEP in conjunction to obtain two-dimensional control of the cursor [35]. A second possible development area is the design of better decoders. Adaptive decoding algorithms, which have the ability to learn while working, transfer learning that uses the information about previous patients to save time on calibration and smaller-scale neural network systems all seek to come nearer to the very much needed decoders that are easy to configure and robust enough to cope with the variability mentioned above [16], [17]. The third improvement possible in terms of hardware: dry electrodes, lights and wireless headsets along with tele-rehabilitation platforms will allow patients to exercise at home, controlled by their therapist remotely.

IV. CONCLUSION

It was decades later, however, before EEG BCIs became testable in a clinical setting and stroke rehabilitation is where most of the results are now emerging. The principle of motor imagery training, attempts at movement and sensorimotor rhythm training is identical to what is seen in the laboratory: the brain activity needs to be coupled with the appropriate feedback, and in controlled experiments, it can be useful to certain patients in improving their upper limb functions. There is little evidence thus far, but: the trials have been small, the outcomes can vary depending on the patient and there has been no conclusive evidence about the extent of the BCI's contribution to the outcome. It will all depend on developing user-friendly devices, adaptive decoders and accurate reporting of the trials. In such a scenario, BCIs could well become a regular part of rehabilitation and speech therapy.

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