Motor Imagery for Brain-Computer Interfaces: A Review

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***Abstract*—Electroencephalogram-based motor imagery (MI) classification is an important paradigm of non-invasive brain-computer interface (BCI). Among various BCI paradigms, MI has gained significant attention due to its non-invasive nature and potential applications in assistive technology, rehabilitation, and human-computer interaction. This paper provides a comprehensive review of the motor imagery paradigm in BCIs, focusing on its principles, methodologies, and practical applications. We begin by discussing the neural basis of motor imagery and the typical EEG patterns associated with it, such as event-related desynchronization (ERD) and synchronization (ERS). The review then delves into the different experimental setups and signal processing techniques used to detect and classify motor imagery signals, including spatial filtering, feature extraction, and machine learning algorithms. We also examine the challenges and limitations of current MI-based BCIs, such as individual variability, signal noise, and user training requirements. Furthermore, we highlight recent advancements in the field, including hybrid BCI systems, real-time feedback mechanisms, and novel applications in neurorehabilitation and assistive devices. Finally, we discuss future directions and potential research avenues that could enhance the robustness and usability of motor imagery-based BCIs, making them more accessible and effective for a wide range of users.**

***Index Terms*—Ensemble learning, fuzzy system, patch learning, regression**

I. A BRIEF REVIEW OF EEG-BASED BCI SYSTEMS

A brain-computer interface (BCI) establishes a direct communication pathway that enables the human brain to interact with external devices [1]. Electroencephalogram (EEG), which records the electrical activities on the scalp of the brain, is the most widely used input signal in non-invasive BCIs due to its affordability and convenience [2].

A closed-loop EEG-based BCI system, shown in Fig. 1, consists of the following components [3]:

1) *Signal acquisition* [4], which uses an EEG device to collect EEG signals from the scalp. In the early days, EEG devices used wired connections and gel to increase conductivity. Currently, wireless connections and dry electrodes are becoming increasingly popular.
2) *Signal processing* [5], which usually includes temporal filtering and spatial filtering. The former typically uses a bandpass filter to reduce interference and noise, such as muscle artifacts, eye blinks, and DC drift. The latter combines different EEG channels to increase the signal-to-noise ratio. Popular spatial filters include common spatial patterns (CSPs) [6], independent component analysis (ICA) [7], blind source separation [8], xDAWN [9], etc.
3) *Feature extraction*, for which time domain, frequency domain [10], time-frequency domain, Riemannian space [11], and/or functional brain connectivity [12] features could be used.
4) *Pattern recognition*, where depending on the application, a classifier or regression model is used.
5) *Controller*, which outputs a command to control an external device, e.g., a wheelchair or a drone, or to alter the behavior of an environment, e.g., the difficulty level of a video game. A controller may not be needed in certain applications, e.g., BCI spellers.

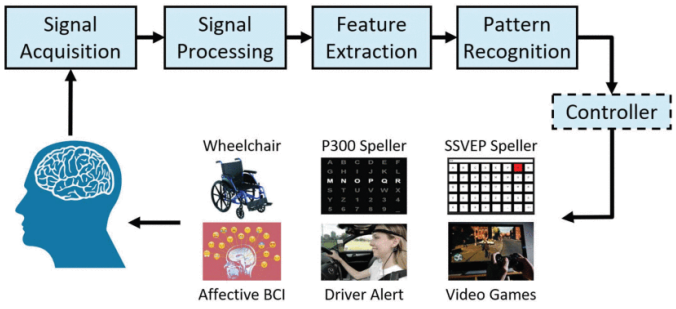

Fig. 1. Flowchart of a closed-loop EEG-based BCI system.

II. NEUROPHYSIOLOGICAL BASIS OF MOTOR IMAGERY

Motor imagery can be seen as mental rehearsal of a motor act without any overt motor output. This type of phenomenal experience imply that the subject feels himself performing a given action. It corresponds to the so-called internal imagery (or first person perspective) of sport psychologists [13]. Motor imagery may be experienced in two ways, or perspectives. The first person perspective which is supposed to rely on motor-kinesthetic information processing, and the third person perspective which would rely more on visuospatial processing. To my knowledge, no neurophysiological or neuroimaging studies concerned with this distinction has been reported. However, a few experiments in cognitive psychology have suggested the relevance to consider the distinction between visual and kinesthetic imagery [14].

Converging evidence from several sources indicates that mental imagination of movements involves similar brain regions/functions which are involved in programming and preparing such movements [15]. According to this view, the

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main difference between performance and imagery is that in the latter case execution would be blocked at some cortico-spinal level [16].

Functional brain imaging studies monitoring changes in regional cerebral blood flow (rCBF) revealed indeed similar patterns of activity during motor imagery and actual movement performance. An increase of the rCBF has mainly been located in the supplementary motor area during imagination of sequential finger movements [17]. Moreover, recent positron emission tomography (PET) [16] and functional magnetic resonance imaging (fMRI) studies [18] revealed activation of a number of cortical and subcortical areas, including, e.g., the premotor cortex, the anterior cingulate gyrus, superior and inferior parietal areas, and the cerebellum. Thus, activation has been observed in various structures involved in the early stage of motor control (i.e., motor programming), but not in the primary sensorimotor cortex. More recent fMRI studies, in contrast, detected some activation in the primary motor cortex during motor imagery, though to a lesser extent than during actual motor performance [19]. Increased motor cortex activation during motor imagery has been supported by studies using transcranial magnetic stimulation in showing an increase of motor responses during mental imagination of movements [20].

Several EEG studies further confirm the notion that motor imagery can activate primary sensorimotor areas [21]. It induces changes in the sensory-motor rhythms (SMR) of corresponding areas of the cerebral cortex, which primarily involve modulations of the μ rhythm (8-12 Hz) and the β rhythm (14-30 Hz) [15]. Specifically, when an MI starts, these rhythmic activities decrease, resulting in event-related desynchronization (ERD); at the end of an MI, these rhythmic activities increase, resulting in event-related synchronization (ERS) [22].

A blocking of the central mu rhythm with motor imagery was reported in early clinical EEG observations [23]. Similar cortical activity over the contralateral hand area during execution and imagination of hand movement has further been found with dc potential measurements [21] and based on dipole source analysis of electric and magnetic fields [24]. Furthermore, high-resolution EEG experiments [25] showed that independent of the required motor task, imagination versus overt execution of a given movement, the most prominent EEG changes were localized over the corresponding primary sensorimotor cortex. During the imagination of a right-hand or left-hand movement, for example, a similar event-related desynchronization (ERD) over the contralateral hand area as is usually found during planning or preparation of a real movement is found. This imagination-related ERD shows different time courses in the alpha and beta bands (Fig. 2, upper panel). Similar to the self-paced movement task, the ERD in the beta band shows a fast recovery and is followed by a short-lasting event-related synchronization (ERS). Examples for the localization of beta ERS mapped on the reconstructed cortical surface of one representative subject (Fig. 2, lower panel) illustrate a focus close to the primary hand area after both a real executed and an imagined right-hand movement. This observation is in line with recent neuromagnetic studies suggesting that the central 20-Hz activity mainly originates in the primary sensorimotor cortex [26] and, moreover, documents the supposed similarity of neural circuitry involved in mental representation and movement execution.

It is of interest, that during overt execution of the movement, the initially contralateral ERD develops a bilateral distribution [27], whereas during mental simulation this ERD remains mostly limited to the contralateral hemisphere. This means that the suppression of mu and central beta rhythms is more pronounced at the contralateral hemisphere when subjects imagine one-sided hand movements [25] than when they actually perform such movements. This observation led us to utilize motor imagery as control strategy to achieve asymmetrical electrocortical responses and to use, e.g., left-right differences in the sensorimotor EEG to provide a control option in one dimension [28]. Besides this, MI also applies to different parts of the body such as the movement of the left hand, right hand, tongue [29], left foot, right foot movement [30], wrist movement (flexion, extension, pronation, and supination) [31], elbow flexion/extension, forearm pronation/supination, hand open/close [32], and finger movements [33].

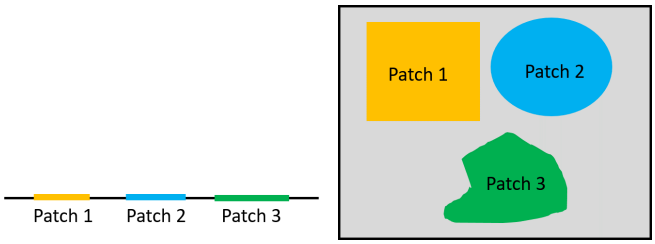

Fig. 2. Patches in 1D and 2D input domains.

III. Experimental Paradigm

To effectively decode EEG signals of MI, BCI research typically employs a variety of experimental setups designed to simulate and record the MI process. Below is a typical setup for an MI-based BCI experiment.

In the standard paradigm, the experimental task is to imagine either right-hand or left-hand movement depending on a visually presented cue stimulus. The subject fixates on a computer monitor 150 cm in front of her/him. Each trial is 8s long and starts with the presentation of a fixation cross at the center of the monitor, followed by a short warning tone (beep) at 2000 ms. At 3000 ms, the fixation cross is overlaid with an arrow at the center of the monitor for 1250 ms, pointing either to the left or to the right (Fig. 3, upper part). Depending on the direction of the arrow, the subject is instructed to imagine, e.g., a movement of the left or the right hand.

Two different types of feedback are used: 1. discrete delayed feedback and 2. continuous feedback. Discrete feedback consists of a symbol presented in the center of the monitor at 6000 ms: the type of symbol (large or small "+" or "-" or "0") depends on how well a subject-specific classifier can distinguish the two EEG patterns related to left versus right motor imagery in a fixed time window from 3250 to 4250 ms. In the case of continuous feedback, the imagination task is

controlled by means of a horizontal feedback bar. Depending on the cue stimulus, the subject's task is to extent a bar toward the right or left boundary of the monitor by mental imagination of moving the right or left hand, respectively. The bar appears at time 4250 ms and is presented over a 4-s period (Fig. 3, lower part). The length of the bar directly corresponds to the linear distance function obtained by online analysis of the EEG signals [28]. Normally, each session consists of four experimental runs of 40 trials (20 "left" and 20 "right" trials) and lasts for about 1 h. The sequence of "left" and "right" trials, as well as the duration of the breaks between consecutive trials (ranging between 500 and 2500 ms), is randomized throughout each experimental run.

IV. Data Acquisition

A. EEG recordings

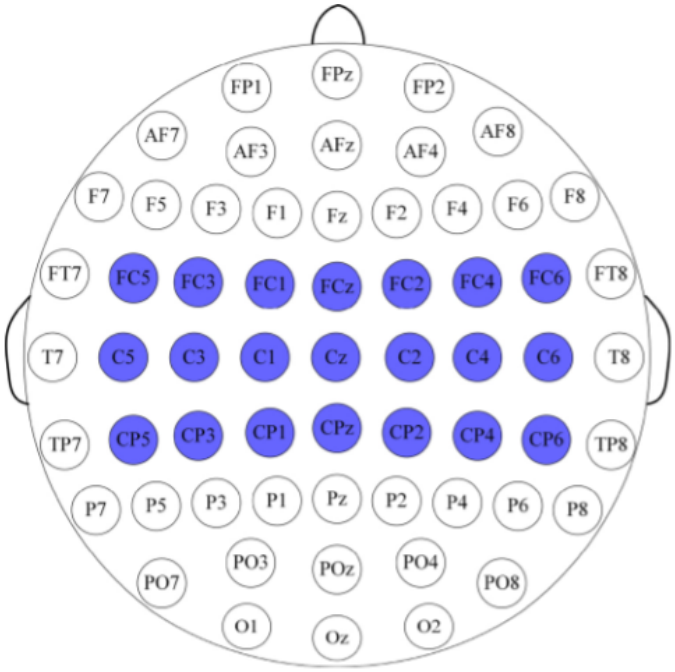

Fig. 3. EEG electrodes placement according to the 10-20 system. The related motor imagery electrodes are identified in blue color.

EEG captures physiological activities of the body by recording electrical signals which are the produced postsynaptic potentials by cortical neurons [34]. The electrical signals are recorded via conducting electrodes that are placed on the scalp according to the well-known 10-20 international placement system as stated in Fig. 3, motor imagery related electrodes are identified in blue color [35]. Each electrode records a one-dimensional vector of raw EEG data. The signals are obtained on the three-dimensional scalp surface through volume conduction across multiple brain tissue [34]. Hence, EEG signals are prone to artifacts originating from different parts of the body like the eye, head, neck, or any other muscle. Moreover, the power cable of the recording device and electrode displacement might both cause some artifacts. This form of recording EEG produces weak, non-stationary, and low signal-to-noise ratio signals. Consequently, it complicates the classification and interpretation of signals belonging to a particular case of consideration.

Despite the inherent drawbacks in raw EEG, it has some advantages over other neurological imaging techniques. It characterized by low cost, portability, and causes no side effects because of its non-invasive style [29]. Thus, EEG has a variety of applications whether as a screening method or for hypothesis-based diagnostics. Depending on the shape of waves, e.g. rapid spikes waves or slow waves, several forms of brain disorders can be assessed, such as epilepsy [36], tumors [36], Alzheimer [37], sleep disorder [38], etc.

Basically, the amplitude and frequency values in EEG signals are used for discriminating various physiological activities. The amplitude is normally fluctuating in microvolts. The frequency range in EEG signals can be split into several bands as shown in Table 1 [39]. The most popular motor imagery frequency bands are also stated in the table. It should be noted that when the Alpha band is recorded from the sensorimotor cortex then it is called mu band. The Gamma band can be recorded consistently using internal electrodes in order to better capture it as it is being weak at the scalp [40]. Slightly different frequency bands or ranges may be found in the literature.

EEG signals are complex in their nature and there exists acute dependency of signal quality on the mental state of the user. Studies proved that the classification accuracy of an intelligent system for a certain task was better at the beginning of the trial than the accuracy at the end of that trial [40]. Therefore, recording or selecting an EEG dataset is crucial for training, validating, and testing machine learning models.

B. Acquisition Process

1) *Preparation*. Ambient electrical noise can significantly interfere with EEG recordings. When setting up a laboratory, and periodically throughout the course of data collection, it is advisable to check noise levels using a handheld gauss meter sensitive to the electrical noise frequency range emitted by power lines, computers, and other electrical appliances. In China, this frequency range is typically 50 Hz, while in the USA, it can be 60 Hz.

   Ensure that the laboratory environment is quiet and free from electromagnetic interference. One effective method for reducing the influence of electrical noise is to collect EEG data in an electrically shielded room or chamber. If such a facility is not available, and a gauss meter indicates the presence of electrical noise, relocating the offending equipment a short distance away from the electrodes and electrode wires can often mitigate the impact of noise on recordings.

   When the study participant arrives at the lab, make them feel comfortable, explain the experiment in detail, and ensure they understand all aspects of it. Have the subject sign the consent form and adjust the stimulation setup to their comfort (e.g., chair height, screen distance, or sound levels) to minimize movement and muscle tension, thereby avoiding interference with the EEG signals.

2) *Adjusting the Equipment*. Select the correct cap size by measuring the participant's head circumference in centimeters (hat size) around the widest point on the head using a flexible tape measure. Cap sizes typically range from 52 to 60 cm in increments of 2 cm. Most labs have 54, 56, 58, and 60 cm sizes as part of a standard EEG setup. If the measurement falls between sizes, try the next larger size. The cap should fit snugly. Ensuring a proper fit is crucial, as a cap that is too large may reduce the quality of EEG recordings or make electrode preparation and impedance reduction more challenging. To check the fit, ask the participant to nod their head up and down and turn it side to side. If the cap shifts, it is too big, and a smaller size should be used. Additionally, when the cap is on the participant's head, gently press down on one of the electrode adaptors towards the scalp. If the adaptor bounces back, there may be too much space between the adaptor and the scalp, indicating that a smaller cap size should be tried. Once the correct cap size is determined, remove the cap from the head and snap in the electrodes.
Plug the electrodes into the EEG amplifier at the appropriate locations. Consult the EEG acquisition software materials for instructions on how to designate channels. Depending on the setup and equipment, it may be necessary to label the channels on the amplifier (e.g., Ground, FP1, CZ, REOG, LEOG).
Before placing the cap on the participant's head, roughly measure the distance between the participant's nasion (bridge of the nose) and inion (bump on the lower base of the skull: to find the inion, place your hand in the middle of the neck and slide upwards) using your hands. The FPz electrode should be placed about 10% of this distance above the nasion in the middle of the forehead. Place the front of the cap on the participant's forehead with FPz in this position, ask the participant to hold the cap in place, and then pull the cap over the head. Next, adjust the position of the CZ electrode so it lies halfway between the nasion and the inion.
Minimize the impedance of the electrical connection between the electrode and the scalp by applying abrasive electrolyte gel. Specifically, fill syringes with abrasive electrolyte gel, and then fill the electrodes with gel using those syringes (ensure the plastic tip of the syringe touches the scalp). Gently scrub the scalp through the electrode opening by twirling the cotton end of the cotton swab between your thumb and index finger.
3) *Begin Data Collection*. Open the EEG acquisition software and load the experiment file. Observe the resting activity of all the electrodes, and ensure there are no "bad" channels; that is, electrodes that produce flat line signals or show excessive activity while the participant is resting. If any bad channels are suspected, it may be necessary to apply more electrode gel and scrub to minimize impedance or replace the electrode. Instruct the participant to avoid blinking and tensing muscles in their forehead or jaw, as these actions can introduce noise into the EEG data.
Once all the electrode signals appear acceptable, begin recording and start the experiment file. If collecting data for an MI experiment or other design where the timing of stimulus presentation is crucial for signal processing, carefully observe the first few trials to ensure that the stimulus presentation software is sending "trigger" markers for stimulus presentation. If timing markers are not being sent, the data cannot be processed using stimulus presentation as a reference point, which is essential for MI designs.

ACKNOWLEDGEMENT

This research was supported by the National Natural Science Foundation of China Grant 61873321.

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